Deep Learning Methods for Ancient Arabic Handwritten Script Recognition: A Review of Challenges and Approaches

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The problem is made more difficult by the fact that the recognition of ancient handwritten Arabic script (AHR) is written in cursive, has different historical styles, and the manuscripts are often damaged. In addition, ancient handwriting does not follow modern standards of handwriting spacing, which includes overly spaced-out words and overly complex diacritics, which makes it extremely difficult to process. This irregularity causes ambiguity in character segmentation and word boundaries, increasing the error rate in automatic recognition systems. Even with modern advancements in deep learning through the use of CNNs, LSTMs, and hybrid models, AHR is still extremely complex and requires a lot of exploration. Some recent models have achieved accuracy between 70% and 90% on modern Arabic datasets, but performance drops to 50%–75% when applied to ancient texts due to noise, script variation, and limited annotated data. The article consolidates the major issues and recent developments with regard to dataset constraints, preprocessing requirements, and machine learning methodologies. This review is based on the analysis of over 50 peer-reviewed papers published between 2016 and 2024. It is also focused on the importance of deep learning in the image feature extraction by CNNs, sequential feature modeling by LSTMs, and combination of both – hybrids. For instance, CNN-LSTM architectures have shown promising results on historical scripts with limited training data. With so little annotated data available, it concentrates on the augmentation of datasets and creation of synthetic data. Techniques such as elastic distortions, GAN-generated samples, and noise injection are discussed as potential solutions. This work aims to improve the accuracy and scalability of AHR through analysis of existing techniques and identification of the gaps for further research to aid in digitization and analysis of manuscripts to safeguard them as a part of cultural heritage. In particular, this review highlights the lack of standardized benchmarks and the need for multilingual ancient Arabic datasets to support reproducible research

Povzetek: Članek se ukvarja s prepoznavo stadoravnih arabskih rokopisov. Novost so celovita taksonomija izzivov, nabor podatkov in smernice za hibridne CNN-LSTM ter sintetični podatki, kar omogoča bolj kvalitetno prepoznavanje kot metoda CNN pri rokopisih.

1 Introduction

Throughout history, handwritten documents have been essential in recording knowledge, history, and traditions. Even in the digital age, handwritten texts remain significant, especially in legal, historical, and educational contexts. Arabic, the fifth most spoken language worldwide with over 315 million native speakers [1], has a rich history and unique script. Arabic writing is not just communication; it is considered an art form [2], with complex, cursive characters that connect fluidly and often include diacritical marks. Segmentation and classification are challenging, due to the evolution of various handwriting styles over time and complexity of this script. This inherent complexity and variability of Arabic scripts recognition makes adapting traditional machine learning techniques, relying to handcrafted features difficult.

Recent advances in deep learning appear, to improve significantly handwriting recognition across various languages [2, 3, 4], these techniques, are particularly Neutral networks based on convolutional architectures (CNNs), Long Short-Term memory (LSTM), and hybrid approaches. Despite that, these techniques are still underutilized in ancient Arabic handwritten texts recognition [2]. The challenges are substantial, as the cursive nature of Arabic script, stylistic variations over time, and document degradation complicate recognition tasks. Also, the lack of annotated and diverse datasets hampers the training of robust deep learning models. This study focuses on assessment of the current approaches, particularly hybrid models and CNNs, to put the finger on strategies that can improve the recognition of ancient Arabic manuscripts.

Recognizing ancient Arabic handwritten scripts is not just a technical challenge; it is also essential for preserving cultural identity and legacy. Improved recognition systems can help transcribe and preserve damaged manuscripts, making them accessible to future generations. An improved recognition of ancient manuscripts will facilitate greater access to historical texts, supporting research and exploration of key historical elements. The advancements made could significantly impact archiving, education, and digital libraries, enabling the preservation of ancient documents.

This research will focus on analyzing deep learning techniques for the recognition of ancient Arabic manuscripts, bridging the gap between modern technology and the cultural significance of these texts. The challenges of recognizing these texts stem from variations in handwriting styles and the physical condition of the manuscripts. For instance, the complexity of cursive writing, along with letter shape variability, is evident in examples of ancient manuscripts. Such manuscripts highlight the need for advanced recognition techniques tailored to these specific characteristics.

Table 1 provides a comparison of modern and ancient Arabic scripts, showing key distinctions in their recognition. Studies have demonstrated how CNNs, when applied to modern Arabic scripts, achieve higher accuracy than traditional methods. However, these models face limitations when dealing with historical Arabic texts. Recent surveys have explored various deep learning methods for Arabic handwritten text, but few have focused on ancient manuscripts. Ahmad et al. [5] reviewed methods for Arabic handwritten character recognition, and Ghadhban et al. [6] focused on the feature extraction techniques [7], showing a preference for CNN-based methods. This paper addresses existing gaps in research, particularly in the deep learning methods used for recognizing ancient Arabic texts.

This paper is structured as follows: Section 1 introduces the challenges of recognizing ancient Arabic manuscripts. Section 2 examines the characteristics of Arabic handwriting, focusing on its historical and stylistic particularities. Section 3 reviews existing research, analyzing modern and ancient datasets used for training deep learning models. Section 4 provides a critical evaluation of current methods, highlighting their strengths and limitations in dealing with ancient manuscripts. Section 5 identifies key challenges and open problems in this field. Finally, Section 6 concludes by summarizing recent advancements and proposing future research directions to enhance the recognition of ancient manuscripts through advanced machine learning techniques.

2 Arabic handwriting recognition

Over time, Arabic script has transformed and has numerous discrepancies between older and modern ones, which makes interpretation, translation as well as analysis difficult. This section first focuses on the Arabic script pertaining to ancient Arabic characters and later deals with the history of Arabic scripts in detail.

2.1 Arabic characters

The Arabic script consists of 28 letters, written in a cursive style from right to left. Consonants are written explicitly, while vowels are often omitted and indicated by diacritical marks. Each letter can take up to four different forms—isolated, initial, medial, or final—depending on its position in a word. This positional variation adds complexity and uniqueness to the script. Table 2 below illustrates all 28 letters in their different forms, showcasing their adaptability and fluidity.

Key Features of Arabic Characters: Arabic script has distinct characteristics, including **position-based letter variability**, **cursive structure**, **absence of uppercase/lowercase distinction**, and **right-to-left writing direction**. Each letter can appear in **isolated, initial, medial, or final forms**, influencing the script's flow. Unlike many languages, Arabic does not differentiate between uppercase and lowercase letters. This flexibility allows for a dynamic representation of the alphabet.

Arabic is inherently **cursive**, meaning letters connect along a baseline, with some featuring **ascenders and descenders**. Ascenders are parts of the letters that extend above the baseline, while descenders fall below it, as depicted in Figure 1.

Figure 1: Baseline, ascenders, and descenders in Arabic script

Additionally, **ligatures** form in specific cases, such as when the letter "Lam" (ل) precedes certain letters like "Alef" ,(ا) forming ligatures like .لا This special form is explained in Table 3, which lists examples of common ligatures in Arabic writing.

Diacritic points play an essential role in distinguishing letters with similar shapes. These diacritics are marks placed above or below the letter to modify its pronunciation. For example, the diacritic points in ب (Ba) and ن (Noon) differentiate them from other letters with similar shapes.

Diacritics such as **Fatha, Damma, Kasra, Shadda, and Sukun** help provide clarity in pronunciation and word meaning. These Tashkeel marks are vital for understanding the nuances of the Arabic language, as shown in Table 4.

Due to its **context-dependent letter forms and complex diacritical system**, Arabic handwriting recognition—especially for historical and stylized scripts—poses unique

Table 1: Comparison of modern and ancient Arabic scripts

Feature	**Modern Arabic Script**	**Ancient Arabic Script**
Letter Structure	Clear and uniform	Complex and varied
Dot Placement	Consistent and well-defined	Inconsistent due to writing deterioration
Dataset Availability	Readily available	Rare and often inaccessible
Handwriting Styles	Limited to contemporary styles	Diverse, including Kufic and early Naskh
Recognition Challenges	Relatively easier for segmentation	Highly challenging due to degradation and variability

Table 2: Arabic grapheme presentation modes – isolated, initial, medial, and final allographs

No.	Pronunciation	Isolated	Beginning	Middle	End	No.	Pronunciation	Isolated	Beginning	Middle	End
1	Alef	ا	ا	ا	ـا	15	Dhad	ض	ضـ	ضـ	ـضـ
2	Baa	ب	بـ	ـبـ	ـب	16	Ta	ط	طـ	طـ	ـطـ
3	Taa	ت	تـ	ـتـ	ـت	17	Thaa	ظ	ظـ	ظـ	ـظـ
4	Thaa	ث	ثـ	ـثـ	ـث	18	Ain	ع	عـ	عـ	ـعـ
5	Jeem	ج	جـ	ـجـ	ـج	19	Ghain	غ	غـ	غـ	ـغـ
6	Haa	ح	حـ	ـحـ	ـح	20	Faa	ف	فـ	فـ	ـفـ
7	Khaa	خ	خـ	ـخـ	ـخ	21	Qaf	ق	قـ	قـ	ـقـ
8	Dal	د	د	ـد	ـد	22	Kaf	ك	كـ	كـ	ـكـ
9	Thal	ذ	ذ	ـذ	ـذ	23	Lam	ل	لـ	لـ	ـلـ
10	Raa	ر	ر	ر	ـر	24	Meem	م	مـ	مـ	ـمـ
11	Zai	ز	ز	ـز	ـز	25	Noot	ن	نـ	نـ	ـنـ
12	Seen	س	سـ	ـسـ	ـس	26	Ha	ه	هـ	هـ	ـهـ
13	Sheen	ش	شـ	ـشـ	ـش	27	Waw	و	و	ـو	ـو
14	Sad	ص	صـ	ـصـ	ـص	28	Yaa	ي	يـ	يـ	ـيـ

Table 3: Examples of ligatures in Arabic script

Ligature	Example
Lam-Alef Ligature	لا
Lam-Haa Ligature	لح
Lam-Meem Ligature	لم

Table 4: Impact of diacritics on word meaning

Word without Diacritics	With Diacritics	Meaning
علم	عَلَم	Flag
علم	عِلْم	Knowledge

challenges. As the letter form depends on its position within a word, and the meaning can be influenced by the diacritics, automatic analysis of Arabic handwriting remains a complex task.

Arabic letters adopt a number of forms depending on their location within a word. This reliance on the letter's context is vital in comprehending the way letters in a word form are interdependent, further complicating Arabic handwriting perception and interpretation, particularly for historical and eccentric styles.

2.2 Ancient Arabic characters

Due to its varying calligraphic styles and intricate decorative details, ancient Arabic differs from modern Arabic far more than other forms of writing. Unlike modern Arabic, which is more standardized, ancient scripts had abstract ligatures and ornamental features that posed challenges for contemporary automated recognition systems. As shown in Figure 2, these advanced letter forms are very difficult to recognize. Figure 2 illustrates an example of ancient Arabic handwriting with dense text layout, irregular spacing between words, and heavy ornamentation. These features increase recognition difficulty because standard CNN or LSTM models assume more regular structure and spacing, which is typically found in modern datasets. Moreover, the presence of faded ink and background noise further complicates the segmentation and feature extraction processes. Ancient Arabic scripts, though maintaining the same position-based letter forms (isolated, initial, medial, and final), exhibit more variation. Letters are often connected by elaborate curves, and ascenders and descenders are more pronounced, especially in styles like **Diwani**, which was used for official and artistic documents. This complexity adds challenges for character recognition systems.

In addition, diacritics played an important role in ancient manuscripts, particularly for religious texts like the

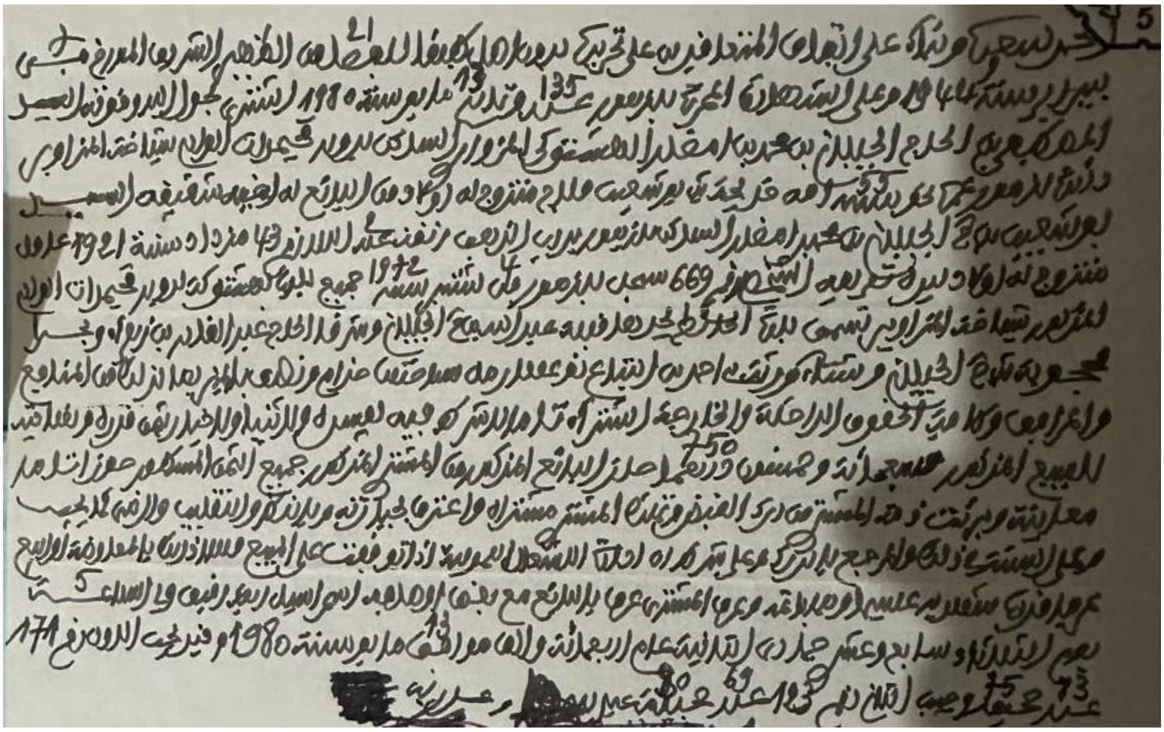

Figure 2: Example of ancient Arabic script: complexity and artistic features

Quran, where their systematic use ensured textual accuracy. Nonetheless, contemporary systems struggle to detect diacritics, especially when they are part of a ligature or situated within complex glyphs.

The fluidity and ligatures in ancient Arabic writing are, as depicted in Figure 3, its unique features. Unlike in modern Arabic, where ligatures follow standardized forms, ancient texts often contain irregular and highly decorative ligatures. These include overlapping strokes, merged glyphs, and non-linear connections, which pose significant challenges to segmentation-based recognition systems. Accurate recognition of such ligatures requires models capable of interpreting complex spatial structures and dealing with inconsistent writing styles. These aspects make recognition as well as the digital recovery of ancient manuscripts difficult. The variability in their letterforms and distinct styles make the recognition of ancient Arabic characters remarkably challenging. The previous figures are sufficient to demonstrate such differences and envision the challenges of recognizing and digitizing characters from ancient manuscripts. The use of advanced technologies in artificial intelligence such as CNNs, LSTMs, and other deep learning architecture has provided improved recognition of intricately handwritten forms which are often deemed to be too complex for basic recognition.

3 Related works

Recognition of handwritten Arabic scripts has become, in recent years, an important field of research focusing on two aspects: recognition system development and dataset production. Through the construction of well-formed annotated datasets and using sophisticated machine leaning methods to address the problems that arise from the complex morphology and calligraphy of Arabic scripts, researchers have enhanced recognition processes.

3.1 Datasets

Datasets serve as a foundational pillar for developing and validating machine learning systems. In the field of handwriting recognition, their role is particularly critical: these systems require extensive and heterogeneous collections, the development of which remains an ongoing effort. These resources provide a standardized benchmark for comparing and refining existing methodologies. Practically, contributors produce handwritten Arabic content (isolated characters, words, sentences, or paragraphs), which are then transformed into offline datasets through processes including digitization, segmentation, labeling, and archiving [8].

Over the past 20 years, various offline datasets of handwritten Arabic texts have been developed to address recognition challenges. They fall into two categories:

(i) General Arabic Handwriting Datasets: Include contemporary writing samples for recognizing characters, words, and sentences in different styles.

(ii) Ancient Arabic Handwriting Datasets: Contain historical manuscripts with script variations, missing diacritics, and stylistic inconsistencies, aiding in the study and recognition of ancient texts.

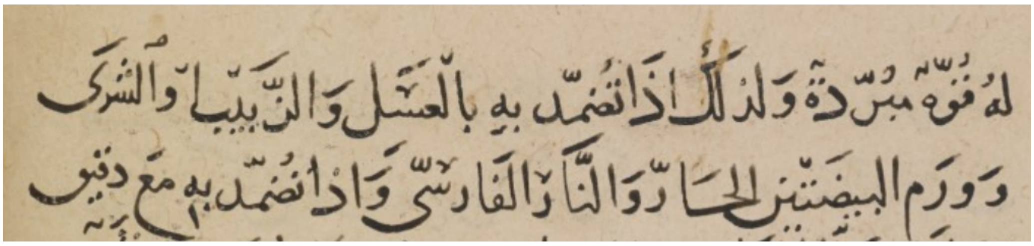

Figure 3: Ancient Arabic manuscript: letter fluidity and ligature characteristics

This section examines both types of datasets—covering modern linguistic units (characters, words) and historical documents—whose utilization is essential for advancing automated recognition methodologies.

3.1.1 Arabic handwritten datasets

Standard datasets for Arabic handwriting recognition are designed to train and test models for recognizing modern Arabic scripts. These datasets include diverse writing styles and variations. Key datasets include:

– **AHCD (Arabic Handwritten Characters Dataset)** [9]: Contains 16,800 images of isolated Arabic letters from 60 participants, annotated and scanned at 300 dpi. It is available for academic research only, with no commercial use allowed.

– **DBAHCL (A Dataset of Arabic Handwritten Characters and Ligatures)** [10]: Includes handwritten Arabic characters and ligatures, supporting research with well-annotated samples from multiple writers. It is available for academic use with restrictions on commercial exploitation.

– **Hijja Dataset** [2]: Comprises over 47,434 Arabic letters in various forms (isolated, beginning, middle, end) from children's handwriting. It is publicly available for research but requires approval for commercial use.

– **KHATT Project** [11]: Contains over 2,000 paragraphs of Arabic handwriting from more than 1,000 writers. It is freely available for academic institutions with some commercial restrictions.

– **IFN/ENIT Database** [12]: Features 26,469 Arabic words from Tunisian village names, divided into classes. It is free for non-commercial use after registration.

– **AHDB (Arabic Handwritten Database)** [13]: Includes handwritten words, sentences, and pages, focusing on commonly used Arabic words. It is free for academic use with strict non-commercial policies.

These datasets are essential for developing and evaluating Arabic handwriting recognition models.

Table 5 provides a technical overview of major Arabic handwriting datasets, detailing their content, number of writers, and resolution.

3.1.2 Ancient handwritten Arabic datasets

Ancient Arabic Handwritten Datasets aim to recognize historical scripts and capture unique features of early Arabic handwriting, which differ significantly from modern Arabic writing. Key datasets include:

– **KERTAS Dataset** [14]: Contains over 2,000 Arabic manuscripts spanning 1,400 years, with geographic and authorial details. It is available only to authorized researchers for academic use, with digitized manuscripts preserving historical context.

– **RASAM Dataset** [15]: Focuses on Maghrebi scripts, capturing rounded and horizontally stretched letters, continuous connections, and diacritics. It is freely available for research and non-commercial use, with annotations highlighting unique Maghrebi writing characteristics.

– **Quran Manuscripts Dataset** [16]: Includes Quranic manuscripts in Algerian, Hijazi, and Kufi scripts, supporting historical and calligraphic research. Available on platforms like Kaggle for academic use, but not for commercial purposes.

These datasets are essential for developing recognition systems for ancient Arabic manuscripts, enabling the preservation and analysis of cultural heritage through advanced deep learning models. However, it is important to note that datasets for ancient Arabic scripts are rare due to the inherent difficulties in processing and deciphering ancient Arabic texts, which often require specialized expertise and resources.

Table 6 summarizes the main ancient Arabic handwriting datasets, highlighting their size, script type, resolution, and usage license.

3.2 Systems and approaches in Arabic handwriting recognition

To address the challenges of Arabic handwritten recognition, significant research has focused on neural network-based technologies, including CNNs, LSTMs, and hybrid models. Every method has its advantages and is appropriate in certain domains of handwriting recognition. Despite the diversity of deep learning models investigated, most existing works focus predominantly on modern handwriting

Table 5: Overview of Arabic handwriting datasets with technical specifications

Dataset	Year	Content	Writers	Specifications
IFN/ENIT [12]	2002	Word-level entries	411	946 Tunisian toponyms, 26,400 terms, 210k characters; 300 dpi scans
AHDB [13]	2004	Structured/Free text	100	96 terms per template + unstructured pages; high-res (600 dpi)
KHATT [11]	2012	Full sentences	1,000	589,924 characters, 16,589 lexical units, 6,712 lines, 2,000 paragraphs; resolutions: 200/300/600 dpi
DBAHCL [10]	2017	Characters & ligatures	50	5,500 base characters + 9,900 contextual combinations; 300 dpi
AHCD [9]	2020	Letter variations	591	47,434 symbols; grayscale images (32×32 pixels); acquisition: 300 dpi
Hajja [2]	2020	Glyph diversity	591	Mirrors AHCD's scale (47,434 items); identical resolution and dimensions

Table 6: Comparison of ancient Arabic handwritten datasets

Dataset	Size	Script(s)	Resolution	License
KERTAS	2,000 manuscripts	Naskh, Thuluth	300 dpi	Academic use only (requires permission)
RASAM	3,500 samples	Maghrebi (rounded Kufic)	Variable	Free for non-commercial research
Quran Manuscripts	500 images	Hijazi, Kufi, Naskh	Up to 600 dpi	Restricted, hosted on Kaggle

datasets such as AHCD, IFN/ENIT, or KHATT, rather than directly evaluating models on ancient manuscripts. This creates a gap between the stated goal of ancient handwriting recognition and the datasets actually used for model validation. Furthermore, each model type has limitations when applied to the distinct challenges of ancient Arabic handwriting. These include degraded scripts, elaborate ligatures, and variable stylistic forms across different historical periods. In the following subsections, we examine the limitations of CNNs in handling spatial distortions due to pooling, the sensitivity of LSTMs to long input sequences typical of cursive styles like Diwani, and the potential of hybrid models with CTC decoding in handling unsegmented sequences.

3.2.1 CNN approach

Training in Arabic handwritten characters recognition is done using Convolutional Neural Networks (CNNs) because of their ability to learn spatial information of images. These networks are based on the convolution function which is performed over the input image to determine features such as contours and images. This can formally be expressed as:

$$\text{Feature Map} = \sum_{y=0}^{\text{columns}} \sum_{x=0}^{\text{rows}} \Big[\text{Input}(x-p, y-q) \times \text{Filter}(x,y) \Big] \tag{1}$$

After convolution, activation functions like ReLU introduce non-linearity:

$$f(x)_{\text{ReLU}} = \max(0,x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{if } x \geq 0 \end{cases} \tag{2}$$

Pooling layers, such as max-pooling, reduce spatial dimensions:

$$\text{Max Pooling} = \max(\text{Window}) \tag{3}$$

Finally, the Softmax function is used for classification:

$$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{k=1}^{N} e^{x_k}} \tag{4}$$

While CNNs are highly effective in extracting local spatial features, they tend to underperform on historical scripts with complex ligatures and overlapping characters. This is primarily due to the loss of fine spatial detail during successive pooling operations, which can distort the positional context of interconnected glyphs. In ancient manuscripts, where character connections often carry semantic weight, this becomes a critical limitation.

A CNN-based architecture for recognizing Arabic handwritten characters was introduced by H. El-Bakry et al. [17] which reached 94.9% accuracy on the AHDC dataset. The model implementation involved stochastic gradient descent (SGD) paired with L2 regularization and precise learning rate adjustment.

In [18], K. Younis et al. put forward a CNN architecture composed of three convolutional layers together with batch normalization and dropout layers and reached 94.7% accuracy when evaluated on the AHCD dataset. The model demonstrated better accuracy performance when extended training epochs and additional filters were applied.

N. Altwaijry et al. [2] created a CNN-based model with three convolutional layers that reached 97% accuracy on the AHCD dataset and 88% accuracy on the Hijja dataset. For their training process they implemented the Adam optimizer along with categorical cross-entropy loss.

Al-Taani and Ahmad [19] studied how residual learning frameworks perform in the classification of individual Arabic script glyphs. The ResNet architecture developed by Al-Taani and Ahmad achieved outstanding performance metrics with recognition rates of 99.8% (MADBase), 99.05% (AIA9K), and 99.55% (AHCD) while outperforming traditional convolutional models due to optimized gradient flow from skip connections.

A. Durayhim et al. [20] built a bespoke CNN framework featuring seven layers that attained 99% accuracy when tested on the Hijja dataset and 98% on AHCD. The researchers assessed a fine-tuned version of VGG-16 which reached 83% and 94% accuracy on two datasets.

The CNN architecture with eight layers proposed by M. Jamjoom et al. [21] achieved a 96.78% accuracy rate on the AHCD dataset through the implementation of Adam optimization and dropout techniques to avoid overfitting.

The CNN-14 model by A. Sayed et al. [22] reached 99.36% accuracy for the AHCD dataset and 94.35% for the Hijja dataset. The architecture of the model incorporated eight convolutional layers along with the Adam optimizer.

Table 7 provides a comprehensive summary of CNN-based methods employed for Arabic handwritten character recognition.

3.2.2 LSTM approach

Because LSTMs can track long-term dependencies, a specific type of RNN [23] known as Long Short-Term Memory Networks is well-known for their efficiency on sequential data such as Arabic handwriting. The key operations in an LSTM cell include the forget gate, input gate, and output gate, which regulate the flow of information. Mathematically, these gates are defined as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad \text{(Forget Gate)} \tag{5}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad \text{(Input Gate)} \tag{6}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad \text{(Output Gate)} \tag{7}$$

The cell state C_t is updated as:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{8}$$

where $\tilde{C}_t$ is the candidate cell state computed using a tanh activation:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{9}$$

The hidden state h_t is then calculated as:

$$h_t = o_t * \tanh(C_t) \tag{10}$$

One of the main challenges when applying LSTM networks to ancient Arabic manuscripts lies in their cursive nature and extended line lengths. Styles such as Diwani often produce very long sequences with irregular spacing, which can exacerbate problems like vanishing gradients or overfitting, especially in settings with limited training data. Regularization methods (e.g., dropout, maxout) partially mitigate this issue, but scalability remains limited without robust data augmentation or transfer learning.

Maalej and Kherallah [24] proposed an MDLSTM-based architecture for Arabic handwriting word recognition, achieving a label error rate of 16.97%. By applying dropout regularization, they reduced the error rate to 12.09%. Further experiments in [25] showed that placing dropout before the MDLSTM layer yielded the best results, with an error rate of 11.62%.

In [26], Maalej and Kherallah introduced the Maxout regularization technique, integrating Maxout units into LSTM cells and feedforward layers. With a Maxout group size of four, they achieved a label error rate of 10.11%, demonstrating significant improvements over the baseline model.

Alkhawaldeh [27] developed a hybrid transfer learning model combining CNNs and LSTMs for recognizing Arabic (Indian) handwritten digits. The CNN extracted spatial features, while the LSTM captured sequential dependencies. This model achieved an accuracy of 98.92%, with precision and recall values close to 100% for most cases, outperforming baseline methods.

While RNN-based models like LSTMs are effective for sequential data, they are generally outperformed by CNNs in tasks involving limited data. However, with the availability of larger datasets, LSTM-based approaches are expected to improve further in Arabic handwriting recognition.The details of LSTM approaches to recognize Arabic handwritten words are presented in summarized form in Table 8.

Table 7: Comprehensive summary of CNN-based methods employed for Arabic handwritten character recognition

Reference	Dataset	Optimizer	Accuracy
H. El-Bakry et al. (2017)[17]	AHDC	SGD	94.9%
K. Younis et al. (2017)[18]	AHCD	SGD	94.7%
N. Altwaijry et al. (2020)[2]	AHCD, Hijja	Adam	97% (AHCD), 88% (Hijja)
A. T. Al-Taani et S. T. Ahmad (2021)[19]	MADBase, AIA9K, AHCD	ResNet	**99.8%** (MADBase), **99.05%** (AIA9K), **99.55%** (AHCD)
A. Durayhim et al. (2023)[20]	Hijja, AHCD	Adam	**99%** (Hijja), 98% (AHCD)
M. Jamjoom et al. (2023)[21]	AHCD	Adam	96.78%
A. Sayed et al. (2023)[22]	AHCD, Hijja	Adam	99.36% (AHCD), 94.35% (Hijja)

Note: Some metrics such as training time, standard deviation, or computational complexity were not available in the original publications

Table 8: Comparative analysis of MDLSTM implementations for Arabic handwriting recognition using the IFN/ENIT corpus

Study	Year	Evaluation Metric	Outcome	Architecture
Alkhawaldeh [27]	2021	Recognition Accuracy	98.92%	MDLSTM
Maalej & Kherallah [26]	2019	Character Error Rate	**10.11%**	MDLSTM
Maalej & Kherallah [25]	2016	Sequence Label Error	11.88%	MDLSTM
Maalej & Kherallah [24]	2016	Label Alignment Error	12.09%	MDLSTM

Note: Some metrics such as training time, standard deviation, or computational complexity were not reported in the original publications and are therefore not included here

3.2.3 Hybrid approaches

In recognition of Arabic handwriting, integrated CNNs and LSTM networks have proven to be very effective. Such models make use of LSTM's sequential modeling capabilities and CNN's spatial feature extracting abilities to achieve maximum accuracy. A key benefit of these models is their ability to learn unsegmented sequence mappings via Connectionist Temporal Classification (CTC) decoding. CTC enables models to align input sequences with output labels without requiring explicit segmentation—a crucial advantage when dealing with ancient scripts where character boundaries are ambiguous or missing. However, only a few works, such as those by Dahbali et al. [28] and Ahmad et al. [29], explicitly report CTC-based decoding performance, and its impact remains underexplored for historical document recognition.

Dahbali et al. [28] enhanced the existing approach with a hybrid model that first extracts features using a convolutional neural network (CNN) and Convolutional Block Attention Module (CBAM), before passing the output to a Bidirectional LSTM (BLSTM) for sequence modeling and decoding with CTC. They applied text line skew corrections and data augmentation as preprocessing methods, reaching a Character Error Rate (CER) of 3.25% as well as a Word Error Rate (WER) of 14.55% using the KHATT dataset.

Ahmad et al. [29] utilized advanced data enrichment techniques to overcome the problem of deficiency in Arabic handwriting datasets on the KHATT corpus. The techniques used were reduction of image distortion, structural outlining of text lines, contour optimization, and simulated ink transfer artifacts. The results were robust with a label error rate of 19.98% alongside a character level error rate of 4.22%, proving that the combined MDLSTM and CTC hybrid architecture significantly improves recognition accuracy.

Maalej and Kherallah [30] propose a comprehensive approach based on deep learning that uses Convolutional Neural Networks (CNNs) for hierarchical pattern recognition, montaged with bidirectional recurrent framework and time-based classifiers for hierarchical time tagging. To circumvent over-specialization of the model, they adopted some form of stochastic regularization alongside changes to the data such as angular and slant shifts and vertical scaling which are considered to be distortions. This methodology exhibited a recognition accuracy of 92.21% on the IFN/ENIT benchmark indicating better generalization ability.

Khemiri et al. [31] conducted a comparative study of Arabic word recognition using Bayesian Networks (BNs) and CNNs. While BNs require manual feature extraction, CNNs automatically learn features. Their best-performing model, a combination of CNNs and Dynamic Naive Bayes (DNB), achieved 95.20% accuracy on the IFN/ENIT dataset, outperforming individual models.

Amrouch et al. [32] explored hybrid CNN-HMM models for Arabic handwriting recognition, demonstrating that larger datasets improve model performance. Their CNN-HMM models achieved 88.95% and 89.23% accuracy on the IFN/ENIT dataset, compared to 87.93% for the baseline HMM model.

Awni et al. [33] investigated ensemble models for Arabic handwritten word recognition, training three ResNet18 models with RMSprop, SGD, and Adam optimizers. The ensemble model achieved an error rate of 6.63%, outperforming individual models with error rates of 11.57%, 9.41%, and 7.21%.

Khudeyer and Al-Moosawi [34] proposed a hybrid model that combines the ResNet50 convolutional neural network with traditional machine learning classifiers, namely Support Vector Machine (SVM) and Random Forest (RF), for Arabic handwritten character recognition. ResNet50 is used as a feature extractor, while the final dense layer is replaced with SVM or RF to improve accuracy and reduce training time. Experiments on AHCD, AIA9K, and Hijja datasets showed that the ResNet50+RF configuration achieved the best performance, reaching up to 99% accuracy, outperforming traditional CNN-based models.

Although hybrid models are still under development, they show significant potential for improving Arabic handwriting recognition. Table 9 summarizes the key characteristics and results of these hybrid approaches.

4 Critical evaluation of current approaches in Arabic handwriting recognition

The field of Arabic handwriting recognition has advanced significantly with the adoption of deep learning techniques such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid models. However, recognizing ancient Arabic scripts presents unique challenges due to their cursive nature, stylistic variations, and physical degradation. This section evaluates the strengths and limitations of current approaches, focusing on their applicability to ancient manuscripts.

4.1 Convolutional neural networks (CNNs)

CNNs excel at extracting spatial features from images, making them effective for modern Arabic handwriting recognition. Studies by El-Bakry et al. [17] and Younis et al. [18] achieved accuracy rates of 94.9% and 94.7%, respectively, on datasets like AHCD. However, CNNs struggle with sequential dependencies, which are crucial for cursive scripts like Arabic. Ancient scripts, with their fluid and interconnected characters, pose additional challenges due to variations in handwriting styles and manuscript degradation, limiting CNN effectiveness.

4.2 Long short-term memory (LSTM) networks

LSTMs are designed for sequential data [35], making them suitable for cursive scripts like Arabic. They can model long-term dependencies, improving recognition accuracy for ancient scripts with varying styles. However, LSTMs tend to overfit, especially with small datasets, and are computationally intensive. Techniques like dropout regularization help mitigate overfitting, but resource requirements remain a challenge for researchers with limited computational power.

4.3 Hybrid approaches

Hybrid models combine CNNs for feature extraction and LSTMs for sequence modeling, offering a robust solution for Arabic handwriting recognition. Ahmad et al. [29] and Maalej and Kherallah [30] demonstrated improved accuracy using hybrid models, particularly for complex scripts. Data augmentation techniques, such as blurring and edge-enhancing, further enhance model robustness. However, hybrid models are complex, computationally expensive, and can produce inconsistent results, especially for ancient scripts lacking standardized datasets.

4.4 Evaluation metrics and challenges

Current evaluation metrics, such as accuracy and precision, do not fully capture the challenges of ancient script recognition, including manuscript degradation and stylistic variations. More sensitive metrics are needed to assess system performance accurately in the context of ancient manuscripts.

4.5 Comparative analysis of SOTA models on ancient Arabic manuscripts

Although state-of-the-art (SOTA) models have demonstrated strong performance on modern Arabic handwriting datasets such as AHCD, KHATT, and IFN/ENIT, there is a notable lack of evaluations on ancient Arabic manuscripts. These manuscripts are characterized by significant physical degradation, complex calligraphy, and high stylistic variability, which pose unique challenges for recognition systems.

Table 10 provides a comparative overview of prominent deep learning approaches and highlights the absence of experiments conducted on datasets such as KERTAS, RASAM, or the Quran Manuscripts Dataset.

Discussion

This comparison reveals a substantial research gap: although the models show promising accuracy on modern datasets, they are rarely or never evaluated on truly ancient manuscripts. This disconnect undermines the applicability of such models to historical contexts, where character ligatures, faded ink, and artistic variations require more specialized recognition strategies. Future work should prioritize benchmarking on datasets like KERTAS, RASAM, and Quran Manuscripts to better assess the real-world applicability of recognition systems for cultural heritage preservation.

Table 9: Comparative overview of hybrid methodologies for Arabic handwritten script recognition

Year	Study	Dataset	Architecture	Performance Metrics
2018	Amrouch et al. [32]	IFN/ENIT	HMM framework integrated with CNN	Accuracy range: 87.93%–89.23%
2018	Maalej & Kherallah [30]	IFN/ENIT	CNN-LSTM hybrid with CTC alignment	Overall accuracy: **92.21%**
2019	Khémiri et al. [31]	IFN/ENIT	Combined DBN, CNN, and DBN-CNN fusion	Accuracy rates: 88.27%, 92.7%, **95.20%**
2019	Awni et al. [33]	IFN/ENIT	ResNet18 with various optimization strategies (Adam, SGD, RMSProp) + ensemble modeling	Error rates: **6.63%** (optimal ensemble)
2020	Ahmad et al. [29]	KHATT	MDLSTM network with CTC decoding	Label error rate: 19.98% Character error rate: 4.22%
2022	Khudeyer & Al-Moosawi [34]	AHCD, AIA9K, Hijja	ResNet50 as CNN + SVM / Random Forest (hybrid model)	Accuracy: AHCD: **99%** AIA9K: 95% Hijja: 92.4%

Note: Some metrics such as training time, standard deviation, or computational complexity were not reported in the original publications and are therefore not included here

Table 10: Comparison of SOTA models evaluated on Arabic handwriting datasets, including the gap in testing on ancient manuscript collections

Model	Architecture	Dataset	Performance	Limitations
El-Bakry et al. (2017) [17]	CNN	AHCD (modern)	94.9% accuracy	Performs well on clean data but lacks robustness to ancient script variability
Maalej & Kherallah (2019) [26]	CNN + BiLSTM + CTC	IFN/ENIT (semi-modern)	92.21% accuracy	Not evaluated on ancient datasets such as KERTAS or RASAM
Ahmad et al. (2020) [29]	CNN + LSTM	KHATT (modern)	CER = 4.22%, LER = 19.98%	Data enrichment used, but no experiments on historical datasets
Dahbali et al. (2024) [28]	CNN + BLSTM + CBAM	KHATT (modern)	CER = 3.25%, WER = 14.55%	Uses attention for better context modeling, but not tested on degraded scripts
–	–	KERTAS / RASAM / Quran	–	**No public benchmark experiments found on ancient datasets**

5 Challenges and open problems

Recognizing ancient Arabic manuscripts involves multiple intertwined challenges that span image quality, script variability, data scarcity, and evaluation limitations. Addressing these issues is essential to improve recognition accuracy and advance the field.

5.1 Preprocessing and image quality

Ancient Arabic manuscripts frequently exhibit significant degradation caused by factors such as ink fading, paper damage, stains, and noise introduced during scanning or digitization. These imperfections severely impact the legibility of the text and, consequently, the performance of recognition systems. To address these issues, advanced preprocessing techniques are crucial. Adaptive binarization methods improve the separation of text from background under varying lighting and degradation conditions. Image super-resolution algorithms can recover lost details from low-resolution scans, while deblurring filters help to correct motion blur or out-of-focus artifacts. Incorporating such preprocessing steps enhances the quality of input images, enabling more accurate feature extraction by subsequent recognition models.

5.2 Style and script transfer

Ancient Arabic scripts differ markedly from modern ones in terms of calligraphic styles, ornamental features, and character formations. This stylistic variability poses a significant challenge for models primarily trained on contemporary datasets. Style transfer techniques, especially those based on Generative Adversarial Networks (GANs), offer a promising solution by enabling the transformation of modern script samples into ancient-style handwriting. Synthetic data generated through GANs can augment limited historical datasets, providing diverse training samples that better capture the complexity of ancient writing styles. Such approaches facilitate the adaptation of recognition models to the unique characteristics of historical manuscripts.

5.3 Cross-lingual transfer learning

The availability of annotated data for ancient Arabic manuscripts is extremely limited, restricting the applicability of supervised deep learning methods. Cross-lingual transfer learning, which leverages similarities between Arabic and other cursive-script languages such as Urdu and Persian, presents an effective strategy to mitigate data scarcity. By pretraining models on related scripts with larger datasets, it becomes possible to transfer learned features and improve recognition accuracy on ancient Arabic texts. This approach exploits shared structural properties such as right-to-left writing direction, cursive connections, and ligature formations.

5.4 Benchmarking and evaluation metrics

Existing evaluation metrics, including accuracy and character error rate, provide a general measure of recognition performance but fail to capture critical aspects unique to ancient manuscripts. Manuscript degradation, diacritic complexity, ligature segmentation, and stylistic variations require more sensitive and task-specific evaluation protocols. Developing standardized benchmarks with carefully annotated ground truth and defining evaluation metrics that consider these challenges are essential steps to enable fair comparison between methods and to drive progress in the field.

5.5 Reproducibility and resource sharing

The advancement of ancient Arabic handwriting recognition is hindered by the lack of publicly available datasets, source codes, and pretrained models. Many research works rely on proprietary or restricted-access resources, limiting reproducibility and independent validation. Promoting open science practices, such as releasing annotated datasets, sharing code repositories, and providing pretrained models, is crucial to foster collaboration and accelerate innovation. This transparency also enables benchmarking across diverse approaches and facilitates the adoption of best practices.

5.6 Limitations in applying modern techniques to ancient Arabic manuscripts

Although recent advances such as transformer-based models, handwriting synthesis, and domain adaptation have significantly improved handwriting recognition on modern scripts, their application to ancient Arabic manuscripts remains very limited. This limitation mainly stems from the scarcity of large, well-annotated datasets for ancient texts, as well as the complex degradation, stylistic variability, and unique structural characteristics of these manuscripts. Furthermore, processing ancient scripts often requires specialized expertise, which restricts widespread research in these areas. Therefore, the absence of these modern techniques in this review is not due to oversight but reflects the current research landscape, emphasizing the need for future efforts to adapt and develop these approaches specifically for ancient Arabic handwriting recognition.

6 Discussion and conclusion

The preservation of ancient Arabic handwritten manuscripts has improved dramatically due to modern strides in artificial intelligence, particularly deep learning. The implementation of Convolutional Neural Networks (CNNs) and Long-Short-Term Memory (LSTM) networks, together in the form of hybrid models, has improved accuracy for the recognition of ancient Arabic scripts. However, there are issues that persist, such as the lack of effective pre-processing approaches, the absence of robust and sensitive evaluation metrics, and the right amount of labeled data.

To address these issues, one needs to focus on systematic eradication of noise, correction of skews, and creation of adequate volumes of qualitatively and quantitatively good annotated data concerning the Arabic scripts from nodes and manuscripts. More importantly, the introduction of new measures that pay special attention to the degradation of the manuscript and the changes in style throughout the text is needed. Lastly, addressing the elimination of resources in hybrid models while focusing on enhancing support for multilingual and cross-domain recognition of pages with mixed scripts is crucial.

A more critical analysis reveals that not all architectures perform equally under various conditions. For instance, LSTM-based models tend to struggle when dealing with highly degraded or noisy scripts, due to their reliance on sequence consistency, whereas CNNs show more resilience in handling such visual distortions but lack temporal context. Transformer-based approaches, although promising, are often data-hungry and prone to overfitting when the training corpus is limited or poorly annotated. This highlights the importance of proper data augmentation techniques, which can significantly improve model robustness and generalization.

Furthermore, a theoretical question arises: can current deep learning architectures be adapted or extended to effectively handle the high variability inherent in calligraphic styles found in ancient Arabic manuscripts ? This includes changes in stroke shape, letter spacing, and stylistic flourishes that standard models may not be equipped to interpret accurately.

To better evaluate model performance, comparative error analysis is essential. Metrics such as Word Error Rate (WER) and Character Error Rate (CER) should be reported systematically across different model types and training settings. Such evaluations would provide deeper insights into where specific models fail and under what conditions, guiding future improvements more effectively.

If these challenges are addressed—through improved model design, targeted data augmentation, and more thorough evaluation—ancient Arabic manuscripts will not only be better preserved but also become more accessible to researchers and the general public, thus contributing to the preservation and dissemination of cultural and historical knowledge.

While the proposed future directions—such as noise removal, skew correction, better annotation strategies, and style-sensitive evaluation—are essential, our current analysis is mostly based on studies evaluated on modern datasets like AHCD, IFN/ENIT, and KHATT. These datasets do not reflect the true complexity of ancient scripts, which include unique calligraphic styles, structural irregularities, and physical degradation. This gap between the identified challenges and the experimental data analyzed highlights a key limitation: the field still lacks large-scale, high-quality, publicly available datasets of ancient Arabic handwriting.

The rarity of such datasets, combined with the technical difficulty of annotating them, has led researchers to rely heavily on modern Arabic data. As a result, most of the reviewed architectures were not tested in conditions representative of ancient manuscript recognition. This review intentionally starts from the broader problem of Arabic handwriting recognition in general to frame and justify the unique research needs specific to ancient Arabic scripts.

Moving forward, research must focus more directly on ancient Arabic handwritten data—by developing dedicated datasets, adapting models to better handle stylistic variability and degradation, and proposing evaluation protocols tailored to these specific challenges. Although transformer-based methods, handwriting synthesis, and domain adaptation are promising trends in handwriting recognition, they remain largely absent from work on ancient scripts due to the same data limitations. This absence should not be seen as an oversight but rather as an indicator of where the field needs to progress.

This review serves as a foundation for future studies in this domain. It aims to consolidate current efforts while drawing attention to critical research gaps. Addressing these issues will not only improve recognition systems but also help preserve, understand, and make accessible a vital part of Arabic cultural and historical heritage.

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References

[1] Dawoud, M., Al-Khatib, M. and Al-Khatib, A. (2020). Introduction. In "Arabic Language and Linguistics" (pp. 1-10). Springer. Available at: `https://www.springer.com/gp/book/9783030252250`.

[2] N. Altwaijry and I. Al-Turaiki, "Arabic Handwriting Recognition System Using Convolutional Neural Network," *Neural Computing and Applications*, vol. 33, no. 1, Apr. 2021. doi: `https://doi.org/10.1007/s00521-020-05070-8`.

[3] I. P. de Sousa, "Convolutional Ensembles for Arabic Handwritten Character and Digit Recognition," *PeerJ Computer Science*, vol. 2018, no. 10, p. e167, Oct. 2018. doi: `https://doi.org/10.7717/peerj-cs.167`.

[4] C. Boufenar, A. Kerboua, and M. Batouche, "Investigation on Deep Learning for Offline Handwritten Arabic Character Recognition," *Cognitive Systems Research*, vol. 50, pp. 180–195, Aug. 2018. doi: `https://doi.org/10.1016/j.cogsys.2017.11.002`.

[5] R. Ahmed et al., "Offline Arabic Handwriting Recognition Using Deep Machine Learning: A Review of Recent Advances," in *Lecture Notes in Computer Science*, vol. 11691, pp. 457–468, 2020. doi: `https://doi.org/10.1007/978-3-030-39431-8_44`.

[6] H. Q. Ghadhban, M. Othman, N. A. Samsudin, M. N. Bin Ismail, and M. R. Hammoodi, "Survey of Offline Arabic Handwriting Word Recognition," in *Advances in Intelligent Systems and Computing*, vol. 978, pp. 358–372, 2020. doi: `https://doi.org/10.1007/978-3-030-36056-6_34`.

[7] N. Alrobah and S. Albahli, "Arabic Handwritten Recognition Using Deep Learning: A Survey," *Arabian Journal for Science and Engineering*, vol. 47, no. 10, Jan. 2022. doi: `https://doi.org/10.1007/s13369-021-06363-3`.

[8] R. Hussain, A. Raza, I. Siddiqi, K. Khurshid, and C. Djeddi, "A Comprehensive Survey of Handwritten Document Benchmarks: Structure, Usage and Evaluation," *Eurasip Journal on Image and Video Processing*, vol. 2015, no. 1, pp. 1–24, Dec. 2015. doi: `https://doi.org/10.1186/s13640-015-0102-5`.

[9] A. El Sawy, H. El-Bakry, and M. Loey, "Arabic Handwritten Characters Dataset (AHCD)," 2015.

[10] N. Lamghari and S. Raghay, "DBAHCL: Database for Arabic Handwritten Characters and Ligatures," Cadi Ayyad University, May 2017. [Online]. Available: https://www.researchgate.net/publication/317204941_DBAHCL_database_for_Arabic_handwritten_characters_and_ligatures.

[11] S. A. Mahmoud et al., "KHATT: An Open Arabic Offline Handwritten Text Database," *Pattern Recognition*, vol. 47, no. 3, pp. 1096–1112, 2014. doi: https://doi.org/10.1016/j.patcog.2013.08.009.

[12] "IFN/ENIT-Database of Handwritten Arabic Words," *ResearchGate*, 2021. [Online]. Available: https://www.researchgate.net/publication/228904501_IFNENIT-database_of_handwritten_Arabic_words.

[13] S. Al-Ma'adeed, D. Elliman, and C. Higgins, "A Data Base for Arabic Handwritten Text Recognition Research," 2004.

[14] K. Adam, A. Baig, S. Al-Maadeed, A. Bouridane, and S. El-Menshawy, "KERTAS: Dataset for Automatic Dating of Ancient Arabic Manuscripts," *International Journal on Document Analysis and Recognition (IJDAR)*, vol. 21, pp. 283–290, 2018. doi: https://doi.org/10.1007/s10032-018-0312-3.

[15] C. Vidal-Gorène, N. Lucas, C. Salah, A. Decours-Perez, and B. Dupin, "RASAM - A Dataset for the Recognition and Analysis of Scripts in Arabic Maghrebi," in *Document Analysis and Recognition – ICDAR 2021 Workshops*, vol. 12916, pp. 265–281, 2021. doi: https://doi.org/10.1007/978-3-030-86198-8_19.

[16] "The Quran Dataset," *Kaggle*, 2021. [Online]. Available: https://www.kaggle.com/datasets/imrankhan197/the-quran-dataset.

[17] Ahmed El-Sawy, Mohamed Loey, and Hazem EL-Bakry. "Arabic Handwritten Characters Recognition using Convolutional Neural Network". In: *WSEAS Transactions on Computer Research* 5 (2017), pp. 11-19. ISSN: 2415-1513. https://www.researchgate.net/publication/313891953_Arabic_Handwritten_Characters_Recognition_using_Convolutional_Neural_Network.

[18] K. S. Younis, "Arabic Handwritten Character Recognition Based on Deep Convolutional Neural Networks," *Jordanian Journal of Computers and Information Technology (JJCIT)*, vol. 3, no. 3, pp. 186–198, 2017. [Online]. Available: https://www.jjcit.org/papers/vol3no3/vol3no3.pdf.

[19] A. T. Al-Taani and S. T. Ahmad, "Recognition of Arabic Handwritten Characters Using Residual Neural Networks," *Jordanian Journal of Computers and Information Technology (JJCIT)*, vol. 7, no. 2, pp. 192–202, June 2021.

[20] A. Bin Durayhim et al., "Towards Accurate Children's Arabic Handwriting Recognition via Deep Learning," *Applied Sciences*, vol. 13, no. 3, p. 1692, 2023. doi: https://doi.org/10.3390/app13031692.

[21] Z. Ullah and M. Jamjoom, "An Intelligent Approach for Arabic Handwritten Letter Recognition Using Convolutional Neural Network," *PeerJ Computer Science*, vol. 8, p. e995, 2022. doi: https://doi.org/10.7717/peerj-cs.995.

[22] A. Alsayed et al., "Arabic Handwritten Character Recognition Using Convolutional Neural Networks," *Springer Nature*, 2023. doi: https://doi.org/10.21203/rs.3.rs-3141935/v1.

[23] Y. Cao, C. Shi, X. Li, M. Li, and J. Bian, "Unbalanced Position Recognition of Rotor Systems Based on Long and Short-Term Memory Neural Networks," *Machines*, vol. 12, no. 12, p. 865, 2024. doi: https://doi.org/10.3390/machines12120865.

[24] R. Maalej, N. Tagougui, and M. Kherallah, "Recognition of Handwritten Arabic Words with Dropout Applied in MDLSTM," in *Lecture Notes in Computer Science*, vol. 9730, pp. 746–752, 2016. doi: https://doi.org/10.1007/978-3-319-41501-7_83.

[25] R. Maalej and M. Kherallah, "Improving MDLSTM for Offline Arabic Handwriting Recognition Using Dropout at Different Positions," in *Lecture Notes in Computer Science*, vol. 9887, pp. 431–438, 2016. doi: https://doi.org/10.1007/978-3-319-44781-0_51.

[26] R. Maalej and M. Kherallah, "Maxout into MDLSTM for Offline Arabic Handwriting Recognition," in *Lecture Notes in Computer Science*, vol. 11955, pp. 534–545, Dec. 2019. doi: https://doi.org/10.1007/978-3-030-36718-3_45.

[27] R. Alkhawaldeh, "Arabic (Indian) Digit Handwritten Recognition Using Recurrent Transfer Deep Architecture," *Soft Computing*, pp. 1–11, 2021. doi: https://doi.org/10.1007/s00500-020-05368-8.

[28] M. Dahbali, N. Aboutabit, and N. Lamghari, "A Hybrid Model for Arabic Script Recognition Based on CNN-CBAM and BLSTM," *Jordanian Journal of Computers and Information Technology (JJCIT)*, vol. 10, no. 3, pp. 294–303, Sept. 2024.

[29] R. Ahmad, S. Naz, M. Afzal, M. Liwicki, and A. Dengel, "A Deep Learning Based Arabic Script Recognition System: Benchmark on KHAT," *International*

Arab Journal of Information Technology, vol. 17, no. 3, 2020. doi: https://doi.org/10.34028/iajit/17/3/3.

[30] R. Maalej and M. Kherallah, "Convolutional Neural Network and BLSTM for Offline Arabic Handwriting Recognition," Mar. 2019. doi: https://doi.org/10.1109/ACIT.2018.8672667.

[31] A. Khémiri, A. K. Echi, and M. Elloumi, "Bayesian Versus Convolutional Networks for Arabic Handwriting Recognition," *Arabian Journal for Science and Engineering*, vol. 44, no. 11, pp. 9301–9319, Nov. 2019. doi: https://doi.org/10.1007/s13369-019-03939-y.

[32] M. Amrouch, M. Rabi, and Y. Es-Saady, "Convolutional Feature Learning and CNN Based HMM for Arabic Handwriting Recognition," in *Lecture Notes in Computer Science*, vol. 10884, pp. 265–274, 2018. doi: https://doi.org/10.1007/978-3-319-94211-7_29.

[33] M. Awni, M. I. Khalil, and H. M. Abbas, "Deep-learning ensemble for offline arabic handwritten words recognition," in *Proceedings - ICCES 2019: 2019 14th International Conference on Computer Engineering and Systems*, pp. 40–45, Dec. 2019. doi: https://doi.org/10.1109/ICCES48960.2019.9068184.

[34] R. S. Khudeyer and N. M. Al-Moosawi, "Combination of Machine Learning Algorithms and ResNet50 for Arabic Handwritten Classification," *Informatica*, vol. 46, no. 9, pp. 39–44, 2022. https://doi.org/10.31449/inf.v46i9.4375

[35] Ahmed Alruwaili, Sardar M. N. Islam, and Iqbal Gondal. *Cybersecurity for Robotic and Autonomous Vehicles*. Taylor & Francis, 2023. https://www.taylorfrancis.com/books/mono/10.1201/9781003610908/cybersecurity-robotic-autonomous-vehicles/-ahmed-alruwaili-sardar-islam-iqbal-gondal. DOI: 10.1201/9781003610908.