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Malayalam Handwritten Words Recognition: A Review

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Abstract - This review examines character segmentation and offers an elegant method for identifying and transforming handwritten Malayalam words from picture documents into text. Character touchings, different writing styles, and noisy, damaged scanned photos make it difficult to recognise handwritten text. Taking use of today's world of rich data and algorithmic developments, the system uses deep convolutional neural networks (CNNs) to address these challenges. The three steps of Malayalam handwritten word recognition are segmentation, recognition, and pre-processing. Making Malayalam character datasets is the first stage, and then pre-processing to improve image quality comes next. Then, in order to maximise the system's capacity to precisely forecast Malayalam characters, a CNN model is built to extract relevant information. The last phase of the recognition process involves the system classifying the characters. This project is significant since it uses CNN filters to enhance feature recognition, which enhances the accuracy of Malayalam character prediction.

***Key Words*:** Deep Learning, Deep Convolution Neural Network (DCNN), Character recognition, Character segmentation,

1.INTRODUCTION

The Malayalam Handwritten Words Recognition System provides an innovative technological solution which is designed to handle the difficult process of reading handwritten Malayalam words from picture documents and translating them into text format. Compared to printed text, handwritten writing presents a different set of hurdles in the area of optical character recognition. By employing deep Convolutional Neural Networks (CNNs), the huge amount of data available in the modern digital world, and the continuous development of algorithmic techniques, the system effectively negotiates these complications.

The project is carried out in a well planned sequence of steps, each of which helps the Malayalam Handwritten Words Recognition System function as a whole. Fundamentally, the first stage involves developing large-scale Malayalam character datasets, which provide the foundation for robust model training. The aforementioned dataset functions as the foundation for the ensuing phases, enabling the creation of a CNN model adapted to the nuances of Malayalam characters. Pre-processing takes similar issues into account, like character touches, different writing styles, and the noise that comes with scanned photos. In order to enhance the correctness of the input data and guarantee that the system's later phases function more accurately, this preparatory step is essential.

This project's main focus is on building and implementing a Convolutional Neural Network (CNN) with great care, designed to identify handwritten Malayalam words. By use of sophisticated composition, the CNN employs filters to identify and emphasise significant features within the characters, deftly negotiating the difficulties presented by disparate writing styles and image deterioration. The method performs robustly across a variety of datasets as a result of the thoughtful application of filters, which dramatically increases the system's accuracy in character prediction and classification. The recognition process proceeds smoothly, from dataset development to feature extraction, demonstrating the convergence of deep learning innovations with linguistic intricacies.

Leveraging deep learning advances and a multitude of available data, the Malayalam Handwritten Words Recognition System opens up new possibilities for automated interpretation in a variety of document pictures. This combination of technology and linguistic nuances not only improves the accuracy of character recognition but also highlights the possibility of automated interpretation in handwritten Malayalam text, which is a noteworthy development in the field of linguistically diverse image recognition systems.

2. RELATED WORKS

[1]In the expansive landscape of artificial intelligence and machine learning, the literature survey on optical character recognition (OCR) and handwritten text recognition highlights the profound implications and ongoing advancements in these pivotal fields. Researchers have dedicated significant attention to the challenges inherent in deciphering handwritten text, recognizing its status as a dynamically evolving study area. The exploration of fundamental OCR methods, particularly those emphasizing the offline identification of handwritten English words, has been a recurring theme in the scholarly discourse. The present research contributes significantly by introducing a cost-effective methodology for the development of a handwritten text recognition system. Central to this approach is the implementation of a three-layer artificial neural network (ANN) using a supervised learning technique, a strategic choice underscored by its demonstrated efficacy in achieving a consistently high level of accuracy. This accomplishment represents a noteworthy advancement, as it facilitates the transformation of handwritten text documents into digital form, thereby presenting a promising avenue for mitigating complex problems and diminishing the requisite human intervention.

[2]In the realm of historical manuscript image analysis, this paper addresses the intricate task of text line segmentation, specifically focusing on challenging images with narrow

interline spaces, touching components, interpenetrating vowel signs, inconsistent font types and sizes, as well as curved, multi-skewed, and multi-directed side note lines. Recognizing the impracticality and time-intensive nature of bounding polygon labeling in such complex scenarios, the paper introduces a novel approach employing line masks that connect components on the same text line. The Fully Convolutional Network (FCN) is then leveraged to predict these line masks. While FCN has been successfully applied in regular handwritten document images, the paper extends its utility to challenging manuscript images. Notably, the authors introduce a new evaluation metric sensitive to both over-segmentation and under-segmentation, showcasing the adaptability and effectiveness of FCN in handling intricate historical manuscripts. The study evaluates its proposed method on a publicly available challenging handwritten dataset, achieving results comparable to a previous work on the same dataset. The literature survey in this domain likely encompasses studies on text line segmentation, particularly in handwritten documents, exploring various techniques and methodologies for handling challenging characteristics such as touching components, complex layouts, and varying font types and sizes. This paper contributes by introducing a novel application of FCN in the context of historical manuscript image analysis, offering insights into the efficacy of the proposed method and its comparability to existing approaches

[3]The digitization of Malayalam handwritten documents poses a significant challenge in the absence of a labeled benchmark dataset for handwritten characters. Addressing this limitation, the paper focuses on developing a pre-trained Convolutional Neural Network (CNN) model for recognizing Malayalam handwritten characters, overcoming the constraints of a small-sized dataset. Two key approaches, transfer learning and fine-tuning, are employed on the pre-trained Deep Convolutional Neural Network (DCNN) architecture ResNet50. The optimization of model design involves experimenting with parameters such as learning rate, batch size, and optimization algorithm. Notably, the highest testing accuracy of 78.05% is achieved with the fine-tuning approach, utilizing a batch size of 16, RMSProp optimization algorithm, and a learning rate of 0.000001. Intriguingly, ResNet50, initially pre-trained on color images, attains a testing accuracy of 78.05% for binary images. The literature survey for this work is likely to delve into studies on character recognition, transfer learning, and fine-tuning strategies in the context of various languages. It may also explore methodologies for optimizing CNN architectures with limited datasets and adapting pre-trained models to specific recognition tasks, showcasing the uniqueness of this research in addressing the challenges of recognizing Malayalam handwritten characters with a constrained dataset.

[4]This paper introduces an innovative method for offline handwritten character detection through the application of deep neural networks. Leveraging the increased availability of vast datasets and advancements in algorithmic techniques, training deep neural networks has become more accessible. The growing computational power required for training neural networks is met by the availability of GPUs and cloud-based services such as Google Cloud Platform and Amazon Web Services. The proposed system adopts image segmentation for handwritten character recognition, utilizing OpenCV for image processing and Tensorflow for neural network training. Developed using the Python programming language, the system represents a contemporary approach to leveraging deep learning for character detection. The literature survey likely encompasses research on offline handwritten character detection, emphasizing the integration of deep neural networks, TensorFlow, and OpenCV. This work contributes by presenting an integrated system that combines image segmentation, neural network training, and practical application using Python, reflecting the current trends and tools available for advancing handwritten character recognition systems.

[5]This paper contributes to the growing field of handwritten document recognition by presenting a system based on Convolutional Neural Network (CNN) techniques. Handwritten document recognition has garnered increased attention, particularly for its potential as an aiding technology for visually impaired users and in automatic data entry systems. The proposed system employs a dataset of English language handwritten character images, undergoing extensive training and testing processes. The system conducts image pre-processing stages to prepare training data using a CNN. Segmented characters are then fed into a CNN for recognition, yielding accurate results on the given dataset. The paper emphasizes the multiple experiments conducted, showcasing the system's robustness and efficiency in achieving recognition results. The proposed work reports a notable accuracy of 93% during CNN training and slightly lower, yet respectable, accuracy of 90.42% during validation. While the literature likely includes studies on CNN-based handwritten document recognition, this paper contributes by offering a comprehensive system that encompasses image pre-processing, segmentation, and recognition stages, with a focus on achieving high accuracy and practical applicability in assisting visually impaired users and automating data entry processes.

3. DESIGN AND ANALYSIS

3.1 Handwritten Text Recognition Using Machine Learning

The first step in offline handwritten character recognition is taking pictures with digital tools like scanners or cameras. To improve quality, these photos are preprocessed using techniques like median and Gaussian filtering to remove noise. Then, either explicitly or implicitly, segmentation techniques are used to extract individual characters from the image. The next step is feature extraction, in which each character's distinct qualities are found. Lastly, classification is carried out, in which the trained algorithm chooses the most likely matching rule for each character by assigning probabilities to it. Preprocessing, segmentation, feature extraction, and classification are done iteratively in order to accurately recognise handwritten letters in digital form. This is necessary for a number of applications, including optical character recognition systems.

3.2 Segmentation for Challenging Handwritten Document Images Using Fully CNN

This work proposes a novel approach that takes use of the differences in alphabet size caused by different handwriting styles to extract text lines from handwritten Malayalam manuscripts. To dynamically adapt to each handwriting style, the technique entails setting thresholds based on average character height and breadth. Text line positions are determined using horizontal projection (HP) values, which handle issues like overlapped line segments and variable character gaps. The approach outperforms languageindependent algorithms such as A* Path Planning and the piecewise painting algorithm, achieving a high accuracy rate of 85.507% on the LIPI database. To aid with evaluation, ground truth images for 7535 text lines are developed alongside a new database of 402 images called LIPI. This method is a first step towards digitising handwritten Malayalam manuscripts, making it easier to sharing of documents in local languages.

3.3 Character Recognition using Transfer Learning and Fine Tuning of Deep CNN's

In order to tackle the task of Malayalam character recognition, the model makes use of Convolutional Neural Networks (CNN) and Transfer Learning (TL). Instead of beginning from zero, the first framework is an already-existing Deep Convolutional Neural Network (DCNN) with a large class set, which improves recognition performance for Malayalam characters. Transfer Learning reduces the risk of overfitting in situations with insufficient training samples. This method relies on pre-trained models, which are frequently trained on ImageNet. Two transfer learning strategies are used: feature extraction, which freezes convolutional layers acting as feature extractors and trains only the Fully Connected Layers (FCLs), and fine-tuning, which bases network development on a pre-trained model and then trains with fresh data. Both test-train and k-fold cross-validation techniques are used with the 90 classe 200 images each that make up the Malayalam Handwritten Character Dataset to assess the performance of the model. By dividing the data into 18 subsets and training and testing the model 18 times, the k-fold cross-validation method ensures a robust evaluation. Various architectures are examined, each providing unique benefits for feature extraction and classification, including DenseNet, VGG, Inception-V4, and AlexNet. These models help with the digitalization of handwritten Malayalam documents by effectively classifying Malayalam characters through the use of convolutional layers and fully connected layers.

3.4 Character Recognition Using Deep-Learning

Covering the creation of an Android app that scans handwritten manuscripts. With this app, users can utilise the cameras on their Android phones to take pictures in order to digitise handwritten material. This system makes use of Convolutional Neural Networks (CNNs) because of its superior performance in image recognition applications. CNNs are made up of convolutional layers that help extract features and max-pooling layers that help reduce the dimensionality of input images. In order to speed up the training process, the system uses the NIST database, where handwritten character pictures are first scaled from 128x128 to 28x28 pixels. Several processes are carried out in order while processing an image: first, pre-processing uses median filtering to remove noise, and then, to reduce processing complexity, conversion to grayscale. Darker handwritten text is separated from a lighter background by a threshold. With the use of horizontal and vertical projection techniques, image segmentation is performed to separate lines, words, and individual characters. Whereas vertical projection detects columns with zero pixel sums to split words, horizontal projection recognizes rows where the sum of pixels is zero, signifying line breaks. The system generates the final recognized text by feeding these segmented components into a pre-trained neural network model for predictions. This all-inclusive method makes it easier to recognize handwritten Malayalam letters accurately and efficiently, which improves the digitization experience for users.

3.5 CNN based Intelligent Document Recognition

The Intelligent Document Recognition system, which uses Convolutional Neural Networks, is divided into multiple stages with the goal of correctly identifying handwritten characters. Image Acquisition is the first step in the process, where uploaded scanned handwritten character pictures are scanned. The next step is pre-processing, which includes binarization to improve image quality, grayscale conversion, and noise removal via median filtering. The handwritten script is segmented into words, characters, and lines. Word segmentation makes use of morphology and dilation techniques, whereas Line segmentation uses a Projection Profile-Based Algorithm. Character Segmentation uses sophisticated algorithms to address issues with over-segmentation and slant correction. Feature extraction is the process of utilizing a convolutional neural network (CNN) to identify pertinent characteristics in an image. Convolutional and completely connected layers make up the CNN architecture, which is optimized during training via backpropagation. This all-inclusive method guarantees accurate and efficient handwritten character recognition for intelligent document processing.

4. DISCUSSION

The importance of precise handwritten text identification is emphasized in the introduction, as is the critical role that pattern recognition techniques play in accomplishing this goal. Handwritten text can be accurately understood by using approaches such as template matching, which normalize patterns based on their position and shape, resulting in dependable recognition results. The Malayalam language is highlighted because of its distinct script, which is derived from the Grantha script. This highlights the language's rich character set and its importance when it comes to handwritten text recognition. The extensive data collection procedure, which involved 77 native Malayalam writers, emphasizes the study's thoroughness, which is necessary for successfully developing and evaluating recognition models. Further highlighting their importance in raising recognition accuracy is the topic of Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs). The intricacy of handwritten text recognition jobs is mostly handled by the long-lasting dependencies and information retention of LSTMs and RNNs, particularly in languages like Malayalam with different letter sets. Additionally, the use of data augmentation methods like grayscale conversion and random shear shows a proactive approach to increasing the diversity of the dataset and boosting recognition performance. These techniques are essential for reducing possible biases and enhancing the resilience of recognition models in practical applications. For scholars and practitioners in the field, the introduction offers a thorough overview of the difficulties and approaches associated with handwritten text recognition, with a particular emphasis on the Malayalam language.

5. CONCLUSIONS

The Malayalam Handwritten Words Recognition System that has been suggested offers a thorough and inventive solution to the complex problems involved in handwritten Malayalam word transcription from picture documents. The process is broken down into discrete stages, each of which is carefully planned to enhance the system's overall performance. The system methodically works its way through the challenges of handwritten character recognition, from dataset construction, pre-processing, and Convolutional Neural Network model development to segmentation, recognition, and output production. The system exhibits a remarkable ability to precisely segment data and apply sophisticated deep learning techniques, such Transfer Learning with CNNs, to reliably predict and categorize characters, even when faced with varying writing styles and character variants.
The system's capacity to adapt to the complexities of handwritten Malayalam text is improved by the combination of character recognition algorithms, connected component labeling, and vertical and horizontal projection profile analysis. The output generation step ensures practical usage by combining the identified characters into an editable text format. Applications in language processing, education, document digitization, and cultural heritage preservation can all benefit from the system's adaptability. The Malayalam Handwritten Character Recognition System is set to make significant progress in automating the interpretation of a wide range of difficult handwritten Malayalam text in image documents thanks to this creative synthesis of technology and rigorous methodology. This will usher in a new era of efficiency and accessibility in linguistic technology.

SOME OF ADVANTAGES

a) Enhancing input images through techniques like Grayscale Conversion, Noise Removal, and Binarization, which standardize the image format and reduce noise.

b) Methods ensure precise separation of text components despite challenges such as slant and over-segmentation, contributing to reliable document analysis.

c) This flexibility enables accurate recognition across diverse handwriting patterns, ensuring reliable performance across different document types and writing conventions.

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