

Research Article

Recognition of *Ziziphus lotus* through Aerial Imaging and Deep Transfer Learning Approach

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There is a growing demand for the detection of endangered plant species through machine learning approaches. *Ziziphus lotus* is an endangered deciduous plant species in the buckthorn family (*Rhamnaceae*) native to Southern Europe. Traditional methods such as object-based image analysis have achieved good recognition rates. However, they are slow and require high human intervention. Transfer learning-based methods have several applications for data analysis in a variety of Internet of Things systems. In this work, we have analyzed the potential of convolutional neural networks to recognize and detect the *Ziziphus lotus* plant in remote sensing images. We fine-tuned Inception version 3, Xception, and Inception ResNet version 2 architectures for binary classification into plant species class and bare soil and vegetation class. The achieved results are promising and effectively demonstrate the better performance of deep learning algorithms over their counterparts.

1. Introduction

Rates for the destruction of habitat and plant species are on the rise worldwide due to several alterations in the land cover and land use which can significantly impact the environment and society. Hence, there is a pressing need for a management system that incorporates solid scientific principles for environmental management of species especially plant species [1]. Among many factors that influence the natural ecosystem, global land cover is perhaps the most important of them. Combined with remote sensing technology, this burgeoning domain has important applications on the Internet of Things (IoT)-based technologies [2]. Remote

sensing datasets if effectively and efficiently processed can discover important patterns that are helpful in sustainable environmental protection efforts [3].

Anthropogenic land use and cover change (LUCC) is one of the primary factors behind alterations in the environment on a global scale. Understanding the underlying factors behind LUCC holds the key to sustainable efforts to reduce deforestation and forest degradation [4]. Shrub and bush, agricultural land, turf, and grass are grassland-type land cover classification systems where research activities on climate change modelling, environmental protection, and regional/national land-use planning are currently underway [5].

Ziziphus lotus is regarded as keystone scrubs, whose seeds are consumed and dispersed by foxes and other vertebrates, that grow on low-land wad terraces and are threatened by the spreading of greenhouse gases, agricultural practices, and land-use patterns [6–9]. Traditionally, species distribution models (SDMs) are used in the identification and location of the population of rare and threatened species. These models are heavily used in the conservation of plant species.

However, due to its enhanced monitoring range, rapid speed, and potential to acquire vast amounts of information, satellite remote sensing represents one of the most practical approaches for land-use patterns. Remote sensing sensors whose spectral bands range from visible to infrared regions of the electromagnetic spectrum are used in the mapping of land cover among other applications [10]. On the downside, there are certain limitations of monitoring the conservation status of habitats with remote sensing as it cannot be directly applied to assess small-scale characteristics [11]. Due to the availability of a wide range of sensors, it is practically possible to accurately estimate the use of different technologies for the protection of wildlife [12]. However, monitoring experts are still in doubt if different remote sensing technologies can meet their demands in financial terms. These experts found it difficult to use their knowledge with these technologies [13]. Furthermore, due to the way spatial information is utilized, it is difficult to assess its impact on the urban expansion especially concerning natural habitats [14].

Despite these limitations, satellite technologies are widely deployed to study land-use patterns [15], fragmentation of forest formations [16], implications of land-use patterns related to population and development [17], and selective species and habitat protection [18] as well as estimate natural and artificial changes in landscapes [19].

Classification methods are widely deployed to study airborne visible/infrared imaging spectroradiometer hyperspectral imagery [20], Landsat images [21], and panchromatic high-resolution data from urban areas [22]. A very high-resolution spatial remote sensing provides detailed information about vegetation [23], man-made, water, green vegetation, and bare soil [24], as well as mapping wildlife habitat [25].

Deep learning techniques such as convolutional neural networks (CNNs) have application in healthcare [26] and other domains [27–30] and are getting popularity for the classification of land cover using light detection and ranging (LIDAR) and Landsat imagery across different time points [31], scene classification using very high-resolution cameras for remote sensing applications [32], and hyperspectral imagery [33–36]. Traditionally, methods based on segmentation approaches, such as object-based image analysis (OBIA) [37–39], are used for the classification of land cover mapping, disaster management, environmental monitoring, and civil and military intelligence. However, there are numerous problems in the successful application of such approaches such as the type of segmentation challenges and conceptual foundations. In essence, OBIA is far from being an operationally established paradigm for specific research or commercial activities.

Emergent artificial intelligence (AI)-based methods such as IoT-based methods have found various applications in wireless sensor networks [40, 41] and are finding their way into connection of millions of objects to help in getting meaningful results from unprocessed data [42]. It is committed to provide best possible solutions to deal with data and information [43, 44]. A big challenge in IoT is to uniquely identify each object with representation and storage of information that is getting exchanged among the objects. Applications of IoT are still in nascent stages with such diversity as natural calamities prediction, water shortage detection, smart homes, healthcare, smart farming, smart transport, smart cities, and smart security.

Because of the inherent limitations of the existing object recognition methods for recognizing objects in high-resolution images obtained from remote sensing apparatus, there is a need for the evaluation of new learning paradigms in this domain. In this research, we present transfer learning as the method of choice for the classification of *Ziziphus lotus* shrub from the bare soil and vegetation in remote sensing images. Distinguishing *Ziziphus lotus* from neighbouring plants is a difficult task for non-experts and the existing computational methods because the surrounding plants and the background soil differ strongly in the close-by regions [45]. We use Xception [46], Inception version 3 [47], and Inception ResNet version 2 [48] deep transfer learning architectures for fine-tuning ImageNet dataset-based features on our problem. We compared our approach with the existing works in the literature and found that our approach outperforms OBIA.

Rest of the contents of this paper are presented as follows. A review of prior art is provided in Section 2. A description of the proposed methodology is given in Section 3 followed by the experiments, discussion, and conclusion in Sections 4, 5, and 6, respectively.

2. Prior Art

A number of attempts have been made in the literature for the conservation of biodiversity especially plant species despite the complexity of the task. The authors [49] deployed a computational approach consisting of image binarization for classification into background and leaf, using steps such as denoising to extract 12 shape-based features to achieve an accuracy of 90%. Jin et al. [50] proposed an approach combining binarization, contour, and corner detection as well as segmentation achieving 76% classification rate for multiclass (8 classes) classification problem. Similarly, Seeland et al. [51] proved the efficacy of speeded up robust features (SURF) in combination with scale-invariant feature transform (SIFT)-based features for plant species identification over traditional approaches. Greg et al. [52] used a dataset comprising 213 endangered plant species using point pattern analyses such as cross pair correlation function to identify how different types of ecosystems are dependent. Studies have also targeted *D. pectinatum* in tropical regions across three national natural reserves in China [53, 54] using artificial neural networks and support vector machine (SVM)-based classifiers. Du et al. [55] used the gap analysis

technique for the conservation of 31 threatened plant species in Sanjiang Plain, China. Hamabata et al. [56] used the RNA sequencing technique to get exhaustive sequences of plant species belonging to marine life finding that these species accumulated variations which lead to their extinction.

Similarly, smart agriculture practices have been applied for the monitoring of apple growth cycle [57] using pattern recognition techniques such as active shape and Gaussian distribution models. In addition, the virtual reality technology provides an environment enabling agricultural students to enhance their talents [58]. Another key technology is remote sensing used to study urban landscape-based systems in the process of urban development [59]. Similarly, fuzzy logic has also been applied to build a system for the management of environmental damage [60] as well as conservation of parrot species using transfer learning [61].

Optical remote sensing images provide rich information content to recognize objects in a fundamental and challenging way, and the task of recognition from aerial images is attaining significant attention [62]. OBIA is an important type of these methods and is used for accurate and timely recognition of weeds [63], vegetation mapping [64], extracting cropland parcels for precision agriculture and other fields [65], mapping small-scale agriculture [66], and mapping of marine life [67].

CNNs are gradient-based optimization networks that are used for the recognition of remote sensing data inclusive of vegetation class [68], land use [69–71], scene classification [32], and multiclass problems [72]. They are known to be universal approximators capable of efficiently representing arbitrarily complex functions given sufficient capacity, and they have excellent generalization power as well as high representational capacity.

When combined with fine-tuning [73], dropout, and data augmentation [74], CNN-based deep architectures can boost the performance significantly on a given problem. However, mathematical understanding and implications of these systems are still in an early stage.

3. Proposed Methodology

3.1. Study Areas. The training and validation zone for training and validating the CNN based model is located in Cabo de Gata-Níjar Natural Park, 36°49'43" North, 2°16'22" West, which is located in the province of Almería, Spain. The vegetation is found to be scarce and patchy, dominated by *Ziziphus lotus* plants that are surrounded by a mix of bare soil and small scrubs [45]. There are two test zones. The first test zone is located one and a half kilometer away from the training zone, 36°49'28" North, 2°17'28" West. The second test zone is located in Rizoelia National Forest Park in Cyprus, 34°56'09" North, 33°34'26" East [45].

3.2. Remote Sensing Dataset. There are two classes in our dataset: *Ziziphus lotus* plant class and bare soil and vegetation class. There are 180 images in the training set, 20 images in the validation set, and 11 images in the test set. There are 90 images each of the two classes in training set

while there are 10 images each of the two classes in the validation set. There are six images of *Ziziphus lotus* class and five images of bare soil and vegetation class in the test set. Sample training and test samples are shown in Figures 1 and 2.

3.3. Classification Using 10-Fold Cross-Validation Approach. Cross-validation [75] is a common approach to assess a model in terms of its performance to an independent dataset which in our case is the validation set of 20 examples of both classes. This method helps in selecting optimal hyperparameters to overcome overfitting. There are a number of ways to implement such a strategy such as k -fold, stratified k -fold, and so on. In this work, we considered k -fold cross-validation approach where k is 10 with balanced classes in the dataset.

4. Experiments

A classifier is a mapping that maps an unlabelled instance to a label. Let z be the set of unlabelled instances and G be the space of possible labels. Let $a = z \times \gamma$ be the set of labelled instances and $X = \{r_1, r_2, \dots, r_n\}$ be a set consisting of n labelled instances, where $r_i = \langle f_i \in z, g_i \in G \rangle$. A classifier β maps an unlabelled instance $f \in z$ to a label $g \in G$. The correct recognition rate of a classifier β is dependent on the probability of correctly mapping $f \in z$ to $g \in G$.

We use the classification architecture shown in Figure 3. The input image to all the models is a tensor of shape $299 \times 299 \times 3$ according to the requirements of Inception version 3, Xception, and Inception ResNet version 2 architectures. The image is then passed through the transfer learning model trained on ImageNet dataset features whose output is then fed to the flatten layer. Flatten layer does not affect the batch size and converts a batch of size $\text{batch} \times \text{channels} \times \text{height} \times \text{width}$ to a simple vector output of shape $\text{batch} \times (\text{channels} \times \text{height} \times \text{width})$.

Fully connected (FC) layer 1 is made up of 256 neurons activated by rectified linear unit (ReLU) activation function. After that, there is a dropout layer with 50% probability to improve overfitting on the model by dropping neurons. Finally, there is another FC layer with a single neuron activated by sigmoid function whose purpose is to classify the input image in one of the two categories. For the training dataset, we use horizontal and vertical flipping as data augmentation techniques and normalize the input through division by 255. For the validation and test sets, we simply normalize the input through division by 255 and do not apply any other form of data augmentation. As a loss function which needs to be minimized, we used binary cross-entropy. The optimizer that we chose to minimize binary cross-entropy is the well-known stochastic gradient descent (SGD). The initial learning rate is set to 0.00001. We decay the learning rate with the passage of epochs using step decay strategy. We also used gradient clipping to make the network robust against overfitting and exploding gradient problems. We trained the model for 30 epochs by setting the batch size to 5.

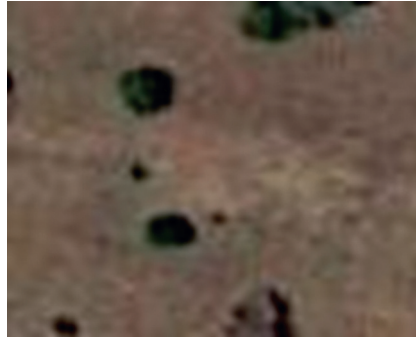


FIGURE 1: A sample of bare soil and vegetation class.



FIGURE 2: A sample of *Ziziphus lotus* class.

4.1. Classification Using Xception Architecture. We used Xception architecture pretrained on the ImageNet dataset and tested the model on an independent test set. This architecture employs the idea of depthwise separable convolution performed over the channels of an input which is then passed through a pointwise 1×1 convolution projecting a channel's output onto a new space. An advantage of such an approach is an efficient use of the model parameters.

4.2. Classification Using Inception Version 3 Architecture. Just like Xception architecture, we used Inception version 3 architecture pretrained on the ImageNet dataset and tested the model on an independent test set. In Figure 4, a canonical Inception version 3 module is presented. In this architecture, cross-channel and spatial correlations are learned by the filters inside convolutional layers. It also uses the idea of auxiliary classifiers, acting as regularizers, to combat the vanishing gradient problem. Large-sized convolutional blocks are replaced with small-sized ones through the process of factorization to save the computations.

4.3. Classification Using Inception ResNet Version 2 Architecture. Just like Xception and Inception version 3 architectures, we used Inception ResNet version 2 architecture pretrained on the ImageNet dataset and tested the model on an independent test set. This architecture is a hybrid version of both Inception and ResNet architectures. It uses residual connections to improve the training speed. In this architecture, each Inception block is followed by a 1×1 convolution without activation used for scaling up the

dimensionality of the filter bank in order to match the depth of the input which allows for compensation in dimensionality reduction induced by the Inception block.

5. Discussion

The training/validation accuracy and loss plots for Inception version 3 architecture are shown in Figures 5 and 6.

As shown in the plots, the training starts with a relatively high error as the classifier is still learning the mapping between the two classes and their corresponding labels. As it gets better and better with the passing of epochs, the classifier returns a better mapping. The fluctuations represent the learning behavior of the gradients due to the stochasticity/randomness in the samples.

The training and validation accuracy and loss plots for the Xception architecture are shown in Figures 7 and 8 while the training and validation accuracy and loss plots for Inception ResNet version 2 architecture are shown in Figures 9 and 10.

A general trend can be seen in these plots/figures in that the Inception ResNet version 2 model performs a bit worse than the other two models. The trend depicts overfitting by the Inception ResNet version 2 architecture which could be due to a large number of parameters of this model as it naturally needs a large number of samples for training. The number of parameters that are required to train the Inception ResNet version 2 model is more than twice that of Inception version 3 and Xception models. As the number of parameters increases, so does the requirement for the number of training samples. The role of regularization such as gradient clipping is to mitigate overfitting in the regime which helps in achieving the effective capacity of the machine learning models.

An interesting dichotomous phenomenon can be observed in Figures 9 and 10. In Figure 9, a rapid decrease in accuracy can be observed near epoch 6 which could be explained by the fact that saturated neurons kill the gradients as ReLU activation function may get saturated in the negative region during the training process. Dead ReLU has problems getting activated or updated. Another possible reason for this phenomenon could be the loss function. The loss function has a high condition number, and, in this case, it is stuck in a local minimum with zero gradients. Learning rate is a hyperparameter of SGD, and it determines the size of the steps to reach a local minimum. The direction of slope of the surface determines the way gradients are

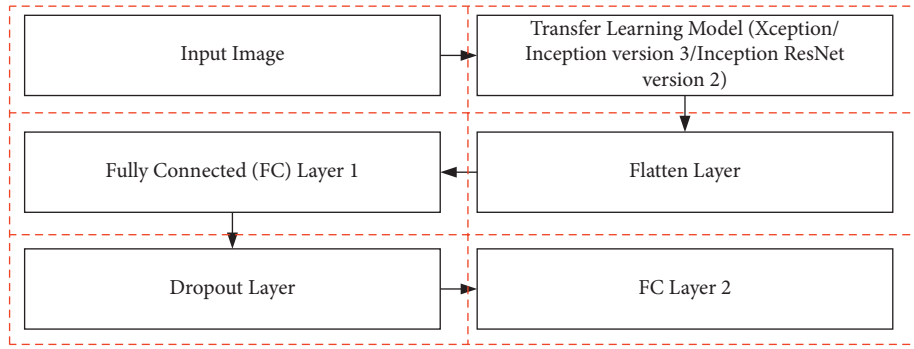


FIGURE 3: Architecture for Xception, Inception version 3, and Inception ResNet version 2-based models.

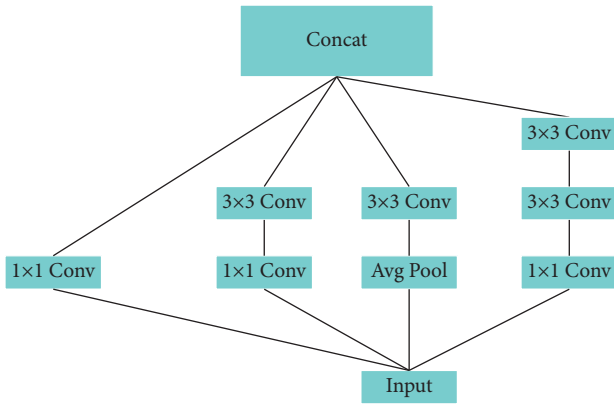


FIGURE 4: A canonical Inception version 3 module.

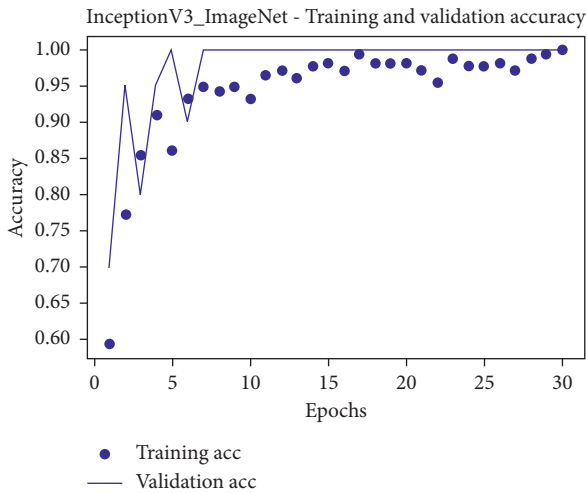


FIGURE 5: Training versus validation accuracy curve achieved at fold-9 for Inception version 3 architecture.

reaching the valley since one update at a time is performed with high variance causing the objective function to fluctuate heavily and getting stuck in a local minimum due to highly non-convex nature of error function since SGD is prone to noise.

We now define accuracy, precision, recall, and F_1 -score in the context of our experiments:

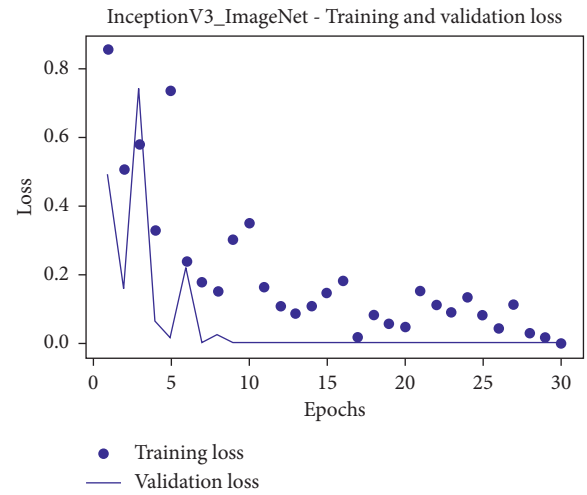


FIGURE 6: Training versus validation loss curve achieved at fold-9 for Inception version 3.

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{precision} = \frac{TP}{TP + FP}$$

$$\text{recall} = \frac{TP}{TP + FN}$$

(1)

$$F_1 - \text{score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Here true positive (TP) represents the *Ziziphus lotus* class samples that are correctly classified as belonging to *Ziziphus lotus* class, false positive (FP) represents the bare soil and vegetation class samples that are incorrectly classified as belonging to *Ziziphus lotus* class, and true negative (TN) represents the bare soil and vegetation class samples that are correctly identified as belonging to bare soil and vegetation class, whereas false negative (FN) represents the *Ziziphus lotus* class samples that are incorrectly classified as belonging to bare soil and vegetation class.

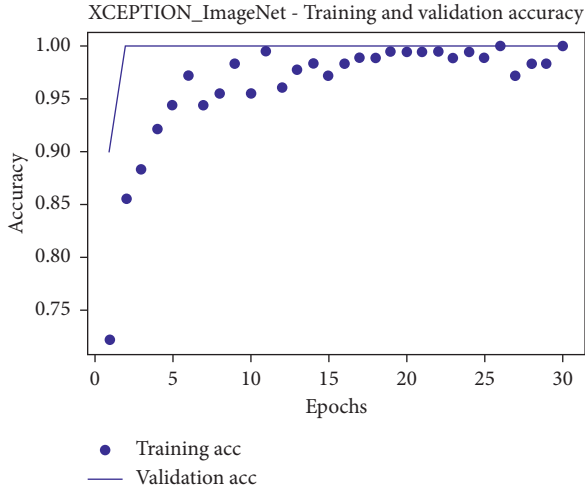


FIGURE 7: Training versus validation accuracy curve achieved at fold-3 for Xception architecture.

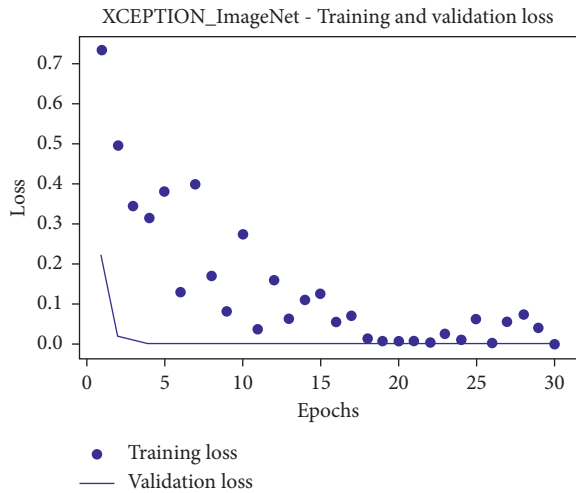


FIGURE 8: Training versus validation loss curve achieved at fold-3 for Xception architecture.

We achieved an accuracy of 100% on the test dataset for all the three architectures. All the 11 samples belonging to the 2 classes in the test dataset are correctly categorized in their respective classes. Hence, we achieved the perfect score of 1 on precision, recall, and F_1 -score for all the three architectures. Sample test dataset results on the Inception ResNet version 2 architecture for the two classes are shown in Figures 11 and 12. The class score for the *Ziziphus lotus* class test sample is 1, and for the bare soil and vegetation class, it is $1.5358785 \times 10^{-10}$.

In comparison, Guirado et al. [45] reported a precision rate of 100%, recall rate of 95%, and an F_1 -score of 96.5% for the ResNet-based deep transfer learning classifier while they reported a precision rate of 91.78%, recall rate of 97.29%, and an F_1 -score of 92.90% for the non-deep learning-based OBIA classifier. The results hence prove the effectiveness of our approach through application of Inception version 3, Xception, and Inception ResNet version 2 transfer learning-based architectures for this problem.

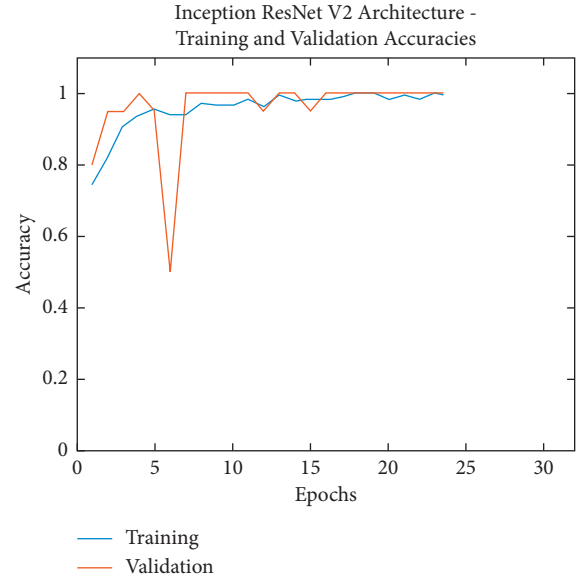


FIGURE 9: Training versus validation accuracy curve achieved at fold-6 for Inception ResNet version 2 architecture.

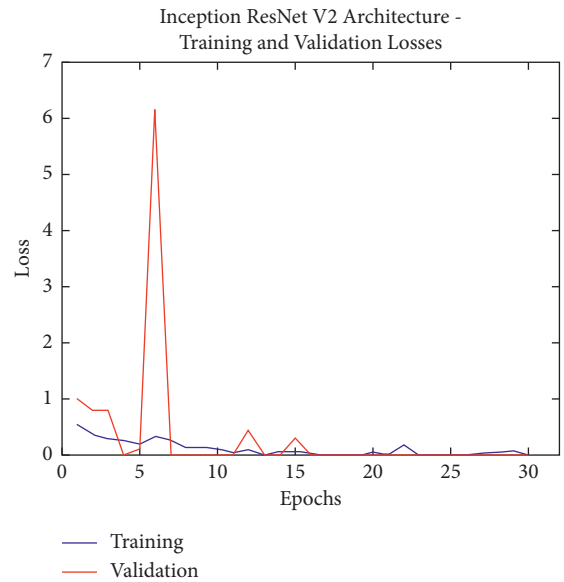


FIGURE 10: Training versus validation loss curve achieved at fold-6 for Inception ResNet version 2.

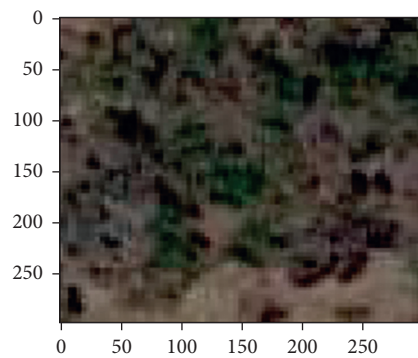


FIGURE 11: Test set *Ziziphus lotus* class sample correctly classified by Inception ResNet version 2 architecture.

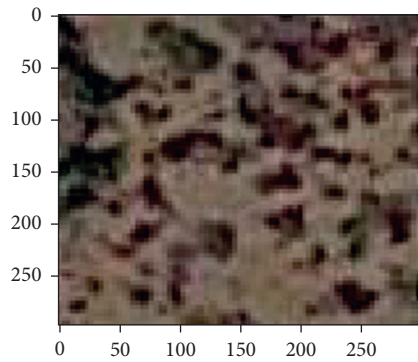


FIGURE 12: Test set bare soil and vegetation class sample correctly classified by Inception ResNet version 2 architecture.

6. Conclusion

In this work, we explored, analyzed, and compared the performance of deep learning architectures for the classification of *Ziziphus lotus* which is an endangered species in the European habitat ecosystem. We fine-tuned Inception version 3, Xception, and Inception ResNet version 2 architectures which were pretrained on ImageNet dataset-based features. We achieved promising results which established the usefulness of deep learning approaches in this domain of problems. We found that these three architectures need minimum human supervision and their inference time is minimal in comparison to the other methods which are not based on deep learning such as OBIA. In the future, we are planning to extend this study through the inclusion of more endangered shrub species in different parts of forests in dryland biomes across the globe in accordance with the global initiatives taken by the Food and Agricultural Organization of the United Nations. We are also planning to deploy novel deep learning architectures such as graph convolutional networks and capsule networks to recognize images of plant species of conservation concern.

Data Availability

The dataset used for the experiments in this study is available upon reasonable request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

ABT was responsible for conceptualization, methodology, investigation, and software. RK was responsible for validation. IU was responsible for formal analysis. OC was responsible for resources. RK and AUR were responsible for data curation. ABT and AY were responsible for original draft preparation. ABT and LA were responsible for review and editing. LA was responsible for visualization. IU and HH were responsible for supervision. IU, WA, HH, YKM, and OC were responsible for project administration. OC was

responsible for funding acquisition. All authors have read and agreed to the published version of the manuscript.

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References

- [1] W. Turner, S. Spector, N. Gardiner, M. Fladeland, E. Sterling, and M. Steininger, "Remote sensing for biodiversity science and conservation," *Trends in Ecology & Evolution*, vol. 18, no. 6, pp. 306–314, 2003.
- [2] R. Congalton, J. Gu, K. Yadav, P. Thenkabail, and M. Ozdogan, "Global land cover mapping: a review and uncertainty analysis," *Remote Sensing*, vol. 6, no. 12, pp. 12070–12093, 2014.
- [3] C. R. Fichera, G. Modica, and M. Pollino, "Land cover classification and change-detection analysis using multi-temporal remote sensed imagery and landscape metrics," *European Journal of Remote Sensing*, vol. 45, no. 1, pp. 1–18, 2012.
- [4] N. Joshi, M. Baumann, A. Ehammer et al., "A review of the application of optical and radar remote sensing data fusion to land use mapping and monitoring," *Remote Sensing*, vol. 8, no. 1, p. 70, 2016.
- [5] L. Wang, C. Li, Q. Ying et al., "China's urban expansion from 1990 to 2010 determined with satellite remote sensing," *Chinese Science Bulletin*, vol. 57, no. 22, pp. 2802–2812, 2012.
- [6] Y. Le Polain de Waroux and E. F. Lambin, "Monitoring degradation in arid and semi-arid forests and woodlands: the case of the argan woodlands (Morocco)," *Applied Geography*, vol. 32, no. 2, pp. 777–786, 2012.
- [7] B. M. Benito, M. M. Martínez-Ortega, L. M. Muñoz, J. Lorite, and J. Peñas, "Assessing extinction-risk of endangered plants using species distribution models: a case study of habitat depletion caused by the spread of greenhouses," *Biodiversity and Conservation*, vol. 18, no. 9, pp. 2509–2520, 2009.
- [8] A. González-Robles, A. J. Manzaneda, J. M. Bastida et al., "Development and characterization of microsatellite primers in the endangered mediterranean Shrub *Ziziphus lotus* (*rhamnaceae*)," *Applications in Plant Sciences*, vol. 4, no. 12, Article ID 1600092, 2016.
- [9] I. Cancio, A. González-Robles, J. M. Bastida, A. J. Salido, and P. J. Rey, "Habitat loss exacerbates regional extinction risk of the keystone semiarid shrub *ziziphus lotus* through collapsing the seed dispersal service by foxes (*vulpes vulpes*)," *Biodiversity and Conservation*, vol. 25, no. 4, pp. 693–709, 2016.
- [10] C. Pelletier, S. Valero, J. Inglada, N. Champion, and G. Dedieu, "Assessing the robustness of random forests to map land cover with high resolution satellite image time series over large areas," *Remote Sensing of Environment*, vol. 187, pp. 156–168, 2016.
- [11] T. Spanhove, J. Vanden Borre, S. Delalieux, B. Haest, and D. Paelinckx, "Can remote sensing estimate fine-scale quality indicators of natural habitats?" *Ecological Indicators*, vol. 18, pp. 403–412, 2012.
- [12] C. Corbane, S. Lang, K. Pipkins et al., "Remote sensing for mapping natural habitats and their conservation status - new opportunities and challenges," *International Journal of Applied Earth Observation and Geoinformation*, vol. 37, pp. 7–16, 2015.

- [13] J. Vanden Borre, D. Paelinckx, C. A. Múcher et al., "Integrating remote sensing in natura 2000 habitat monitoring: prospects on the way forward," *Journal for Nature Conservation*, vol. 19, no. 2, pp. 116–125, 2011.
- [14] C. He, Z. Liu, J. Tian, and Q. Ma, "Urban expansion dynamics and natural habitat loss in China: a multiscale landscape perspective," *Global Change Biology*, vol. 20, no. 9, pp. 2886–2902, 2014.
- [15] A. M. Dewan and Y. Yamaguchi, "Land use and land cover change in greater Dhaka, Bangladesh: using remote sensing to promote sustainable urbanization," *Applied Geography*, vol. 29, no. 3, pp. 390–401, 2009.
- [16] L. A. B. Jorge and G. J. Garcia, "A study of habitat fragmentation in southeastern Brazil using remote sensing and geographic information systems (gis)," *Forest Ecology and Management*, vol. 98, no. 1, pp. 35–47, 1997.
- [17] L. M. Hunter, G. Gonzalez, M. Stevenson et al., "Population and land use change in the California Mojave: natural habitat implications of alternative futures," *Population Research and Policy Review*, vol. 22, no. 4, pp. 373–397, 2003.
- [18] F. Schulz and G. Wiegand, "Development options of natural habitats in a post-mining landscape," *Land Degradation & Development*, vol. 11, no. 2, pp. 99–110, 2000.
- [19] J. T. Kerr and M. Ostrovsky, "From space to species: ecological applications for remote sensing," *Trends in Ecology & Evolution*, vol. 18, no. 6, pp. 299–305, 2003.
- [20] F. Melgani and L. Bruzzone, "Classification of hyperspectral remote sensing images with support vector machines," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 42, no. 8, pp. 1778–1790, 2004.
- [21] F. Wang, "Fuzzy classification of remote sensing images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 28, no. 2, pp. 194–201, 1990.
- [22] J. A. Benediktsson, M. Pesaresi, and K. Arnason, "Classification and feature extraction for remote sensing images from urban areas based on morphological transformations," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 41, no. 9, pp. 1940–1949, 2003.
- [23] Y. Qian, P. Gong, N. Clinton, G. Biging, M. Kelly, and D. Schirokauer, "Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery," *Photogrammetric Engineering and Remote Sensing*, vol. 72, no. 7, pp. 799–811, 2006.
- [24] D. Tuia, F. Ratle, F. Pacifici, M. F. Kanevski, and W. J. Emery, "Active learning methods for remote sensing image classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 7, pp. 2218–2232, 2009.
- [25] A. K. Skidmore, A. Gauld, and P. Walker, "Classification of kangaroo habitat distribution using three GIS models," *International Journal of Geographical Information Systems*, vol. 10, no. 4, pp. 441–454, 1996.
- [26] A. B. Tufail, Y.-K. Ma, Q.-N. Zhang et al., "3D convolutional neural networks-based multiclass classification of Alzheimer's and Parkinson's diseases using PET and SPECT neuroimaging modalities," *Brain Informatics*, vol. 8, no. 1, p. 23, 2021.
- [27] R. Khan, Q. Yang, I. Ullah et al., "3D convolutional neural networks based automatic modulation classification in the presence of channel noise," *IET Communications*, 2021.
- [28] I. Ahmad, I. Ullah, W. U. Khan et al., "Efficient algorithms for E-healthcare to solve multiobject fuse detection problem," *Journal of Healthcare Engineering*, vol. 2021, Article ID 9500304, 16 pages, 2021.
- [29] S. Yu, J. Liu, J. Wang, and I. Ullah, "Adaptive double-threshold cooperative spectrum sensing algorithm based on history energy detection," *Wireless Communications and Mobile Computing (WCMC)*, vol. 2020, Article ID 4794136, 12 pages, 2020.
- [30] A. B. Tufail, Y. K. Ma, M. K. Kaabar et al., "Deep learning in cancer diagnosis and prognosis prediction: a minireview on challenges, recent trends, and future directions," *Computational and Mathematical Methods in Medicine*, vol. 2021, Article ID 9025470, 28 pages, 2021.
- [31] Z. Xu, K. Guan, N. Casler, B. Peng, and S. Wang, "A 3d convolutional neural network method for land cover classification using lidar and multi-temporal Landsat imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 144, pp. 423–434, 2018.
- [32] F. Hu, G.-S. Xia, J. Hu, and L. Zhang, "Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery," *Remote Sensing*, vol. 7, no. 11, pp. 14680–14707, 2015.
- [33] W. Zhao, Z. Guo, J. Yue, X. Zhang, and L. Luo, "On combining multiscale deep learning features for the classification of hyperspectral remote sensing imagery," *International Journal of Remote Sensing*, vol. 36, no. 13, pp. 3368–3379, 2015.
- [34] L. Wang, J. Zhang, P. Liu, K.-K. R. Choo, and F. Huang, "Spectral-spatial multi-feature-based deep learning for hyperspectral remote sensing image classification," *Soft Computing*, vol. 21, no. 1, pp. 213–221, 2017.
- [35] P. Liu, K.-K. R. Choo, L. Wang, and F. Huang, "SVM or deep learning? a comparative study on remote sensing image classification," *Soft Computing*, vol. 21, no. 23, pp. 7053–7065, 2017.
- [36] X. Ma, J. Geng, and H. Wang, "Hyperspectral image classification via contextual deep learning," *EURASIP Journal on Image and Video Processing*, vol. 2015, no. 1, 2015.
- [37] T. Blaschke, "Object based image analysis for remote sensing," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 65, no. 1, pp. 2–16, 2010.
- [38] U. C. Benz, P. Hofmann, G. Willhauck, I. Lingenfelder, and M. Heynen, "Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 58, no. 3–4, pp. 239–258, 2004.
- [39] T. Blaschke, G. J. Hay, M. Kelly et al., "Geographic object-based image analysis-towards a new paradigm," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 87, pp. 180–191, 2014.
- [40] M. Asif, W. U. Khan, H. M. Rehan Afzal et al., "Reduced-complexity LDPC decoding for next generation IoT networks," *Wireless Communications and Mobile Computing (WCMC)*, vol. 2021, Article ID 2029560, 10 pages, 2021.
- [41] N. Nasri, S. Mnasri, and T. Val, "3D node deployment strategies prediction in wireless sensors network," *International Journal of Electronics*, vol. 107, no. 5, pp. 808–838, 2020.
- [42] R. Mehta, J. Sahni, and K. Khanna, "Internet of Things: vision, applications and challenges," *Procedia Computer Science*, vol. 132, pp. 1263–1269, 2018.
- [43] S. Kumar, P. Tiwari, and M. Zymbler, "Internet of Things is a revolutionary approach for future technology enhancement: a review," *Journal of Big Data*, vol. 6, 2019.
- [44] S. Mnasri, N. Nasri, M. Alrashidi, A. Van den Bossche, and T. Val, "IoT networks 3D deployment using hybrid many-objective optimization algorithms," *Journal of Heuristics*, vol. 26, no. 5, pp. 663–709, 2020.
- [45] E. Guirado, S. Tabik, D. Alcaraz-Segura, J. Cabello, and F. Herrera, "Deep-learning versus obia for scattered shrub

- detection with google earth imagery: ziziphus lotus as case study,” *Remote Sensing*, vol. 9, no. 12, p. 1220, 2017.
- [46] F. Chollet, “Xception: Deep learning with depthwise separable convolutions,” in *Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1800–1807, IEEE, Honolulu, HI, USA, July 2017.
- [47] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the inception architecture for computer vision,” in *Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2818–2826, IEEE, Las Vegas, NV, USA, June 2016.
- [48] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. Alexander, “Inception-v4, inception-ResNet and the impact of residual connections on learning,” in *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence*, pp. 4278–4284, AAAI, San Francisco, CA, USA, 2017.
- [49] S. G. Wu, F. S. Bao, E. Y. Xu, Y. X. Wang, Y. F. Chang, and Q. L. Xiang, “A leaf recognition algorithm for plant classification using probabilistic neural network,” in *Proceedings of the IEEE International Symposium on Signal Processing and Information Technology*, pp. 11–16, Giza, Egypt, December 2007.
- [50] T. Jin, X. Hou, P. Li, and F. Zhou, “A novel method of automatic plant species identification using sparse representation of leaf tooth features,” *PLoS One*, vol. 10, no. 10, Article ID e0139482, 2015.
- [51] M. Seeland, M. Rzanny, N. Alaqraa, J. Wäldchen, and P. Mälder, “Plant species classification using flower images—a comparative study of local feature representations,” *PLoS One*, vol. 12, no. 2, pp. 1–29, 2017.
- [52] P. Greg, K. Ingo, and M. Von der Lippe, “Endangered plants in novel urban ecosystems are filtered by strategy type and dispersal syndrome, not by spatial dependence on natural remnants,” *Frontiers in Ecology and Evolution*, vol. 8, 2020.
- [53] C. Wu, Y. Chen, C. Peng, Z. Li, and X. Hong, “Modeling and estimating aboveground biomass of *Dacrydium pierrei* in China using machine learning with climate change,” *Journal of Environmental Management*, vol. 234, pp. 167–179, 2019.
- [54] H. Liu, C. Qiao, X. Liu et al., “Variation patterns of plant composition/diversity in *Dacrydium pectinatum* communities and their driving factors in a biodiversity hotspot on Hainan Island, China,” *Global Ecology and Conservation*, vol. 22, 2020.
- [55] B. Du, Y. Zheng, J. Liu, and D. Mao, “Threatened plants in China’s Sanjiang plain: hotspot distributions and Gap analysis,” *Sustainability*, vol. 10, no. 1, p. 194, 2018.
- [56] T. Hamabata, G. Kinoshita, K. Kurita et al., “Endangered island endemic plants have vulnerable genomes,” *Communications Biology*, vol. 2, no. 1, p. 244, 2019.
- [57] W. Li, Y. Yuan, S. Hu, M. Li, W. Feng, and J. Zheng, “Positioning of apple’s growth cycle based on pattern recognition,” *Mobile Information Systems*, vol. 2021, Article ID 9687950, 11 pages, 2021.
- [58] Y. Wang, “The influence of virtual reality technology on the cultivation of agricultural students,” *Mobile Information Systems*, vol. 2021, Article ID 7699106, 8 pages, 2021.
- [59] T. Hu and W. Gong, “Urban landscape information atlas and model system based on remote sensing images,” *Mobile Information Systems*, vol. 2021, Article ID 9613102, 7 pages, 2021.
- [60] D. Liu, “Fuzzy comprehensive evaluation method of ecological environment damage compensation system and management based on improved association rule algorithm,” *Mobile Information Systems*, vol. 2021, Article ID 8493817, 12 pages, 2021.
- [61] D. Choe, E. Choi, and K. Dong, “The real-time mobile application for classifying of endangered parrot species using the CNN models based on transfer learning,” *Mobile Information Systems*, vol. 2020, Article ID 1475164, 13 pages, 2020.
- [62] G. Cheng and J. Han, “A survey on object detection in optical remote sensing images,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 117, pp. 11–28, 2016.
- [63] A. De Castro, J. Torres-Sánchez, J. Peña, F. Jiménez-Brenes, O. Csillik, and F. López-Granados, “An automatic random forest-OBIA algorithm for early weed mapping between and within crop rows using UAV imagery,” *Remote Sensing*, vol. 10, no. 3, p. 285, 2018.
- [64] Q. Feng, J. Liu, and J. Gong, “UAV remote sensing for urban vegetation mapping using random forest and texture analysis,” *Remote Sensing*, vol. 7, no. 1, pp. 1074–1094, 2015.
- [65] L. Xia, J. Luo, Y. Sun, and H. Yang, “Deep extraction of cropland parcels from very high-resolution remotely sensed imagery,” in *Proceedings of the 2018 7th International Conference on Agro-Geoinformatics (Agro-Geoinformatics)*, August 2018.
- [66] V. Lebourgeois, S. Dupuy, É. Vintrou, M. Ameline, S. Butler, and A. Bégué, “A combined random forest and OBIA classification scheme for mapping smallholder agriculture at different nomenclature levels using multisource data (simulated sentinel-2 time series, VHRS and DEM),” *Remote Sensing*, vol. 9, no. 3, p. 259, 2017.
- [67] D. Ventura, A. Bonifazi, M. F. Gravina, A. Belluscio, and G. Ardizzone, “Mapping and classification of ecologically sensitive marine habitats using unmanned aerial vehicle (UAV) imagery and object-based image analysis (OBIA),” *Remote Sensing*, vol. 10, no. 9, p. 1331, 2018.
- [68] M. Långkvist, A. Kiselev, M. Alirezaie, and A. Loutfi, “Classification and segmentation of satellite orthoimagery using convolutional neural networks,” *Remote Sensing*, vol. 8, no. 4, p. 329, 2016.
- [69] D. Marmanis, M. Datcu, T. Esch, and U. Stilla, “Deep learning earth observation classification using imagenet pretrained networks,” *IEEE Geoscience and Remote Sensing Letters*, vol. 13, no. 1, pp. 105–109, 2016.
- [70] E. Maggiori, Y. Tarabalka, G. Charpiat, and P. Alliez, “Fully convolutional neural networks for remote sensing image classification,” in *Proceedings of the 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, pp. 5071–5074, IEEE, Beijing, China, July 2016.
- [71] K. Makantasis, K. Karantzalos, A. Doulamis, and N. Doulamis, “Deep supervised learning for hyperspectral data classification through convolutional neural networks,” in *Proceedings of the 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, pp. 4959–4962, IEEE, Milan, Italy, July 2015.
- [72] G. Cheng, P. Zhou, and J. Han, “Learning rotation-invariant convolutional neural networks for object detection in VHR optical remote sensing images,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 12, pp. 7405–7415, 2016.
- [73] G. E. Dahl, D. Dong Yu, L. Li Deng, and A. Acero, “Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition,” *IEEE Transactions on Audio Speech and Language Processing*, vol. 20, no. 1, pp. 30–42, 2012.
- [74] D. C. Ciresan, U. Meier, and J. Schmidhuber, “Multi-column deep neural networks for image classification,” in *Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern*

Recognition, pp. 3642–3649, IEEE, Providence, RI, USA, June 2012.

- [75] R. Kohavi, “A study of cross-validation and bootstrap for accuracy estimation and model selection,” in *Proceedings of the 14th International Joint Conference on Artificial Intelligence*, pp. 1137–1143, Morgan Kaufmann, Montreal, Canada, August 1995.