Feature Extraction and Classification Approaches for Handwritten Devanagari Text Recognition: A Comprehensive Survey

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Abstract - *The character recognition system is a crucial part of pattern recognition. Because different people write in different ways, handwritten character identification is an intriguing, difficult, and complex undertaking. Such systems' accuracy is largely dependent upon the process of feature extraction and selection. Many scholars have suggested a variety of feature extraction and classification methods for a few scripts, such as Devanagari. In light of this, this article offers a thorough analysis of feature extraction and classification techniques that have been taken into consideration thus far for both online and offline Handwritten Character Recognition (HCR) for Devanagari script, which is crucial for research on Optical Character Recognition (OCR). The authors' methods, the dataset they employed, and the accuracy of the work currently accessible for the OCR research are all presented in this article. The most recent research, research gaps, difficulties, and prospects for future work in the field of Devanagari text recognition are presented in this article. To help future researchers, methods for feature extraction and classification in the field of Devanagari character recognition are also methodically outlined. Deep learning techniques are reportedly being used in place of conventional feature extraction and classification techniques in order to improve recognition accuracy in this field.*

Key Words: Devanagari script. Handwritten character recognition. Feature extraction. Classification and deep learning

1. INTRODUCTION

Within the field of pattern recognition, character recognition is a field of current research. It automatically transforms physical text data (numbers, letters, and symbols) into a machine-readable digital representation [58]. There are two types of character recognition: offline and online. Online character recognition entails writing on an electronic surface, such as an electronic tablet, with a special pen or digitizer. In particular, pen up/down data, speed, and a sequence of strokes are used to record characters. As soon as a character is written, these algorithms detect it instantly [45]. The process of converting offline handwritten characters into a machine-readable format is known as offline character recognition. Offline character recognition can be further divided into optical and magnetic character recognition because it uses optical or magnetic scanning to extract information from a paper document [57]. Character shapes, a wide range of character symbols, document quality, and the lack of stroke information make offline character recognition more difficult [45].
As a result, offline character recognition is more difficult than online character recognition. Fig. 1 shows the categorization of character recognition. As shown in Table 1, offline and online. Both handwritten and printed characters can be recognized. The main problems with handwritten character identification are the wide range of composition styles, including character thickness, speed, and shape. In comparison to handwritten character recognition frameworks, printed character recognition frameworks currently produce higher recognition accuracy. As a result, handwritten character recognition is still limited. Furthermore, a segmentation approach may or may not be used for handwritten character recognition.

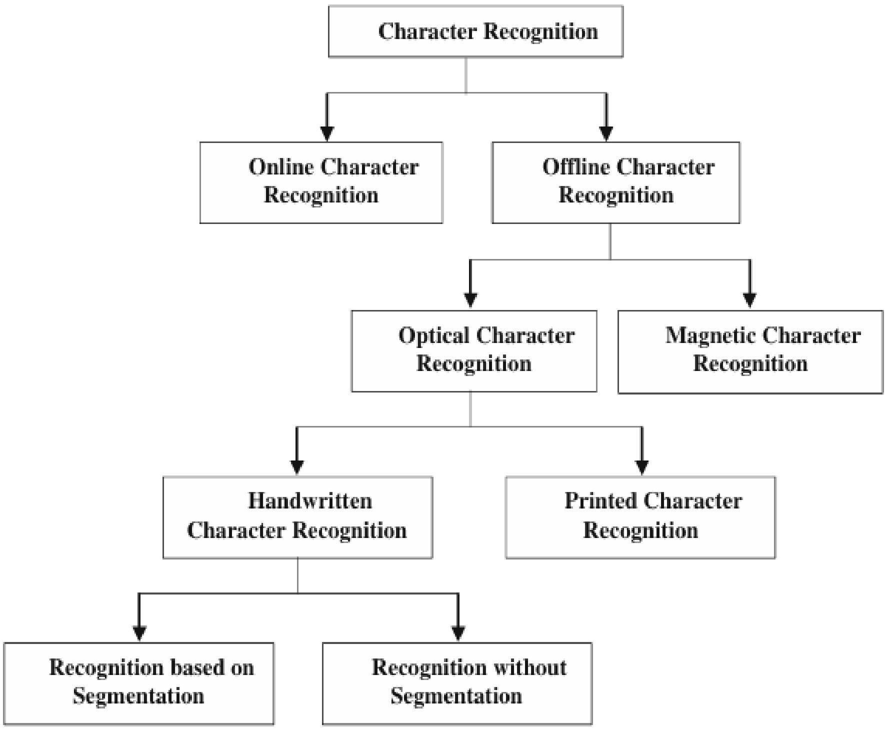

Fig. 1 Classifications of character recognition

Table 1 Online versus offline character recognition

Parameters	Online character recognition	Offline character recognition
Accuracy	Sufficiently higher	Lower
Availability of strokes	Yes	No
Raw data requirement	Samples per second	Dots per inch
Recognition speed	Sufficiently higher	Lower
Writing media	Digital pen on an electronic surface	Paper document

For automatic number plate identification, check reading, postcode recognition, signature verification, and as a reading assistance for the blind, among other applications, a computer system that recognizes handwritten characters accurately, robustly, and reliably would be very helpful.

The remaining portion of the paper is organized as follows: The background, uses, and difficulties of Devanagari Handwritten Character Recognition (HCR) are described in Section 2. An overview of the Devanagari script is examined in Section 3. The motivation for readers and academics working in the relevant field is presented in Section 4. Section 5 presents the HCR approach. The literature review on feature extraction and classification techniques taken into consideration for Devanagari HCR, along with a comparison analysis, is provided in Section 6. Section 7 lists research gaps. Section 8 presents challenges for the current work. A few suggestions for the future of Devanagari character recognition have been covered in Section 9. Lastly, Section 10 presents findings.

2. Background

It is crucial to provide background knowledge on the underlying issues, applications, and technical difficulties in order to determine the importance of optical character recognition (OCR) techniques in general. The field of pattern recognition and image analysis has been encouraged by OCR, which is methodically a sub-component of pattern recognition. Table 2 provides a quick overview of the development of script recognition.

2.1 Applications

Techniques that attempt automatic optical character or script identification or recognition are in high demand these days. This subsection [22] lists several sorts of strategies that address diverse needs of various domains of such applications. Readers of airline tickets Automatic recognition of license plates Systems for handling bills Reading a check Classification of data using the learning process Modifying outdated papers Reading and verifying employee codes Analysis of forensic documents Processing of forms Reading handwritten notes and Signature verification.

Table 2 History of machine recognition of scripts

Year(s) with Caption		Highlights
Period	OCR Generation	Key Developments
1870–1940	Initial Concepts	Early ideas of OCR emerged. Retina scanner and sequential scanner were invented to assist visually impaired people. Punched cards were used for data entry.
1940–1950	Early Development	Development of modern OCR concepts began and experiments were conducted to recognize printed characters.
1950–1960	First OCR Machines	First OCR machines appeared and became commercially available. Devices, such the IBM 1418, were able to identify a small number of text styles and character shapes.
1960–1965	1st Generation OCR	Systems could recognize regular machine-printed characters but supported only a limited number of fonts. Recognition accuracy improved.
1965–1975	2nd Generation OCR	More efficient and cost-effective OCR systems developed (e.g., IBM 1287). Automatic postal code recognition systems were introduced. OCR-A and OCR-B standard fonts were defined.
1975–1985	3rd Generation OCR	Early handwritten characters and poor printing might be recognized because to hardware developments. OCR machines became more sophisticated.
1985–1995	4th Generation OCR	OCR systems could process complex documents containing text, tables, and mathematical symbols. Support for multiple languages and scripts increased.
1995–2010	Robust OCR Systems	Image processing and pattern recognition techniques were integrated with Artificial Intelligence to improve accuracy and efficiency in document processing.
2010–Present	Modern OCR	The accuracy of recognition was enhanced by deep learning techniques. OCR are using different area as mobile device, real time application and many more for text extraction from images.

2.2 Challenges for Devanagari HCR

Since the accuracy of the OCR system directly depends on the quality of the input image, high-quality or high-resolution images (with some basic structural qualities like highly distinguishing text and background) are desirable. Many errors must be eliminated in order to successfully automate OCR procedures because they frequently have a significant impact on image quality [15, 52]. These flaws are explained as follows:

Degradation and blurring for character segmentation and recognition to be more accurate, character sharpness is necessary. Either a slight shift in point of view or catching a moving object causes uneven concentration. It causes input images to become blurry and degraded, which further lowers an OCR system's accuracy [71].

Complexity of characters Additionally, the form and shape of handwritten Devanagari characters make them more intricate. They have a sizable character set with additional loops, curves, and other character characteristics.

Complicated background Additionally, the OCR system may face far more difficulties when working over a complicated background than when working over a typical background.

Various character sizes and forms Because handwritten characters vary in size and shape, segmentation and classification become difficult tasks for handwritten character recognition.

Absence of a standard test database Regretfully, there isn't a large publicly accessible standard handwritten character database for Devanagari script that can be used as a benchmark for testing and comparing the efficacy common platform. Background noise In general, it is evident that throughout the scanning process, noise is introduced to the document or image. Later on, when doing digitalization or binarization, it becomes difficult to eliminate such background noise.

Complexity of the scene many man-made items, like buildings and paintings, have similar structural characteristics and seem like text in a natural setting. It makes it difficult for OCR systems to discern text from non-text in the processed image due to difficulties with text recognition.

Characters with similar shapes Identifying symbols or characters with similar shapes presents another difficulty for character identification. There are numerous character pairings in Devanagari script that share a similar shape, including फ and घ.

Skewness Skew correction has remained a barrier for optical character recognition systems [19, 65]. If a skewed image is entered straight into the OCR system without using any appropriate preprocessing techniques, poor outcomes could be seen.

Text layout or typeface variations because they overlap, characters in script typefaces and cursive or italic styles can make segmentation challenging. When the class number is high, meaning that there are many pattern sub-spaces and significant within-class variances, it will be challenging to identify the characters.

Different human writing styles each person writes in a unique way, which might make it challenging to identify the characters. Individual differences exist in character size, shape, alignment, etc.

3. Overview of the Devanagari script

Devanagari is a script from India, Nepal, Tibet, and the South Asian subcontinent that is a member of the Brahmic family [2]. More than 500 million people use it to write in a variety of languages, including Hindi,and other languages of the subcontinent of South Asia [23, 55]. As shown in Fig. 2, the Devanagari script has 13 vowels, 34 consonants, and 14 vowel modifiers.

Apart from above mentioned a compound characters that are made by two or more characters. Compound characters and modifiers can be attached to the top or bottom of the basic character, adjacent to each other [21]. The vowels play a crucial role to change the shape accordingly added position of consonants, these vowels are also called matras or modifier. All characters, including text and numbers, are written from left to right, and lower and upper letters are not comprehended. Certain composition rules in Devanagari script allow for the combination of vowels, consonants, and modifiers [13]. Another characteristic of Devanagari is the horizontal line on top of characters called a header line or shirorekha [30].

Devanagari word script is distinguish by top bottom and core strips, while header line splits the bottom and core strips, whereas the virtual baseline splits the top and core strips. In a sense, being familiar with a language's script facilitates the use of one's mental vocabulary to interpret words associated with that script. Figure 2 shows the consonants, half forms, vowels, and modifiers in the Devanagari script. Three strips of a word in the Devanagari script are displayed in the following Fig. 3.

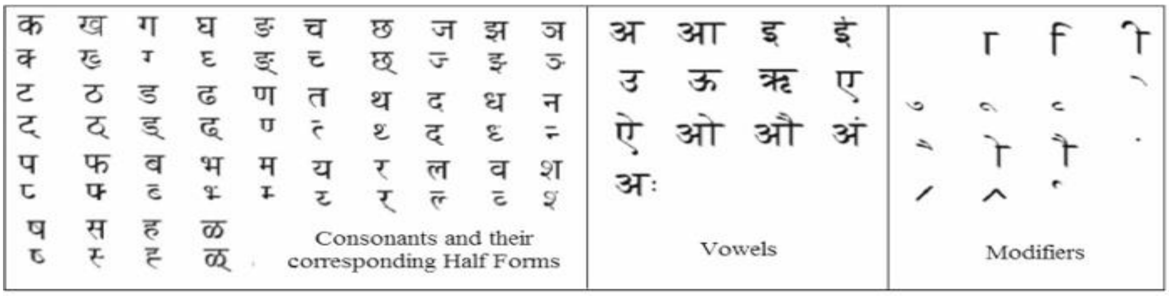

Fig. 2 Devanagari script (**a**) Consonants and their corresponding half forms (**b**) Vowels (**c**) Modifiers

Fig. 3 Three strips of a word in Devanagari script

4 Handwritten character recognition approaches

Generally speaking, there are two types of approaches to handwritten character recognition: the classic approach, which use conventional techniques for feature extraction and classification, and the deep learning approach, which is shown in Fig. 4.

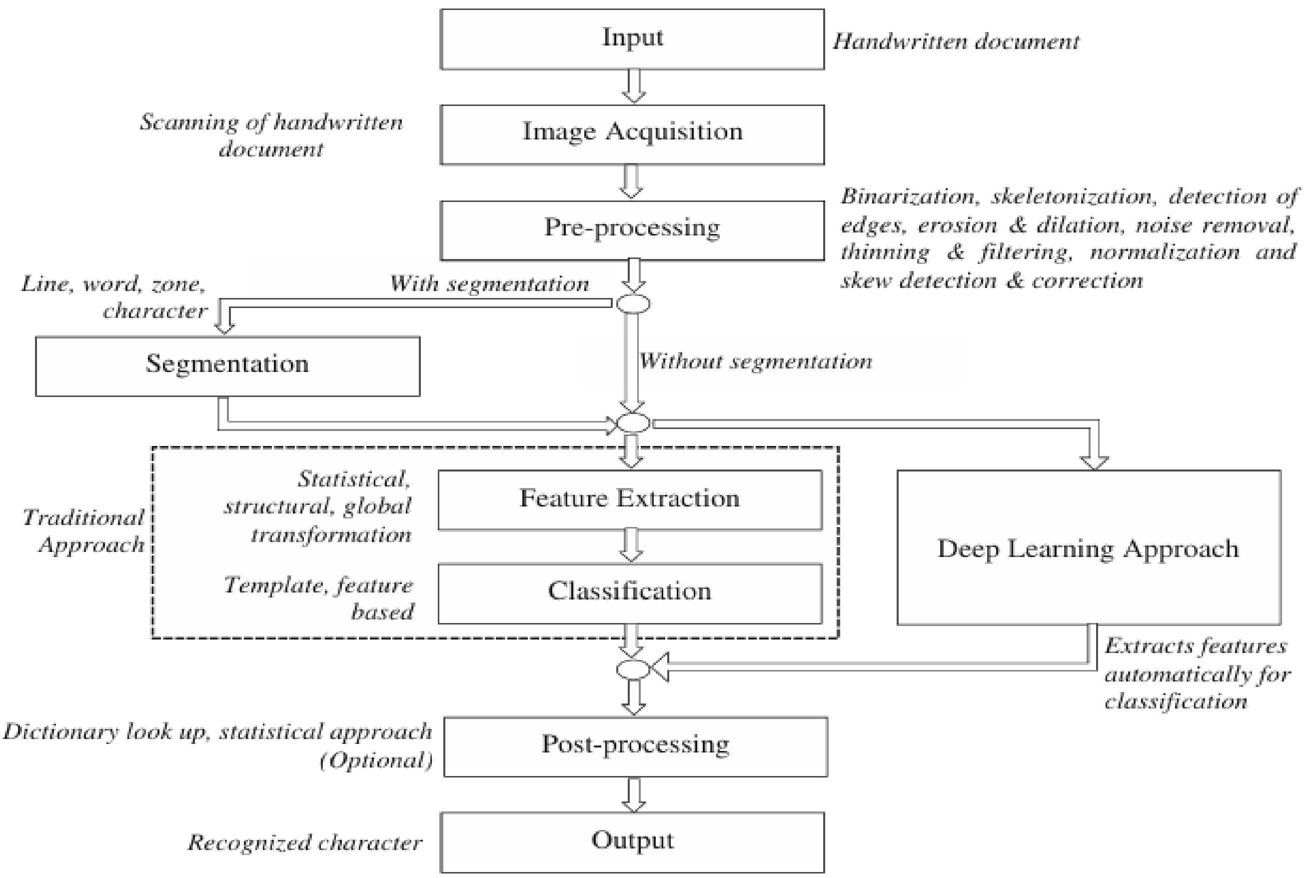

Fig. 4 Steps for handwritten character recognition

4.1 Image acquisitions or digitization

A handwritten document on paper is scanned to create an electronic version known as digitization or a bitmap image. It produces a digital image that can be used for pre-processing.

4.2 Pre-processing

It is an initial stage that creates a normalized bitmap image with the goal of minimizing the degradation of the acquired image. Binarization, skeletonization, dilation of images, edge detection, noise removal, image enhancing techniques for contrast stretching, thinning and filling, normalization, skew detection and correction, and more pre-processing[6,34,47].

4.3 Segmentation

Segmentation, which divides the scanned page into paragraphs, lines, words, and characters, is an important part of HCR [93]. Because there are many different writing styles, segmenting handwritten characters is a difficult task [77]. The precision of HCR systems strongly requires on identifying the optimal segmentation sites for words, characters, paragraphs, and lines [34]. The components of segmentation are as follows:

Segmenting lines: It is the first step in the segmentation process and a challenging task. Based on projection profile, Hough-transform, smearing techniques, and thinning operations, researchers have created a variety of line segmentation approaches that can be broadly categorized into four types.

Word segmentation: The handwritten text is divided into words using word segmentation. For this aim, the majority of current methods employ a vertical projection profile. Several studies additionally divide a handwritten text in pitch method.

Segmenting zones: In Devanagari horizontal zone are used for splits the text upper or bottom or middle, this header line also known as shirorekha, always splits the zone the upper zone from the middle zone. The top or higher zone denotes the area or territory above the headline, whereas the area or region immediately below the headline and above the lower or bottom zone is referred to as the middle zone. The lowest area that has some vowel components as part of vowel modifiers is the lower or bottom zone. Upper and lower modifiers have not always been required in Hindi words.

Character segmentation: splits a text region into multiple regions of single characters. Vertical projection profile analysis was an early method for character Multimedia Tools and Applications segmentation. Character segmentation involves extracting the individual characters without including some components of adjoining characters, even though these characters are not touching. Recognition-free and recognition-based segmentation are the methods used for character segmentation. In the case of overlapping or touching characters its become more complex.

4.4 Feature extraction

In pattern recognition fundamental role is feature extraction. The characteristics are specific details taken from segmented characters (words or symbols) that set one character apart from the others. The Handwritten character recognition accuracy affected by extraction methods means better approach provide better accuracy. There are other methods for extracting features, but it is crucial to extract those that can distinguish between different patterns or character classes. Some main features are described below:

Statistical features Statistical features are characteristics of the bitmap image's pixel value distribution. The statistical distribution of points, such as moments, zones, histograms, or projections, can be used to calculate these properties.

Features of the structure by providing both local and global aspects, structural features illustrate a pattern's topology and geometry, geometric features of a symbol or character, such as loops, stroke directions, stroke intersections, and ends are define these properties.

Features based on global transformation the pixel representation can be changed into a corresponding denser form using global transformation techniques including the Fourier transform, discrete cosine transform, wavelet transform, Hough transform, and moments. By a linear combination of sequences represent signals that signals are linear combination of simpler, well-defined functions. The sequence expansion offers a concise encoding by employing the coefficient of the linear combination matching features are compared with pixel-by-pixel of features based on template matching reveals patterns. Character recognition using this method usually does not require preprocessing such as thinning and trimming [16]. These approaches, however, are more susceptible to changes in font and character size. These characteristics are used to recognize compound characters and are not suitable for texts with a noisy background.

4.5 Classification

In order to determine the class membership in the pattern recognition system, the classification or recognition phase makes use of the characteristics that were retrieved in the previous phase [10]. Matching feature is obtained with comparison of input parameter with class input. It can be carried out typically using feature-based techniques or a template

4.6 Deep learning

Researchers are re-experimenting the current issues using deep learning techniques to better the current outcomes. The introduction of researcher’s recent years have seen the development of several deep learning designs, including recurrent neural networks, deep convolutional neural networks, and deep belief networks. Nowadays, researchers are extensively using machine learning approaches for character recognition. Deep learning techniques are essentially made up of several hidden layers, each of which is made up of several neurons that determine the deep network's appropriate weight.

4.7 Post processing

This stage is not necessary still some time this is enhanced the accuracy. If the output is limited by a list of terms that are allowed to appear in a document, the accuracy of the HCR system can be improved. It helps to improve the outcomes of the classification. Two popular post-processing methods for error correction are dictionary lookup and statistical analysis [90].

5. Related works

Despite numerous obstacles and a lack of a commercial market, there has always been a significant demand for study in the field of HCR for Indian languages [28]. Although initial research on Devanagari recognition was described in 1977 [95] using a structural approach, research on Indian HCR has received a lot of interest in recent years. The several feature extraction methods for Devanagari HCR that have been put forth over the previous few decades are briefly summarized in the following subsections.

5.1 Feature extraction methods

This section presents the feature extraction techniques that have been described by different researchers in this specific field. While Bajaj et al. [17] took into account density, moment, and descriptive component features for handwritten Devanagari numeral/character identification, Arica and Yarman-Vural [11] computed both statistical and structural features. Elnagar and Harous [33] used end, branch, and cross point features based on strokes and cavity information to identify handwritten Hindi numerals.

In 2004, Kaur derived features based on zoning and Zernike moments to identify the Devanagari script. Gradient, structural, and concavity (GSC) features were retrieved by Kompalli et al. [53] for machine-printed and multi-font Devanagari text recognition. While Sharma et al. [9] employed directional chain code information of the character contour points as features for recognition. [43] have suggested a box technique that divides the numerical representations spatially into boxes in order to recognize handwritten digits. Additionally, Pal et al. [44] recognized Devanagari numerals using gradient-based features and chain coding.

Pal et al. [44] employed the data obtained from the arctangent of the gradient and Gaussian filter as a feature for HCR. More and Rege [72] used basic geometric and Zernike moments to identify Devnagari hindi characters and numbers, Shaw et al. [9] used the histogram of chain code directions in the image strips as a feature vector to recognize handwritten Devanagari words. The image strips were scanned from left to right using a sliding window.

Using the Devanagari handwritten dataset, Kumar [56] conducted a comparative examination of several feature extraction techniques, including Kirsch directional edges, distance transforms chain code, gradient, and directional distance distribution. Additionally, this article presented a novel feature by quantizing gradient direction into four directional levels, where each gradient map is separated into 4 x 4 sections. For the purpose of handwritten numeral recognition, Bhattacharya and Chaudhuri [20] retrieved high-level features based on contour representations of all four frequency components of the wavelet filtered image: high–high, high–low, low–high, and low–low. Basu et al. [18] used a Quad-Tree-based Longest Run (QTLR) feature to recognize or classify handwritten numbers. By calculating shadow and CH properties, Arora et al. [14] were able to identify handwritten Devanagari compound characters. For feature extraction, Aggarwal et al. [3] employed the gradient representation. Samples with 7200 characters were standardized to 90 × 90 pixels.

Kumar et al. [64] investigated hybrid characteristics for Gurumukhi script offline handwritten character recognition. They used the Ada Boost method in conjunction with a variety of characteristics and classifiers to assess the system's performance. On a corpus of 14,000 characters, the authors achieved a maximum accuracy of 96.3%. A technique for identifying handwritten Arabic words based on structural characteristics was created by Abuzaraida et al. [1]. The authors investigated the KNN classifier and achieved 99.10% accuracy on the 2500-word corpus. Kaur and Kumar [51] investigated different feature selection techniques for handwritten word recognition. The authors used Random Forest (RF) classification and Chi-Squared Attribute (CSA) based feature sections to obtain 87.42% recognition accuracy on the corpus of 40,000 handwritten words (Gurumukhi).

5.2 Deep learning- based methods

Classification algorithms like Naive Bayes Classifier, Nearest Neighbor, Logistic Regression, Decision Trees, Random Forest, Neural Network, and KNN Classification essentially analyze the training database in order to classify the testing/target database in statistics and machine learning [19].Deore and Pravin [26] produced a dataset of 5800 isolated images that included 58 different character classes: 12 vowels, 36 consonants, and 10 numerals. The authors created a two-stage VGG16 deep learning model to identify handwritten characters in Devanagari.Their models had testing accuracy increases of 94.84% (First Model) and 96.55% (Second Model) with training losses of 0.18 and 0.12, respectively. Ghosh [36] extracted structural and directional features from publically available signature samples.

They looked at the deep learning network known as the Recurrent Neural Network (RNN). They used two models to detect and verify offline signatures: Bidirectional Long-Short Term Memory (BLSTM) and Long-Short Term Memory (LSTM). The authors came to the conclusion that, in terms of accuracy, their suggested RNN-based system for signature verification outperformed Convolutional Neural Networks (CNN) and other cutting-edge techniques. Convolutional Neural Networks (CNNs) were employed by Narang et al. [48] to identify a variety of old manuscripts written in Devanagari script. Using a corpus of 5484 characters, they investigated a deep learning model for feature extraction and achieved 93.73% recognition accuracy. Alrobah and Albahli [7] created a method that uses a Conventional Neural Network (CNN) as a feature extractor to recognize handwritten Arabic letters. To increase the recognition accuracy, the authors merged two classifiers: SVM and eXtreme Gradient Boosting (XGBoost). On the Hijaa Arabic dataset, they attained a recognition rate of 96.3%. A deep learning-based method for handwritten word recognition in Gurumukhi script was created by Singh et al. [41].

They used a word-based, holistic approach to class labeling in order to get acceptable recognition outcomes.For their dataset of Gurmukhi words, the authors' recognition accuracy was 97%. A CNN architecture was created by Mushtaq et al. [59] to identify handwritten Urdu characters. For their corpus of Urdu characters (74, 285 training and 21, 223 testing samples), the authors achieved 98.82% recognition accuracy. A method for Arabic handwriting identification based on the Generic Feature-Independent Pyramid Multilevel Model (GFIPML) was developed by Korichi et al. [54].The authors improved their system's performance evaluation by using the AHDB dataset. A thorough survey for Arabic text recognition utilizing several deep learning techniques was published by Alrobah and Albahli [8]. Some flaws, problems, and difficulties with Arabic text recognition have been noted by authors. A CNN and RNN-based odia character recognition by Dey et al.[29].
On their corpus of characters with 112 classes, the authors' recognition accuracy was 86.56%. Convolutional Neural Networks (CNN) and Mathematical Morphology Operations (MMO) were used by Elkhayati et al. [32] to segment Arabic words for recognition. When compared to basic CNN, the authors' proposed directed CNN produced superior results. The effectiveness of segmentation-based and segmentation-free methods for CNN and transfer learning-based Devanagari conjunct character identification has been compared by Gupta and Bag [40]. To reduce the complexity of classification, the authors employed a CNN-RNN hybrid architecture. For the several methodologies they used, they obtained recognition accuracies of 94.56% (analytic approach), 99.30% (CNN-based holistic approach), and 94.65% (CNN-RNN-based holistic approach). For the aim of recognition, Prashanth et al. [25] created a corpus of 38,750 pictures of Devanagari numbers.

In order to identify handwritten Devanagari numerals, the authors investigated many CNN architectures, including CNN, Modifed Lenet CNN (MLCNN), and Alexnet CNN (ACNN). Significant recognition outcomes have been attained by authors. Mittal and Sachdeva [23] created a system that uses the ResNet model of a convolutional neural network (CNN) to recognize handwritten Devanagari compound letters. For the experimental work, they investigated their own corpus and obtained good recognition outcomes. A CNN-based system for Gurumukhi city name recognition was created by Sharma et al. [6]. By investigating the Adam optimizer with the CNN model, the authors were able to achieve 99.13% recognition accuracy on the corpus of 4000 words (city names).

Table 3 Brief Summary of Handwritten Character Recognition of Devanagari Script

Authors	Feature	Classifier	Data Set (Size)	Accuracy (%)
Arora et al. [13]	Combined	Multi-Layer Perceptrons (MLP)	1,500	89.58
Arora et al. [15]	Longest Run Shadow and	MLP and Combinational	4,900	90.74

	Chain Code			
Arora et al. [12]	Structural	Feedforward Neural Network (FFNN)	50,000	89.12
Bhattacharya et al. [21]	SRF	HMM	29,900	88.09
Deshpande et al. [27]	Chain Code	Regular Expressions (RE) & MED	5,000	82.00
Dixit et al. [30]	Wavelet	Backpropagation Neural Network	2,000	70.00
Dongre and Mankar [31]	Geometric and Structural	MLP	4,300	82.70
Ghosh and Roy [37]	Structural and Directional	SVM	5,000	84.10
Ghosh and Roy [38]	Structural & Directional (ZSD) and Zone wise Slopes of Dominant Points (ZSDP)	SVM	10,000	85.10 (ZSD); 90.63 (ZSDP)
Gupta and Bag [39]	Shadow and cumulative stretch feature	Random Forest; SVM; MLP	3,000	95.10; 95.57; 96.09
Hanmandlu et al. [43]	Vector Distance	Fuzzy	4,750	90.65
Kale et al. [47]	Legendre Moment	Feed Forward Neural Network	27,000	98.25
Kubatur et al. [55]	Discrete Cosine Transform	Artificial Neural Network	2,760	97.20
Kumar [56]	Gradient	Support Vector Machines (SVM)	25,000	94.10
Kumar et al. [61]	Multiple BLSTM-NN	Raw, Convex, Curvature and Writing Direction	3,750	79.46 (Lexicon based); 71.86 (ROVER combination)
Mahesh and Sumit [66]	GLAC	SVM	36,172; 20,305	93.21; 95.21
Mahesh and Sumit [67]	Masking	SVM	36,172	96.58
Mahesh and Sumit [68]	DCNN finds best features	DCNN and Layer-wise DCNN	36,172	96.02

	automatically			
Mahesh and Sumit [69]	Gradient based	SVM	36,172	96.58
Mane and Ragha [70]	Eigen Deformation	Elastic Matching	3,600	94.91
Narang et al. [50]	Intersection points, open endpoints, centroid, horizontal peak	CNN, NN, Multilayer Perceptron, RBF-SVM, Random Forest	6,152	88.95
Narang et al. [49]	SIFT and Gabor filter	Poly-SVM	5,484	91.39
Pal et al. [44]	Gradient and Gaussian filter	Quadratic	36,172	94.24
Pal et al. [42]	Gradient	Mirror Image Learning (MIL)	36,172	95.19
Pant et al. [35]	Geometric and Statistical	Radial Basis Function (RBF)	7,380	80.25
Shelke et al. [6]	Multistage viz. Structural, Random Transform and Euclidean Distance	Multistage viz. Neural Network and Template Matching	16,000	95.40
Shelke and Apte [4]	Pixel Density	Multistage viz. Fuzzy Inference System and Structural Parameters	40,000	96.95

Table 4 Brief Summary of Handwritten Character Recognition of Devanagari Script (feature wise)

Features	Authors	Classifier	Data Set (Size)	Accuracy (%)
Structural features	Arora et al. [12]	Feedforward Neural Network (FFNN)	50,000	89.12
	Ghosh and Roy [38]	SVM	10,000	90.63
	Shelke and Apte [4]	Multistage viz. Fuzzy Inference System and Structural Parameters	40,000	96.95
Statistical	Deshpande et	Regular Expressions (RE) & EMD	5,000	82.00

Features	Authors	Classifier	Data Set (Size)	Accuracy (%)
features	al. [27]			
	Hanmandlu et al. [43]	Fuzzy	4,750	90.65
	Kale et al. [47]	Feed Forward Neural Network	27,000	98.25
	Mane and Ragha [70]	Elastic Matching	3,600	94.91
Gradient features	Kumar [56]	SVM and MLP	25,000	94.10; 91.90
	Mahesh and Sumit [66]	SVM	36,172; 20,305	93.21; 95.21
	Mahesh and Sumit [69]	SVM	36,172	96.58
	Pal et al. [44]	Quadratic	36,172	94.24
	Pal et al. [42]	Mirror Image Learning (MIL)	36,172	95.19
Global Transform features	Dixit et al. [30]	Back propagation Neural Network	2,000	70.00
	Kabutar et al. [55]	Artificial Neural Network	2,760	97.20
Structural and Statistical features	Arora et al. [13]	Multi-Layer Perceptrons (MLP)	1,500	89.58
	Arora et al. [15]	MLP and Combinational	4,900	90.74
	Dongre and Mankar [31]	MLP	4,300	82.70
	Ghosh and Roy [37]	SVM	5,000	84.10
	Ghosh and Roy [38]	SVM	10,000	85.10
Multi-features	Pant et al. [35]	Radial Basis Function (RBF)	7,380	80.25
	Gupta and Bag [39]	Random Forest; SVM; MLP	3,000	95.10; 95.57; 96.09
	Kumar et al. [61]	Raw, Convex, Curvature and Writing Direction	3,750	79.46 (Lexicon based); 71.86 (ROVER combination)

Features	Authors	Classifier	Data Set (Size)	Accuracy (%)
Deep features	Shelke and Apte [41]	Multistage viz. Neural Network and Template Matching	16,000	95.40
	Narang et al. [48]	CNN	5,484	93.73
	Prashanth et al. [25]	CNN	38,750	96
	Harikesh et al. [5]	Capsnet	92000	95.69
	Gupta and Bag [40]	CNN-RNN-based	20,000	99.30

6. Deep learning-based approach and research challenges

Character recognition is one of the many areas of pattern recognition where deep learning-based techniques can be used [5, 26]. Due to its potent potential, this will assist in resolving numerous challenging tasks/steps, such as feature extraction and image modifying the parameters and structure of several deep learning models. Even while deep learning-based methods have a lot of promise to replace more traditional methods, there are still several research obstacles to overcome [60]:

a. Determining the amount of network layers and, consequently, additional neurons in deep learning-based models is a difficult task.
b. Since the accuracy depends on the training samples, a larger dataset or database is required.
c. Since the networks of deep learning-based models have a variety of parameters, choosing the best parameter is another research difficulty.
d. Reducing or lowering a number of characteristics, including as memory space, computing calculations, and bandwidth requirements, are difficult tasks in the development of effective deep learning-based models.

7. Suggestions for future

Future research in the field of handwritten character recognition could go in many different directions because current methods for segmentation, feature extraction, and classification can be expanded to increase the Here are some recommendations for future approaches for handwritten character recognition research:

a. Creation of suitable and efficient preprocessing methods: Developing suitable and efficient preprocessing methods, such as detecting and correcting text degradation/wrapping, orientation, and tilting, can increase recognition accuracy. Additionally, The accuracy of character recognition systems can be increased by developing an appropriate method for converting artistic text into linear text.
b. Maintain character shape: Following binarization or normalization, characters may change shape and important information may be lost. Therefore, it is necessary to maintain the character's shape.
c. Using an architecture with several classifiers: Combining the decisions of several independent classifiers can improve character recognition results. The combination can be carried out in accordance with their design, such as cascade, parallel, or hierarchical, based on the outcomes generated by each classifier.
d. Utilize the different optimizers: In order to increase the recognition rates of deep convolution neural networks, researchers may employ the different optimizers in conjunction with a deep learning approach.

8. Conclusion

Hindi is the most widely spoken language in India, which is based on the Devanagari script. Devanagari is one of the working scripts for the Hindi language in government offices in India apart from English. In view of that, research on the Devanagari script is focused on in this article so as to serve as a guide and update for readers working in the area of handwritten character recognition. . This paper presents a widespread survey on feature extraction and classification methods considered so far for online and offline HCR for Devanagari script, which is essential in OCR research as presented in Tables 3 and 4. There is a lack of a standard database on various Indic scripts for experimental work. Devanagari is one of these scripts. In this article, also various challenges are identified which will give a direction for future researchers. Future research will not be directly concerned with character recognition, but also words, phrases, and even complete document recognition.

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