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REVIEW ARTICLE

A study of deep learning techniques for handwritten digit recognition and classification

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ABSTRACT

As computers play an increasingly vital role in human life and daily activities across various domains, humans have leveraged their intelligence and creativity to use computers in natural and effective ways. Hence, a reliable method for recognizing handwritten digits is essential. Handwritten Digit Recognition (HDR) can offer a clear benefit in this aspect. Deep Learning (DL) has been a powerful tool for solving various problems with high accuracy in recent years. This paper first surveys the different methods for HDR that have been developed by various researchers. Machine learning has enriched this analysis with different approaches that involve supervised learning, unsupervised learning and reinforcement learning. Next, the paper reviews the applications of deep learning methods to different languages in real-world scenarios. DL techniques are specially designed for handling complex data formats. Many natures inspired Convolutional Neural Network (CNN) models are discussed in this section. Lastly, the paper discusses the different classification techniques in handling the handwritten digit which could provide useful references for researchers who want to experiment more in this field.

Keywords: pattern recognition; handwritten images; deep convolutional neural networks; prediction models; classification algorithms

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1. Introduction

Handwriting is a general form of establishing communication with individuals and widely used in envelopes, notebooks, cheques, letters, etc. It is considered the natural way to acquire, store, and transmit information, and the original purpose is to facilitate communication and expand human memory. This application involves automatic reading of handwritten amounts on checks, improving efficiency and reducing errors. The significant target of this research is to imitate the ability of humans to read and recognize handwritten digits[1–5]. The preliminary handwritten characteristics are provided in three diverse folds: 1) it is composed of artificial marks over the surface, 2) establish communication, and 3) attain virtual marks over the regional languages. The cultural and civilization attributes pave the way for regional handwriting establishment[6]. The motivation towards this research does not rely on the research challenges and the advantages related to it over commercial applications. By considering the significance of document validation, the benefits of automatic handwritten digit recognition are apparent[7]. It not only helps in the establishment of communication among the human community but also serves as the mode of communication among machines and humans. The investigators intend to analyze the intellectual characteristics of humans and their ability to recognize and read the handwritten and printed content[8]. The vast advancements in computers and technological growth lay the path for making human life more manageable, and these sorts of improvements promise to enhance efficiency and communication. The evolution of modern computers is integrated with human and pledges' everyday activities to make the accessibility in a user-friendly manner[9]. The mode of communication among computers and humans shows a direct effect making computers universal tools. Ubicomp computer interfaces help in the natural form of human communication like gestures, speech, and handwriting as a substitute to GUI interaction. Handwriting is the most prevalent way of communication with dual benefits, i.e. being natural and relatively permanent[10]. The supremacy of handwriting is multiplied by the massive number of handwritten documents and cabinets filing business. Electronic communication is indispensable to the business world, where the recognition does not gain any global benefits. Machine-based human reading has been an extensive way of research for the past few decades. Moreover, various prevailing investigations are constrained by the power and memory of the computers[11]. With the boom of information technology, there is a drastic increase in the research field for constructing a structural language script. The applications of HDR are computer vision algorithms, detect characteristics from pictures, touch-screen devices and e-readable form. The ability for machines to interpret handwritten digits, or handwritten digit recognition (HDR), acts as a bridge between the physical and digital, fostering smooth interaction with technology across diverse fields. For example, HDR is the foundation of automated check processing in banks, helping to streamline financial operations and save time and costs by accurately reading millions of handwritten numbers every day. HDR plays a crucial role in self-service kiosks and ATMs as well, enabling customers to enter PINs and other numerical data for safe transactions and access. HDR plays a crucial role in self-service kiosks and ATMs as well, enabling customers to enter PINs and other numerical data for safe transactions and access. HDR is used in postal automation, which goes beyond financial services. By identifying zip codes on envelopes, it helps sort mail and greatly increases productivity. Moreover, HDR is used in educational technology, allowing devices such as tablets and smart pens to identify handwritten responses and give pupils instant feedback, improving the learning process.

The objectives of this paper are:

- To annotate on the various deep learning techniques that are used for HDR.
- To comprehend those numeral values (0, 1, 2, 3, 4, 5, 6, 7, 8 and 9) are language specific and to attempt to analyze these images for prediction.
- To understand the stages involved in handwritten digit recognition.
- To choose a better HDR approach that is appropriate for the language.

1.1. Handwritten data

Handwriting data is considered the most dominant way of handwriting recognition. It possesses two diverse handwritten data: online and offline data[12]. The former model is captured during the process of writing using an electronic surface or special pen. Online data specifies that the data is collected from various modern devices like tablets or smartphones from which the information is determined using the specified sequence of data points. In the handwritten data recognition area, online data is commonly referred to as online signal. The coordinates of the data points are captured and specified as spatial positions[13,14]. The device offers a pressure of pen/pencil, data acquisition, and inclination of pen and these devices rely on spatial sampling. The data point's coordinates are given, and the distances among the consecutive points are homogeneous. Similarly, some other data points depend on temporal sampling, and the distance among the consecutive points are determined to be heterogeneous. The data point density while writing slowly is essential than writing rapidly. The offline data specifies documents obtained during hard copies and scanning of documents with scanners and cameras stored in the image format. It is nothing but the transformation of graphical marks into electronic representation[15]. Generally, the documents used for the process rely on physical support like papers, magazines, historical documents, music score, journals, administrative forms, etc. The digitization process outcomes are grayscale, color or binary format to meet digitization objectives.

1.2. Representation of handwriting

The researchers used some standard terms when performing the automatic handwriting: identification, interpretation, and recognition. A recognition process transforms the graphical marks related to handwritten script into symbols stored in the ASCII form or Unicode. Performance is based on readers used for determining the handwritten text[16,17]. The handwritten variations are referred to as the mail format. Identification is the task of predicting the handwriting fragment, and the samples include signature verification. The task of predicting the handwritten signature based on specific writing is essential in the forensics field to indicate the suspect's handwriting[18]. Identification concentrates on the analysis of computerized handwriting as the prediction process relies on the unique fragmenting nature of the handwriting samples for differentiating the individuals. The recognition and interpretation process needs variation to be eliminated from the provided handwriting fragments. It makes the process to be uniform and easier for extracting the meaning and messages efficiently.

1.3. Advances in HDR

HDR technology has seen significant advancements and diverse applications in recent years. While a single, all-encompassing set of statistics is challenging due to the varied nature of its use, here's a breakdown of its applications and their estimated market size:

Financial services: The global market for automated check processing using HDR was estimated at USD 1.3 billion in 2023 and is projected to reach USD 2.1 billion by 2028 at a CAGR of 9.2% (Source: Grand View Research). This application involves automatic reading of handwritten amounts on checks, improving efficiency and reducing errors. In fraud detection, HDR plays a role in fraud detection, analyzing handwritten signatures and other information to verify their authenticity [19]. While specific market size data is unavailable, it's a growing application.

Postal and logistics: The global market for intelligent mail processing using optical character recognition (OCR) technology, which often includes HWR capabilities, was valued at USD 5.2 billion in 2022 and is expected to reach USD 7.1 billion by 2027 at a CAGR of 6.3% (Source: Grand View Research). This application automates sorting and routing of handwritten addresses on envelopes and packages.

E-commerce and retail: The global market for self-service kiosks was valued at USD 8.9 billion in 2022 and is expected to reach USD 14.2 billion by 2027 at a CAGR of 9.2% (Source: Grand View Research). HDR can be integrated into these kiosks for users to enter information like PINs or confirmation codes through handwriting.

2. Steps in handwritten digit recognition

The preliminary steps in HDR are image acquisition, where the document with the textual or digital content is digitized[20]. However, some initial processes are applied to the image to make it more appropriate for feature extraction and classification. During the segmentation process, the provided lines are predicted, and these lines, digits, characters and words are separated[21]. The images should be supplied for feature extraction, and this process is performed to enhance the classification or prediction accuracy. Finally, the recognition of digits from the given image is performed. Pattern Recognition, Image Processing, Machine Learning (ML) approaches, and deep learning approaches are considered as the primary research area used for predicting handwriting data[22,23]. Image processing refers to the processing of images using a digital computer[24]. Various algorithms are used in image processing for handling the recognition process and include image pre-processing, thinning, binarization, segmentation, noise elimination, and normalization approaches. Pattern recognition comes under the sub-topic of machine learning approaches, and it is exhibited as the process of providing the raw data and processes it. After this process, the decision-making is done for categorizing the data. It organizes the data patterns based on the statistical information or prior knowledge from those patterns. It is composed of a collection of observations to be described or classified. Similarly, the feature extraction process helps to predict the representative information from these observations[25]. Thus, the classification is based on the extracted features, and it is either unsupervised or supervised learning. In supervised learning, the classification is performed using patterns that are described or known already. In unsupervised learning, the system is not given the prior labeling patterns, and the system itself classified the pattern regularities[26–29]. The section given below discusses some of the machine learning concepts. It paves the way for the booming of the deep learning approach, which is discussed in the successive sections. **Figure 1** shows the generic steps that are followed in HDR.

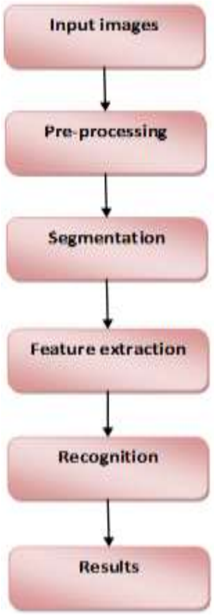

Figure 1. Generic steps in HDR.

3. Deep learning approaches

Wang et al.[30] stated that DL is a subset of ML that relies on the Artificial Neural Networks (ANNs) computing paradigm inspired by human brain functionality[31]. Like the human brain, the learning model is composed of various computing cells known as neurons. It performs a more straightforward operation and interacts with one another to make the appropriate decision. It is a learning process where credit assignments over various NN layers are accurate and efficient[32]. The complexities encountered in conventional approaches are necessary to choose the appropriate feature, which is essential for processing an image data[33]. When the number of classes increases, the feature extraction process turns to be cumbersome[34]. Also, feature definition needs a plethora of parameters that the engineers fine-tune. While comparing this traditional concept, DL introduces a concept known as an End-to-end learning process where the machine is provided with a set of the image dataset[35]. It is known that DNN is well-established and performs more effectively than conventional algorithms. The workflow of the Computer Vision (CV) model and DL approaches are given in **Figure 2**.

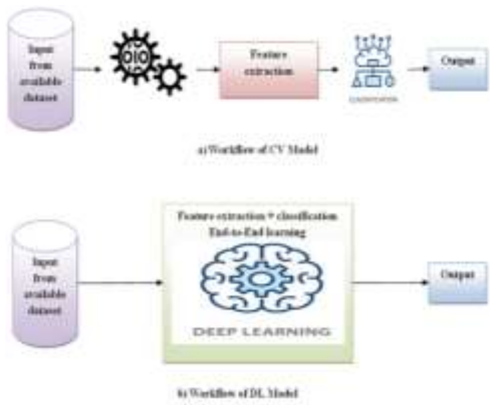

Figure 2. Workflow of traditional and modern algorithm[36].

It establishes a trade-off between the training time and computing requirements[37,39–41]. The CV model's functionality is changed drastically with expertise and knowledge during the extraction of hand-crafted features[42].

4. Deep learning performance

The development of DNN shows tremendous influence over the computer vision field, and it is accountable for efficient object prediction. This prediction process is enabled by the increase in computing power and the vast amount of data needed for training Neural Network (NN). The widespread usage of DNN architecture over a CV is apparent.

5. Algorithms of deep learning

With the significant advantages, in recent times, DL shows tremendous growth in its adaptability and popularity. **Table 1** depicts various algorithms in the field of deep learning.

Table 1. Comparison of various DL algorithms[43].

S. No.	Algorithms	Description
1	Deep Neural Networks (DNN)[44]	It is a simple algorithm with more than two hidden layers. It was adopted for classification and regression-based applications.
2	Convolutional Neural Networks (CNN)[44]	It works effectively for image-based applications. This network model is highly efficient for 2D data.
3	Recurrent Neural Networks (RNN)[44]	This network model is applied for sequence format data. Network weights are shared among the network nodes.
4	Deep Belief Networks (DBN)[45]	It is significantly needed for unsupervised and supervised learning models. A hidden layer of sub-networks are available for next sub-network.
5	Deep Auto-encoders (DA)[46]	It is applied for image-based dimensionality reduction. Input and output size is the same. It is a supervised learning algorithm.
6	Deep Boltzmann Machine (DBM)[46]	It works in a unidirectional manner like Boltzmann's family. It is an extended version of RNN.
7	Deep Convolutional Extreme Learning Machine[46]	This network model is used for sampling local connections, and it is applied with a Gaussian probability function.

6. Deep convolutional neural networks (DCNNs)

DCNN uses kernel function (for filtering) to identify the given input image features (image edges). The kernel is a matrix of weights that are trained for predicting certain features[47]. The concept behind CNN is to convolve kernel spatially over the provided input image and validate whether the features are meant for prediction. The convolutional function is performed by evaluating the kernel dot products and input where kernels are overlapped[48]. The learning process of kernel weight is facilitated using the convolution layer output and summed with both bias term and non-linear activation function. Specifically, Activation Functions (AF) are non-linear functions such as ReLU (Rectified Linear Unit), TanH, and Sigmoid. Based on the data nature and classification tasks, AFs are chosen. For instance, ReLU is represented with neurons over the brain. **Figure 3** depicts the generic view of the CNN model.

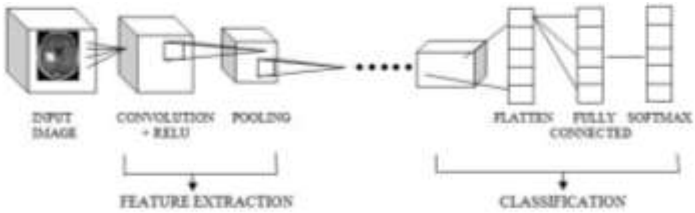

Figure 3. Framework of the deep convolutional neural networks (DCNN).

The training process is quickened, and the total memory consumed is reduced over the network[49]. Often, the pooling layer follows the convolutional layer for eliminating redundant data from the input feature[50]. For instance, the max-pooling layer moves the window from input to output to reduce the image pixel's maximal value. Deep CNN possesses various convolutional and pooling layer pairs. Finally, Fully Connected Layers (FCL) flattens the previous layer's volume, and the output layer evaluates the score (probability and confidence) for output features and classes throughout the network[51]. The output is fed to regression functions like soft max as it maps the vector values. This model provides efficient outcomes with magnificent results for image prediction tasks[52,53]. From the extensive analysis of deep learning over image processing, it is evident that DL plays a crucial role in pattern recognition applications[54,55]. DL acts as a bridge between the learning and visualization process. It works effectively over the enormous amount of data accessible over the dataset with reduced computational cost and time. With this analysis, it is noted that DCNN plays a predominant role in classification[56].

7. Handwritten text/digit recognition

The prominence of information relies on the interpretation of three factors known as medium, equipment, and person. These three factors are interrelated with one another and outcomes in the creative communication process assists in spreading knowledge among the human community. **Figure 4** shows the different language representations of the values 0 to 9.

Figure 4. Numeral system in different ancient languages.
Source: https://www.pinterest.com/pin/655344183267671982/

Handwritten data carries a prominent mode of communication for more than thousands of years[57]. In a country like India, the ancient cultures and other factors are provided in the corresponding regional language. Recently, the information is captured using bank forms, questionnaires, medical forms, form filling, admission form, etc. In the present digital society, handwritten documents require to be in digital format. It is more beneficial for searching the keywords, easily accessible, sorting from security, storage, movement, converted to speech and processing via a word processor[58]. mentions that the handwritten documents digitization is scanned and captured, and used as the outcome of the image. The images are also considered a digital document where the information cannot be searched, processed, or interpreted[59–61]. The skews are introduced over the image during the scanning process, devoid of any alignment. The detection process is based on cross-correlation, rough transformation, horizontal and vertical projection profiles[62]. Similarly, the thinning process diminishes the character irregularities with proper character width. It diminishes the amount of pixel data and assists in extracting features from stroke thickness[63–65]. The general flow of digit recognition that is used widely in DCNN models when dealing with images are pre-processing, segmentation, feature extraction and classification.

Handwritten digit recognition (HDR) technology can be integrated into digital pens and tablets, allowing students to seamlessly transition from writing on paper to working electronically. This technology unlocks a range of benefits, including:

- Instant feedback: The system can automatically grade written tests, providing immediate feedback and facilitating student learning.
- Personalized learning paths: Based on the student's performance through HDR-enabled tools, educators can personalize learning paths and offer targeted support.
- Immediate problem-solving assistance: In subjects like mathematics, the system can utilize HDR to recognize and analyze handwritten work, offering immediate solutions or guidance.

EdTech exemplifies these potential benefits. They implemented an HDR-based learning platform for elementary school mathematics, demonstrating that students using the platform significantly improved their problem-solving skills and overall mathematical comprehension compared to those using traditional methods. This case study underscores the transformative potential of HDR technology in enhancing the learning experience, personalizing education, and fostering improved student outcomes.

7.1. Neural network models for handwritten digit recognition

The proposed method by Das et al.[66] performs detection of Image Net Large-scale visual recognition and attempts the prediction process using a deep CNN model. The author makes use of the resource completely with a profound architectural model. This architecture intends to produce significant-quality gain with a moderate increase in computational requirements compared to narrow and shallow architecture. It describes that the deep CNN model is well-suited for image-based feature extraction. The images with diverse modalities and dimensions are offered to recognize and test model performance anticipated[67]. The author anticipated a novel deep learning model for multi-haptic feature extraction and recognizes the objects from multi-modal haptic images. The outcomes rely on the multi-modal data fusion superior performance when compared to single-modal data. The model proposed by Alheraki et al.[68] offers a simple and highly modularized network model for classifying the images. The anticipated model provides a network size of 34.4M and outputs a superior Wide ResNet model, which various investigators utilize in a wider manner[69–71]. The method proposed by Seide et al.[72] evaluated the theoretical efficiency of the data-parallel and model parallel distribution with stochastic gradient descent-based DCNN training. Moreover, the author did not handle these robustness issues to deal with the failures or other issues that occur during the training process and not the convergence speed. The model proposed by Amiri et al[73] perform experimentation with two superior models like Conv Net, which is publicly available to provide superior research over the deep visual representation in computer vision. **[53]** modeled diverse feature extraction approaches like global transformation, statistical feature-based model, and structural feature-based model. The wok used an SVM-based offline handwritten digit recognition system and concluded that SVM outcomes are superior while performing it over the NIST SD'19 standard dataset. Bengio et al.[74] provided a hypothetical model using the recurrent network model, which is extremely powerful in representing the principal features based on sequential model and training is provided by two diverse factors with the same issues, i.e., long-term dependencies[75,76]. The experimentation is performed over the music and text data. It offers superior outcomes with the merged effect of Hessian Free (HF) and Stochastic Gradient Descent (SGD) techniques to better reduce the training and testing errors[77].

7.2. OCR datasets

Bag and Harit[78] describe the need to evaluate various algorithms with OCR benchmark dataset. The dataset is composed of an enormous amount of data for testing and training purposes. It is the preliminary requirement for carrying out quality research[79]. The research over the OCR evolves over six different languages. They are Arabic, English, Urdu, Indian, Chinese, Persian, and Farsi script. Therefore, some online accessible datasets are used for languages known as CADER, UCOM, MNIST, CENPARMI, and so on[80–82]. The author describes the popular Arabic database constructed in 2002 by the Technical University of Braunschweig. It comprises 26,459 handwritten images where 212,211 characters are extracted from 411 different writers. Various researchers extensively use it for the efficient recognition of Arabic characters. The author discusses the CENPARMI dataset, which was constructed in the year 2006. It is composed of 18,000 samples partitioned as 2000 for verification, 5000 samples for testing, 11,000 for training samples. This dataset is constructed by extracting 102,352 digits extracted from the high school registration form. It is the second form of the most extensive dataset. It comprises 432,357 images, including words, dates, isolated letters, numerical strings, documents, and special symbols. **Table 2** depicts the comparison of handwritten datasets.

Table 2. Comparison of handwritten datasets.

S. No	Dataset	Developed year and language	Recognition format	Samples	Training and testing samples
1	CEDAR	The University of Buffalo 2002 and digit	Handwritten characters	Images scanned at 300 dpi	-
2	MNIST	1998 and digit	Handwritten digits	20 × 20 grayscale images and 28 × 28 normalized images	10,000 testing samples, 60,000 training samples
3	UCOM	Urdu language and 2013	Character recognition and writer identification	Images are scanned at 300 dpi	53,248 characters and 62,000 words 0.004% to 0.006% error rate
4	IFN/ENIT	The Technical University of Braunschweig in 2002 and Arabi database	Handwritten images	-	212,211 characters
5	CENPAR MI	The Farsi dataset in 2006 Extended version 2007 by Khosravi	Farsi numerals (words, dates, isolated letters, numeral strings, special symbols)	-	Eighteen thousand samples with 5000 testing samples, 2000 verification samples, and 11,000 training samples. Extended version-102, 352 digits
6	HCL 2000	Chinese character database and 2000.	Chinese characters and writers' information dataset	-	3755 Chinese characters from 1000 subjects
7	IAM	English language from Lancaster Oslo Bergen corpus and 1999	English language sentences	-	82,227 words 98% successful identification

7.3. ML classifiers

Jain and Kiran[83] explored the use of Multi-Layer Perceptron (MLP) classifiers for handwritten digit recognition. Their research achieved an accuracy of 91% in recognizing handwritten numerals. Sahare et al.[84] developed a Hindi OCR where feature extraction is performed via k-mean clustering while classification is done with a linear kernel. The author divided the work into three different stages like pre-processing, feature extraction, and classification and performed a handwritten recognition with ANN for Marathi characters. The experimentation is validated with 500 characters taken from various people. The author attained an accuracy of 92%. Broumandnia and Shanbehzadeh[85] provided an OCR system for predicting the Sanskrit characters using Support Vector Machine (SVM). The author considers multiple datasets for various languages with an accuracy of 98%. Elleuch et al.[86] anticipate a reliable approach for character recognition and segmentation for the Latin language. The segmentation process is done by analyzing the structural properties where the joined and overlapped characters are segmented with the adoption of graph distance theory[87,88]. Here, the k-NN classifier is used for printed input characters and handwritten digit recognition, where the SVM classifier is used for validating the segmentation outputs. The accuracy attained by the author for the Latin script is 97%. Lin et al.[89] modeled a system for handwritten recognition for isolated characters with ensemble classifiers. Binarization is used for character image processing; then, the Histogram oriented gradient is applied for extracting the essential features. Finally, Neural Networks (NN), k-NN, and SVM are used for classification. The results from these classifiers are merged to form an ensemble classifier. The class labels are attained with the maximal voting technique. The accuracy attained with this process is 88% after ensembling. Tayyab et al.[90] perform handwritten recognition with Deep Neural Networks (DNN). Here, extensive network architecture is used with changing sizes. Here, the accuracy is 96% with the CNN classifier, which is comparatively higher than other approaches. Also, the performance with hybridized methods is composed of 5 convolutional layers, two fully connected layers and 2 LSTM layers, respectively. Fu et al.[91] anticipated OCR with ANN classifier for characters and words. The accuracy obtained after the segmentation process is 84% for characters and 100% for word and line. But the segmentation process is more complicated for Devanagari scripts. The OCR performance using the proposed model gives a massive number of features for further classification[92]. The author considers three sets of features known as projection histogram, chain code histogram, and Histogram of aligned gradients. The overall system accuracy is 91%, respectively. **Table 3** depicts the comparison of handwritten recognition of various languages using existing classifiers.

Table 3. Comparison of handwritten recognition for various languages.

S. No	Year	Language	Techniques
1	2016	Chinese	Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Hidden Markov Model (HMM)
2	2017	Chinese	Neural Network, CNN
3	2016	English	LSTM architecture
4	2017	Chinese and English	CNN
5	2017	Arabic	CNN and SVM
6	2018	Arabic	DCNN (Deep Convolutional neural network)
7	2018	Arabic	Histograms of Oriented Gradient (HOG), SVM
8	2017	Urdu	Multi-dimensional Long Short-Term Memory Neural Networks (MDLSTM) and Hierarchical combination of CNN
9	2018	Urdu	SVM, Histogram of Oriented Gradient (HOG), k-NN, MLP, and RF
10	2018	Urdu	LSTM and CNN
11	2018	Indian	SVM and HOG
12	2018	Indian	k-NN, Gradient features, SVM, RF, and DT
13	2018	Persian	ANN, SVM, k-NN
14	2018	Persian	Multi-scale CNN
15	2018	Persian	CNN
16	2023	Urdu	Transfer learning+AlexNet
17	2023	Arabic	CNN
18	2023	Gujarathi	Transfer Learning

Sahara and Dhok[93] apply a template matching technique for character classification using pre-defined templates. Here, distance similarity metrics like city block distance, Euclidean distance, normalization, and cross-correlation are used. The most common method used for character recognition is deformable template matching. The deformed images are used for evaluating the images of the known database. Therefore, classification is done with deformed shapes.

7.4. Prediction models

From the early 90's, digit handwritten digit prediction has been considered a major research field. Various efforts are given for languages like Arabic, English, Bangla, Hindi, Odia, and Lanna dhamma, and so on. There are various handwritten prediction models which need huge attention from researchers. Recently, deep learning has gained the huge attention of researchers due to its growing prediction accuracy. Here, unsupervised learning has been determined as the predominant solution for complexities encountered during the labeling of training data. Montavon et al.[94] employed a conventional clustering model to provide feature specification. The inputs are normalized with patches for training images to learn various kinds of lower features with centroids. Then, the images are specified by predicting the similarity among the k-centroids and every local patch to generate an extremely large amount of image responses. The feature specification is done by polling the local features spatially with k-response images. Indeed, of this message's simplicity, it is extremely complex to construct a productive deep network model owing to the lack of various topological orders with k-means centroids and increased with several image responses. Lawrence et al.[95] discuss the topological neuron orders over SOM grids. The model provides a suitable and appropriate SOM model for higher data dimensionality and feature representation, and data visualization. The integration of CNN with SOM is made to deal with the face prediction problem[96]. Here, SOM is adopted for quantization of facial image patches over the topological space to diminish the dimensionality by increasing the robustness for the least variations. Here, CNN is trained with input images that are mapped and learned to analyze larger features. Tan et al.[97] conduct experimentation with SOM for the prediction of invariant face occlusion. Here, the topological properties are mapped to the local patches and neuron coordinates. The modified k-NN model intends to give an ensemble classifier model to develop an appropriate match among the facial images with the topological representation. The hierarchical model was designed for feature extraction visually using map dimension. It is merged with Gabor filters for the construction of hierarchical representation for digit recognition. Wang et al[94] modeled a stacked multi-layer organizing map for dealing with the background images. The author used a deep mapping model for automatic classification and feature extraction from data streaming. The author anticipates the hierarchical model for organization mapping for human recognition. Here, CNN and Self Organizing Map (SOM) is developed for sign language prediction. Malakar and Bhowmik[98] anticipate a holistic model for predicting handwritten words. The extracted features are ratio, area, pixel ratio, density, centroid, and long-run from the provided images. However, MLP predicts words obtained from the input script specifying the state capitals and Indian union territories. Sueiras[99] adopt segmentation with features of long-term memory to categorize English words. The author uses two different databases known as RIMES and IAM to verify the model efficiency. Jana and Bhattacharyya[100] anticipates a novel CNN for predicting words (Malayalam) and validates it on 314 classes from the available dataset. The features attained with SVM provide a robust accuracy. But the model does not consider the batch normalization concept; thereby, it works poorly over a dataset of huge size. Recently, the author has initiated the design of a holistic model with shape-dependent feature descriptors that merges the tetragonal, elliptical, and vertical pixel density-based histogram model. Similarly, negative refraction properties with shape-feature descriptors to recognize accuracy holistically[101]. It includes 80 handwritten city names over bangle scripts. This model attains an accuracy of 88% over the 12,000 handwritten word samples by merging the prevailing logistic classifiers and self-organizing mapping model. The above analysis shows that the feature extraction, segmentation process reduces the prediction accuracy[102–106]. Therefore, it paves the way for modeling a deep learning-based classification model along with the optimizer to attain global solutions. Thus, a deep learning-based layered CNN model with squirrel search optimization is proposed to improve the prediction accuracy with reduced execution time.

Based on the above studies, achieving a truly "exhaustive" representation of all possible techniques is impractical due to the continuous evolution of the field and the vast number of potential combinations, we can delve deeper into existing categories and explore additional aspects. **Figure 5** is an expanded hierarchy of HDR-specific CNN classification techniques with levels and sub-levels, aiming for comprehensiveness within its limitations.

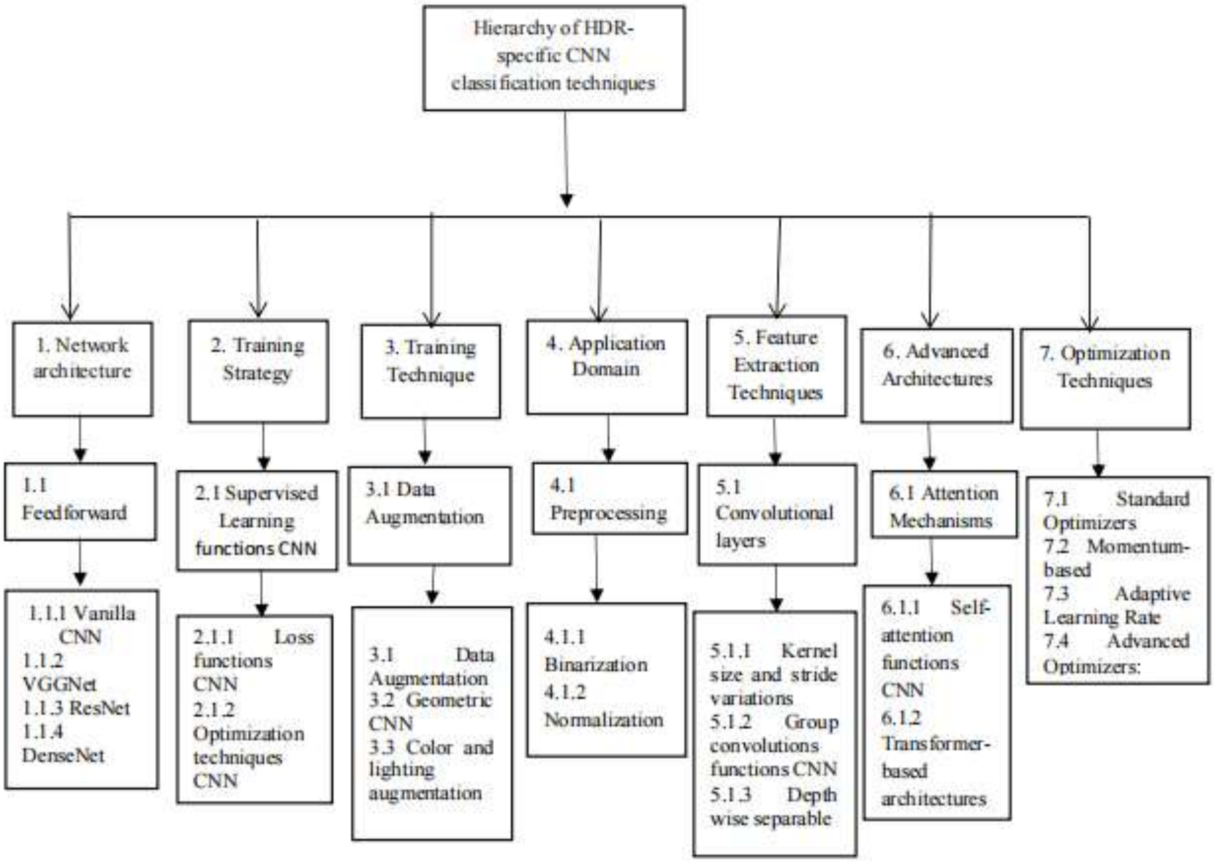

Figure 5. HDR specific CNN classification techniques.

8. Recent advances in HDR

This section provides a detailed discussion on three cutting-edge deep learning techniques impacting the field of HDR.

Generative adversarial networks (GANs) for generating training data:

- Challenge: Traditional HDR methods rely on pre-existing datasets of labeled handwritten digits. These datasets can be limited in size and diversity, potentially hindering the model's ability to generalize to unseen variations in handwriting styles.
- GAN solution: GANs represent a powerful approach to address this challenge. They consist of two competing neural networks:
- Generator: Aims to generate realistic and diverse images of handwritten digits, mimicking the real data distribution.
- Discriminator: Attempts to distinguish between real (from the actual dataset) and fake (generated by the generator) digits.
- Benefits: Through an iterative training process, the generator improves its ability to create realistic digits, while the discriminator becomes better at detecting fakes. This continuous refinement ultimately leads to

a diverse and high-quality dataset of synthetic handwritten digits, which can be used to train HDR models more effectively.

Attention mechanisms for focusing on critical information:

- Challenge: Handwritten digits can contain irrelevant information like background noise or pen strokes outside the intended character. This can lead to confusion and errors during the recognition process.
- Attention mechanism solution: These mechanisms are neural network modules that learn to selectively focus on crucial parts of the input image while ignoring irrelevant information.
- Benefits: By focusing on the critical features, such as line endings and curvature within the digit, attention mechanisms help the model extract more accurate representations and improve its ability to differentiate between similar-looking digits, leading to more accurate recognition.

Self-supervised learning for unlabeled data:

- Challenge: Labeling large datasets of handwritten digits can be a time-consuming and expensive process. Traditional approaches often require significant amounts of labeled data for effective training.
- Self-supervised Learning Solution: This approach aims to train models using unlabeled data by creating its own supervisory signals. This can be achieved through various techniques, such as:
- Predicting the rotation of an image: The model learns to predict the rotated version of a digit based on the original image.
- Coloring a grayscale image: The model predicts the color channels of a grayscale digit image, learning to associate specific patterns with specific colors.
- Benefits: This approach allows training models on vast quantities of unlabeled data, potentially significantly improving the overall accuracy and robustness of HDR models, particularly when labeled data is scarce.

9. Conclusion

This paper presented a comprehensive analysis of various approaches, applications, and limitations in handwritten digit recognition (HDR). We conducted a systematic review of the field, tracing its origin, evolution, and conceptualization. Additionally, we identified and categorized neural network models employed across different HDR domains, aiding researchers in tackling challenges related to diverse handwritten patterns. Notably, we emphasized the importance of performance evaluation metrics such as accuracy, precision, recall, F-measure, error rate, recognition rate, training, and testing accuracy. Our findings showcase the significant advancements made in HDR technology. Furthermore, the paper also discussed recent advancements in cutting-edge technologies like Generative Adversarial Networks (GANs) for generating training data, attention mechanisms for focusing on critical information, and self-supervised learning for utilizing unlabeled data. These advancements hold immense potential to address existing challenges in HDR, such as limited training data and robustness to variations in handwriting styles. By incorporating these innovative techniques, researchers can pave the way for the development of even more accurate, robust, and scalable HDR models, expanding their applicability in various real-world scenarios. However, several challenges remain, including the ability to recognize digits with complex backgrounds, variations in writing styles, and scalability to real-world applications. Addressing these challenges will require further research in areas such as:

- Development of robust deep learning architectures specifically designed for HDR tasks.
- Exploration of transfer learning techniques to leverage knowledge from other image recognition domains to improve performance on smaller HDR datasets.
- Investigation of techniques for data augmentation to generate more diverse and realistic training data.

By focusing on these areas, researchers can further improve the accuracy, robustness, and scalability of HDR models, paving the way for wider adoption in various real-world applications. We believe this paper provides a valuable foundation for future research and development in this ever-evolving field.

Conflict of interest

The authors declare no conflict of interest.

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