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Project Report

Towards a scientific workflow featuring Natural Language Processing for the digitisation of natural history collections

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Abstract

We describe an effective approach to automated text digitisation with respect to natural history specimen labels. These labels contain much useful data about the specimen including its collector, country of origin, and collection date. Our approach to automatically extracting these data takes the form of a pipeline. Recommendations are made for the pipeline's component parts based on some of the state-of-the-art technologies.

Optical Character Recognition (OCR) can be used to digitise text on images of specimens. However, recognising text quickly and accurately from these images can be a challenge for OCR. We show that OCR performance can be improved by prior segmentation of specimen images into their component parts. This ensures that only text-bearing labels are submitted for OCR processing as opposed to whole specimen images, which inevitably contain non-textual information that may lead to false positive readings. In our testing Tesseract OCR version 4.0.0 offers promising text recognition accuracy with segmented images.

Not all the text on specimen labels is printed. Handwritten text varies much more and does not conform to standard shapes and sizes of individual characters, which poses an additional challenge for OCR. Recently, deep learning has allowed for significant advances in this area. Google's Cloud Vision, which is based on deep learning, is trained on large-scale datasets, and is shown to be quite adept at this task. This may take us some way towards negating the need for humans to routinely transcribe handwritten text.

Determining the countries and collectors of specimens has been the goal of previous automated text digitisation research activities. Our approach also focuses on these two pieces of information. An area of Natural Language Processing (NLP) known as Named Entity Recognition (NER) has matured enough to semi-automate this task. Our experiments demonstrated that existing approaches can accurately recognise location and person names within the text extracted from segmented images via Tesseract version 4.0.0. Potentially, NER could be used in conjunction with other online services, such as those of the Biodiversity Heritage Library to map the named entities to entities in the biodiversity literature (https://www.biodiversitylibrary.org/docs/api3.html).

We have highlighted the main recommendations for potential pipeline components. The document also provides guidance on selecting appropriate software solutions. These include automatic language identification, terminology extraction, and integrating all pipeline components into a scientific workflow to automate the overall digitisation process.

Keywords

automated text digitisation, text processing, named entity recognition, optical character recognition, handwritten text recognition, language identification, terminology extraction, scientific workflows, natural history specimens, label data

1.Introduction

1.1 Background

We do not know how many specimens are held in the world's museums and herbaria. However, estimates of three billion seem reasonable (Wheeler et al. 2012). These specimens are irreplaceable and contribute to a diverse range of scientific fields (Suarez and Tsutsui 2004; Pyke and Ehrlich 2010). Their labels hold data on species distributions, scientific names, traits, people and habitats. Among those specimens are nomenclatural types that underpin the whole of formal taxonomy and define the species concept. These specimens span more than 200 years of biodiversity research and are an important source of data on species populations and environmental change. This enormous scientific legacy is largely locked into the typed or handwritten labels mounted with the specimen or in associated ledgers and field notebooks. It is a significant challenge to extract these data digitally, particularly without introducing errors. Furthermore, the provenance of these data must be maintained so that they can be verified against the original specimen.

Perhaps the method most widely used today to extract these data from labels is for expert technicians to type the specimen details into a dedicated collection management system. They might, at the same time, georeference specimens where coordinates are not already provided on the specimen. Volunteers have also been recruited to help with this process and in some cases transcription has been outsourced to companies specializing in document transcription (Engledow et al. 2018; Ellwood et al. 2018).

Nevertheless, human transcription of labels is slow and requires both skill to read the handwritten labels and knowledge of the names of places, people, and organisms. These labels are written in many languages often in the same collection and sometimes on the same label. Furthermore, abbreviations are frequently used and there is little standardisation on where each datum can be found on the label.

Full or partial automation of this process is desirable to improve the speed and accuracy of data extraction and to reduce the associated costs. Automating even the simplest tasks such as triaging the labels by language or writing method (typed versus handwritten) stands to improve the overall efficiency of the human-in-the-loop approach. Optical Character Recognition (OCR) and Natural Language Processing (NLP) are two technologies that may support the automation. OCR concerns the automatic detection of printed text in a given document and the subsequent conversion of that text to a format that may be processed by machine (Mori et al. 1999). NLP concerns the interpretation of text by machine (Indurkhya and Damerau 2010).

OCR and NLP proved effective for extracting data from biodiversity literature (Thessen et al. 2012; Hoehndorf et al. 2016). However, specimen labels pose additional problems compared to formally structured text such as that found in literature. The context of individual words is often difficult to determine; specimens that overlap with the label may obscure some words; the orientation of labels typically varies; typed and handwritten text may coexist within the same label and the handwriting on the same specimen may come from different people (Fig. 1). Therefore, the task of digitising the text found in specimen labels is far from simple and requires different approaches from standard text recognition.

This document examines the state of the art in automated text digitisation with respect to specimen images. The recommendations within are designed to enhance the digitisation and transcription pipelines that exist at partner institutions. They are also intended to provide guidance towards a proposed centralised specimen enrichment pipeline that could be created under a pan-European Research Infrastructure for biodiversity collections (DiSSCo 2020). This pipeline would provide state-of-the-art label digitisation services to institutions that need them.

In this document we focus mainly on herbarium specimens, even though similar data extraction problems exist for pinned insects, liquid collections, and animal skins. Herbarium specimens are among the most difficult targets and we know from recent successful pilot studies for large-scale digitisation such as Herbadrop (EUDAT 2017) that they provide a good test of the technology. Furthermore, herbaria have been among the first to mass image their collections, so there is a vast number of specimen images available for testing.

Figure 1.

A range of sample specimens that demonstrate the wide taxonomic range of specimens encountered in collections. They also demonstrate the diversity of label types, which include handwritten, typed, and printed labels. Note the presence of various barcodes, rulers, and a colour chart in addition to labels describing the origin of the specimen and its identity.

a: Herbarium specimen (Natural History Museum 2007a) doi
b: Pinned insect specimen (Natural History Museum 2018) doi
c: Microscope slide (Natural History Museum 2017) doi
d: Fossilised animal skin (Natural History Museum 2009) doi
e: Liquid preserved specimen (Natural History Museum 2010) doi

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1.2 Digitisation Workflow

We now outline a potential digitisation workflow, which is designed to process specimens and extract targeted data from them (Fig. 2). Starting with the original specimen, it is initially converted to a digital image. Though a digital object itself, the image does not immediately contain digitised text. In other words, though readable by humans, the image of the text is not yet searchable by machine. The role of OCR is to convert text images into searchable text documents.

To make these text documents searchable by the type of information that they contain, another layer of information (metadata) is required on top of the original text. This step requires deeper analysis of the textual content, which is performed using NLP techniques including language identification, Named Entity Recognition (NER), and terminology extraction. The role of language identification here is twofold. If the labels are to be transcribed manually, then language identification can help us direct transcription tasks to the transcribers with suitable language skills. Similarly, if the labels were to be processed automatically, then the choice of tools will also depend on the given language.

NER will support further structuring of the text by interpreting relevant portions of the text, such as those referring to people and locations. In addition to the extracted data and the associated metadata, the digitised collection should also incorporate a terminology that facilitates the interpretation of the scientific content described in the specimens. Many specimen labels contain either obscure or outdated terminology. Therefore, standard terminologies need to be supplemented by terminology extracted from the specimens.

Finally, the performance of both OCR and NLP can be improved by restricting their view to only the labels on the specimen. This can be achieved by segmenting images prior to processing by identifying the areas of the image that relate to individual labels. However, there are trade-offs between the time it takes to segment images compared to the improved performance of OCR and NLP. In a production environment processing time is limited because of the need to ingest images into storage from a production line through a

pipeline that includes quality control, the creation of image derivatives, and image processing.

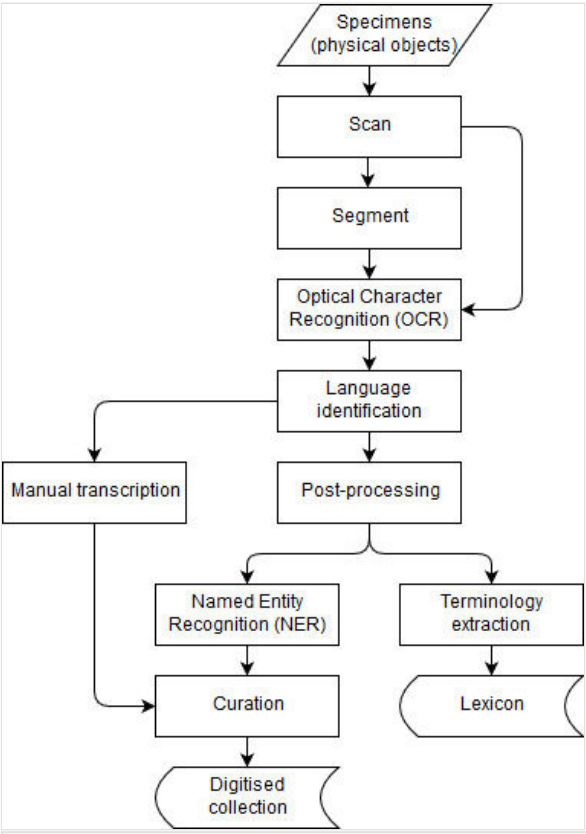


Figure 2. doi

A possible semi-automatic digitisation workflow to extract data from the labels of collection specimens.

To help determine the subsequent steps in the pipeline it may be necessary to establish the language of the text recognised in the OCR step. This next step may be the deployment of language-specific NLP tools for identifying useful information in the target specimen. Or it may be the channelling of the text for manual transcription. A number of software solutions exist for performing language identification and are explored in section 3.3.

An approach to automatic identification of data from OCR recognised text might include NER. This is an NLP task that identifies categories of information such as people and places. This approach may be suitable for finding a specimen's collector and collection country from text. Section 3.4 investigates this possibility using an NER tool.

1.3 Project Context

This project report was written as a formal Deliverable (D4.1) of the ICEDIG Project and was previously made available on Zenodo without a formal review process (Owen et al. 2019). While the differences between the two versions are minor the authors consider this the definitive version of the report.

2. Data

2.1 Data Collection

As noted above there is a large body of digitised herbarium specimens available for experimentation. A herbarium is a collection of pressed plant specimens and associated data (Fig. 1a). As indicated in Fig. 2, the first step in digitisation of these specimens is to produce a digital image. This requires physical manipulation of specimens, which is beyond the scope of the present task. Instead of gaining access to the original specimens, we collected their images in JPEG format from the partner institutions (Dillen et al. 2019). The choice of images sampled from these collections was based on the requirement to test OCR on a representative sample of the specimens in terms of their temporal and spatial coverage. This is because the age and origin of specimens may present different OCR challenges. For example, specimens can include printed, typed, or handwritten labels, which may be partially obscured or have different orientations.

Each partner herbarium contributed 200 images containing a geographical and temporal cross-section of nomenclatural type and non-type herbarium specimens (Fig. 3). A type specimen is used to name a newly identified species.

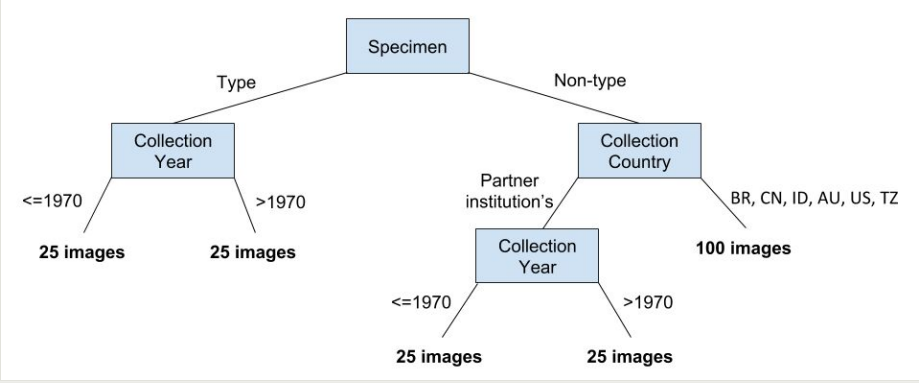


Figure 3. doi

The criteria used by partner institutions to compile a test set of herbarium specimens. We did not attempt global coverage but instead aimed at a representative sample from BR=Brazil, CN=China, ID=Indonesia, AU=Australasia, US=United States of America, and TZ=Tanzania.

A total of nine herbaria, described in Table 1, each contributed 200 specimen images giving a total of 1800 images, which formed a dataset for use in this study.

Table 1.
Contributing institutions and their codes from Index Herbariorum.

Institution	Index Herbariorum Code	ICEDIG Partner
Naturalis Biodiversity Center, Leiden, Netherlands	L	Yes
Meise Botanic Garden, Meise, Belgium	BR	Yes
University of Tartu, Tartu, Estonia	TU	Yes
The Natural History Museum, London, United Kingdom	BM	Yes
Muséum National D'Histoire Naturelle (MNHN), Paris, France	P	Yes
The Royal Botanic Gardens Kew (RGBK), Richmond, United Kingdom	K	Yes
Finnish Museum of Natural History, Helsinki, Finland	H	Yes
Botanic Garden and Botanical Museum, Berlin, Germany	B	No
Royal Botanic Garden, Edinburgh, United Kingdom	E	No

2.2 Data Properties

To illustrate the textual content of these images and to better understand the challenges posed to the OCR, Fig. 4 provides an example of labels attached to a specimen shown in Fig. 1a. In general, the labels can contain the following information:

1. **Title**: Organisation that owns the specimen.
2. **Barcode**: The specimen's machine readable identifier.
3. **Species name**: Scientific or common name of the species.
4. **Determined by and date**: The person who identified the specimen and the date of identification.
5. **Locality**: The geographical location where the specimen was collected.
6. **Habitat and altitude**: The habitat in which the specimen was collected and its altitude.
7. **Notes**: Additional notes written by the collector, often related to the characters of the species.
8. **Collector name, specimen number, and collection date**: The name of the person(s) who collected the specimen, the identifier that they used to record and manage specimens, and the date that the specimen was collected.

The above list is non-exhaustive and more or less information may be recorded by the collector or determiner.

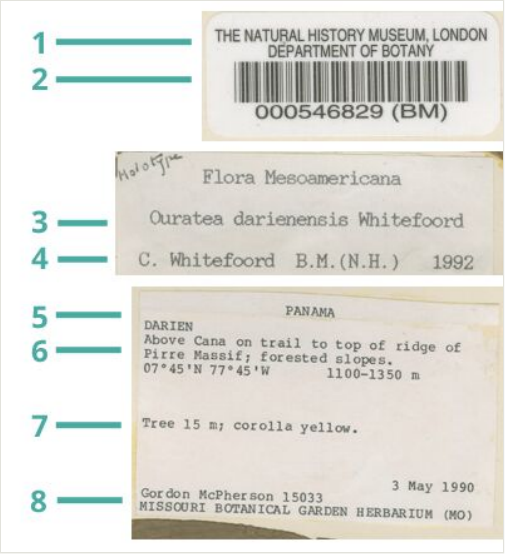


Figure 4. doi

An example of specimen labels. 1=Title, 2=Barcode, 3=Species name, 4=Determined by and date, 5=Locality, 6=Habitat and altitude, 7=Notes, 8=Collector name, species number, and collection date.

The properties of textual content of the given herbarium have been extrapolated from a random sample of 10 specimens per institution (Table 2).

Table 2.

A summary of specimen properties. The Names and Index Herbariorum codes for the contributing herbaria are listed in Table 1.

Contributor	Words Per Specimen	Handwritten Content
BR	47	49.0%
H	77	21.3%
P	45	42.3%
L	64	22.0%
BM	59	32.8%
B	61	50.1%
E	54	68.0%
K	79	17.8%
TU	26	62.2%
Average	**57**	**40.6%**

A subset of 250 images with labels written in English has been selected to test the performance of image segmentation and its effects on OCR and NER. For the purposes of

these tests these images were manually divided into a total of 1,837 label segments, which were then processed separately. *Nieva de la Hidalga et al. 2020*discuss segmentation methods and results from the ICEDIG project.

The segments effectively separate labels, barcodes, and colour charts. Examples can be seen in Fig. 5. Item 1 is a label containing the species name, the collection location, and the collector's name. Some of the information is printed while some of it is handwritten. In contrast, the label shown as Item 2 contains printed text only. However, its vertical orientation may cause additional difficulties. The label seen in Item 3 contains printed text that states the organisation that owns the specimen together with a barcode that identifies the specimen locally. However, the barcode stripes can sometimes be misinterpreted as text by overzealous OCR software. A colour chart, such as the one shown in Item 4, contains no text, so it does not need to be processed further. Finally, Item 5 presents a ruler, which is accompanied by text that is not specific to the specimen and therefore does not need to be considered. A machine learning classifier can be trained on segmented images to differentiate between different classes of labels in order to triage them ahead of the subsequent steps in the digitisation workflow.

Figure 5. doi

An impression of the different challenges presented by specimen image segments. 1=Label with both printed and handwritten text, 2=Printed label placed non-horizontally, 3=Barcode composed of unhelpful characters, 4=Colour chart containing no text, 5=Ruler containing no useful text.

2.3 Metadata

The role of OCR is to convert image text into searchable text. To make this text searchable by the type of information that they contain, another layer of information (metadata) is required on top of the original text. The term *metadata* simply means data about data (Weibel 2005). We can differentiate between three different types of metadata (Riley 2017):

1. *Descriptive* metadata facilitate searching using descriptors that qualify their content. For example, digitised specimens can be accessed by a species name, its collection location, or its collector.
2. *Structural* metadata describe how the components of the data object are organised thereby facilitating navigation through its content. For example, labelling each segment of a digitised specimen by its type can facilitate their management. As shown in Fig. 5, segment types include colour chart, ruler, barcode, collector's label, and determination.
3. *Administrative* metadata convey technical information that can be used to manage data objects. Examples include time of creation, digital format, and software used.

While metadata can take many forms, it is important to comply with a common standard to improve accessibility to the data. Darwin Core (Wieczorek et al. 2012) is one such standard maintained by the Darwin Core Maintenance Group of the Biodiversity Information Standards organisation (TDWG). It includes a glossary of terms intended to facilitate the sharing of information on biological diversity by providing global identifiers, labels, and definitions. Darwin Core is primarily based on taxa, their occurrence in nature as documented by observations, specimens, samples, and related information. Fig. 6 shows how the text content of the specimen shown in Fig. 4 could be structured using Darwin Core standard, version 2014 (Darwin Core Maintenance Group, Biodiversity Information Standards (TDWG) 2014; Biodiversity Information Standards (TDWG) 2020). Once structured, the data can be stored in a database allowing for complex queries and efficient retrieval. For example, the geographic coordinates can be used to retrieve data referring to specimens collected within a given radius, which may be further restricted by a time period.

The problem of populating a predefined template such as the one defined by Darwin Core with information found in free text is an area of NLP known as Information Extraction (IE) (Doleschal et al. 2020). The complexity of the template usually requires a bespoke IE system to be developed, which is beyond the scope of this feasibility study. Therefore, we will be focusing on information that could be extracted using NER, a subtask of IE, which can be supported using off-the-shelf software. Here, we focus on two commonly supported named entities, namely location and person names. Specifically, in the context of Darwin Core, we aim to automatically extract a specimen's country and collector name, which have been associated with an increase of over 50% in the speed of semi-automatic digitisation (Drinkwater et al. 2014).

RecordLevelTerms		**LocationTerms**	
institutionCode	NHMUK	higherGeography	North America; Panama
collectionCode	BOT	continent	North America
basisOfRecord	PRESERVED_SPECIMEN	country	Panama
OccurrenceTerms		verbatimLatitude	08° 30′ 25.88″ N
catalogNumber	BM000546829	verbatimLongitude	080° 06′ 09.59″ W
recordNumber	15033	decimalLatitude	8.507188
recordedBy	Gordon McPherson	decimalLongitude	-80.102665
EventTerms		**IdentificationTerms**	
year	1990	identifiedBy	Caroline Whitefoord
month	5	typeStatus	Holotype
day	3	**TaxonTerms**	
		scientificName	Ouratea dariensis Whitefoord
		genus	Ouratea
		specificEpithet	dariensis

Figure 6. doi

An example of an instantiated Darwin Core record.

3. Digitisation Experiments

This section describes a selection of software tools that can be used to automate the steps of the digitisation workflow shown in Fig. 2 together with the test results obtained using the data described in section 2.

3.1 Optical Character Recognition

OCR is a technology that allows the automatic recognition of characters through an optical mechanism or computer software (Mori et al. 1999). OCR can be used to convert image-borne characters to text documents that are machine readable in the sense that the text can then be indexed, searched, edited, or processed by NLP software.

We tested three off-the-shelf OCR software tools, described in Table 3. Tesseract is reportedly the most accurate open-source OCR software with respect to the task of extracting text from specimen labels (Haston et al. 2015). Its development is sponsored by Google (Google Open Source 2018) and it has the native ability to recognise more than 100 languages. We originally considered version 3.0.51 of Tesseract, but later extended our experiments to version 4.0.0, which was released in the meantime and was reported to offer significantly higher accuracy than its earlier version (Ooms 2018). The software development kit ABBYY FineReader Engine 12.0 allows software developers to integrate OCR functionality into their applications to extract textual information from paper documents, images, or displays (ABBYY 2018).

Microsoft's OneNote is a note taking and management application for collecting, organising, and sharing digital information (Microsoft Corporation 2018). It contains native OCR functionality whose performance had not been evaluated in another recent investigation into automating data capture from natural history specimens (Haston et al.

2015). Unlike Tesseract and ABBYY FineReader Engine, OneNote is a stand-alone software application whose OCR functionality cannot readily be integrated into other software.

Table 3.

Comparison of selected OCR software tools.

	Founded Year	Latest Stable Version	License	Windows	Macintosh	Linux
Tesseract	1985	4.0.0	Apache	Windows 10	Mac OS X 10.14.x	Ubuntu 18.04, 18.10
ABBYY FineReader Engine	1989	12.0	Proprietary	Windows 10, 8.1, 8, 7-SP1	Mac OS X 10.12.x, 10.13.x	Ubuntu 17.10, 16.04.1, 14.04.5
Microsoft OneNote	2012	17.10325.20049	Proprietary	Windows 10, 8.1	Mac OS X, 10.12 or later	Ubuntu 18.04, 18.10

To evaluate the OCR performance of the aforementioned software tools, we ran two sets of experiments, one against the whole digital images of specimens and the other against the segmented images with an expectation that the latter would result in shorter processing time and higher accuracy. Indeed, the results shown in Table 4 demonstrate that the processing time was reduced by 49% on average when images were segmented prior to undergoing OCR. Out of the three batch processing software tools considered, Tesseract 3.0.51 was the fastest in both scenarios. All experiments were performed using the following configuration: a desktop computer containing an Intel i5-4590T 2.00GHz 4 Core CPU (Central Processing Unit), 8.00 GB RAM (Gigabytes of Random Access Memory) and Microsoft Windows 10 Education Version 10.0.17134.

Table 4.

Processing times for OCR programs using whole images and segments.

	Processing Time (h:m:s)			
	250 Whole Images	**1,837 Segments**	**Difference**	**Difference (Percentage Saving)**
Tesseract 4.0.0	01:06:05	00:45:02	-00:21:03	-31.9%
Tesseract 3.0.51	00:50:02	00:23:17	-00:26:45	-53.5%
ABBYY FineReader Engine 12.0	01:18:15	00:29:24	-00:48:51	-62.4%

The accuracy of OCR will be measured in terms of **line correctness** as described by Haston et al. (2015). To create a gold standard, the text from a digital image is manually transcribed verbatim and the number of original lines counted. The lines from the OCR output are then compared against the gold standard and classified into one of three classes: correct, partially (in)correct and incorrect and scored 1, 0.5, and 0, respectively. An example can be seen in Fig. 7. The line scores are then aggregated into overall accuracy. This method considers only printed text and not handwritten text.

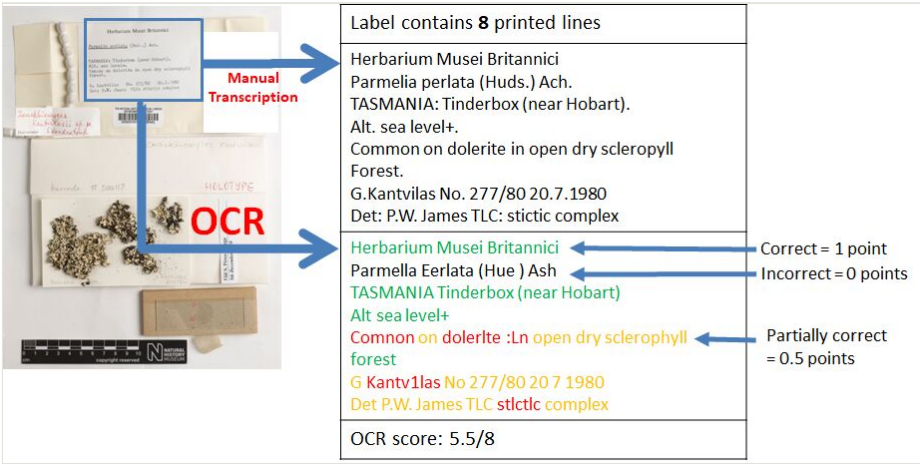


Figure 7. doi

Measuring OCR accuracy.

Specimen source: NHM Data Portal (Natural History Museum 2007b).

Bearing in mind the time and effort involved in creating the gold standard, only a subset of the dataset (250 specimen images and their segments) available for testing was used to evaluate the correctness of the OCR. Five herbarium sheet images, their segments and manual transcriptions, and OCR text used in these experiments can be found in Section 2 of Suppl. material 1. A summary of results is given in Table 5.

Table 5.

Line correctness for OCR using whole images and their segments.

	5 Whole Images Mean Line Correctness (%)	22 Segments Mean Line Correctness (%)	Difference
Tesseract 4.0.0	72.8	75.2	+2.4
Tesseract 3.0.51	44.1	63.7	+19.6
ABBYY FineReader Engine 12.0	61.0	77.3	+16.3
Microsoft OneNote 2013	78.9	65.5	-13.4

Apart from ABBYY FineReader Engine all other tools recorded an accuracy around 70%, with Tesseract 4.0.0 proving to be the most robust with respect to image segmentation. Its performance could be improved by further experiments focusing on its configuration parameters.

3.2 Handwritten Text Recognition

As mentioned in section 1.1, not all specimen labels bear printed text. A huge volume of specimen labels bear handwritten text in place of or in addition to printed text. Similar to

using OCR technologies to automatically read printed specimen labels, we can use Handwritten Text Recognition (HTR) technologies to automatically read handwritten specimen labels. HTR is described as the task of transcribing handwritten text into digital text (Scheidl 2018).

ABBYY FineReader Engine 12.0 and Google Cloud Vision OCR v1 (Google Cloud 2018) are both capable of performing HTR. Google Cloud Vision currently supports 56 languages. Its language settings can be adjusted to improve speed and accuracy of the text recognition. It is a paid service and has a limit of 20MB and 20M pixels per image submitted to it for processing.

We performed an experiment to measure the HTR performance of both ABBYY FineReader Engine and Google Cloud Vision with respect to handwritten specimen labels. The five specimen whole images used in section 3.1 were reused in this experiment. These whole images, each of which bear handwritten text, were submitted to ABBYY FineReader Engine and Google Cloud Vision to undergo HTR.

The HTR results from ABBYY FineReader Engine and Google Cloud Vision were compared with the gold standard for each specimen image using Levenshtein distance (Levenshtein 1966). The Levenshtein distance measures the minimum difference between two strings by counting the number of insertions, deletions, and substitutions needed to change one string into the other. Note that this metric is not case sensitive.

One must be cautious when comparing *interpreted* gold standard data. For example, where the catalog number is "BM000521570" Google Cloud Vision finds "000521570 (BM)". Technically, Google Cloud Vision has found the correct string, but because the gold standard contains an interpreted value it appears that Google Cloud Vision is not correct. Another example concerns the fact that the gold standard contains fields that use abbreviations, such as country codes. This means that "Australia" and its country code "AU" will rightly be considered identical.

Specific fields were identified for HTR analysis: catalogNumber, genus, specificEpithet, country, recordedBy, typeStatus, verbatimLocality, verbatimRecordedBy. Verbatim coordinates are likely too complex or too often open to interpretation to be compared reliably in this analysis. For example, verbatimEventDate was ignored because it is not technically verbatim; it may be written “3/8/59” on a specimen label, but recorded as “1959-08-03” in a specimen database (Finnish Biodiversity Info Facility 2018). Year was therefore used instead, although we acknowledge that this is not as precise or as informative as a complete date. We acknowledged this limitation in our analysis; when comparing Years we insisted that Levenshtein distance considered them identical for them to be deemed a match. All Levenshtein distances between two Years that were greater than 0 (meaning not identical) were therefore omitted from further analysis.

Please note that typeStatus is not always present in a specimen image. It is therefore often inferred based on other data that is present. typeStatus was nevertheless included for analysis because of its importance in biodiversity taxonomy.

Fig. 8 shows the count of Levenshtein distance scores for all selected fields combined, Lev $_{year}$>0 excluded. Google Cloud Vision scores better. The high count of results with a distance greater than 4 (indicating large dissimilarity) is partly due to certain fields being interpreted. Such fields might include typeStatus.

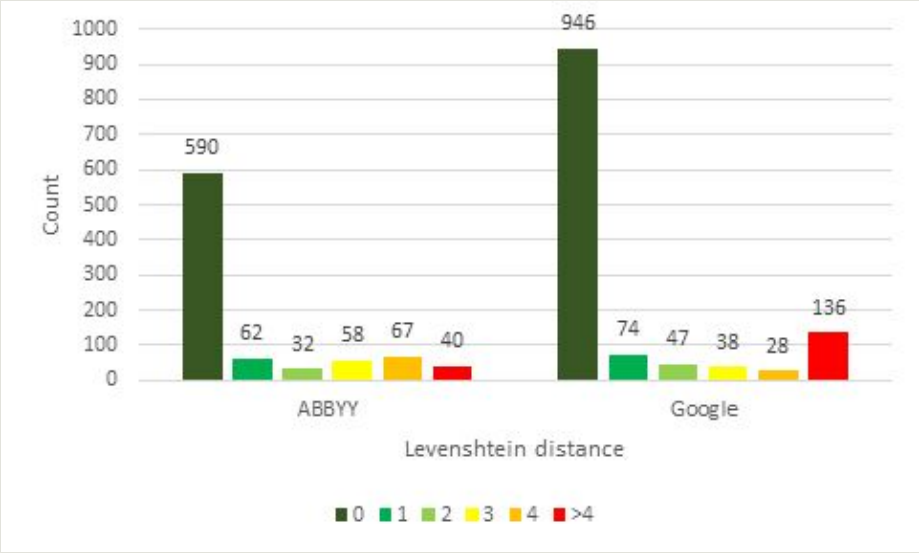


Figure 8. doi

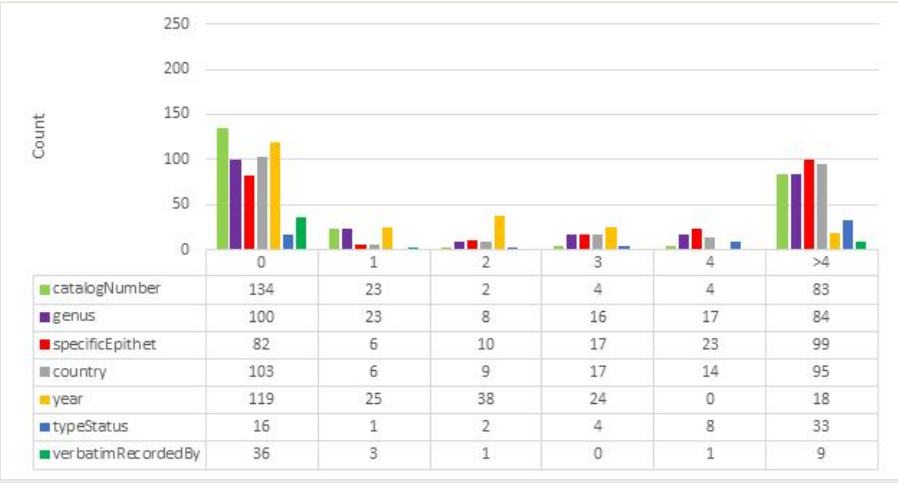
Comparison of Levenshtein distance scores for ABBYY FineReader Engine and Google Cloud Vision for selected fields, Levyear>0 excluded.

Examining the results in Fig. 8 it shows that the Google Cloud Vision scores are higher for the three best distances. Comparing the results in Fig. 9 and Fig. 10 show that Google Cloud Vision has more results in the best category for each field, while ABBYY FineReader Engine has a higher count of Lev≥4 for each field. Distances greater than 4 can be considered low quality results. When Lev≥4 and Lev_{year}>0 results are excluded, Google Cloud Vision obtained 1133 results while ABBYY FineReader Engine obtained 809. When the results are weighted for accuracy (5 for distance=0, 1 for distance≥4, Lev_{year}>0 excluded) Google Cloud Vision scored 6540 while ABBYY FineReader Engine scored 4689.

In conclusion, this comparative test indicates that the results from Google Cloud Vision are of higher quality than ABBYY FineReader Engine. The results are of even higher quality when the lowest scoring categories are excluded. These results demonstrate that HTR can be used to retrieve a considerable volume of data of high quality. HTR should no longer be dismissed as ineffective because it has already become a viable technique.

3.3 Language Identification

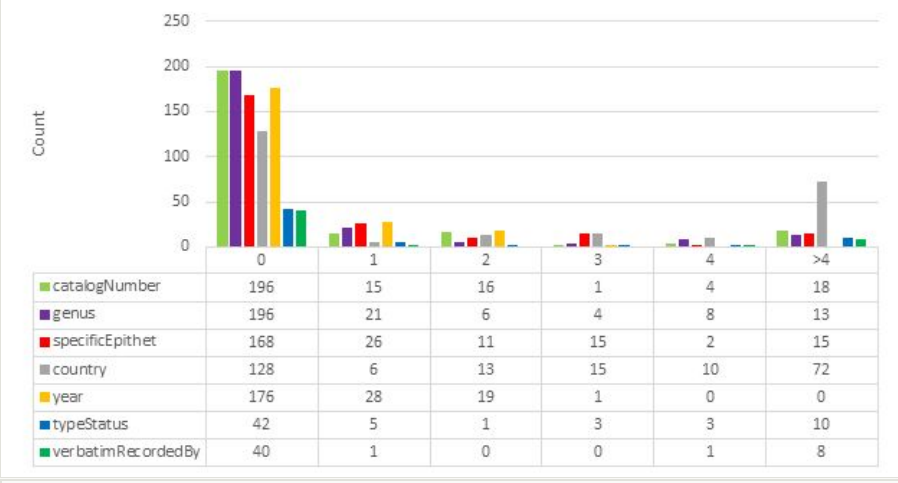
Language identification is the task of determining the natural language that a document is written in. It is a key step in automatic processing of real-world data where a multitude of languages exist (Lui and Baldwin 2012). Languages used on specimen labels can vary across a collection as can be seen in Fig. 11. In the context of digitisation workflows knowing the languages that specimen labels are written in allows us to inform the subsequent steps, including NLP. It also offers the opportunity to improve manual curation of the results by being able to forward them to people with the required language skills.



	0	1	2	3	4	>4
catalogNumber	134	23	2	4	4	83
genus	100	23	8	16	17	84
specificEpithet	82	6	10	17	23	99
country	103	6	9	17	14	95
year	119	25	38	24	0	18
typeStatus	16	1	2	4	8	33
verbatimRecordedBy	36	3	1	0	1	9

Figure 9. doi

Results per field from ABBYY FineReader Engine.



	0	1	2	3	4	>4
catalogNumber	196	15	16	1	4	18
genus	196	21	6	4	8	13
specificEpithet	168	26	11	15	2	15
country	128	6	13	15	10	72
year	176	28	19	1	0	0
typeStatus	42	5	1	3	3	10
verbatimRecordedBy	40	1	0	0	1	8

Figure 10. doi

Results per field from Google Cloud Vision.

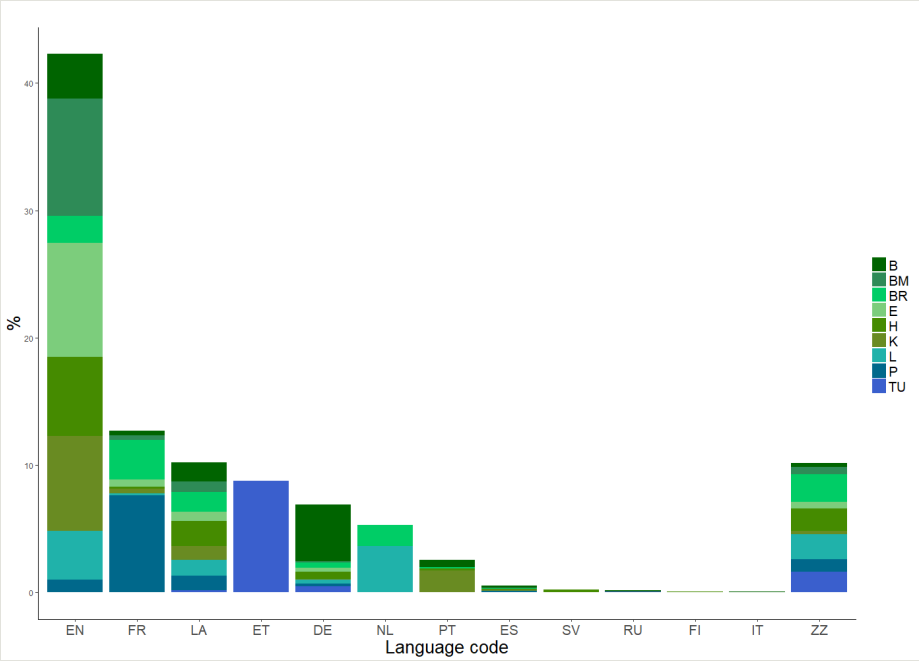


Figure 11. doi

The distribution of languages across the specimen and herbaria. EN=English, FR=French, LA=Latin, ET=Estonian, DE=German, NL=Dutch, PT=Portuguese, ES=Spanish, SV=Swedish, RU=Russian, FI=Finnish, IT=Italian, ZZ=Unknown. The codes for the contributing herbaria are listed in Table 11 (from Dillen et al. 2019).

A number of off-the-shelf software tools can be used to perform language identification, examples of which can be seen in Table 6. The given tools can all be integrated into larger software applications.

Table 6.

Language identification software tools and their properties.

Software	Licence	Organisation
langid.py	Open Source	University of Melbourne
langdetect	Apache License Version 2.0	N/A
language-detection	Apache License Version 2.0	Cybozu Labs, Inc.

Table 7 provides output obtained by langid.py from a sample of our test data. The automatically identified language is quantified with a probability estimate. langid.py is able to identify 97 different languages without requiring any special configuration. It generally outperforms langdetect (Danilák 2018) in terms of accuracy. langid.py is also reportedly the faster of the two (Lui and Baldwin 2012). The corpus used in the evaluation contained

government documents, online encyclopaedia entries, and software documentation (Lui and Baldwin 2012; Baldwin and Lui 2010).

Table 7.

Example of langid.py usage with fragments of OCR text. Output lines denote the language identified in the input text and the probability estimate for the language.

Input: “Unangwa Hill about 6 km. E. of Songea in crevices in vertical rock faces” **Output**: English [99%]
Input: “Herbier de Jardin botanique de l'Etat” **Output**: French [99%]
Input: “Tartu olikooli juures oleva loodusuurijate seltsi botaanika sekstsiooni” **Output**: Estonian [99%]
Input: “Arbusto de ca. 2 m, média ramificação.” **Output**: Portuguese [100%]

The program language-detection (Shuyo 2014) provides a third option for language detection. Unlike langid.py and langdetect no evaluation of its performance appears to have been published. It advertises 99% precision over 53 languages although texts of 10 to 20 words are recommended to support accurate detection. This may prove problematic when used with short fragments of OCR text obtained from specimen images.

3.4 Named Entity Recognition

NER is commonly used in information extraction to identify text segments that refer to entities from predefined categories (Nadeau and Sekine 2009). The state-of-the-art approaches use conditional random fields trained on data manually labelled with these categories to learn automatically how to extract named entities from text. Traditionally, these categories include persons, organisations, and locations. Therefore, pre-trained models for these categories are readily available. Stanford NER (The Stanford Natural Language Processing Group 2018) provides such models.

As mentioned in section 2.3, in this study we are interested in two categories of named entity: country (subcategory of location) and collector (subcategory of person). Pre-trained NER software can only identify names of locations and persons, but cannot verify that a location is a country or that a person is a collector. Therefore, we will generalise our NER problem into that of recognising persons and locations in general and will accordingly measure the performance of Stanford NER on our dataset. A subset of specimen labels was manually transcribed and annotated with person and location labels to create a gold standard against which to evaluate Stanford NER. Fig. 12 shows a specimen label. Fig. 13 shows the results of both manual transcription and NER with respect to that specimen label.

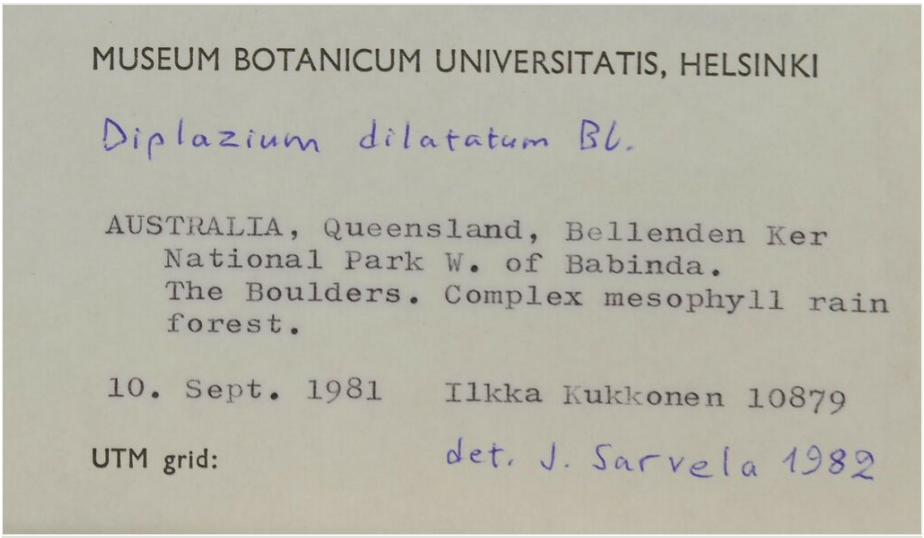


Figure 12. doi

An example of a specimen label.

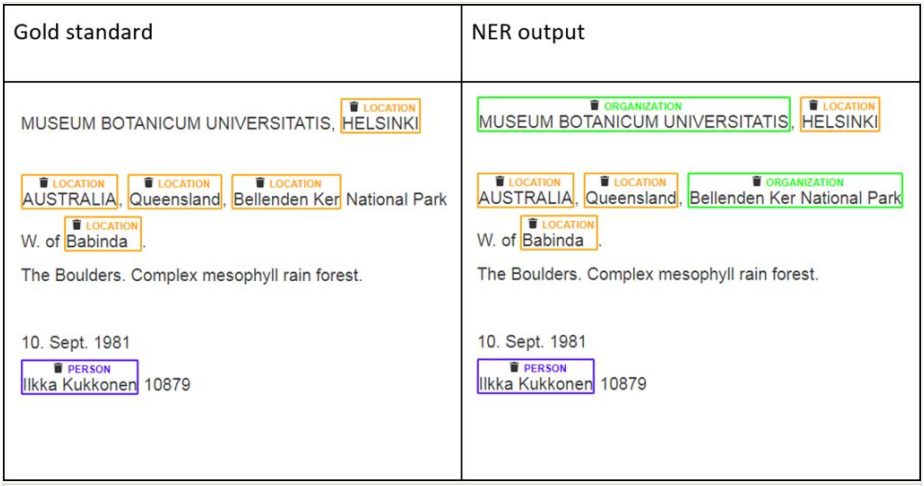


Figure 13. doi

Gold standard versus NER output.

According to Jiang et al. (2016) a named entity is recognised correctly if either of the following criteria is met:

1. Both boundaries of a named entity and its type match. For example, the segment “Ilkka Kukkonen” in Fig. 13 is recognised fully and correctly as a person.
2. Two text segments overlap partially and match on the type.

Either way, the NER results are usually evaluated using the three most commonly used measures in NLP: precision, recall, and F1 score. **Precision** is the fraction of automatically recognised entities that are correct. **Recall** is the fraction of manually annotated named entities that were successfully recognised by the NER system. **F1 score** is a measure that combines precision and recall - it is the harmonic mean of the two.

Table 8 and the formulae below show how these might be calculated. An example follows that explains the terms used.

Table 8.

Confusion matrix for predicted and actual labels.

		Predicted (NER)	
		Negative	**Positive**
Actual (Gold Standard)	**Negative**	True Negative	False Positive
	Positive	False Negative	True Positive

Formulae for Precision, Recall, and F1 Score:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$Recall = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

$$F1Score = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

To evaluate the performance of NER on our dataset, we selected a subset of five herbarium sheet images and their segments, which are to be found in Section 3 of Suppl. material 1. These are the same images and segments used to calculate line correctness in section 3.1. The OCR output used is that obtained using Tesseract 4.0.0.

Table 9 and Table 10 show the results of Stanford NER performance.

Table 9.

NER performance on OCR text retrieved from whole images.

	PERSON	**LOCATION**	**Overall**
Precision	0.81	0.38	0.69
Recall	0.71	0.21	0.53
F1	0.76	0.27	0.60

Table 10.

NER performance on OCR text retrieved from image segments.

	PERSON	LOCATION	Overall
Precision	0.85	0.43	0.74
Recall	0.74	0.50	0.69
F1	0.79	0.46	0.71

An improvement across all measures can be observed when using OCR text from segmented images. This is consistent with the increased line correctness observed described in section 3.1.

3.5 Terminology Extraction

To improve the accessibility of a specimen collection, its content needs to be not only digitised but also organised in alphabetical or some other systematic order. This is naturally expected to be done by species name. The problem with old specimens is that the content of their labels is not likely to comply with today's standards. Therefore, matching them against existing taxonomies will fail to recognise non-standard terminology. To automatically extract species names together with other relevant terminology, we propose an unsupervised data-driven approach to terminology extraction. FlexiTerm is a method developed in-house at Cardiff University. It has been designed to automatically extract multi-word terms from a domain-specific corpus of text documents (Spasić et al. 2013; Spasić 2018).

OCR text extracted from specimens in a given herbarium fits a description of a domain-specific corpus; therefore FlexiTerm can exploit linguistic and statistical patterns of language use within a specific herbarium to automatically extract relevant terminology. Section 4 of Suppl. material 1 shows the multi-word terms extracted from the text recognised using Tesseract 4.0.0 on the segmented images. The results show that the majority of extracted terminology refers to organisations (herbaria) that host the specimens, such as “Royal Botanic Gardens Edinburgh” or “Nationaal Herbarium Nederland”. There are also mentions of collectors, such as “Ilkka Kukkonen” that were also recognised as persons by NER. In that respect, there is some overlap between NER and terminology extraction. Regardless of their type, the multi-word terms extracted by FlexiTerm will represent the longest repetitive phrases found in a collection. Therefore, their recognition can facilitate transcription or curation of a digital collection should these activities be crowdsourced.

4. Putting It All Together

Many scientific disciplines are increasingly data driven and new scientific knowledge is often gained by scientists putting together data analysis and knowledge discovery “pipelines” (Ludäscher et al. 2006). These “pipelines” are known as scientific workflows.

Interpreting data and attaching meaning to it creates information. Interpreting information in the context of prior knowledge, experience and wisdom can lead to new knowledge.

A scientific workflow consists of a series of analytical steps. These can involve data discovery and access, data analysis, modelling and simulation, and data mining. Steps can be computationally intensive and therefore are often carried out on high-performance computing clusters. Herbadrop, a pilot study of specimen digitisation using OCR, demonstrated successful use of high performance digital workflows (EUDAT 2017). In this section, we review workflow management systems that can be used to automate the workflow presented in Fig. 2.

The tools that allow scientists to compose and execute scientific workflows are generally known as workflow management systems, of which Apache Taverna and Kepler are among the most well-known and best established examples.

Apache Taverna is open-source and domain-independent (The Apache Software Foundation 2018). It is designed for use in any scientific discipline and is supported by a large community of users.

Taverna has been successfully deployed within the domain of biodiversity via BioVeL - a virtual laboratory for data analysis and modelling in biodiversity (Hardisty et al. 2016). BioVeL allows the building of workflows through the selection of a series of data processing services and can process large volumes of data when the services needed to do that are distributed among multiple service providers.

Taverna supports BioVeL users by allowing them to create workflows via a visual interface as opposed to writing code. Users are presented with a selection of processing steps and can “drag and drop” them to create a workflow. They can then test the workflow by running it on their desktop machine before deploying it to more powerful computing resources.

Kepler is a scientific workflow application also designed for creating, executing and sharing analyses across a broad range of scientific disciplines (Altintas et al. 2004). Application areas include bioinformatics, particle physics and ecology.

Like Taverna, Kepler provides a graphical user interface to aid in the selection of analytical components to form scientific workflows (Barseghian et al. 2010). It also offers data provenance features that allow users to examine workflow output in detail for diagnostic purposes (Liew et al. 2016). This supports the reliability and reproducibility of evidence from data, which is necessary for the presentation of conclusions in research publications.

Tools like Apache Taverna and Kepler can be used for creating workflows for OCR, NER, and IE, like that depicted in Fig. 2. When managed and executed in virtual research environments such as BioVeL, the data and results can be collated, managed, and shared appropriately. Such workflows can be run repeatedly, reliably, and efficiently with the possibility to process many tens of thousands of label images in parallel within a single workflow run.

5. Conclusions

We designed a modular approach for automated text digitisation with respect to specimen labels (Fig. 1). To minimise implementation overhead, we proposed implementing this approach as a scientific workflow using off-the-shelf software to support individual components. An additional advantage of this approach is an opportunity to run the workflow in a distributed environment, thus supporting large-scale digitisation as well as an optimal use of resources across multiple institutions. Based on the local experience and expertise associated with both development and applications, we recommend the use of Apache Taverna for implementing and executing the workflow. We evaluated off-the-shelf software that can support specific modules within the workflow. Our recommendations are summarised in Table 11. Further research is needed with respect to image segmentation, which has been shown to have significant effect on the performance across all tasks listed in Table 11.

Table 11.

A summary of recommendations.

Task	Software	Comment
Optical Character Recognition	Tesseract 4.0.0	Robust with respect to image segmentation
Handwritten Text Recognition	Google Cloud Vision	Supports 56 languages
Language identification	langid.py	Supports 97 languages
Named Entity Recognition	Stanford NER	A wide variety of entities recognised including location, organisation, date, time, and person
Terminology extraction	FlexiTerm	Robust with respect to orthographic variation (such as that introduced by OCR)

6. Appendices

For the sake of brevity the Appendices can be found in the supplementary document "Appendices". The document contains the following principal information concerning the Digitisation Experiments:

- OCR Software Settings
- OCR Line Correctness Analysis Data
- NER Analysis Data
- Non-standard Terminology Extraction Analysis Data

7. Glossary

- **Automated text digitisation** - The process of converting written words found in a document to a format that can be understood by a computer. In biodiversity, documents may typically include printed or handwritten specimen labels.
- **Conditional Random Field** - A device used in machine learning tasks that involve examining a sequence of data. It helps the machine determine the nature of a piece of data in the series by considering the nature of neighbouring data. For example, an unnamed image containing part of a leaf may appear in a sequence of plant specimen images. A machine may be able to determine that the leaf belongs to a "deciduous holly" if a named image of that plant neighbours the leaf image in the sequence.
- **Deep learning** - A specialised type of machine learning. It uses computer programs that mimic the workings of the human brain to learn the properties of selected data types, which could include plants or insects. Deep learning is widely considered to yield better performance in comparison to traditional machine learning approaches.
- **Gold standard** - A description of the properties of some subject of interest, which is normally used to support some scientific experiment. The gold standard is often produced by hand. In the task of automated text digitisation of a specimen label a human may first read the label and write its contents down. This forms a definitive reference against which the computer tasked with automatically digitising the label will be judged. The closer the computer gets to digitising all of the text seen in the gold standard the better it is judged to have performed.
- **Handwritten Text Recognition (HTR)** - One of a number of specialist tasks that might be performed during automated text digitisation. This particular task entails the automatic recognition of text written by the human hand. It also involves the subsequent conversion of the recognised text to a format that can be understood by a computer.
- **High performance computing cluster** - This approach to computing involves the working of one or more computers alongside one another to complete a task. This is traditionally known as parallel processing. The co-location of computers expected to perform subtasks in parallel is known as a cluster.
- **Information Extraction (IE)** - The task of taking data from an unstructured source, such as a specimen label, and placing that data in a structured destination, such as a Darwin Core record. We might aim to deploy a specially designed computer program to perform this task automatically.
- **JPEG** - A special format for computer image files that is designed to make them easier to store and to send between computers. The format ensures that images are compressed. This means that the files are generally small in size, which makes for speedy transmission between computers.
- **Language identification** - A specialist Natural Language Processing (NLP) task whereby a computer program ascertains the human language that a given body of text is written in.

- **Machine learning** - The practice of teaching a computer to determine properties of some data that it might receive. The machine does this based on what it knows about the properties of similar data that it might have seen before. For example, a computer may have learnt that leaves of the holly species of plant contain several pointed ends if it has seen many such images in the past. If it later sees an image of a rounded leaf it may determine that the leaf is unlikely to belong to that of a holly species of plant.
- **Metadata** - Data that describes some accompanying principal piece of data. A digital photograph of a plant specimen is a piece of data. This photograph may be accompanied by data such as the date and time that it was taken, the name of the camera used, and the resolution of the image. Metadata can make the task of searching a large collection of digital photographs much easier.
- **Named Entity Recognition (NER)** - A specialist Natural Language Processing (NLP) task whereby a computer program identifies subjects of interest in a body of text. Typical subjects of interest might include countries, cities, names of organisations, and names of people.
- **Natural Language Processing (NLP)** - The task of using computer programs to understand human languages such as English. The understanding can be used to automate tasks such as sorting a collection of data into categories. A collection of digitised specimen labels may be sorted by country of origin if a computer program can identify country names or cities mentioned in the label.
- **Optical Character Recognition (OCR)** - One of a number of specialist tasks that might be performed during automated text digitisation. This particular task entails the automatic detection of printed text and the subsequent conversion of it to a format that can be understood by a computer.
- **Scientific workflow** - The description of a process in terms of tasks and sub-tasks that must be completed to meet some research goal. A process might include the acquisition, categorisation, manipulation, and publication of data.

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Mathias Dillen: Resources, Visualisation. **Sarah Phillips**: Methodology, Resources. **Zhengzhe Wu**: Resources.

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Supplementary material

Suppl. material 1: Appendices doi

Authors: David Owen
Data type: text, images
Brief description: For the sake of brevity the Appendices can be found in this supplementary document. The document contains the following principal information concerning the Digitisation Experiments:

- OCR Software Settings
- OCR Line Correctness Analysis Data
- NER Analysis Data
- Non-standard Terminology Extraction Analysis Data

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