Review

A Comprehensive Overview of Handwritten Recognition Techniques: A Survey

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Abstract: Deep learning and deep neural networks, particularly Convolutional Neural Networks (CNNs), are rapidly growing areas of machine learning and are currently the primary tools used for image analysis and classification applications. Handwriting recognition involves using computer algorithms and software to interpret and recognize handwritten text and drawings and has various applications such as automated handwriting analysis, document digitization, and handwriting-based user interfaces. Many deep learning models have been applied in the field of handwriting recognition and various datasets have been used to evaluate new computer vision techniques. This article provides an overview of the current state-of-the-art approaches and contributions to handwriting recognition using different datasets. Furthermore, the paper explains the most commonly used algorithms for recognizing handwritten characters, words, and numbers. Compares them based on their accuracy. This study covered different aspects and methods of machine learning and Deep Learning (DL) for handwritten recognition that showed different achievements for each.

Keywords: Handwritten Datasets, CNN, Deep Learning, Handwritten Recognition, Handwritten Word Recognition

Introduction

Handwritten recognition is the most striking research area in artificial intelligence. As it is the age everything is digitized, for more than three decades despite the rapid progress in terms of techniques used in the recognition. One of the many classification problems in artificial intelligence is handwriting analysis, which has attracted the attention of a wide range of scientists, including computer scientists and handwritten specialists. It makes a lot of things easier for users to store written data without typing any words manually into a text document. This saves users the amount of time and effort they spent on storing and bringing back the document. Handwriting recognition is an essential process of image recognition.

A study by Rajyagor and Rakholia (2020) states that handwriting recognition is the most exciting area of research in artificial intelligence. As of then, everything has been digitized for more than three decades despite rapid advances in recognition techniques. One of the many artificial intelligence classification problems is handwriting analysis, which has attracted the attention of a wide range of scientists, including computer scientists and handwriting specialists. This makes it much easier for users to store typed data without typing any words manually in a text document. It saves users the time and effort spent on storing and retrieving the document. Handwriting recognition is an essential process in image recognition.

A convolutional neural network is one of the most recognized and widely used methods in deep learning which represents a type of neural network capable of mechanically extracting features from multidimensional input data to solve difficulties in the computer's field of view, this was explained in the studies by Baldominos *et al*. (2019); Tahir and Pervaiz (2020). An additional category of DNNs that are also widely used in handwriting are Recurrent Neural Networks, (RNNs) which include Restricted Boltzmann Machines (RBM), Deep Belief Networks, (DBN) Long Short-Term Memory, (LSTM) as well as many other types of CNN handwriting recognition used to be promising these days. Furthermore, deep learning algorithms such as convolutional neural networks give more accurate results than other learning algorithms through performance. In a study by Shamim *et al*. (2018), the authors explore the convolutional neural network has been widely used in the field of image processing, in addition, it is used in the field of Natural Language Processing (NLP) and sentiment recognition using various parameters.

The core problems in handwritten recognition turn around misrepresentations and pattern inconsistency, therefore; feature extraction is of foremost position. Pasi and Naik (2016) select features manually may cause inadequate data that is being available to precisely expect the class character. But, mostly a large number of features lead to problems as a result of increased dimensionality. In addition, Bora *et al*. (2020) state that manual feature selection may render the available data inadequate to accurately expect the character of the class. But, for the most part, a large number of features lead to problems due to higher dimensionality. The main contribution of this study is to explain both deep learning and machine learning for handwritten recognition since many studies have indicated both types. This survey covered, the most recent works on handwriting recognition that are being proposed by different researchers. The methods used in the different approaches are presented and the accuracy of the state of the art is compared.

The researchers Baldominos *et al*. (2019) conducted a survey of handwritten character recognition with MNIST and EMNIST databases, providing an extensive review of the state of the art in this field. In another paper by Somashekar (2021), the researcher presents a comprehensive overview of handwritten character recognition using a neural network as a machine learning tool. After extensive research, it was discovered that no single technique or method can fully meet the requirements of handwritten character recognition. Therefore, offline handwritten character recognition remains an open research field, where researchers continue to work on developing and improving techniques to recognize and address various complexities associated with this problem. This proposed survey compared to the above-mentioned surveys is more detailed as it employs various datasets used in handwritten characters, digits, and text recognition. Furthermore, machine learning algorithms are conducted yet, the survey deals with deep learning approaches and various subsections of DNN. Such as custom CNN, transfer learning CNN, and other approaches of DNN. Furthermore, this survey outlined the state-of-the-art results for each dataset that was utilized by the researcher covered in this study.

This survey discusses the utilization and evaluation of successful handwritten recognition datasets such as MNIST, Hijja, and HEBIU to train and test models for solving the handwriting recognition problem across different languages. The survey covers a range of approaches, including machine learning and deep learning algorithms. The commonly used machine learning algorithms include Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Naive Bayes. SVM is a supervised learning model that analyzes data and recognizes patterns, while KNN is a type of instance-based learning that classifies objects based on similarity to other objects in the dataset. Naïve Bayes is a probabilistic algorithm based on Bayes' theorem for classification problems. In contrast, deep learning has shown significant improvement in accuracy, particularly in image recognition tasks. Convolutional Neural Networks (CNNs) are a popular deep learning approach that uses convolutional layers to extract image features. Researchers often use custom CNNs or transfer-learning CNNs in handwriting recognition tasks. Other deep learning methods for handwritten recognition include Recurrent Neural Networks (RNNs) for sequence processing tasks and Generative Adversarial Networks (GANs) for generating new data samples similar to the training data. These approaches have shown promising results in improving handwriting recognition models' accuracy.

Datasets

Handwriting recognition is a growing area of research that already contains detailed ways of implementation, including large training datasets, popular algorithms, feature scaling and feature extraction methods Table 1 shows some of the datasets.

Arabic Dataset

- Hijja dataset: The Hijja dataset is a collection of handwritten Arabic script images, used for training and evaluating machine learning models for handwritten character recognition. The dataset consists of 47,434 images of handwritten characters, including letters, digits, and symbols written by 591 participants in different forms (Altwaijry and Al-Turaiki, 2021). The images in the dataset are grayscale and have a resolution of 32×32 pixels. The characters and digits in the dataset are written by a diverse group of writers, with different writing styles and levels of proficiency. Figure 1 shows the samples of the Hijja dataset
- AHCD: This dataset is an Arabic handwritten character dataset composed of 16,800 characters written by 60 participants; the age range is between 19 and 40 years. Researchers Altwaijry and Al-Turaiki (2021) used the CNN method based on CNN Arabic handwriting recognition. The authors evaluated their model in accordance with two datasets, the Hijja dataset, Arabic Handwritten Character Dataset (AHCD). Consistent with the result, their model accomplished 88 and 95% accuracies of the Hijja and AHCD, respectively

Table 1: Datasets covered by researchers in this survey

References	Dataset name	No of image	Size of image pixels	No of classes
Altwaijry and Al-Turaiki (2021)	Hijja	47,434	32*32	29,28
	AHCD	16,800	32*32	
El Abed *et al*. (2009)	ADAB	20,575	30*30	
Illouz *et al*. (2018)	HEBIU	810	400*400	
Upender and Pasupuleti (2021)	MNIST	70,000	28*28	10
Bonyani *et al*. (2021)	HODA	102,352	32*32	10

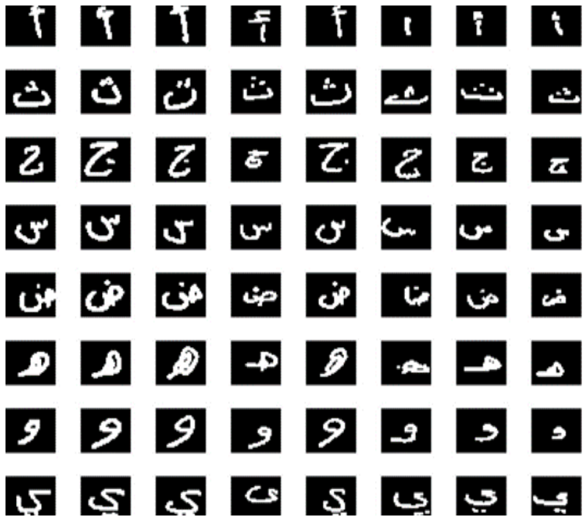

Fig. 1: Hijja dataset samples

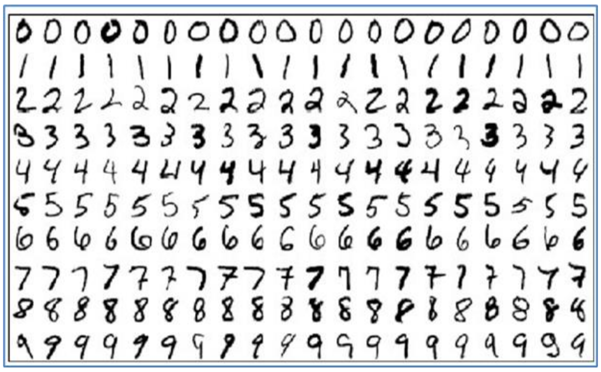

Fig. 2: MNIST dataset samples

- ADAB: The ADAB database was used to train and test online Arabic handwriting recognition systems. It includes 20,575 Arabic words written by 165 different writers and was used in the online Arabic handwriting recognition competition at ICDAR 2009. In the competition, three groups with seven systems participated and the systems were tested on known and unknown data sets. They were evaluated based on their recognition rate and speed and the results showed that online Arabic handwriting recognition systems had made significant progress, with many of the participating systems achieving high accuracy and some exhibiting high speed. El Abed *et al*. (2009) used this dataset in their study. Table 1: Datasets samples

English Dataset

- Hebrew English Bar Ilan University (HEBIU): The Hebrew English Bar Ilan University (HEBI) dataset is a collection of parallel texts in Hebrew and English. It is used for research and development in the field of machine translation and natural language processing. The dataset includes more than 100,000 sentence pairs, with each pair consisting of a sentence in Hebrew and its English translation. This dataset contains 810 Hebrew and English handwriting samples from a group of 405 participants, has been compiled. Researchers Illouz *et al*. (2018) utilized the BEBIU dataset in the work they worked on
- MNIST: The MNIST dataset is a modified version of the NIST database that includes handwritten images and is widely used for handwritten digit recognition research. It consists of 70,000 samples, which are divided into 60,000 training samples and 10,000 test samples. The MNIST dataset is preprocessed, making it easy to adapt for specific applications (Upender and Pasupuleti, 2021). It is structured in the form of "magic numbers," with each example starting at 00. Many researchers got this Dataset in their work. A sample of the MNIST dataset is presented in Fig. 2

Persian Dataset

- HODA: This Persian dataset is a very large body of Arabic and Farsi handwritten alphanumerical characters with each image containing a single digit or character. It is the first dataset of handwritten Farsi digits and the total samples of this dataset is 102,352 samples (Bonyani *et al*., 2021). The images in the dataset are grayscale and have a resolution of 32×32 pixels

Preprocessing Techniques

Dewangan and Sahu (2021) used the pre-processing phase in this study which is the first step in the recognition system that converts the data into a format that will be more easily and efficiently processed. Therefore, the main objective is to adjust the images so that they are easier and faster to learn by recognition. While image resizing to similar extents is useful for consistency and simplicity, blurring leads to data loss by oversizing or shrinking these images, which could affect the result Moreover, increasing the size of the image also entails a significant computational cost, which grows with the target dimensions. Whereas, Shakunthala and Pillai (2021) covered the key points of pre-processing are eliminating noise, and data and compressing the amount of information to take, resizing, and scaling.

Preprocessing data in Machine Learning (ML) is also used in different studies in the field (Ahamed *et al*., 2021) as a critical phase to help enhance the quality of data and promote meaningful insights from data extraction. In simple words, data preprocessing in machine learning is data mining which is utilized to filter and remove the noise from the data for selecting the best sample.

Data Augmentation for Handwritten Methods

Augmentation is a data analysis strategy used to increase the amount of data by adding data that already exists, such as clipping, padding, rotation, white balance, and flipping, which are commonly used in NN. The methods are used to artificially vary the training data set. Current data augmentation methods use simple adjustments to incorporate attractiveness similar to image transformations and color adjustments. Data augmentation was used by Mikołajczyk and Grochowski in their work (Mikołajczyk and Grochowski, 2019).

Mustafa and Elbashir (2020a) covered that traditional affine and elastic transformations have proven to be more effective in enhancing data: Transforming images by rotating or mirroring them, zooming in and out, resizing, distorting, changing their color palette, etc. Despite their many advantages, simple classical operations are not always enough to improve neural network accuracy or eliminate the overfitting problem. The researcher Pratt *et al*. (2016) showed that for identification and categorization of diabetic retinopathy, each image was randomly rotated between 0 and 90°C, flipped horizontally and vertically, and scrolled horizontally and vertically. Image augmentation methods can help reduce the errors of network generalization, besides improving training facilities and addressing data overfitting concerns. Shorten and Khoshgoftaar (2019) explained data augmentation in their study. On the image, data were used to create the diversity of images regarding rescale, zoom, horizontal flip, and shears operations. These procedures were carried out using the functionality of the image data generator from TensorFlow, Keras framework.

Ashiquzzaman and Tushar (2017), added data augmentation to avoid overfitting, they simply took their image dataset and transformed it by rotating, changing color, and adding noise to make the model more robust against overfitting and digitally increased the size of the dataset. In the study, they applied ZCA whitening as magnification, the images were rotated through a range of 10°C, then the images were shifted horizontally and vertically by 20% of the original dimensions at random and they enlarged random images up by 10%. During this process of increase.

Feature Selection (FS)

Feature Selection (FS) methods have become critical learning mechanisms to deal with the challenge of a large number of input features. As a dimensionality reduction strategy, feature selection picks a small subset of the essential characteristics from the original ones, removing irrelevant, redundant, or noisy information, this was stated by Banerjee *et al*. (2021) explained and used. The purpose of feature selection is to reduce the number of features that must be examined during the classification process. As a result, it is carried out by reducing irrelevant or noisy aspects from the entire set of options. Feature selection can lead to improved learning performance, such as increased learning accuracy, lower computational costs, and better model interpretability. The researchers Souza *et al*. (2021). The changeability of handwriting in HR makes features more or less effective and provides better assistance for method selection assessment.

Kalita *et al*. (2019) used in their study a simple offline handwritten character recognition developed by extracting features in two ways character geometry and gradient feature extraction. They used the EMNIST dataset for digits that had 2, 40,000 images in the training set and 40,000 images in the testing set. An acceptable accuracy is obtained for digits. When feature selection methods were applied, the accuracy showed better results. It is made on the accuracy that is obtained from three different feature selection techniques, minimum Redundancy and Maximum Relevance (mRMR), Joint Mutual Information feature selection (JMI), relief feature selection that selects the best features from the feature vector obtained from the feature extraction technique. From the experimental results, it can be concluded that this model can be an optimized solution for handwritten character recognition.

Machine Learning-Based Handwritten Methods

Machine learning is a field that uses computer systems to learn how to solve real-world problems without being explicitly programmed. Pashine *et al*. (2021) applied three machine learning models to handwritten digit recognition using the MNIST dataset, including SVM, CNN, and MLP. They found that CNN was the most accurate model for this task and is suitable for any type of prediction problem that uses image data as input. The study by Singh *et al*. (2021a), used an SVM algorithm that learns the relationship between data and labels in a training set. It has been applied to handwritten digit images written in four scripts commonly used in India, including Arabic, Bangla, Devanagari, and Latin, and achieved accuracies ranging from 95.53 to 98.18%. Whereas, the decision tree develops a classification model as a tree structure. As part of the training process, a random forest gathers data from a large number of decision trees to solve classification, regression, and other problems. Devi *et al*. (2021) proposed describing several machine learning techniques that employ various classifiers. Several supervised and unsupervised machine learning techniques, including random forest, logistic regression, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN), are evaluated for their accuracy in detecting characters. Hazra *et al*. (2017) showed that KNN appears to have the highest accuracy of the algorithms mentioned, at roughly 98% using Optical Character Recognition (OCR) to extract unique features from an input image in order to classify it as containing specific characters, such as letters and digits.

In a study of a machine learning approach for Bengali handwritten vowel character recognition, (Ahsan *et al*., 2022) devised a novel method using face mapping to enhance the recognition of handwritten Bengali characters. This approach is highly successful in distinguishing between different characters. The work outlines a new technique that uses SVM in Python for identifying handwritten characters with minimal training. The system is capable of efficiently recognizing Bengali vowels and has the potential to work well with other languages too. The Bengali language has fifty fundamental characters with many similar symbols. To achieve better performance, the approach concentrated on eleven vowel characters. Bangla Lekha isolated dataset was used in their work for the training and testing part. The accuracy rates achieved by this method were noteworthy, with up to 94% accuracy for a single character and an average of 91% for all characters. This study was anticipated to reveal important insights and drove progress in the field. In comparison to existing methods for recognizing Bengali handwriting, this approach yielded superior results and was more efficient.

Adhikary *et al*. (2023) in their study, the authors of the study aimed to employ machine learning techniques to recognize handwritten Dzongkha digits and explore their potential for identifying and categorizing these numerals. Due to the lack of an existing dataset, the authors manually compiled data using Google Jamboard with a digital pen tablet. Additionally, they stated that there has been no attempt to recognize handwritten Dzongkha digits. Therefore, they developed a Handwritten Digit Recognition (HDR) for the Dzongkha language due to the lack of previous work and datasets. Their work is the first in this language domain. The study utilized various machine learning algorithms, including support vector machines, K-nearest neighbors, and decision trees, to recognize and categorize the handwritten digits. The support vector machine algorithm outperformed the other methods, with an accuracy of 98.29%. The K-nearest neighbor algorithm achieved a recognition and classification accuracy rate of 96.00%, while the decision tree algorithm produced an accuracy rate of 78.86% for recognizing and classifying Dzongkha handwritten digits. The authors also noted the limited resources and complexity of recognizing Dzongkha digits compared to English digits.

Alrobah and Albahli (2021) proposed in their study a method for recognizing Arabic handwritten characters by using a hybrid model of (CNN) with Support Vector Machine (SVM) and extreme Gradient Boosting (XGBoost) classifiers. The authors found irregularities in the state-of-the-art Arabic dataset called Hijaa, which was previously used to develop a CNN for feature extraction and classification, resulting in an accuracy of 88%. The authors addressed the dataset imbalance and used a hybrid model to combine the strengths of CNNs for feature extraction and ML models for classification, resulting in an accuracy of 96.3, 8% higher than the original Hijja experiment. The hybrid model's accuracy was comparable to the one conducted on the AHCD dataset using the Hijja model, indicating its effectiveness.

Demirkaya and Çavuşoğlu (2022) investigated the effectiveness and performance of various machine learning algorithms in recognizing handwriting. To conduct the tests, an interface was created and multiple recognition models were sampled using different algorithms, including ANN, CNN, K-NN, Naive Bayes algorithm, SVM, and decision trees. The experiments were carried out on the MNIST dataset and Python programming language was used along with Keras, TensorFlow, and sci-kit learn libraries for different aspects of the testing. Accuracy values were calculated using the sci-kit learn library metrics to compare the success rates of the algorithms. In total, six different algorithms were utilized and the ANN and CNN models were found to be the most successful with 98.66 and 99.45% accuracy rates, respectively. The results indicated that neural networks outperformed the other algorithms, but the architecture and activation functions used had a significant impact on their success. Traditional classification algorithms like K-NN and SVM also achieved high accuracy rates of over 97%. The K-NN achieved 97.05, 83.57% for Naive Bayes, 97.71% accuracy achieved for the support vector machine, and 88.34% for the decision tree. The study differed from similar research as it examined nearly all classification algorithms with the MNIST dataset and various parameters was tested to identify the most efficient combinations. Table 2 shows machine learning classifier accuracies.

Table 2: Researchers used machine learning classifiers

Reference	Classifier	Feature selection	Dataset	Accuracy (%)
Pashine *et al*. (2021)	SVM, MLP and CNN	HCR	MNIST	94.005 98.850 99.310
Singh *et al*. (2021a)	SVM	SBI	India Arabic, Bangla, Devanagar, and Latin	98.180 96.220 96.520 95.530
Devi *et al*. (2021)	(SVM) HMM, NN, SVM KNN classifier	Hybrid features zoning method, convex hull algorithm OCR	CEDAR CCC benchmark custom image of any language	97.160 80.580 98.000
Hazra *et al*. (2017)	KNN classifier	OCR	Custom image of any language	98.000
Ahsan *et al*. (2022)	SVM	Scikit learn	Bangla Lekha	94.000 91.000
Adhikary *et al*. (2023)	SVM, KNN, decision tree	HOG and	ISI numeral dataset CMATERDB	98.290 96.000 78.860
Alrobah and Albahli (2021)	CNN + SVM XGBoost	Hybrid features	Hijja	96.300
Demirkaya and Çavuşoğlu (2022)	ANN, CNN, K-NN, Naïve Bayes the algorithm, SVM and decision trees		MNIST	98.660 99.450 97.050 83.570 97.710 88.340

Deep Learning-Based Handwritten Methods

Deep learning is a subset of artificial intelligence, which is a machine learning technique, that involves layering algorithms to create an artificial neural network that can learn and make intelligent judgments on its own. Its strength is its capacity to work with raw data, allowing feature extraction to be built into the classifier and the system to be trained as a whole. Deep Learning (DL) research on handwritten recognition has garnered a lot of attention and has proven to be useful in recent years because it has greatly increased recognition capability. In recent years, deep learning has had remarkable success in a range of application fields. Machine learning is a rapidly growing field that has impacted a variety of industries. Although there are several deep learning-based methods in the literature, CNNs have been shown to be effective for feature extraction for exact tasks. Arora and Bhatia (2018) use DL in their work. Unlike classical feature extraction, which requires a lot of human intervention, deep learning extracts valuable characteristics automatically and speeds up the process (Dutta *et al*., 2018).

The authors of this study Badie-Modiri *et al*. (2002), discovered that multidimensional recurrent layers are important for handwriting recognition. While the state-of-the-art approaches often employ multidimensional long short-term memory networks, these can be computationally expensive and extract features similar to those obtained using cheaper convolutional layers. This suggests that the two-dimensional dependencies modeled by multidimensional recurrent layers may not be essential for achieving good recognition accuracy, at least in the lower layers of the architecture. In this study, an alternative model that only uses convolutional and one-dimensional recurrent layers was investigated and found to produce results that were either better or equivalent to the current state-of-the-art architecture while running significantly faster.

The accuracy of the model was also improved through the use of random distortions during training as synthetic data augmentation.

Bluche *et al*. (2017) proposed a new neural network architecture for handwriting recognition that serves as an alternative to multi-dimensional Long Short-Term Memory (MD-LSTM) recurrent neural networks. The model consists of a convolutional encoder for input images and a bidirectional LSTM decoder for character sequence prediction. It utilizes a convolutional encoder to generate generic, multilingual, and reusable features for transfer learning and is optimized for fast training on GPUs and fast decoding on CPUs. The main contribution of the study is the incorporation of convolutional gates in the encoder, which enable hierarchical context sensitive feature extraction.

Custom Convolutional Neural Network

Convolutional neural networks are one of the most extensively used types of DNNs in handwritten recognition (CNN). The CNN model can be used in two ways: Manually building it or automatically extracting features from multi-dimensional inputs and reducing vast, complicated datasets into highly accurate predictive and transformational output. Jadhav *et al*. (2019). Furthermore, CNN combines feature extraction and classification phases in order to reduce pre-processing and feature extraction time. A CNN can extract affluent and related elements from photos repeatedly. Furthermore, even if only a little amount of training data is provided, it can yield significant recognition accuracy. Figure 3 depicts the CNN architecture.

On the SUST-ALT characters database, (Mustafa and Elbashir, 2020b) used a CNN model for Arabic handwritten character recognition. The database was normalized to 20*20 pixels in pre-processing stage and the normalized photos were then centered into scaled images of 28*28 pixels; also, the images were reversed to a black backdrop and white foreground colors. The accuracy obtained as test accuracy is 93.5%, which is superior to other approaches that used the same dataset. However, the generalization scope of the model recognition tests was not expanded to include solitary offline Arabic handwritten digits and words, and recognition accuracy was improved. For handwritten character identification, the researchers employed CNN, a deep learning approach (Khandokar *et al*., 2021). The research focuses on CNN’s capacity to accurately recognize characters from the NIST dataset. It was discovered as the number of training images increases the accuracy gained from the first 200 photographs improves. With 1000 training photos, the accuracy jumps to 92.91%. As a result, increasing the number of training photographs improved accuracy to a certain point.

Illouz *et al*. (2018), the authors created a 6-layer CNN for automated gender classification in handwriting. An English and Hebrew dataset comprised of 405 samples of handwriting was provided by the researchers. Gender is determined by three main classes: Intra language, which includes both training and testing in one language; inter-language, which includes training in one language but testing in another; and combination, which includes both training and testing in both languages. According to the results, Hebrew's intra-language classification accuracy is 73.02 %, while English's inter-language and combined language classification accuracy is 58.29%, for an overall accuracy of 77%. The authors presented two datasets Hazra *et al*. (2021). They were Mayek27 and ISI Bangla datasets. Their research employs the deep CNN architecture model. Furthermore, a comparison of the dataset’s functionality with different batch sizes and optimization methods. The authors set a new milestone for Manipuri “Mayek27” character recognition, with 99.27 and 99.32% accuracy for ISI Bangla numeric data identification.

Zhuang *et al*. (2021) proposed CNN and median filtering in their approach to the Chinese handwritten recognition system. They utilized the median filtering method which reduced noise and enhanced the accuracy rate by 1.8%, compared with the 90.48% accuracy rate of a model without median filtering. Hossain *et al*. (2021) suggested a multi-zoned character segmentation and merging approach for producing Bangla handwritten terms. The accuracy achieved using the Convolutional Neural Network (CNN) is 84% for the letter level and 82% for the word level. In their study on English handwritten characters, researchers offered two models: GAN for generating English handwritten character recognition and the CNN model. The experiment's findings suggested that the produced English character pictures improved the performance of character classifiers. GAN's accuracy was 96.14%, while CNN's with 95.36% accuracy. The authors, Hemangee and Gayatri (2021) Proposed a convolution neural network algorithm for handwritten character recognition, where they first removed the noise in the input image by using the median filter, and the image is segmented. Then, the feature extraction and recognition are extracted from the input image. The authors used a handwritten Bangla word database that contains 18000 Bangla word images of 120 different categories and it obtained a recognition accuracy of 96.17%.

The researchers Mishra and Tripathi (2021) proposed the CNN model by training a deep learning model to implement the search engine for biomedical images. Furthermore, for boosting the performance of biomedical search engines, a fusion of DCNN and vector space-based biomedical picture query similarity matching techniques were presented. By translating the vector space model to a classification issue, the DCNN model was created. They developed a biological picture search engine with an accuracy of 79.42%. On the other hand, Gnanasivam *et al*. (2021) used CNN on Tamil handwritten character recognition which utilized the Tamil letter dataset collected from the students and the Kaggle website. The CNN model accuracy is 95% for their study they could expect 121 classes from 247 Tamil characters that can identify words given on the combinations of 121 characters.

Narayan and Muthalagu (2021) presented the CNN model on image character recognition. For detecting English handwritten characters with text pictures. The model has shown to be quite good at recognizing characters in real-time, which broadens its use. Preprocessing is a crucial step in assuring the model’s good performance. Image preparation methods improve the image’s characteristics, which improves recognition accuracy. With a recognition accuracy of 97.59%, the CNN model was successful (Ahmed *et al*., 2021). In their study, the authors presented a deep learning model for the contextual identification of Arabic handwritten letters using a Deep Convolutional Neural Network (CNN).

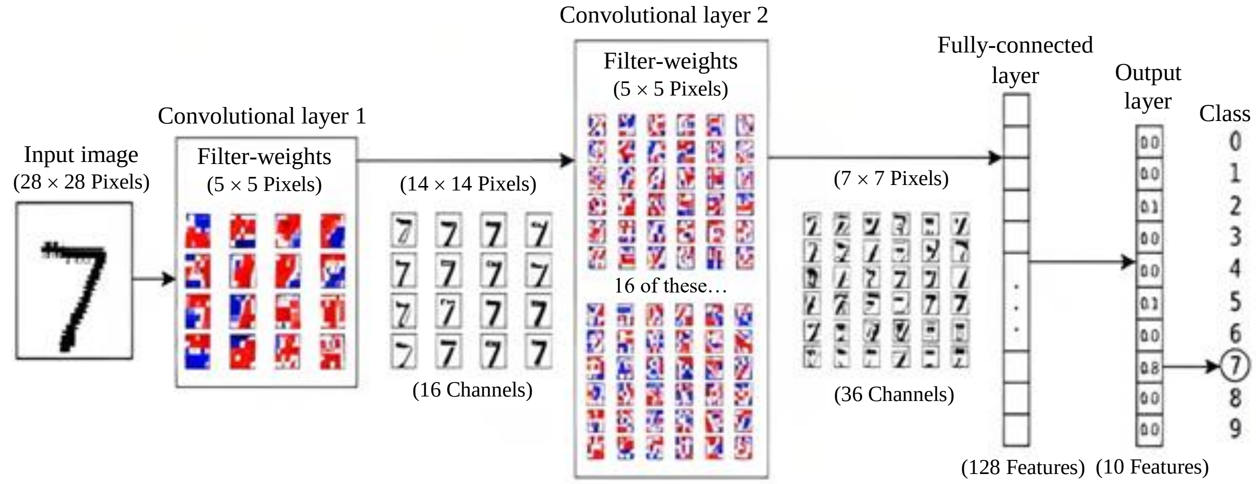

Fig. 3: CNN architecture

They employed a supervised CNN to avoid overfitting and improve generalization performance. The proposed method effectively processed high-dimensional data by extracting optimal characteristics automatically and contextually. The model demonstrated strong performance on four Arabic handwriting databases (madbase, CMATERDB, HACDB, and three types of SUST-ALT databases), achieving testing accuracies ranging from 99.72-99.95%. It also exhibited exceptional accuracy and precision on the MNIST English digits database, with a testing accuracy of 99.94% and a precision of 99.68%.

The authors suggested a unique technique to text baseline recognition using a recurrent convolutional neural network in their study (Wödlinger and Sablatnig, 2021). The authors discovered that combining the raw input image with a segmentation map trained to predict text baselines improved the performance of the recurrent CNN. They also presented a comprehensive baseline extraction pipeline that involves extracting start points and angles from the input image using the segmentation map and then using a line rider model to recover the coordinates of each baseline. The CBAD 2019 dataset was utilized in their approach. A two-stage approach of Arabic and Hindi handwritten Numerals using CNN models is presented in (Alqudah *et al*., 2021). Convolutional Neural Networks were used to classify the data (CNNs). The method's initial step was to determine if the input numeral was Arabic or Hindi. The second stage is to determine which language the input number comes from.

The researchers' main aim was to simplify a user's experience in converting physical documents into digital files with ease and comfort. Zin *et al*. (2021), developed an application for handwritten characters that can be used as a teaching aid for children. The application allows for self-study, enabling children to learn without the need for a teacher. It also includes character segmentation processes to address segmentation problems and uses a CNN for character classification, processing each segmented character individually. The study found that the accuracy of the approach was 95.6% on 1000 randomly chosen words and 98.7% on each character. Huda *et al*. (2022) the authors used two widely used datasets, Bangla Lekha Isolated and NumbtaDB, to train a convolutional neural network model for recognizing both digits and characters in the Bangla script. They employed a shifting strategy to increase the size of their dataset and conducted multiple trials on vowels, numbers, and characters. The model achieved an accuracy of 96.42% on the Bangla Lekha dataset and 98.92% on the NumtaDB dataset. The authors also developed two applications based on this concept: A license plate recognition system and a smart e-learning platform.

The researchers in Agrawal *et al*. (2021) used CNN for handwriting digit recognition utilizing 4 convolutional layers. Moreover, the input layers of the model included 32 filters of size 3 × 3 and the authors evaluated the use of seven different optimizers in order to extract the optimal characteristics. The model achieved an accuracy of 99.60% on standard data. They used MNIST in their research as the main dataset. Jain *et al*. (2021) proposed the CNN model to show that its classifier beat over neural network with critically enhanced computational efficiency without surrendering implementation utilizing the MNIST dataset that was divided into two parts training and test dataset. For the experiment within the model, the authors used some libraries of Python for example

NumPy, Pandas, and Keras. The model accuracy of CNN with Adam analyzer was 99.89% for the MNIST information base, respectively. Table 4, the most recent handwritten recognition works are proposed, the methodologies utilized in various ways are provided and the accuracy of the state of the art is compared. This section displays the CNN state models. Table 3 depicts custom convolutional neural network with the accuracies shown.

Transfer Learning CNN

Bonyani *et al*. (2021) proposed in their study three different datasets in the study, which are HODA, Sadri, and Iranshahr. Dense net architectures were used within these datasets. On the HODA dataset, the advanced recognition rates were improved to 99.49% for digits and 98.40% for characters, on the Sadri dataset, to 99.72% for digits, 89.99% for characters, and 98.82% for words and on the Iranshahr dataset, 98.99% for words, respectively. The ability of word recognition is referred to as complete image classification, in turn, it enhances the resulting speed and adaptability pointedly, moreover, it does not require obvious character patterns, unlike HMM and CRNN. Nirmalasari *et al*. (2021) proposed Lexicon CNN and Fully Convolutional Network were the two models used in this study (FCN). The authors used a two-level recognition system in the study, with the first level using a lexicon Convolutional Neural Network (CNN) model to recognize terms that appear frequently in the text. When the Lexicon CNN model fails to recognize a word in the first level, the second level uses Fully Convolutional Networks to recognize characters (FCN). As a training dataset, the experiment used NIST special database 19 and a handwritten word on screen as a testing dataset. The highest accuracy was 99.98% for word recognition, 98.56% for character number prediction, and 83.52% for character recognition. The authors of this study (Ghanim *et al*., 2020) proposed a multi-stage cascading approach for offline Arabic handwriting recognition, which was tested on the IFN/ENIT Arabic database. The effects of SVM and CNN were evaluated individually for classification, with the CNN classification relying on the raw pixel values of the input image and the SVM classification based on a feature vector derived from the input image. When applied to the database, the multi-stage technique achieved 95.6% accuracy using the AlexNet CNN architecture without any character level segmentation.

In their study, Kabakus and Erdogmus (2021) proposed a novel method for recognizing Turkish handwritten letters using the CNN models VGG19, InceptionV3, and Xception. They applied the transfer learning technique to these models on a dataset of 25,875 handwritten Turkish letter samples and compared the performance of the resulting model with previous research in the field. The authors applied a total of 38 epochs in their approach and found that the model achieved an accuracy of 96.07% on the handwritten Turkish letter dataset, outperforming benchmark models. The model was also tested on the EMNIST gold standard dataset and achieved an accuracy of 80.54%, which was higher than the benchmark models. When trained and tested on the EMNIST dataset, the model outperformed related work with an accuracy of 94.61%. Whereas, (Mihir *et al*., 2021) proposed an approach based on the Assamese alphabet Convolutional Neural Networks (CNN). They evaluated the model on a dataset of 52 characters, with over 12k images in total. They applied LeNet-5, ResNet-50, InceptionV3 and DenseNet-201 models. The best accuracy of over 94.62% is obtained on the test data. This is, currently, state of an art performance in Assamese character recognition. Rahmanian and Shayegan (2021) proposed advanced CNNs, DenseNet201, InceptionV3, and Xception in their paper on handwritten-based gender and handedness classification. In their study, IAM for English texts and KHATT for Arabic texts were the two databases. The findings demonstrated that the suggested CNN designs improved classification results, with 84, 1.27% accuracy, the IAM database was used for gender classification and the KHATT database was used for handedness classification, with 99.14% accuracy (28.23%).

In this study by Abdallah *et al*. (2020). The authors investigated the use of attention-based encoder decoder networks for handwritten text recognition in the Kazakh and Russian languages. They developed a novel neural network model that combines a fully gated Convolutional Neural Network (CNN) with multiple Bidirectional Gated Recursive Units (BGRU) and attention mechanisms to perform complex tasks. This model was the first to support both Kazakh and Russian languages. The model achieved a high level of recognition accuracy using a small number of parameters, as tested on handwritten text databases in English, Russian, and Kazakh. The model also outperformed state-of-the-art results on the Kazakh and Russian handwritten dataset (HKR) and the English-based IAM, Saint Gall, Bentham, and Washington datasets, as well as the Russian Kazakh HKR dataset. The transfer learning CNN accuracies is shown in Table 5.

Table 3: Custom convolutional neural network

References	Model of CNN	The size of the image	Number of epochs	Activation function	Dataset	Accuracy (%)
Mustafa and Elbashir (2020b)	CNN	28*28 pixels		RELU	SUST-ALT characters	93.50
Khandokar *et al*. (2021)	CNN	28*28 pixels		ReLU	NIST dataset 1000 images	92.91
Illouz *et al*. (2018)	CNN HEBIU	400*400 pixels	500 epochs	Relu sigmoid	- Hebrew (intra) English Hebrew (inter) English Hebrew (Mixed) English overall mixed	73.02 75.26 75.65 58.29 74.61 79.34 77.00
Hazra *et al*. (2021)	CNN	32*32 pixels	500 epochs	Relu	Mayek27 ISI Bangla	99.27 99.32
Zhuang *et al*. (2021)	CNN	28*28 pixels	5000 epochs	Softmax	CASIA-HWDB1.1	92.28
Hossain *et al*. (2021)	CNN	32*32 pixels	7 epochs		Bangla handwritten on word & char images	84-character level 82-word level
Hemangee and Gayatri (2021)	CNN	32*32 pixels	15 epochs	Relu	Bangla database with 1800 words	96.170
Mishra and Tripathi (2021)	Deep CNN based vector space model	224*224 pixels	262	Softmax	Biomedical search engine dataset	79.420
Gnanasivam *et al*. (2021)	CNN	64*64 pixels	50 epochs	Relu	Tamil letter dataset collected from students and Kaggle website	95.000
Narayan and Muthalagu (2021)	CNN		10 epochs	Relu softmax	English language dataset (74 k) 26.416	97.590
Ahmed *et al*. (2021)	DCNN	28*28 pixels	200 epochs	Relu softmax	MADBase, CMATERDB, HACDB, SUST-ALTdigits, characters and words MNIST English digits	99.910 99.720 99.910 99.820 99.860 99.950 99.940
Wödlinger and Sablatnig (2021)	CNN	32*23 pixels	80 epochs	Relu	CBAD dataset From ICDAR	
Alqudah *et al*. (2021)	CNN	32*32 pixels		Relu	The images obtained by scanning huge number of handwritten numerals	100
Zin *et al*. (2021)	CNN	64*64 pixels	4 epochs	Relu	MNIST EMNIST	95.600 98.700
Huda *et al*. (2022)	CNN	28* 28 pixels	64 and 50 epochs	Softmax	BanglaLekha-Isolated and NumbtaDB	96.420 98.920
Agrawal *et al*. (2021)	CNN	28* 28 pixels	100 epochs	Relu	MNIST	99.600
Jain *et al*. (2021)	CNN	28* 28 pixels	5 epochs	Relu	MNIST	99.890

Table 4: Other approaches to deep neural network

References	Model of CNN	The size of the image	Activation function	Dataset	Accuracy (%)
Wang and Du (2016)	DNN-HMM	64*64 pixels	logistic sigmoid function	CASIA-HWDB database	94.30
Sasipriyaa *et al*. (2021)	CNN model GAN model	28*28 pixels	Relu and sigmoid	English dataset upper class and class contain 400 images	95.36 with CNN 96.14 with GAN
Al Rababah *et al*. (2014)	CNN, RNN	24*24 pixels	Softmax	IFN/ENIT	
Rajalakshmi and Kumar (2020)	CNN and RNN	images resized to (200, 50)	Softmax Relu	IAM contain 100.000 images of word	83.00
Singh *et al*. (2021b)	RNN	30*30 pixels converted to grayscale picture of size 128×32	Relu sigmoid		90.00
Bastas *et al*. (2020)	CNN CNN-LSTM	28*28 pixels	ReLU	Sequential MNIST	98.50 97.5.0

Table 4: Continue

	LSTM, BLSTM TCN-Dynamic TCN-Static LSTM and CNN				99.50 99.00 97.50 97.00 98.00
Keshri *et al*. (2018)	LSTM and BLSTM	32*32 pixels	Sigmoid	Devanagari scripts	99.50 96.94
Das *et al*. (2020)	LSTM	32*32 pixels softmax	Sigmoid	IIT-Bhubaneswar	97.93
Maalej and Kherallah (2020)	DBLSTM	depend on the number of characters in the dataset and the length of each NCR in ADAB dataset	SoftMax ReLU and maxout	ADAB	84.40
Shkarupa *et al*. (2016)	RNN-CTC Seq2Seq	300*400 pixels 600*400 pixels	ReLU	KNMP and stanford training dataset	78.10 72.79
He and Schomaker (2021)	GR-RNN	64*64 pixels	ReLU	IAM	99.10
Zhang *et al*. (2023)	LSTM, CNNs,	and BiLSTM	Tanh softmax	A dataset containing 8190 finger writing lowercase letter samples	98.31 95.87 99.82

Table 5: Transfer learning CNN

References	Model of CNN	The size of the image	Number of epochs	Activation function	Dataset	Accuracy (%)
Bonyani *et al*. (2021)	DenseNet and Xception	80 × 80 and 64 × 64 pixels	150 epochs	Relu	HODA Digits and characters Sadri digits, characters and words Iranshahr dataset	99.49 98.10 99.72 89.99 98.82 98.99
Nirmalasari *et al*. (2021)	Lexicon CNN and Fully Convolutional Network (FCN)	32*16 pixels	50 epochs	Relu	NIST word recognition, character number prediction, character recognition	99.98 98.56 83.52
Ghanim *et al*. (2020)	DCNN, Res Net VGG16, Dese Net Inception	24*24 pixels		Relu Softmax	IFN/ENIT Arabic dataset	95.60
Kabakus and Erdogmus (2021)	VGG19, Inception V3 and Xception	127 *127 pixels	38	ReLU	Turkish letters 25,875 samples	96.07
Narayan and Muthalagu (2021)	LeNet-5, ResNet -50, InceptionV3, DenseNet-201	96*96 pixels	100	ReLU classified linear unit softmax	52 characters	94.62
Rahmanian and Shayegan (2021)	Dense Net 201 Inception V3 Xception	400*100 pixels	100 epochs	Relu Softmax	IAM for English text KHATT for Arabic text	84 for 99.14
Abdallah *et al*. (2020)	Fully gated CNN Attention-Gated-CNN-BGRU		50 epochs	ReLU	Kazakh and Russian	
Finjan *et al*. (2021)	ResNets	28*28 pixels		ELU	MADBase	99.60
Awni *et al*. (2022)	ResNet18	224*224 300*300 pixels	45 epochs	ReLU	AlexU-W IFN/ENIT	99.52 96.11
Wahi *et al*. (2015)	ResNet -50	128*128 pixels		ReLU	HPL-Tamil -Iso-Char	96.00
Sudana *et al*. (2020)	VGG19	100*1200 pixels	100 epochs	Softmax	IAM	92.30

The paper by Finjan *et al*. (2021) emphasizes the importance of recognizing Arabic digits. The study proposed using Convolutional Neural Networks (CNNs) with the ResNet-34 architecture. The ResNet-34 model contains multiple convolutional layers and residual blocks that aid in learning image features and preventing the vanishing gradient problem during training. The study used a dataset of 60,000 Arabic handwritten digits called MAD base and 1000 testing samples was later converted to grayscale to make them more manageable during the training process, which was preprocessed and augmented to increase its diversity and size. Data augmentation techniques such as rotation, scaling, and shifting were used to enhance the dataset. The results of the study indicate that the proposed model accurately recognizes handwritten Arabic digits, with a classification accuracy of 99.6%. Furthermore, the proposed model's performance is compared with other state-of-the-art models, showing that it outperforms them. The study's findings demonstrate the effectiveness of using CNNs with ResNet-34 architecture in recognizing handwritten Arabic digits, contributing to the field of Arabic handwriting recognition.

Awni *et al*. (2022) in their study, the authors compare the performance of randomly initialized deep convolutional neural networks with that of a ResNet18 model pre-trained on the ImageNet dataset for recognizing Arabic handwritten words. They then propose a sequential transfer learning approach using the pre-trained ResNet18 model to improve recognition accuracy. The approach is evaluated on two popular offline Arabic handwritten word datasets, AlexU-W and IFN/ENIT, through four different sets of experiments. The results showed that using the ImageNet dataset as a source improves recognition accuracy by 14% for ten frequently misclassified words in the IFN/ENIT dataset, while the proposed approach achieved a 35.45% improvement. Additionally, in their study, the authors first trained the ResNet18 model by freezing the first Conv1 layer and the following two residual blocks. They then fine-tuned the remaining layers using the IFN/ENIT dataset with an input image size of 224*224. Finally, they applied the progressive resizing technique by increasing the image resolution of the IFN/ENIT dataset from 224*224-300*300. Overall, the proposed approach achieved recognition accuracy of up to 96.11%, a significant improvement compared to other state-of-the-art methods, and 99.52% accuracy was achieved for the AlexU-W dataset.

Wahi *et al*. (2015) utilized ResNet-50 in their work as it is a key feature of Tamil character recognition because it allows for the efficient training of hundreds or thousands of layers. ResNet-50 uses an "identity short connection" layer to overcome the problem of the gradient becoming very small with more layers, which allows for fewer and no deep layers in the system. When working with small datasets, a single stage character recognition scheme is employed, but a multi-stage recognition scheme is used for larger datasets. The study used the HPL Tamil Iso Char database with 15,000 images, but only 5,000 images covering 156 Tamil characters were used for the study. A Tamil character recognition system using ResNet-50 with a 96% accuracy rate was proposed, which includes a database, algorithm, and application. The dataset contains many visually similar characters and over 15,000 128*128 images. The proposed system could be used for a complete handwritten documenting and digitizing system. In another study by Sudana *et al*. (2020), the researchers proposed a handwritten identification method using sentence segmented handwriting forms seems promising. By using sentence forms, the method can capture more complete handwriting characteristics than using single characters or words. The IAM dataset used is divided into three categories of images: Binary, grayscale, and inverted binary, with all datasets having the same image but different in color and consisting of 100 epochs. The authors used a pre-trained model, VGG19. This allows the model to leverage the knowledge learned from a large dataset to improve performance on a smaller, more specific dataset. The highest result is achieved with grayscale images, with a genuine acceptance rate of 92.3% accuracy and an equal error rate of 7.7%, which is promising. Moreover, the proposed model is able to accurately identify handwriting even when presented with grayscale images, which are more challenging than binary or inverted binary images.

Other Methods for Handwritten Recognition

In another study by Wang and Du (2016), the authors presented a new approach for recognizing handwritten Chinese text using a Deep Neural Network Hidden Markov Model (DNN-HMM) with writer adaptation. They evaluated their method using the ICDAR 2013 Chinese handwriting competition database and found that the new writer adaptation DNN-HMM achieved a higher recognition rate than the writer-independent DNN-HMM. Sasipriyaa *et al*. (2021) in their study on English handwritten characters, researchers offered two models: GAN for generating English handwritten character recognition and the CNN model. The study's findings suggested that the produced English character pictures improved the performance of character classifiers. GAN's accuracy was 96.14%, while CNN's was 95.36%.

Al Rababah *et al*. (2014) this study propose a neural network architecture that uses CNN and RNN, to solve the Arabic text recognition task without being constrained by a dictionary or a language model. The writers changed the ground truth format to characters as a modeling unit and applied 3 types of augmentations. The authors proposed a new neural network architecture that achieves a state-of-the-art result in the unconstrained recognition task. They used this approach to recognize letters regardless of their shapes and this model accepted inputs of all sizes. Whereas the researchers in the same model study (Rajalakshmi and Kumar, 2020) proposed CNN and RNN models in this study. The authors incorporated multiple domains in computer science, including machine learning android application development and database storage, to develop a system for extracting handwritten content from images and converting it into textual files that can be easily accessed and edited within a secure application. In another study by Singh *et al*. (2021b), a recurrent neural network was used to identify the arrangement of characters in handwritten text. The authors preprocessed the images by resizing them to 30 × 30 pixels and converting them to grayscale, then resizing them again to 128 × 32. While OCR systems for formal typed English are readily available, those for handwritten text are scarce and often have poor accuracy. The model was implemented using the Tensor flow Framework within the Conda environment and achieved an output accuracy of 90% for transcribing handwritten text as printed text.

Bastas *et al*. (2020) authors of this study explored the use of deep learning architectures for recognizing text written in three-dimensional space, using a leap motion controller sensor to capture the motion trajectories of handwritten digits (0-9) as multidimensional time series data. They compared several approaches, including dynamic and static models, using Long Short-Term Memory (LSTM) networks, bidirectional LSTM (BLSTM) networks, 1D Convolutional Neural Networks (CNNs) combined with LSTM networks (CNN-LSTM), Temporal Convolutional Networks (TCN) with dilated causal convolutions and TCN with static convolutions. The best performing model was LSTM, followed by BLSTM, CNN, CNN-LSTM, and TCN-Dynamic, with TCN-Static performing the least well. The evaluation was conducted on a dataset of approximately 1200 examples written by 10 participants, with each digit written at least 10 times.

Keshri *et al*. (2018) the authors proposed a new method for online handwritten word recognition in the Devanagari script by building two models based on Recurrent Neural Networks: Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BLSTM). In their analytical scheme, they labeled the strokes of the words and used a lexicon of 10,000 words to train the system. This allowed the system to recognize unknown words that were not used to train it, resulting in a high recognition rate. The results of the experiment demonstrated that the proposed system outperforms all other existing online word recognition systems, including those based on hidden Markov models, by 99.50%. The recognition rates of the systems being compared were 87.99 and 93.82%. While the writer's Das *et al*. (2020) developed a method for recognizing handwritten Odia numerals using an LSTM network. They used a large database of handwritten numbers to improve the accuracy of the system. They also took time into consideration in order to improve the performance of the system. In their approach, they achieved an accuracy of 97.93% in recognizing handwritten Odia numerals, which is a very good result.

Maalej and Kherallah (2020) applied DBLSTM to an online Arabic handwriting recognition system and used dropout to prevent overfitting. They used ReLU, Maxout, and SoftMax activation functions to address the vanishing gradient problem. They tested the system on a large ADAB database to demonstrate its performance in challenging conditions. The experimental results showed that the best-tested architecture produced a 10.99% reduction in the label error rate compared to the baseline system. In another study, by Shkarupa *et al*. (2016), the authors evaluated two approaches based on RNN with LSTM for recognizing handwritten Latin texts from history. The first approach used a Connectionist Temporal Classification (CTC) output layer, while the second approach was based on sequence-to-sequence learning. They built a handwriting recognition system that took an unsegmented word image as input and provided a decoded string as output. The results of the approaches were promising, with 78.10-72.79% word-level accuracy on the test dataset for the respective methods. The results showed that the connectionist temporal classification approach consistently outperformed the sequence-to-sequence learning approach in terms of generalization and predicting long words.

In another study by He and Schomaker (2021), the authors presented an end-to-end neural network system that uses handwritten word images to identify writers through handwritten word images. The system integrates global context information, which is extracted from the neural network using a global average pooling step, with a sequence of local and fragment-based features, which are extracted from a low-level deep feature map containing detailed information about the handwriting style. The proposed method called the Global Context Residual Recurrent Neural Network (GR-RNN) method, was evaluated on four public data sets and showed a state-of-the-art performance. The results also showed that neural networks trained on grayscale images performed better than those trained on Binarized and contour images, indicating that texture information is important for writer identification.

Zhang *et al*. (2023) presented a finger writing character recognition system that used an array of Time of Flight (ToF) distance sensors mounted on a low-power microcontroller STM32F401, equipped with deep learning algorithms. The system is designed to recognize 26 English lower-case letters in real-time, without the need for users to wear additional devices. A dataset containing 8190 finger writing lowercase letter samples was recorded. Users wrote on a flat surface, such as a desk and the ToF sensors acquire pair distance values between each sensor and the writing finger within a specific zone. The work’s method was tested on data collected from 21 subjects and multiple deep-learning algorithms were evaluated for their performance in finger writing recognition including LSTM, CNNs, and BiLSTM. The best result was achieved with the LSTM algorithm, which achieved 98.31% accuracy and 50 ms of maximum latency. 99.82% and the CNN model achieved the lowest accuracy with 95.87%.

Previous studies have utilized deep neural networks for feature extraction and classification using machine learning models. However, the accuracy of these methods has been suboptimal due to challenges in properly adjusting the hyperparameters of both the deep neural network and the learning model, or because the deep neural network is not effectively extracting the appropriate features for the learning model.

Discussion

In recent years there has been a number of challenges regarding Handwritten Recognition (HR) in the field of AI. For example, the quality of the image is critical in handwritten recognition. Yet, OCR must deal with different image sizes that come in various levels of quality of images that generates noise, and the running time of the process that tends to be shared as high-quality images with background elimination noise such challenges are in the scanning processes. These reasons are poor quality of original documents that result in deteriorating paper easily, texts may be incomprehensible or unreadable due to different alphabets, for example, the letter "u" is written as "v", "d' as "a". While writing down on the forms that are required from the participants which are not written in the text and character fields on the document. Additionally, connected handwriting, or handwriting in which letters are joined together, poses another challenge for computers. It can be difficult for computers to recognize individual characters when they are connected, as in the case of an "r" and an "n" that might be mistaken for an "m".

Another challenging problem in the field is when reading others' handwriting, people face difficulties reading the text in return how will the programs figure the characters out? As the problem of a wide range of better and worse handwriting. Thus, it will make the program work hard to recognize the handwriting. In addition, the type of handwriting such as cursive makes the job of the computer programs even harder as neighboring letters might be connected. Also, Handwriting recognition from photos can also be challenging due to the possibility of awkward angles. If a photo is taken at an angle that obscures the character, it may be more difficult for a computer to accurately identify it.

The datasets of handwriting recognition that don’t have different languages and don’t contain all language characters are also considered a big challenge for HR. Furthermore, the accuracy of handwriting analysis to make a meaningful comparison between uppercase and lowercase letters. Accuracy is a common challenge in handwriting recognition, as people often have difficulty reading handwriting written by others. Moreover, the variability in handwriting quality presents a challenge for programmers in terms of obtaining sufficient representative examples of each character. Furthermore, the similarity in appearance among certain characters can make it difficult for a computer to discern them accurately.

There are various challenges that can impact the performance of online handwriting recognition systems, such as variations that are specific to individual writers, specific machines, or specific scripting languages. Additionally, there are general challenges that are prevalent across most scripting languages, including variations in handwriting style, constrained and unconstrained handwriting, and hardware and behavioral factors.

Future Direction

There are a few potential gaps in the field of handwritten recognition using Convolutional Neural Networks (CNNs) that researchers and developers may need to address in the future.

There are limited datasets for Arabic handwritten which affect the model's quality. Moreover, the cursive nature of Arabic writing where some characters are joined together for making the writing faster.

There are challenges in using some datasets for character recognition due to the inclusion of distorted or blurry images, as well as the sensitivity of certain languages to small changes in characters. To address these issues, potential solutions include using higher quality images as inputs, applying machine learning techniques to remove backgrounds, improving image capture practices, and designing more sophisticated recognition algorithms. Additionally, more precise handwriting management may also be beneficial.

Handwriting can vary significantly from person to person and even within the same person over time. This variability can make it difficult for CNNs to accurately recognize handwritten characters and words. Future research may focus on developing more robust and adaptive CNN models that can handle a wide range of handwriting styles and variations.

Handwritten recognition systems may need to support multiple languages in order to be widely applicable. Developing CNN models that can accurately recognize handwriting in multiple languages could be an area of the future.

Overall, the future of handwriting recognition looks promising, with ongoing research and advancements in technology. As technology continues to improve, we can expect to see more applications of handwriting recognition in various fields, such as education, healthcare, and finance.

Conclusion

Convolutional Neural Networks (CNNs) are a type of machine learning model that can be used for handwritten recognition tasks. CNNs are specifically designed to recognize patterns and features in images and are often used for image classification and object recognition tasks which are different from classical image recognition. Therefore, the image's raw pixel data are taken by the CNN model, trains and later the features automatically are extracted for better classification. The innovative and well-known methodologies for handwriting recognition were discussed, as well as the number of strategies employed in conjunction with these methods and their accuracy was compared. Handwriting recognition was more challenging than image recognition for scripts produced by computers because handwriting can vary significantly from one person to another. This means that handwriting was more difficult to detect compared to scripts from computers, which had a standardized shape. However, the findings of several studies showed that the preprocessing step, which included noise reduction, cropping, and resizing, played a significant influence in enhancing the accuracy rate. Compared to the state of artworks, different important datasets were explained in different states of art such as MNIST, HODA, NIST, and many more. This study investigated the effectiveness of using deep learning methods, particularly convolutional neural networks, for recognizing handwriting. Previous research had shown that these techniques excel at capturing the structural features of handwritten characters.

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Author's Contributions

Sardar Hasen Ali: Designed the research plan and organized the study; coordinated the data analyzed and contributed to the written of the manuscript.

Maiwan Bahjat Abdulrazzaq: Participated in edited the written manuscript.

Ethics

I undersigned that this article has not been published elsewhere. The authors declare no conflict of interest.

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