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U.PORTO
FACULDADE DE CIÊNCIAS
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Dark side of e-commerce: tracking illegal trade of pangolin species on social media

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Todas as correções determinadas
pelo júri, e só essas, foram efetuadas.
O Presidente do Júri,
Porto, ______/______/_________

Abstract

Over-exploitation and wildlife trafficking are one of the main drivers of global loss of biodiversity. Wildlife commerce feeds a vast industry, through which thousands of animal and plant species, as well as their associated products are commercialized for many purposes, including furs, leathers, pets, medicine, food and hunting trophies. The increase of unregulated or illegal wildlife commerce has become a major conservation challenge, leading to unsustainable wildlife management and to the threatening of already endangered wild species.

Monitoring wildlife trade, and particularly the commerce of illegally traded products, is quite difficult due to the mass amount of existing information and its clandestine nature. With recent technological advancements, e-commerce and social medial platforms have become an important source for sharing information among interested customers and for selling illegal species of wild flora and fauna. Consequently, animal e-commerce, either legal or illegal, has grown exponentially on social media networks due to their ease of use and access by an increasing number of users. Through social media, wildlife dealers can post pictures and information about the available products, thus attracting new clients and selling their merchandize through networks of clients crafted through word of mouth and easily found products. Tracking the illicit traffic of species on social media is, therefore, a pressing matter.

Machine learning offers many new opportunities in this regard, helping with the development of tools that more quickly and efficiently help with the analysis of large amounts of data extracted from social media websites to monitor wildlife transactions. Specifically, the advancement of machine learning models and algorithms have brought complementary insights to detecting the presence of a species in question among the data pulled from social media networks, by automatically examining images, texts and videos shared online.

The goal of this thesis is twofold. First, it intends to evaluate the state of the art of mammal trade in the scientific literature, particularly, it aims to: (1) understand which are the countries and continents with the most reported incidences of mammal wildlife trafficking; (2) identify which are the most popular mammal species being traded; and (3) assess the main purposes and commercialization means (including social media) for mammal trade. Then, it aims to understand whether freely available machine learning models can support the identification of potential situations of wildlife trade on social media images, using pangolins as a case study. Specifically, it aims to understand whether: (4) freely-available machine learning algorithms can be developed to support an automated classification of social media photographs in the context of potential wildlife trade; (5) which existing machine learning algorithms show the highest potential to promote statistically reliable image classifications of potential situations of wildlife trade; and, (6) at which point can those algorithms and models be used to identify potentially traded species and their commercialized products. To do so, a machine learning architecture was trained using pangolin species as a case study.

Since 1975, pangolin species (*Manis*) have been listed in the Appendix II of the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES), being moved since 2016 to CITES Appendix I, prohibiting the international commerce of pangolin species. Nonetheless, due to their popular nature, reports show that over a million pangolins have been illegally traded globally in the last decade to satisfy the rising consumer demand, particularly from Asia.

In general, our results show that, according to a literature revision there's a massive gap in knowledge when it comes to online illegal wildlife trade, and, thus, a lack of preventive and monitorization measures set to fight this pressing conservation topic. Additionally, our practical component illustrates that it is possible to train a well performing algorithm to identify pangolin species and their tradable parts in social media images. The use and implementation of machine learning tools appears to be promising for complementing existing approaches that aim at screening and surveying online data for preventing and halting wildlife illegal trade.

Keywords: Illegal commerce, digital conservation, transfer learning, online trade, wildlife commerce.

Resumo

Sobre-exploração e tráfico de vida selvagem são uns dos fatores principais responsáveis pela perda global da biodiversidade. Comércio de vida selvagem alimenta uma grande indústria, através da qual milhares de espécies de animais e plantas, tal como os seus produtos derivados, são comercializados a fim de várias funcionalidades, incluindo peles e couros, animais de estimação, medicina, alimento e troféus de caça. O aumento de comércio não regulado ou ilegal de vida selvagem tem-se tornado um grande desafio para a conservação, levando a uma gestão insustentável da vida selvagem e à ameaça de extinção de espécies já em perigo.

Monitorizar tráfico de vida selvagem, e particularmente o comércio ilícito de produtos, é difícil devido à quantidade enorme de informação disponível e também à sua natureza clandestina. Com os recentes avanços tecnológicos, comércio eletrónico e plataformas de redes sociais tem-se tornado em uma fonte importante de compartilha de informação entre clientes interessados e venda de espécies ilícitas de flora e fauna selvagem. Consequentemente, comércio eletrónico de animais, tanto legal como ilegal, tem crescido exponencialmente nas redes sociais devido à facilidade de uso e acesso por uma quantidade crescente de usuários. Através das redes sociais os traficantes de vida selvagem podem partilhar fotografias e informação sobre os produtos disponíveis e, desta forma, atrair novos clientes e vender as suas mercadorias por meio de redes de clientes criadas conhecimentos e produtos facilmente encontrados. Monitorizar o tráfego ilícito de espécies nas redes sociais é, portanto, uma questão urgente.

A aprendizagem de máquina ou automática oferece novas oportunidades para este caso, ajudando no desenvolvimento de ferramentas que irão auxiliar a análise de grandes quantidades de dados extraídos das redes sociais a fim de monitorizar transações de vida selvagem, mais rapidamente e eficientemente. Especificamente, o avanço nos modelo e algoritmos de aprendizagem automática tem trazido perceções complementares à deteção da presença de espécies em questão entre os dados extraídos das redes sociais, examinando automaticamente as imagens, texto e vídeos partilhados online.

Esta tese tem dois grandes objetivos. Primeiro, tem como intenção avaliar o estado de arte do comércio de mamíferos tendo em conta a literatura científica, particularmente visa a: (1) perceber quais são os países e continentes com o maior número de casos de tráfico de mamíferos; (2) identificar quais são as espécies de mamíferos mais traficadas; e (3) avaliar a finalidade principal, tal como os métodos de comercialização (incluindo as redes sociais) dos mamíferos traficados. Para além disso, tem como objetivo perceber se os modelos de aprendizagem automática disponíveis conseguem suportar a identificação de casos potenciais de comércio de vida selvagem nas redes sociais, usando o pangolim como caso de estudo. Especificamente, tem como objetivo perceber se: (4) os modelos de aprendizagem de máquina disponíveis podem ser desenvolvidos para suportar a classificação de imagens de fotografias das redes sociais em contexto de comércio de vida selvagem; (5) quais modelos já existentes demonstram maior potencial para promover uma classificação de imagens estatisticamente significativa de casos potenciais de comércio de vida selvagem; e. (6) até que ponto esses modelos podem ser utilizados para identificar espécies traficadas e os seus produtos derivados. De forma a realizar estes objetivos, um modelo de aprendizagem de máquina foi treino usando pangolins como casos de estudo.

Desde 1975 que as espécies de pangolins (*Manis*) estão incluídas no Apêndice II da Convenção sobre o Comércio Internacional das Espécies da Fauna e da Flora Silvestres Ameaçadas de Extinção (CITES) e, em 2016, foram movidas para o Apêndice I, efetivamente proibindo a sua venda internacional. Contudo, devido à sua popularidade, relatórios declaram que mais de um milhão de pangolins foram ilegalmente comercializados globalmente durante a década passada, de modo a satisfazer a crescente demanda de consumidores do continente asiático.

Em geral, os nossos resultados mostraram que, de acordo com a revisão de literatura, existe um enorme vazio no conhecimento, no que toca ao comércio ilegal online de vida selvagem, e, desta forma, existe uma falta de medidas e prevenção e monitorização para combater este tópico de conservação. O uso e implementação de ferramentas de aprendizagem automática parece promissor a fim de complementar abordagens já existentes que tem como alvo a triagem e levantamento de dados online de forma a prevenir e parar com o comércio de vida selvagem.

Palavras-chave: comércio ilegal, conservação digital, transfer learning, comercio online, comercio de vida selvagem.

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Contents

List of Tables

List of Figures

List of abbreviations

IWT Illegal wildlife trade

IUCN International Union for Conservation of Nature

CNNs Convolutional neural networks

ANNs Artificial neural networks

NGOs Non-governmental organizations

ACC Accuracy

SPEC Specificity

SEN Sensitivity

F_1 F1-score

TP True Positive

TN True Negative

FP False Positive

FN False Negative

ML Machine learning

NLP Natural language processing

IFAW International Fund for Animal Welfare

CITES Convention on International Trade in Endangered Species of Wild Fauna and Flora

Chapter 1

Introduction

1.1 Biodiversity and wildlife trafficking

Broadly speaking, biodiversity refers to the diversity of all living beings, including plants, animals, fungi and microorganisms on Earth and the communities and ecosystems they are a part of (Rosenzweig, 1995). Since the last century, biodiversity has been continually endangered, particularly, due to human influence (Ceballos et al., 2010; Díaz et al., 2019). Biodiversity loss is one of the most critical environmental problems that threaten ecosystem services and, consequently, human well-being (Dirzo et al., 2014; Dirzo & Raven, 2003; Maheshwari, 2020). As is seen in the rapid decline of many species, like saiga (*Saiga tatarica*) (Milner-Gulland et al., 2001), pangolins (*Manis*) (Challender, 2011; Nijman et al., 2016), tigers (*Panthera tigris*) (Walston et al., 2010), Asiatic black bears (*Ursus thibetanus*) (Foley et al., 2011), tortoises and freshwater turtles (Horne et al., 2012), among many others (Wyler & Sheikh, 2008).

One of the main drivers of biodiversity's rapid decline has been illegal wildlife trade (IWT) (Barnosky et al., 2011). IWT can be understood as the practice of illicit tracking, trading, processing, exploiting, or killing of wildlife, while directly breaking national and international laws (Kurland et al., 2017). IWT is a booming business that is estimated to generate between 9 and 20 billion US dollars, annually (Barber-Meyer, 2010). Thousands of species, including elephants, rhinos, pangolins, bears, tigers, turtles, among others, are sold illegally for their body parts like pelts, scales, nails, teeth, meat, or as pets (Broad et al., 2014; Nijman, 2010; Petrossian et al., 2016).

International ivory trade was banned in 1989 in response to the emblematic African elephant situation, which was by then moved up from the Appendix II to the Appendix I of the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES), also known as the Washington Convention. Nonetheless, in many countries, like the United Kingdom (UK), United States of America (USA), Thailand and Japan, domestic ivory sales are still legal and are being sold under a certification as coming from legal stockpiles or antiques (Bennett, 2015; Walker & Stiles, 2010). Still, ivory trade is the most profitable section of illegal trafficking (Bennett, 2015). For instance, from 2006 and onwards, the increase in economic and infrastructure links between Asia and Africa, as well as the boost in East Asia's increase in disposable income, led to the increment in elephant poaching and illegal international trade in ivory (Milliken & Sangalakula, 2010; UNEP, 2013). Since 2007 the ivory trade business has doubled and is more than three times greater than it was in 1998 (Cites, 2013).

Many animal and plant populations have suffered a great decline because of illegal wildlife trade. Examples of this trend can be illustrated with the cases of: (1) the African savannah elephant (*Loxodonta africana africana*), which has lost about 76% of individuals between 1985 and 2010, while the forest elephants (*L. a. cyclotis*) have suffered a decline of 62% of their population between 2002 and 2011 (Bouché et al., 2011; Maisels et al., 2013); (2) the wild harvested orchids whose overexploitation and habitat destruction (Subedi et al., 2013) caused enormous biodiversity erosion and revenue loss to Nepal (Singh Jalal et al., 2008); (3) and organized crime on the high seas supporting illegal fisheries and marine species trade (Aceves-Bueno et al., 2021), which led to detrimental effects on pelagic species and ecosystems, as well as coastal habitats and ecosystem services that support local communities (Aceves-Bueno et al., 2021; Falautano et al., 2018; Ye & Valbo-Jørgensen, 2012).

Another activity of illegal wildlife trafficking is pet trade. For this market, the USA are the leading buyers, relying on a small group of gatekeepers, launderers that integrate the wild-caught animals into legal breeding facilities and a limited number of USA intermediaries (Lyons & Natusch, 2011; Natusch & Lyons, 2012). An example of illegal pet trade is that of Madagascar's endemic tortoises. The radiated tortoise (*Astrochelys radiata*), ploughshare tortoise (*Astrochelys yniphora*), spider tortoise (*Pyxis arachnoides*) and flat-tailed tortoise (*Pyxis planicauda*) are all listed on CITES Appendix I and are characterized as critically endangered by the International Union for Conservation of Nature (IUCN) Red List (Leuteritz et al., 2005; Leuteritz & Pedrono, 2013; Velosoa et al., 2013). The ploughshare tortoise, specifically, is one of the rarest tortoises in the world and studies regarding their population size and poaching have been done, asserting the fact that this over-collection practice is leading to their populations' decline (Mandimbihasina et al., 2020).

Currently, amongst the most trafficked mammal species in the world are pangolins (Heinrich et al., 2017). Pangolin species (*Manis* spp.) have been included in the CITES Appendix II and a prohibition on their trade has been set since the year 2016, effectively banning all commercial trade for Asian pangolin species (Xu et al., 2016). However, for example, in the period between the years 2000 and 2013 it was estimated to have occurred over a million of pangolins poached for trading, most of which were destined to clients in China and Vietnam (Heinrich et al., 2017). The high demand for all eight species of the Manidae family, endemic to South Asia and Central and South Africa (Figure 1), is their biggest threat to survival.

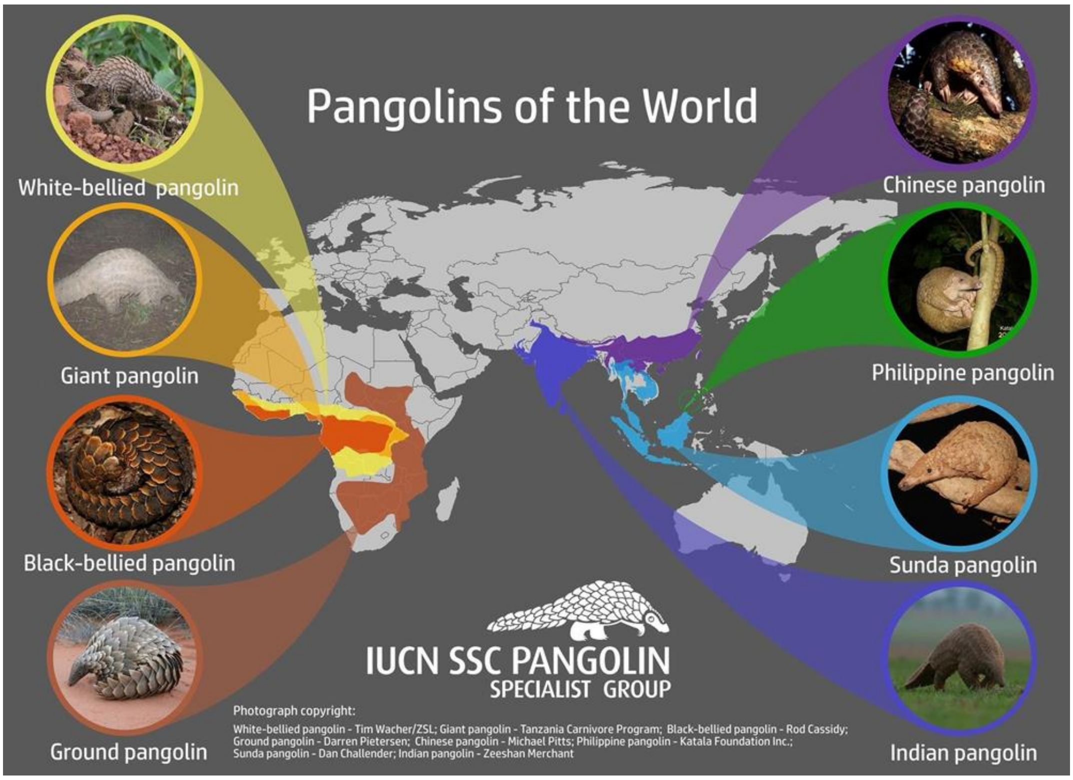

*Figure 1 - World distribution of all eight pangolin species – White-bellied pangolin (*Phataginus tricuspis*), Giant pangolin (*Smutsia gigantea*), Black-bellied pangolin (*Phataginus tetradactyla*), Ground pangolin (*Smutsia temminckii*), Chinese pangolin (*Manis pentadactyla*), Philippine pangolin (*Manis culionensis*), Sunda pangolin (*Manis javanica*), Indian pangolin (*Manis crassicaudata*). Taken from the Pangolin Crisis Fund website (https://www.pangolincrisisfund.org/).*

Pangolins are hunted for consumption, as their meat is considered a luxury food and is also used as a source of nourishment for local populations (Gimeno-Gilles et al., 2016; Shairp et al., 2016). Their skins are transformed into leathers and their scales are used for ornamental purposes and for traditional medicine (Heinrich et al., 2017; Katuwal et al., 2013). Some studies have been conducted to evaluate the veracity of the claims that pangolin scales possess medicinal qualities and have found them to be simply normal keratinous scales, equal to our nails (Chon et al., 2017). These cultural practices have led to a big decline in pangolin population size. For example, prior to 2013 there were no registered pangolin shipments over 500 kg; however, after the middle of the 2010s about 16 ton of pangolin scales and skins started being shipped per year, with rising numbers (Shepherd et al., 2017). China has been the main destination for the large quantity of shipments of pangolin scales, nevertheless, other countries such as Hong Kong, the Netherlands and Vietnam are also main buyers (Figure 2; Heinrich et al., 2017). This commercial harvest and trade are firmly suspected to be unsustainable and have led to the decline of pangolin populations worldwide over the past couple of decades (Cheng et al., 2017; Nijman et al., 2016).

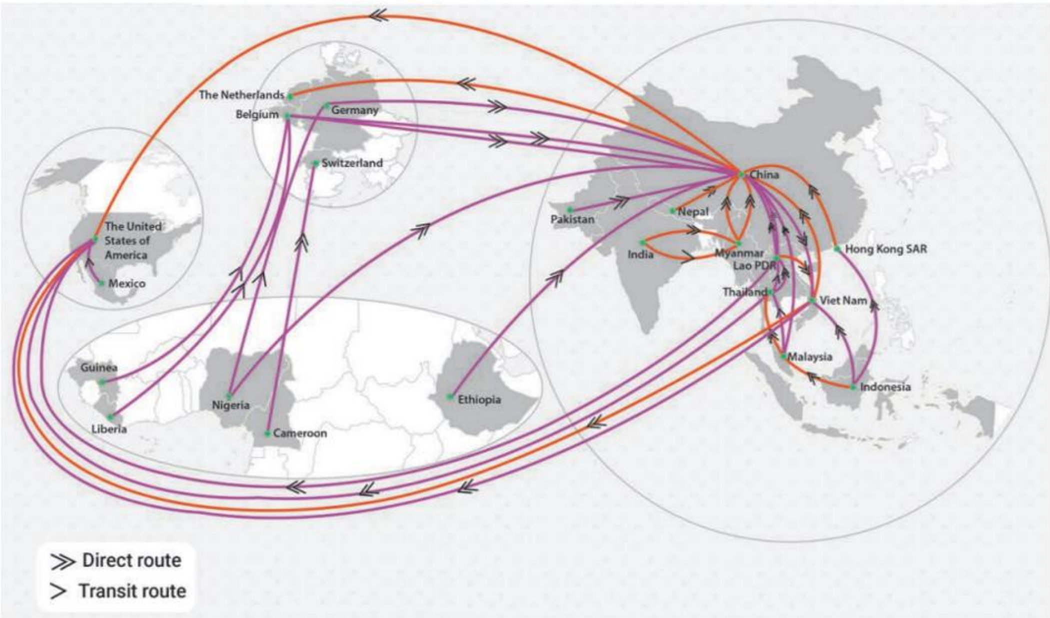

Figure 2 - International trafficking routes for pangolins (2010-2015). All these routes have been used five times or more for international trafficking of pangolins and the routes in orange have been used in five or six consecutive years. Image taken from (Heinrich et al., 2017).

Southeast Asia, including China's international borders and parts of Indonesia, has been established as a "wildlife trade hotspot", meaning it is the region with the most incidents of wildlife trade (Rural Development, 2008; Sodhi et al., 2004). Recently, with the renewed interest in conservation efforts from the government and non-governmental organizations (NGOs) as well as the general public, there has been a surge in proposals of new preventive and monitorization measures to help prevent illicit commerce (Beastall et al., 2016; United Nations Office of Drugs and Crime, 2016; Warchol, 2004). In order to improve the effectiveness of conservation interventions, alternative livelihoods, increased authority enforcement, demand reduction and incentive-oriented approaches are needed (Phelps et al., 2016). However, the study and debate over the conservation field is aggravated by the lack of set frameworks to dissect the phenomenon of IWT (South & Wyatt, 2011). There is an increasing need for surveying tools that allow monitoring the range of buyers, sellers, transactions, routes, and products that compromise the field of IWT (Laird et al., 2011; von Lampe, 2012).

1.2 Social media and wildlife trade

Wildlife trade has conventionally been done in physical markets. Nevertheless, with the increasing usage of Internet, social media has become a popular channel for both legal and illegal wildlife trade (Harrison et al., 2016; Hinsley et al., 2018; Regueira & Bernard, 2012; Rosa et al., 2013).

Initially illegal trade was being conducted mostly on the dark web, which is an assortment of anonymous, untraceable networks, due to their encryption methods, specifically designed to offer users anonymity (Harrison et al., 2016). It is almost impossible to measure the true size of the dark web since most of the information is hidden or blocked. Nevertheless, it is possible to communicate and exchange financial resources through this network, allowing for complete anonymity and making illegal transactions almost impossible to track (Weimann, 2016).

A popular example showcasing the usage and difficulty of tracking online networks for illegal trade is the Silk Road, which is a known online marketplace for selling illegal articles, such as drugs (Pace, 2017). A study from Harrison et al. (2016), surveyed the dark net discovering little evidence of illegal wildlife trade. While the results did not show many hits for wildlife trade, it could have been related to this anonymous network's methods of technological as well as language encryption (Harrison et al., 2016). On the one hand, such results suggest that a regular internet user, might have difficulties finding the products that interest them, since the dark web could be too complicated and not user friendly for first time clients, as this network's purpose is not discoverability, on the contrary – it is secrecy (Pace, 2017; Weimann, 2016).

On the other hand, with an increasing number of Internet users, ease of navigation and lack of authority monitorization, social media networks have been serving as a way to promote criminal activity (Patton et al., 2017; Soomro & Hussain, 2019), including illegal wildlife trade (Harrison et al., 2016; Xiao et al., 2017; Yu & Jia, 2015). With law enforcement's slight success in controlling and monitoring illegal wildlife trade on e-commerce websites, illicit trade has appeared to move to alternative platforms, particularly social media networks (Yu & Jia, 2015). Wildlife dealers can use social media's ease of connection to release photos and information pertaining to their products of choice and, thus, attract new customers marketing their merchandize to a network of contacts (Di Minin et al., 2018).

Since 2004, the International Fund for Animal Welfare (IFAW) has been investigating wildlife commerce over the Internet, concluding that thousands of wild beings, their products and parts are readily available for online sales, although the lack of access to the product and the little information displayed about it makes the ability to ascertain the legality very difficult (Hastie & McCrea-Steele, 2014). The issue released in 2014, Wanted – Dead or Alive: Exposing Online Wildlife Trade (Hastie & McCrea-Steele, 2014) found that out of the 280 investigated websites, 3047 online advertisements were regarding ivory, followed by 2509 broadcasts for reptiles, including turtles and tortoises (Hastie & McCrea-Steele, 2014).

Furthermore, Feddema et al (2020), conducted a study on the strategies and persuasion tactics used by exotic pet vendors, through Facebook (https://www.facebook.com/). This social media platform, for example, allows for the users to create private or public groups, many of which are possible to be joined by conservationists to directly monitor the content of their posts. Since many of these “buy and sell” groups are confined to cities or suburbs, it is feasible to observe and analyze the geographical patterns of these commerce instances, allowing for conservation programs to be more involved in the online monitoring process (Feddema et al., 2020). Nonetheless, not all social media websites allow for an easy integration and discoverability for authority figures, therefore it is necessary to come up with new ways to help in the prevention and monitorization of online (illegal) wildlife trade.

1.3 Machine learning for tracking wildlife trade

With illegal wildlife trade’s recent digital migration and online popularization, new methods are necessary to survey and monitor this trade method (Di Minin et al., 2019). Machine learning offers many opportunities to analyze and detect large quantities of digital data, thereby helping to prevent online illegal deals (Di Minin et al., 2018).

Machine learning (ML) refers to the set of successful algorithms and models that can perform a task without human guidance or at least be specifically programmed to solve it with minimum human assistance (Di Minin et al., 2018; Wäldchen & Mäder, 2018). ML allows for algorithms to learn from previous data without the help or guidance of humans, turning it into a rather automated, fast and efficient process (Loussaief & Abdelkrim, 2018). ML algorithms can be trained to detect species or wildlife products that appear in images, videos, or text, using audio clues and image or text detection parameters (Guo, 2017).

ML algorithms, and more specifically deep learning models, can be used in speech to text transcription, search engine fine tuning where it has the ability to match the search subject with the relevant news, posts, videos and websites, as well as in image classification and object detection (Lecun et al., 2015). For visual understanding deep learning models are based on artificial neural networks (ANNs), which are based on a set of connected units or nodes named artificial neurons that are organized into multiple layers between which the connections only occur in the immediately preceding and following layers (Mishra & Srivastava, 2014). ANNs can be used for object detection, image classification and for application with unclear data, however it cannot be used for instances when the nature of the input and output is familiar (Dongare et al., 2012; Harvey & Harvey, 1998).

For instance, in a deep learning model, a digital image is presented in the shape of a matrix of pixel values, for colored imaged, associated to 3 channels that correspond to the RGB (Red, Green, Blue) channels. Then the ANN is divided into layers of neurons, that will receive an image as an input, process the information within them, and finally give an output that will correspond to the classification of that image (Guo, 2017; Lecun et al., 2015). For training an ANN on images, a large dataset of manually labeled information is first required to then allow the learning networks to learn how to associate the input with the output. This means that even though deep learning algorithms can provide useful information in an automatized way, they still require human inputs and validation (Alnajjar, 2021; Di Minin et al., 2019).

Convolutional neural networks (CNNs) are the most used algorithms when working with deep learning techniques for visual imagery (Guo, 2017). CNN architectures have layers of convolution and pooling, consisting of neurons which assimilate inputs and produce outputs based on weights and biases (Figure 3; Lecun et al., 2015). They are comprised of convolutional layers, pooling layers, and a fully connected layer, and by stacking them in different ways, different architectures are formed (Saiharsha et al., 2020). The convolutional layer is the main building block, consisting of filters that travel through the dataset by selecting a specific region at a time, and are then used to extract certain features from that data. The pooling layer is used to reduce the chances of overfitting, by taking small portions from the convolutional layer and giving out the minimum (min pooling), maximum (max pooling) and average (average pooling) of values. The fully connected layers are the last ones to be added, as they connect the neurons of preceding layers to neurons of the present layer (Huang et al., 2017; Simonyan & Zisserman, 2015; Wäldchen & Mäder, 2018).

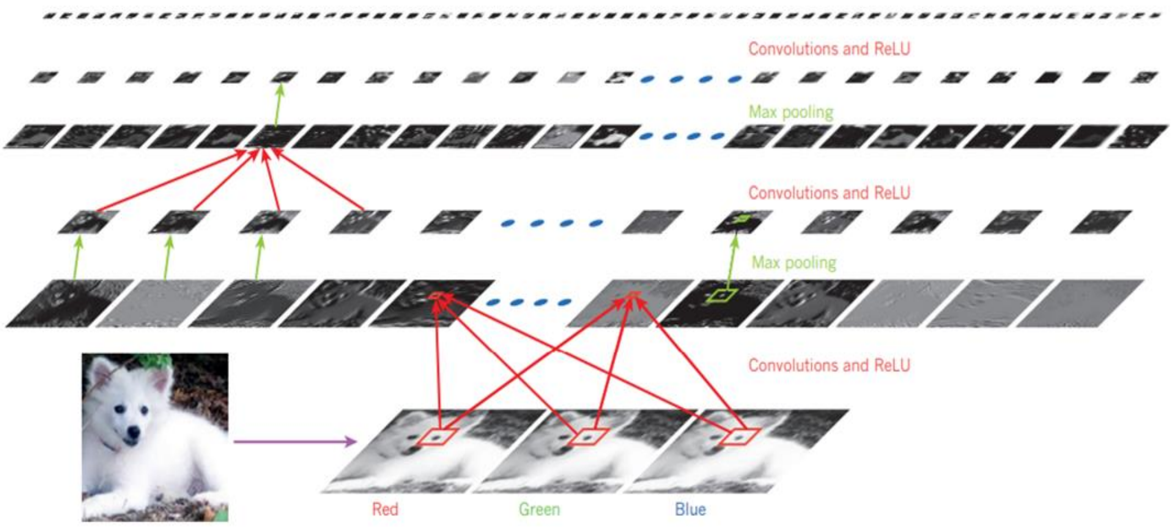

Figure 3 - Simplified representation of a convolutional network. The outputs of each horizontal layer of a CNN applied to an image of a Samoyed dog – bottom left and it's RGB simplification on the bottom right. Each rectangle is a feature map that corresponds to the output for one of the learned features. As such information flows bottom up and the lower-level features are acting as oriented edge detectors. Image taken from Lecun et al., (2015).

With deep learning it becomes potentially possible to infer whether an image of an animal, or its derived product, was shared with the intent of being commercialized or for leisure purposes, through natural language processing (NLP) and computer vision. NLP is a branch of ML that allows an algorithm to process a data set of human language, in the form of voice or text, understanding the meaning of that data (Olsson, 2009). As curiosity, NLP algorithms grant computer programs the ability to respond to spoken commands in the form of artificial intelligence assistants like Siri or Alexa, as well as voice operated GPS systems, translating text from one language to another, and summarizing large volumes of text to streamline business operations and simplify business processes (Olsson, 2009). Computer vision in its turn enables systems to derive meaningful information from digital images and other visual inputs (such as videos), acting according to that information (Loussaief & Abdelkrim, 2018). Computer vision is used in many fields like industries ranging from utilities and energy to manufacturing and automotive, with a growing market. Through deep learning computer vision, analyzing specific patterns and recognizing specific objects over large amounts of digital and visual data becomes possible (Loussaief & Abdelkrim, 2018). Such is done by breaking images down into pixels and giving labels to those images, which is then used by the algorithm to make predictions on what is seen in the picture, based on the information collected from previous iterations (Mitchell, 2006; Simonyan & Zisserman, 2015).

Deep learning has been used in many technological fields that aid our online experiences, such as web searches, content filtering on social networks, recommendations on e-commerce websites and searching browsers (Mjolsness & DeCoste, 2001). An emblematic example is the use of deep learning for fire-arm detection in closed-circuit television (CCTV), with the aim of detecting potential unsecure actions and threats in daily situations (Kanehisa & Neto, 2019; Verma & Dhillon, 2017).

Through the application of deep learning algorithms, it is also potentially possible to investigate human online behavior and possibly present new methods of prevention and monitoring of illegal wildlife trade (Di Minin et al., 2018). An example of such possibility can be found in Xu et al. (2016), who used machine learning to detect cases of wildlife product sales on twitter using unlabeled textual data. The authors found that it is possible to detect groups of tweets specific to illegal wildlife trade, outlining a set of policy and technology recommendations and challenges to better perform surveillance on social media, and thus combat online wildlife trafficking (Xu et al., 2019).

However, the application of deep learning tools, and specifically of computer vision models to survey and detect potential situations of wildlife trade is still in its infancy.

1.4 Research objectives and thesis structure

The goal of this thesis is twofold. First, it intends to evaluate the state of the art of mammal trade in the scientific literature, with particular emphasis on the role of social media information in this trade. Particularly, it aims to:

(1) understand which are the countries and continents with the most reported incidences of mammal wildlife trafficking,

(2) identify which are the most popular mammal species being traded; and,

(3) assess the main purposes and commercialization means (including social media) for mammal trade.

Then, it aims to understand whether freely available machine learning models can support the identification of potential situations of wildlife trade on social media images, using pangolins as a case study. Specifically, it aims to understand whether:

(4) freely available machine learning algorithms can be developed to support an automated classification of social media photographs in the context of potential wildlife trade;

(5) which existing machine learning algorithms show the highest potential to promote statistically reliable image classifications of potential situations of wildlife trade; and,

(6) at which point can those algorithms and models be used to identify potentially traded species and their commercialized products.

To do so, this thesis includes five chapters. Chapter 1 functions as a general introduction, outlining and giving a brief insight into the context, the motivation, and objectives of this thesis. Chapter 2 examines the systematic literature review on animal trafficking by searching, filtering, and evaluating the studies found in relation to illegal wildlife commerce. Also, this chapter serves as a justification for this thesis, as we showcase the lack of works and subsequent gap in knowledge regarding online wildlife trade. Chapter 3 focuses on the validity of a possible solution to the rise of online animal commerce, through tracking of images of pangolin species, used as a case study, with the help of machine learning algorithms. This chapter demonstrates the methodology, results, and their discussion with a conclusion that it is indeed possible to identify pangolins, and their tradeable parts, in images using machine learning algorithms through pre-trained models and transfer learning, for a more efficient and less time-consuming search. Chapter 4 is an overall discussion of all the obtained results, the limitations present with this type of study and plans going forward. Finally, Chapter 5 is a consolidation of ideas and all the obtained results throughout this project.

Chapter 2

Systematic literature review on mammal trafficking

2.1. Background

Illegal wildlife trade is the process of acquisition, transport, and distribution, either national or international, of wildlife – plants, animals, their parts or derivates (Wyler & Sheikh, 2008). Trafficked wildlife can include live animals for pet trade, fashion accessories, cultural artifacts, hunting trophies, ingredients for traditional medicine, meat for human consumption and other products (Wyler & Sheikh, 2008). Wildlife trade is one of the biggest drivers of the decline of species and biodiversity (Bennett & Robinson, 2000; Broad et al., 2014; van Uhm, 2016), and has been among the most lucrative businesses in the world, making an estimate of 8 to 12 billion dollars per year (Barber-Meyer, 2010; Rosen & Smith, 2010). There has been a resurgence and renewed interest from non-governmental organizations (NGOs), the government and the general public, over the past few years, in developing measures for preventing and halting illegal wildlife trade. The renewed interest has been partially prompted by a rise in consumer demand from Eastern Asia, where there is a big market for ivory, pangolins, felines, sharks, and many other species as well as their body parts (Beastall et al., 2016; United Nations Office of Drugs and Crime, 2016; Warchol, 2004).

Providing an accurate global assessment of wildlife commerce is tricky since each country has its own laws set in order to protect animals, fish and plant life, so to try and facilitate that the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) grants a framework to regulate international trade (United Nations Office of Drugs and Crime, 2016). On the other hand, each country's focus on domestic species regulation and lesser effort in international smuggling monitorization indicates CITES importance, since it allows governments to reciprocally protect non-native species by following a conventional set of rules (United Nations Office of Drugs and Crime, 2016).

CITES is a contractual arrangement between countries that contains a list of species internationally agreed to be protected globally, leaving poaching and illegal domestic trade to stay as matters for national governments. CITES contains three main appendices - I, II and III -, which include lists of species and their levels of protection in regard to trading. Specifically, Appendix I includes species that are most endangered and threatened with extinction, for which international trade is prohibited, except when the purpose of species movements is non-commercial, such as for scientific research; Appendix II includes species that are not threatened with extinction but may become so due to over-exploitation, and without proper monitorization; finally, Appendix III includes species at the request of an outside party that specifies in their regulation and needs the cooperation of extra countries to prevent its illegal exploitation. While species lists in Appendices I and II can only be changed by the Conference of the Parties, in Appendix III, species lists can be changed at any time and by any party unilaterally (CITES, 1997; Draft Framework for Reviewing National Wildlife Trade Policies, 2007; Simmons et al., 1976; Wijnstekers & Wijnstekers, 2011).

As CITES focuses on international trade, it leaves domestic trafficking to each country's own responsibility, allowing them to manage CITES-listed species at their own accordance as long as they do not leave their borders. This means that poaching and illegal domestic trade are not governed by CITES and thus all the governing power stops at ports of entry like airports, harbors, and national borders, leaving physical domestic markets and online markets to each country to regulate. This regulation is difficult since proving the illegality of a wildlife species or product is challenging, considering each countries governmental division and lack of communication between smaller municipal authorities and environmental organizations (CITES, 1997; Wijnstekers & Wijnstekers, 2011). The disorganization and fragmented communication between governmental agencies should be addressed and resolved to better settle new issues and disseminate new preventive measures and policies.

Therefore, a review of published literature is necessary to have a better idea of the state of the art regarding wildlife trade. This evaluation is important to know which taxonomic groups and geographical patterns are more prioritized, as well as which fields are well researched, and which need further analysis. There's a large focus on physical wildlife trade, neglecting the online aspect that has been rising over the past years. Thus, it is crucial to have a defined well of information regarding wildlife commerce to understand which aspect needs more attention more clearly.

In this review we evaluate and discuss the current state of literature regarding the illegal trafficking and smuggling of animal wildlife. Specifically, we aim to: (1) understand which are the countries and continents with the most reported incidences of animal wildlife trafficking, (2) identify which are the most popular animal species being traded; and (3) assess the main purposes and means for animal trade. Our results are discussed with an emphasis on the Internet as an opportunity for online wildlife markets.

2.2. Methods

2.2.1 *Methodological overview*

To conduct our literature review, we followed three main steps: (1) preparing the review by establishing a question regarding a certain topic, a search strategy, review plan and data collection and analysis; (2) searching for studies, filter them through inclusion and exclusion criteria and evaluate their relevancy to the research goal and topic (see section 2.2.2); and, (3) reviewing the content from the retrieved studies and organizing their information, through a quantitative or qualitative analysis, so as to answer the established research question (see sections 2.2.3 and 2.2.4).

2.2.2 *Literature search*

A search of published scientific literature on illegal trafficking was done in Scopus (at: https://www.scopus.com/) and ISI Web of Science (at: http://webofknowledge.com/) search engines. Twenty unambiguous keywords were used in the search string to reach the largest amount of published research. Keywords were obtained from a list of reference papers (Kurland et al., 2017; Patel et al., 2015; Pires & Moreto, 2016; Sas-Rolfes et al., 2019; Thomas-Walters et al., 2020; Van Uhm & Moreto, 2018; van Uhm & Wong, 2019) with reference to the topic at hand (Table 1). The search string used was TITLE-ABS-KEY (“wildlife" OR "animal" OR "mammal") AND (TITLE-ABS-KEY ("black market" OR "black-market") OR (TITLE-ABS-KEY ("commerce" OR "trade" OR "purchase" OR "transaction" OR "traffic" OR "trafficking") AND TITLE-ABS-KEY ("illegal" OR "crime" OR "illicit" OR "illegitimate" OR "banned" OR "criminal" OR "prohibited"))). This was done with the intent of including several variations for wildlife, with a focus on mammals, as well as variations of illegal trade, to find as many publications as possible. TITLE-ABS-KEY searches for titles, abstracts and keywords for the specified terms of published research.

Table 1 - Keywords used for searching literature regarding the illegal wildlife trade.

KEYWORDS				
Wildlife	Animal	Mammal	Black market	Commerce
Trade	Purchase	Transaction	Traffic	Trafficking
Poaching	Smuggling	Smuggle	Illegal	Illicit
Crime	Illegitimate	Banned	Criminal	Prohibited

The searches were conducted between November 2020 and January 2021. The list of papers retrieved by our search was organized in an Excel spreadsheet, and duplicates were removed. A total of 4446 unduplicated records were retrieved by the combined search. Afterwards, we applied the inclusion and exclusion criteria to the main dataset to eliminate non-relevant information. Specifically, we excluded records that did not focus on mammals. Likewise, we excluded records which did not explicitly explore animal trade. For instance, studies focused solely on poaching without exploring trade were not considered. The exclusion criteria were first applied by checking the title and abstract of each individual article, and then to the full content of each article, resulting in a total number of selected records of 225 (Appendix I, Figure 4).

Figure 4 - Flowchart illustrating the literature review process for illegal trafficking of mammal wildlife. First a search was done on Scopus and ISI Web of Science using 20 keywords (Table 1), afterwards the exclusion criteria was applied leading to a total of 225 publications up for review. Finally, each individual publication was reviewed to understand which continents and countries had more incidences of illegal trafficking searches, what were the main trafficked families, the main methodology of the publications and which were the main uses for the species in question as well as their derivatives.

2.2.3 *Literature review*

Each of the 225 records was then fully reviewed and assessed in order to extract information on: (1) geographic patterns of mammal trade; (2) taxonomic information of traded mammals; (3) products and purposes for trading mammals; and (4) assessment methodologies for mammal trade (Figure 4). Firstly, we noted which countries and continents were targeted by the studies, as well as what were the exportation and importation routes, if mentioned, per country or continent. Then, we analyzed which mammal species and families were studied in the selected publications. Next, we marked what were the uses of each species in question (e.g., aesthetic, nutritional, for traditional medicine or pet trade). Finally, we reviewed which main methodology was followed in the studies (e.g., social surveys, database analysis, reviews and commentaries, social media analysis and in-situ observations).

2.2.4 *Data visualization*

The data obtained from the review of our dataset (section 2.2.2) was compiled and analyzed in Excel (see Appendix II). A dynamic table was used to generate bar and pie charts in relation to the total number of published records per year, for an intuitive descriptive analysis of the results. To analyze research methodologies and product usages a pie chart was made, for taxonomic patterns a pie chart as well as a bar graph was used when observed with geographic patterns. Finally, for geographic patterns pie charts was also used, as well as a general world map based on the import/export results per continent.

2.3. Results and discussion

The time span of the set of studies found in our literature search was from 1973 up until the end of the year 2020. Interestingly, the first record found in 1973 (Mountfort, 1973) appears to have emerged around the same time as the creation of CITES (T. Rosen, 2020). In general, there was an increasing tendency of articles per year regarding illegal trafficking, which agrees with other observations.

An integral part of any market system is consumer demand, therefore, to fully understand IWT it is necessary to be fully aware of consumer demand and its influence (Sas-Rolfes et al., 2019; Veríssimo et al., 2020). With the renewed interest in conservation efforts, there has been a focus on regulation and law enforcement in an effort to approach the sale and supply side of trade, as well as an increase in demand reduction activities (Challender & MacMillan, 2014; Veríssimo et al., 2012). The demand reduction activities aim to change the consumer's purchasing behavior in a voluntary manner, through numerous awareness and educational campaigns and social marketing (Olmedo et al., 2018; Wallen & Daut, 2018).

This understanding of consumer's preference will allow for governmental and non-governmental environmental agencies to better adapt their policies and realize which taxonomic groups and geographic patterns require more attention, in the form of new preventive and monitorization measures (Ayling, 2016; Megias et al., 2017).

2.3.1 *Geographic patterns*

Incidence of studies per continent and country

Our literature review allowed us to observe that Asia was the most popular continent (47% of all reviewed records), with China (11%) and Vietnam (6%) as the countries with the most published studies on mammal trade (Figures 5 and 6). These values were followed by Africa (16%) and South America (16%), with Brazil (6%) and Peru (8%) having the larger number of studies, specially focused on domestic exotic pet trade and illegal sales at open markets. Even though Central and South America altogether represent the world third largest biodiversity hotspot, with plenty of species protected under CITES, there is limited attention, data, and funding for conservation efforts in this region (Gluszek et al., 2021). The continued exploitation for legal and illegal trade is in dire need of a new approach, low-cost and effective measures to prevent the decline of biodiversity (Arias et al., 2020).

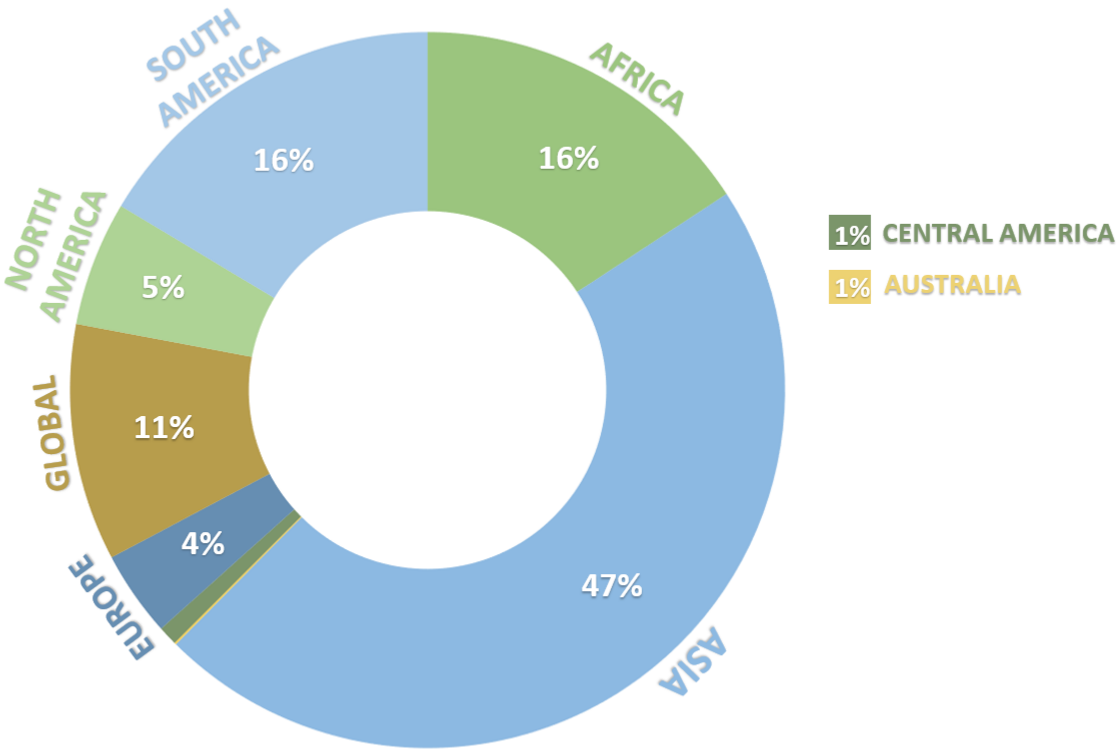

Figure 5 - Percentages of continents among the total analyzed publications. Asia is the most common continent (47%), followed by both South America and Africa at 16%, then a Global analysis (11%), North America (5%) and finally Europe (4%).

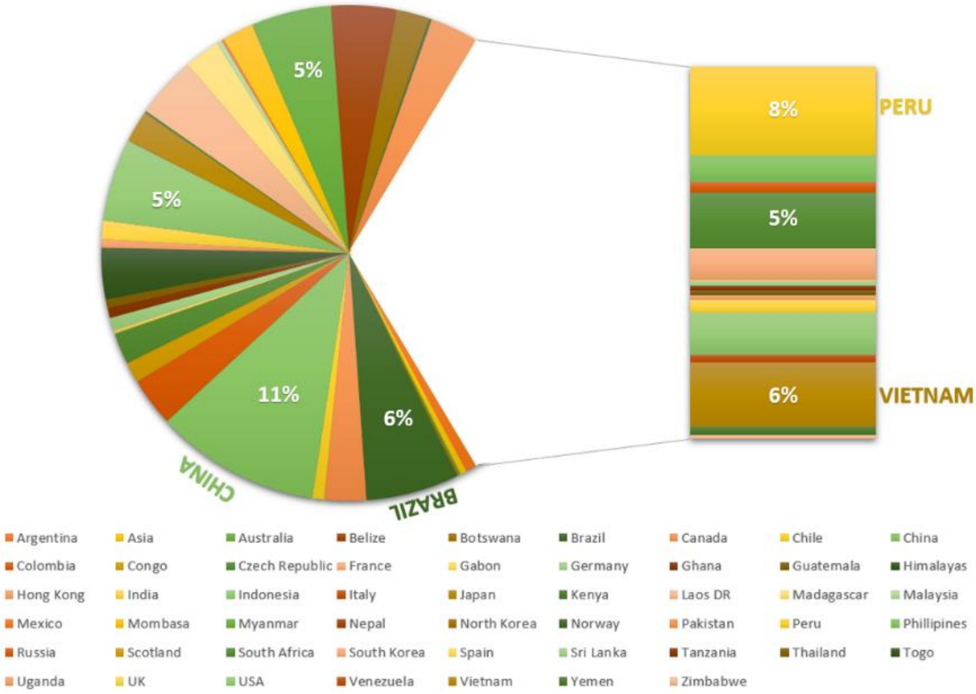

Figure 6 - Percentages of countries among the total analyzed publications. China is the most mentioned (11%), then Peru (8%) and Brazil and Vietnam (6%).

The topics covered by studies in African countries were poaching and bushmeat, while also referencing their high export numbers. While poaching is still a common practice in African countries it seems that global ivory prices have peaked and may begin to fall, possibly due to the bans of ivory sales (Schlossberg et al., 2020; Sosnowski et al., 2019).

Exportation and importation routes among continents and countries

Asia and Africa were the continents with the most exports while China was the country with the most recorded international imports (Figure 7). South America mostly focused on domestic trade, while USA, and Europe have incidences of imports from both Africa and Asia (Alfino & Robert, 2020; Ia, 2011; Schifani & Paolinelli, 2018; Shepherd et al., 2020).

China stands out as a big buyer country for illegal wildlife products. This is largely due to their cultural and religious beliefs, which give importance to traditional methods of medicine using products derived from illegally traded species like pangolins, felines, and elephants (Hastie & McCrea-Steele, 2014; Jacobs et al., 2019; Morcatty et al., 2020).

On the other hand, Africa and Asia's high rates of exportation are linked with high consumer demand for a taxonomic group, as is observed for ivory trade and pangolins, as well as the area's poverty levels (Anderson & Jooste, 2013; Challender, 2011; Mainka & Trivedi, 2002;

Sosnowski et al., 2019). Therefore, one of the major challenges in mitigating wildlife trade are of socioeconomic origin. Population growth, chronic shortage of expertise and funding for conservation resources, poverty and corruption are the main reasons for the population's need to resort to poaching and wildlife trade (Sodhi et al., 2004).

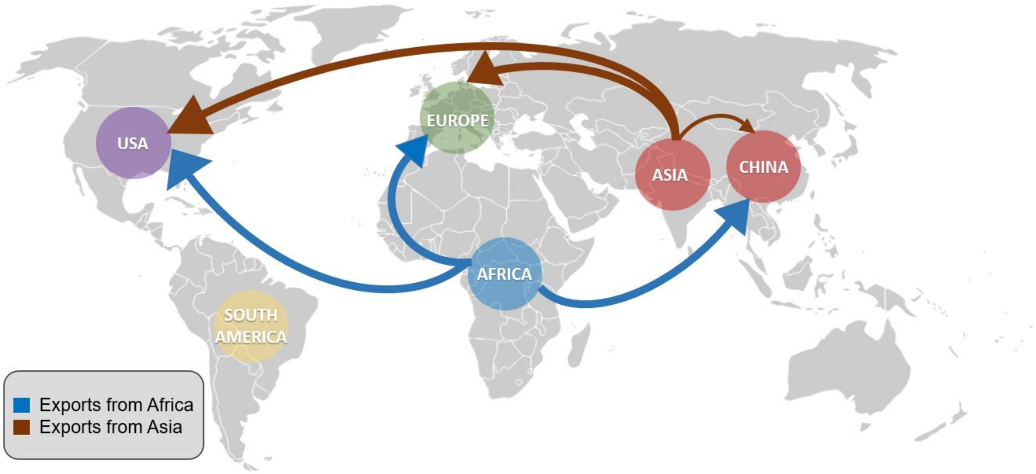

Figure 7 - Map of exports from Asia and Africa to USA, Europe and specifically China. While South America had no published works regarding international trade.

2.3.2 *Taxonomic patterns*

Global patterns

Regarding taxonomic patterns, our literature review shows that most studies focused on one particular species (77%), with the remaining focusing on two or more species (23%). From the 225 publications analyzed in our literature review the most reported family is Elephantidae (23%), followed by Rhinocerontidae (17%), Felidae (15%) and Manidae (14%) (Figure 8). These results agree with previous research showing ivory and feline pelts as some of the biggest commodities in black-markets (Alfino & Robert, 2020; Arias et al., 2020; Permata & Wahyuni, 2020).

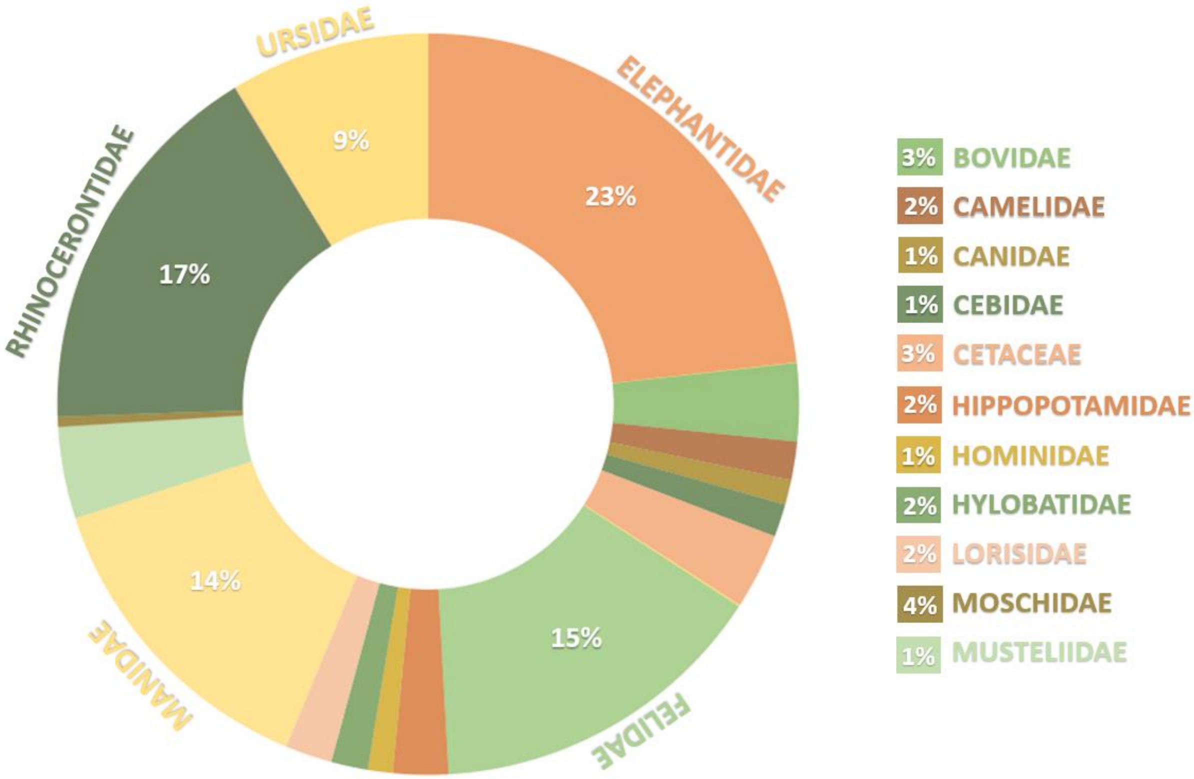

Figure 8 - Percentages of families among the total analyzed publications. Elepahntidae is the most mentioned family (23%), followed by Rhinocerontidae (17%), Felidae (15%), Manidae (14%) and Ursidae (9%).

Taxonomic patterns per continent

The families studied per continent were diverse, but Elephantidae and Felidae were still the most reported in all continents (Figure 9). In Africa, Elephantidae was the most mentioned family, and largely due to the great number of publications on poaching and ivory trade (Cooney et al., 2017; Hastie & McCrea-Steele, 2014; Underwood et al., 2013). Studies in Asia had a larger variety of families, besides Elephantidae as a prominent taxon, Manidae was also largely reported and associated to pangolin's popular uses for traditional medicine and luxury food (Cheng et al., 2017; Nijman et al., 2016; Semiadi et al., 2008). In Central America only Felines were reported, specifically associated to the high demand of paws, nails, and fur in Mexico (Kelly, 2018). Studies in Europe reported largely on Ursidae for fur and claws, Elephantidae for ivory, and Canidae for fur and pet trade (Alfino & Robert, 2020; Ambarli et al., 2016; Shepherd et al., 2020). In North America there was a high percentage of reported bear trade, as well as Cetacea (Ambarli et al., 2016), while in South America, studies mostly reported on

Camelidae and Cebidae, mainly due to Cebidae's role in pet trade (Mainka & Trivedi, 2002; McAllister et al., 2009).

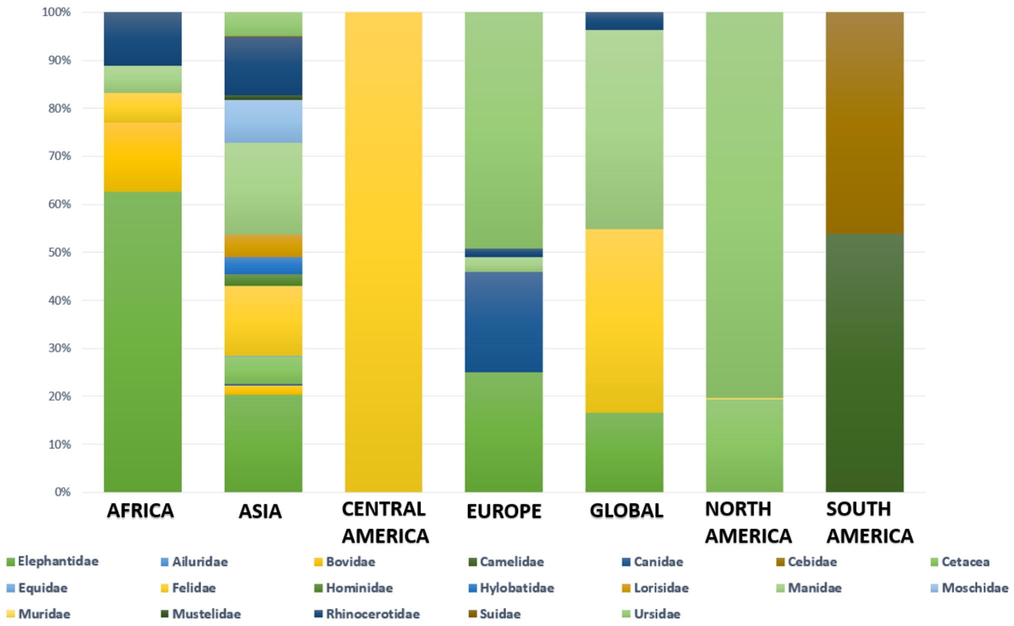

Figure 9 - Graphic representation of which families are studied per continent.

2.3.3 *Animal products and uses*

Regarding the reported uses of the traded wildlife, most studies mentioned more than one usage per taxonomic family (Figure 10). Aesthetic purposes (35%) were most mentioned, and included ornamental, fashion, and cultural motivation for acquiring illegal wildlife and their derivatives. Like orchids, which are highly sought out by consumers for their beauty and as a hobby (Hinsley et al., 2018; Williams et al., 2018), feline derivatives are also in high demand, like paws, teeth, fur, and others, particularly throughout Mexico, Central and South America (Gonzalez-Maya et al., 2010; Kelly, 2018).

Traditional medicine (33%) was another main motivation for the purchase of illegal goods, like the rhinoceros' horn which has had a resurgence due to an urban myth about miracle cures, insinuating that it can be used as a treatment for cancer, and also used as an expensive detoxicant for hangovers (Broad & Burgess, 2016).

Nutritional motivation was reported in 26% of studies, particularly covering the use of bushmeat or luxury food from pangolins (Nijman et al., 2016; Pantel & Chin, 2009).

Finally pet trade (6%) was dominated by Hylobatidae (50%) and Canidae (31%) (Grey, 2012; Nijman et al., 2009; Pavlin et al., 2009).

These results were expected as aesthetic purposes and traditional medicine are the main drivers for illegal wildlife trade (Eikelboom et al., 2020; Gao & Clark, 2014; Veríssimo et al., 2020; Wang et al., 2020), while nutritional motivations are more relevant to domestic trade and poaching (Cooney et al., 2017; Maisels et al., 2013; McAllister et al., 2009), and pet trade is not researched enough to fully understand its impact and consequences (Burivalova et al., 2017; Grey, 2012; Mandimbihasina et al., 2020).

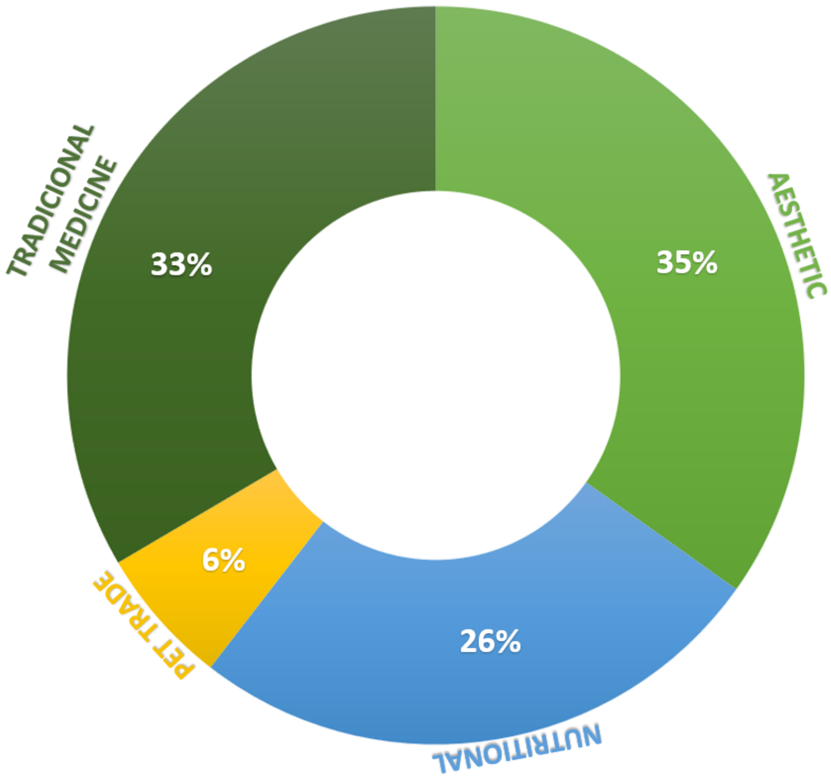

Figure 10 - Percentages of uses among the total analyzed publications. Aesthetic (35%) and traditional medicine (33%) were the most common usage, followed by nutritional value (26%) and pet trade (6%).

2.3.4 *Data and research approaches*

We found six different types of methodologies used in the reviewed studies to tackle mammal trade (Figure 11). Database analysis was the most common one (59%) and included the usage of global databases such as from CITES, or national, regional, and local databases from shipment, airport, and border patrol seizures documentation, among others (Anderson & Jooste, 2013; Reuter & O'Regan, 2017; Runhovde, 2015). Social surveys were also prominent in the reviewed literature (26%) and included online or face-to-face questionnaires about people's opinion regarding wildlife trafficking. Some studies also focused on *in-situ* observations in open wildlife markets (6%) (Chow et al., 2014; Warchol et al., 2003), for instance to annotate which and how many mammals were placed at physical markets.

Literature reviews and general commentaries (5%) on the subject of mammal trade were also found, specifically showcasing possible preventive measures or monitorization methods based on policies or previous literatures (Eikelboom et al., 2020; Norconk et al., 2020). Social media analysis was the least represented methodological approach (3%), and mostly included studies on how low and unutilized this field is faced with the rising popularity of online and social media wildlife commerce.

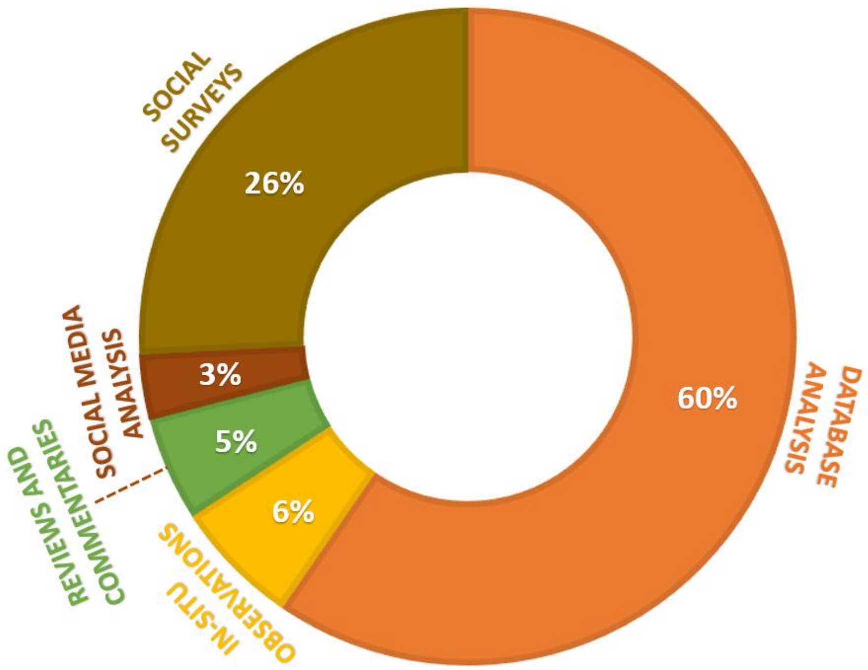

Figure 11 - Percentages of methodologies among the total analyzed publications. The most common methodology was database analysis (59%), then social surveys (26%), afterwards in-situ observations (6%), reviews and commentaries (5%), social media analysis (3%), and in yellow is forensic genetics (1%).

These results were as expected since most wildlife studies focus on database analysis. This focus is so that it is possible to quantify, and therefore, have a specific number when reporting the findings to the general public, in order to more easily change the public's perception regarding wildlife traffic (Veríssimo et al., 2020). Public's perception plays into the more efficient decrease of consumer demand of a wildlife product, as well as the government's willingness to implement new policies and preventive measures (Thomas-Walters et al., 2021; Veríssimo & Wan, 2019).

Nonetheless the low results for social media analysis indicate the massive gap in knowledge that exists for this new trend. Therefore it is necessary to shift some focus to online platforms before wildlife dealers completely dominate social media and make species and product detection almost impossible (Stringham et al., 2021). For that new preventive and monitorization measures are needed. Having in mind the large amount of information that is available online an efficient and timely process is required to be able to disrupt this online flow of illegal trade.

2.4 Conclusions

For this chapter, our goal was to evaluate the state of the art of mammal trade in the available published scientific literature. To achieve this goal, we analyzed which countries and continents reported the most incidents of mammal wildlife trade, which taxonomic groups were the most traded, what were the main purposes of the traded mammals and their products, as well as the most utilized methodologies for overseeing studies.

To conduct the systematic literature review we established a set of keywords to allow us to search for studies, filtered and analyzed them in order to review the content through a quantitative and qualitative analysis.

Through this systematic literature review we can conclude that regarding geographic patterns Asia was the most popular continent, with the most amount of studies done regarding China and Vietnam, followed by Africa and South America, with Brazil and Peru standing out among the literature found. This was also supported by Asia and Africa being the most export rich continents, with China being the country with the highest amount of demand for wildlife products. For taxonomic patterns, Elephantidae and Rhinocerontidae were the most studied family with their animal products falling in the most used categories for aesthetic and traditional medicine purposes. Finally, we could see that database analysis was the most popular methodology approach and there is a big lack of social media analysis.

These results allowed us to answer our initial question regarding the general state of the art for wildlife trade, as well as realize that there is a massive gap in knowledge when it comes to online wildlife commerce. For the next chapter we try to address and explore this lack of studies, by trying to implement a new measure of tracking instances of wildlife trade occurring on social media platforms.

Chapter 3

Tracking wildlife trade using machine learning: a test case with pangolin species in social media images

3.1. Background

With recent technological advances, the Internet has become one of the biggest marketplaces in the world, emerging as an important platform for wildlife commerce and allowing for cyberspace criminals to take advantage of more secure and rapid methods of communications (Lavorgna, 2014). In most regions worldwide, e-commerce is free, limitless, and mostly unregulated, allowing for the creation of opportunities for illegal and criminal activities, with easy and anonymous selling and buying transactions (Hastie & McCrea-Steele, 2014). For example, China has the largest online community in the world, with more than 730 million users, and their e-commerce platforms have been the main mode of wildlife sales, half of it involving ivory trade (Komosny & Mehic, 2018; Yu & Jia, 2015).

Over the last decade, there has been a shift to trading wildlife in active social media platforms, causing a surge in illegal sales (Xiao et al., 2017). Social media platforms allow for the sellers to share information and exhibit pictures about wildlife trade products in order to attract and interact with potential buyers (Yu & Jia, 2015). The use of these platforms is an improvement as opposed to other e-commerce platforms (e.g., e-Bay), since it allows the seller to become more selective and private with the buyers, thereby making it hard to track seller-buyer communications and transactions (Xiao et al., 2017). In fact, most social media platforms have privacy setting for users' profiles, leading to transactions with only recognized or vouched for customers (Lavorgna, 2014).

Despite the former challenges, recent developments in artificial intelligence, such as machine learning, have been showing promising opportunities for tracking wildlife sales (Di Minin et al., 2018). Machine learning refers to algorithms that can perform a task without human guidance while being specifically programed to solve it (Di Minin et al., 2018; Wäldchen & Mäder, 2018). Machine learning algorithms have the ability to learn from previous tasks during a process called training and later on they perform the previously trained task on a new dataset (Mjolsness & DeCoste, 2001). When the training is well performed, machine learning can be highly successful in identification, classification, and detection of image (i.e., computer vision) or textual content (i.e., natural language processing) (Wäldchen & Mäder, 2018). Machine learning thereby becomes promising for analyzing the content of any digital data e.g., from Web pages, personal advertisements, social media content and e-commerce information (Abadi et al., 2016; Lecun et al., 2015). Besides wildlife trade, applications of machine learning in conservation include, for instance, the analysis of texts (e.g., Twitter posts), images (e.g., Facebook photographs) and audio-visual content (e.g., YouTube videos) shared by people about ecosystems' health, invasive alien species or protected/emblematic species (Allain, 2019; Hausmann et al., 2018).

Deep learning is a subfield of machine learning that undertakes the learning process of high-level abstractions in data using hierarchical architectures, by eliminating the manual task of feature extraction and leaving that process and classification to the algorithm (Guo, 2017). Deep learning has gained popularity due to its exceedingly increased processing abilities, the lowered cost of computing hardware and the considerable strides forward in the machine learning algorithms (Jiang et al., 2017).

Deep learning models come with many advantages when used for image classification. Machine learning depends on how good the original data is labeled, while deep learning models don't always need labeling, as neural networks perform well at learning without guidelines (Najafabadi et al., 2015; Wäldchen & Mäder, 2018). Another advantage is that for fields like language, speech and vision, deep learning consistently produces great results, outperforming other alternatives (August et al., 2020; Saiharsha et al., 2020). Nonetheless, this algorithm also requires large amounts of data in order to produce more accurate results and overfitting is a prevalent problem that can affect the model performance negatively when using real time scenarios (Jiang et al., 2017; Rangarajan & Purushothaman, 2020; Wäldchen & Mäder, 2018).

This chapter aims to understand whether freely available machine learning models can support the identification of potential situations of wildlife trade on social media images. Specifically, it aims to understand whether: (1) freely-available machine learning algorithms can be developed to support an automated classification of social media photographs in the context of potential wildlife trade; (2) which existing machine learning algorithms show the highest potential to promote statistically reliable image classifications of potential situations of wildlife trade, and (3) at which point can those algorithms and models be used to identify potentially traded species and their commercialized products

To achieve these goals, we considered pangolin species as our case study, due to its endangered status, high trafficking rates and since it is an animal that is getting quite a lot of attention due to its initial uncertainty of being a covid-19 virus carrier (Liu et al., 2020; Volpato et al., 2020; Zhang et al., 2020). Many pangolin species are endangered, like the White-bellied pangolin (*Phataginus tricuspis*), Giant pangolin (*Smutsia gigantea*), Chinese pangolin (*Manis* *pentadactyla),* Philippine pangolin (*Manis culionensis*), Sunda pangolin (*Manis javanica*) and Indian pangolin (*Manis crassicaudata*), according to International Union for Conservation of Nature (IUCN) Red List and have been under growing demand in Eastern Asian countries, especially China (Gaudin et al., 2009; Pietersen et al., 2014). These animals are found in tropical regions, throughout Central and Southern Africa and South Asia, they range from one 30 centimeters to one meter, tail excluded, with short legs, small ears and a long, worm-like tongue used to capture ants, making them nocturnal insectivores (Linnaeus & Heath, 1992). However, their main feature is a scaly armor that covers their whole body and tail, except for the under surface of the body, formed by overlapping keratinous scales (Spearman, 1967; Wang et al., 2016; Yu et al., 2015).

3.2 Methods

3.2.1 Methodological overview

Our methodological framework included three main steps: (1) data acquisition and pre-processing, (2) model training and (3) model testing. First, we compiled a dataset of images with and without pangolins from various sources, followed by a manual process of image labeling and resizing. Then, we trained a set of relevant machine learning models, through transfer learning, and evaluated their ability to classify images exhibiting pangolins and their sellable parts. Finally, we evaluate the performance of those models based on a series of matrix and validate the results.

3.2.2 Data acquisition

To start this project, we compiled and organized a large dataset of images containing pangolin species and their parts to train the classification models (see section 3.2.3). The images were obtained from online databases such as iNaturalist (https://www.inaturalist.org/), Google (https://www.google.com/), Flickr (https://www.flickr.com/) and also provided by colleagues from Nanjing University, China, Chi Xu and Zixiang Xiao. The extraction of the images from iNaturalist and Flickr was done manually: in each platform, we searched for general terms pertaining to pangolins, and well as the common name of six pangolin species (Table 2) and extracted the corresponding (public) images. The six pangolin species considered were: the White-bellied pangolin (*Phataginus tricuspis*), Giant pangolin (*Smutsia* *gigantea*), Chinese pangolin (*Manis pentadactyla*), Philippine pangolin (*Manis culionensis*), Sunda pangolin (*Manis javanica*) and Indian pangolin (*Manis crassicaudata*).

To facilitate the process of image extraction from Google we adopted the python program google-images-download (https://github.com/hardikvasa/google-images-download), which is a script that uses keywords or key phrases to then download those results from Google Images. We focused on images with pangolins while they were alive in their natural habitats, dead in wildlife markets or seizure instances, and their derivatives like scales or full pelts. Also, as a control group, we extracted, using the same python script, images without pangolins in their wild habitat and in wildlife markets. For the images without pangolins, a manual search was done using the location feature of Google Images to broaden the dataset. The locations chosen to widen the search were from the Asian continent as this is the location with the most instances of pangolin trafficking – Myanmar, Vietnam, China, Thailand, Singapore, Indonesia, and Laos (Cheng et al., 2017; Lim, 2009).

Table 2 - Keywords and key phrases used to extract images from Google using the python script google-images-download.

Pangolins	Without pangolins
▪ Pangolin ▪ Pangolin iNaturalist ▪ Manidae ▪ White-bellied pangolin ▪ Giant pangolin ▪ Chinese pangolin ▪ Philippine pangolin ▪ Sunda pangolin ▪ Indian pangolin	▪ Asian wet market ▪ Asian public market ▪ Wildlife market

After the image compilation, the dataset underwent a manual verification process of filtering and transformation steps, resulting in a total of 2634 images (see Figure 12 for examples), with the resolution of 257 and 465 pixels, height, and width respectively. All images were then tagged using a Microsoft Excel spreadsheet with their corresponding label according to their content: One pangolin (1pan), one specific part or parts of pangolin's body (1 part), multiple pangolins (mulpan), pangolin not in its entirety (mulpart) and no pangolins (np) (Table 3). Each label had a specific meaning according to what they displayed in the content: 1pan showed one pangolin; 1part showed only a specific part like scales, pelt, teeth, or nails; mulpan showed more than one pangolin; mulpart showed as absence of entire pangolins, e.g., cropped pictures or close shots of pangolins; and np showed no pangolins, but instead their usual settings (in the wild or markets), serving as control group. All images were resized, and their corresponding labels were transformed into binary class matrices.

Table 3 - Table containing each label, its meaning and how many images were associated with it.

LABEL	CLASSIFICATION	TOTAL IMAGES
1PAN	One pangolin	800
1PART	Specific part or parts	14
MULPAN	Multiple pangolins	139
MULPART	Pangolin not in its entirety	72
NP	No pangolins	1057

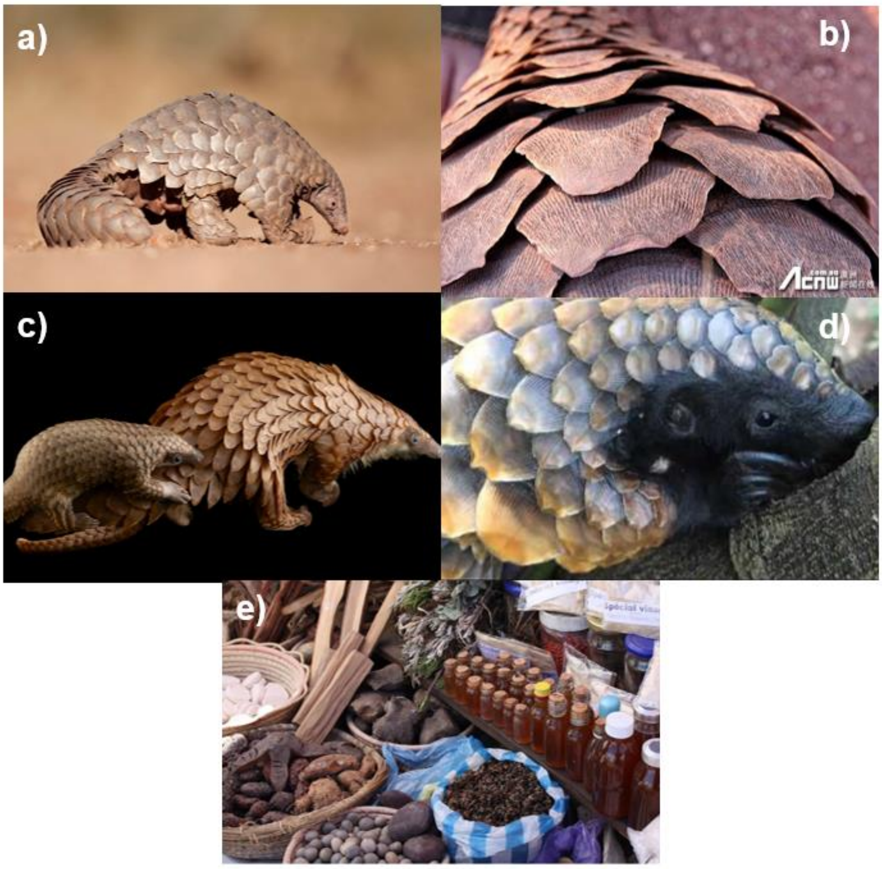

Figure 12 - Examples of images extracted from online platforms for each label. a) one pangolin (1pan); b) part of a pangolin (1part); c) multiple pangolins (mulpan); d) pangolins not in their entirety, cropped or close shots; e) no pangolins but instead their usual settings.

3.2.3 Model implementation

Transfer learning

To implement the machine learning models, we used transfer learning. Transfer learning is a technique adopted to improve a model by transferring information from a related domain (Weiss et al., 2016). It consists of an optimization method used to save time by reducing the data collection efforts and achieve better performance (Shu, 2019), being useful for dealing with limited training data (Weiss et al., 2016). Transfer learning can be defined as the application of a dataset with similar features to the dataset of interest, in order to extract pre-trained weights necessary for model implementation (Weiss et al., 2016). In our case we used the ImageNet database (http://www.image-net.org/) which consists of a large-scale image database, with applications in a wide range of areas. It includes more than fourteen million annotated images in over 21 thousand categories, making it into an incredibly diverse coverage of the digital image world (Mettes et al., 2016).

Model training

Five models were selected for the training process: Vgg16 (Simonyan & Zisserman, 2015), DenseNet121, DenseNet201 (Huang et al., 2017), EfficientNetB0 and EfficientNetB1 (Tan & Le, 2019). Vgg16 is a model composed of a total of 16 layers divided into convolution, max pooling and fully connected layers, achieving great performance in the image competition field (Qassim et al., 2018). For densely connected convolutional networks (DenseNet), the main feature is that each layer connects to every other layer in a feed-forward manner, passing its own features to all subsequent layers (Man et al., 2020). EfficientNet tries to achieve more efficient results by uniformly scaling resolution, width and depth, while scaling down the model (Atila et al., 2021). These models were selected because of their overall adaptability to all kinds of datasets making them the most appropriate for this type of study.

The training process was done using the freely available TensorFlow platform (https://www.tensorflow.org/), which is a free and open-source software library that focuses on training and inference of deep neural networks (Abadi et al., 2016). Model implementation was done through the “Google Colaboratory” or “Colab” website, which is a product from Google Research that allows to write and execute arbitrary python code through the browser and is especially well suited to machine learning. More technically, Colab is a hosted Jupyter notebook service that requires no setup to use, while providing free access to computing resources including GPUs (https://colab.research.google.com/notebooks/intro.ipynb).

For all five models the optimizer utilized was Adam, due to its efficiency, straightforwardness and little memory requirements, making it the best choice for this type of study (Kingma & Ba, 2015). Due to the limitations regarding the processing memory available in Colab, during the model training the batch size was set to 10, with 100 epochs and learning rates of 0.001 and 0.000001. The data was run in five folds, having the five labels in mind, therefore each model ran 10 times – one for each fold per learning rate.

Model performance

To evaluate the performance of each model, we used the following evaluation metrics (Table 4): accuracy (ACC), sensitivity (TPR – true positive rate or recall), specificity (TNR – true negative rate) and F1 score (F1, f-score or f-measure), as these are the most utilized and analyzed metrics when faced with classification problems (Tharwat, 2018). Accuracy is the closeness of the measurements to a specific value, while specificity measures an algorithm's ability to correctly identify negative results for negative instances. Sensitivity on the other hand, measures an algorithm's ability to correctly identify the positive results for positive instances. Finally, F1-score is a measure of a test's accuracy as it calculates the harmonic mean of the precision and recall.

Table 4 - Equations for each of the four performance metrics: TP represents the True Positives, TN the True Negatives, FP the False Positives and FN the False Negatives.

Metrics	Equation
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
Specificity	$\frac{TN}{TN + FP}$
Sensitivity	$\frac{TP}{TP + FN}$
F1-score	$\frac{2TP}{2TP + FP + FN}$

These metrics are computed from confusion matrices, which organize observed values (as labeled by the user) vs. predicted values (as labeled by the model algorithm), allowing to showcase the number of true positives, false positives, true negatives, and false negatives (Theckedath & Sedamkar, 2020; Loussaief & Abdelkrim, 2018; Powers, 2020). In our case the term positive refers to the presence of pangolins in the images, while negative to their absence (Table 5). For each metric, a mean was calculated for each set of five folds per learning rate, allowing us to determine which model and learning rate were the best ones.

Table 5 - Example of a confusion matrix used to compare the manual and automatic classification of extracted pangolin images, where Positives are labels with pangolins (1pan, 1part, mulpan, mulpart) and Negatives are labels with no pangolins (np).

		Predicted label				
		1pan (Positive)	1part (Positive)	mulpan (Positive)	mulpart (Positive)	np (Negative)
Actual label	1pan (Positive)					
	1part (Positive)					
	mulpan (Positive)					
	mulpart (Positive)					
	np (Negative)					

3.3 Results and discussion

The main purpose of this chapter was to investigate whether the adoption of freely available machine learning models could allow the identification of pangolin individuals in images extracted from social media networks, and, consequently, establish a new way to assist in the surveillance and monitoring of potential situations of online illegal trafficking.

3.3.1 *Detecting pangolin species*

From the five architectures used in this chapter, DenseNet121 with learning rate of 0.001 showed the best results, with an accuracy of 81,474 (Figure 13). This was followed by DenseNet201, also with learning rate of 0.001 (Accuracy of 81,238) and Vgg16 with a learning rate of 0.000001 (Accuracy of 78,332). While EfficientNet had the worst results, both for learning rate 0.000001 (EfficientNetB0 had an accuracy of 61,998 and EfficientNetB1 had an accuracy of 61,214). Vgg16 had the most consistent means between both learning rates, while DenseNet showed the best performance overall for this evaluation metric. These results suggest that in 100 classified images, 81 corresponded to the correct pangolin identification, or that of pangolins parts. Therefore, the DenseNet models are the most appropriate ones for a correct identification, when compared to the manually annotated images.

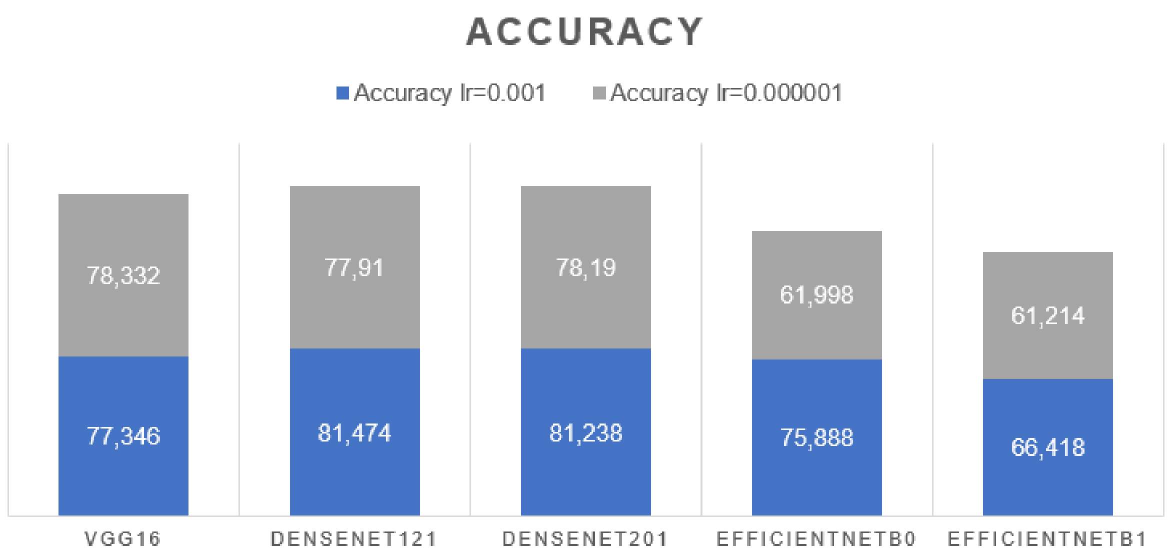

Figure 13 - Accuracy for the five model performances (Vgg16, DenseNet121, DenseNet201, EfficientNetB0 and EfficientNetB1) bearing in mind the two learning rates lr=0.001 and lr=0.000001.

In regard to sensitivity (Figure 14), the DenseNet121 with a learning rate 0.001 also had the highest result (62,248), followed by DenseNet201 (sensitivity of 60,708 for the same learning rate). Again, Vgg16 had the most consistent means between both learning rates, while DenseNet performed better and EfficientNet did the worst, both for the lowest learning rate (EfficientNetB0 with 38,234 and EfficientNetB1 with 35,108). This means, for DenseNet121, for each 100 classified images 62 were positively identified as the correct images of pangolins, or their parts.

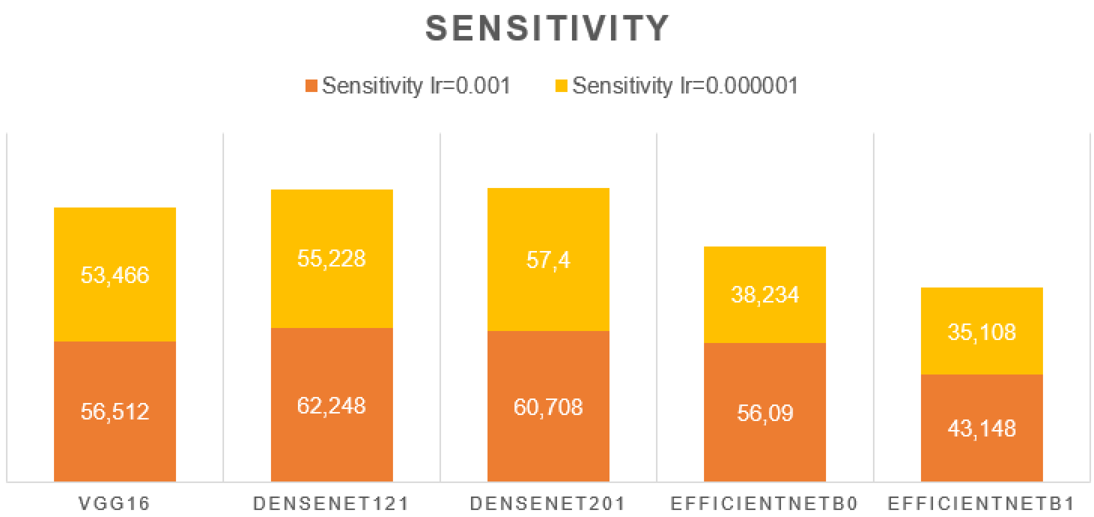

Figure 14 - Sensitivity for the five model performances (Vgg16, DenseNet121, DenseNet201, EfficientNetB0 and EfficientNetB1) bearing in mind the two learning rates lr=0.001 and lr=0.000001.

On the other hand, specificity (Figure 15) had the most consistent results across all models, which makes sense as the true negatives had only one label associated to them, thus not having too many mislabeling instances between the term negative. We can see that once again DenseNet121 performed the best for learning rate 0.001 (specificity of 94,628) closely followed by DenseNet201 with the same learning rate (94,562). Again, Vgg16 had the most consistent means between both learning rates and Efficient Net performed the worst, for the lowest learning rate once again (EfficientNetB0 with 87,732 and EfficientNetB1 with 86,94). Specificity identifies true negatives for negative instances, therefore the identification of images without pangolins was easily done throughout all five models. These results suggest that, for the best performing model (DenseNet121), for each 100 classified images 94 were correctly identified as not having pangolins.

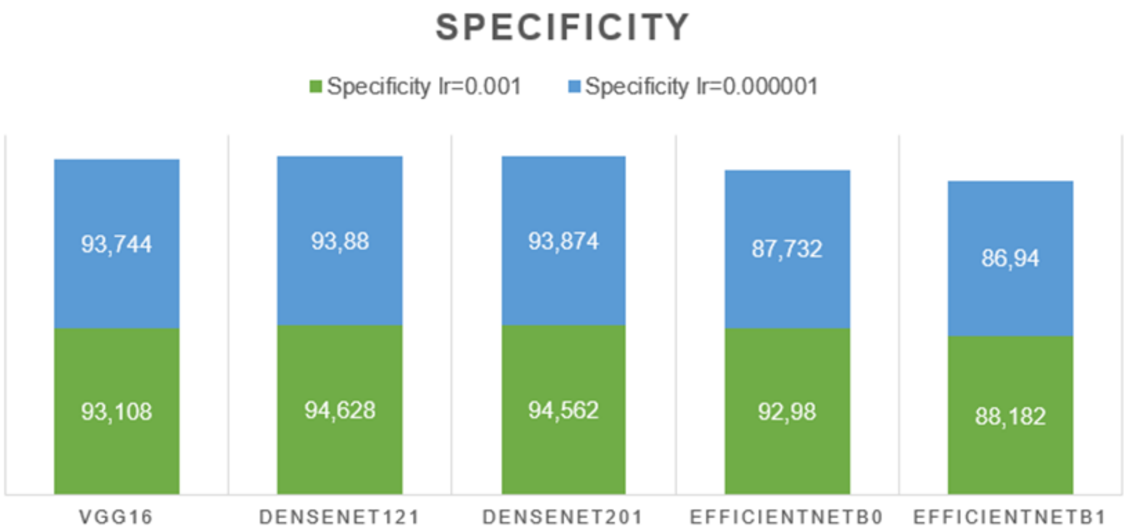

Figure 15 - Specificity for the five model performances (Vgg16, DenseNet121, DenseNet201, EfficientNetB0 and EfficientNetB1) bearing in mind the two learning rates lr=0.001 and lr=0.000001.

Finally, the F1 score (Figure 16) had the best performance with DenseNet121 (63,844) closely followed by DenseNet201 (63,544). Vgg16 had the most consistent means between learning rates, once again and EfficientNet had the worst results for learning rate 0.000001 (EfficientNetB0 with 36,904 and EfficientNetB1 34,176). This supports DenseNet121's overall good performance, while EfficientNetB1 has very low values, which is also observed through its confusion matrix further ahead, since it showcases many instances of mislabeling.

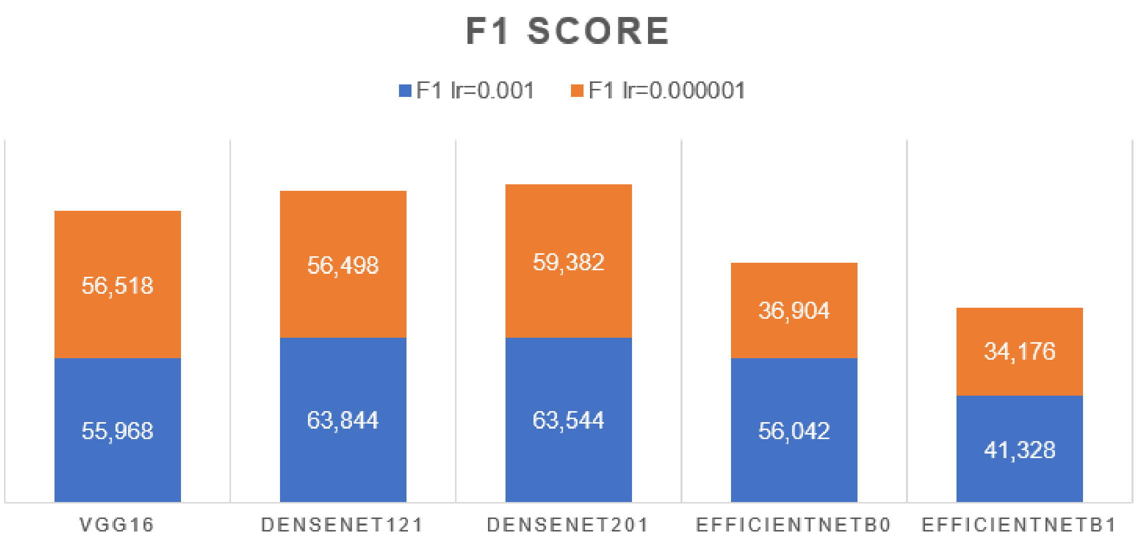

Figure 16 - F1 score for the five model performances (Vgg16, DenseNet121, DenseNet201, EfficientNetB0 and EfficientNetB1) bearing in mind the two learning rates lr=0.001 and lr=0.000001.

3.3.2 *Tracking tradable pangolin parts*

After analyzing the label classification from the five models, we observe that, in general, pictures with pangolins not in their entirety (mulpart) showed the most amount of false positives, frequently being mistaken for images with one pangolin (1pan). This would be expected results, considering these are the most similar classes of images. Conversely, pictures displaying only one pangolin were usually very accurate, as well as images with no pangolins, which is expected since pangolins have very distinguishable features like their body shape and scales. The similarity between the labels for one pangolin (1pan) and pangolins not in their entirety (mulpart), as well as mulpart’s frequent mislabeling could lead us to believe that it is an unnecessary label, because it does represent more of the same and there is no pressing need for a separation between both.

Specifically for each model, we could see that for Vgg16 the most accurately labeled images were those with no pangolins (np), being more frequently confused with the labeled images with pangolins not in their entirety (mulpart). This result can be seen in the image below (Figure 17) where we see the algorithm’s label prediction, represented as Predicted label, as well as the actual label given manually by us, represented as a vector by Actual label. The label for the vectors is identified by a number one in the correct order, therefore: if it is represented as [1.0.0.0.0.] that corresponds to the label 1pan; [0.1.0.0.0.] corresponds to the label 1part; [0.0.1.0.0.] correlates to the label mulpart; [0.0.0.1.0.] represents the label mulpan and [0.0.0.0.1.] corresponds to the label np.

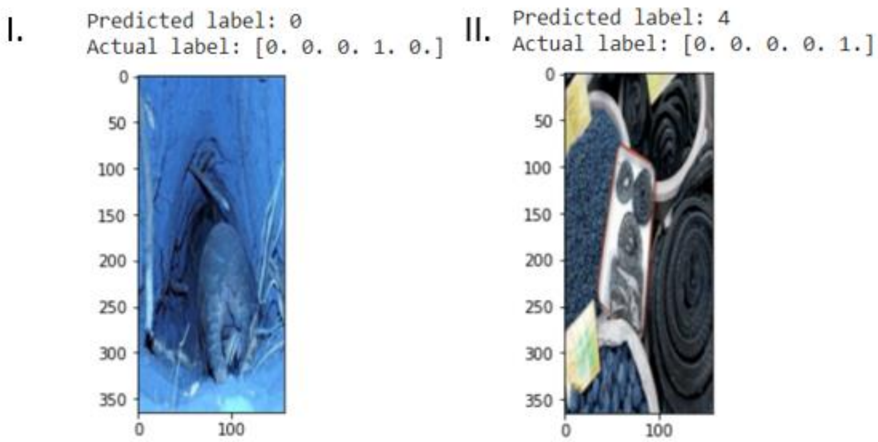

Figure 17 - Examples of images with I. incorrectly represented labels and II. correctly represented labels for the model Vgg16.

For the models DenseNet121 and DenseNet201 (Figures 18 and 19) the label best identified was, once again, no pangolins (np) as well as one pangolin (1pan), while the label with the most incorrect classifications was again, for pangolins not in their entirety (mulpart). The latter was frequently confused with images with one pangolin (1pan). With the exception of DenseNet201, which also struggles with correctly labeling images with multiple pangolins (mulpan), also confusing them with images of one pangolin (1pan).

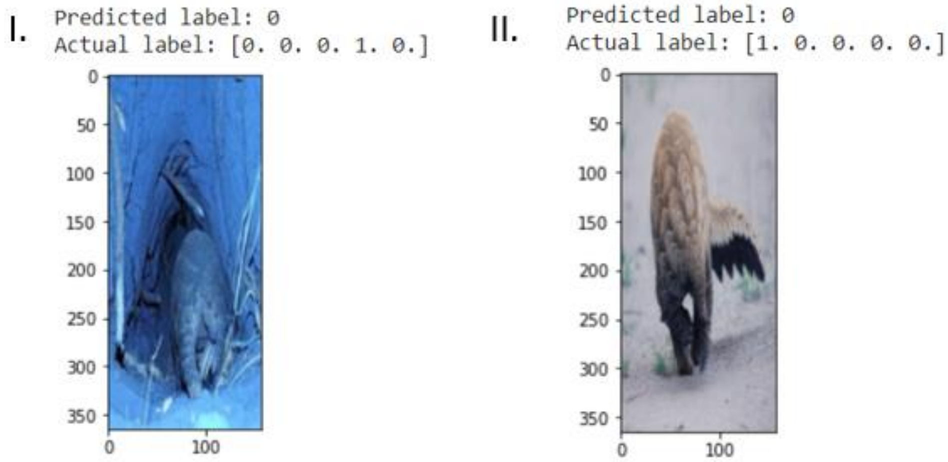

Figure 18 - Examples of images with I. incorrectly represented labels and II. correctly represented labels for the model DenseNet121.

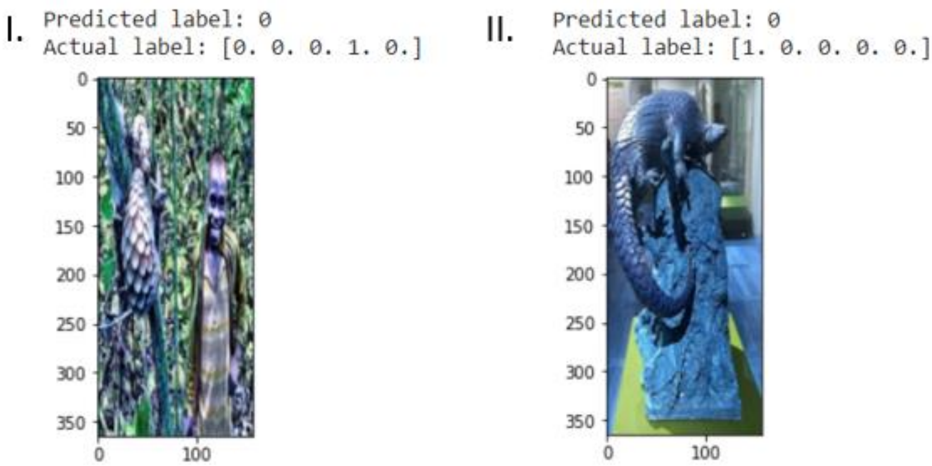

Figure 19 - Examples of images with I. incorrectly represented labels and II. correctly represented labels for the model DenseNet201.

EfficientNetB0 and EfficientNetB1 showed the least promising results for our dataset. For EfficientNetB0 images with no pangolins (np) were the most correctly labeled, while images with multiple pangolins (mulpan) and pangolins not in their entirety (mulpart) showed the most instances of mislabeling for images with one pangolin (1pan) (Figure 20). For EfficientNetB1 images with no pangolins were the most correctly labeled (np), however for all the other labels there was a lot of confusion with that same label (np), resulting in no pangolins (np) being labeled most of the time for all labels in general (Figure 21).

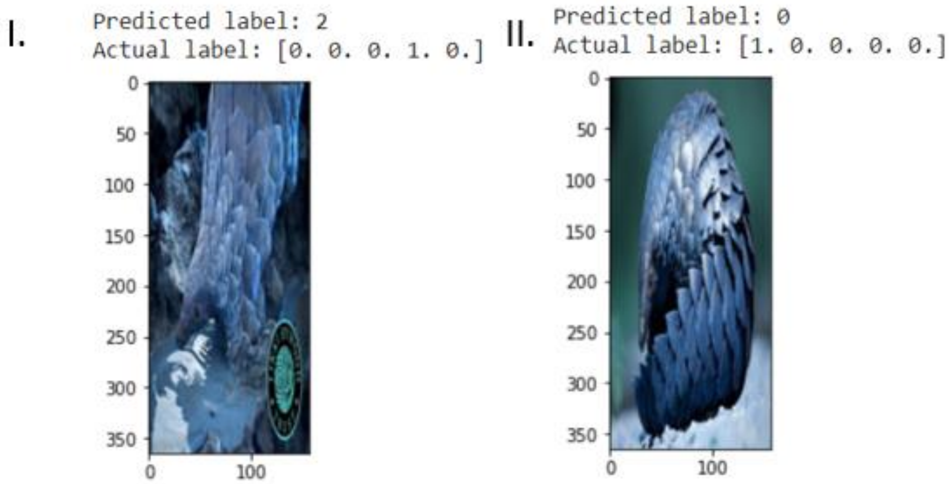

Figure 20 - Examples of images with I. incorrectly represented labels and II. correctly represented labels for the model EfficientNetB0.

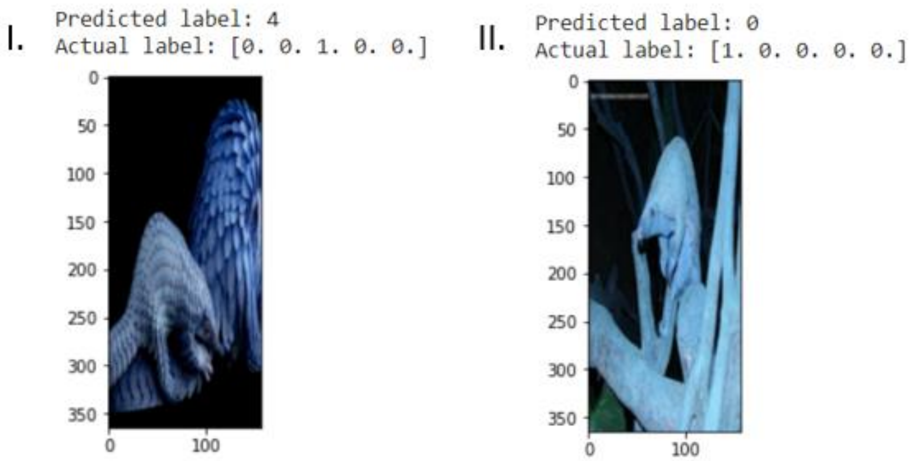

Figure 21 - Examples of images with I. incorrectly represented labels and II. correctly represented labels for the model EfficientNetB1.

3.3.3 *Best performing architectures*

Overall DenseNet121 had a better performance for our targeted dataset of images, closely followed by DenseNet201 and Vgg16 (Table 6). EfficientNet does not seem to fit this dataset, having the model's poor performance metrics in mind.

Table 6 - Performance metrics for both learning rates scenarios trained for each model. ACC – Accuracy, SEN – Sensitivity, SPEC – Specificity and F1 – F1 score.

	lr=0.001				***lr=0.000001***			
	ACC	**SEN**	**SPEC**	**F1**	**ACC**	**SEN**	**SPEC**	**F1**
Vgg16	77.346	56.512	93.108	55.97	78.33	53.47	93.74	56.52
DenseNet121	81.474	62.248	94.628	63.84	77.91	55.23	93.88	56.5
DenseNet201	81.238	60.708	94.562	63.54	78.19	57.4	93.87	59.38
EfficientNetB0	75.888	56.09	92.98	56.04	62	38.23	87.73	36.9
EfficientNetB1	66.418	43.148	88.182	41.33	61.21	35.11	86.94	34.18

Regarding the confusion matrix for the best performing model – DenseNet121, we can see that images with no pangolins (np), one pangolin (1pan) and one specific part (1part) showed the best results, while multiple pangolins (mulpan) and cropped out pangolins (mulpart) showed the worst (Table 7). Mulpan was often confused with the label 1pan (7 times) and mulpart was mislabeled as 1pan almost the same amount of times as it got correctly identified (23 to 25).

Table 7 - Confusion matrix for DenseNet121.

		Labels predicted by the model				
		One Pangolin	One pangolin part	Multiple pangolins	Cropped pangolins	No pangolins
Manually classified labels	One Pangolin	100	1	3	14	10
	One pangolin part	1	6	1	1	2
	Multiple pangolins	7	1	9	2	4
	Cropped pangolins	23	2	1	25	3
	No pangolins	1	1	1	0	208

For DenseNet201 we can see the same result (Table 8). Images with no pangolins, one pangolin and one part show the best labeling results, while images with multiple pangolins and pangolins not in their entirety showed the largest amount of mislabeling. As we can see for the crossover between 2-0 (nine identifications) and 2-2 (seven identifications), meaning that the label for multiple pangolins (mulpan) was mislabeled more often for one pangolin (1pan) than correctly identified. Same for images with pangolins not in their entirety (mulpart) as their correct labeling happened 29 times (3-3), but they got misidentified as one pangolin (1pan) 21 times (3-0).

Table 8 - Confusion matrix for DenseNet201.

		Labels predicted by the model				
		One Pangolin	One pangolin part	Multiple pangolins	Cropped pangolins	No pangolins
Manually classified labels	One Pangolin	97	0	2	19	9
	One pangolin part	1	5	0	2	2
	Multiple pangolins	9	0	7	2	3
	Cropped pangolins	21	1	0	29	4
	No pangolins	1	0	0	1	209

For the model Vgg16 we got more of the same (Table 9). Once again, the images with no pangolins, one pangolin and one specific part got the best results, while images with multiple pangolins and pangolins cropped out got the most cases of mislabeling. Both the worst labels got incorrectly classified for one pangolin more often than correctly labeled.

Table 9 - Confusion matrix for Vgg16.

		Labels predicted by the model				
		One Pangolin	One pangolin part	Multiple pangolins	Cropped pangolins	No pangolins
Manually classified labels	One Pangolin	89	1	6	13	17
	One pangolin part	2	5	0	1	1
	Multiple pangolins	6	1	5	1	5
	Cropped pangolins	24	2	1	19	8
	No pangolins	1	0	0	0	209

Regarding the model EfficientNetB0 we see once gain the same results as the previous ones (Table 10). The images with one pangolin, one part and no pangolins appear to be correctly labeled, while images with multiple pangolins and pangolins not in their entirety are mislabeled often for one pangolin.

Table 10 - Confusion matrix for EfficientNetB0.

		Labels predicted by the model				
		One Pangolin	One pangolin part	Multiple pangolins	Cropped pangolins	No pangolins
Manually classified labels	One Pangolin	92	1	6	14	14
	One pangolin part	2	5	1	1	2
	Multiple pangolins	6	1	7	2	4
	Cropped pangolins	26	2	3	17	6
	No pangolins	4	0	1	2	202

Finally, for EfficientNetB1 we see a large amount of mislabeling for images with no pangolins (Table 11). All the labels were identified as np more often than correctly labeled for this model.

Table 11 - Confusion matrix for EfficientNetB1.

		Labels predicted by the model				
		One Pangolin	One pangolin part	Multiple pangolins	Cropped pangolins	No pangolins
Manually classified labels	One Pangolin	52	1	3	15	56
	One pangolin part	1	3	0	0	6
	Multiple pangolins	2	0	4	1	13
	Cropped pangolins	12	1	1	16	25
	No pangolins	2	0	0	1	208

These results are compatible with other previous studies, since Vgg16 has also previously exhibited good results for image classification (Krishnaswamy & Purushothaman, 2020; Man et al., 2020) as well as DenseNet (Huang et al., 2020; Li et al., 2020; Zhong et al., 2020). On the other hand, EfficientNet has also produced well performing results in past works, which makes It unclear on why for this topic it did not (Alhichri & Alswayed, 2021; Atila et al., 2021; Duong et al., 2020). One thing to have in mind is that most past publications that use these models for image classification are very recent and most of them focus on cancer research or on plant disease research, having a very big gap in knowledge and research published for animal image classification.

3.4 Conclusion

The main objective of this chapter was to understand whether machine learning models can be utilized to identify situations of wildlife trade on social media images, with pangolins as a case study. To achieve this objective, we used the freely available machine learning models Vgg16, DenseNet121, DenseNet201, EfficientNetB0 and EfficientNetB1 to understand which would be the best performing model, in order to develop an automated classification algorithm to identify potentially traded species and their commercialized products.

For the development of the machine learning algorithm, we compiled a dataset of images with and without pangolins, from diverse sources, and manually labeled and resized the extracted images. Subsequently we trained the machine learning models mentioned above, through transfer learning, evaluating their capability to classify images showcasing pangolins and their commercialized parts, as well as the models' performance metrics.

Our results showed that it is possible to obtain a well performing model regarding the identification of pangolins and their tradeable parts. For our dataset the best performing model was DenseNet121, closely followed by DenseNet201, however there are still more studies and practice required with different parameters and other models, to fully understand all the possibilities this methodology can allow.

Chapter 4

Discussion

Our literature review showcased how Asia was the continent with the most studies performed which is expected due to its large customer base. With the recent socio-economic development in Asian countries, specifically China there's been an increase in disposable income, which in turned into a surge in illicit wildlife trade (Nijman, 2010). This can easily explain the high number of studies done in this continent as researchers try to quantify the illegal trades and, in turn, propose new methods of dealing with these occurrences (Chow et al., 2014; Foley et al., 2011; Heinrich et al., 2016; H. Zhang et al., 2015).

Regarding the taxonomic patterns the combined percentage of Elephantidae and Rhinocerontidae (40%) demonstrates how prevalent ivory trade still is (Burn et al., 2011). Even facing the recent ban on ivory trade its illegal commerce is still being committed as African poachers depend on it as their main source of income, while customers still consider it a commodity and status symbol (Bennett, 2015; Sas-Rolfes et al., 2019). Manidae and Felidae are on almost equal grounds due to both being used mostly for aesthetic and traditional medicine purposes, with pangolins used for their scales and meat, while felines are killed for their pelts, nails and teeth (Kelly, 2018; Volpato et al., 2020). Which is supported by the results showcasing which are the main uses for animal product, revealing that aesthetic purposes and traditional medicine are the main uses for animals and their derivatives.

Transnational trade has grown and continues to grow at a far greater rate than our collective ability to regulate it, leading to the laundering of illicit merchandise, this includes wildlife products which need new effective and cost friendly ways to protect the threatened species and our planet's biodiversity (United Nations Office of Drugs and Crime, 2016). Wildlife crimes have low priority on the law enforcement agenda as most governments consider it an environmental issue, thus these investigations are generally sparce and scarce (Ratchford et al., 2008). The substantial gap in the literature regarding the types of criminal opportunities the Internet offers, and illegal wildlife trade done through online platforms, and, more specifically, social media shows that there's a deficit of openly available tools that can be used to help track illicit commerce (Ratchford et al., 2008; Wu, 2007).

Even though our main purpose with this literature review was to get a general idea of the state of the art regarding illegal wildlife trade, it was still important to see the main data and research approaches to reveal the secondary purpose of this project. The lack of studies regarding online wildlife trade exposed the giant gap in knowledge regarding this booming trade opportunity, and, therefore, justified the need for new measures to be implemented in order to try and monitor and prevent these business deals.

4.1 Tracking online wildlife traffic through machine learning

After an initial analysis we could see that the results were very promising, specifically for both DenseNet and Vgg16 architectures, while the low performance of EfficientNet could be due to overfitting caused by our relatively small dataset, which was due to GoogleColab's small RAM availability not permitting the fulfillment of data augmentation.

DenseNet combines other networks' advantages to alleviate the vanishing gradient problem in deep neural networks by ensuring the maximum information flow between layers. A possible explanation for DenseNet's good performance is its ability to concatenate features from different layers, strengthening their propagation and feature re-usage, while also having narrow layers, and thus needing less parameters to train. All these characteristics make DenseNet into the easiest and most efficient to train classification algorithm (Man et al., 2020).

It would also be interesting to use other models like ResNet (Targ et al., 2016), GoogLeNet (Szegedy et al., 2015) and AlexNet (Krizhevsky et al., 2017), considering these are also used in image classification problems with good results.

4.2 Research limitations and further prospects

This is not to say that this methodology does not have its limitations. As previously mentioned, our main goal is to find out whether this methodology is possible to apply on images extracted from social media. If we pose a hypothetical scenario and decide that it is possible for the algorithm to identify pangolins in a random dataset of images extracted from a social media network, we still must face other issues before we are 100% certain that we got a lead for a criminal seller. This is because often times people take and post pictures however and of whoever they want to. Solely from the detection of a pangolin we cannot be sure whether that picture was posted for leisure or for an illegal activity, meaning that we will need additional information in the form of tags or the text in the image's description, the comments or the original poster's (OP) account itself (Dorwart et al., 2020).

Additionally, most social media platforms have a privacy setting. This means that the seller can restrict access to their account only to trusted customers, whether through going private or utilizing the blocking feature (Hastie & McCrea-Steele, 2014). It is also important to keep in mind that for public accounts, many sales could be initiated in the comments, publicly, but then moved to direct messages (DMs) for an easier means of communication, but also for more privacy (Xu et al., 2020).

Going forward, we want to continue testing the algorithm to find out if it is possible to apply this tracking method to other species. From these preliminary results we could assume that it is, therefore, we will soon have a more efficient and less time-consuming way of dealing with this new problem. Our only issue will be thinking of how to implement this into a proper new preventive measure that will not be ignored by the government and will be acted upon.

Chapter 5

Conclusion

Illegal trafficking has suffered a massive rise in utilization on online platforms over the past few years, mainly because of social media network's rise in popularity due to its anonymity and ease of use. For this thesis our main goal was to evaluate the state of the art of mammal trade in the available scientific literature, with a focus on geographic patterns, taxonomic groups, the uses for the traded animals and their parts, and the methodologies most commonly utilized for wildlife trade studies. And to understand if freely available machine learning models can be useful for identifying potential situations of wildlife trade on social media images, adopting pangolins as a case study, as well as which models show the highest potential for this task. This practical component was achieved through a manual compilation of images with and without pangolins, their resizing, and subsequent use for model training, through transfer learning.

The systematic literature review regarding wildlife trade showed Asia's, and particularly China's, large role in wildlife commerce, with a focus on the most trafficked taxonomic groups, such as Elephantidae, Manidae and Felidae. It was also possible to see a massive gap in knowledge when it comes to online wildlife trade which is concerning considering the large role it has been playing in the illegal trade industry. Additionally, the practical component allowed us to realize that it is possible to train an already available model to identify images with and without pangolins. The best performing model was DenseNet121, closely followed by DenseNet201, as these showed the best results for their respective performance metrics and correctly labeled the images.

Therefore, social media mining and the development of machine learning models that can aid in the identification of trafficked species is an important step into finding possible solutions for this rising problem. By making the tracking process of illegally trafficked species automated, and thus, more efficient and less time consuming, it will be possible to propose a new measure of management and monitorization by identifying instances of online sales through detecting the individuals in question.

Bibliography

Abadi, M., Barham, P., Jianmin, C., Zhifend, C., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, S., Murray, D. G., Steiner, B., Tucker, P., Vasudevan, V., Warden, P., … Zheng, X. (2016). TensorFlow: A System for Large-Scale Machine Learning. Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI ’16). https://doi.org/10.1016/0076-6879(83)01039-3

Aceves-Bueno, E., Read, A. J., & Cisneros-Mata, M. A. (2021). Illegal fisheries, environmental crime, and the conservation of marine resources. Conservation Biology, 35(4), 1120–1129. https://doi.org/10.1111/cobi.13674

Alfino, S., & Robert, D. L. (2020). Code word usage in the online ivory trade across four European Union member states. Oryx, 54(4), 494–498. https://doi.org/10.1017/S0030605318000406

Alhichri, H., & Alswayed, A. S. (2021). Classification of Remote Sensing Images Using EfficientNet-B3 CNN Model With Attention. 9. https://doi.org/10.1109/ACCESS.2021.3051085

Allain, S. J. R. (2019). Distribution of invasive species - rupestrian fields. 148, 11–14.

Alnajjar, M. (2021). Image-Based Detection Using Deep Learning and Google Colab. International Journal of Academic Information Systems Research, 5(1), 30–35. www.ijeais.org/ijaisr

Ambarli, H., Ertürk, A., & Soyumert, A. (2016). Current status, distribution, and conservation of brown bear (Ursidae) and wild canids (gray wolf, golden jackal, and red fox; canidae) in Turkey. Turkish Journal of Zoology, 40(6), 944–956. https://doi.org/10.3906/zoo-1507-51

Anderson, B., & Jooste, J. (2013). Wildlife Poaching : Africa ’ s Surging Trafficking Threat. Africa Center for Strategic Studies, 28, 1–8.

Appendices I, II and III. (2017). CITES, 32.

Arias, M., Hinsley, A., & Milner-Gulland, E. J. (2020). Characteristics of, and uncertainties about, illegal jaguar trade in Belize and Guatemala. Biological Conservation, 250(August), 108765. https://doi.org/10.1016/j.biocon.2020.108765

Atila, Ü., Uçar, M., Akyol, K., & Uçar, E. (2021). Plant leaf disease classification using EfficientNet deep learning model. Ecological Informatics, 61(June 2020), 101182. https://doi.org/10.1016/j.ecoinf.2020.101182

August, T. A., Pescott, O. L., Joly, A., & Bonnet, P. (2020). AI Naturalists Might Hold the Key to Unlocking Biodiversity Data in Social Media Imagery. Patterns, 1(7), 100116. https://doi.org/10.1016/j.patter.2020.100116

Ayling, J. (2016). Transnational environmental crime: meeting future challenges through networked regulatory innovations. In Greening Criminology in the 21st Century (Issue September, pp. 73–90).

Barber-Meyer, S. M. (2010). Dealing with the clandestine nature of wildlife-trade market surveys. Conservation Biology, 24(4), 918–923. https://doi.org/10.1111/j.1523-1739.2010.01500.x

Barnosky, A. D., Matzke, N., Tomiya, S., Wogan, G. O. U., Swartz, B., Quental, T. B., Marshall, C., McGuire, J. L., Lindsey, E. L., Maguire, K. C., Mersey, B., & Ferrer, E. A. (2011). Has the Earth's sixth mass extinction already arrived? Nature, 471(7336), 51–57. https://doi.org/10.1038/nature09678

Beastall, C., Shepherd, C. R., Hadiprakarsa, Y., & Martyr, D. (2016). Trade in the Helmeted Hornbill Rhinoplax vigil: The "ivory hornbill." Bird Conservation International, 26(2), 137–146. https://doi.org/10.1017/S0959270916000010

Bennett, E. L. (2015). Legal ivory trade in a corrupt world and its impact on African elephant populations. Conservation Biology, 29(1), 54–60. https://doi.org/10.1111/cobi.12377

Bennett, E. L., & Robinson, J. G. (2000). Hunting of wildlife in tropical forests: implications for biodiversity and forest peoples. Toward Environmentally and Socially Sustainable Development. Environment Department Paper No. 76, 76(September), 56. https://openknowledge.worldbank.org/bitstream/handle/10986/18297/multi0page.pdf?sequence=1&isAllowed=y

Bergin, D., Chng, S. C. L., Eaton, J. A., & Shepherd, C. R. (2018). The final straw? An overview of Straw-headed Bulbul Pycnonotus zeylanicus trade in Indonesia. Bird Conservation International, 28(1), 126–132. https://doi.org/10.1017/S0959270917000302

Bouché, P., Douglas-Hamilton, I., Wittemyer, G., Nianogo, A. J., Doucet, J. L., Lejeune, P., & Vermeulen, C. (2011). Will elephants soon disappear from West African Savannahs? PLoS ONE, 6(6). https://doi.org/10.1371/journal.pone.0020619

Broad, S., & Burgess, G. (2016). Synthetic biology, product substitution. TRAFFIC Bulletin, 28(1).

Broad, S., Mulliken, T., & Roe, D. (2014). The nature and extent of legal and illegal trade in wildlife. In Regulation for Conservation (pp. 25–44).

Burivalova, Z., Lee, T. M., Hua, F., Lee, J. S. H., Prawiradilaga, D. M., & Wilcove, D. S. (2017). Understanding consumer preferences and demography in order to reduce the domestic trade in wild-caught birds. Biological Conservation, 209, 423–431. https://doi.org/10.1016/j.biocon.2017.03.005

Burn, R. W., Underwood, F. M., & Blanc, J. (2011). Global trends and factors associated with the illegal killing of elephants: A hierarchical bayesian analysis of carcass encounter data. PLoS ONE, 6(9). https://doi.org/10.1371/journal.pone.0024165

Ceballos, G., Ehrlich, P. R., Barnosky, A. D., García, A., Pringle, R. M., & Palmer, T. M. (2015). Accelerated modern human-induced species losses: Entering the sixth mass extinction. Science Advances, 1(5), 9–13. https://doi.org/10.1126/sciadv.1400253

Ceballos, G., García, A., & Ehrlich, P. R. (2010). The Sixth Extinction Crisis Loss of Animal Populations and Species. Journal of Cosmology, 8(November 2009), 1821–1831.

Challender, D., & MacMillan, D. (2014). Poaching is more than an enforcement problem. Conservation Letters, 7(5), 484–494. https://doi.org/10.1111/conl.12082

Challender, D. W. S. (2011). Asian Pangolins: increasing affluence driving hunting pressure. TRAFFIC Bulletin, 23(3), 92–93.

Cheng, W., Xing, S., & Bonebrake, T. C. (2017). Recent Pangolin Seizures in China Reveal Priority Areas for Intervention. Conservation Letters, 10(6), 757–764. https://doi.org/10.1111/conl.12339

Chon, M. J., Daly, M., Wang, B., Xiao, X., Zaheri, A., Meyers, M. A., & Espinosa, H. D. (2017). Lamellae spatial distribution modulates fracture behavior and toughness of african pangolin scales. Journal of the Mechanical Behavior of Biomedical Materials, 76, 30–37. https://doi.org/10.1016/j.jmbbm.2017.06.009

Chow, A. T., Cheung, S., & Yip, P. K. (2014). Wildlife markets in south China. Human-Wildlife Interactions, 8(1), 108–112. https://doi.org/10.26077/esnr-ky11

CITES. (2016). Secretariat. "Status of Elephant populations, levels of illegal killing and trade in ivory: A report to the CITES standing committee." Conv. Int. Trade Endanger. Species Wild Fauna Flora. 3.1:56

CITES. (1997). Disposal of confiscated live specimens of secies included in the Appendices. Can be viewed at https://cites.org/eng/res/10/10-07R15.php

Cooney, R., Roe, D., Dublin, H., Phelps, J., Wilkie, D., Keane, A., Travers, H., Skinner, D., Challender, D. W. S., Allan, J. R., & Biggs, D. (2017). From Poachers to Protectors: Engaging Local Communities in Solutions to Illegal Wildlife Trade. Conservation Letters, 10(3), 367–374. https://doi.org/10.1111/conl.12294

Di Minin, E., Fink, C., Hiippala, T., & Tenkanen, H. (2019). A framework for investigating illegal wildlife trade on social media with machine learning. Conservation Biology, 33(1), 210–213. https://doi.org/10.1111/cobi.13104

Di Minin, E., Fink, C., Tenkanen, H., & Hiippala, T. (2018). Machine learning for tracking illegal wildlife trade on social media. Nature Ecology and Evolution, 2(3), 406–407. https://doi.org/10.1038/s41559-018-0466-x

Díaz, S., Settele, J., Brondízio, E. S., Ngo, H. T., Agard, J., Arneth, A., Balvanera, P., Brauman, K. A., Butchart, S. H. M., Chan, K. M. A., Lucas, A. G., Ichii, K., Liu, J., Subramanian, S. M., Midgley, G. F., Miloslavich, P., Molnár, Z., Obura, D., Pfaff, A., … Zayas, C. N. (2019). Pervasive human-driven decline of life on Earth points to the need for transformative change. Science, 366(6471). https://doi.org/10.1126/science.aax3100

Dirzo, R., & Raven, P. H. (2003). Global state of biodiversity and loss. Annual Review of Environment and Resources, 28, 137–167. https://doi.org/10.1146/annurev.energy.28.050302.105532

Dirzo, R., Young, H. S., Galetti, M., Ceballos, G., Isaac, N. J. B., & Collen, B. (2014). Defaunation in the Anthropocene. Science, 345(6195), 401–406. https://doi.org/10.1126/science.1251817

Doerr, E. D., Dorrough, J., Davies, M. J., Doerr, V. A. J., & Mcintyre, S. (2015). Maximizing the value of systematic reviews in ecology when data or resources are limited. Austral Ecology, 40(1), 1–11. https://doi.org/10.1111/aec.12179

Dongare, A. D., Kharde, R. R., & Kachare, A. D. (2012). Introduction to Artificial Neural Network (ANN) Methods. International Journal of Engineering and Innovative Technology (IJEIT), 2(1), 189–194. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.1082.1323&rep=rep1&type=pdf

Dorwart, C. E., Moore, R. L., & Leung, Y. F. (2020). Visitors' perceptions of a trail environment and effects on experiences: A model for nature-based recreation experiences. Leisure Sciences, 32(1), 33–54. https://doi.org/10.1080/01490400903430863

Draft Framework for Reviewing National Wildlife Trade Policies. (2007). 17(June), 3–15.

Duong, L. T., Nguyen, P. T., Di Sipio, C., & Di Ruscio, D. (2020). Automated fruit recognition using EfficientNet and MixNet. Computers and Electronics in Agriculture, 171(August). https://doi.org/10.1016/j.compag.2020.105326

Eikelboom, J. A. J., Nuijten, R. J. M., Wang, Y. X. G., Schroder, B., Heitkönig, I. M. A., Mooij, W. M., van Langevelde, F., & Prins, H. H. T. (2020). Will legal international rhino horn trade save wild rhino populations? Global Ecology and Conservation, 23. https://doi.org/10.1016/j.gecco.2020.e01145

Falautano, M., Castriota, L., Cillari, T., Vivona, P., Finoia, M. G., & Andaloro, F. (2018). Characterization of artisanal fishery in a coastal area of the Strait of Sicily (Mediterranean Sea): Evaluation of legal and IUU fishing. Ocean and Coastal Management, 151(March 2017), 77–91. https://doi.org/10.1016/j.ocecoaman.2017.10.022

Feddema, K., Harrigan, P., Nekaris, K. A. I., & Maghrifani, D. (2020). Consumer engagement behaviors in the online wildlife trade: Implications for conservationists. Psychology and Marketing, 37(12), 1755–1770. https://doi.org/10.1002/mar.21423

Foley, K.-E., Stengel, C. J., & Shepherd, C. R. (2011). Pills, powders, vials and flakes: the bear bile trade in Asia. TRAFFIC Southeast Asia.

Foster, S. J., Kuo, T. C., Wan, A. K. Y., & Vincent, A. C. J. (2019). Global seahorse trade defies export bans under CITES action and national legislation. Marine Policy, 103(September 2018), 33–41. https://doi.org/10.1016/j.marpol.2019.01.014

Gaudin, T. J., Emry, R. J., & Wible, J. R. (2009). The phylogeny of living and extinct pangolins (mammalia, pholidota) and associated taxa: A morphology based analysis. Journal of Mammalian Evolution, 16(4), 235–305. https://doi.org/10.1007/s10914-009-9119-9

Gimeno-Gilles, C., Lelièvre, E., Viau, L., Malik-Ghulam, M., Ricoult, C., Niebel, A., Leduc, N., Limami, A. M., Schmidt-Lebuhn, A. N., Fuchs, J., Hertel, D., Hirsch, H., Toivonen, J., Kessler, M., Loureiro, J., Lavania, U. C. U. C., Srivastava, S., Lavania, S., Basu, S., … Yao, J. L. (2016). The conservation Status, illegal trade and use of pangolins (Manis spp.). Euphytica, 18(2), 22280. http://dx.doi.org/10.1016/j.jplph.2009.07.006%0Ahttp://dx.doi.org/10.1016/j.neps.2015.06.001%0Ahttps://www.abebooks.com/Trease-Evans-Pharmacognosy-13th-Edition-William/14174467122/bd

Gluszek, S., Ariano-Sánchez, D., Cremona, P., Goyenechea, A., Luque Vergara, D. A., McLoughlin, L., Morales, A., Reuter Cortes, A., Rodríguez Fonseca, J., Radachowsky, J., & Knight, A. (2021). Emerging trends of the illegal wildlife trade in Mesoamerica. Oryx, 55(5), 708–716. https://doi.org/10.1017/S0030605319001133

Gonzalez-Maya, J. F., Zarate, D., Hernandez, A., Cepeda, A. A., Balaguera, S., Castaño, C., & Angel, C. (2010). Traditional uses of wild felids in the Caribbean region of Colombia: new threats for conservation? Revista Latinoamericana de Conservacion Latin American Journal of Conservation, 1(1).

Grant, M. J., & Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. Health Information and Libraries Journal, 26(2), 91–108. https://doi.org/10.1111/j.1471-1842.2009.00848.x

Grey, S. (2012). Conservation difficulties for Hylobates lar: white-handed gibbons and Thailand's illegal pet trade. Consortium: A Journal of Crossdisciplinary Inquiry, 32.

Guo, Y. (2017). A Comprehensive Review of Deep Learning Methods and Applications. Deep Learning for Visual Understanding, 7–58. https://linkinghub.elsevier.com/retrieve/pii/S0925231215017634

Haddaway, N. R., Woodcock, P., Macura, B., & Collins, A. (2015). Making literature reviews more reliable through application of lessons from systematic reviews. Conservation Biology, 29(6), 1596–1605. https://doi.org/10.1111/cobi.12541

Harrison, J. R., Roberts, D. L., & Hernandez-Castro, J. (2016). Assessing the extent and nature of wildlife trade on the dark web. Conservation Biology, 30(4), 900–904. https://doi.org/10.1111/cobi.12707

Harvey, S., & Harvey, R. (1998). An introduction to artificial intelligence. Appita Journal, 51(1). https://doi.org/10.2514/6.1994-294

Hastie, J., & McCrea-Steele, T. (2014). Wanted - Dead or Alive: Exposing Online Wildlife Trade. International Fund for Animal Welfare, 33. https://s3.amazonaws.com/ifaw-pantheon/sites/default/files/legacy/IFAW-Wanted-Dead-or-Alive-Exposing-Online-Wildlife-Trade-2014.pdf

Hausmann, A., Toivonen, T., Slotow, R., Tenkanen, H., Moilanen, A., Heikinheimo, V., & Di Minin, E. (2018). Social Media Data Can Be Used to Understand Tourists' Preferences for Nature-Based Experiences in Protected Areas. Conservation Letters, 11(1), 1–26. https://doi.org/10.1111/conl.12343

Heinrich, S., Wittman, T. A., Ross, J. V, Shepherd, C. R., Challender, D. W. S., & Cassey, P. (2017). The Global Trafficking of Pangolin: A comprehensive summary of Seizures and trafficking routes from 2010-2015. In Traffic (Issue December). http://static1.1.sqspcdn.com/static/f/157301/27779360/1513337200303/global-pangolin-assessment.pdf

Heinrich, S., Wittmann, T. A., Prowse, T. A. A., Ross, J. V., Delean, S., Shepherd, C. R., & Cassey, P. (2016). Where did all the pangolins go? International CITES trade in pangolin species. Global Ecology and Conservation, 8, 241–253. https://doi.org/10.1016/j.gecco.2016.09.007

Hinsley, A., De Boer, H. J., Fay, M. F., Gale, S. W., Gardiner, L. M., Gunasekara, R. S., Kumar, P., Masters, S., Metusala, D., Roberts, D. L., Veldman, S., Wong, S., & Phelps, J. (2018). A review of the trade in orchids and its implications for conservation. Botanical Journal of the Linnean Society, 186(4), 435–455. https://doi.org/10.1093/botlinnean/box083

Horne, B. D., Poole, C. M., & Walde, A. D. (2012). Conservation of asian tortoises and freshwater turtles: setting priorities for the next ten years. Recommendations and conclusions from the workshop in Singapore. In Wcs/Tsa (Issue April 2015).

Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely Connected Convolutional Networks Gao. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 4700–4708.

Huang, Z., Zhu, X., Ding, M., & Member, S. (2020). Medical Image Classification Using a Light-Weighted Hybrid Neural Network Based on PCANet and DenseNet. 24697–24712.

Hughes, J. D. (2003). Europe as consumer of exotic biodiversity: Greek and Roman times. Landscape Research, 28(1), 21–31. https://doi.org/10.1080/01426390306535

Hulme, P. E. (2021). Unwelcome exchange: International trade as a direct and indirect driver of biological invasions worldwide. One Earth, 4(5), 666–679. https://doi.org/10.1016/j.oneear.2021.04.015

Ia, T. U. D. (2011). EU trade policy and the European. 3–23.

Jacobs, R. L., McClure, P. J., Baker, B. W., & Espinoza, E. O. (2019). Myth debunked: Keratinous pangolin scales do not contain the analgesic tramadol. Conservation Science and Practice, 1(9), 1–6. https://doi.org/10.1111/csp2.82

Jiang, Z., Xu, D., & Liang, J. (2017). A Deep Reinforcement Learning Framework for the Financial Portfolio Management Problem. 1–31. http://arxiv.org/abs/1706.10059

Kanehisa, R. F. D. A., & Neto, A. D. A. (2019). Firearm Detection using Convolutional Neural Networks. ICAART 2019 - Proceedings of the 11th International Conference on Agents and Artificial Intelligence, 2(Icaart), 707–714. https://doi.org/10.5220/0007397707070714

Katuwal, H. B., Neupane, K. R., Adhikari, D., & Thapa, S. (2013). Pangolins Trade , Ethnic Importance and its Conservation in Eastern Nepal (Issue May). https://doi.org/10.13140/RG.2.2.27446.91201

Kelly, J. R. (2018). Insights into the illegal trade of feline derivatives in Costa Rica. Global Ecology and Conservation, 13, e00381. https://doi.org/10.1016/j.gecco.2018.e00381

Kingma, D. P., & Ba, J. L. (2015). Adam: A method for stochastic optimization. 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings, 1–15.

Komosny, D., & Mehic, M. (2018). The Value of Geographic Locations Submitted by Internet Users. IEEE Access, 6, 62699–62706. https://doi.org/10.1109/ACCESS.2018.2876973

Krishnaswamy, R. A., & Purushothaman, R. (2020). Disease Classification in Eggplant Using Pre-trained VGG16 and MSVM. Scientific Reports, 10(1), 1–11. https://doi.org/10.1038/s41598-020-59108-x

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6), 84–90.

Kurland, J., Pires, S. F., McFann, S. C., & Moreto, W. D. (2017). Wildlife crime: A conceptual integration, literature review, and methodological critique. Crime Science, 6(1). https://doi.org/10.1186/s40163-017-0066-0

Laird, S. A., Wynberg, R., & McLain, R. J. (2011). Regulating Complexity: Policies for the Governance of Non-timber Forest Products. 227–253. https://doi.org/10.1007/978-3-642-17983-9_11

Larsen, P. O., & von Ins, M. (2010). The rate of growth in scientific publication and the decline in coverage provided by science citation index. Scientometrics, 84(3), 575–603. https://doi.org/10.1007/s11192-010-0202-z

Lavorgna, A. (2014). Wildlife trafficking in the Internet age. Crime Science, 3(1), 1–12. https://doi.org/10.1186/s40163-014-0005-2

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539

Leuteritz, T. E. J., Lamb, T., & Limberaza, J. C. (2005). Distribution, status, and conservation of radiated tortoises (Geochelone radiata) in Madagascar. Biological Conservation, 124(4), 451–461. https://doi.org/10.1016/j.biocon.2005.02.003

Leuteritz, T., & Pedrono, M. (2013). Astrochelys yniphora. November 2013, 47–49. https://doi.org/10.3854/crm.6.a08p47

Li, X., Shen, X., Zhou, Y., Id, X. W., & Id, T. L. (2020). Classification of breast cancer histopathological images using interleaved DenseNet with SENet (IDSNet). 1–13. https://doi.org/10.1371/journal.pone.0232127

Linnaeus, M., & Heath, B. M. E. (1992). Manis pentadactylao. 414, 1–6.

Liu, P., Jiang, J. Z., Wan, X. F., Hua, Y., Li, L., Zhou, J., Wang, X., Hou, F., Chen, J., Zou, J., & Chen, J. (2020). Are pangolins the intermediate host of the 2019 novel coronavirus (SARS-CoV-2)? PLoS Pathogens, 16(5), 1–13. https://doi.org/10.1371/journal.ppat.1008421

Lortie, C. J. (2014). Formalized synthesis opportunities for ecology: Systematic reviews and meta-analyses. Oikos, 123(8), 897–902. https://doi.org/10.1111/j.1600-0706.2013.00970.x

Loussaief, S., & Abdelkrim, A. (2018). Machine Learning framework for image classification. Advances in Science, Technology and Engineering Systems, 3(1), 1–10. https://doi.org/10.25046/aj030101

Lyons, J. A., & Natusch, D. J. D. (2011). Wildlife laundering through breeding farms: Illegal harvest, population declines and a means of regulating the trade of green pythons (Morelia viridis) from Indonesia. Biological Conservation, 144(12), 3073–3081. https://doi.org/10.1016/j.biocon.2011.10.002

Maheshwari, A. (2020). Extinction is inevitable in the globalized world. Human Dimensions of Wildlife, 00(00), 1–2. https://doi.org/10.1080/10871209.2020.1860271

Mainka, S., & Trivedi, M. (2002). Links between Biodiversity Conservation, Livelihoods and Food Security. In IUCN Species Survival Commission (Issue 24).

Maisels, F., Strindberg, S., Blake, S., Wittemyer, G., Hart, J., Williamson, E. A., Aba'a, R., Abitsi, G., Ambahe, R. D., Amsini, F., Bakabana, P. C., Hicks, T. C., Bayogo, R. E., Bechem, M., Beyers, R. L., Bezangoye, A. N., Boundja, P., Bout, N., Akou, M. E., … Warren, Y. (2013). Devastating Decline of Forest Elephants in Central Africa. PLoS ONE, 8(3). https://doi.org/10.1371/journal.pone.0059469

Man, R., Yang, P., & Xu, B. (2020). Classification of Breast Cancer Histopathological Images Using Discriminative Patches Screened by Generative Adversarial Networks. IEEE Access, 8, 155362–155377. https://doi.org/10.1109/ACCESS.2020.3019327

Mandimbihasina, A. R., Woolaver, L. G., Concannon, L. E., Milner-Gulland, E. J., Lewis, R. E., Terry, A. M. R., Filazaha, N., Rabetafika, L. L., & Young, R. P. (2020). The illegal pet trade is driving Madagascar's ploughshare tortoise to extinction. Oryx, 54(2), 188–196. https://doi.org/10.1017/S0030605317001880

McAllister, R. R. J., McNeill, D., & Gordon, I. J. (2009). Legalizing markets and the consequences for poaching of wildlife species: The vicuña as a case study. Journal of Environmental Management, 90(1), 120–130. https://doi.org/10.1016/j.jenvman.2007.08.014

Megias, D. A., Anderson, S. C., Smith, R. J., & Veríssimo, D. (2017). Investigating the impact of media on demand for wildlife: A case study of Harry Potter and the UK trade in owls. PLoS ONE, 12(10), 1–13. https://doi.org/10.1371/journal.pone.0182368

Mettes, P., Koelma, D. C., & Snoek, C. G. M. (2016). The ImageNet Shuffle: Reorganized Pre-training for Video Event Detection. 175–182.

Michels, C., & Schmoch, U. (2012). The growth of science and database coverage. Scientometrics, 93(3), 831–846. https://doi.org/10.1007/s11192-012-0732-7

Milliken, T., & Sangalakula, L. (2010). MIKE – ETIS UPDATES ETIS update number two: Progress in the implementation of the Elephant Trade Information System du système d ' informations sur le commerce d ' éléphants. 46, 2007–2009.

Milner-Gulland, Kholodova, Bekenov, Bukreeva, Grachev, Amgalan, & Lushchekina. (2001). Dramatic declines in saiga antelope populations. Oryx, 35(4), 340–345. https://doi.org/10.1046/j.1365-3008.2001.00202.x

Mishra, M., & Srivastava, M. (2014). A View of Artifical Neural Network. Engineering & Technology Research.

Mitchell, T. M. (2006). The Discipline of Machine Learning. Machine Learning, 17(July), 1–7. http://www-cgi.cs.cmu.edu/~tom/pubs/MachineLearningTR.pdf

Mjolsness, E., & DeCoste, D. (2001). Machine learning for science: State of the art and future prospects. Science, 293(5537), 2051–2055. https://doi.org/10.1126/science.293.5537.2051

Morcatty, T. Q., Bausch Macedo, J. C., Nekaris, K. A. I., Ni, Q., Durigan, C. C., Svensson, M. S., & Nijman, V. (2020). Illegal trade in wild cats and its link to Chinese-led development in Central and South America. Conservation Biology, 34(6), 1525–1535. https://doi.org/10.1111/cobi.13498

Mountfort, G. (1973). Saving the Tiger. Oryx, 12(1), 109–112. https://doi.org/10.1017/S0030605300011157

Najafabadi, M. M., Villanustre, F., Khoshgoftaar, T. M., Seliya, N., Wald, R., & Muharemagic, E. (2015). Deep learning applications and challenges in big data analytics. Journal of Big Data, 2(1), 1–21. https://doi.org/10.1186/s40537-014-0007-7

Natusch, D. J. D., & Lyons, J. A. (2012). Exploited for pets: The harvest and trade of amphibians and reptiles from Indonesian New Guinea. Biodiversity and Conservation, 21(11), 2899–2911. https://doi.org/10.1007/s10531-012-0345-8

Nijman, V. (2010). An overview of international wildlife trade from Southeast Asia. Biodiversity and Conservation, 19(4), 1101–1114. https://doi.org/10.1007/s10531-009-9758-4

Nijman, V., Martinez, C. fui Y., & Shepherd, C. R. (2009). Saved from trade: Donated and confiscated gibbons in zoos and rescue centres in Indonesia. Endangered Species Research, 9(2), 151–157. https://doi.org/10.3354/esr00218

Nijman, V., Zhang, M. X., & Shepherd, C. R. (2016). Pangolin trade in the Mong La wildlife market and the role of Myanmar in the smuggling of pangolins into China. Global Ecology and Conservation, 5, 118–126. https://doi.org/10.1016/j.gecco.2015.12.003

Norconk, M. A., Atsalis, S., Tully, G., Santillán, A. M., Waters, S., Knott, C. D., Ross, S. R., Shanee, S., & Stiles, D. (2020). Reducing the primate pet trade: Actions for primatologists. American Journal of Primatology, 82(1), 1–9. https://doi.org/10.1002/ajp.23079

Olmedo, A., Sharif, V., & Milner-Gulland, E. J. (2018). Evaluating the Design of Behavior Change Interventions: A Case Study of Rhino Horn in Vietnam. Conservation Letters, 11(1), 1–9. https://doi.org/10.1111/conl.12365

Olsson, F. (2009). A literature survey of active machine learning in the context of natural language processing. T2009(06). http://soda.swedish-ict.se/3600/1/SICS-T--2009-06--SE.pdf

Pace, J. (2017). Exchange relations on the dark web. Critical Studies in Media Communication, 34(1), 1–13. https://doi.org/10.1080/15295036.2016.1243249

Pantel, S., & Chin, S. Y. (2009). Proceedings of the workshop on trade and conservation of pangolins native to South and Southeast Asia. In Proceedings ofthe Workshop on Trade and Conservation of Pangolins Native to South and Southeast Asia, 30 June-2 July 2008, Singapore Zoo, Singapore. TRAFFIC Southeast Asia, Petaling Jaya, Selangor, Malaysia (Vol. 30, Issue July).

Paré, G., Trudel, M. C., Jaana, M., & Kitsiou, S. (2015). Synthesizing information systems knowledge: A typology of literature reviews. Information and Management, 52(2), 183–199. https://doi.org/10.1016/j.im.2014.08.008

Patel, N. G., Rorres, C., Joly, D. O., Brownstein, J. S., Boston, R., Levy, M. Z., & Smith, G. (2015). Quantitative methods of identifying the key nodes in the illegal wildlife trade network. Proceedings of the National Academy of Sciences of the United States of America, 112(26), 7948–7953. https://doi.org/10.1073/pnas.1500862112

Patton, D. U., Brunton, D. W., Dixon, A., Miller, R. J., Leonard, P., & Hackman, R. (2017). Stop and frisk online: Theorizing everyday racism in digital policing in the use of social media for identification of criminal conduct and associations. Social Media and Society, 3(3). https://doi.org/10.1177/2056305117733344

Pautasso, M. (2012). Publication growth in biological sub-fields: Patterns, predictability and sustainability. Sustainability, 4(12), 3234–3247. https://doi.org/10.3390/su4123234

Pavlin, B. I., Schloegel, L. M., & Daszak, P. (2009). Risk of importing zoonotic diseases through wildlife trade, United States. Emerging Infectious Diseases, 15(11), 1721–1726. https://doi.org/10.3201/eid1511.090467

Permata, I. M., & Wahyuni, E. (2020). Behind the Ivory Trade Shutdown in China. Journal of International Wildlife Law and Policy, 23(3), 151–165. https://doi.org/10.1080/13880292.2020.1825055

Petrossian, G. A., Pires, S. F., & van Uhm, D. P. (2016). An overview of seized illegal wildlife entering the United States. Global Crime, 17(2), 181–201. https://doi.org/10.1080/17440572.2016.1152548

Phelps, J., Biggs, D., & Webb, E. L. (2016). Tools and terms for understanding illegal wildlife trade. Frontiers in Ecology and the Environment, 14(9), 479–489. https://doi.org/10.1002/fee.1325

Pietersen, D. W., McKechnie, A. E., & Jansen, R. (2014). A review of the anthropogenic threats faced by Temminck’s ground pangolin, Smutsia temminckii, in southern Africa. African Journal of Wildlife Research, 44(2), 167–178. https://doi.org/10.3957/056.044.0209

Pires, S. F., & Moreto, W. (2016). The Illegal Wildlife Trade. In Choice Reviews Online (Vol. 50, Issue 11). https://doi.org/10.5860/choice.50-5912

Powers, D. M. W. (2020). Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. 37–63. http://arxiv.org/abs/2010.16061

Qassim, H., Verma, A., & Feinzimer, D. (2018). Compressed residual-VGG16 CNN model for big data places image recognition. 2018 IEEE 8th Annual Computing and Communication Workshop and Conference, CCWC 2018, 2018-Janua, 169–175. https://doi.org/10.1109/CCWC.2018.8301729

Ratchford, M., Allgood, B., & Todd, P. (2008). THE GLOBAL SECURITY IMPLICATIONS OF THE ILLEGAL WILDLIFE TRADE. International Fund for Animal Welfare.

Regueira, R. F. S., & Bernard, E. (2012). Wildlife sinks: Quantifying the impact of illegal bird trade in street markets in Brazil. Biological Conservation, 149(1), 16–22. https://doi.org/10.1016/j.biocon.2012.02.009

Reuter, P., & O'Regan, D. (2017). Smuggling wildlife in the americas: Scale, methods, and links to other organised crimes. Global Crime, 18(2), 77–99. https://doi.org/10.1080/17440572.2016.1179633

Rosa, I. L., Defavari, G. R., Nóbrega, R. R., Pereira, A. and T., & Oliveira, R. (2013). Seahorses in Traditional Medicine: A global Overview. In Animals in Traditional Folk Medicine. https://doi.org/10.1007/978-3-642-29026-8

Rosen, G. E., & Smith, K. F. (2010). Summarizing the evidence on the international trade in illegal wildlife. EcoHealth, 7(1), 24–32. https://doi.org/10.1007/s10393-010-0317-y

Rosen, T. (2020). The Evolving War on Illegal Wildlife Trade. International Institute for Sustainable Development, 1–8. https://www.iisd.org/system/files/2020-10/still-one-earth-wildlife-trade.pdf

Rosenzweig, M. L. (1995). Species diversity in space and time. Cambridge University Press., 1(2).

Runhovde, S. R. (2015). Seizures of inconvenience? Policy, discretion and accidental discoveries in policing the illegal wildlife trade at the Norwegian border. Crime, Law and Social Change, 64(2–3), 177–192. https://doi.org/10.1007/s10611-015-9596-0

Rural Development, N. R. and E. S. U. & I. T. N. (2008). What's Driving the Wildlife Trade? A Review of Expert Opinion on Economic. Traffic, October.

Saiharsha, B., Abel Lesle, A., Diwakar, B., Karthika, R., & Ganesan, M. (2020). Evaluating performance of deep learning architectures for image classification. Proceedings of the 5th International Conference on Communication and Electronics Systems, ICCES 2020, Icces, 917–922. https://doi.org/10.1109/ICCES48766.2020.09137884

Sas-Rolfes, M., Challender, D. W. S., Hinsley, A., Veríssimo, D., & Milner-Gulland, E. J. (2019). Illegal Wildlife Trade: Scale, Processes, and Governance. Annual Review of Environment and Resources, 44, 201–228. https://doi.org/10.1146/annurev-environ-101718-033253

Schifani, E., & Paolinelli, R. (2018). Forums and social media help to discover exotic species in Europe and monitor their spread: The case of Exaireta spinigera (Wiedemann, 1830)

(Diptera, Stratiomyidae) in the Italian Peninsula and Sicily. Graellsia, 74(2). https://doi.org/10.3989/graellsia.2018.v74.213

Schlossberg, S., Chase, M. J., Gobush, K. S., Wasser, S. K., & Lindsay, K. (2020). State-space models reveal a continuing elephant poaching problem in most of Africa. Scientific Reports, 10(1), 1–9. https://doi.org/10.1038/s41598-020-66906-w

Semiadi, G., Dedy, D., & Arief, A. J. (2008). WORKSHOP ON TRADE AND CONSERVATION OF Pangolins vative to south and southeast asia. In Sunda Pangolin Manis javanica Conservation in Indonesia: Status & Problems (Issue July). https://doi.org/10.13140/2.1.4826.9125

Shairp, R., Veríssimo, D., Fraser, I., Challender, D., & Macmillan, D. (2016). Understanding urban demand for wild meat in Vietnam: Implications for conservation actions. PLoS ONE, 11(1), 1–14. https://doi.org/10.1371/journal.pone.0134787

Shepherd, C. R., Connelly, E., Hywood, L., & Cassey, P. (2017). Taking a stand against illegal wildlife trade: The Zimbabwean approach to pangolin conservation. Oryx, 51(2), 280–285. https://doi.org/10.1017/S0030605316000119

Shepherd, C. R., Kufnerová, J., Cajthaml, T., Frouzová, J., & Gomez, L. (2020). Bear trade in the Czech Republic: an analysis of legal and illegal international trade from 2005 to 2020. European Journal of Wildlife Research, 66(6). https://doi.org/10.1007/s10344-020-01425-7

Shu, M. (2019). Deep learning for image classification on very small datasets using transfer learning. Creative Components, 14–21.

Simmons, J. B., Beyer, R. I., Brandham, P. E., Lucas, G. L., & Parry, V. T. H. (1976). Convention on International Trade in Endangered Species of Wild Fauna and Flora. Conservation of Threatened Plants, 279–303. https://doi.org/10.1007/978-1-4684-2517-8_29

Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings, 1–14.

Singh, A., & Duggal, S. (2009). Medicinal Orchids - An Overview. Ethnobotanical Leaflets, 13(2), 399–412.

Singh Jalal, J., Kumar, P., & Pangtey, Y. P. S. (2008). Ethnomedicinal Orchids of Uttarakhand, Western Himalaya. Ethnobotanical Leaflets, 12, 1227–1257.

Sodhi, N. S., Koh, L. P., Brook, B. W., & Ng, P. K. L. (2004). Southeast Asian biodiversity: An impending disaster. Trends in Ecology and Evolution, 19(12), 654–660. https://doi.org/10.1016/j.tree.2004.09.006

Soomro, T. R., & Hussain, M. (2019). Social Media-Related Cybercrimes and Techniques for Their Prevention. Applied Computer Systems, 24(1), 9–17. https://doi.org/10.2478/acss-2019-0002

Sosnowski, M. C., Knowles, T. G., Takahashi, T., & Rooney, N. J. (2019). Global ivory market prices since the 1989 CITES ban. Biological Conservation, 237(February), 392–399. https://doi.org/10.1016/j.biocon.2019.07.020

South, N., & Wyatt, T. (2011). Comparing illicit trades in wildlife and drugs: An exploratory study. Deviant Behavior, 32(6), 538–561. https://doi.org/10.1080/01639625.2010.483162

Spearman, R. I. C. (1967). On the nature of the horny scales of the pangolin. Journal of the Linnean Society of London, Zoology, 46(310), 267–273. https://doi.org/10.1111/j.1096-3642.1967.tb00508.x

Subedi, A., Kunwar, B., Choi, Y., Dai, Y., van Andel, T., Chaudhary, R. P., de Boer, H. J., & Gravendeel, B. (2013). Collection and trade of wild-harvested orchids in Nepal. Journal of Ethnobiology and Ethnomedicine, 9(1), 1–10. https://doi.org/10.1186/1746-4269-9-64

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015). Going deeper with convolutions. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 07-12-June, 1–9. https://doi.org/10.1109/CVPR.2015.7298594

Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. 36th International Conference on Machine Learning, ICML 2019, 2019-June, 10691–10700.

Targ, S., Almeida, D., & Lyman, K. (2016). Resnet in Resnet: Generalizing Residual Architectures. 1–7. http://arxiv.org/abs/1603.08029

Tharwat, A. (2018). Classification assessment methods. Applied Computing and Informatics, 17(1), 168–192. https://doi.org/10.1016/j.aci.2018.08.003

Theckedath, D., & Sedamkar, R. R. (2020). Detecting Affect States Using VGG16, ResNet50 and SE-ResNet50 Networks. SN Computer Science, 1(2), 1–7. https://doi.org/10.1007/s42979-020-0114-9

Thomas-Walters, L., Veríssimo, D., Gadsby, E., Roberts, D., & Smith, R. J. (2020). Taking a more nuanced look at behavior change for demand reduction in the illegal wildlife trade. Conservation Science and Practice, 2(9), 1–10. https://doi.org/10.1111/csp2.248

Underwood, F. M., Burn, R. W., & Milliken, T. (2013). Dissecting the Illegal Ivory Trade: An Analysis of Ivory Seizures Data. PLoS ONE, 8(10). https://doi.org/10.1371/journal.pone.0076539

UNEP, CITES, IUCN, & TRAFFIC. (2013). Elephants in the dust - the African elephant crisis. A rapid response assessment. 77. https://portals.iucn.org/library/node/10345

United Nations Office of Drugs and Crime. (2016). World Wildlife Crime Report. http://www.unodc.org/unodc/en/data-and-analysis/wildlife.html

van Uhm, D. P. (2016). The Sixth Mass Extinction. Worster 1988, 17–32. https://doi.org/10.1007/978-3-319-42129-2_2

Van Uhm, D. P., & Moreto, W. D. (2018). Corruption Within the Illegal Wildlife Trade: A Symbiotic and Antithetical Enterprise. British Journal of Criminology, 58(4), 864–885. https://doi.org/10.1093/bjc/azx032

van Uhm, D. P., & Wong, R. W. Y. (2019). Establishing Trust in the Illegal Wildlife Trade in China. Asian Journal of Criminology, 14(1), 23–40. https://doi.org/10.1007/s11417-018-9277-x

Velosoa, J., Woolaver, L., Randriamahita, Bekarany, E., Randrianarimangason, F., Mozavelo, R., Garcia, G., & Lewis, R. (2013). An integrated research, management, and community conservation program for the Rere (Madagascar Big-headed Turtle), Erymnochelys madagascariensis (Issue July 2016). https://doi.org/10.3854/crm.6.a27p171

Veríssimo, D., Challender, D. W. S., & Nijman, V. (2012). Wildlife trade in Asia: start with the consumer. Asian Journal of Conservation Biology, 1(2), 49–50.

Veríssimo, D., Vieira, S., Monteiro, D., Hancock, J., & Nuno, A. (2020). Audience research as a cornerstone of demand management interventions for illegal wildlife products: Demarketing sea turtle meat and eggs. Conservation Science and Practice, 2(3), 1–14. https://doi.org/10.1111/csp2.164

Verma, G. K., & Dhillon, A. (2017). A Handheld Gun Detection using Faster R-CNN Deep Learning. ACM International Conference Proceeding Series, 84–88. https://doi.org/10.1145/3154979.3154988

Volpato, G., Fontefrancesco, M. F., Gruppuso, P., Zocchi, D. M., & Pieroni, A. (2020). Baby pangolins on my plate: Possible lessons to learn from the COVID-19 pandemic. Journal of Ethnobiology and Ethnomedicine, 16(1), 1–12. https://doi.org/10.1186/s13002-020-00366-4

von Lampe, K. (2012). Transnational organized crime challenges for future research. Crime, Law and Social Change, 58(2), 179–194. https://doi.org/10.1007/s10611-012-9377-y

Wäldchen, J., & Mäder, P. (2018). Machine learning for image based species identification. Methods in Ecology and Evolution, 9(11), 2216–2225. https://doi.org/10.1111/2041-210X.13075

Walker, J. F., & Stiles, D. (2010). Consequences of legal ivory trade. Science.

Wallen, K. E., & Daut, E. F. (2018). The challenge and opportunity of behaviour change methods and frameworks to reduce demand for illegal wildlife. Nature Conservation, 26, 55–75. https://doi.org/10.3897/natureconservation.26.22725

Walston, J., Robinson, J. G., Bennett, E. L., Breitenmoser, U., da Fonseca, G. A. B., Goodrich, J., Gumal, M., Hunter, L., Johnson, A., Ullas Karanth, K., Leader-Williams, N., MacKinnon, K., Miquelle, D., Pattanavibool, A., Poole, C., Rabinowitz, A., Smith, J. L. D., Stokes, E. J., Stuart, S. N., … Wibisono, H. (2010). Bringing the tiger back from the brink-the six percent solution. PLoS Biology, 8(9), 6–9. https://doi.org/10.1371/journal.pbio.1000485

Wang, B., Yang, W., Sherman, V. R., & Meyers, M. A. (2016). Pangolin armor: Overlapping, structure, and mechanical properties of the keratinous scales. Acta Biomaterialia, 41, 60–74. https://doi.org/10.1016/j.actbio.2016.05.028

Warchol, G. L., Zupan, L. L., & Clack, W. (2003). Transnational criminality: An analysis of the illegal wildlife market in Southern Africa. International Criminal Justice Review, 13(1), 1–27.

Warchol, Greg L. (2004). The Transnational Illegal Wildlife Trade. Criminal Justice Studies, 17(1), 57–73. https://doi.org/10.1080/08884310420001679334

Weimann, G. (2016). Going dark: Terrorism on the dark web. Studies in Conflict and Terrorism, 39(3), 195–206. https://doi.org/10.1080/1057610X.2015.1119546

Weiss, K., Khoshgoftaar, T. M., & Wang, D. D. (2016). A survey of transfer learning. In Journal of Big Data (Vol. 3, Issue 1). Springer International Publishing. https://doi.org/10.1186/s40537-016-0043-6

Wijnstekers, W., & Wijnstekers, W. (2011). The Evolu Ɵ on of by.

Williams, S. J., Gale, S. W., Hinsley, A., Gao, J., & St. John, F. A. V. (2018). Using consumer preferences to characterize the trade of wild-collected ornamental orchids in China. Conservation Letters, 11(5), 1–8. https://doi.org/10.1111/conl.12569

Wilson-Wilde, L. (2010). Wildlife crime: A global problem. Forensic Science, Medicine, and Pathology, 6(3), 221–222. https://doi.org/10.1007/s12024-010-9167-8

Wu J. (2007). World Without Borders: Wildlife Trade on the Chinese-language Internet. TRAFFIC Bulletin, 21(2), 75–84.

Wyler, L. S., & Sheikh, P. A. . (2008). International Illegal Trade in Wildlife: Threats and U.S. Policy. CRS Report to Congress. 1–52. http://www.dtic.mil/cgi-bin/GetTRDoc?Location=U2&doc=GetTRDoc.pdf&AD=ADA486486

Xiao, Y., Guan, J., & Xu, L. (2017). Wildlife cybercrime in China: e-commerce and social media monitoring in 2016. 12.

Xiao, Y., & Watson, M. (2019). Guidance on Conducting a Systematic Literature Review. Journal of Planning Education and Research, 39(1), 93–112. https://doi.org/10.1177/0739456X17723971

Xu, L., Guan, J., Lau, W., & Xiao, Y. (2016). An Overview of Pangolin Trade in China. Traffic Briefing Paper, 10.

Xu, Q., Cai, M., & MacKey, T. K. (2020). The illegal wildlife digital market: An analysis of Chinese wildlife marketing and sale on Facebook. Environmental Conservation, 47(3), 206–212. https://doi.org/10.1017/S0376892920000235

Xu, Q., Li, J., Cai, M., & Mackey, T. K. (2019). Use of Machine Learning to Detect Wildlife Product Promotion and Sales on Twitter. Frontiers in Big Data, 2(August), 1–8. https://doi.org/10.3389/fdata.2019.00028

Ye, Y., & Valbo-Jørgensen, J. (2012). Effects of IUU fishing and stock enhancement on and restoration strategies for the stellate sturgeon fishery in the Caspian Sea. Fisheries Research, 131–133, 21–29. https://doi.org/10.1016/j.fishres.2012.06.022

YU, J., Jiang, F., Peng, J., YIN, X., & MA, X. (2015). The First Birth and Survival of Cub in Captivity of Critically Endangered Malayan Pangolin (Manis javanica). Agricultural Science & Technology, 16(10), 7–10.

Yu, X., & Jia, W. (2015). Moving targets: tracking online sales of illegal wildlife products in China. TRAFFIC Briefing, 1009649(February 2015), 1–10.

Zhang, H., Miller, M. P., Yang, F., Chan, H. K., Gaubert, P., Ades, G., & Fischer, G. A. (2015). Molecular tracing of confiscated pangolin scales for conservation and illegal trade monitoring in Southeast Asia. Global Ecology and Conservation, 4, 414–422. https://doi.org/10.1016/j.gecco.2015.08.002

Zhang, T., Wu, Q., & Zhang, Z. (2020). Probable Pangolin Origin of SARS-CoV-2 Associated with the COVID-19 Outbreak. Current Biology, 30(7), 1346-1351.e2. https://doi.org/10.1016/j.cub.2020.03.022

Zhong, Z., Zheng, M., Mai, H., Zhao, J., & Liu, X. (2020). Cancer image classification based on DenseNet model Cancer image classification based on DenseNet model. 0–6. https://doi.org/10.1088/1742-6596/1651/1/012143

Appendix I

Table 1 – Information reviewed from studies extracted from Scopus and ISI Web of Knowledge with the following set of keywords and search string: TITLE-ABS-KEY (“wildlife" OR "animal" OR "mammal") AND (TITLE-ABS-KEY ("black market" OR "black-market") OR (TITLE-ABS-KEY ("commerce" OR "trade" OR "purchase" OR "transaction" OR "traffic" OR "trafficking") AND TITLE-ABS-KEY ("illegal" OR "crime" OR "illicit" OR "illegitimate" OR "banned" OR "criminal" OR "prohibited"))). For a preliminary review the authors, title, year and DOI (when available) were annotated.

PAPER	AUTHORS	TITLE	YEAR	DOI
1	Arkhipova M.V., Bormotova E.G., Yakushevskaya E.A., Golovin Y.O., Arsentyeva V.S.,	International cooperation in the fight against environmental crime: A modern mechanism for combating illegal trade in wildlife	2021	10.1007/978-3-030-57831-2_95
4	Roe D., Dickman A., Kock R., Milner-Gulland E.J., Rihoy E., ’t Sas-Rolfes M.,	Beyond banning wildlife trade: COVID-19, conservation and development	2020	10.1016/j.worlddev.2020.105121
7	Arias M., Hinsley A., Milner-Gulland E.J.,	Characteristics of, and uncertainties about, illegal jaguar trade in Belize and Guatemala	2020	10.1016/j.biocon.2020.108765
8	Xu Q., Cai M., MacKey T.K.,	The illegal wildlife digital market: An analysis of Chinese wildlife marketing and sale on Facebook	2020	10.1017/S0376892920000235
10	Aguirre A.A., Catherina R., Frye H., Shelley L.,	Illicit Wildlife Trade, Wet Markets, and COVID-19: Preventing Future Pandemics	2020	10.1002/wmh3.348
12	Basu S., Jabin G., Ghosh A., Singh S.K., Mitra A., Chandra K., Thakur M.,	Ascertaining Suspected Wildlife Trade from Detained Parcels Under International Shipment	2020	10.1007/s12595-019-00312-7
13	Zhang H., Ades G., Miller M.P., Yang F., Lai K.-W., Fischer G.A.,	Genetic identification of African pangolins and their origin in illegal trade	2020	10.1016/j.gecco.2020.e01119

14	Eikelboom J.A.J., Nuijten R.J.M., Wang Y.X.G., Schroder B., Heitkönig I.M.A., Mooij W.M., van Langevelde F., Prins H.H.T.,	Will legal international rhino horn trade save wild rhino populations?	2020	10.1016/j.gecco.2020.e01145
17	Acharya K.P., Thapa R.K., Kuwar K.J., Thapalia B.P., Paudel P.K.,	Policy and management actions that resulted in curbing rhinoceros poaching	2020	10.1111/1365-2664.13692
19	Bista D., Baxter G.S., Murray P.J.,	What is driving the increased demand for red panda pelts?	2020	10.1080/10871209.2020.1728788
21	Alfino S., Robert D.L.,	Code word usage in the online ivory trade across four European Union member states	2020	10.1017/S0030605318000406
22	Esmail N., Wintle B.C., t Sas-Rolfes M., Athanas A., Beale C.M., Bending Z., Dai R., Fabinyi M., Gluszek S., Haenlein C., Harrington L.A., Hinsley A., Kariuki K., Lam J., Markus M., Paudel K., Shukhova S., Sutherland W.J., Verissimo D., Wang Y., Waugh J., Wetton J.H., Workman C., Wright J., Milner-Gulland E.J.,	Emerging illegal wildlife trade issues: A global horizon scan	2020	10.1111/conl.12715
24	Kurohata M.,	Effect of the CITES trade ban on preferences for ivory in Japan	2020	10.1007/s10018-019-00261-7
25	Hitchens R.T., Blakeslee A.M.H.,	Trends in illegal wildlife trade: Analyzing personal baggage seizure data in the Pacific Northwest	2020	10.1371/journal.pone.0234197
28	Sharma S., Sharma H.P., Katuwal H.B., Chaulagain C., Belant J.L.,	People's knowledge of illegal Chinese Pangolin trade routes in Central Nepal	2020	10.3390/SU12124900

29	Davis E.O., Willemsen M., Dang V., O'Connor D., Glikman J.A.,	An updated analysis of the consumption of tiger products in urban Vietnam	2020	10.1016/j.gecco.2020.e00960
31	Ghimire P., Raut N., Khanal P., Acharya S., Upadhaya S.,	Species in peril: Assessing the status of the trade in pangolins in Nepal	2020	10.11609/jott.5698.12.8.15776-15783
33	Nguyen D.H.,	International cooperation and mutual legal assistance in criminal matters in handling with transnational wildlife trafficking crimes in Vietnam	2020	10.1051/e3sconf/202016411006
34	[No author name available],	Legal challenge launched over live exports	2020	10.1136/vr.m1754
35	Lunstrum E., Givá N.,	What drives commercial poaching? From poverty to economic inequality	2020	10.1016/j.biocon.2020.108505
38	Sosnowski M.,	Black Markets: A Comparison of the Illegal Ivory and Narcotic Trades	2020	10.1080/01639625.2019.1568360
42	Davis E.O., Glikman J.A.,	An assessment of wildlife use by northern Laos nationals	2020	10.3390/ani10040685
45	Lei Z., Haga T., Obara H., Sekiyama H., Sekiguchi S., Hombu A., Fujihara M., Lei L., Hsu S., Zhang X., Ishitsuka I., Atagi Y., Sato T., Sugiura K.,	A questionnaire survey of the illegal importation of pork products by air travelers into Japan from China and exploration of causal factors	2020	10.1016/j.prevetmed.2020.104947
47	Nguyen D.H., Dinh T.M.,	Impacts of wildlife trade and sustainable development in Vietnam	2020	10.1051/e3sconf/202015703001
52	Sosnowski M.C., Petrossian G.A.,	Luxury Fashion Wildlife Contraband in the USA	2020	10.1007/s10393-020-01467-y
54	Matlhola D.M., Chen R.,	Telecoupling of the trade of donkey-hides between	2020	10.3390/su12051730

		Botswana and China: Challenges and opportunities		
62	Zaychenko E.A., Petrenko E.V., Polyanskaya V.V., Parshikova V.N.,	The role of the Federal Customs Service in the conservation of Siberian biodiversity	2020	10.1088/1755-1315/421/8/082010
63	Lemaître S., Hervé-Fournereau N.,	Fighting Wildlife Trafficking: An Overview of the EU's Implementation of Its Action Plan Against Wildlife Trafficking	2020	10.1080/13880292.2020.1775949
66	Nožina M.,	The Czech Rhino Connection: a Case Study of Vietnamese Wildlife Trafficking Networks' Operations Across Central Europe	2020	10.1007/s10610-020-09453-4
67	Gluszek S., Gluszek S., Ariano-Sánchez D., Ariano-Sánchez D., Cremona P., Goyenechea A., Luque Vergara D.A., McLoughlin L., Morales A., Reuter Cortes A., Rodríguez Fonseca J., Radachowsky J., Knight A.,	Emerging trends of the illegal wildlife trade in Mesoamerica	2020	10.1017/S0030605319001133
68	Chawla M.M., Srivathsa A., Singh P., Majgaonkar I., Sharma S., Punjabi G., Banerjee A.,	Do wildlife crimes against less charismatic species go unnoticed? A case study of golden jackal canis aureus Linnaeus, 1758 poaching and trade in India	2020	10.11609/JOTT.5783.12.4.15407-15413
71	Norconk M.A., Atsalis S., Tully G., Santillán A.M., Waters S., Knott C.D., Ross S.R., Shanee S., Stiles D.,	Reducing the primate pet trade: Actions for primatologists	2020	10.1002/ajp.23079
74	Roberts D.L., Hinsley A.,	The Seven Forms of Challenges in the Wildlife Trade	2020	10.1177/1940082920947023

75	Tittensor D.P., Harfoot M., McLardy C., Britten G.L., Kecse-Nagy K., Landry B., Outhwaite W., Price B., Sinovas P., Blanc J., Burgess N.D., Malsch K.,	Evaluating the relationships between the legal and illegal international wildlife trades	2020	10.1111/conl.12724
76	Wong R.W.Y.,	Shadow operations in wildlife trade under China's Belt and Road Initiative	2020	10.1177/0920203X20948680
77	Banjade M., Adhikari P., Oh H.-S.,	Illegal wildlife trade in local markets of Feuang and Mad districts of Vientiane Province, Lao People's Democratic Republic	2020	10.1016/j.japb.2020.07.006
79	Waseem M., Raza A., Aisha H., Awan M.N., Ahmad T., Nazir R., Mahmood T.,	Scale of illegal killing and trade associated with Indian pangolin (Manis crassicaudata) in Pakistan	2020	10.17582/journal.pjz/2020.52.1.69.77
81	Puri G., Timilsina Y.P., Huettmann F., Regmi G.R., Lama R.P.,	Poaching and illegal trade of wildlife: What do the media say for the nepali-chinese and nepali-indian border?	2020	10.1007/978-3-030-36275-1_36
82	Lee T.E., Roberts D.L.,	Moving Beyond Simple Descriptive Statistics in the Analysis of Online Wildlife Trade: An Example From Clustering and Ordination	2020	10.1177/1940082920958401
84	Gomez L., Shepherd C.R., Khoo M.S.,	Illegal trade of sun bear parts in the Malaysian states of Sabah and Sarawak	2020	10.3354/ESR01028
85	Morcatty T.Q., Bausch Macedo J.C., Nekaris K.A.-I., Ni Q., Durigan C.C., Svensson M.S., Nijman V.,	Illegal trade in wild cats and its link to Chinese-led development in Central and South America	2020	10.1111/cobi.13498

86	Segniagbeto G.H., Agbodji K.T., Leuteritz T.E.J., Dendi D., Fa J.E., Luiselli L.,	Insights into the illegal ivory trade and status of elephants in Togo, West Africa	2020	10.1111/aje.12748
87	Toomes A., Stringham O.C., Mitchell L., Ross J.V., Cassey P.,	Australia's wish list of exotic pets: Biosecurity and conservation implications of desired alien and illegal pet species	2020	10.3897/NEOBIOTA.60.51431
92	Fukushima C., West R., Pape T., Penev L., Schulman L., Cardoso P.,	Wildlife collection for scientific purposes	2020	10.1111/cobi.13572
96	Moshier A., Steadman J., Roberts D.L.,	Network analysis of a stakeholder community combatting illegal wildlife trade	2020	10.1111/cobi.13336
99	Gomez L., Shepherd C.R.,	Bearly on the radar – an analysis of seizures of bears in Indonesia	2019	10.1007/s10344-019-1323-1
101	Everatt K.T., Kokes R., Lopez Pereira C.,	Evidence of a further emerging threat to lion conservation	2019	
103	Hauenstein S., Kshatriya M., Blanc J., Dormann C.F., Beale C.M.,	African elephant poaching rates correlate with local poverty, national corruption and global ivory price	2019	10.1038/s41467-019-09993-2
105	Andini A.R., Purnaweni H.,	The Pattern of Cooperation between the Ministry of Environment and Forestry of the Republic of Indonesia and the Wildlife Conservation Society-Indonesia Programme in Dealing with the Illegal Transnational Trade of Pangolins in Indonesia	2019	10.1051/e3sconf/201912501022

106	Sas-Rolfes M., Challender D.W.S., Hinsley A., Veríssimo D., Milner-Gulland E.J.,	Illegal Wildlife Trade: Scale, Processes, and Governance	2019	10.1146/annurev-environ-101718-033253
108	McEvoy J.F., Connette G., Huang Q., Soe P., Pyone K.H.H., Valitutto M., Htun Y.L., Lin A.N., Thant A.L., Htun W.Y., Paing K.H., Swe K.K., Aung M., Min S., Songer M., Leimgruber P.,	Two sides of the same coin – Wildmeat consumption and illegal wildlife trade at the crossroads of Asia	2019	10.1016/j.biocon.2019.108197
109	Heinrich S., Koehncke A., Shepherd C.R.,	The role of Germany in the illegal global pangolin trade	2019	10.1016/j.gecco.2019.e00736
111	Siriwat P., Nekaris K.A.I., Nijman V.,	The role of the anthropogenic Allee effect in the exotic pet trade on Facebook in Thailand	2019	10.1016/j.jnc.2019.125726
117	Farhadinia M.S., Maheshwari A., Nawaz M.A., Ambarlı H., Gritsina M.A., Koshkin M.A., Rosen T., Hinsley A., Macdonald D.W.,	Belt and Road Initiative may create new supplies for illegal wildlife trade in large carnivores	2019	10.1038/s41559-019-0963-6
120	Mills G.,	Parliamentary inquiry launched into puppy trade	2019	10.1136/vr.l5070
121	Harris L., Gore M., Mills M.,	Compliance with ivory trade regulations in the United Kingdom among traders	2019	10.1111/cobi.13277
123	Mills G.,	Interpol leads crackdown on wildlife trafficking	2019	10.1136/vr.l4853
124	Wasser S.K., Gobush K.S.,	Conservation: Monitoring Elephant Poaching to Prevent a Population Crash	2019	10.1016/j.cub.2019.06.009
126	Davis E.O., Glikman J.A., Crudge B., Dang V., Willemsen M., Nguyen T., O'Connor D., Bendixsen T.,	Consumer demand and traditional medicine prescription of bear products in Vietnam	2019	10.1016/j.biocon.2019.04.003

129	Lagat K.M., Kamau P.,	Examining The Current Status Of Elephant Poaching And Challenges Facing Implementation Process Of The Three-Prong Initiative, Narok County	2019	https://www.scopus.com/inward/record.uri?eid=2-s2.0-85071748885&partnerID=40&md5=80902058ee0e82df903cf9a9f19f94d8
130	Power A., Ingleby S., Chapman J., Cozzolino D.,	Lighting the Ivory Track: Are Near-Infrared and Chemometrics Up to the Job? A Proof of Concept	2019	10.1177/0003702819837297
132	Gikonyo C.,	The Jeddah Amendment and the Fight Against Wildlife Trafficking	2019	10.1007/s10609-019-09364-y
135	Veríssimo D., Wan A.K.Y.,	Characterizing efforts to reduce consumer demand for wildlife products	2019	10.1111/cobi.13227
137	Farah N., Boyce J.R.,	Elephants and mammoths: The effect of an imperfect legal substitute on illegal activity	2019	10.1017/S1355770X18000554
138	Villalva P., Moracho E.,	Tiger trade threatens big cats worldwide	2019	10.1126/science.aax5200
140	Gomez L., Shepherd C.R.,	Stronger international regulations and increased enforcement effort is needed to end the illegal trade in otters in Asia	2019	https://www.scopus.com/inward/record.uri?eid=2-s2.0-85078912819&partnerID=40&md5=7bafefb7dc215a785c933ccc9470efe1
143	van Uhm D.P., Wong R.W.Y.,	Establishing Trust in the Illegal Wildlife Trade in China	2019	10.1007/s11417-018-9277-x
147	Di Minin E., Fink C., Hiippala T., Tenkanen H.,	A framework for investigating illegal wildlife trade on social media with machine learning	2019	10.1111/cobi.13104
149	Sollund R.A.,	The crimes of wildlife trafficking: Issues of justice, legality and morality	2019	10.4324/9781315550428

151	Nijman V., Morcatty T., Smith J.H., Atoussi S., Shepherd C.R., Siriwat P., Nekaris K.A.-I., Bergin D.,	Illegal wildlife trade–surveying open animal markets and online platforms to understand the poaching of wild cats	2019	10.1080/14888386.2019.1568915
152	Nijman V., Ardiansyah A., Bergin D., Birot H., Brown E., Langgeng A., Morcatty T., Spaan D., Siriwat P., Imron M.A., Nekaris K.A.-I.,	Dynamics of illegal wildlife trade in Indonesian markets over two decades, illustrated by trade in Sunda Leopard Cats	2019	10.1080/14888386.2019.1590236
153	Van Uhm D.,	Chinese wildlife trafficking networks along the silk road	2019	10.4324/9780429031045-7
154	Demeau E., Monroy M.E., Jeffrey K.,	Wildlife trafficking on the internet: A virtual market similar to drug trafficking?	2019	https://www.scopus.com/inward/record.uri?eid=2-s2.0-85070066986&partnerID=40&md5=7400467959e9036aea8018c503c56e8f
156	Arroyo-Quiroz I., Wyatt T.,	Wildlife trafficking between the European union and Mexico	2019	10.5204/ijcjsd.v8i3.1243
160	Wong R.W.Y.,	Protected wildlife on the one belt, one road: A case study of illegal tiger skins trade	2019	10.4324/9780429031045-8
161	Titeca K.,	Illegal Ivory Trade as Transnational Organized Crime? An Empirical Study into Ivory Traders in Uganda	2019	10.1093/bjc/azy009
162	Lopes A.A.,	Transnational links in rhino poaching and the black-market price of rhino horns	2019	10.1111/1467-8489.12286
163	Bager Olsen M.T., Geldmann J., Harfoot M., Tittensor D.P., Price B., Sinovas P., Nowak K., Sanders N.J., Burgess N.D.,	Thirty-six years of legal and illegal wildlife trade entering the USA	2019	10.1017/S0030605319000541
173	Harrington L.A., D'Cruze N., Macdonald D.W.,	Rise to fame: Events, media activity and public interest in pangolins and pangolin trade, 2005-2016	2018	10.3897/natureconservation.30.28651

174	D'Cruze N., Singh B., Mookerjee A., Harrington L.A., Macdonald D.W.,	A socio-economic survey of pangolin hunting in Assam, Northeast India	2018	10.3897/natureconservation.30.27379
177	Siriwat P., Nijman V.,	Illegal pet trade on social media as an emerging impediment to the conservation of Asian otters species	2018	10.1016/j.japb.2018.09.004
186	Mak G.J.K., Song W.,	Transnational norms and governing illegal wildlife trade in China and Japan: elephant ivory and related products under CITES	2018	10.1080/09557571.2018.1530636
187	Runhovde S.R.,	Merely a transit country? Examining the role of Uganda in the transnational illegal ivory trade	2018	10.1007/s12117-016-9299-7
189	Mambeya M.M., Baker F., Momboua B.R., Koumba Pambo A.F., Hega M., Okouyi Okouyi V.J., Onanga M., Challender D.W.S., Ingram D.J., Wang H., Abernethy K.,	The emergence of a commercial trade in pangolins from Gabon	2018	10.1111/aje.12507
192	van Uhm D.P.,	The social construction of the value of wildlife: A green cultural criminological perspective	2018	10.1177/1362480618787170
202	Gomez L., Shepherd C.R.,	Trade in bears in Lao PDR with observations from market surveys and seizure data	2018	10.1016/j.gecco.2018.e00415
208	Ariffin M., Nan M.B.C.,	Sunda pangolin protection and trade-related crimes: Assessing local community knowledge in Kedah, Malaysia	2018	https://www.scopus.com/inward/record.uri?eid=2-s2.0-85049833729&partnerID=40&md5=bb411efb018fa4d78fe0811c1f962551

209	Wong R.W.Y.,	‘Do you know where I can buy ivory?’: The illegal sale of worked ivory products in Hong Kong	2018	10.1177/0004865817722186
212	Bending Z.J.,	Improving conservation outcomes: Understanding scientific, historical and cultural dimensions of the illicit trade in rhinoceros horn	2018	10.3197/096734018X15137949591891
213	Hanley N., Sheremet O., Bozzola M., MacMillan D.C.,	The Allure of the Illegal: Choice Modeling of Rhino Horn Demand in Vietnam	2018	10.1111/conl.12417
219	Shepherd C.R., Gray T.N.E., Nijman V.,	Rhinoceros horns in trade on the Myanmar-China border	2018	10.1017/S003060531600168X
220	Krishnasamy K., Shepherd C.R., Or O.C.,	Observations of illegal wildlife trade in Boten, a Chinese border town within a Specific Economic Zone in northern Lao PDR	2018	10.1016/j.gecco.2018.e00390
222	Maheshwari A., Niraj S.K.,	Monitoring illegal trade in snow leopards: 2003–2014	2018	10.1016/j.gecco.2018.e00387
225	Wyatt T., Johnson K., Hunter L., George R., Gunter R.,	Corruption and Wildlife Trafficking: Three Case Studies Involving Asia	2018	10.1007/s11417-017-9255-8
228	Linkie M., Martyr D., Harihar A., Mardiah S., Hodgetts T., Risdianto D., Subchaan M., Macdonald D.,	Asia's economic growth and its impact on Indonesia's tigers	2018	10.1016/j.biocon.2018.01.011
230	Ingram D.J., Coad L., Abernethy K.A., Maisels F., Stokes E.J., Bobo K.S., Breuer T., Gandiwa E., Ghiurghi A., Greengrass E., Holmern T., Kamgaing T.O.W., Ndong Obiang A.-M., Poulsen	Assessing Africa-Wide Pangolin Exploitation by Scaling Local Data	2018	10.1111/conl.12389

	J.R., Schleicher J., Nielsen M.R., Solly H., Vath C.L., Waltert M., Whitham C.E.L., Wilkie D.S., Scharlemann J.P.W.,			
232	Heurich L., Heurich M.,	The poaching crisis in Africa: Causes, consequences and possible solution [Die Wildereikrise in Afrika: Ursachen, Konsequenzen und Lösungsansätze]	2018	10.17433/3.2018.50153555.106-113
235	Symes W.S., McGrath F.L., Rao M., Carrasco L.R.,	The gravity of wildlife trade	2018	10.1016/j.biocon.2017.11.007
238	Harper C., Ludwig A., Clarke A., Makgopela K., Yurchenko A., Guthrie A., Dobrynin P., Tamazian G., Emslie R., van Heerden M., Hofmeyr M., Potter R., Roets J., Beytell P., Otiende M., Kariuki L., du Toit R., Anderson N., Okori J., Antonik A., Koepfli K.-P., Thompson P., O'Brien S.J.,	Robust forensic matching of confiscated horns to individual poached African rhinoceros	2018	10.1016/j.cub.2017.11.005
243	Smith M.S.,	Framing rhino horn demand reduction in Vietnam: Dismissing medical use as voodoo	2018	10.24135/pjr.v24i2.403
244	Tricorache P., Nowell K., Wirth G., Mitchell N., Boast L.K., Marker L.,	Pets and Pelts: Understanding and Combating Poaching and Trafficking in Cheetahs	2018	10.1016/B978-0-12-804088-1.00014-9
246	Nowell K., Rosen T.,	Global Cheetah Conservation Policy: A Review of International Law and Enforcement	2018	10.1016/B978-0-12-804088-1.00021-6

251	Cheung H., Mazerolle L., Possingham H.P., Biggs D.,	Medicinal Use and Legalized Trade of Rhinoceros Horn From the Perspective of Traditional Chinese Medicine Practitioners in Hong Kong	2018	10.1177/1940082918787428
253	Ni Q., Wang Y., Weldon A., Xie M., Xu H., Yao Y., Zhang M., Li Y., Li Y., Zeng B., Nekaris K.A.I.,	Conservation implications of primate trade in China over 18 years based on web news reports of confiscations	2018	10.7717/peerj.6069
263	Shanee N., Mendoza A.P., Shanee S.,	Diagnostic overview of the illegal trade in primates and law enforcement in Peru	2017	10.1002/ajp.22516
266	Cheng W., Xing S., Bonebrake T.C.,	Recent Pangolin Seizures in China Reveal Priority Areas for Intervention	2017	10.1111/conl.12339
267	Freund C., Rahman E., Knott C.,	Ten years of orangutan-related wildlife crime investigation in West Kalimantan, Indonesia	2017	10.1002/ajp.22620
268	Nijman V., Spaan D., Rode-Margono E.J., Wirdateti, Nekaris K.A.I.,	Changes in the primate trade in indonesian wildlife markets over a 25-year period: Fewer apes and langurs, more macaques, and slow lorises	2017	10.1002/ajp.22517
270	Nijman V.,	Orangutan trade, confiscations, and lack of prosecutions in Indonesia	2017	10.1002/ajp.22652
271	Reuter K.E., Schaefer M.S.,	Illegal captive lemurs in Madagascar: Comparing the use of online and in-person data collection methods	2017	10.1002/ajp.22541
272	Meng M., Ma J., Yin F., Chen W., Ji J.,	Investigation of the current trade situation of alien vertebrate species in China and	2017	10.17520/biods.2017177

		analysis of corresponding management strategies		
274	Williams V.L., Loveridge A.J., Newton D.J., Macdonald D.W.,	A roaring trade? The legal trade in Panthera leo bones from Africa to East-Southeast Asia	2017	10.1371/journal.pone.0185996
275	Williams V.L., Loveridge A.J., Newton D.J., Macdonald D.W.,	Questionnaire survey of the pan-African trade in lion body parts	2017	10.1371/journal.pone.0187060
287	Lemieux A.M., Clarke R.V.,	The international ban on ivory sales and its effects on elephant poaching in Africa	2017	10.4324/9781315084589
295	Offord-Woolley S.,	The Chi initiative: A behaviour change initiative to reduce the demand for rhino horn in Viet Nam	2017	https://www.scopus.com/inward/record.uri?eid=2-s2.0-85035039891&partnerID=40&md5=130bd138d634042846afb9b88ba5ca9b
300	Reuter P., O'Regan D.,	Smuggling wildlife in the americas: Scale, methods, and links to other organised crimes	2017	10.1080/17440572.2016.1179633
302	Shepherd C.R., Connelly E., Hywood L., Cassey P.,	Taking a stand against illegal wildlife trade: The Zimbabwean approach to pangolin conservation	2017	10.1017/S0030605316000119
308	Nijman V., Oo H., Shwe N.M.,	Assessing the Illegal Bear Trade in Myanmar Through Conversations With Poachers: Topology, Perceptions, and Trade Links to China	2017	10.1080/10871209.2017.1263768
318	Yeo L.M., McCrea R.S., Roberts D.L.,	A novel application of mark-recapture to examine behaviour associated with the online trade in elephant ivory	2017	10.7717/peerj.3048
323	Stahl J., De Meulenaer T.,	CITES and the international trade in wildlife	2017	https://www.scopus.com/inward/record.uri?eid=2-s2.0-85016252817&partnerID=40&md5=6ef23739bc8f78cdd0499d47f4225d96
325	Rocheleau B.,	Wildlife politics	2017	10.1017/9781316941218

329	Rubino E.C., Pienaar E.F.,	Applying a conceptual framework to rhinoceros conservation on private lands in South Africa	2017	10.3354/esr00844
341	Haas T.C., Ferreira S.M.,	Combating rhino horn trafficking: The need to disrupt criminal networks	2016	10.1371/journal.pone.0167040
342	Phelps J., Biggs D., Webb E.L.,	Tools and terms for understanding illegal wildlife trade	2016	10.1002/fee.1325
345	Davis E.O., O'Connor D., Crudge B., Carignan A., Glikman J.A., Browne-Nuñez C., Hunt M.,	Understanding public perceptions and motivations around bear part use: A study in northern Laos of attitudes of Chinese tourists and Lao PDR nationals	2016	10.1016/j.biocon.2016.09.009
351	D'Cruze N., Macdonald D.W.,	A review of global trends in CITES live wildlife confiscations	2016	10.3897/natureconservation.15.10005
364	Duffy R.,	The illegal wildlife trade in global perspective	2016	https://www.scopus.com/inward/record.uri?eid=2-s2.0-85058923589&partnerID=40&md5=406a546e30effb84b26b72f415161380
366	Truong V.D., Dang N.V.H., Hall C.M.,	The marketplace management of illegal elixirs: illicit consumption of rhino horn	2016	10.1080/10253866.2015.1108915
370	Maheshwari A., Meibom S.V.,	Monitoring Illegal Trade in Snow Leopards (2003-2012)	2016	10.1016/B978-0-12-802213-9.00007-9
371	Azam A.W.M., Jayasuriya K.M.G.G., Musthafa M.M., Marikar F.M.M.T.,	Sri Lanka is a hot spot for illegal transnational trading of biodiversity and wildlife materials from South Asian region	2016	10.1007/s12198-016-0167-0
375	Petrossian G.A., Pires S.F., van Uhm D.P.,	An overview of seized illegal wildlife entering the United States	2016	10.1080/17440572.2016.1152548

381	Leberatto A.C.,	Understanding the illegal trade of live wildlife species in Peru	2016	10.1007/s12117-015-9262-z
384	Kideghesho J.R.,	The Elephant poaching crisis in Tanzania: A need to reverse the trend and the way forward [La crise du braconnage des éléphants en Tanzanie: La nécessité d'inverser la tendance et la voie à suivre] [A crise caça ilegal de elefantes na Tanzânia: A necessidade de inverter a tendência e o caminho a seguir] [La crisis de caza furtiva de elefantes en Tanzania: La necesidad de invertir la tendencia y el camino a seguir]	2016	10.1177/194008291600900120
395	Bell T.,	Combating wildlife trafficking: National strategy, implementation plan and restrictions on elephant ivory trade	2016	https://www.scopus.com/inward/record.uri?eid=2-s2.0-85022079166&partnerID=40&md5=3736e47210d28a62b9e851acb8d990d9
396	Goyes D.R., Sollund R.,	Contesting and contextualising CITES: Wildlife trafficking in Colombia and Brazil	2016	10.5204/ijcjsd.v5i4.331
397	Wong R.W.Y.,	The organization of the illegal tiger parts trade in China	2016	10.1093/bjc/azv080
398	Murrill B.J., Shedd D.T.,	Restrictions on trade in elephant ivory	2016	https://www.scopus.com/inward/record.uri?eid=2-s2.0-85021922291&partnerID=40&md5=869ce2133aa794e9373f1a1e3c5e09f9
400	Nijman V., Zhang M.X., Shepherd C.R.,	Pangolin trade in the Mong La wildlife market and the role of Myanmar in the smuggling of pangolins into China	2016	10.1016/j.gecco.2015.12.003
405	D’Cruze N., Macdonald D.W.,	Clouded in mystery: the global trade in clouded leopards	2015	10.1007/s10531-015-1010-9

410	Zhang L.,	China must act decisively to eradicate the ivory trade	2015	10.1038/527135a
412	Williams V.L., Loveridge A.J., Newton D.J., Macdonald D.W.,	'Skullduggery': Lions align and their mandibles rock!	2015	10.1371/journal.pone.0135144
419	Lavorgna A.,	The Social Organization of Pet Trafficking in Cyberspace	2015	10.1007/s10610-015-9273-y
420	Challender D.W.S., Harrop S.R., MacMillan D.C.,	Understanding markets to conserve trade-threatened species in CITES	2015	10.1016/j.biocon.2015.04.015
421	Patel N.G., Rorres C., Joly D.O., Brownstein J.S., Boston R., Levy M.Z., Smith G.,	Quantitative methods of identifying the key nodes in the illegal wildlife trade network	2015	10.1073/pnas.1500862112
426	Daut E.F., Brightsmith D.J., Peterson M.J.,	Role of non-governmental organizations in combating illegal wildlife-pet trade in Peru	2015	10.1016/j.jnc.2014.10.005
427	Sollund R.,	Wildlife trafficking in a globalized world: An example of motivations and modus operandi from a Norwegian case study	2015	10.1007/978-3-319-22246-2_25
430	Hernandez-Castro J., Roberts D.L.,	Automatic detection of potentially illegal online sales of elephant ivory via data mining	2015	10.7717/peerj-cs.10
448	Lavorgna A.,	Wildlife trafficking in the Internet age	2014	10.1186/s40163-014-0005-2
449	Moyle B.,	The raw and the carved: Shipping costs and ivory smuggling	2014	10.1016/j.ecolecon.2014.09.001
457	Chow A.T., Cheung S., Yip P.K.,	Wildlife markets in south China	2014	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84904555824&partnerID=40&md5=f743b1f6a841d1393a2f130e68230c8d
459	Wittemyer G., Northrup J.M., Blanc J., Douglas-Hamilton I., Omondi P., Burnham K.P.,	Illegal killing for ivory drives global decline in African elephants	2014	10.1073/pnas.1403984111

462	White R.,	Transnational environmental crime	2014	10.1017/CCO9780511762116.028
467	Collard R.-C.,	Putting Animals Back Together, Taking Commodities Apart	2014	10.1080/00045608.2013.847750
468	Nijman V., Shepherd C.R., Nekaris K.A.-I.,	Trade in Bengal Slow Lorises in Mong La, Myanmar, on the China Border	2014	10.1896/052.028.0112
472	Nijman V., Shepherd C.R.,	Emergence of Mong La on the Myanmar-China border as a global hub for the international trade in ivory and elephant parts	2014	10.1016/j.biocon.2014.08.010
479	Nijman V., Nekaris K.-I.,	Traditions, taboos and trade in slow lorises in sundanese communities in southern Java, Indonesia	2014	10.3354/esr00610
484	Underwood F.M., Burn R.W., Milliken T.,	Dissecting the Illegal Ivory Trade: An Analysis of Ivory Seizures Data	2013	10.1371/journal.pone.0076539
486	do Nascimento R.A., Schiavetti A., Montaño R.A.M.,	An assessment of illegal capuchin monkey trade in Bahia State, Brazil [Avaliação do comércio ilegal de macacos-prego na Bahia, Brasil]	2013	10.4013/nbc.2013.82.03
492	Lewis M.G., Takahashi M.A.,	A prescription for conservation: Strengthening Japan's role in curbing the illegal international trade of bear bile for medicinal use	2013	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84878290231&partnerID=40&md5=d32a5fa2a78e983b729eba4294536044
493	Cao Ngoc A., Wyatt T.,	A Green Criminological Exploration of Illegal Wildlife Trade in Vietnam	2013	10.1007/s11417-012-9154-y

500	Ferrier P.,	The economics of agricultural and wildlife smuggling	2013	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84895307941&partnerID=40&md5=41cc0117b10630bc8154770e45569957
503	Biggs D., Courchamp F., Martin R., Possingham H.P.,	Legal trade of Africa's Rhino horns	2013	10.1126/science.1229998
505	Dudley N., Stolton S., Elliott W.,	Editorial: Wildlife crime poses unique challenges to protected areas	2013	10.2305/IUCN.CH.2013.PARKS-19-1.ND.en
508	Cressey D.,	Tusk tracking will tackle illegal trade	2013	10.1038/494411a
511	Martin E., Martin C., Vigne L.,	Successful reduction in rhino poaching in Nepal	2013	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84911409837&partnerID=40&md5=69603d7b3950170e82d41927cee2db45
512	Sharma B.K., Nathawat B.S., Sharma S., Kulshreshtha S.,	Wildlife conservation in Rajasthan: The legal framework versus the wildlife trade	2013	10.1007/978-3-319-01345-9_19
513	Vigne L.,	Recent findings on the ivory and rhino-horn trade in lao people’s democratic republic	2013	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84911402456&partnerID=40&md5=3fbca099cd54f3a7e3fcb1e7bf732826
514	Falk H., Dürr S., Hauser R., Wood K., Tenger B., Lörtscher M., Schüpbach-Regula G.,	Illegal import of hushmeat and other meat products into Switzerland on commercial passenger flights	2013	10.20506/rst.32.2.2221
517	Sonricker Hansen A.L., Li A., Joly D., Mekaru S., Brownstein J.S.,	Digital Surveillance: A Novel Approach to Monitoring the Illegal Wildlife Trade	2012	10.1371/journal.pone.0051156
519	Mahmood T., Hussain R., Irshad N., Akrim F., Nadeem M.S.,	Illegal mass killing of Indian pangolin (Manis crassicaudata) in Potohar region, Pakistan	2012	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84868115896&partnerID=40&md5=9dbb5b3924ec1dace711fd567da82326
523	Morgan G.E., Hill D.,	The Lacey Act: Federal regulation and protection of wildlife and plants	2012	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84936093335&partnerID=40&md5=fbad01030517d2ee4ee1da83656cebc9

524	Alexander K.,	The Lacey Act: Protecting the environment by restricting trade	2012	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84936064458&partnerID=40&md5=6e3e98b3b3d038615318d34000a05fd9
525	Sheikh P.A.,	The Lacey Act: Compliance issues related to importing plants and plant products	2012	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84936094852&partnerID=40&md5=0f9fb11913ec9ce99ef074fda68546ff
536	Conrad K.,	Trade bans: A perfect storm for poaching?	2012	10.1177/194008291200500302
537	Shanee N.,	Trends in local wildlife hunting, trade and control in the tropical andes biodiversity hotspot, northeastern Peru	2012	10.3354/esr00469
542	Petersen L.M., Moll E.J., Collins R., Hockings M.T.,	Development of a compendium of local, wild-harvested species used in the informal economy trade, Cape Town, South Africa	2012	10.5751/ES-04537-170226
554	Mbete R.A., Banga-Mboko H., Ngokaka C., Bouckacka III. Q.F., Nganga I., Hornick J.-L., Leroy P., Vermeulen C.,	Profile sellers of bushmeat and evaluation of biomass sold in municipal markets of Brazzaville, Congo [Profil des vendeurs de viande de chasse et évaluation de la biomasse commercialisée dans les marchés municipaux de Brazzaville, Congo]	2011	https://www.scopus.com/inward/record.uri?eid=2-s2.0-79959877835&partnerID=40&md5=89a4375b5941cd7d57bad076bcb50d9d
556	Stiles D.,	Elephant meat and ivory trade in central Africa	2011	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84861164195&partnerID=40&md5=afc9a9198f5ada6834c5bb7072d2ca70
566	Wyler L.S., Sheikh P.A.,	International illegal trade in wildlife: Threats and U.S. policy	2011	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84895391180&partnerID=40&md5=ca4a2759c98545ca01f096948398aadf
567	Williams H.O., Grante V.T.,	Illegal trade in wildlife	2011	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84895339386&partnerID=40&md5=96114c2f41a8538ddc8d57767c73658e
570	Lindsey P.A., Romañach S.S., Matema S., Matema C., Mupamhadzi I., Muvengwi J.,	Dynamics and underlying causes of illegal bushmeat trade in Zimbabwe	2011	10.1017/S0030605310001274

575	Kawanishi K., Gumal M., Shepherd L.A., Goldthorpe G., Shepherd C.R., Krishnasamy K., Hashim A.K.A.,	The Malayan Tiger	2010	10.1016/B978-0-8155-1570-8.00029-3
577	Baker C.S., Steel D., Choi Y., Lee H., Kim K.S., Choi S.K., Ma Y.-U., Hambleton C., Psihoyos L., Brownell R.L., Funahashi N.,	Genetic evidence of illegal trade in protected whales links JaPan with the US and South Korea	2010	10.1098/rsbl.2010.0239
578	Nekaris K.A.I., Shepherd C.R., Starr C.R., Nijman V.,	Exploring cultural drivers for wildlife trade via an ethnoprimatological approach: A case study of slender and slow lorises (Loris and Nycticebus) in South and Southeast Asia	2010	10.1002/ajp.20842
581	Ceballos-Mago N., González C.E., Chivers D.J.,	Impact of the pet trade on the Margarita capuchin monkey Cebus apella margaritae	2010	10.3354/esr00289
582	Rosen G.E., Smith K.F.,	Summarizing the evidence on the international trade in illegal wildlife	2010	10.1007/s10393-010-0317-y
585	Martin E.,	Effective law enforcement in Ghana reduces elephant poaching and illegal ivory trade	2010	https://www.scopus.com/inward/record.uri?eid=2-s2.0-79953327945&partnerID=40&md5=978ad1b1ae49cb03ea3b7da34d02b1e8
589	Shepherd C.R.,	Illegal primate trade in Indonesia exemplified by surveys carried out over a decade in North Sumatra	2010	10.3354/esr00276
593	Nijman V.,	An overview of international wildlife trade from Southeast Asia	2010	10.1007/s10531-009-9758-4
595	Altherr S.,	Traditional Chinese medicine and international species' protection [Traditionelle	2010	10.1007/BF03378983

		Chinesische medizin und internationaler artenschutz]		
596	Cheyne S.M.,	Challenges and opportunities of primate rehabilitation - Gibbons as a case study	2009	10.3354/esr00216
597	Nijman V., Martinez C.Y., Shepherd C.R.,	Saved from trade: Donated and confiscated gibbons in zoos and rescue centres in Indonesia	2009	10.3354/esr00218
598	Maldonado A.M., Nijman V., Bearder S.K.,	Trade in night monkeys Aotus spp. in the Brazil-Colombia-Peru tri-border area: International wildlife trade regulations are ineffectively enforced	2009	10.3354/esr00209
600	Wyatt T.,	Exploring the organization of Russia Far East's illegal wildlife trade: Two case studies of the illegal fur and illegal falcon trades	2009	10.1080/17440570902783947
601	Moyle B.,	The black market in China for tiger products	2009	10.1080/17440570902783921
602	Lemieux A.M., Clarke R.V.,	The international ban on ivory sales and its effects on elephant poaching in africa	2009	10.1093/bjc/azp030
606	McAllister R.R.J., McNeill D., Gordon I.J.,	Legalizing markets and the consequences for poaching of wildlife species: The vicuña as a case study	2009	10.1016/j.jenvman.2007.08.014
611	Gratwicke B., Mills J., Dutton A., Gabriel G., Long B., Seidensticker J., Wright B., You W., Zhang L.,	Attitudes toward consumption and conservation of tigers in China	2008	10.1371/journal.pone.0002544
612	Van Song N.,	Wildlife trading in Vietnam: Situation, causes, and solutions	2008	10.1177/1070496508316220

613	Zhang L., Hua N., Sun S.,	Wildlife trade, consumption and conservation awareness in southwest China	2008	10.1007/s10531-008-9358-8
614	Wyler L.S., Sheikh P.A.,	International Illegal Trade in Wildlife	2008	https://www.scopus.com/inward/record.uri?eid=2-s2.0-77949542238&partnerID=40&md5=797272bcef88625853d348136beddf55
620	Wilczek Ch.,	Import of dogs by public animal shelters and private animal protection societies [Einfuhr/verbringen von hunden durch tierheime und private tierschutzorganisationen]	2008	10.2377/0341-6593-115-101
627	Gross L.,	In the shadows of the Congo Basin forest, elephants fall to the illegal ivory trade	2007	10.1371/journal.pbio.0050115
634	Thomas P.O., Albert M.R.,	Data on wildlife trade [1]	2006	10.1111/j.1523-1739.2006.00437_1.x
640	Fisher S.J., Reeves R.R.,	The global trade in live cetaceans: Implications for conservation	2005	10.1080/13880290500343624
642	Rainsford F.,	Alpaca prices ease but goat smuggling is most pressing problem	2005	https://www.scopus.com/inward/record.uri?eid=2-s2.0-18344364642&partnerID=40&md5=5575debc182a28bfab48b19cd3d204bd
644	Lee R.J., Gorog A.J., Dwiyahreni A., Siwu S., Riley J., Alexander H., Paoli G.D., Ramono W.,	Wildlife trade and implications for law enforcement in Indonesia: A case study from North Sulawesi	2005	10.1016/j.biocon.2005.01.009
646	Naylor R.T.,	The underworld of ivory	2005	10.1007/s10611-005-2143-7
647	Stiles D.,	The ivory trade and elephant conservation	2004	10.1017/S0376892904001614
650	Ringuet S.,	NGOs and the international trade in wild species: The case of TRAFFIC [Les ong et le commerce international des	2004	https://www.scopus.com/inward/record.uri?eid=2-s2.0-3342944505&partnerID=40&md5=7ba34f27a791d4b4142b031851228eb0

		espèces sauvages: L'exemple de TRAFFIC]		
652	Missios P.C.,	Wildlife trade and endangered species protection	2004	10.1111/j.1467-8489.2004.00264.x
656	Warchol G.L., Zupan L.L., Clack W.,	Transnational criminality: An analysis of the illegal wildlife market in Southern Africa	2003	10.1177/105756770301300101
659	Martin E., Redford T.,	Wildlife for sale	2000	https://www.scopus.com/inward/record.uri?eid=2-s2.0-0034139455&partnerID=40&md5=5363bd0ede8cc85c6ae6e1f33861f765
661	Li Y.-M., Gao Z., Li X., Wang S., Jari N.,	Illegal wildlife trade in the Himalayan region of China	2000	10.1023/A:1008905430813
667	Li Y., Li D.,	The dynamics of trade in live wildlife across the Guangxi border between China and Vietnam during 1993-1996 and its control strategies	1998	10.1023/A:1008873119651
670	Iriarte J.A., Feinsinger P., Jaksic F.M.,	Trends in wildlife use and trade in Chile	1997	10.1016/S0006-3207(96)00150-4
671	Plowden C., Bowles D.,	The illegal market in tiger parts in northern Sumatra, Indonesia	1997	10.1046/j.1365-3008.1997.d01-4.x
672	[No author name available],	Wildlife crime	1996	https://www.scopus.com/inward/record.uri?eid=2-s2.0-0030433725&partnerID=40&md5=4c613dcf676cbd613244cfb47bd30e87
674	Heinen J.T., Leisure B.,	A new look at the Himalayan fur trade	1993	10.1017/S0030605300028143
676	Gray-Schofield L., McMahan L.,	Trends in wildlife trade from India to the United States	1990	https://www.scopus.com/inward/record.uri?eid=2-s2.0-0025563534&partnerID=40&md5=3ae51ea7f95598caaa25df074ce97ac0
677	Varisco D.M.,	Beyond rhino horn—wildlife conservation for north yemen	1989	10.1017/S003060530002305X
678	Oza G.M.,	The himalayan musk deer: Encashed for extinction	1988	10.1007/BF02243603
682	Martin E., Martin C., Vigne L.,	The decline in carving African and Asian elephant tusks in Nepal and the decrease in ivory	2013	https://www.scopus.com/inward/record.uri?eid=2-s2.0-84911378885&partnerID=40&md5=583536489c022ddb928e857ed81195d5

		items for retail sale in Kathmandu		
691	Milner-Gulland E.J., Leader-Williams N.,	Illegal exploitation of wildlife	1992	https://www.scopus.com/inward/record.uri?eid=2-s2.0-0027063761&partnerID=40&md5=dc3fd6cdc9c36ac9b294035f69cb2e11

Appendix II

Table 1 – Data reviewed and categorized from the systematic literature review of articles extracted from Scopus and ISI Web of Knowledge, regarding mammal illegal wildlife trade. This information was categorized into taxonomic groups per order, family, genera and common name, as well as the number of species reviewed; the study location per continent, country and scale of analysis (whether global, single country or multiple countries); per country and continent of importation and exportation; the uses for the traded mammals or their derived products; and the methodology used during the studies.

Paper	Year	Other taxonomic groups	Taxonomic group	Number of species	Order	Family	Genera	Common name	Continent - Study loc	Study Location	Scale of Analysis	Continent - Export	Exportation	Continent - Import	Importation	Uses	Methodology
4	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Not specified	Database Analysis
7	2020		Mammals	Single	Carnivora	Felidae	Panthera	Jaguar	Central America	Belize	Multi-country	Not specified	Not specified	Domestic	Domestic	Nutritional	Social Surveys
7									Central America	Guatemala				Asia	China	Aesthetic	
8	2020	Reptiles	Mammals	Multiple	Proboscidea	Elephantidae	Several	Elephant	Asia	China	Country	Not specified	Not specified	Asia	Taiwan	Not specified	Social media Analysis
8	2020				Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros						Asia	China		
8	2020				Artiodactyla	Bovidae	Several	Antelope									
8	2020				Carnivora	Ursidae	Several	Bear									
10	2020		Mammals	Single	Chiroptera	Several	Several	Bat	Asia	China	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis

10																Nutritional	
12	2020		Mammals	Single	Rodentia	Muridae	Rattus	Rat	North America	USA	Country	Asia	India	North America	USA	Not specified	Forensic Genetics
13	2020		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Hong Kong	Country	Africa	Africa	Asia	Asia	Traditional medicine	Forensic Genetics
13																Nutritional	
13																Aesthetic	
14	2020		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Global	Global	Global	Africa	Africa	Asia	Asia	Traditional medicine	Reviews and Commentaries
14																Aesthetic	
17	2020		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Asia	Nepal	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
19	2020		Mammals	Single	Carnivora	Ailuridae	Ailurus	Red panda	Asia	Nepal	Country	Asia	Nepal	Asia	Nepal	Aesthetic	Database Analysis
19																	Social Surveys
21	2020		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Europe	UK	Multi-country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Social media Analysis
21									Europe	France						Aesthetic	
21									Europe	Italy							
21									Europe	Spain							
22	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified		Database Analysis

24	2020		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Asia	Japan	Country	Africa	Africa	Asia	Japan	Traditional medicine	Database Analysis
24																Aesthetic	
25	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	North America	USA	Country	Asia	East Asia	North America	USA	Traditional medicine	Database Analysis
25																Nutritional	
25																Aesthetic	
28	2020		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Nepal	Country	Asia	China	Asia	Nepal	Traditional medicine	Database Analysis
28																Nutritional	
28												Asia	Vietnam			Aesthetic	
29	2020		Mammals	Single	Carnivora	Felidae	Panthera	Tiger	Asia	Vietnam	Country	Asia	East Asia	Asia	Vietnam	Traditional medicine	Database Analysis
29												Asia	South Asia			Nutritional	
31	2020		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Nepal	Country	Asia	China	Asia	Nepal	Traditional medicine	Database Analysis
31												Asia	Vietnam			Nutritional	
31																Aesthetic	
33	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Vietnam	Country	Not specified	Not specified	Not specified	Not specified	All	Database Analysis
34	2020		Mammals	Not specified	Not specified	Not specified	Not specified	Not specified	Europe	Scotland	Multi-country	Europe	Scotland	Europe	Spain	Nutritional	Database Analysis

34									Europe	Spain							
35	2020		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Africa	South Africa	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
35																Aesthetic	
38	2020		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Global	Global	Global	Africa	Africa	Not specified	Not specified	Traditional medicine	Database Analysis
38																Aesthetic	
42	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Laos DR	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Social Surveys
45	2020		Mammals	Single	Artiodactyla	Suidae	Sus	Domestic pig	Asia	Japan	Multi-country	Not specified	Not specified	Asia	Japan	Nutritional	Social Surveys
45									Asia	China				Asia	China		
47	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Vietnam	Country	Not specified	Not specified	Asia	Vietnam	Traditional medicine	Database Analysis
47																Nutritional	
47																Aesthetic	
52	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	North America	USA	Country	Not specified	Not specified	North America	USA	Aesthetic	Database Analysis
54	2020		Mammals	Single	Perissodactyla	Equidae	Equus	Donkey	Asia	China	Country	Africa	Botswana	Asia	China	Aesthetic	Database Analysis
62	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Russia	Country	Asia	Russia	Not specified	Not specified	Traditional medicine	Database Analysis

62																Nutritional	
62																Aesthetic	
63	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Europe	EU	Continental	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
63																Nutritional	
63																Aesthetic	
66	2020		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Europe	Czech Republic	Country	Africa	Africa	Asia	Vietnam	Traditional medicine	Database Analysis
66																Aesthetic	
67	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Central America	Mesoamerica	Multi-country	Not specified	Not specified	Not specified	Not specified	Not specified	Database Analysis
68	2020		Mammals	Single	Carnivora	Canidae	Canis	Golden jackal	Asia	India	Country	Asia	India	Asia	India	Traditional medicine	Database Analysis
68																Aesthetic	
71	2020		Mammals	Single	Primates	Several	Several	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Pet trade	Reviews and Commentaries
74	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Not specified	Reviews and Commentaries
75	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	North America	USA	Multi-country	Not specified	Not specified	Not specified	Not specified	Not specified	Database Analysis
75									Europe	EU							
76	20		Mammals	Multiple	Carnivora	Felidae	Panthera	Tiger	Asia	China	Country	Not specified	Not specified	Not specified	Not specified	Not specified	Database Analysis

	20																
76	2020				Pholidota	Manidae	Several	Pangolin									
77	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Laos DR	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	In-situ observation
77																Nutritional	
77																Aesthetic	
79	2020		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Pakistan	Country	Asia	India	Asia	Pakistan	Traditional medicine	Social Surveys
79																Nutritional	
79																Aesthetic	
81	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Nepal	Country	Asia	Nepal	Asia	Nepal	Traditional medicine	Social media Analysis
81												Asia	China	Asia	China	Nutritional	
81												Asia	India	Asia	India	Aesthetic	
82	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
82																Nutritional	Social media Analysis
82																Aesthetic	
84	2020		Mammals	Single	Carnivora	Ursidae	Several	Bear	Asia	Malaysia	Country	Asia	Asia	Asia	Asia	Traditional medicine	Social Surveys

85	2020		Mammals	Single	Carnivora	Felidae	Several	Not specified	Central America	Central America	Multi-country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
85									South America	South America						Nutritional	
85									Asia	China						Aesthetic	
86	2020		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Togo	Country	Africa	Central Africa	Not specified	Not specified	Not specified	Database Analysis
86																	Social Surveys
87	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Australia	Australia	Continental	Not specified	Not specified	Not specified	Not specified	Pet trade	Database Analysis
99	2019		Mammals	Single	Carnivora	Ursidae	Several	Bear	Asia	Indonesia	Country	Asia	Indonesia	Not specified	Not specified	Traditional medicine	Database Analysis
99																Aesthetic	
99																Pet trade	
101	2019		Mammals	Single	Carnivora	Felidae	Panthera	Lion	Africa	South Africa	Country	Africa	South Africa	Asia	Asia	Aesthetic	Database Analysis
103	2019		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Africa	Continental	Africa	Africa	Asia	China	Traditional medicine	Database Analysis
103																Nutritional	
103																Aesthetic	
105	2019		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Indonesia	Country	Asia	Indonesia	Not specified	Not specified	Traditional medicine	Database Analysis

105																Nutritional	Social Surveys
105																Aesthetic	
106	2019		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Not specified	Reviews and Commentaries
108	2019		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Myanmar	Country	Asia	Myanmar	Asia	Asia	Traditional medicine	Database Analysis
108																Nutritional	
108																Aesthetic	
109	2019		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Europe	Germany	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
109																Nutritional	
109																Aesthetic	
111	2019		Mammals	Not specified	Primates	Several	Several	Not specified	Asia	Thailand	Country	Not specified	Not specified	Not specified	Not specified	Pet trade	Social media Analysis
117	2019		Mammals	Not specified	Carnivora	Several	Several	Not specified	Asia	China	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
117																Nutritional	
117																Aesthetic	
120	2019		Mammals	Single	Carnivora	Canidae	Canis	Dog	Europe	UK	Country	Not specified	Not specified	Not specified	Not specified	Pet trade	Database Analysis
121	2019		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Europe	UK	Country	Africa	Africa	Not specified	Not specified	Traditional medicine	Social Surveys

121																Aesthetic	
124	2019		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Botswana	Country	Africa	Africa	Not specified	Not specified	Traditional medicine	Database Analysis
124																Aesthetic	
126	2019		Mammals	Single	Carnivora	Ursidae	Several	Bear	Asia	Vietnam	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Social Surveys
129	2019		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Kenya	Country	Africa	Africa	Asia	Asia	Traditional medicine	Social Surveys
129																Aesthetic	
132	2019		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Africa	Africa	Continental	Africa	Africa	Not specified	Not specified	Not specified	Reviews and Commentaries
135	2019		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Not specified	Reviews and Commentaries
137	2019		Mammals	Multiple	Proboscidea	Elephantidae	Several	Elephant	Asia	Russia	Country	Africa	Africa	Not specified	Not specified	Traditional medicine	Database Analysis
137	2019				Proboscidea	Elephantidae	Mammuthus	Mammoth				Asia	Russia			Aesthetic	
138	2019		Mammals	Single	Carnivora	Felidae	Panthera	Tiger	Global	Global	Global	Asia	Asia	Not specified	Not specified	Aesthetic	Database Analysis
140	2019		Mammals	Single	Carnivora	Mustelidae	Several	Otter	Asia	Asia	Continental	Asia	Indonesia	Asia	Japan	Pet trade	Database Analysis
140												Asia	Thailand				

147	2019		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Not specified	Social media Analysis
149	2019		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Europe	Norway	Multi-country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
149																Nutritional	
149									South America	Colombia						Aesthetic	
151	2019		Mammals	Single	Carnivora	Felidae	Panthera	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Traditional medicine	In-situ observation
151																Nutritional	Social media Analysis
151																Aesthetic	
152	2019		Mammals	Single	Carnivora	Felidae	Panthera	Leopard	Asia	Indonesia	Country	Asia	Indonesia	Not specified	Not specified	Pet trade	Database Analysis
153	2019		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	China	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Reviews and Commentaries
154	2019		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Not specified	Reviews and Commentaries
154																	Social media Analysis
156	2019		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Europe	EU	Multi-country	Not specified	Not specified	Not specified	Not specified	All	Database Analysis
156																	Social Surveys
156									South America	Mexico							Reviews and

																	Commentaries
160	2019		Mammals	Single	Carnivora	Felidae	Panthera	Tiger	Asia	China	Country	Asia	Tibet	Asia	China	Traditional medicine	Reviews and Commentaries
160																Aesthetic	
161	2019		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Uganda	Country	Africa	Africa	Asia	China	Traditional medicine	Database Analysis
161																Aesthetic	
162	2019		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Africa	South Africa	Multi-country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
162									Asia	India						Aesthetic	
163	2019		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	North America	USA	Country	Asia	Asia	North America	USA	Not specified	Database Analysis
173	2018		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Global	Global	Global	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
173																Nutritional	
173												Asia	Asia			Aesthetic	
174	2018		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	India	Country	Asia	India	Asia	Asia	Traditional medicine	Social Surveys
174																Nutritional	
174																Aesthetic	
177	2018		Mammals	Single	Carnivora	Mustelidae	Several	Otter	Asia	Thailand	Country	Domestic	Domestic	Domestic	Domestic	Pet trade	Social media Analysis

186	2018		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Asia	China	Country	Africa	Africa	Asia	Asia	Traditional medicine	Reviews and Commentaries
186																Aesthetic	
187	2018		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Uganda	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
187																Aesthetic	
189	2018		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Africa	Gabon	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
189																Nutritional	Social Surveys
189																Aesthetic	
192	2018		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	All	Reviews and Commentaries
202	2018		Mammals	Single	Carnivora	Ursidae	Several	Bear	Asia	Laos DR	Country	Asia	China	Not specified	Not specified	Traditional medicine	Database Analysis
202												North America	USA				
202												Asia	Vietnam				
208	2018		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Malaysia	Country	Africa	Africa	Asia	Asia	Traditional medicine	Social Surveys
208												Asia	Asia			Nutritional	
208																Aesthetic	
209	2018		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Asia	Hong Kong	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis

209																Aesthetic	Social Surveys
212	2018		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Global	Global	Global	Africa	Africa	Asia	Asia	Traditional medicine	Reviews and Commentaries
212																Aesthetic	
213	2018		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Asia	Vietnam	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
213																Aesthetic	
219	2018		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Asia	Myanmar	Country	Africa	Africa	Asia	Asia	Traditional medicine	In-situ observation
219																Aesthetic	
220	2018		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Laos DR	Country	Asia	China	Asia	Laos DR	Traditional medicine	In-situ observation
220																Nutritional	
220																Aesthetic	
222	2018		Mammals	Single	Carnivora	Felidae	Panthera	Snow leopard	Asia	Central Asia	Continental	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
222									Asia	South Asia						Aesthetic	Social Surveys
225	2018	Reptiles	Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Asia	Asia	Continental	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Reviews and Commentaries
225																Nutritional	
225																Aesthetic	
228	20		Mammals	Multiple	Pholidota	Manidae	Several	Pangolin	Asia	China	Country	Domestic	Domestic	Domestic	Domestic	Traditional	Database Analysis

	18															medicine	
228																Nutritional	
228	2018				Carnivora	Felidae	Panthera	Tiger								Aesthetic	
230	2018		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Africa	Central Africa	Continental	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
230																Nutritional	
230												Asia	Asia			Aesthetic	
232	2018		Mammals	Multiple	Proboscidea	Elephantidae	Several	Elephant	Africa	Africa	Continental	Africa	Africa	Asia	Southeast Asia	Traditional medicine	Database Analysis
232	2018				Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros								Aesthetic	
235	2018		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	North America	USA	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
235																Nutritional	
235																Aesthetic	
238	2018		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Africa	South Africa	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
238																Aesthetic	
243	2018		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Asia	Vietnam	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
243																Aesthetic	

244	2018		Mammals	Single	Carnivora	Felidae	Acinonyx	Cheetah	Global	Global	Global	Africa	Africa	Asia	United Arab Emirates	Aesthetic	Social media Analysis
244																Pet trade	
246	2018		Mammals	Single	Carnivora	Felidae	Acinonyx	Cheetah	Global	Global	Global	Africa	Africa	Not specified	Not specified	Traditional medicine	Reviews and Commentaries
246																Aesthetic	Social Surveys
246																Pet trade	
251	2018		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Asia	Hong Kong	Country	Africa	Africa	Asia	Asia	Traditional medicine	Social Surveys
253	2018		Mammals	Single	Primates	Several	Several	Not specified	Asia	China	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
253																Pet trade	
263	2017		Mammals	Single	Primates	Several	Several	Not specified	South America	Peru	Country	Not specified	Not specified	Not specified	Not specified	Aesthetic	Database Analysis
263																Pet trade	
266	2017		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	China	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
266																Nutritional	Social media Analysis
266												Asia	Asia			Aesthetic	
267	2017		Mammals	Single	Primates	Hominidae	Pongo	Orangutan	Asia	Indonesia	Country	Asia	Indonesia	Not specified	Not specified	Aesthetic	Database Analysis

267																Pet trade	
268	2017		Mammals	Single	Primates	Hominidae	Pongo	Orangutan	Asia	Indonesia	Country	Domestic	Domestic	Domestic	Domestic	Aesthetic	In-situ observation
268																Pet trade	
270	2017		Mammals	Single	Primates	Hominidae	Pongo	Orangutan	Asia	Indonesia	Country	Domestic	Domestic	Domestic	Domestic	Aesthetic	Database Analysis
271	2017		Mammals	Single	Primates	Several	Several	Lemur	Africa	Madagascar	Country	Domestic	Domestic	Domestic	Domestic	Pet trade	Database Analysis
271																	Social media Analysis
272	2017		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	China	Country	Not specified	Not specified	Not specified	Not specified	Pet trade	In-situ observation
274	2017		Mammals	Single	Carnivora	Felidae	Panthera	Lion	Global	Global	Global	Africa	Africa	Asia	Southeast Asia	Traditional medicine	Database Analysis
274																Aesthetic	
275	2017		Mammals	Single	Carnivora	Felidae	Panthera	Lion	Africa	Africa	Continental	Africa	Africa	Domestic	Domestic	Traditional medicine	Social Surveys
275														Asia	Asia	Aesthetic	
287	2017		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Africa	Continental	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
287																Aesthetic	
295	20		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Asia	Vietnam	Country	Africa	Africa	Asia	Asia	Traditional	Social media Analysis

	17														medicine	
295															Aesthetic	
300	2017		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	North America	America	Continental	Domestic	Domestic	Domestic	Domestic	Traditional medicine	Database Analysis
300									Central America							Nutritional	Social Surveys
300									South America							Aesthetic	
302	2017		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Africa	Zimbabwe	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
302																Nutritional	
302												Asia	Asia			Aesthetic	
308	2017		Mammals	Single	Carnivora	Ursidae	Several	Bear	Asia	Myanmar	Country	Asia	Asia	Asia	Asia	Traditional medicine	Social Surveys
318	2017		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Europe	UK	Country	Africa	Africa	Not specified	Not specified	Traditional medicine	Social media Analysis
318																Aesthetic	
329	2017		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Africa	South Africa	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
329																Aesthetic	
345	2016		Mammals	Single	Carnivora	Ursidae	Several	Bear	Asia	Laos DR	Country	Asia	Laos DR	Asia	China	Traditional medicine	Social Surveys
351	2016		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Aesthetic	Database Analysis

366	2016		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Asia	Vietnam	Country	Africa	Africa	Asia	Asia	Traditional medicine	Social Surveys
366																Aesthetic	
370	2016		Mammals	Single	Carnivora	Felidae	Panthera	Snow leopard	Global	Global	Global	Not specified	Not specified	Australia	Australia	Aesthetic	Database Analysis
370														Asia	Myanmar		Social Surveys
370														Asia	United Arab Emirates		In-situ observation
370														North America	USA		
371	2016		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Sri Lanka	Country	Not specified	Not specified	Not specified	Not specified		Database Analysis
375	2016		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	North America	USA	Country	Central America	Mexico	Not specified	Not specified	Traditional medicine	Database Analysis
375												North America	Canada			Nutritional	
375												Asia	Thailand			Aesthetic	
381	2016		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	South America	Peru	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Social Surveys
381																Nutritional	
381																Aesthetic	
384	2016		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Tanzania	Country	Africa	Tanzania	Asia	Asia	Traditional medicine	Reviews and Commentaries
384																Aesthetic	

397	2016		Mammals	Single	Carnivora	Felidae	Panthera	Tiger	Asia	China	Country	Domestic	Domestic	Domestic	Domestic	Aesthetic	Social Surveys
400	2016		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Myanmar	Country	Not specified	Not specified	Asia	China	Traditional medicine	In-situ observation
400																Nutritional	
400																Aesthetic	
405	2015		Mammals	Single	Carnivora	Felidae	Panthera	Leopard	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Aesthetic	Database Analysis
412	2015		Mammals	Single	Carnivora	Felidae	Panthera	Lion	Africa	South Africa	Country		South Africa	Asia	Southeast Asia	Traditional medicine	Database Analysis
412												Africa		Asia	China	Aesthetic	
420	2015		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Global	Global	Global	Not specified	Not specified	Asia	China	Traditional medicine	Database Analysis
420																Nutritional	
420																Aesthetic	
430	2015		Mammals	Multiple	Proboscidea	Elephantidae	Several	Elephant	Europe	UK	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Social media Analysis
430	2015				Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros								Aesthetic	
449	2014		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Global	Global	Global	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
449																Aesthetic	

457	2014		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	China	Country	Not specified	Not specified	Asia	Asia	Traditional medicine	In-situ observation
457																Nutritional	Social Surveys
457																Aesthetic	
467	2014		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Central America	Guatemala	Country	Not specified	Not specified	Not specified	Not specified	Pet trade	Social Surveys
468	2014		Mammals	Single	Primates	Lorisidae	Nycticebus	Slow loris	Asia	Myanmar	Country	Asia	Southeast Asia	Asia	China	Nutritional	In-situ observation
468																Aesthetic	
468																Pet trade	
472	2014		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Asia	Myanmar	Country	Africa	Africa	Asia	China	Traditional medicine	In-situ observation
472																Aesthetic	
479	2014		Mammals	Single	Primates	Lorisidae	Nycticebus	Slow loris	Asia	Indonesia	Country	Asia	Southeast Asia	Asia	China	Nutritional	Database Analysis
479																Aesthetic	
479																Pet trade	
486	2013		Mammals	Single	Primates	Cebidae	Several	Capuchin monkey	South America	Brazil	Country	Domestic	Domestic	Domestic	Domestic	Aesthetic	Social Surveys
486																Pet trade	
492	2013		Mammals	Single	Carnivora	Ursidae	Several	Bear	Asia	Japan	Country	Domestic	Domestic	Domestic	Domestic	Traditional medicine	Database Analysis

493	2013		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Vietnam	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
493																Nutritional	
493																Aesthetic	
500	2013		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	North America	USA	Country	Central America	Mexico	North America	USA	Traditional medicine	Database Analysis
500												Asia	China			Nutritional	
500																Aesthetic	
511	2013		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Asia	Nepal	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
511																Aesthetic	
513	2013		Mammals	Multiple	Proboscidea	Elephantidae	Several	Elephant	Asia	Laos DR	Country	Africa	South Africa	Asia	Asia	Traditional medicine	In-situ observation
513	2013				Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros								Aesthetic	
517	2012		Mammals	Multiple	Proboscidea	Elephantidae	Several	Elephant	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
517	2012				Carnivora	Felidae	Panthera	Tiger								Nutritional	Social media Analysis
517	2012				Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros								Aesthetic	
517	20				Carnivora	Felidae	Panthera	Leopard									

	12																
517	2012				Pholidota	Manidae	Several	Pangolin									
519	2012		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Pakistan	Country	Africa	Africa	Asia	Asia	Traditional medicine	Social Surveys
519																Nutritional	
519												Asia	Asia			Aesthetic	
536	2012		Mammals	Multiple	Carnivora	Felidae	Panthera	Tiger	Global	Global	Global	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
536	2012				Proboscidea	Elephantidae	Several	Elephant				Asia	Asia			Aesthetic	
536	2012				Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros									
537	2012		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	South America	Peru	Country	Domestic	Domestic	Domestic	Domestic	All	Database Analysis
542	2012		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Africa	South Africa	Country	Domestic	Domestic	Domestic	Domestic	Traditional medicine	Reviews and Commentaries
542																Nutritional	Social Surveys
542																Aesthetic	
554	2011		Mammals	Not specified	Not specified	Not specified	Not specified	Not specified	Africa	Congo	Country	Domestic	Domestic	Domestic	Domestic	Nutritional	In-situ observation

556	2011		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Central Africa	Multi-country	Domestic	Domestic	Domestic	Domestic	Traditional medicine	Database Analysis
556																Nutritional	
556																Aesthetic	
577	2010		Mammals	Single	Artiodactyla	Cetacea	Several	Whale	North America	USA	Multi-country	Not specified	Not specified	Not specified	Not specified	Nutritional	Forensic Genetics
577									Asia	South Korea							
577									Asia	Japan							
578	2010		Mammals	Single	Primates	Lorisidae	Nycticebus	Slow loris	Asia	South Asia	Multi-country	Asia	Laos DR	Asia	South Asia	All	Database Analysis
578												Asia	Cambodia				
578												Asia	Thailand				
581	2010		Mammals	Single	Primates	Cebidae	Several	Capuchin monkey	South America	Venezuela	Country	South America	Venezuela	Not specified	Not specified	Nutritional	Database Analysis
581																Pet trade	
582	2010		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Not specified	Database Analysis
585	2010		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Ghana	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
585																Nutritional	
585																Aesthetic	

589	2010		Mammals	Single	Primates	Several	Several	Not specified	Asia	Indonesia	Country		Domestic	Domestic	Domestic	Pet trade	In-situ observation
593	2010		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Asia	Vietnam	Europe	EU	All	Database Analysis
593												Asia	Indonesia	Asia	Japan		
593												Asia	China				
595	2010		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	China	Country	Not specified	Not specified		China	Traditional medicine	Database Analysis
597	2009		Mammals	Single	Primates	Hylobatidae	Several	Gibbon	Asia	Indonesia	Country	Domestic	Domestic	Domestic	Domestic	Pet trade	Social Surveys
597	2009		Mammals	Single	Primates	Hylobatidae	Several	Gibbon	Asia	Indonesia	Country	Domestic	Domestic	Domestic	Domestic	Pet trade	Social Surveys
598	2009		Mammals	Single	Primates	Several	Several	Monkey	South America	Brazil	Multi-country	South America	Brazil	South America	Brazil	Pet trade	Social Surveys
598									South America	Colombia		South America	Colombia	South America	Colombia		
598									South America	Peru		South America	Peru	South America	Peru		
600	2009		Not specified	Multiple	Several	Several	Several	Not specified	Asia	Russia	Country	Not specified	Not specified	Asia	Russia	Aesthetic	Social Surveys
601	2009		Mammals	Single	Carnivora	Felidae	Panthera	Tiger	Asia	China	Country	Asia	Asia	Asia	China	Traditional medicine	Database Analysis
601																Nutritional	
601																Aesthetic	

602	2009		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Africa	Continental	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
602																Nutritional	
602																Aesthetic	
606	2009		Mammals	Single	Artiodactyla	Camelidae	Vicugna	Vicuna	South America	Argentina	Country	South America	South America	South America	Argentina	Nutritional	Database Analysis
606																Aesthetic	
611	2008		Mammals	Single	Carnivora	Felidae	Panthera	Tiger	Asia	China	Country	Asia	Asia	Asia	China	Traditional medicine	Social Surveys
611																Aesthetic	
612	2008		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Vietnam	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
612																Nutritional	
612																Aesthetic	
613	2008		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	China	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
613																Nutritional	
613																Aesthetic	
614	2008		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	North America	USA	Country	Not specified	Not specified	North America	USA	Traditional medicine	Database Analysis
614																Nutritional	
614																Aesthetic	

620	2008		Mammals	Single	Carnivora	Canidae	Canis	Dog	Europe	Germany	Country	Europe	EU	Europe	Germany	Pet trade	Database Analysis
627	2007		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Congo	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
627																Nutritional	
627																Aesthetic	
640	2005		Mammals	Single	Cetacea	Several	Several	Not specified	Global	Global	Global	Not specified	Not specified	Asia	Russia	Nutritional	Database Analysis
640														Central America	Central America	Aesthetic	
640														Africa	West Africa	Pet trade	
640														Asia	Southeast Asia		
642	2005		Mammals	Single	Artiodactyla	Camelidae	Vicugna	Alpaca	South America	Peru	Country	South America	Peru	South America	Bolivia	Nutritional	Database Analysis
642														South America	Chile	Aesthetic	
644	2005		Mammals	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Indonesia	Country	Not specified	Not specified	Asia	Indonesia	Traditional medicine	Database Analysis
644																Nutritional	
644																Aesthetic	
656	2003		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Africa	South Africa	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
656																Nutritional	
656																Aesthetic	

659	2000		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Myanmar	Country	Domestic	Domestic	Domestic	Domestic	Traditional medicine	Social Surveys
659																Nutritional	
659																Aesthetic	
661	2000	Bird	Mammals	Multiple	Artiodactyla	Bovidae	Pantholops	Tibetan antelope	Asia	Himalayas	Country	Not specified	Not specified	Asia	China	Traditional medicine	Database Analysis
661																Nutritional	
661	2000				Carnivora	Ursidae	Ailuropoda	Giant panda								Aesthetic	
667	1998		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	China	Multi-country	Africa	Africa	Asia	Asia	Traditional medicine	In-situ observation
667																Nutritional	Social Surveys
667									Asia	Vietnam		Asia	Asia			Aesthetic	
670	1997		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	South America	Chile	Country	South America	Chile	Not specified	Not specified	Traditional medicine	Database Analysis
670																Nutritional	
670																Aesthetic	
671	1997		Mammals	Single	Carnivora	Felidae	Panthera	Tiger	Asia	Indonesia	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
671																Nutritional	
671												Asia	Asia			Aesthetic	

674	1993		Mammals	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Nepal	Country	Asia	India	Asia	Nepal	Aesthetic	In-situ observation
676	1990		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	India	Multi-country	Asia	India	North America	USA	Traditional medicine	Database Analysis
676																Nutritional	
676									North America	USA						Aesthetic	
677	1989		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Africa	Yemen	Country	Africa	Africa	Africa	Yemen	Traditional medicine	Database Analysis
677														Asia	Asia	Aesthetic	
678	1988		Mammals	Single	Artiodactyla	Moschidae	Moschus	Musk deer	Asia	Japan	Country	Asia	Himalayas	Asia	Japan	Traditional medicine	Database Analysis
682	2013		Mammals	Multiple	Proboscidea	Elephantidae	Several	Elephant	Asia	Nepal	Country	Africa	Africa	Asia	Nepal	Traditional medicine	Database Analysis
682	2013				Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros				Asia	Asia			Aesthetic	
1730	2020		Mammals	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	Nepal	Country	Not specified	Not specified	Not specified	Not specified	All	Database Analysis
1744	2020		Mammals	Single	Carnivora	Ursidae	Several	Bear	Europe	Czech Republic	Country	North America	Canada	Not specified	Not specified	Traditional medicine	Database Analysis
1744												Asia	Russia			Nutritional	
1744																Aesthetic	

1766	2020		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Asia	China	Country	Not specified	Not specified	Not specified	Not specified	All	Database Analysis
1766																	Social Surveys
1783	2019		Mammals	Single	Primates	Several	Several	Lemur	Africa	Madagascar	Country	Africa	Madagascar	Not specified	Not specified	Pet trade	Database Analysis
1797	2019		Mammals	Multiple	Proboscidea	Elephantidae	Several	Elephant	Africa	Mombasa	Country	Africa	Mombasa	Not specified	Not specified	Traditional medicine	Database Analysis
1797	2019				Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros								Aesthetic	
1797	2019				Artiodactyla	Hippopotamidae	Hippopotamus	Hippopotamus									
1843	2018		Mammals	Single	Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros	Asia	Vietnam	Country	Africa	Africa	Asia	Asia	Traditional medicine	Social Surveys
1843												Africa				Aesthetic	
1850	2018		Mammals	Single	Carnivora	Felidae	Panthera	Jaguar	Asia	China	Country		Africa	Asia	Asia	Traditional medicine	Social Surveys
1850																Aesthetic	
1865	2018		Mammals	Multiple	Artiodactyla	Bovidae	Ourebia	Oribi	Africa	South Africa	Country	Africa	South Africa	Domestic	Domestic	Traditional medicine	Social Surveys
1865	2018				Carnivora	Felidae	Leptailurus	Serval								Nutritional	

1894	2018		Mammals	Single	Artiodactyla	Cetacea	Several	Whale	Asia	South Korea	Multi-country	Not specified	Not specified	Asia	Korea	Nutritional	Database Analysis
1894									Asia	North Korea							
1968	2017		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Myanmar	Country	Not specified	Not specified	Asia	Asia	Traditional medicine	Database Analysis
1968																Nutritional	
1968																Aesthetic	
1974	2016		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
1974																Nutritional	
1974																Aesthetic	
2063	2015		Mammals	Not specified	Not specified	Not specified	Not specified	Not specified	South America	Brazil	Multi-country	Domestic	Domestic	Domestic	Domestic	Nutritional	Database Analysis
2063									South America	Colombia							
2063									South America	Peru							
2064	2015		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Asia	Phillipines	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
2064																Nutritional	
2064																Aesthetic	
2095	2014		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	Global	Global	Global	Not specified	Not specified	Not specified	Not specified	All	Reviews and Commentaries

2136	2013		Mammals	Multiple	Proboscidea	Elephantidae	Several	Elephant	Asia	Laos DR	Country	Africa	Africa	Asia	Asia	Traditional medicine	Database Analysis
2136	2013				Perissodactyla	Rhinocerotidae	Rhinoceros	Rhinoceros								Aesthetic	
2145	2012		Mammals	Single	Pholidota	Manidae	Several	Pangolin	Asia	Pakistan	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Database Analysis
2145																Nutritional	
2145																Aesthetic	
2198	2011		Mammals	Single	Proboscidea	Elephantidae	Several	Elephant	Africa	Central Africa	Multi-country	Not specified	Not specified	Not specified	Not specified	Nutritional	Database Analysis
2198																Aesthetic	
2209	2010		Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	South America	Brazil	Country	Not specified	Not specified	Not specified	Not specified	Traditional medicine	Social Surveys
2302	2006		Mammals	Single	Artiodactyla	Moschidae	Moschus	Musk deer	Asia	Himalayas	Country	Asia	Russia	Europe	France	Traditional medicine	Social Surveys
2302														Europe	Germany	Nutritional	
2302														Europe	Switzerland		
2302														Asia	Asia		
2402	1999		Mammals	Single	Carnivora	Ursidae	Several	Bear	North America	Canada	Country	North America	Canada	Asia	Asia	Traditional medicine	Database Analysis
2402																Aesthetic	

2435	1988		Mammals	Single	Several	Several	Several	Not specified	South America	Peru	Country	Domestic	Domestic	Domestic	Domestic	Nutritional	Social Surveys
2435																Aesthetic	