



Paper Type: Review Article

## Deep Learning Algorithms for Arabic Optical Character Recognition: A Survey

Mohamed G. Mahdi <sup>1,2,\*</sup> , Ahmed Sleem <sup>3</sup> , and Ibrahim Elhenawy <sup>4</sup> 

<sup>1</sup> Department of Computer Science, Higher Institute for Computer Sciences and Information Systems, 5th Settlement, New Cairo, Egypt; [mohamed.grisha@cis.edu.eg](mailto:mohamed.grisha@cis.edu.eg).

<sup>2</sup> Department of Computer Science, Faculty of Computers and Informatics, Zagazig University, Zagazig, Sharqiyah, Egypt; [m.gresha@fci.zu.edu.eg](mailto:m.gresha@fci.zu.edu.eg).

<sup>3</sup> Department of Computer Science, Faculty of Computers and Informatics, Tanta University, Tanta, Egypt; [ahmed.selim@ics.tanta.edu.eg](mailto:ahmed.selim@ics.tanta.edu.eg).

<sup>4</sup> Department of Computer Science, Faculty of Computers and Informatics, Zagazig University, Zagazig, Sharqiyah, Egypt; [ielhenawy@zu.edu.eg](mailto:ielhenawy@zu.edu.eg).

Received: 30 Sep 2023

Revised: 13 Jan 2024

Accepted: 20 Jan 2024

Published: 26 Jan 2024

### Abstract

In recent years, deep learning has begun to supplant traditional machine learning algorithms in a variety of fields, including machine translation (MT), pattern recognition (PR), natural language processing (NLP), speech recognition (SR), and computer vision. Systems for optical character recognition (OCR) have recently been developed using deep learning techniques with great success. Within the area of pattern recognition and computer vision, the procedure of handwritten character recognition is still considered to be one of the most challenging. The height, orientation, and width of the handwritten characters do not always correspond with one another because different people use different writing instruments and have their own unique writing styles. This makes the job of handwritten recognition challenging and difficult. The regional languages of Arabic and Urdu have received less research. In this article, a summary and comparison of the most significant techniques of deep learning that are used in the recognition of Arabic-adapted scripts like Arabic and Urdu have been provided.

**Keywords:** Arabic Natural Language Processing; Urdu Natural Language Processing; Optical Character Recognition; Handwritten Character Recognition; Deep Learning.

## 1 | Introduction

Optical Character Recognition (OCR), refers to the automated conversion of printed or handwritten text images captured by scanning or photography into text that can be read by machines. The technology of OCR has been in existence since the early days of computing and has undergone continuous enhancement through the evolution of machine learning and computer vision techniques [1-3].



Corresponding Author: [mohamed.grisha@cis.edu.eg](mailto:mohamed.grisha@cis.edu.eg); [m.gresha@fci.zu.edu.eg](mailto:m.gresha@fci.zu.edu.eg)



<https://doi.org/10.61356/j.mawa.2024.26861>



Licensee **Multicriteria Algorithms with Applications**. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0>).

The functioning of OCR technology involves analyzing the visual features of the input image, including the individual characters' size, shape, and placement. Classification algorithms are then employed to identify each character and transform it into digital text. This technology is applicable to various types of documents, such as receipts, books, newspapers, handwritten notes, and business cards [4].

The practical uses of OCR technology are extensive and include tasks like streamlining data entry tasks, digitizing historical documents, and enhancing accessibility for visually impaired individuals. When combined with other technologies, such as natural language processing (NLP) and machine translation (MT), OCR can facilitate advanced applications such as sentiment analysis (SA) and automated language translation (ALT) [5].

Although OCR technology has significantly transformed how textual information is processed and analyzed, it is not entirely error-free, and there are certain challenges related to its application. One of the foremost difficulties is managing the variations present in the input image, such as differences in font style, size, variations, or spacing in writing style for handwritten text. To ensure precise outcomes, OCR algorithms must be meticulously designed and trained to handle such variations. Nonetheless, OCR technology's impact on society is projected to expand in the future [6-8].

Deep learning has revolutionized OCR by allowing more accurate character recognition than ever before. With the use of deep neural networks, OCR systems can learn to recognize characters and words with high accuracy, even when dealing with noisy or distorted images [9, 10].

One of the main advantages of deep learning-based OCR systems is that they can recognize characters and words based on their visual features rather than relying on pre-defined patterns or templates. This means that they are more adaptable to new fonts, styles, and languages, which makes them more practical for real-world applications [11].

There are two main approaches to deep learning-based OCR: fully supervised learning and semi-supervised or unsupervised learning. Fully supervised learning requires a large dataset of labeled images of input characters or words to train, while semi-supervised or unsupervised learning can work with fewer labeled images and can also utilize unlabeled data during training [2, 10].

Overall, deep learning has led to significant improvements in the accuracy and efficiency of OCR systems and has enabled a wide range of new applications for character recognition, including document digitization [12] and automatic text recognition in images or video surveillance [13, 14].

The study of recognizing handwritten characters is a field of research that concentrates on formulating algorithms and methodologies for the automatic identification and conversion of handwritten characters into machine-readable or digital text. This field has a significant role to play in various sectors, such as healthcare, education, and finance, which still rely heavily on handwritten documents [15].

With the progress in machine learning and computer vision, the field of recognizing handwritten characters has progressed significantly in recent years. These systems first pre-process the incoming image, then segment the characters into their constituent parts, and finally use classification algorithms to identify each character. Deep learning techniques like convolutional neural networks (CNN) have been particularly effective in achieving state-of-the-art performance in handwritten character recognition. However, obstacles such as the diversity of handwriting styles and the need for substantial amounts of annotated data still exist. Nonetheless, further progress in this field offers immense potential for enhancing the processing and analysis of handwritten documents.

This work explores different deep learning techniques used in the recognition of Arabic-adapted scripts and Urdu. In this research, the studies conducted in the last 5 years were listed, taking into account the existence of survey papers in this field. The studies also covered various other years, providing a comprehensive overview. The structure of this paper is as follows: In the second section, we review previous studies that have used deep learning for Arabic language recognition. Section 3: We examine past research that has utilized

deep learning techniques for recognizing other languages, like Urdu. The conclusion is presented in Section 4.

## 2 | Arabic Natural Language Processing

The Arabic language is the one that is used the most frequently among the Semitic languages. Arabic is the official language of a total of 26 countries, and it is estimated that 372 million people around the globe are able to speak the language. The Arabic language is used by Muslims around the world to read the Holy Quran, which is written in Arabic. This places Arabic as the sixth most common language in use today. In addition to this, it is one of the six languages that the United Nations (UN) recognizes as official, along with Chinese, English, French, Russian, and Spanish [16]. Writing in Arabic uses a cursive form of the Arabic language, and it is read from right to left. There are 28 different characters used in the Arabic language. The size of the character is not set in stone; rather, it changes depending on the shape of the character, the font used, and its location within the word (beginning, middle, end, or isolated), as shown in Table 2. In addition, the writing system of Arabic makes use of diacritical marks to symbolize short vowels and other sounds. Some examples of these marks or diacritics include "fatha," "dhumma," "Tanween," and "kasra," as shown in Table 3. In addition, Arabic has a large number of ligatures, which are created by combining two or more characters, such as the combination "alif-laam." It's possible for a single character to have any number of dots, from one to three, as well as unique characters like "Hamza," as shown in Table 1. It's possible for a single term in English to have multiple meanings when translated into Arabic, as is the case with the words "good" and "love." In addition, other languages, such as Farsi, Kurdish, Urdu, and Pashto, borrow words, characteristics, and structural elements from Arabic. In light of the foregoing, this constitutes a significant obstacle for researchers working in the field of Arabic language comprehension [17-19].

In [20], the authors introduce Hijja, a new dataset of Arabic letters written by children aged 7-12, and propose an automatic handwriting recognition model based on CNN. They train their model on both Hijja and the Arabic Handwritten Character Dataset (AHCD) and achieve promising results, with accuracies of 97% and 88% on the AHCD and Hijja datasets, respectively. The authors also find that their model outperforms other models in the literature on all metrics. However, they note that the Hijja dataset is more challenging than the AHCD dataset, as their model performs worse on it. Overall, this paper demonstrates the potential of using convolutional neural networks for recognizing Arabic handwriting.

In [21], authors present a new deep learning system called AHCR-DLS for recognizing Arabic handwritten characters, aiming to address the challenges associated with this task. The AHCR-DLS system achieves high accuracy rates on the train dataset, with an average accuracy of 97.3% for HMB1 and 96.8% for HMB2, and on the test dataset, with an average accuracy of 95.5% for HMB1 and 94.9% for HMB2, demonstrating the effectiveness of the proposed approach.

In [22], the authors propose a novel approach for classifying handwritten Arabic characters using a CNN and an optimized leaky ReLU activation function. The results showed that the proposed approach achieved high accuracy, outperforming both ReLU (97.8%) and leaky ReLU (97.9%) with the four datasets used in this study. Overall, this paper demonstrates that using deep learning techniques can significantly improve the performance of handwritten Arabic character recognition systems compared to traditional methods or other activation functions like ReLU or leaky ReLU.

Elkhayati and Elkettani [23] introduce a new directed CNN model (UnCNN) for recognizing isolated Arabic handwritten characters. The paper reports the effectiveness of the approach by comparing it with BsCNN and other recent models. The proposed UnCNN model is evaluated using four benchmark databases: IFHCDB, AHCD, AIA9K, and HACDB. Compared to recent models in the literature, UnCNN achieves competitive performance with some models and outperforms others.

In [24], Alghyaline presents a novel approach for recognizing printed Arabic characters using deep learning. The approach called Printed Arabic Optical Character Recognition (PAOCR) is based on the state-of-the-art

You Only Look Once (YOLO) object detector and consists of four techniques. The first technique involves customizing and training YOLO4 on deep CNNs to recognize Arabic characters. The second technique involves processing overlapped bounding boxes to ensure the most accurate box is selected for each character. The third technique uses the Hunspell library to check word spelling and correct any errors. Finally, the fourth technique uses edit distance to compare OCR misspelled words with Hunspell's suggestions and choose the closest correct word. The proposed PAOCR system achieved an impressive accuracy rate of 82.4% on a dataset of printed Arabic characters.

Table 1. Hamza and its combination with other letters in Arabic.

Name	shape	Example	Pronunciation	Meaning In English
Hamza on an Alef	ء	ءآدم	hamza-adam	Adam
Hamza above an Alef	أ	أبوين	abayn	parents
Hamza below an Alef	إ	إبراهيم	ibrahim	Ibrahim
Hamza on top of Ya	ئ	سئمت	sa'imtu	I got tired
Hamza under Ya	يء	مُتَلِفٌ	muta'llifun	a novelist
Hamza on top of Ya with Alef	ئا	فئة	fa'atun	"a group" or "a category"
Hamza on top of Ya with Waw	ئو	مئوي	ma'wiyyun	square
Hamza on top of Waw	ؤ	مؤمنون	mu'minoon	believers

Table 2. The pronunciation of each Arabic letter in English and Arabic and its location within the word (beginning, middle, end, or isolated).

No.	Pronunciation in English	Pronunciation in Arabic	Isolate	Position		
				Beginning	Middle	End
1	Alef	الف	ا	ا	ا	ا
2	Baa	باء	ب	ب	ب	ب
3	Taa	تاء	ت	ت	ت	ت
4	Thaa	ثاء	ث	ث	ث	ث
5	Jim	جيم	ج	ج	ج	ج
6	Ha	حاء	ح	ح	ح	ح
7	Kha	خاء	خ	خ	خ	خ
8	Dal	دال	د	د	د	د
9	Thal	ذال	ذ	ذ	ذ	ذ
10	Ra	راء	ر	ر	ر	ر
11	Zayn	زين	ز	ز	ز	ز
12	Seen	سين	س	س	س	س
13	Sheen	شين	ش	ش	ش	ش
14	Sad	صاد	ص	ص	ص	ص
15	Dad	ضاد	ض	ض	ض	ض
16	Taa	طه	ط	ط	ط	ط
17	Zaa	ظه	ظ	ظ	ظ	ظ
18	'Ayn	عين	ع	ع	ع	ع
19	Ghayn	غين	غ	غ	غ	غ
20	Fa	فاء	ف	ف	ف	ف
21	Qaf	قاف	ق	ق	ق	ق
22	Kaf	كاف	ك	ك	ك	ك
23	Lam	لام	ل	ل	ل	ل
24	Meem	ميم	م	م	م	م
25	Noon	نون	ن	ن	ن	ن
26	Ha	هاء	ه	ه	ه	ه
27	Waw	واو	و	و	و	و
28	Ya	ياء	ي	ي	ي	ي

**Table 3.** Arabic diacritics with examples and pronunciations.

Name	Diacritics	Example	Pronunciation	Meaning In English
Fatha	◌َ	كَتَبَ	Kataba	he wrote
Kasra	◌ِ	كِتَابِ	kitabin	a book
Damma	◌ُ	كُتِبَ	kutiba	it was written
Sukun	◌ْ	كتب	k-t-b	Books
Shadda	◌ّ	كِتابّ	Kittab	writer
Tanween	Fathatan	كِتَابًا	Kitaban	a book
	Kasratan	كِتَابٍ	Kitabin	a book
	Dammatan	كِتَابٌ	kitabun	a book

## 2.1 | CNN Hybrid with Other Algorithms

In [25], this study introduces a novel model for single font and multi-font types using support vector machines (SVM) and CNN classifiers. The model incorporates dropout to address overfitting and performs automatic classification and feature extraction. The authors propose a depth neural network training rule and combine max-margin minimum classification error (M3CE) and cross-entropy approaches for improved results. The model is evaluated on several databases and compared to state-of-the-art Arabic text recognition methods, demonstrating favorable outcomes.

In [26], researchers discuss the use of deep learning and genetic algorithms for recognizing handwritten Arabic characters. This study aims to automate Arabic content recognition, which is still in its early stages compared to Latin and Chinese content recognition. This study focuses on text processing, particularly text segmentation and recognition. It discusses the challenges of text segmentation and proposes solutions for each challenge. The recognition phase utilizes a CNN to improve classification algorithms by automatically extracting features from images. The study evaluates 14 different CNN architectures and achieves a maximum testing accuracy of 91.96% on handwritten Arabic characters. To optimize training parameters, a transfer learning and genetic algorithm approach called "HMB-AHCR-DLGA" is introduced, achieving a testing accuracy of 92.88% through five optimization experiments.

In [27], researchers compare the performance of Bayesian and CNNs for recognizing Arabic handwritten words. The study reports that the CNN-based system outperforms the Bayesian-based system, achieving an accuracy rate of 96.8% compared to 91.5%. The paper describes the proposed system based on probabilistic graphical models (PGM) and CNN models and provides details on the experiments conducted to compare the performance of these models on the IFN-ENIT database. Overall, this paper provides valuable insights into the effectiveness of different machine learning methods for Arabic handwriting recognition.

## 2.2 | Long Short-Term Memory (LSTM)

In [28], the performance of 1D and 2D LSTM architectures for recognizing handwritten Arabic is compared. The authors demonstrate that using a simple pre-processing step to normalize the position and baseline of letters, 1D LSTM can achieve superior performance while being faster in learning and convergence. The authors report achieving an accuracy of 91.5% on the IFN/ENIT database using their proposed pipeline, which outperforms both manually crafted features with 1D LSTM (87.4%) and 2D LSTM networks (72.9%).

The authors also compare their results with previous work that concluded the better performance of manually crafted over automatically learned features (using 1D LSTM) for Arabic handwriting recognition and demonstrate the superior performance of their proposed system over manually crafted features for this task.

### 2.3 | LSTM Hybrid with other Algorithms

In [13], the authors present a deep learning-based system for recognizing Arabic script that has been benchmarked on the KHATT dataset. The deep learning model is based on an MDLSTM architecture with a CTC layer for alignment, and data augmentation techniques are introduced to enrich the input feature space. The system achieves an accuracy of 80% on the KHATT dataset, representing a significant improvement over the previous method. The authors attribute this improvement to the use of deep learning and data augmentation techniques.

In [29], a new approach uses an LSTM network with the aid of an Elephant Herding Optimization (EHO) algorithm. Hybrid feature descriptors, such as ELBP and IDMN, are employed to extract feature values from segmented individual characters. The EHO algorithm is then utilized to optimize the dimension of these features, reducing overfitting concerns and improving the training and testing mechanisms of the classifier. The optimized features are then inputted into the LSTM network for character classification. The simulation results show that the proposed EHO-LSTM model achieves high accuracy rates of 96.66%, 96.67%, and 99.93% for English, Kannada, and Arabic character recognition on the chars74K and MADbase digit datasets.

### 2.4 | Other Techniques

In [30], this research paper presents a model for Arabic handwriting recognition that combines the ResNet50 architecture with either SVM or Random Forest (RF) algorithms. The study finds that combining ResNet50 with Random Forest produces more accurate and consistent results compared to using ResNet50 alone. The experimental work conducted in this study involves three datasets: the Arabic Handwritten Character Dataset (AHCD), the Alexa Isolated Alphabet Dataset (AIA9K), and the Hijja Dataset. The modified ResNet50 architecture achieves recognition rates of 92.37%, 98.39%, and 91.64% for three datasets, while the combined architecture achieves recognition rates of 95%, 99%, and 92.4% for the same datasets, respectively.

In [31], this study proposes the use of residual neural networks (ResNets) for recognizing Arabic offline isolated handwritten characters. The methodology consists of pre-processing, training the ResNet, and testing it on datasets. The approach achieves high accuracy on three datasets (MADBase, AIA9K, and AHCD) and validation accuracy on a combined dataset.

In [32], authors present a comprehensive handwritten Arabic-Maghrebi character database and propose a new approach for recognizing them using a deep auto-encoder scheme. The database includes all basic Arabic alphabets written in the Maghrebi style, which has not been previously studied. The proposed approach achieves a recognition rate of 88% using a backpropagation neural network with the CENPRMI dataset and 76.54% using a combination of multiple HMM classifiers with the IFN/ENIT dataset.

The authors of [33] suggest a two-step method for detecting and recovering out-of-vocabulary words in Arabic handwritten text recognition. The effectiveness of this approach is compared to one-step methods that use a large static lexicon or a combination of sub-word modeling methods. The results presented in this article show that the proposed two-step approach outperforms the other methods, achieving an accuracy rate of 91.5% for out-of-vocabulary word detection and 87.3% for out-of-vocabulary word recovery. This paper provides valuable insights into improving Arabic handwriting recognition systems by addressing the challenge of out-of-vocabulary words.



**Table 4.** Summary of some deep learning applied on Arabic language.

Reference	Approach	Dataset	Accuracy
Altwaijry et al. 2021[20]	CNN	AHCD	97%
		Hijja	88%
Guptha et al. 2022[29]	EHO-LSTM	chars74K	96.66%
		MADbase	99.93%
Ahmad et al. 2020[34]	MDLSTM	KHATT	80%
Yousefi et al. 2015[28]	1D LSTM	IFN/ENIT	87.4%
	2D LSTM		72.9%
Alghyaline 2022[24]	PAOCR	APTI	82.4%
Balaha et al. 2021[26]	CNN and genetic algorithms	HMBD	92.88%
Nayef et al. 2022[22]	CNN+ leaky ReLU	AHCD	99%
		Hijja	90
		AIA9K	94
		D.MNIST	99
Khémiri et al. 2019[27]	PGM+CNN	IFN/ENIT	96.8
Elkhayati et al. 2022[23]	UnCNN	AIA9K	96.1
		IFHCDB	98.4
		AHCD	98.7
		HACDB	95.4
Djaghbellou et al. 2022[32]	deep auto-encoder	HAMCDB	98.63
		AHCD	98.95

## 2.5 | Arabic Datasets

### 2.5.1 | Printed Arabic

The **APTI dataset**<sup>1</sup> was created to evaluate OCR performance on printed Arabic [35]. This extensive dataset comprises 45,313,600 images, each containing a single Arabic word with approximately 250 million Arabic characters. The dataset is synthetic, generated from a distinct set of 113,284 words, and features ten font types, ten font sizes ranging from 6 pt to 24 pt, and four font styles. It is split into five sets, with the fifth set reserved for testing and the others for training. The first four sets were publicly released by the author. A sample of APTI dataset is shown in Figure 1.

The **MMAC dataset**<sup>2</sup> is a collection of printed Arabic text that was created in 2010[36]. It comprises a significant number of unique words and Printed Arabic Word Images (PAWS), which are individual images of the words. It comprises of 282,593 unique words and 66,725 PAWS. The data was gathered from a range of sources, including old books, Arabic research, and the Holy Quran. A notable feature of the MMAC dataset is that the images have been subjected to skewing and noise addition to triple their quantity. This makes the dataset more inclusive and reflective of the variations of images that one might encounter in practical applications. Sample images from the MMAC dataset can be seen in Figure 2.

The **KAFD dataset**<sup>3</sup> was created through a collaboration between King Fahd University and Qassim University [37]. The dataset comprises 15,068 printed text images and 2,576,024 lines. The images have varying resolutions of 100 dpi, 200 dpi, 300 dpi, and 600 dpi, and feature four different Arabic fonts, ten font

<sup>1</sup> <https://diuf.unifr.ch/main/diva/APTI/download.html>

<sup>2</sup> <http://www.ashrafraouf.com/mmac>

<sup>3</sup> <http://kafd.ideas2serve.net>

sizes ranging from 8 to 24 points, and four font styles: Normal, Bold, Italic, and Bold Italic. The dataset is divided into training, testing, and validation sets and is a valuable resource for researchers and developers working on OCR and Arabic language processing.

- A : نقدّم في هذا البحث قاعدة بيانات لكلمات عربية  
 B : نقدّم في هذا البحث قاعدة بيانات لكلمات عربية  
 C : نقدّم في هذا البحث قاعدة بيانات لكلمات عربية  
 D : نقدّم في هذا البحث قاعدة بيانات لكلمات عربية  
 E : نقدّم في هذا البحث قاعدة بيانات لكلمات عربية  
 F : نقدّم في هذا البحث قاعدة بيانات لكلمات عربية  
 G : نقدّم في هذا البحث قاعدة بيانات لكلمات عربية  
 H : نقدّم في هذا البحث قاعدة بيانات لكلمات عربية  
 I : نقدّم في هذا البحث قاعدة بيانات لكلمات عربية  
 J : نقدّم في هذا البحث قاعدة بيانات لكلمات عربية

**Figure 1.** Fonts used to generate the **APTI Database**: (A) Andalus, (B) Arabic Transparent, (C) Advertising Bold, (D) Diwani Letter, (E) Deco Type Thuluth, (F) Simplified Arabic, (G) Tahoma, (H) Traditional Aatbic, (I) Deco Type Naskh, (J) M Unicode Sara.



**Figure 2.** A representative image from the **MMAC** dataset.

The **Yarmouk Arabic OCR dataset**<sup>1</sup> is a collection of printed Arabic text images [38]. The dataset comprises 8,994 images with a resolution of 300 dpi, and the images contain 436,921 words extracted from the Wikipedia website.

The **APTID/MF dataset** is a collection of printed Arabic text images that was developed in 2013 [39]. The dataset consists of 1,845 images with a resolution of 300 dpi, containing 27,402 characters. The images were taken from 387 pages of Arabic documents and include ten different font types, two font styles (normal and bold), and four font sizes (12 pt, 14 pt, 16 pt, and 18 pt).

The **ARABASE dataset** is a collection of printed and handwritten Arabic text images [40]. The handwritten images were written by over 400 writers, mostly from Tunisia, while the printed text was obtained from daily newspapers and a book published by the Tunisian national library on the internet. The images have resolutions ranging from 200 dpi to 600 dpi.

### 2.5.2 | Arabic Handwritten

The **HACDB dataset**<sup>2</sup> is a collection of Arabic handwritten characters developed by a team of researchers [41]. It consists of 6,600 characters, with each of the 50 writers producing 132 shapes of characters. The shapes depict the different ways Arabic characters can be written in various positions within a word, such as the beginning, middle, end, and when they stand alone. This dataset is highly valuable for researchers and

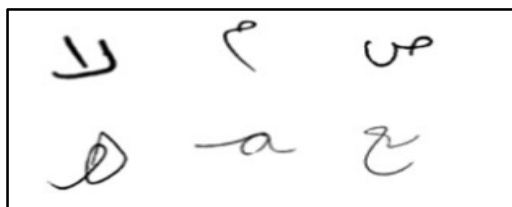
<sup>1</sup><https://drive.google.com/drive/folders/0B4Kx3iMuktgsdC12Ui1neknMzQ?resourcekey=0dX3YkFT4xArRrT81wQ2wSw>

<sup>2</sup> <https://www.kaggle.com/datasets/mloey1/ahcd1>



developers working on Arabic character recognition and OCR tasks. It has been used in several studies related to Arabic handwriting recognition and is particularly advantageous in evaluating machine learning algorithms' performance. One of the HACDB dataset's outstanding features is its inclusion of various handwriting styles, as it was collected from a diverse group of writers. This aspect makes it more reflective of the variations in Arabic handwriting that can be encountered in real-world scenarios. Sample images from the HACDB dataset can be seen in Figure 3.

The **Hijja dataset**<sup>1</sup> is a collection of handwritten Arabic letters that were obtained from school children between the ages of 7 and 12 who speak Arabic [20]. The data was collected in Riyadh, Saudi Arabia, from January to April 2019, and comprises a total of 47,434 characters written by 591 participants in various forms. Examples of images from the Hijja dataset are available for viewing in Figure 4.



**Figure 3.** A representative image from the HACDB dataset.



**Figure 4.** Sample picture from the Hijja dataset.

The **KHATT dataset**<sup>2</sup> is a collection of handwritten text [42]. It includes one thousand forms written by one thousand distinct writers and consists of two thousand paragraphs with 9,327 lines sourced from forty-six different sources. The dataset is available in three resolutions, which are 200 dpi, 300 dpi, and 600 dpi, and is partitioned into 70% for training, 15% for testing, and 15% for validation purposes. The KHATT dataset is a valuable resource for researchers and developers working on OCR applications and recognizing handwritten text. It has been used in several studies related to handwritten text recognition and OCR.

The **IFN/ENIT database**<sup>3</sup> is a dataset of handwritten text images [43]. It contains 2,200 images of Tunisian cities with a resolution of 300 dpi, comprising 26,459 words and 212,211 Arabic characters. Considered one of the earliest handwritten text datasets available, the database has been cited 640 times, making it the most widely referenced Arabic OCR database. The IFN/ENIT dataset is a valuable resource for researchers and developers working on OCR applications, particularly for Arabic handwriting recognition. It has been used in various research studies related to OCR and handwriting recognition.

### 3 | Urdu Natural Language Processing

Urdu, the fifth most spoken language in the world, serves 4.7 percent of the global population and is widely spoken in Pakistan as the national language and in India as one of the 22 official languages [44]. Urdu language speakers are dispersed across 20 different countries, including India, Pakistan, Turkey, Saudi Arabia, Bangladesh, Afghanistan, Iran, Azerbaijan, and Nepal [45]. The Urdu language is a composition of various languages such as Arabic, Persian, Turkish, and Hindi, and is non-scripting [46]. Due to its cursive nature and heavy influence from Arabic and Persian scripts, it has no concept of capital or small letters, and shares similarities at the writing level.

Urdu is known as a bidirectional language because it combines two writing systems: the Urdu script, which is written from right to left, and numerals, which are written from left to right. The Urdu script consists of 38

<sup>1</sup> <https://github.com/israksu/Hijja2>

<sup>2</sup> <http://khatt.ideas2serve.net/KHATTDownload.php>

<sup>3</sup> <http://www.ifnenit.com/>

basic letters and 10 numeric letters, as depicted in Figure 5. Additionally, this character set is a superset of other Urdu-based scripts, such as Arabic, which has 28 characters, and Persian, which has 32 characters[47]. Each character in the Urdu language has multiple forms or shapes (isolated, initial, medial, and final) depending on its position within a word. For instance, characters such as Beh (ب), Peh (پ), and Teh (ت) can join with other characters from both directions, i.e., from the preceding and subsequent characters within the same word. However, characters such as Alif (ا), Daal (د), and Reh (ر) only join from right to left, i.e., with the preceding alphabet in a word. Additionally, there are some characters that have no joining ability at all, such as Hamza (ء). Based on these joining properties, Urdu characters can be broadly divided into two categories: joiners and non-joiners. Joiners can acquire all four shapes depending on the neighboring character, whereas non-joiners can only acquire the isolated and final shape.

د	خ	ح	چ	ج	ث	ٹ	ت	پ	ب	ا
dāl	khe	he	che	jīm	se	te	te	pe	be	alif
[d]	[x]	[h]	[tʃ]	[ʃ]	[s]	[t]	[t]	[p]	[b]	[ɑ/ə]
ط	ض	ص	ش	س	ژ	ز	ڑ	ر	ذ	ڈ
toe	zvād	svād	śīn	sīn	že	ze	re	re	zāl	qāl
[t]	[z]	[s]	[ʃ]	[s]	[ʒ]	[z]	[t]	[r]	[z]	[d]
ن	ن	م	ل	ک	ک	ق	ف	غ	ع	ظ
nūn-e ḡunnah	nūn	mīm	lām	gāf	kāf	qāf	fe	ḡain	'ain	zoe
[~]	[n]	[m]	[l]	[g]	[k]	[q]	[f]	[ɣ]	C_[ɑ]; [Ø/ʔ/ə]	[z]
۰	۱	۲	۳	۴	۵	۶	۷	۸	۹	
0	1	2	3	4	5	6	7	8	9	

Figure 5. Urdu character set with phonemes and numerals with their Roman equivalences.

## 4 | Previous Studies in Urdu

In [48], a deep neural network-based system for recognizing handwritten Urdu characters is introduced. The system was trained on a dataset of 74,285 samples and tested on a dataset of 21,223 samples. The proposed system achieved an impressive recognition rate of 98.82% for 133 classes, surpassing the performance of all existing state-of-the-art systems for Urdu language recognition. Moreover, the system's effectiveness was tested on datasets containing numeral characters from five different languages. The combined multilanguage database achieved an average recognition accuracy of 99.26%, with a precision of 99.29%. The recognition accuracy for each individual language was 99.322%.

In [49], researchers present a hybrid approach for recognizing cursive Urdu Nastaliq script using convolutional and recursive neural networks. The proposed methodology combines CNN and MDLSTM for character recognition. The CNN extracts low-level, translational in-variant features, which are then forwarded to MDLSTM for contextual feature extraction and learning. The experiments were conducted on the publicly available Urdu Printed Text-Line Image (UPTI) dataset using the proposed hierarchical combination of CNN and MDLSTM. The system achieved an accuracy of up to 98.12% for 44 classes, outperforming state-of-the-art results on the UPTI dataset. Therefore, this approach shows promising results in recognizing contemporary Urdu Nastaliq script with high accuracy without extracting traditional features.

In [50], the authors propose an encoder-decoder-based hybrid deep learning approach with a CNN for the feature extraction part, a bi-directional gated recurrent unit network (BiGRU) as the encoder, and a gated recurrent unit network (GRU) as the decoder to recognize printed Urdu script in Nastaleeq font. The dataset

was divided into three parts: a training dataset for model building (50%), a validation dataset for hyperparameter tuning (30%), and a test dataset for testing accuracy (20%). Two types of experiments were performed on Urdu script to evaluate the proposed method. The first experiment was related to the variations of shapes based on the position of the character, i.e., beginning, ending, middle, and isolation, which together made 191 unique categories. In the second experiment type, only 99 basic categories were used. The proposed model achieved an accuracy of 98.5% on the test dataset.

In [51], a Conv-transformer architecture is proposed for recognizing unconstrained off-line Urdu handwriting. The model first uses a CNN, followed by a vanilla full transformer, and is trained on both printed and handwritten Urdu text lines. The convolution layers help to reduce the spatial resolutions and address the complexity of transformer multi-head attention layers, while the printed text images in the training phase assist the model in learning more ligatures and improving the language model. The proposed model achieves state-of-the-art accuracy with a CER of 5%, but the authors note that the limited amount of available training data is a significant challenge. They suggest that a full transformer without convolution layers could be used if there were more data, but with the current limited data, the convolution layers are crucial for achieving the best results. Moreover, although the proposed model achieves state-of-the-art accuracy for Urdu handwriting recognition, its performance on other languages with similar scripts or other types of handwriting recognition tasks is uncertain.

In [52], the authors propose a new approach for recognizing Urdu Nasta'liq text using implicit segmentation based on multi-dimensional LSTM neural networks. The proposed system is compared with state-of-the-art Urdu text line recognition systems and is found to provide significant improvement in results. Specifically, the authors achieved a recognition accuracy of  $98 \pm 0.25\%$ .

In [53], researchers present an implicit segmentation-based recognition system for Urdu text lines in Nasta'liq script using a multi-dimensional LSTM recurrent neural network (MDLSTM RNN) with a connectionist temporal classification (CTC) output layer that labels the character sequences. The proposed technique involves sliding overlapped windows on lines of text and extracting a set of statistical features. These extracted features are then fed to the MDLSTM RNN, which achieves a promising recognition rate of 94.5% on the standard Urdu Printed Text-Line Image (UPTI) database.

In [54], a multi-dimensional recurrent neural network and statistical features are utilized to recognize Urdu Nasta'liq text. The proposed methodology involves three stages: pre-processing and feature extraction, MDLSTM, and the CTC output layer. The system is tested on the UPTI dataset and achieves an accuracy of 91.5%, demonstrating the effectiveness of the approach in recognizing the complex Nasta'liq script. However, the paper acknowledges a few limitations of the proposed system. Firstly, the system does not account for shape variation, which can affect recognition accuracy. Secondly, the dataset used in the experiment is limited to UPTI and may not be representative of all types of Urdu Nasta'liq text. Finally, the paper does not compare the proposed system with other state-of-the-art systems for Urdu Nasta'liq text recognition.

## 5 | Conclusion

An accurate and fast OCR system for Arabic can benefit people in Arab and Muslim communities. However, most current OCR approaches operate offline and cannot recognize Arabic text in real-time. Arabic character recognition remains challenging for several reasons, and research in this area is ongoing to improve existing systems. Many approaches are limited to private datasets or recognizing words or paragraphs, making it difficult to assess their performance on real-world Arabic text.

This study aimed to thoroughly review previous research on Arabic OCR and identify key trends, issues, and challenges. A systematic analysis was conducted to evaluate deep learning techniques for feature extraction based on recognition performance. The findings suggest that hybrid feature extraction and classification methods are needed to achieve optimal Arabic OCR accuracy.

Over the last decade, CNNs have been widely applied to Arabic OCR, demonstrating substantial gains over handcrafted approaches. This paper presents a comprehensive review of recent advances in Arabic OCR, including the characteristics of Arabic, different OCR systems, and research contributions. It also compares existing Arabic and Urdu OCR methods, serving as a primer for researchers interested in Arabic script recognition.

Future work entails customizing and training well-known CNNs like GoogLeNet, VGGNet, AlexNet, and DenseNet to develop a new Arabic OCR system. Using large datasets to train CNN models can improve recognition rates, while combining recurrent neural networks (RNNs) with CNNs enables recognizing handwritten and printed Arabic text. Finally, evaluating the proposed approach on a standard benchmark can measure actual Arabic OCR system performance.

In summary, this study conducted a systematic review of deep learning techniques for Arabic OCR and identified avenues for enhancing their recognition capability through hybrid models and customized CNN training on large datasets. Evaluating proposed approaches on a standard benchmark was also highlighted as a key step toward measuring real-world performance. The rephrased summary outlines these key objectives and findings in a concise yet comprehensive manner.

The previously mentioned studies lack a temporal or sequential order in their work or performance improvement, and there is no researcher who has built their work based on other research. On the contrary, some of the studies have yielded results that are almost unreliable and inaccurate. Therefore, we will apply some of these studies and compare them, providing links to scientific codes that validate the accuracy of the results we will refer to in our future work.

In summary, the key objectives and proposals of this study were:

- Critically analyze existing research on Arabic OCR and identify major trends and challenges.
- Systematically evaluate deep learning techniques for feature extraction based on recognition performance.
- Propose that hybrid approaches may be required to improve Arabic OCR accuracy.

## Acknowledgments

The author is grateful to the editorial and reviewers, as well as the correspondent author, who offered assistance in the form of advice, assessment, and checking during the study period.

## Author Contribution

All authors contributed equally to this work.

## Funding

This research has no funding source.

## Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

## Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

## References

- [1] S. Alghyaline, "Arabic Optical Character Recognition: A Review," *Computer Modeling in Engineering & Sciences*, vol. 135, no. 3, pp. 1825–1861, Nov. 2022, doi: 10.32604/CMES.2022.024555.
- [2] M. Al-Ayyoub, A. Nuseir, K. Alsmearat, Y. Jararweh, and B. Gupta, "Deep learning for Arabic NLP: A survey," *J Comput Sci*, vol. 26, pp. 522–531, May 2018, doi: 10.1016/J.JOCS.2017.11.011.
- [3] IBM Cloud Education, "What Is Optical Character Recognition (OCR)? | IBM," IBM, Jan. 05, 2022. <https://www.ibm.com/cloud/blog/optical-character-recognition> (accessed Mar. 29, 2023).
- [4] N. Altwaijry and I. Al-Turaiki, "Arabic handwriting recognition system using convolutional neural network," *Neural Comput Appl*, vol. 33, no. 7, pp. 2249–2261, Apr. 2021, doi: 10.1007/S00521-020-05070-8.
- [5] M. N. Aljarrah, M. M. Zyout, and R. Duwairi, "Arabic Handwritten Characters Recognition Using Convolutional Neural Network," 2021 12th International Conference on Information and Communication Systems, ICICS 2021, pp. 182–188, May 2021, doi: 10.1109/ICICS52457.2021.9464596.
- [6] M. N. Aljarrah, M. M. Zyout, and R. Duwairi, "Arabic Handwritten Characters Recognition Using Convolutional Neural Network," 2021 12th International Conference on Information and Communication Systems, ICICS 2021, pp. 182–188, May 2021, doi: 10.1109/ICICS52457.2021.9464596.
- [7] X. Wu, D. Hong, and J. Chanussot, "UIU-Net: U-Net in U-Net for Infrared Small Object Detection," *IEEE Transactions on Image Processing*, vol. 32, pp. 364–376, 2023, doi: 10.1109/TIP.2022.3228497.
- [8] D. Hong, L. Gao, J. Yao, B. Zhang, A. Plaza, and J. Chanussot, "Graph Convolutional Networks for Hyperspectral Image Classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, no. 7, pp. 5966–5978, Jul. 2021, doi: 10.1109/TGRS.2020.3015157.
- [9] C. Wick, C. Reul, and F. Puppe, "Calamari—a high-performance tensorflow-based deep learning package for optical character recognition," *arXiv preprint arXiv:1807.02004*, 2018.
- [10] N. O'Mahony et al., "Deep Learning vs. Traditional Computer Vision," *Advances in Intelligent Systems and Computing*, vol. 943, pp. 128–144, 2020, doi: 10.1007/978-3-030-17795-9\_10.
- [11] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," *Nature* 2015 521:7553, vol. 521, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539.
- [12] S. Malik et al., "An efficient skewed line segmentation technique for cursive script OCR," *Sci Program*, vol. 2020, 2020, doi: 10.1155/2020/8866041.
- [13] L. Liu et al., "Deep Learning for Generic Object Detection: A Survey," *Int J Comput Vis*, vol. 128, no. 2, pp. 261–318, Feb. 2020, doi: 10.1007/S11263-019-01247-4.
- [14] A. S. Abdalkafor, "Survey for Databases on Arabic Off-line Handwritten Characters Recognition System," 1st International Conference on Computer Applications and Information Security, ICCAIS 2018, Aug. 2018, doi: 10.1109/CAIS.2018.8442001.
- [15] F. Soumia, G. Djamel, and M. Haddad, "Handwritten Arabic Character Recognition: Comparison of Conventional Machine Learning and Deep Learning Approaches," *Lecture Notes on Data Engineering and Communications Technologies*, vol. 72, pp. 1127–1138, 2021, doi: 10.1007/978-3-030-70713-2\_100.
- [16] J. Owens, *The Oxford handbook of Arabic linguistics*. Oxford University Press, 2013.
- [17] R. Ahmed et al., "Offline arabic handwriting recognition using deep machine learning: A review of recent advances," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11691 LNAI, pp. 457–468, 2020, doi: 10.1007/978-3-030-39431-8\_44.
- [18] S. Alghyaline, "Arabic Optical Character Recognition: A Review," *CMES - Computer Modeling in Engineering and Sciences*, vol. 135, no. 3. Tech Science Press, pp. 1825–1861, 2023. doi: 10.32604/cmcs.2022.024555.
- [19] N. Alrobah and S. Albahli, "Arabic Handwritten Recognition Using Deep Learning: A Survey," *Arab J Sci Eng*, vol. 47, no. 8, pp. 9943–9963, Aug. 2022, doi: 10.1007/s13369-021-06363-3.
- [20] N. Altwaijry and I. Al-Turaiki, "Arabic handwriting recognition system using convolutional neural network," *Neural Comput Appl*, vol. 33, no. 7, pp. 2249–2261, Apr. 2021, doi: 10.1007/s00521-020-05070-8.
- [21] H. M. Balaha, H. A. Ali, M. Saraya, and M. Badawy, "A new Arabic handwritten character recognition deep learning system (AHCR-DLS)," *Neural Comput Appl*, vol. 33, no. 11, pp. 6325–6367, Jun. 2021, doi: 10.1007/s00521-020-05397-2.
- [22] B. H. Nayef, S. N. H. S. Abdullah, R. Sulaiman, and Z. A. A. Alyasseri, "Optimized leaky ReLU for handwritten Arabic character recognition using convolution neural networks," *Multimed Tools Appl*, vol. 81, no. 2, pp. 2065–2094, Jan. 2022, doi: 10.1007/s11042-021-11593-6.
- [23] M. Elkhayati and Y. Elkettani, "UnCNN: A New Directed CNN Model for Isolated Arabic Handwritten Characters Recognition," *Arab J Sci Eng*, vol. 47, no. 8, pp. 10667–10688, Aug. 2022, doi: 10.1007/s13369-022-06652-5.



- [24] S. Alghyaline, "A Printed Arabic Optical Character Recognition System using Deep Learning," *Journal of Computer Science*, vol. 18, no. 11, pp. 1038–1050, 2022, doi: 10.3844/jcssp.2022.1038.1050.
- [25] A. A. A. Ali and S. Mallaiyah, "Intelligent handwritten recognition using hybrid CNN architectures based-SVM classifier with dropout," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 6, pp. 3294–3300, Jun. 2022, doi: 10.1016/J.JKSUCI.2021.01.012.
- [26] H. M. Balaha et al., "Recognizing arabic handwritten characters using deep learning and genetic algorithms," *Multimed Tools Appl*, vol. 80, no. 21–23, pp. 32473–32509, Sep. 2021, doi: 10.1007/s11042-021-11185-4.
- [27] A. Khémiri, A. K. Echi, and M. Elloumi, "Bayesian Versus Convolutional Networks for Arabic Handwriting Recognition," *Arab J Sci Eng*, vol. 44, no. 11, pp. 9301–9319, Nov. 2019, doi: 10.1007/s13369-019-03939-y.
- [28] M. R. Yousefi, M. R. Soheili, T. M. Breuel, and D. Stricker, "A comparison of 1D and 2D LSTM architectures for the recognition of handwritten Arabic," in *Document Recognition and Retrieval XXII, SPIE*, Feb. 2015, p. 94020H. doi: 10.1117/12.2075930.
- [29] N. S. Gupta, V. Balamurugan, G. Megharaj, K. N. A. Sattar, and J. D. Rose, "Cross lingual handwritten character recognition using long short term memory network with aid of elephant herding optimization algorithm," *Pattern Recognit Lett*, vol. 159, pp. 16–22, Jul. 2022, doi: 10.1016/j.patrec.2022.04.038.
- [30] 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, Jan. 2023, doi: 10.31449/INF.V46I9.4375.
- [31] [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. 07, no. 02, 2021.
- [32] S. Djaghbello, A. Attia, A. Bouziane, and Z. Akhtar, "Local features enhancement using deep auto-encoder scheme for the recognition of the proposed handwritten Arabic-Maghrebi characters database," *Multimed Tools Appl*, vol. 81, no. 22, pp. 31553–31571, Sep. 2022, doi: 10.1007/s11042-022-13032-6.
- [33] S. K. Jemni, Y. Kessentini, and S. Kanoun, "Out of vocabulary word detection and recovery in Arabic handwritten text recognition," *Pattern Recognit*, vol. 93, pp. 507–520, Sep. 2019, doi: 10.1016/j.patcog.2019.05.003.
- [34] R. Ahmad, S. Naz, M. Afzal, S. Rashid, 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, pp. 299–305, May 2020, doi: 10.34028/iajit/17/3/3.
- [35] F. Slimane, R. Ingold, S. Kanoun, A. M. Alimi, and J. Hennebert, "A new Arabic printed text image database and evaluation protocols," *Proceedings of the International Conference on Document Analysis and Recognition, ICDAR*, pp. 946–950, 2009, doi: 10.1109/ICDAR.2009.155.
- [36] A. AbdelRaouf, C. A. Higgins, T. Pridmore, and M. Khalil, "Building a multi-modal Arabic corpus (MMAC)," *International Journal on Document Analysis and Recognition*, vol. 13, no. 4, pp. 285–302, Dec. 2010, doi: 10.1007/S10032-010-0128-2/METRICS.
- [37] H. Luqman, S. A. Mahmoud, and S. Awaida, "KAFD Arabic font database," *Pattern Recognition*, vol. 47, no. 6, pp. 2231–2240, Jun. 2014, doi: 10.1016/J.PATCOG.2013.12.012.
- [38] I. A. Doush, F. Aikhateeb, and A. H. Gharibeh, "Yarmouk Arabic OCR Dataset," *2018 8th International Conference on Computer Science and Information Technology, CSIT 2018*, pp. 150–154, Oct. 2018, doi: 10.1109/CSIT.2018.8486162.
- [39] F. K. Jaiem, S. Kanoun, M. Khemakhem, H. El Abed, and J. Kardoun, "Database for Arabic printed text recognition research," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 8156 LNCS, no. PART 1, pp. 251–259, 2013, doi: 10.1007/978-3-642-41181-6\_26.
- [40] N. Amara, O. Mazhoud, N. Bouzrara, and N. Ellouze, "ARABASE: A Relational Database for Arabic OCR Systems," *International Arab Journal of Information Technology*, vol. 2, no. 4, pp. 259–266, 2005.
- [41] A. Lawgali, M. Angelova, and A. Bouridane, "HACDB: Handwritten Arabic characters database for automatic character recognition," in *European Workshop on Visual Information Processing (EUVIP)*, 2013, pp. 255–259.
- [42] S. A. Mahmoud et al., "KHATT: Arabic offline Handwritten Text Database," *Proceedings - International Workshop on Frontiers in Handwriting Recognition, IWFHR*, pp. 449–454, 2012, doi: 10.1109/ICFHR.2012.224.
- [43] M. Pechwitz, S. S. Maddouri, V. Märgner, N. Ellouze, and H. Amiri, "IFN/ENIT-database of handwritten Arabic words," in *Proc. of CIFED*, Citeseer, 2002, pp. 127–136.
- [44] M. Jain, M. Mathew, and C. V. Jawahar, "Unconstrained OCR for Urdu using deep CNN-RNN hybrid networks," *Proceedings - 4th Asian Conference on Pattern Recognition, ACPR 2017*, pp. 753–758, Dec. 2018, doi: 10.1109/ACPR.2017.5.
- [45] S. S. R. Rizvi, A. Sagheer, K. Adnan, and A. Muhammad, "Optical Character Recognition System for Nastalique Urdu-Like Script Languages Using Supervised Learning," *Intern J Pattern Recognit Artif Intell*, vol. 33, no. 10, p. 1953004, Sep. 2019, doi: 10.1142/S0218001419530045.
- [46] S. N. Khan et al., "Urdu Word Segmentation using Machine Learning Approaches," *IJACSA International Journal of Advanced Computer Science and Applications*, vol. 9, no. 6, pp. 193–200, 2018.
- [47] M. Husnain et al., "Recognition of Urdu handwritten characters using convolutional neural network," *mdpi.com*, 2019, doi: 10.3390/app9132758.



- 
- [48] F. Mushtaq, M. M. Misgar, M. Kumar, and S. S. Khurana, "UrduDeepNet: offline hand-written Urdu character recognition using deep neural network," *Neural Comput Appl*, vol. 33, no. 22, pp. 15229–15252, Jun. 2021, doi: 10.1007/S00521-021-06144-X.
- [49] S. Naz et al., "Urdu Nastaliq recognition using convolutional–recursive deep learning," *Neurocomputing*, vol. 243, pp. 80–87, Jun. 2017, doi: 10.1016/J.NEUCOM.2017.02.081.
- [50] S. Zia et al., "Recognition of printed Urdu script in Nastaleeq font by using CNN-BiGRU-GRU Based Encoder-Decoder Framework," *Intelligent Systems with Applications*, vol. 18, p. 200194, May 2023, doi: 10.1016/J.ISWA.2023.200194.
- [51] N. Riaz, H. Arbab, A. Maqsood, K. Nasir, A. Ul-Hasan, and F. Shafait, "Conv-transformer architecture for unconstrained off-line Urdu handwriting recognition," *International Journal on Document Analysis and Recognition*, vol. 25, no. 4, pp. 373–384, Dec. 2022, doi: 10.1007/S10032-022-00416-5.
- [52] S. Naz, A. I. Umar, R. Ahmed, M. I. Razzak, S. F. Rashid, and F. Shafait, "Urdu Nasta'liq text recognition using implicit segmentation based on multi-dimensional long short term memory neural networks," *Springerplus*, vol. 5, no. 1, pp. 1–16, Dec. 2016, doi: 10.1186/S40064-016-3442-4.
- [53] S. Naz et al., "Offline cursive Urdu-Nastaliq script recognition using multidimensional re-current neural networks," *Neurocomputing*, vol. 177, pp. 228–241, Feb. 2016, doi: 10.1016/J.NEUCOM.2015.11.030.
- [54] S. Naz, A. I. Umar, R. Ahmad, S. B. Ahmed, S. H. Shirazi, and M. I. Razzak, "Urdu Nasta'liq text recognition system based on multi-dimensional recurrent neural network and sta-tistical features," *Neural Comput Appl*, vol. 28, no. 2, pp. 219–231, Feb. 2017, doi: 10.1007/S00521-015-2051-4.