Part I

INCEPTION

Why we are doing what we are doing?
INTRODUCTION

The study of handwritten historical documents, often referred to as manuscript studies, involves systematically analyzing the documents’ contents, surface materials, and handwriting. Analysis of handwriting, usually the most challenging of the tasks, provides essential insights into the writers, writing styles, time of production, and even the geographical location of the document. The handwritten texts from the manuscript are extracted, processed, and extensively examined to gain those insights. However, this analysis is highly labor-intensive and prone to bias and error if done manually. To achieve an efficient and reliable outcome, techniques from computer vision (CV), pattern recognition (PR), and artificial intelligence (AI) can be used in handwriting analysis. These modern quantitative approaches and statistical analyses open a new door to understanding, revising, and updating the current hypothesis on many critical historical manuscripts.

In general, handwritten document images contain explicit information (characters, words, text lines) and implicit information (writer, date, location), which can be inferred by analyzing the images. Optical character recognition (OCR), a commonly used technology that converts scanned or photographed text into machine-encoded text, can easily recognize explicit information for modern homogeneous documents [188]. However, OCR systems often fail to perform well in historical manuscripts with various scripts, styles, and surface materials. In addition, OCR systems do not help in comprehending implicit information. Therefore, a robust and sophisticated design is needed to study and understand historical documents instead of straightforward character recognizers.

In addition to being handwritten, the historical manuscript analysis poses numerous challenges. First, many manuscripts are centuries old and fragile, making them difficult to handle and analyze without causing damage. Additional challenges come from unique scripts, variability in writing style, limited availability, and a lack of accompanying metadata. Second, these documents are often rare and valuable, and only a limited number of scholars may have access to them, which can limit their study and analysis. Besides, analyzing these documents manually can be very demanding and time-consuming and involves the risk of human biases, especially for more extensive collections. The Dead Sea Scrolls (DSS), written over two thousand years ago, is one such collection with immense historical, religious, and linguistic significance. Figure 1.1 shows a few fragments from one of the manuscripts of the DSS collection, the Psalms Scroll, also referred to as 11Q5. It is one of the very few Psalms manuscripts (four certain ones with a possibility of a fifth one) discovered in Cave 11 in the area of Qumran near the Dead Sea.
introduction

Figure 1.1: Four fragments (partially damaged) of the Psalms scroll (11Q5), one of the manuscripts of the Dead Sea Scrolls written on parchment (Plate 976, source: Israel Antiquities Authority (IAA) [10]).

The scope of the featured research is within the pioneering project on the DSS sponsored by the European Research Council (EU Horizon 2020), which aims to shed new light on ancient scribal culture by investigating two aspects of the scrolls’ palaeography: handwriting recognition (the typological development of writing styles) and writer identification. Recognizing the handwriting would solve the when, which, and where questions, and identifying the writer would end up answering the who question. These are the four most essential perspectives (Figure 1.2) in the study of palaeography and book history [274]. The digitization of the DSS has opened the door for machine learning (ML) and PR techniques to be applied in answering those four questions (4-W). This thesis aims to bridge the gap between computational science and traditional palaeography by solving the who and when questions with a potential impact on digital palaeography beyond DSS studies. The which question is partially addressed throughout this thesis for the works of writer identification and dating. However, the where question is beyond the scope of this work.

Who? - Writer identification
When? - Temporal alignment
Which? - Manuscript identification
Where? - Localization

Figure 1.2: The four interesting questions for manuscript understanding (image from the DSS manuscript PAM 43.754, source: Brill scans [165]).

The following section (1.1) further describes the topics of handwriting analysis for historical manuscripts, especially the who (writer identification) and when (temporal alignment or dating) questions, followed by a brief overview of pattern recognition techniques and artificial neural networks and their uses in related works. Finally,
the current chapter ends by further specifying the research motivation and novelty of the work and outlining the rest of the thesis.

1.1 BACKGROUND KNOWLEDGE

This section briefly presents the background knowledge on the data and the topics of handwriting analysis, including writer identification and dating for historical manuscripts. The themes of knowledge integration and other common approaches throughout the thesis are also introduced here in general terms.

Figure 1.3: The digital images of the Dead Sea Scrolls used in this thesis comes from two different sources: Israel Antiquities Authority (IAA) [10] and Brill Publishers [165]).

1.1.1 Dead Sea Scrolls (DSS)

The DSS collection includes ancient manuscripts discovered in the mid-20th century in the Judaean Desert, between Jerusalem and the Dead Sea. Most were written over a period of almost four centuries (ca. 250 BCE to ca. 135 CE) [213, 214, 287] in characters commonly known as the Hebrew alphabet, which actually derives from the Aramaic script [316]. The DSS were written on various materials, including mostly parchments (leather), about 10% papyrus, and in one case, copper. There are approximately a thousand manuscripts, consisting of tens of thousands of fragments, making it extremely difficult for researchers to make systematic and quantitative analyses of the handwriting manually. Moreover, the writers and the exact dates for these manuscripts remain largely unknown as they were written anonymously without any indication of authorship and date. However, the recent digitization of
the scrolls has made it possible to use computer algorithms and artificial intelligence to analyze them in new and innovative ways to provide a better understanding.

Figure 1.4: Example of the high-resolution multi-spectral images from IAA. The first image from the left is the RGB-color image of the plate 307. The next three are the monochromatic images of the top left fragment of this plate, captured in wavelengths of 475nm, 924nm, and 656nm. The monochromatic fragment images correspond to band-image numbers 20, 12, and 7 in the DSS collection.

There are various sources for digital images of the DSS manuscripts. Among those, two sources of images are used throughout this thesis (see Figure 1.3). The first source of images comes from the Brill Publishers [165]. There are 2463 images in the Brill collection with varied resolutions from 600 by 600 pixels to 2800 by 3400 pixels, approximately (Figure 1.2 shows an image from the Brill collection). The other source is the high-resolution multi-spectral images of the DSS provided by the Israel Antiquities Authority (IAA), which derive from their Leon Levy Dead Sea Scrolls Digital Library project [10].

The IAA produces multi-spectral images of scrolls’ fragments on both the recto and verso in 28 exposures, creating a file of 56 monochrome exposures per fragment. The system then generates a 57th file of a color image that combines all visible wavelengths: the full-spectrum color image. The resolution of the files is 1215 pixels per inch at a 1:1 ratio, capturing approximately 4 gigabytes of information per fragment [260]. In addition to the fragment images, there are also color images of the full plates where the fragments are physically preserved (see Figure 1.4). Depending on the arrangement, a full plate may contain one fragment or several different fragments. Images from all the DSS fragments are not available to work with, primarily due to not being pictured, being too fragile to handle, and not being available to IAA. This thesis utilizes 1038 full plate images and 16,525 fragment images from IAA (unfortunately, many of the images are not usable due to the extreme degradation and tiny sizes of the physical fragments containing no to only a
few characters). Each fragment has multiple band images (for different monochrome exposures), making it a total of more than four terabytes of image data. Table 1.1 shows a list of available images from IAA, along with their surface materials and writing styles.

Table 1.1: An overview of the available images (for the study of this thesis) from IAA. The number of plates for major writing styles is also shown, along with the approximate number of characters per plate and the writing surface materials.

<table>
<thead>
<tr>
<th>Type of images</th>
<th>No. of images</th>
<th>Handwriting styles</th>
<th>No. of plates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plates with fragments</td>
<td>1056</td>
<td>Formal</td>
<td>289</td>
</tr>
<tr>
<td>Full plates (available)</td>
<td>1038</td>
<td>Semiformal</td>
<td>118</td>
</tr>
<tr>
<td>Missing full plates</td>
<td>18</td>
<td>Cursive</td>
<td>34</td>
</tr>
<tr>
<td>Individual fragments</td>
<td>16525</td>
<td>Semicursive</td>
<td>39</td>
</tr>
<tr>
<td>Total fragments (bands)</td>
<td>152321</td>
<td>Mixed</td>
<td>77</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Approx. no. of characters</th>
<th>No. of plates</th>
<th>Surface materials</th>
<th>No. of plates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 50</td>
<td>528</td>
<td>Papyrus</td>
<td>244</td>
</tr>
<tr>
<td>50 to 100</td>
<td>274</td>
<td>Parchment</td>
<td>803</td>
</tr>
<tr>
<td>More than 100</td>
<td>227</td>
<td>Other</td>
<td>7</td>
</tr>
</tbody>
</table>

1.1.2 Handwriting recognition

Handwriting recognition is the process of converting handwritten text into a machine-readable format. It involves automatically translating written shapes into letter codes (ASCII and Unicode), which can be recognized and processed by a computer. This process can be performed either online or offline. Online recognition refers to the real-time recognition of handwriting as it is being written, such as on a touch screen or graphics tablet. In contrast, offline recognition involves the recognition of handwriting after it has been written, such as on a paper document that is scanned and then processed by a computer. Both online and offline recognition methods involve complex algorithms that analyze the shape, size, stroke order, etc.

1.1.3 Multidisciplinary knowledge integration

Handwriting recognition for historical manuscripts is a complex process that requires integrating knowledge from different fields along with AI. The most important field contributing to AI-based analysis of historical manuscripts is palaeography, which involves the study of ancient writing techniques and the evolution of handwriting over time. Palaeography experts can provide valuable insights into the historical context of manuscripts and aid in identifying the writer or date of a given text. In
addition, the palaeographers provide expertise in writer identification based on linguistic patterns and content analysis. In the case of dating historical manuscripts, radiocarbon ($^{14}$C) dating is a valuable tool for determining the age, which can be further integrated into AI techniques to identify the writer’s handwriting style and establish a more precise dating. Combining these various sources of knowledge can enhance the accuracy and reliability of handwriting recognition, providing valuable insights into historical texts, their authors, and dates.

1.1.4 Writer identification

Numerous factors influence an individual’s handwriting, including biomechanical constraints, handwriting education, writing posture, writing instrument, paper type, and background. Furthermore, variables such as stress, the impact of alcohol, motivation, and the intended purpose of the handwriting [103]. A note can drastically differ from a formal letter written by the same person. However, several early research in writer identification already demonstrates that handwriting possesses adequate unique features to serve as a viable means of identification [272].

Writer identification refers to the process of identifying the writer or scribe of a handwritten document by analyzing the writing style, such as stroke width, letter shapes, spacing between words, etc., and comparing it with handwritten samples of known authorship. This computer-aided process often involves using PR techniques and ML algorithms to extract and analyze the features of the handwritten text. The basic assumption is that the handwriting styles of an individual are consistent and that of different writers are distant. Individuals possess a prototype of character in their brain that influences their handwriting style from the outset, which results in a relatively consistent writing style [283]. The variation in handwriting styles observed between different individuals may be attributed to factors such as the type of handwriting training received and familiarity with the script, among others. These factors can manifest in distinct characteristics of handwriting. The primary obstacle in writer identification is to develop a system that can employ PR and ML techniques to eliminate the variations in writing that arise from the same writer while highlighting the distinctions among different writers.

Writer identification techniques can be classified into two general categories: text-dependent and text-independent methods [210]. Text-dependent methods utilize a comparison between individual characters or words that have known semantic content. These methods require the preliminary localization and segmentation of the relevant information, typically carried out interactively by a human user. Conversely, text-independent methods for writer identification rely on statistical features extracted from the entire image of a text block. In order to obtain stable features that are insensitive to the text content of the samples, a minimum amount of handwriting is required.
In the instance of the DSS, the identity of the writers remains unknown, as the scribes authored their texts anonymously. Despite numerous hypotheses regarding the authors’ identities, such conjectures are frequently subject to debate. Many different manuscripts are thought to be written by single scribes. On the contrary, there are single manuscripts that might have more than one writer (one such example is the Great Isaiah Scroll, one of the best-preserved biblical scrolls in the DSS collection. It contains the entire Book of Isaiah in Hebrew, apart from some small damaged parts. Knowing about the writers of this long scroll is essential for gaining insight into the text’s historical context, language, authorship, and interpretation. The scroll can be seen in Figure 1.5). All these debates present a significant obstacle for ML-based systems, as the lack of established metadata (label; writer identity) complicates the approach. This thesis examines several methods for resolving this issue in the coming chapters.

1.1.5 Date estimation

The date or time of producing historical manuscripts is an essential aspect of research for humanities scholars. Manuscripts lacking exact dates pose a challenge in determining their significance as historical sources. Hence, estimating or predicting the dates of undated manuscripts is necessary. The fundamental presumption underlying the dating of historical documents is that writing styles underwent a gradual, continuous evolution, mainly within a limited period during ancient times. The justification for this assumption of a gradual style progression stems from the observation that new scribes received formal training from experienced, established scribes. Historically, this task has been deemed the exclusive domain of a few specialists who possess the necessary expertise to properly assess specific
Figure 1.6: An AI-based dating model should be able to predict the dates of undated manuscripts from the DSS collection by integrating results from radiocarbon dating (\textsuperscript{14}C). This system can be used to make a typological development of writing styles for DSS. In this illustration, CE stands for Common Era and BCE for Before Common Era.

handwriting characteristics, despite occasionally rendering divergent conclusions. Systems based on statistical pattern recognition and AI can be helpful in this regard to provide automatic, unbiased, and efficient predictions of the dates.

Dating the DSS has long been a challenge for scholars due to the absence of internally dated manuscripts and the lack of relevant and contemporary data from the same period. While AI-based models can be used to address this problem, they are limited by the lack of reliable labeled data with available dates. However, radiocarbon (\textsuperscript{14}C) dating presents a viable solution \cite{26}. Although it requires the destruction of a small sample of the manuscript, it provides a reliable date estimation and complements the dating of the scrolls through palaeographic analysis. In addition, a promising approach for accurately dating the DSS involves the integration of both AI and C\textsubscript{14} dating (see Figure 1.6). This combination could provide a more complete and nuanced understanding of the manuscripts’ origins and help to shed light on the chronology.

However, the challenge remains in integrating \textsuperscript{14}C-dates with AI-based models to provide a reliable, robust date prediction. Therefore, this thesis also studies several novel techniques and design models that can perform prediction tasks.

1.1.6 Pattern recognition techniques

Pattern recognition models have become increasingly valuable for historical document analysis, focusing on techniques such as image preprocessing, feature extraction, and supervised and unsupervised learning. Image preprocessing is a crucial step in preparing the image for feature extraction. Standard preprocessing measures include binarization, noise reduction, skew correction, etc. Feature extraction involves identifying and extracting relevant information from the images, such as textural and allographic handwriting features. Supervised learning involves training
a model on labeled data to identify specific patterns or characteristics, while unsu-
ervised learning involves identifying patterns or structures in unlabeled data. In
this thesis, several techniques are employed to analyze the DSS. They are explained
in detail in the relevant chapters.

1.1.7 Artificial neural networks

Neural networks are mathematical models inspired by biological neurons found
in the central nervous system. These networks integrate various processes, such as
excitatory and inhibitory connections between neurons, firing rate, and learning.
Artificial neural networks aim to replicate the function of biological neurons to solve
a particular task. For example, neural networks are designed to fit a curve or line,
which can be used for regression or classification [161]. The perceptron is the most
straightforward neural network architecture that takes multiple inputs and produces
a single output, where the input weights are used to adjust the contribution of each
input. The result of the perceptron is then passed through a non-linear activation
function. The multi-layer perceptron is a more complex neural network architecture
that includes a hidden layer and non-linear activation functions, which enables it to
learn more complex input-output mappings. Other neural network architectures are
generally more complex variations of the basic structures.

The neural networks need to be trained to become functional. Training refers to
adjusting the weights and biases of the neurons in a neural network, using a set of
labeled training data to enable the web to make accurate predictions on new, unseen
data. The training aims to minimize the difference between the predicted output of
the neural network and the actual output. The process involves iteratively feeding
the training data into the network, adjusting the weights and biases using a loss
function, and updating the parameters using an optimization algorithm, such as
gradient descent. The training process continues until the model’s performance on
the training data has reached a satisfactory level or until a stopping criterion is met.
Once a neural network has been trained, it can be used to make predictions on new,
unseen data.

Deep neural networks, with multiple hidden layers, can be highly complex and
powerful. The relationship between training, testing, and validation scores reflects the
generalizability of the system or how well it can perform on novel data. Achieving
an appropriate balance between the available data and the size or complexity of the
neural network in terms of trainable parameters is essential during training. If there
are more trainable parameters than available examples, the network risks overfitting
by memorizing examples rather than learning patterns from the data. Conversely,
if the network structure has too few trainable parameters, it may not capture the
underlying patterns, resulting in underfitting. To address these risks, a validation
set can be used to optimize the network structure. This validation set is a subset of
A Kohonen network (KN), a self-organizing map (SOM), or a Kohonen map, is a type of artificial neural network used for unsupervised learning and visualization of high-dimensional data. It was developed by the Finnish professor Teuvo Kohonen in the 1980s [150]. The purpose of a Kohonen map is to represent complex data in a lower-dimensional space while preserving the topological relationships between the data points. This thesis uses Kohonen maps in several chapters for allographic feature calculations on the DSS character shapes.

A deep convolutional neural network (DCNN, DCN, or simply CNN), designed for visual data analysis, employs convolutional layers to learn hierarchical representations of the input data by applying learnable filters to capture local patterns and features [162]. These layers are followed by pooling layers that downsample the feature maps, reducing spatial dimensions while retaining important information. Finally, fully connected layers at the network's end enable complex feature combinations and final predictions. This thesis explores and uses several variants of CNN, including U-Net architectures [245]. The U-Net architecture is characterized by its U-shaped design, consisting of an encoder path and a corresponding decoder path with skip connections (Figure 1.8). This architecture effectively addresses the challenge of limited training data, which is the case for the DSS collection.

A generative adversarial network (GAN) consists of two neural networks: a generator and a discriminator. The generator network generates fake samples, such
as images or text, while the discriminator network tries to distinguish between real and fake samples [94]. This thesis also utilizes GANs and conditional GANs in image-processing tasks.

1.2 RESEARCH MOTIVATIONS

This thesis aims to integrate the palaeographic knowledge and $^{14}$C data to develop AI-based methods for analyzing the DSS. This pioneering work tackles numerous challenges, including the diversity of data, lack of homogeneity, lack of labeled data, etc. The research motivations and novel contributions of this thesis to the field are summarized in the four main themes (1.2.1 - 1.2.4).

1.2.1 Identifying the scribes

Question 1: What about the feasibility of writer identification in ancient manuscripts? This thesis starts with investigating whether writer identification for the DSS with AI-based methods is feasible. Although many existing writer-identification methods have achieved high accuracy on carefully scanned documents, they are yet to be tested on DSS scans. Moreover, many of these methods depend on a large number of labeled data which is difficult to acquire in the case of DSS. Even though textural and allographic feature-based techniques are helpful in many historical collections with limited known writers, their usability for the script of DSS needs to be tested, as well. So the initial investigation will enable the articulation of challenges in this ancient collection and possible resolutions to achieve better results.
1.2.2 Enhancing handwriting

**Question 2: How can grayscale, color and multi-spectral images be used for ancient document image analysis?**

Based on the outcome of the initial investigation, this thesis establishes the need for sophisticated image preprocessing techniques that can handle the diverse collection to better separate the text from the background. This process is called binarization, where the background is presented as entirely white with the ink in black. Even though many techniques from handwriting analysis can be used directly on the (raw) color or grayscale images, there is the risk of misclassifying documents for the wrong reasons. For example, instead of clustering documents based on similar writing styles, the model may cluster them based on their similar background. So it is necessary to make a clear ink and background separation. This is even more true for ancient documents, especially for DSS, due to the diverse and damaged background material. Traditional computer vision and pattern recognition techniques that performs binarization based on intensity struggle with such a heterogeneous collection. Hence, this thesis investigates artificial neural network-based architectures (e.g., U-Net [245], GAN [93], etc.) to provide a robust binarization method.

In search for an appropriate binarization technique to enhance handwriting eventually leads to four new tangents (sub-research questions) and an anecdote (1.2.2.1 - 1.2.2.5).

1.2.2.1 **Tangent 1: How to take advantage of the multi-spectral images?**

This sub-research question aims to explore the optimal utilization of multi-spectral images from IAA (see an example in Figure 1.4). Multi-spectral images capture information at different wavelengths across the electromagnetic spectrum. So, each band image provides valuable and specific information beyond what traditional RGB (color) images can offer. This thesis also explores various approaches to developing algorithms and machine learning models capable of extracting meaningful data from the multi-spectral images of DSS.

1.2.2.2 **Tangent 2: Can the door for damaged character reconstruction be opened?**

This sub-research question explores the potential benefits of manuscript binarization in character reconstruction. Character reconstruction refers to recovering missing or damaged parts of the characters in handwritten text. Reconstructing damaged text can enable scholars and researchers to easily read and understand the texts and the contexts in which the manuscripts were written. In addition, a good binarization technique can help extract the text from the background accurately and, in the process, can help improve the accuracy of character reconstruction algorithms. To address this research question, various binarization and character reconstruction
methods can be explored, including machine learning algorithms, image processing
techniques, and statistical analysis.

1.2.2.3 Tangent 3: What about image-based material analysis?

In connection with the original research theme of binarization, this thesis also ex-
plores tangential research of image-based material analysis. A good binarization
technique provides the foreground (ink) and means to extract the background (parch-
ment and papyrus in the DSS collection). This enables various pattern recognition
techniques in the background materials without any handwriting. So, as additional
research, this thesis studies the repetitive patterns found in parchment and papyrus
to identify specific documents or determine the origins of the materials. By uti-
лизizing these techniques, scholars can uncover new information and gain a deeper
understanding of the historical context in which these manuscripts were written.

1.2.2.4 Tangent 4: How to gather more handwriting when the scribes died over two
thousand years ago?

One research question that needs to be explored over this whole thesis is acquiring
more relevant data for reliable experimentation with AI-based models. Due to the
limited number of manuscripts that can be used on a particular experiment, different
data augmentation techniques are studied and implemented within the scope of this
thesis. Data augmentation techniques generate additional data by applying various
transformations to the existing data. This can help increase the dataset’s size and
improve the generalization of pattern recognition models. This thesis also explores
the effect of augmentation on handwriting and how much transformation can be
allowed to keep the text close to the original.

1.2.2.5 An anecdote: Is it worth investing in binarization?

The thesis also scrutinizes if this is worth investing in the research efforts for a
sophisticated binarization. This is exemplified in the novel investigative works on
the Great Isaiah Scroll (Figure 1.5) to revisit the current hypothesis on the writers
of this scroll. Finally, this thesis also examines if a better quantification can be
achieved in analyzing near-identical handwriting when presented with clear ink and
background separation.
1.2.3 *Dual-perspective time axis*

**Question 3: Is it possible to achieve a date prediction model that integrates AI, radiocarbon dating, and palaeographic knowledge?**

Following binarization and writer identification, this thesis explores the possibility of developing a date prediction model with multidisciplinary knowledge $^{14}$C dating results and traditional palaeography. If realized, an AI-based date prediction model will minimize the need for physical samples to be destroyed during radiocarbon dating, which is extremely important for historical manuscripts. Thus, this thesis investigates several AI techniques to design a robust date prediction model with limited data from $^{14}$C dating and inputs from palaeographic scholars.

1.2.4 *Ingenuity, adaptation, interpretability, and explainability*

**Question 4: Can the methods be interpreted and explained transparently to a multidisciplinary audience?**

Ingenuity in designing AI models involves thinking creatively and innovatively to develop solutions for complex problems. It involves finding novel solutions, thinking outside the box, and pushing the boundaries of what is currently known or commonly practiced in the field.

Ingenuity becomes a necessary part of the different multidisciplinary works within the scope of this thesis. It is clear from the previous research questions that understanding how different algorithms work and their strengths and limitations can help design models suitable for specific tasks and data constraints. This thesis also explores statistical methods for understanding the underlying patterns in data, estimating uncertainties, and making sound inferences. Techniques such as Bayesian statistics can be employed to incorporate prior knowledge and make more reliable predictions with limited data. Additionally, domain knowledge is crucial for informed decisions in designing models and choosing appropriate techniques. The work of this thesis, thus, looks into ways to incorporate learning from experts in other disciplines.

Adaptation is required to allow different disciplines to integrate, collaborate, and contribute effectively towards a common goal. Therefore, this thesis also considers the effectiveness of adaptation in multidisciplinary works and how it facilitates knowledge integration, innovation, holistic problem-solving, addressing complexity, and practical application in historical manuscript analysis.

Last but not least, the work always focuses on the interpretability and explainability of the methods to provide transparent, reproducible, and scalable systems. Interpretability and explainability in modern AI are essential in general but a must in the context of historical document analysis within the scope of this thesis. By un-
derstanding the model’s decision-making process, humanities scholars can verify the accuracy and reliability of the results. This is crucial for DSS, where interpretation and contextual understanding are paramount. Explainability also helps build trust and transparency in the AI-based models and gives different domain experts confidence in the results. As a whole, this thesis keeps tight collaboration with scholars and attempts to provide a high explainability of all the research accomplished.

1.3 Thesis Outline

The thesis deals with the complete journey from data acquisition to setting up extensive experiments for analyzing historical manuscripts, especially the DSS. The thesis comprises eight chapters, including this introduction, organized into five distinct parts. The chapters are based on several publications by the author. A list of all publications can be found on page 304. At the beginning of each chapter, the author’s associated publication and contribution are mentioned at the beginning of each chapter. The structure of the thesis is described briefly here.

Part I The first part of the thesis comprises two chapters, including the current one. Chapter 2 presents the pilot test on writer identification to investigate the feasibility of PR-based methods for DSS. The chapter proposes a complete PR pipeline and demonstrates the results of the very first writer identification test on DSS. This chapter lays the foundation for the following parts of the thesis by indicating the need for a better ink-background separation method for the multi-spectral IAA images to continue the rest of the works. Chapter 2 addresses the first research theme (Question 1 in 1.2.1).

Part II The second part has one chapter. Chapter 3 proposes an advanced method for binarizing (separating ink from the background) the DSS images. The proposed model (BiNet) shows better performance than other available techniques. The model is also transferable to be used in other historical manuscripts. This chapter also introduces image fusion techniques for the multi-spectral images of the DSS. Chapter 3 addresses the second research theme (Question 2 in 1.2.2) along with the first sub-research question (Tangent 1 in 1.2.2.1).

Part III This part also has one chapter. Chapter 4 presents a complete experimental setup and results for identifying writers in the Great Isaiah Scroll. This work aims to calibrate and evaluate the methods in the identification domain of the DSS but will be expanded into the dating domain in the later chapters.

Using cleaner data from BiNet, Chapter 4 finds new evidence for a breaking point in the series of columns in the scroll without prior assumption of writer identity, based on point clouds of the reduced-dimensionality feature space. With this chapter,
the thesis opens a new door to revisit the old hypothesis on the identity of scribes for many other historical documents. This chapter also reinforces the necessity of producing cleaner data from sophisticated binarization techniques for the DSS. Chapter 4 addresses the anecdotal sub-research question of the second research theme (An anecdote in 1.2.2.5).

PART IV This part has two chapters. Chapter 5 presents the experimental setup and results of feature extraction techniques in estimating the periods of the DSS manuscripts from the writing styles. This chapter lays the foundation for a complete date prediction model in the next chapter. Chapter 6 then integrates the $^{14}$C dating results and the palaeographic knowledge to propose Enoch, the final date prediction model. This chapter uses the Bayesian regression technique to produce probabilities on the time axis for any sample manuscript from the DSS. Thus a dual-perspective time axis is presented. Chapter 5 and Chapter 6 addresses the third research theme (Question 3 in 1.2.3).

PART V This is the final part of the main body of the thesis, containing one chapter. Chapter 7 finally closes the main parts of this thesis with discussions and conclusions. This chapter provides a bird-eye view of all the chapters and their main findings. Finally, this chapter concludes with the use of AI in historical manuscript analysis, especially on DSS. The chapter finishes with a few directions for future research.

PART VI The epilogue contains the appendices (Chapter 8 addresses the third sub-research question in Tangent 3 in 1.2.2.3), Chapter 9 addresses the fourth sub-research question in Tangent 4 in 1.2.2.4), bibliography, list of publications, list of abbreviations, and other supplementary information.