Arabic Handwritten Text Recognition Systems Challenges and Opportunities

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Abstract: ***Arabic handwritten text recognition faces significant challenges despite the large number of Arabic speakers. A critical review paper has analyzed previous research in this field, identifying problem areas and challenges faced by researchers. The paper focuses on trends in offline handwriting recognition systems and the unique characteristics of the Arabic language that pose technical challenges. The analysis involved comparing and contrasting previous research methods and performances to summarize critical problems and enumerate issues that must be addressed. The paper highlights several Arabic datasets that can be utilized as benchmarks for training, testing, and comparisons. These datasets are essential for evaluating the performance of Arabic handwriting recognition systems. Additionally, the paper concludes with a fundamental comparison and discussion of remaining open problems and trends in the field. It identifies several unresolved technical issues, such as the need for improved feature extraction and modeling techniques, as well as the need for large-scale, diverse datasets to facilitate better training and testing of Arabic handwriting recognition systems. Overall, the paper provides a comprehensive overview of the challenges and issues facing Arabic handwriting recognition and highlights areas where further research is needed.***

Keywords: ***Arabic handwritten character recognition; Artificial intelligence; Machine learning; natural scene images; Optical character recognition, Natural Language Processing.***

1 INTRODUCTION

Arabic is the official language of 26 nations and is spoken as a first language by 280 million people globally. As a second language, it can be understood by a far larger number of people. The Arabic alphabet, like Hebrew's, is written from right to left. The language is one of the six official languages of the United Nations since it is so widely spoken around the globe. English, French, Spanish, Russian, and Chinese are the others[1].

Although Arabic is an official language in many nations, it is not spoken in the same way in all of them. Modern Standard Arabic, Egyptian Arabic, Gulf Arabic, Maghrebi Arabic, Levantine Arabic, and a variety of additional dialects exist. Some dialects are sufficiently dissimilar from one another that speakers struggle to comprehend one another[2].

There are two types of Arabic: 1. The Qur'an is written in the classical Arabic (Al-Fusha) language. 2. Modern Standard Arabic (MSA), the most widely understood Arabic dialect[3].

When it comes to operating an international firm that is attempting to expand into new markets, Arabic is becoming increasingly vital. Learning Arabic opens up several job opportunities in a variety of areas, including oil, energy, travel, finance, translation, and government[4].

Handwritten text is difficult to retain and access effectively and appropriately. Searching through them and sharing them with others is a time-consuming process. A lot of critical knowledge could be lost and not utilized efficiently if that text was not available in digital form.

Recognizing printed or handwritten English text using optical character recognition is a well-researched area that has yielded excellent results[5]. However, there is a lack of similar research on Arabic text due to the complexity of the Arabic alphabet and the various forms of the same letter, making it a challenging task[6].

Artificial intelligence (AI) plays a critical role in the development of optical character recognition (OCR) for handwritten text, including Arabic script. AI techniques such as machine learning(ML), deep learning(DL), and neural networks(NN) train OCR algorithms to recognize and interpret handwritten text more accurately by analyzing visual features and identifying patterns corresponding to specific characters[7]. AI-powered OCR can segment text into individual characters, identify language and script, and has numerous practical uses, including digitizing historical documents, automating data entry, and assisting visually impaired individuals[8]. Machine learning algorithms use statistical models, while deep learning uses neural networks to identify complex patterns and relationships, enabling OCR to recognize the unique features of each character and the context in which it appears[9]. Deep learning and machine learning also make OCR more versatile, allowing it to recognize text in different languages and scripts. Overall, deep learning and machine learning are essential in the development of OCR for handwritten text, enhancing its accuracy, versatility, and usefulness in numerous applications.

Ref.[10] the authors developed a CNN-based OCR system for recognizing Arabic handwritten characters, using a dataset of 15,599 images of Arabic characters. They used a three-layer CNN architecture with max-pooling and dropout and trained the model using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. They evaluated the model using a separate test set of 2,259 images and compared its performance to that of a traditional feature-based OCR system. They found that the CNN-based OCR system achieved higher accuracy than the traditional feature-based system, with an overall accuracy of 97.8% compared to 95.2%. They also found that the CNN model performed better than the traditional system for all Arabic characters except for one and that it was more robust to variations in handwriting style and noise. The authors concluded that their CNN-based OCR system showed promise for recognizing Arabic handwritten text and could be further improved with more training data and optimization of the model architecture.

Ref.[11] the authors developed a deep learning model for recognizing Bengali handwritten characters and words, using a dataset of 50,000 images. They used a combination of CNNs and LSTM networks to extract features from the images and recognize the characters and words. The model achieved an accuracy of 94.8% on a test set of 1,000 words, outperforming several other OCR methods. The authors also demonstrated that the model was able to recognize words in noisy and distorted images.

Ref.[12] the authors proposed a new method for recognizing Arabic handwritten digits using deep learning techniques. They used the Arabic Handwritten Digit Database, which contains 6,500 images of Arabic digits written by 55 different individuals, dividing it into training and testing sets with a 70:30 ratio. The proposed approach involves two phases, with a Restricted Boltzmann Machine used to pre-train the Convolutional Neural Network (CNN) in the first phase. The pre-trained CNN is then fine-tuned using backpropagation with labeled training data in the second phase. The CNN architecture used consists of two convolutional layers and two fully connected layers, and data augmentation techniques were applied to increase the training set size and reduce overfitting. The proposed approach achieved a testing set accuracy of 96.37%, outperforming other state-of-the-art methods for Arabic handwritten digit recognition. The authors also conducted experiments to test the robustness of the proposed approach to different types of noise, with promising results suggesting real-world applications for Arabic handwritten digit recognition.

Ref.[13] the authors developed a deep learning model for recognizing Amharic handwritten characters and words, using a dataset of 22,904 images. They used a combination of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to extract features from the images and recognize the characters and words. The model achieved an accuracy of 92.2% on a test set of 2,700 words, outperforming several other OCR methods. The authors also demonstrated that the model was able to recognize words in noisy images and images with variations in handwriting style.

Ref.[14] the authors conducted a comprehensive review of recent research on OCR for Arabic handwritten text using deep learning techniques. They analyzed 40 papers and identified the most commonly used methods, including CNNs, RNNs, LSTMs, and GANs. They also identified the major challenges in this field, such as the lack of large and diverse datasets and the need for more robust techniques for handling noise and variations in handwriting style. The authors found that deep learning-based OCR methods generally achieved higher accuracy than traditional methods, particularly when using large and diverse datasets for training. They also identified several promising research directions, such as the use of attention mechanisms and reinforcement learning.

Ref.[15] This paper proposes a novel approach for generating synthetic Arabic handwriting data using GANs to improve the performance of an OCR system. The authors trained a GAN on a dataset of real Arabic handwriting samples and used it to generate synthetic samples to augment the training data. They then trained a convolutional neural network on the augmented dataset and achieved recognition accuracy of 92.8%.

Ref.[16] This paper proposes a handwriting recognition system that combines GANs and CNNs for recognizing Arabic handwritten text. The authors first used a GAN to generate synthetic samples and then trained a CNN on the augmented dataset. They achieved recognition accuracy of 97.43%, outperforming several state-of-the-art methods.

Ref.[17] This paper proposes a conditional GAN-based approach for recognizing Arabic handwritten text. The authors used a dataset of real Arabic handwriting samples and trained a conditional GAN to generate synthetic samples conditioned on the input text. They then trained a CNN on the augmented dataset and achieved recognition accuracy of 97.7%, outperforming several state-of-the-art methods.

Ref.[18] This paper proposes a conditional GAN-based approach for recognizing Arabic handwritten text in offline scenarios (i.e., where the text is not written in real-time). The authors used a dataset of real Arabic handwriting samples and trained a conditional GAN to generate synthetic samples conditioned on the input text. They then trained a CNN on the augmented dataset and achieved recognition accuracy of 95.8%.

Ref.[19] This paper proposes an approach for enhancing deep Arabic handwriting recognition using GANs and synthetic data. The authors used a dataset of real Arabic handwriting samples and trained a GAN to generate synthetic samples to augment the training data. They then trained a deep convolutional neural network on the augmented dataset and achieved recognition accuracy of 97.14%.

Ref.[20] This paper proposes a deep convolutional GAN-based approach for recognizing Arabic handwritten text. The authors used a dataset of real Arabic handwriting samples and trained a deep convolutional GAN to generate synthetic samples to augment the training data. They then trained a CNN on the augmented dataset and achieved recognition accuracy of 96.7%.

Ref.[21] The paper proposes a system for recognizing Arabic cursive text from natural scene images using a series of components such as text localization, binarization, segmentation, feature extraction, and recognition. The recognition component uses a combination of hidden Markov models (HMMs) and a neural network to recognize individual characters and assemble them into words. The system achieved a recognition rate of 80.5% on a dataset of 600 natural scene images containing Arabic cursive text.

Ref.[22] the authors conducted a comprehensive study of various deep learning models, including CNNs, RNNs, and hybrid models, for recognizing Arabic handwritten text. They used two publicly available datasets and evaluated the models based on recognition accuracy and time complexity. The best-performing model for them was a hybrid CNN-RNN model, which achieved a recognition accuracy of 97.56% on one dataset and 94.51% on the other dataset. The authors also found that data augmentation techniques, such as rotation and scaling, can improve recognition accuracy.

Ref.[23]proposes a system for recognizing Arabic handwritten scripts based on a deep convolutional neural network architecture. The methodology involves image preprocessing, feature extraction, and classification. The image preprocessing stage includes binarization and normalization, and the feature extraction stage involves extracting both local and global features from the images using the proposed deep CNN architecture. The classification stage involves a contextual recognition approach that considers the surrounding characters of a given character to improve recognition accuracy. The system was evaluated on three datasets, and the results show that it achieved recognition rates of 96.2%, 95.1%, and 94.9%.

Ref.[24] the authors surveyed various deep learning models for recognizing Arabic handwritten text, including CNNs, RNNs, and hybrid models. They also analyzed the impact of various factors, such as dataset size, preprocessing techniques, and data augmentation, on recognition accuracy. The authors found that CNNs and hybrid models outperformed RNNs for Arabic handwritten recognition. They also found that data augmentation techniques, such as rotation and scaling, can improve recognition accuracy. Additionally, they highlighted the importance of preprocessing techniques, such as normalization and binarization, in improving OCR performance.

Ref.[25] the authors propose a system for Arabic handwriting recognition using a combination of deep learning techniques and a support vector machine (SVM) classifier. The authors created their own dataset, which consisted of 16,000 Arabic handwritten characters collected from 100 different writers. The system achieved an accuracy of 94.6%.

Ref.[26] This paper presents a deep learning approach for recognizing Arabic handwritten digits. The proposed system consists of a convolutional neural network (CNN) followed by a fully connected neural network. The authors used the Arabic Handwritten Digits Dataset, which contains 6,000 images of Arabic handwritten digits. The system achieved an accuracy of 98.4%.

Ref.[27]they present a system for Arabic handwriting recognition based on a convolutional neural network (CNN) architecture. The authors used the Arabic Handwritten Character Dataset, which consists of 16,800 images of Arabic handwritten characters. The system achieved an accuracy of 97.5%.

Ref.[28] they propose a system for Arabic handwriting recognition that combines deep learning techniques with feature extraction methods. The authors used the Arabic Handwritten Character Dataset, which consists of 16,800 images of Arabic handwritten characters. The system achieved an accuracy of 94.45%.

Ref.[29] the authors present a system for Arabic handwriting recognition that utilizes deep learning and image processing techniques. The authors used the Arabic Handwriting Dataset, which consists of 1,220 images of Arabic words and phrases written by 20 different writers. The system achieved an accuracy of 95.3%.

The paper is organized as follows. Section 2 presents in detail the characteristics of the Arabic language with its issues. Section 3 describes the main processes for building Arabic handwritten models(preprocessing, feature extraction, classification, and variant deep learning approaches). Section 4 Challenges and Future Directions for the field with examples of available datasets in handwritten Arabic. Section 5 applications of Arabic Handwritten Recognition. Section 6 gives the conclusion and future work as a result of this study.

2 The Arabic Language Characteristics

Arabic is written from right to left and comprises 28 alphabetical letters, all of which represent consonants. The Semitic alphabet, from which it descended, contains twenty-two of these letters. They're merely changed in the letterform. The remaining six letters indicate sounds that were not present in the prior alphabet's languages[30].
When the six following characters (ا, د, ذ, ر, ز, و) avoid splitting a word into two words, this must be considered. Words in which all characters are related are given as examples.فأر, تلميذ, معاذ

Table 1

DIFFERENT SHAPES FOR THE LETTERS DEPEND ON THEIR PLACE

Character	**Character Shape According To Its Position**				**Character**	**Character Shape According To Its Position**			
	isolated	**begin**	**Middle**	**End**		**isolated**	**begin**	**Middle**	**End**
Alif	ا	أ	ﺎ	ﺎ	daad	ض	ﺿ	ﺿ	ض
Baa	ب	ﺑ	ﺑ	ب	Tah	ط	ط	ط	ط
Taa	ت	ﺗ	ﺗ	ت	Zaah	ظ	ظ	ظ	ظ
Thaa	ث	ﺛ	ﺛ	ث	Eyen	ع	ﻋ	ﻌ	ع
Jim	ج	ﺟ	ﺟ	ج	ghayn	غ	ﻏ	ﻐ	غ
Haa	ح	ﺣ	ﺣ	ح	faa	ف	ﻓ	ﻓ	ف
Khaa	خ	ﺧ	ﺧ	خ	qaf	ق	ﻗ	ﻗ	ق
dal	د	د	د	د	kaaf	ك	ﻛ	ﻛ	ك
zal	ذ	ذ	ذ	ذ	laam	ل	ﻟ	ﻟ	ل
raa	ر	ر	ر	ر	meem	م	ﻣ	ﻣ	م
Zay	ز	ز	ز	ز	noon	ن	ﻧ	ﻧ	ن
Seen	س	ﺳ	ﺳ	س	haa	ه	ﻫ	ﻬ	ﻪ
sheen	ش	ﺷ	ﺷ	ش	Waw	و	و	و	و
saad	ص	ﺻ	ﺻ	ص	yaa	ى	ﻳ	ﻳ	ي

Sub-words are examples of words: وجيز, غانم, ماليزيا
Certain characters in the Arabic script may have closed loops, which is an important characteristic to take into account. Some characters, such as ج ,ح, and, have an open section that can be closed to form a triangle when written by hand. Additionally, characters like م ,و, and ع have closed loops. However, it is important to note that the loop in characters can sometimes become too small, causing the internal opening to disappear[31]. Overall, recognizing and accounting for the presence or absence of loops is crucial in accurately identifying Arabic characters.

Arabic script is unique in that each letter changes its shape based on its location in a word. For instance, the letter "ب" may take on different forms based on whether it appears at the beginning, middle, end, or isolated position in a word as shown in Table 1.

Moreover, diacritical marks are used in Arabic to indicate short vowels and other sounds like fat-ha, dhamma, and kasra, as shown in Table 2 and Table 3. Ligatures, which are combinations of two or more letters, are also common in Arabic script. In addition, prefixes are frequently used in Arabic, and they can alter the meaning of a word. For instance, the word "وبالوالدين" contains three prefixes "و" ",ب," and "ال," which affect the meaning of the word[32].

Table 2: TANWEEN FORMS

Name	**Shape**
Tanween bel fath	ً
Tanween bel kaser	ٍ
Tanween bel zam	ٌ

Table 3: DIFFERENT DIACRITIC MARKS

Diacritic Mark Name	**Diacritic Mark Shape**
Zamah	ُ
fathah	َ
Kasrah	ِ
Chadha	ّ

Recognition of handwritten characters can be challenging due to variations in size and shape, as well as differences in writing styles among individuals as shown in Figure 1. Additionally, the presence of overlaps, ligatures, and linkages between adjacent characters, as well as similarities in shape between different characters, can further complicate the identification process.

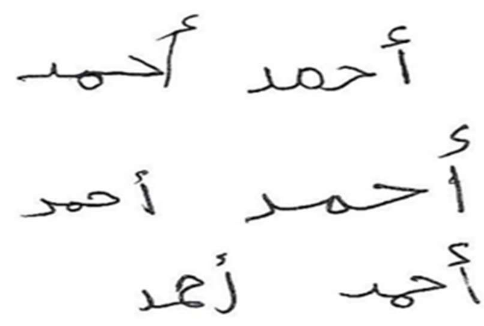

Figure 1 Same Word Written by Different Persons

The Arabic language has a unique system of punctuation marks that differs significantly from English. Arabic writing does not use traditional punctuation marks, such as the period or the semicolon. Instead, Arabic employs its own set of symbols, which are typically positioned above or below the text. One common punctuation mark used in Arabic is the reversed comma (،), which is used in place of the English comma. Unlike the English comma, which is positioned below the text, the Arabic comma is positioned above the line. This punctuation mark is used to separate items in a list, to separate clauses in a sentence, or to indicate a pause in speech[33]. For example, the sentence "I like to read books, watch movies, and listen to music" would be written in Arabic as "أحب قراءة الكتب، مشاهدة الأفلام، والاستماع إلى الموسيقى".

Another punctuation mark used in Arabic is the question mark (؟), which is used to indicate a question. In contrast to the English question mark, which is shaped like a hook, the Arabic question mark is shaped like a dot with a small circle above it. This punctuation mark is placed at the end of a sentence that asks a question, such as "هل تحب القراءة؟" (Do you like reading?).

In addition to these marks, Arabic also employs the colon (:) to introduce a quote or a list. This punctuation mark is placed at the end of the introductory phrase, with the quote or list following it. For example, "قال الشاعر: 'الحب هو أعظم شعور في الحياة'" (The poet said, "Love is the greatest feeling in life") or "قائمة التسوق: الحليب، الخبز، البيض" (Shopping list: milk, bread, eggs)[34].

It is essential to have a grasp of Arabic punctuation marks to fully comprehend written Arabic. While they may differ from the punctuation used in English, these marks are crucial in shaping the meaning of both sentences and texts.

When writing Arabic, many ambiguities can arise due to the language's complex rules for word formation and pronunciation. For example, the word "ktb" (كتب) can mean "books" or "he wrote" depending on the context. Other ambiguities arise due to the use of similar letters or letter combinations in Arabic. For instance, the letters "b" (ب) and "t" (ت) look very similar, and can easily be confused, especially when written quickly or with poor handwriting. The letters "s" (س) and "sh" (ش) are also similar in appearance and can be easily confused.

In addition to these visual ambiguities, Arabic also has many ambiguities related to pronunciation. For example, the letters "qaf" (ق) and "kaf" (ك) are pronounced very similarly in many dialects of Arabic, and can be difficult to distinguish in spoken language. The same is true for the letters "sin" (س) and "sad" (ص), which are also pronounced similarly in some dialects. These ambiguities make Arabic a challenging language to read and write, especially for non-native speakers. They also underscore the importance of context and the use of diacritical marks in written Arabic, as well as the need for careful attention to pronunciation in spoken language[35].

A. The Arabic Language Characteristics Challenges

Arabic is a Semitic language with unique characteristics that can present challenges for language learners. One of the most challenging aspects of Arabic is its complex script, which is written from right to left in a cursive style with many different letter shapes. Pronunciation can also be difficult due to the presence of guttural and emphatic consonants that are not commonly found in other languages. Additionally, Arabic vocabulary is rich and diverse, with many words having multiple meanings and nuances, and the grammar system is complex, including gender, noun declensions, verb conjugations, and intricate sentence structures[36]. Another challenge of learning Arabic is the presence of many regional dialects that can vary significantly in vocabulary, grammar, and pronunciation. Understanding the cultural context is also essential to fully comprehending the language. Lastly, resources for learning Arabic can be limited, especially for learners who are not in Arabic-speaking countries. Nonetheless, learning Arabic can be highly rewarding, as it grants access to a rich literary and cultural tradition and enables communication with millions of people worldwide[37].

1) Different Writing Styles

There are several types of Arabic writing styles, including typewritten (Naskh), handwritten (Raqqah), and a few others used for decorative calligraphy, such as (Kofi, Thuluth, and Diwani). This will make recognition more difficult and increase the size of the system's database. The Arabic language presents a challenge to scholars not just in terms of its social characteristics, but also in terms of its fundamental linguistic structure, which will be discussed further below[38].

2) Differ in Translated Word Shape

One problem is when Arabic texts include many translated and transliterated named entities whose spelling, in general, tends to be inconsistent in Arabic texts. For example, a named entity such as the city of Washington could be spelled ‘وشنطن‘ ,’’واشنغطن‘ ,’واشنطن‘ ,’واشنجطن’.

3) Position-Dependent Letter Shaping

Some characters have identical shapes, but the difference is in the placement and amount of dots, which can occur above or below the characters. For example, three characters such as (ث ,ت ,ب) have similar shapes. Dots may appear as two distinct dots or may be connected into a line in the handwritten text as shown in Table 4.

Table 4

LETTERS WITH DOTS

Number of Dots in The Characters		
One dot	Two dots	Three dots
ب ج خ ذ ز ض ظ غ ف ن	ت ق ي	ث ش

Furthermore, short marks such as a "hamza", can be placed above or below five particular characters or can appear as isolated characters. Some Arabic characters have a loop, such as (و ,ف ,ص)
Additionally, Arabic text is cursive, which means that the letters of a word are linked together by an imagined horizontal line known as a baseline. Ascenders and descenders are lines that occur above and below the baseline as shown in Figure 2.

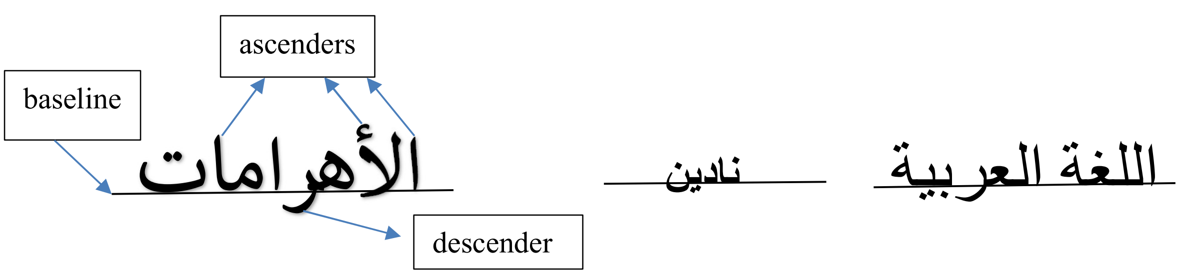

Figure 2 The Shape of Letters on The Baseline

In addition, there are six characters (ا, د, ذ, ر, ز, و)that have no shapes at the beginning and in the middle of the word, Therefore, these characters do not connect to a subsequent characters in a word and this causes a separation of the word into parts. These parts are called sub-words [39]. Spaces separate words and short spaces separate sub-words. The same word in a handwritten Arabic text could have different styles and sizes for the same writer as well as for different writers.

4) Letter Connectivity

In Arabic literature, a script alphabet is used, which uses a baseline to connect successive letters inside a word. To suit the baseline, each letter in the Arabic alphabet has four variants: an isolated form, a beginning form, a medial form, and a final form. Certain letters in the alphabet break this norm and have different shapes in their medial and terminal forms[40]. When one of these non-joining characters appears in a word, the preceding letter becomes its final (or isolated) form, while the non-joiner becomes its starting (or isolated) form. Because of this connectedness characteristic, segmentation will be more challenging. Unlike other languages, Arabic text is always cursive, whether printed or handwritten. As a result, Arabic characters have a lower recognition rate than those languages[41].

Arabic text is composed of interconnecting blocks of characters that are typed and printed cursively. Character classification and recognition are made more complex by the cursive aspect of Arabic characters, as well as the different forms of Arabic characters. A ligature that might occur when characters such as (,) appear after certain other characters. Illustrates the overlapping in the first three characters(ا, ل, خ)[42]. Moreover, two characters can be vertically overlapped without touching one another, such as characters(ر, ا, ع). In some cases, two characters may touch by mistake, such as characters (و, ر).

3 Main Steps in The Process of Developing The Arabic Handwriting Recognition Model.

A. Preprocessing

Preprocessing techniques play a crucial role in the Arabic handwritten recognition field. The main goal of preprocessing is to enhance the quality of the input image before feeding it into the recognition algorithm. In this survey, we explore different preprocessing techniques used in Arabic handwritten recognition, including binarization, noise removal, Contrast enhancement, thinning, and normalization[43].

- Binarization is a common preprocessing technique used to convert a grayscale image into a binary image. This process is essential because most recognition algorithms require binary images as input. Many binarization techniques have been proposed in the literature, such as thresholding, adaptive thresholding, and Otsu's method. The choice of binarization technique depends on the type of document and the level of noise present in the image.

- Noise removal is another important preprocessing step that aims to remove unwanted noise from the image while preserving the essential features. Various noise removal techniques have been proposed, including median filtering, Gaussian filtering, and morphological filtering. These techniques can be used alone or in combination with other techniques, depending on the type and level of noise present in the image.

- Thinning is a morphological operation used to reduce the thickness of the strokes in the image while preserving the connectivity between the different components. Thinning can improve the recognition accuracy by reducing the variations in the stroke width, which can affect the feature extraction process.

- Contrast enhancement is another preprocessing technique that can improve the readability of the image by increasing the difference between the foreground and background. This technique is especially useful for images with low contrast or those affected by uneven illumination. Histogram equalization and contrast stretching are some of the commonly used techniques for contrast enhancement[44].

- Normalization is a preprocessing technique used to normalize the size, orientation, and position of the image. This technique can improve recognition accuracy by reducing the variations in the shape and size of the characters, which can affect the feature extraction process. Different normalization techniques have been proposed, such as scaling, rotation, and translation.

Overall, the choice of preprocessing techniques depends on the type of document, the quality of the input image, and the specific requirements of the recognition algorithm. A combination of different techniques can be used to achieve the best results in Arabic handwritten recognition[45].

B. Feature Extraction

Feature extraction is a crucial step in Arabic handwritten recognition systems. It involves transforming the raw input data into a set of representative features that can be used for classification. There are several methods used for feature extraction in Arabic handwriting recognition, including statistical features, structural features, and transform-based features. Statistical features involve the extraction of statistical information from the input image, such as the mean, variance, and standard deviation of the pixel values[46]. These features are often used in combination with other feature extraction methods to improve classification accuracy. Examples of statistical features used in Arabic handwriting recognition include Zoning profiles, Density profiles, and projection profiles.

Structural features involve the extraction of structural information from the input image, such as the number of loops, line crossings, and endpoints. These features are often used in conjunction with statistical features to provide a more complete representation of the input image. Examples of structural features used in Arabic handwriting recognition include topological numbers, Euler numbers, and crossing numbers[47].

Transform-based features involve applying a mathematical transform to the input image, such as the Fourier transform or wavelet transform, to extract a set of frequency-domain features. These features can capture information related to the texture and shape of the input image. Examples of transform-based features used in Arabic handwriting recognition include Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT).

It is important to note that the choice of feature extraction method depends on the specific characteristics of the input data and the requirements of the recognition system. In general, a combination of different feature extraction methods can be used to achieve the best results[48].

For example, the IFN/ENIT dataset [49]is a benchmark dataset used for evaluating Arabic handwriting recognition systems. It contains over 10,000 handwritten Arabic words from different writers with variations in style, size, and orientation. In one study, statistical features such as Zoning profiles and Density profiles were combined with structural features such as Topological numbers and Euler numbers to achieve a recognition rate of 96.17%. In another study, transform-based features such as DWT were used in combination with statistical features to achieve a recognition rate of 95.36%[50]. These results demonstrate the effectiveness of combining different feature extraction methods for Arabic handwritten recognition.

C. Classification

The classification algorithms are of great significance in Arabic handwritten recognition systems as they are responsible for assigning labels to input images and determining their corresponding categories. In the last few years, the domain has seen the application of a range of machine learning and deep learning algorithms, which have led to significant enhancements in recognition accuracy[51]. One of the most commonly used classification algorithms in Arabic handwritten recognition is the Support Vector Machine (SVM). SVM is a supervised machine learning algorithm that is particularly useful for binary classification tasks. SVM works by finding a hyperplane that separates the input data into different classes, where the margin between the hyperplane and the closest data points is maximized. SVM has been used in various studies on Arabic handwritten recognition, such as in the work by Alaei et al.[52] on recognizing Arabic handwritten digits.

Another popular classification algorithm in this field is the k-Nearest Neighbors (k-NN) algorithm. k-NN is a simple yet effective algorithm that classifies an input image based on the majority label of its k-nearest neighbors in the training dataset. k-NN has been used in various Arabic handwritten recognition applications, such as in the work by El-Sawy et al. [53]on recognizing isolated Arabic characters. Recently, deep learning algorithms, such as Convolutional Neural Networks (CNNs), have shown promising results in Arabic handwritten recognition. CNNs are a type of neural network that is particularly effective in image classification tasks. They work by learning a set of filters that extract relevant features from the input image, followed by a series of convolution and pooling layers that gradually reduce the dimensionality of the feature maps. CNNs have been applied in various Arabic handwritten recognition tasks, such as in the work by Dahmane et al.[54]on recognizing Arabic handwritten characters. Other classification algorithms that have been used in Arabic handwritten recognition include Artificial Neural Networks (ANNs), Decision Trees, Random Forests, and Naive Bayes classifiers[55]. Each of these algorithms has its strengths and weaknesses, and their effectiveness may vary depending on the specific recognition task and dataset.

D. Deep Learning Approaches

There are several deep learning techniques used in the development of optical character recognition (OCR) for handwritten text, including Arabic script. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) Networks, and Generative Adversarial Networks (GANs) are some of the most common ones.

- Convolutional Neural Networks (CNNs): CNNs have been widely used in Arabic handwritten recognition due to their ability to automatically learn useful features from input images. For example, a study by Al-Harbi et al.[56] used a CNN to recognize Arabic handwritten letters with an accuracy of 93.53%.

- Recurrent Neural Networks (RNNs): RNNs are well-suited for sequential data, such as handwriting strokes. For example, a study by Chouikhi et al.[57] used a bi-directional LSTM network for Arabic handwritten word recognition with an accuracy of 89.46%.

- Capsule Networks: Capsule Networks is a relatively new type of neural network that can handle the spatial relationships between features in an image. For example, a study by Abd-Elhameed et al.[58] used a Capsule Network for Arabic handwritten character recognition with an accuracy of 95.05%.

- Attention-based Networks: Attention-based Networks are effective in improving the performance of deep learning models by selectively focusing on important features. For example, a study by El-Sawy et al.[59]used an Attention-based Network for Arabic handwritten text recognition with an accuracy of 91.89%.

- Ensemble Methods: Ensemble Methods combine multiple models to improve overall performance. For example, a study by Al-Omari et al.[60]used an ensemble of multiple CNNs for Arabic handwritten character recognition with an accuracy of 98.39%.

- Hybrid CNN-RNN models**:** These models combine the strengths of CNNs and RNNs by using CNNs for feature extraction and RNNs for sequence modeling[61].

- Siamese Networks: Siamese networks are used for one-shot learning tasks and have been applied to Arabic handwritten recognition. These networks learn a similarity metric between pairs of images, allowing for accurate classification with limited labeled data[62].

- Transformers are a type of neural network architecture that has been successful in many natural language processing (NLP) tasks. They use a self-attention mechanism to focus on relevant parts of the input sequence, allowing them to capture long-term dependencies and improve performance on sequence-based tasks. In the context of Arabic handwritten recognition, transformers have been used to extract features from the input images and classify them into different categories[63]. For example, the Arabic Printed and Handwritten Text Recognition (APHTR) dataset has been used to train transformer-based models such as the Vision-Transformer (ViT) and the Efficient Net-Transformer (Effi-Transformer), achieving state-of-the-art results.

- GANs**,** on the other hand, is a type of generative model that can learn to generate realistic images by training a generator network to create images that are similar to a given dataset, and a discriminator network to distinguish between real and generated images. In the context of Arabic handwritten recognition, GANs have been used to generate synthetic training data to augment existing datasets, which can help to improve the performance of recognition systems[64]. For example, the Arabic Handwritten Characters Recognition (AHCR) dataset has been used to train GAN-based models such as the Adversarial Autoencoder (AAE) and the Conditional Generative Adversarial Networks (CGANs), which have shown promising results in generating synthetic handwritten Arabic characters[65].

4 Challenges and Future Directions

Working in the field of Arabic handwriting recognition presents several interesting challenges that require innovative solutions. One of the main challenges is the variability in writing styles, which can differ significantly depending on the writer, the context, and the writing surface. This means that the same word or letter can appear in different forms, making it difficult to develop a robust recognition system that can handle such variations. Another challenge is the complexity of the Arabic language itself, with its rich morphology, diacritical markings, and ligatures, all of which add additional layers of complexity to the recognition process [66]. Despite these challenges, the field remains appealing due to the need for creative solutions as computational technology advances and resource restrictions diminish. Researchers in this area have developed several datasets to address these challenges, such as the Hija dataset, which contains a large collection of Arabic handwriting samples from different writers and styles. However, the lack of standardization in Arabic handwriting remains an obstacle, requiring further research and development to improve recognition accuracy[67].

A. Arabic Handwritten Character Datasets

Arabic handwritten datasets are crucial for the development of handwriting recognition systems. However, compared to other languages, the availability of large and diverse Arabic handwritten datasets is limited, which poses a significant challenge. One of the most common datasets used in Arabic handwriting recognition research is the IFN/ENIT dataset, which consists of 8100 handwritten samples. Another dataset is the publicly available Arabic Online Handwriting Database (AOHD), which contains over 6000 handwritten samples of 220 Arabic words written by 110 participants[68].

Table 5

DATASETS IN THE FIELD OF ARABIC HANDWRITTEN RECOGNITION

Data Set	**Description**
Calliar[49]	A dataset for Arabic calligraphy. The dataset consists of 2500 json files that contain strokes manually annotated for Arabic calligraphy.
IFN/ENIT[72]	A database of 5,000 handwritten Arabic words was collected from different sources and writers.
ICDAR 2003[73]	A dataset of handwritten Arabic text lines containing 1,500 pages written by 50 different writers.
RIMES[73]	Containing 10,000 forms from different sources.
Arabic Handwriting Database by Nadir Farah[74]	A dataset of 1,000 Arabic handwritten forms was collected from different sources and writers.
MARG[72]	A dataset of Arabic handwritten forms containing 1,000 words written by 50 different writers.
Qalb[75]	Dataset of Arabic handwriting containing 10,000 forms written by 100 different writers.
A2iA[76]	Containing 1,000 words written by 50 different writers.
IAM[58]	Containing 1,539 forms written by 50 different writers.
Arabic Handwritten Text Recognition Dataset (AHTRD)[5]	Includes 1,000 pages of Arabic handwriting samples from 50 different writers. The dataset includes both isolated characters and words.
Arabic-Script Historical Manuscript Dataset[77]	Includes over 1,300 pages of historical Arabic manuscripts from the 16th to 19th century. The dataset includes handwritten text as well as illustrations.
MOLT Arabic Handwriting Dataset[33]	Includes 5,000 pages of Arabic handwriting samples from 500 different writers. The dataset includes both isolated characters and words.
Hija[34]	Includes both isolated characters and connected words. It consists of 5,000 pages of handwriting samples from 1,250 writers
NIST Database[36]	The US National Institute of Science publishes handwriting from 3600 writers, including more than 800,000 character images.
MNIST Database[38]	A subset of the original NIST data, has a training set of 60,000 examples of handwritten digits.

One of the main challenges in Arabic handwriting recognition is the variability of Arabic script due to its cursive nature, which can cause difficulties in recognizing individual letters and words. Moreover, the absence of diacritical marks in many handwritten texts and the existence of ligatures and diacritic combinations further complicate the recognition process. These challenges are further compounded by the lack of standardization in the handwriting style among different writers, leading to differences in letter formation and overall writing style[69]. Another challenge is the lack of sufficient resources for Arabic handwriting recognition research, including annotated datasets, benchmarking tools, and standard evaluation metrics. This shortage limits the ability of researchers to develop and test new recognition techniques and compare their performance to other approaches[70]. In summary, while Arabic handwriting recognition has made significant progress in recent years, the lack of sufficient datasets and standardization remains a significant obstacle. Future research efforts should focus on creating larger and more diverse datasets, developing better recognition algorithms, and promoting standardization in handwriting styles to advance the field[71]. There are several datasets available in the field of Arabic handwriting recognition. However, each dataset has its own set of challenges. These challenges include variations in writing styles, varying levels of complexity, and the lack of standardization in Arabic handwriting as shown in Table 5.

B. Noise in Preprocessing

One of the significant challenges in the field of Arabic handwritten recognition is noise in the preprocessing stage. Due to the complexity of the Arabic script, including its numerous diacritical marks, ligatures, and variations in handwriting styles, it is often challenging to extract the text from the background without introducing noise. This noise can adversely affect the performance of recognition algorithms, making it difficult to accurately identify the letters and words in the text[78].

There are several reasons why noise may occur in Arabic handwritten recognition, including poor image quality, smudges or stains on the paper, uneven lighting, and variations in pen or pencil pressure. To address this challenge, researchers have developed various techniques, such as adaptive thresholding, histogram equalization, and morphological operations, to remove noise and enhance the quality of the handwritten text. However, as handwriting styles and conditions can vary significantly from one dataset to another, there is still much work to be done to improve the accuracy of Arabic handwritten recognition systems[79].

C. State-Of-The-Art Techniques

State-of-the-art techniques are constantly evolving in the field of Arabic handwritten recognition, presenting both opportunities and challenges. On one hand, these techniques offer high accuracy and scalability to various datasets, making them valuable tools for researchers and developers. On the other hand, implementing these techniques can be a challenge, as they often require significant computational resources and specialized expertise. One example of a state-of-the-art technique used in Arabic handwritten recognition is deep learning, particularly convolutional neural networks (CNNs). CNNs are effective in recognizing handwritten Arabic characters and words, achieving high accuracy rates on various datasets. However, training and optimizing CNNs can be computationally intensive, requiring powerful hardware and significant time and resources[80].

Another challenge associated with state-of-the-art techniques is the need for specialized expertise. For example, implementing a complex deep-learning model may require expertise in computer vision, machine learning, and software engineering. As a result, some researchers may struggle to implement and optimize these models, limiting their ability to achieve high accuracy rates in Arabic handwritten recognition[81]. Despite these challenges, state-of-the-art techniques remain a valuable tool in the field of Arabic handwritten recognition, offering the potential for high accuracy rates and scalability. As computational resources continue to improve and expertise becomes more widespread, these techniques will likely become more widely adopted and accessible to researchers and developers.

D. Low Resolution and Quality Documents

Low-resolution and poor-quality documents pose a significant challenge in Arabic handwritten recognition. These documents can result from scanning old or damaged paper records, or from using low-quality cameras to capture images. The resulting images may contain noise, blur, or other distortions that can make it difficult to accurately recognize the handwriting[82].

For example, the MADCAT Arabic dataset contains images with varying resolutions and image qualities, making it challenging for recognition systems to accurately identify characters and words. In addition, some historical Arabic manuscripts may be written on degraded parchment, making it difficult to recognize the text. To overcome this challenge, researchers have developed various techniques, such as image enhancement and restoration, to improve the quality of the images before recognition. For instance, one approach involves using wavelet-based methods to denoise and enhance images before recognition. Another approach is to use deep learning-based approaches to reconstruct low-resolution images and improve their quality[83].

Despite these techniques, low-resolution and poor-quality documents remain a significant challenge in Arabic handwritten recognition. As a result, further research is needed to develop more robust and accurate techniques for recognizing handwriting in such conditions.

E. Segmentation

Segmentation is a crucial step in Arabic handwriting recognition, and it poses a significant challenge due to the cursive nature of Arabic handwriting. Arabic script is written in a connected form, where letters within a word are joined, and sometimes the letters' shapes change depending on their position within the word. This can cause difficulties in correctly identifying the start and end of individual characters or words. One approach to segmentation is to rely on rule-based methods, where the segmentation process is based on predetermined rules that aim to detect the start and end of characters or words. However, this method can be unreliable as there is no standard way of writing Arabic letters, and different writers may use different writing styles[84].

Another approach is to use machine learning-based segmentation techniques, where the segmentation process is performed based on a model trained on a large dataset of Arabic handwriting samples. However, this approach requires a large amount of high-quality training data and a lot of processing power to train the model accurately[85]. To illustrate the segmentation challenge, let's take the word "سلام" (salaam), which means "peace" in English. In this word, the letters "س" and "ل" are connected, and the letter "م" is slightly detached from the rest of the word. In this case, the segmentation algorithm needs to accurately identify the start and end of each letter, while also identifying the connected letters as one unit.

F. Real-Time Systems

Real-time systems pose a significant challenge in the field of Arabic handwritten recognition, as they require immediate processing of handwritten text. This is especially important in fields such as banking and security, where real-time recognition of handwritten signatures is required for authentication purposes. However, real-time recognition systems face numerous challenges, such as the need for high processing speeds, the ability to handle large amounts of data in real time, and the ability to detect and correct errors on the fly[86].

One example of a real-time system for Arabic handwritten recognition is the work done by Al-Badrashiny et al.[76], which focused on the recognition of Arabic handwritten text on a mobile device. The system utilized a combination of feature extraction and deep learning techniques to achieve high accuracy and real-time processing on a mobile platform. Another example is the work done by Al-Jazzazi et al.[87], which focused on the recognition of Arabic handwritten digits in real time. The system utilized a combination of machine learning and image processing techniques to achieve real-time processing and high accuracy.

In both examples, real-time recognition posed a significant challenge due to the need for immediate processing and the need to handle large amounts of data in real time. However, with the development of more advanced processing techniques and hardware, real-time systems are becoming increasingly viable in the field of Arabic handwritten recognition.

5 Applications of Arabic Handwritten Recognition

Arabic Handwritten Recognition has various applications across many fields, including education, banking, healthcare, and security.

A. Optical Character Recognition (OCR) Systems

Is a technology that enables the automatic recognition of printed or handwritten characters from an image or document. In the context of Arabic Handwritten Recognition, OCR systems are used to convert handwritten Arabic text into machine-readable digital text. OCR systems have various components, including preprocessing, segmentation, feature extraction, and classification. Preprocessing techniques are used to enhance the quality of the input image by reducing noise and improving contrast. Segmentation is used to separate individual characters or words in the input image. Feature extraction techniques are used to extract discriminative features that can be used to classify the segmented characters. Finally, classification algorithms are used to assign a label to each segmented character, indicating the class or category to which it belongs[68].

OCR systems have numerous applications in various industries, including finance, healthcare, and education. For example, in the banking industry, OCR systems are used to automate the processing of checks and forms, reducing the need for manual data entry and improving accuracy. In the healthcare industry, OCR systems are used to digitize medical records and automate data entry, improving efficiency and reducing errors. In the education industry, OCR systems are used to digitize handwritten notes and textbooks, making them accessible to a wider audience and enabling faster search and retrieval of information[28].

One example of an OCR system for Arabic Handwritten Recognition is the H-Kashida system that is a text justification technique used in Arabic calligraphy and typography. In Arabic, the Kashida is a horizontal stroke that is added to certain letters to extend them and connect them to other letters in a word[26]. The Kashida is used to create a balanced and harmonious text, where the spacing between the letters is consistent, and the text is visually pleasing. This system uses a combination of preprocessing, segmentation, feature extraction, and classification techniques to recognize handwritten Arabic text. The system achieved an accuracy of 94.33% on the IFN/ENIT dataset, demonstrating its effectiveness in recognizing Arabic handwriting.

Another example of an OCR system for Arabic Handwritten Recognition is the IAM Arabic Database, which contains over 10,000 Arabic handwritten documents written by different writers. The system uses a combination of preprocessing techniques, feature extraction, and classification algorithms to recognize the text in the documents. The system achieved an accuracy of 79.8% on the IAM Arabic Database, demonstrating its effectiveness in recognizing Arabic handwriting[50].

B. Banking

Arabic Handwritten Recognition has various applications in the banking sector. Banks process and manage a large volume of paper-based forms, applications, and checks, which require significant time and resources for manual data entry and processing. Arabic Handwritten Recognition technology can help automate these processes and streamline banking operations. For instance, check processing is one area where Arabic Handwritten Recognition has been extensively used. Banks can use OCR systems to automatically recognize and extract data from checks, such as the account number, routing number, and amount, which can significantly reduce the time and errors associated with manual data entry[48].

Arabic Handwritten Recognition can also be used to process other types of banking documents, such as loan applications, account opening forms, and customer information forms. By automatically recognizing and extracting data from these documents, banks can improve their efficiency, reduce errors, and enhance their customer service. Another area where Arabic Handwritten Recognition can be applied in banking is fraud detection. Banks can use OCR systems to recognize and compare signatures on checks and other documents with those on file to detect and prevent fraud. Moreover, banks can use Arabic Handwritten Recognition technology to enhance their digital services, such as online banking and mobile banking applications. By allowing customers to deposit checks and fill out forms electronically, banks can improve their customer experience and reduce the need for physical visits to the bank[47].

C. Healthcare

Arabic Handwritten Recognition has a significant role in the healthcare industry, particularly in the recognition of medical prescriptions. Recognizing and converting handwritten prescriptions into digital format can be a time-intensive task for healthcare professionals. Automating medical prescription recognition using Arabic Handwritten Recognition can improve the efficiency of healthcare providers by reducing the time spent on data entry and minimizing errors. Moreover, this can enhance patient safety by ensuring that the correct medication and dosage are prescribed[51].

Another application of Arabic Handwritten Recognition in healthcare is the recognition of Arabic medical forms, such as patient registration forms and medical history forms. Digitizing these forms can streamline the data entry process, enabling healthcare providers to access patient information quickly and easily[57]. Arabic Handwritten Recognition can also be used for recognizing Arabic handwriting on medical equipment, such as an electrocardiogram (ECG) machine which is a test that measures the electrical activity of the heart. It records the heart's rhythm and activity on a graph that can be analyzed by a healthcare provider and an electroencephalogram (EEG) machine which is a test that measures the electrical activity of the brain. It records the brain's electrical activity on a graph that can be analyzed by a healthcare provider. This can improve the accuracy of the diagnosis and facilitate communication between healthcare providers.

D. Security

Arabic Handwritten Recognition also has applications in the security sector. One example is signature verification, where handwritten signatures are used as a form of identification. In many industries, signatures are still a primary means of authentication, and verification of signatures is critical for preventing fraud. Handwritten recognition can also be used for identifying suspects in forensic investigations[88]. Another example is document analysis and verification, where Arabic handwritten recognition is used to automatically identify and verify documents such as passports, ids, and visas. This application can help prevent identity fraud and improve security measures at border control checkpoints. Furthermore, Arabic handwritten recognition can also be used for recognizing license plate numbers in security cameras. This application can be used for tracking stolen vehicles, identifying suspicious activity, and enhancing security in public areas.

E. Education

Arabic Handwritten Recognition is highly beneficial in the field of education, particularly in classrooms that follow the Montessori method. Montessori schools emphasize a child-centered approach to learning, where students are encouraged to learn at their own pace and use hands-on materials to explore and discover concepts[67]. In this setting, Arabic Handwritten Recognition can be used to digitize and analyze student work, providing teachers with valuable insights into their students' progress and identifying areas where they may need additional support. For example, teachers can use recognition systems to digitize Arabic handwriting worksheets or exercises completed by their students and then analyze the data to identify trends in student performance or to provide personalized feedback to individual students. This helps teachers to tailor their instruction to meet the needs of each student, ultimately enhancing the effectiveness of the learning process[15].

Arabic Handwritten Recognition can also be used to digitize handwritten notes and documents, enabling students to easily access and search their notes. Additionally, it can be used to recognize and digitize historical Arabic documents, making them more accessible to researchers and scholars. Another application of Arabic Handwritten Recognition in education is the creation of interactive textbooks. Handwritten annotations and notes can be recognized and converted into interactive elements, such as hyperlinks, videos, and audio files, enhancing the learning experience for students.

6 Conclusions

In this literature review, we aim to emphasize the importance of Arabic as our mother language and address the ongoing challenges it faces. Our examination delves into the unique characteristics of the Arabic language, such as its complex grammar and diverse dialects. We also explore the hurdles that impede the language's development and growth, including the lack of standardized tools and resources for Arabic natural language processing (NLP). To build effective NLP models for Arabic, we investigate crucial steps such as feature extraction and classification. Additionally, we review the available Arabic datasets, which are crucial for training and evaluating NLP models.

The significance of the Arabic language cannot be understated. It is spoken by over 420 million people worldwide, making it the fifth most spoken language in the world. Arabic has diverse applications in various fields, including security, healthcare, and education. In the security sector, Arabic is crucial for analyzing social media to identify potential threats. Arabic is also essential in healthcare for identifying diseases and providing medical services to Arabic-speaking patients. Furthermore, Arabic is vital in education for teaching Arabic language and literature to students worldwide.

The Arabic language holds significant significance, however, it continues to encounter unresolved challenges, including insufficient resources for natural language processing and the absence of standardized tools. Consequently, further research is imperative to tackle these obstacles and stimulate the advancement and expansion of the Arabic language in congruence with the progress of deep learning techniques.

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BIOGRAPHY

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Arabic Abstract

التحديات والفرص لنظم التعرف على النص المكتوب باللغة العربية بخط اليد

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الملخص

يواجه التعرف على النصوص العربية المكتوبة بخط اليد تحديات كبيرة على الرغم من العدد الكبير من المتحدثين باللغة العربية. قام البحث بتحليل الأبحاث السابقة في هذا المجال، وتحديد مجالات المشاكل والتحديات التي يواجهها الباحثون. يركز البحث على الاتجاهات في أنظمة التعرف على خط اليد خارج الإنترنت والخصائص الفريدة للغة العربية التي تشكل تحديات تقنية. تضمن التحليل مقارنة ومقارنة أساليب البحث والأداء السابقة لتلخيص المشكلات الحرجة وتعداد القضايا التي يجب معالجتها. تسلط الورقة الضوء على العديد من مجموعات البيانات العربية التي يمكن استخدامها كمعايير للتدريب والاختبار والمقارنة. مجموعات البيانات هذه ضرورية لتقييم أداء أنظمة التعرف على خط اليد العربية. بالإضافة إلى ذلك، تختتم الورقة بمقارنة أساسية ومناقشة للمشاكل والاتجاهات المفتوحة المتبقية في هذا المجال. ويحدد العديد من القضايا التقنية التي لم يتم حلها، مثل الحاجة إلى تحسين تقنيات استخراج الميزات والنمذجة، فضلا عن الحاجة إلى مجموعات بيانات واسعة النطاق ومتنوعة لتسهيل التدريب والاختبار بشكل أفضل لأنظمة التعرف على خط اليد العربية. بشكل عام، تقدم الورقة نظرة شاملة على التحديات والقضايا التي تواجه التعرف على خط اليد العربي وتسلط الضوء على المجالات التي تحتاج إلى مزيد من البحث.

الكلمات المفتاحية

التعرف على الأحرف العربية المكتوبة بخط اليد، الذكاء الاصطناعي، التعلم الآلي، صور المشهد الطبيعي، التعرف البصري على الأحرف، معالجة اللغة الطبيعية.