Deep Learning Character Recognition of Handwritten Devanagari Script: A Complete Survey

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Deep Learning Character Recognition of Handwritten Devanagari Script: A Complete Survey

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Abstract— **Recognition of handwritten characters is a concept in which the single characters are classified, it is a facility of an electronic device to scan and decipher the handwritten input from a variety of sources, including written texts, images, and other digital touch-screen devices. This concept is being used in distinctive sectors such as the processing of bank checks, form data entry, and parcel posting and nowadays it is becoming a very important issue in the pattern recognition domain and a very challenging task to resolve it. Since deep learning is a crucial strategy in solving detection and pattern recognition problems, several algorithms are available to classify the characters with better prediction rates on different datasets, and ultimately, whichever algorithm gives the optimized results will be considered the best solution for the character recognition problem. As a result, various solutions proposed by the existing researchers are discussed using deep learning algorithms in this survey article.**

Keywords— Pattern Recognition, Character Recognition, Deep Learning, Computer Vision

I. INTRODUCTION

The use of pattern character recognition is widespread today, especially when it comes to handwritten character recognition in data entry, mail sorting, bank check processing, and package posting. Because there are many different ways to write characters and each person's handwriting style is different, some of them create characters that are different sizes and shapes, the earlier mentioned application makes mistakes when correctly classifying the characters, which has an impact on the entire process. For this reason, handwritten recognition is currently an extensive concern in the domain of sample acknowledgment.

Furthermore, to solve this problem, the primary goal is to apply various deep learning algorithms to ensure error-free handwritten character recognition. But why deep learning? Because deep learning contains efficient and optimized algorithms that can successfully recognize patterns, it will be very helpful to use them in practical applications.

A computer or other device's ability to read handwriting from sources like printable paper documents, pictures, and other electronics as inputs or to directly feed handwritten into a touchpad and convert it to words is known as handwritten character recognition.

A tool for discovering patterns is typically fed an image, such as a photograph of handwritten text, or real-time recognition utilizing a camera for optical scanning as the input. A 2014 study by Princeton and UCLA found that students who take handwritten notes perform better than those who use laptops and retain more knowledge.

People who take notes by hand must rephrase concepts in their words. The ultimate objective of handwritten character recognition is to imitate human reading skills so that a computer can use neural networks to read, comprehend, edit, and handle text in the same way that a human would. Simply put, machine learning is the ability to mimic an individual action. The term "Neural Networks" is used in machine learning to interpret each person's behaviour. Neural networks are a collection of different algorithms that aim to understand the connections between various sets of data to function similarly to the human brain.

Additionally, machine learning has some inherent problems, such as a lack of optimized performance for large data sets because the algorithms are ineffective at effectively training the data. Then the field of deep learning emerges to address the shortcomings of machine learning. Deep learning, used by digital assistants and voice-activated TV remote controls, teaches machines to carry out actions that people do automatically. Deep learning's principal objective is to enhance statistics with various categories of specimens, which can be either orderly or unorderly. Deep learning algorithms are very good at instantaneously training themselves with different features.

However, this will make the idea of handwritten character recognition more error-free in the future, making it easier to use in brand-new applications. This use-primary case's objective is to address the problem that is emerging as this idea is applied to various contexts. Deep learning algorithms are being used to address this problem because they are effective at producing better results in the domain of sample acknowledgment. Through a process called character recognition, computers can able to recognize printed or written elements, specifically figures or words, and convert them into a form that can be understood. Even with the help of the below figures, it is clearly understood why is recognition of handwritten characters is problematic.

Figure 1 is describing the printed image being typed in a machine while Figure 2 is defining the handwritten image written with a pen.

Hand handwriting has been given less emphasis recently than handprinted writing recognition, but this is changing as pen-based systems become more widely used. Millions of individuals are still hostile to the affirmation of Cyrillic (script) text. There is a wide range of handwriting, both good and bad, which is the problem. Because of this, it can be challenging for programmers to give enough examples of how each character might appear. Additionally, characters can

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sometimes have a lot in common, making it challenging for a computer to recognize them correctly.

Fig. 1. Printed Image of Hindi Word Antim

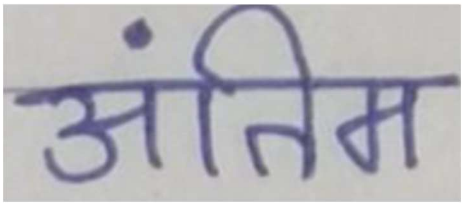

Fig. 2. Handwritten Image of Hindi Word Antim

Recognizing the printed character in comparison to the Handwritten character is easy because they can be easily distinguished from one another and there is little variation, printed characters are much simpler to understand. Utilizing such standards causes the user the most distress because he will constantly attempt to quickly return to his writing style. This results in pseudo-cursive writing or sloppily written printed characters. Even though many people write in a mixed printed/cursive style, connecting groups of letters that frequently appear together, the separation may still be simpler.

Without the use of vectorized input, it is nearly impossible to discern cursive writing, and because it is less difficult to separate the characters, Utterances as a group are easier to discern than individual characters. The realization of phrases entails the consumption of a lexicon because only recognizable terms can be addressed. The inevitability of dictionaries does not change the fact that no single dictionary will ever contain all the words that a person might want to use, and indeed take into account issues with proper names or storage space. One solution is to use customizable dictionaries, but there will still be a need for another method of letter-by-letter word entry.

There is no universally recognized set of handwritten text because each writer has his or her distinct writing style. But there are some fundamental forms that everyone is familiar with (and probably learned in school) and that are necessary to make a text readable by others. From that original estimate of variabilities, one ought to be able to formulate a customer interpretation of his look. One method is to give the recognizer samples of one's handwriting; another is to focus on providing the individual with a catalog of curves to choose from. Two very different paradigms can collaborate, however only as an arrangement. Over time, the person's style of writing will alter, and the presented specimens often detract from the person's written text because the user is less involved with his style of writing.

The discriminator ought to therefore be malleable enough even to be aware of the person's way of writing and absorb new information as he writes. When a user corrects a word that has been incorrectly recognized, for instance, the recognizer can learn. As a result of the learning, the initial setup may be reset to more closely reflect Quantities may be initialized or innovative design pre-sets decided to add if the good style differentiates from what the person meant. The main objective is to recognize handwritten text, including letters, words, lines, and paragraphs, in online documents. There have been numerous reviews and significant efforts in the field of handwriting recognition. The technique is to recognize handwriting by using templates. Researchers continue to maintain individual user profiles that enable each user to create their own training sets in addition to this researcher.

II. Related Work

The research suggested by [1] for the Devanagari script generated identification rates of (83.44%) after unsupervised learning and (91.81%) after tuning with supervised learning. To recognize offline Devanagari and Kannada handwriting, [2] proposed a GRNN classifier-based system. Even though the letter structures in Kannada are very intricate, the investigation with 49 classes of Kannada produced positive results from their approach. In their research article, the Researchers [3] explained that The highest detection rate of 97.28% was reached when they combined three neural networks, with an average of 50 neurons per hidden layer. There is no voting or scoring procedure used during the combining process. It is calculating the average of the matching output neurons in all models. Our system's accuracy has increased as a result of this design.

In computer vision and data analysis, deep learning is one of the significant techniques that has undergone empirical research, according to [4]. To distinguish free-form Devanagari handwriting, they created a deep convolutional neural network. To achieve the maximum perfection rate of 96.02%, the network design and RMS-Prop—an adaptive gradient optimizer procedure—were used. The authors of the summary [5] created a quadratic classifier-based method for differentiating handwritten Devanagari script elements. The characteristics used by the diagnosis are derived from the character's edge marks. Using the suggested system, they were able to identify Devnagari characters and numerals with a precision of 98.86% and 80.36%, respectively. Devanagari character recognition is feasible, according to [6], who mainly focused on Using deep convolution neural networks. Devanagari Lippi was used to creating twelve Indian languages. They optimize the network by selecting the best network hyperparameters. A dataset of pictures of characters used in the Devanagari script was described by the researchers [7]. A deep learning architecture is also suggested for character recognition. The suggested design had a test accuracy rating of 98.47%, which was the highest on their dataset. Using these methods in Deep CNN, researchers were proficient in marginally improving test trustworthiness. According to [8] , a novel deep neural approach for offline detecting handwritten characters was presented. Networks. The amount of data currently available has made training deep neural networks much easier. The neural network was trained using TensorFlow, and OpenCV was used to process images. According to the extensiveness of research [9] suggested The issue of authenticating written Gurmukhi symbols is still open due to the complexity of the characters. A common baseline dataset is necessary for HDCR to make it easier to create deep learning models. Three different architectures are used to build convolution neural networks (CNNs). They were able to achieve a generalization performance with CNN of 96% for training data and 94% for untrained data.

The digitization of Gurmukhi artifacts from the intervening decades that are currently held in national museums is a part of the Government of India's language documentation and digital archiving effort, according to [10] who explained this in their research article. Premised on the hidden unit activation functions of convolutional neural systems that have been invariably learned on components, researchers imply knowledge construction learning of pixel intensities. According to the research summary by the authors [11], Hindi, the official language of India, uses the Devanagari script. Character and word recognition present significant challenges because of the multiplicity of symbols and their close visual proximity. It employs the Curvelet Transform. Curvelet with k-NN produced generally positive efficacy to SVM classifiers, according to the results of Curvelet's feature extractor and classifiers. According to [12], Sanskrit, Marathi, and other languages are among those written in the Devanagari script. Even though the fact that a sizable portion of Indians does not speak English, they frequently use it when creating important records. The Devanagari script needs to be recognized, which calls for a solid technological solution. The study suggested by [13] Convolutional neural networks (CNNs) is increasingly used to remove features from input pictures. Literary Tests, in contrast to the Devanagari script, do not even support a unified CNN model for character identification. In the early stages of their research, they are considering using the readily searchable databases of transliterated Gurmukhi alphanumeric characters to examine various CNN models. This shows that the primary focus of our research, which considers trainable traits, retraining rates, and memory usage, is comparative. Later, they propose and set up Dev-Net an altered CNN model that led to significant impressive implications, even though our primary goals are to reduce computational time and memory usage. According to [14], The method for identifying Hindi characters suggested in this study entails four steps: inspecting, sorting, specifying, and semantic segmentation are the first three steps. Thresholding is a component of pre-processing, binarization, normalization, and thinning. The emergence of feature space is the aspiration of extracting the features from the thinning image that contains some pertinent data. The character image's normalized pixel values make up the feature vector. For characterization, a backpropagation neural network is rehired. Eclectic results show that this strategy outperforms other strategies in terms of Validation precision, training effectiveness, and characterization speed. The study examines the transfer of previously trained Deep Convolution Neural Network models for handwritten Devanagari alphabet recognition, according to [15]. (DCNN). Alex-Net, Dense-Net, Vgg, and Inception Conv-Net are used in this study as depictions for constant attributes. For the following networks, which included Alex-Net, Dense-Net 121, Dense-Net 201, Vgg 11, Vgg 16, Vgg 19, and Inception V3, they used 15 epochs. Findings show that Inception V3 significantly improved computational efficiency, achieving the highest exactness with a mean epoch time of 16.3 minutes, while Alex-Net performs better and facilitates tremendous appropriateness.

In the realm of observable hastily scribbled Devanagari character/numerical conflation, Multilayer Perceptron learning incorporating mini-batch stochastic gradient descent (SGD) is discussed in the outline of the author's [16] research. The hierarchical memory architecture found in all current processes is used to great effect in this method. and reduces the gradient estimate's variation. L2-weight decay is also incorporated into the minibatch SGD to avoid overfitting. The first studies make use of the direct component index values as features. This is followed by a test of the proposed adaptable area-based gradient feature extraction heuristic. The aftereffects seem to be encouraging for the majority of the Devanagari characters and numbers in the common dataset.

The author [17] contended This study examines the performance of several popular classifiers while taking into account the practical difficulty of examining published scripts using image data from official Indian documents. The MBT (model building time) and AAR (average accuracy rate) were indeed two crucial evaluation factors that are established for this performance evaluation. 5 fold cross-validation was used in the experiment, which included 459 printed document images. With an AAR of 98.9%, the Simple Logistic model has the highest AAR of any model. Bayes Net and Random Forest models have median prediction performances of 96.7% and 98.2%, respectively, with a minimal MBT of 0.09 seconds.

According to [18], Numerous classifiers are used in the study that is suggested in this paper to systematize the authentication of handwritten Hindi discrete characters. The histogram of directed gradients and the profile projection histogram is used as two features for feature extraction. Quadratic SVM outperforms other classifiers using these features, according to quantitative analysis of their performance.

According to [19], According to the current trend, researchers in this study examined the transfer learning strategy to distinguish between electronic handwritten Bengali and principal characters in Devanagari. Those certain simulations of transfer learning are VGG-16., ResNet-50, and Inception-V3. By including a variety of characteristics in the input data, they have expanded the training datasets and given the models some extrinsic constraints. Additionally, from the beginning, all three transfer learning models have been trained for the same action recognition (In other words, without relying on the periodic mass of the pre-trained model types). Additionally, they evaluated the results of the two approaches (i.e., commencing over and constructing trained models). The statistics of the model types are optimistic, demonstrating their viability for developing a top-notch digital handwriting recognition system.

The author [20] claims This academic paper illustrates the recognition of handwritten words mechanism incorporating machine learning and deep learning from source images. Another method makes use of the 70,000-piece Hindi handwritten number digit dataset from the UCI machine learning database. Four machine learning and deep learning algorithms as well as a sequence identification technique are researched. With the help of the template matching scheme, researchers were successful in accomplishing a classification accuracy of 86% for Decision Trees, 91% for Support Vector Machines, 97% in the case of artificial neural networks, and 98.84% for Convolutional Neural Networks. leveraging the Convolutional Neural Network procedure, which employs the Vgg16 network in the Deep Learning approach, the digit dataset from MNIST was trained, and a finesse of 98.84%was procured.

As stated by [21] The suggested framework includes a central hub of encoders and decoders that a learning algorithm can use. The analyzer for extracting pertinent and sophisticated information from the parent images is a convolutional neural network (CNN). The encoder also arranges the features that were extracted into a sequence. The decoder uses a connectionist temporal classification (CTC) layer after an Architecture for bidirectional long-term memory (BLSTM) with an attentiveness trigger to order to foretell the text within images. The decoder can choose which of the encoder's high-level functionalities to use through the use of an attention mechanism. Researchers have given training, authenticated, and inspected the suitability of the proposed model on three datasets: the publicly available IIIT-H scene image dataset, the synthetic dataset, and the exact dataset accumulated for this research. The proposed research model's likely outcomes for the three datasets conflict with earlier work in the field, according to researchers. On the three datasets, they found that our suggested model performed better than the output from other models.

According to [22], This paper describes the novel research on the DOC Architecture of a convolutional neural network (CNN) for accuracy and efficiency. The Dataset of Devanagari Handwritten Characters (DHCD) A set of data was used to train the model, ensuring maximum efficacy and precision on the dataset.

Apparently, [23] The scientists in this task reveal a finger-point-based system for classifying and identifying signed language symbols in text using RGB image datasets. An algorithm based on convolution neural networks is created by pre-processing the palm-sized photographs with different sizes, backgrounds, and orientations. According to the paper, this method augments the 47 Devanagari script symbols with the reference ruleset created especially for our needs and uses Alex net for the pre-processing requirements. This method offers an impressive recognition performance at the primary level, which suggests that our research will soon need to be refined. When developing the algorithm on the MATLAB console that utilizes various built-in machine learning repositories, they have provided detailed instructions and a description of the categorization parameters that encompass.

As stated by [24], To complete all the information required by the specific organization's policy, the method suggested in this article applies to any business, institution of higher learning, hospital, etc. Because handwriting is unique to each person and challenging to imitate, researchers are collecting handwritten input in this case. They can further improve the confidentiality of that information by combining it with sensors. A more intelligent, productive, and environmentally sound environment can be manufactured using the Internet of Things (IoT) and machine learning contraptions. According to [25], In this article, provides several techniques for identifying the distinctive characters in handwritten Indian script in word documents (or pseudo-characters). For precise attribution and delineation of the shiroreakha, researchers used a convolutional neural network predicated on encoder-decoder technology ShiroreakhaNet. The shiroreakha structural patterns and attributes are then used to separate modifying words upper and lower. To assess the effectiveness of the solutions, they gathered information from a range of domains. It was found that the proposed methods significantly outperformed cutting-edge methodologies.

According to [26], This study suggests a method for identifying city names. One of the potential areas for postal automation is the interpretation of scrawled town names. to recognize objects using a segmentation-free technique (Holistic approach). One of the deep learning architectures is convolutional neural networks (CNNs), and the speculated study clarifies how they work. With batch sizes of 2, 4, and 8 and learning rates (LR) of 0.001, 0.01, and 0.1, Adam and the stochastic gradient descent (SGD) optimizer of the proposed CNN system have been trained, validated, and examined. Ten classes of 400 samples each of Gurmukhi-scripted city names that were scrawled are utilized for the model's training and testing. According to their analysis, the CNN model has the highest average coefficient of determination, coming in at 99.13 with a batch size of 4, LR of 0.001, and Adam optimizer.

According to [27], Despite extensive research in the area, it is still difficult to separate handwritten text because of several problems, such as lines that are crooked and interlocking, letters that have been impacted, dented, or somehow debased, and a variety of literary styles. As a necessary consequence, researchers in this field are desperately trying to keep up with innovative methods for the appropriate automatic detection of characters. At the line, word, and character levels, In the phase of character recognition, sequencing can be used. The very first step in the procedure of letter recognition is text region fragmentation. Such an article investigated the row morphological operations for text detection in inscriptions. With an emphasis on line segmentation, Research has been conducted on phrase and text categorization, among several other thresholds of fragmentation.

According to [28], This work's main objective is to use convolutional neural networks to accurately identify characters (CNN). After proper scaling, decision trees and other common algorithms like Naive Bayes were also fitted. The CNN model employs layers that are convolutional, max-pooling, dense, and dropout. Except for the blatant exception of the final dense layer, which frequently uses the SoftMax initialization operation, all layers have been stimulated using ReLU. CNN has an advantage over the earlier models in that it can recognize important traits without human oversight. Gray scaling, straightening, smoothing, and enlarging the user-input image for the English alphabet were some of the pre-processing methods used. From previously processed input, the model predicts the characters. Experimental results showed that the CNN model delivered 93% more accuracy compared to conventional models.

According to [29], this research is essential and is still helpful for informing the creation of systems for human-machine interfaces. Developing countries like India are prime examples. HCR streamlines the procedure for automatically scanning tax and admission forms, bank checks, addresses, and postal codes. Compared to Unconstrained handwritten attribution seems to be more strenuous than printed character recognition because it occasionally depends heavily on the writing style, convexity, breadth, slashes, and density of the alphabet. Indian scripts have received relatively little research compared to other foreign handwritten scripts like Arabic, Chinese, and Japanese. The well-known Indian scripts of Tamil, Telugu, Kannada, and Gujarati are compared and contrasted in this proposal. Depending on the dataset, methods, and level of precision used in this work, it provides a comprehensive exploration.

The author [30] claims The ancient Indian script "MODI lipi," which is still unidentified, is one of them. It is still important for historians to research both the antiquated Maratha history and the heritage of certain other Indian regions, even though it is no longer in use. A transform invariant technique is required for MODI recognition due to the severe deformation of MODI documents. Although Techniques for feature extraction have been implemented in the early years to sustain variational hastily scribbled character recognition, there is still room for improvement under global transformations. Pooling-convolution architecture and data augmentation in convolutional neural networks now only show local transform invariance. Utilizing the envisaged classifier is utilized, actuality descriptor, and Convolution neural transfer learning spectrum of the aligned differential, regional randomness is maintained for MODI recognition. The invariant property is chosen and the groups that contribute to the low acknowledgment rate are highlighted using an empirical investigation centered on PCA and confusion matrices. The envisaged classification techniques are assessed on a converted MODI dataset after becoming instructed on a self-generated handwritten MODI character dataset. The perceptions exhibited that without the necessity for network or data augmentation, the advocated layout can persist to apprehend MODI handwritten characters after upgrades.

III. INFERENCES DRAWN FROM THE LITERATURE REVIEW

Following a thorough analysis of all recent works, it is clear that some researchers employed deep learning techniques like convolutional neural networks and transfer learning, while others employed Support vector machines and decision trees are instances of machine learning algorithms. Thus, it can be concluded that deep learning algorithms, particularly transfer learning models like Vgg and AlexNet models, are highly optimized and provide extremely high exactness values as well as decreasing complexity time or running time. The primary disadvantage of using machine learning models is that they are incapable of admitting functionalities instinctually, which makes them less capable of producing meaningful results. However, they outperform deep learning models in terms of learning features automatically.

IV. CONCLUSION

It might be challenging to identify the digital characters used in diverse contexts, hence there are sophisticated methods available to address this problem. As a consequence, in this survey article, a thorough description of the various excellent solutions is provided. These solutions are very capable of producing effective outcomes in both Hindi and other languages written in the Devanagari script. This study also discusses the various approaches for character identification and feature extraction for Devanagari handwritten characters. According to the survey, Transfer Learning is the best deep learning algorithm for recognizing handwritten characters because it comes with various built-in optimized frameworks that are highly structured to produce better results. The models could ultimately be enhanced by incorporating a sizable database and additional Latin and Indian characters to create a universal system that could be used in languages or scripts of other kinds.

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