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Marathi Handwritten Recognition System Using Machine Learning Techniques

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Abstract: The Marathi language presents a considerable barrier in handwriting recognition because of the wide range of writing styles and intricate script. Systems for correctly recognizing handwritten Marathi text can be developed with the aid of machine learning techniques. The official language of Maharashtra, Marathi, originates from Devanagari script. In the globe, it is fifteenth most spoken language, in India, it ranks fourth. The Marathi language is written using Devanagari script, which includes 36 consonants and 12 vowels. Recognizing handwritten characters in any script is a difficult issue for researchers. These days, the most difficult issue is identifying handwritten Marathi characters. Physical document sharing takes a lot of effort and time. Handwritten Marathi characters differ in their shape, structure, writing styles, and number of strokes. The Marathi handwriting recognition technique is crucial in many ways, the safeguarding of cultural heritage. The literacy legacy of Marathi, an old language, is extensive. Through the digitization of handwritten Marathi literature and documents, technology contributes to the continuation and protection of Marathi culture and legacy for future generations. People who are blind or have trouble using text entry methods can more easily access Marathi information because of the recognition system, which promotes accessibility.

This system recognizes and transcribes characters and words from handwritten Marathi script using machine learning techniques like deep learning, convolutional neural networks, and bidirectional long short term memory (BLSTM). Usually, it starts with a training phase in which the system picks up skills from a dataset of handwritten Marathi samples extracted from standard datasets. It then uses skills to identify and translate new handwritten input.

Keywords: ML, DL, CNN, BSLTM, neural networks, recognition, speech conversion.

I. INTRODUCTION

There is a wealth of historical writings, manuscripts, and literature available in Marathi. The process of digitizing Marathi language information and encouraging its usage on digital platforms can be greatly aided by handwriting recognition. Memos, notes, and handwritten communications can all be understood using Marathi handwriting recognition software. More digital material in Marathi can be produced by improving handwriting recognition, which will support regional language content. Handwriting recognition can lead to new business prospects for companies targeting Marathi-speaking customers. It can be used for jobs involving data entry, document processing, customer service, and efficiency improvement.

The study examines several machine learning algorithmic approaches in handwritten recognition systems, with a particular emphasis on Devanagari script character recognition. In order to examine the effectiveness of different machine learning classifiers in character recognition from Sanskrit, Hindi, Marathi, and Maithili languages, the researchers deploy Decision Tree, Nearest Centroid, KNN, Extra Trees, and Random Forest classifiers. The difficulties in identifying handwritten text are discussed in the paper, along with the requirement for effective classification and pattern recognition methods and differences in writing styles.

II. LITERATURE REVIEW

Handwritten recognition systems have been using various machine learning methods for decades.

Using a straightforward architecture, George Retsinas et al.[1] surpasses previous approaches in achieving state-of-the-art results. Suggested recommended practices provide useful adjustments for CNN-LSTM training and performance enhancement. On the IAM dataset, competitive results for line-level recognition are obtained. In the absence of extra modules, the system's default network operates badly. The system's lack of complexity might make it less flexible for applications requiring sophisticated features or more complicated datasets.

Focus is placed on a CNN-based OCR framework by Ambadas Shinde and Yogesh Dandawate [2] that can recognize handwritten Marathi words and produce excellent printed Marathi text. Due to the limited availability of the Marathi training dataset, a bespoke dataset was created. Those between the ages of 8 and 45 contributed to the creation of the dataset, which consists of 9,360 words (104 words with 90 images apiece). The technology is the greatest choice for digitizing handwritten Marathi data because of its ability to adjust to different handwriting styles.

Raphaela Heil and Malin Nauwerck [3] use the LION dataset to create a baseline for handwritten stenography recognition. Remarkably better recognition outcomes are achieved when pre-training methods and stenographic subject knowledge are combined. The LION dataset, which includes other texts and drafts by Lindgren, will help advance the field of handwritten stenography recognition study in the future. Recognizing the phonetic symbols and abbreviations that make up the Melin stenographic system employed in the dataset is difficult. The study emphasizes how difficult it is to transliterate handwritten stenography automatically. The difficult nature of stenography identification is demonstrated by the significant error rates on the LION dataset.

Bineet Kumar Jha and Shilpa Mangesh Pande [4] are concentrating on creating a machine learning-based handwritten character identification system for Devanagari script. Many machine learning classifiers, such as Decision Tree, Nearest Centroid, KNN, Extra Trees, and Random Forest classifier, were used in the system's implementation, which included Sanskrit, Hindi, Marathi, and Maithili. Grid search was used to compare performance and determine the algorithms' score. The dataset was constructed using several font sizes and styles. The Random Forest and Extra Tree classifiers outperform all others in terms of accuracy. The hybrid technique will be used in future studies to increase the model's accuracy.

Yash Gurav, Rajeshri Jadhav, and Priyanka Bhagat concentrate on Devanagari character recognition using a dataset they self-created that contains 29 consonants and 1 modifier [5]. Deep Convolutional Neural Network (DCNN) is what they employ. To extract high-level characteristics for recognition, the system leverages CNN architecture's successive convolutional layers. The offline handwritten character recognition is the main emphasis of the technology. When working with material that contains capital letters, the system might not take letter capitalization into account, which could cause issues. The identified text is not properly understood by the system in its context.

Anupama Thakur et al.'s[6] novel approach, which focuses on certain consonants and vowels, is intended to aid in the recognition of Hindi letters written in Devanagari. The method increases recognition rate by fusing Neural Networks with the k-NN methodology. Although it can investigate the recognition of intricate derivative words in the Devanagari script, the suggested method concentrates on individual consonants and vowels.

Deep learning techniques are used to assess the method for handwritten Devnagari character recognition by Mimansha Agrawal et al. [7]. CNN has been utilized in conjunction with other neural networks including ANN and RNN. Pre-processing, post-processing, segmentation, prediction, and feature extraction are the five fundamental phases of this recognition system. The method for handwritten Devanagari character recognition has been examined by the author. Research on Devnagari word and sentence recognition as well as whole handwritten papers with half characters could be conducted using this future system.

Munish Kumar and Harmandeep Kaur [8] provide a method for deciphering offline handwritten Gurumukhi words. The system uses a thorough technique to recognize words, treating each word as a separate entity. To extract the desired qualities from the text images, zoning features, diagonal features, junction & open-end point features are taken into consideration. It is challenging to compare suggested and current methods in the Gurumukhi script due to the absence of a consistent dataset. Segmentation is further complicated by handwritten words' overlapping characters and contacting neighboring letters.

For the purpose of segmenting handwritten Bangla text, Sheikh Mohammad Jubaer et al.[9] present BN-DRISHTI, a technique that combines YOLO with Hough and Affine transformation. BN-DRISHTI outperformed other datasets and algorithms, achieving high F-scores for line and word segmentation. For precise line segmentation, skew correction using the Hough and Affine transform was essential. In terms of Bangla handwritten recognition, BN-DRISHTI is state-of-the-art when compared to earlier systems. An 'End-To-End Bangla Handwritten Image Recognition system' is what this work attempts to incorporate, using supervised character recognition. The overlap accuracy between ground truth and forecasts was impacted by skew correction prior to line segmentation, which had an effect on the outcomes of the automated evaluation.

In Hindi, Sanskrit, and Marathi texts, Shalini Puria and Satya Prakash Singh [10] concentrate on using the SVM model to effectively classify Devnagari characters in handwritten and printed text. To improve the multi-font and italic text system, the system can be expanded to recognize and classify modified characters and half-characters.

Manoj Sonkure, Roopam Gupta, and Asmita Moghe [11] aim to find the most accurate classification strategy for Handwritten Devnagari Script Recognition by considering multiple factors, such as the database being used, sample size, training, test set ratio, class size, data normalization size, and recognition accuracy. It offers a survey of the literature on the Devanagari script and talks about how various network models, including CNN, BLSTM, and a hybrid CNN-BLSTM, are implemented. The number of convolutional layers in CNN is found to boost its recognition accuracy. To improve the recognition performance, more research can be done on the use of transfer learning for DCNN and the development of a hybrid model combining KNN and ANN classifier for individual vowel and consonant recognition.

Sarayut Gonwirat and Olarik Surinta [12] focus on the difficult task of predicting the sequence pattern of handwritten text images, which is caused by the variety of writing styles, the scarcity of training data, and the potential for background noise to appear in the text images. They claimed that word recognition for handwritten text has been successfully achieved by combining Convolutional Neural Networks (CNN) with Recurrent Neural Networks (RNN), or CRNN. In order to enhance the performance and accuracy of handwritten recognition systems, future research could concentrate on investigating other iterations of the CRNN architecture or alternative deep learning models.

In their approach, D. Saraswathi and Sanaa Mohamed Sherif [13] capture, identify, and translate characters from several sources into machine-coded form. The method made use of convolutional neural networks (CNNs), which are popular deep learning algorithms for image classification and computer vision. The projected output was also visualized by the system using OpenCV, an open-source computer vision toolkit. Data normalization was done to balance the model's inputs and outputs and increase accuracy. It is possible to investigate techniques to improve the recognition rate, like integrating segmentation procedures to identify words, phrases, and paragraphs. The model's applicability can be increased by extending its recognition capabilities to many languages.

Offline handwriting recognition is helpful for digitizing existing handwritten documents, such as forms, postal addresses, and free-form random papers, according to Evans Ehiorobo, Rukayat Koleoso, and Charles Uwadia [14]. A neural network is often built and trained using obtained image data, after which a series of photos is gathered and labeled for the purpose of constructing a software application for offline handwriting recognition. Another way to get training data for handwritten text recognizers is to train a Generative Adversial Network (GAN) to automatically generate images of handwritten text. The Extended MNIST dataset is utilized for training the GAN. Subsequent investigations may concentrate on resolving the difficulties in GAN training, like appropriately decreasing loss functions, preventing comparable results for various input data and ensure effective feedback between generative and discriminative networks

In order to create a deep learning-based application for handwritten text recognition (HTR) that uses convolutional neural networks (CONVNETs) to achieve higher accuracy, Rohini Khalkar et al.[15] propose a system of deep learning for HTR. There are 7850 photos in the training set and 876 images in the validation set. Image processing techniques are used for segmentation after preprocessing methods like thinning, inversion, and grayscale inversion are applied to the pictures. One potential area for improvement is to make the model more flexible and to utilize it with other languages like Marathi, Hindi, and other regional languages. Enhancing the precision and effectiveness of the model is an additional focus area.

The field of character recognition in computer vision and the difficulties machines have while recognizing handwritten text are covered by Yugandhar Manchala et al. [16]. Text recognition entails feature extraction, categorization, and picture processing. The algorithm has been trained to distinguish between different handwriting samples and their similarities. The system's goal is to create a neural network-based system that can effectively identify the style and format of handwritten text. The authors also note that a dataset with isolated and labeled sentences is available for validation, testing, and training purposes. Plans for the future include expanding the study to more datasets and taking various embedding models into account.

An OCR system that transforms text into machine-readable format is described by Jamshed Memon et al. [17]. This system preserves historical data, legal papers, and educational records while facilitating the retrieval of needed information. A growing area of study within OCR is handwritten OCR, which is divided into offline and online systems. The development of OCR systems for languages other than the most widely spoken ones is hampered by the low availability of datasets for these languages. The application of handwritten OCR in varied linguistic contexts is limited by the absence of research on OCR systems for languages other than the languages that are commonly studied.

A proposal for Pattern Recognition of Handwritten Documents using Convolutional Neural Networks is made by M. Rajalakshmi, P. Saranya, et al. [18]. The primary task of handwriting recognition systems is to categorize handwritten words, which can be block, cursive, or tilted. A functional model that acts as an interface between people and machines and translates handwritten format to digital format solves this problem. The hardest parts of this system are classifying and recognizing patterns. To reconstruct the word, characters are taken from word pictures and categorized separately. In order to do this, the features that were taken from the characters must be analyzed and compared to a library of image models.

Using pictures from mobile cameras, I Joe Louis Paul et al.[19] create a handwritten character recognition system that is capable of accurately identifying any handwritten character. By turning handwritten language into a text document, the authors hope to lessen human labor and promote a paperless world. The system employs a Long Short Term Memory (LSTM) neural network for increased efficiency and quicker execution times than earlier neural networks. The character recognition system makes predictions about the characters. Character recognition accuracy may be hampered by the system's usage of mobile camera photos, which are noisier than OCR-scanned images. The system's Long Short Term Memory (LSTM) neural network has a lengthy training phase that demands a lot of computational resources.

According to Hao Zeng [20], handwriting has been a common way to document and communicate in daily life from ancient times. Research is essential, particularly in the area of handwritten digit identification, as handwriting recognition is an essential application in daily operations. The author concentrates on employing more straightforward neural networks rather than complex ones, which demand highly accurate computer configurations in order to identify handwritten numerals with somewhat encouraging accuracy. In order to achieve this, a neural network that uses the Softmax Regression algorithm to accurately identify handwriting in the MNIST dataset is constructed.

Many difficulties have been found in the research on character identification in handwritten text using deep learning and machine learning approaches, covering a wide range of languages and writing styles. These difficulties include handwriting style variances, noise in mobile camera photos, a lack of consistent datasets, and the requirement for increased identification accuracy. It is necessary to build new systems and approaches in order to handle these difficulties. Novel methods such as fusing domain-specific expertise with deep learning techniques, investigating hybrid architectures, and leveraging advances in computer vision and natural language processing should all be incorporated into the system.

III. NEED OF WORK

Handwritten identification technology now faces a number of significant challenges, which highlights the necessity for ongoing research and improvement. One major limitation exists in the realm of feature extraction and classification methods. Often, the methods employed to classify discrete characters or symbols into essential elements of handwritten text are flawed, resulting in less-than-ideal recognition accuracy.

This shortcoming jeopardizes the reliability and usability of the recognition system, necessitating improvements to feature extraction techniques and classification models. There is a problem that needs to be handled with regard to swiftly and efficiently detecting text. Text that is produced quickly or haphazardly needs to be transcribed accurately by software for recognizing handwriting. To improve the system's usability and effectiveness in real-world situations, innovative methods for quickly comprehending and write content transcriptions.

The advancement of handwritten recognition research necessitates concentrating research and development efforts on finding solutions to these limitations. Improved feature extraction and classification techniques, improved performance in a range of handwriting styles, increased overall accuracy, expanded functionality to recognize special symbols, better recognition of text written quickly, and accurate identification of modified characters are all ways to make handwriting recognition systems more dependable, efficient, and versatile. These enhancements will make it easier to integrate the systems across a variety of applications and domains and enable wider use of the systems. The proposed effort intends to improve the handwriting recognition system so that Marathi speakers can use digital tools more easily and productively.

IV. COMPONENTS OF MARATHI HANDWRITTEN RECOGNITION SYSTEM USING MACHINE LEARNING TECHNIQUES

The scanned photos are first input into the system architecture of the suggested system, which preprocesses them to improve their quality and eliminate noise. Use image-enhancement methods. division of the text into separate words or letters. Take pertinent elements out of the previously processed photos. Using labeled data, the training module trains the recognition model and adjusts its parameters to enhance performance. The task of recognizing and classifying objects, patterns, or information from incoming data is frequently assigned to a recognition module in a system. Following text recognition, there is an optional module that speaks the editable text so the user may hear the words or text. A GUI allows for the visualization of the system's output.

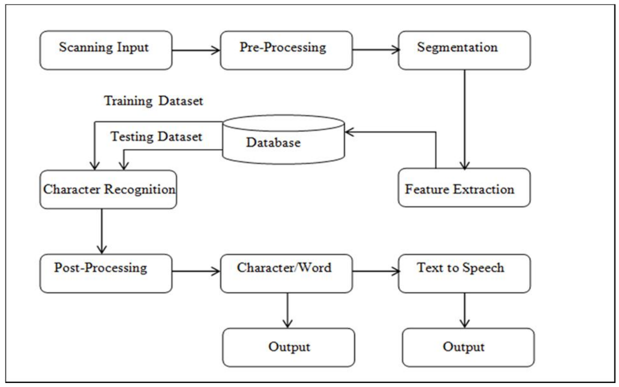


Fig. 1.1 System Architecture for Marathi Handwritten Recognition System Using Machine Learning Techniques

Translating the described technique into executable code is the first step in implementing the suggested modules. An outline of how each module can be used is provided below:

1) Module 1 Data Collection and Preparation:

Gather a sizable collection of handwritten Marathi samples with a range of writing styles and levels of difficulty. This dataset can be gathered from a variety of sources, such as web resources, historical archives, and academic institutions. Amass a varied collection of handwritten Marathi samples. Next Preprocess the pictures to improve readability, equalize size, and get rid of noise. The dataset should be divided into three primary subsets: testing, validation, and training. A typical split is 70:15:15, meaning that training uses 70% of the data, validation uses 15%, and testing uses 15%.

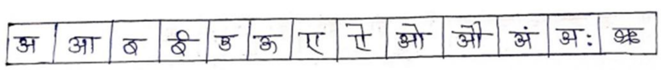


Fig. 3.1. Marathi Handwritten Vowels

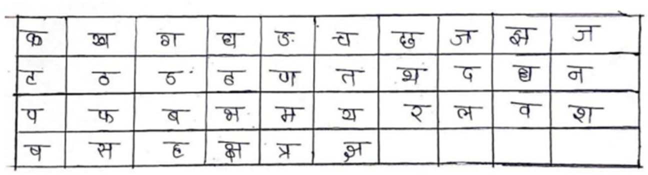


Fig. 3.2. Marathi Handwritten Consonants

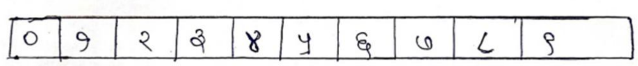


Fig. 3.3. Marathi Handwritten Numerals

2) Module 2 Data Pre-processing and Segmentation

Pre-process the photos to improve their quality and get rid of noise before extracting features. Typical pre-processing methods include adding filters to eliminate background noise, turning the photos to grayscale, and shrinking them to a standard size. Use image-enhancing techniques, such as blurring, sharpening, smoothing, and noise reduction, to boost the quality of your images. To ensure consistent input, normalize and standardize the photos. Consider breaking up the handwritten text into separate words or characters if it is written in many lines or paragraphs. This can lessen ambiguity and increase recognition accuracy. Find lines in the text and divide it into different lines or paragraphs. Divide lines into words or characters by utilizing bounding boxes and contour detection.

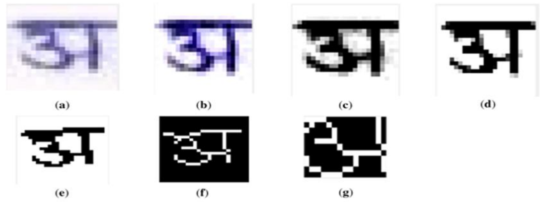


Fig. 3.4. Preprocessing of Character

3) Module 3 Feature Extraction

From the pre-processed photos, extract pertinent features including curvature analysis, edge identification, and an oriented gradient histogram. By capturing the distinctive qualities of the Marathi script, these attributes allow machine learning algorithms to precisely identify handwriting patterns. Take characteristics out of every segmented word or character. Make use of methods like deep learning-based feature extraction (convolutional neural networks) or Histogram of Oriented Gradients (HOG). Every approach has advantages and disadvantages, and the selection of an edge detection method is influenced by the application's particular needs, computing complexity, and image noise levels.

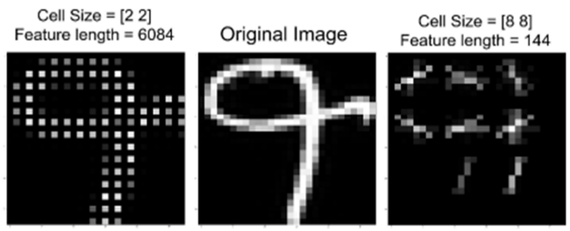


Fig. 3.5. HOG Features of Handwritten Character

4) Module 4 Training

Any machine learning system, including those used for tasks like handwriting recognition, must have a training module. Using labeled data, this module trains the recognition model and optimizes its parameters for better performance. The Bidirectional Long Short Term Memory (BLSTM) algorithm will be used to train the Convolutional Neural Networks (CNN). This is because BLSTM is well suited for modeling sequences, as it can capture dependencies in both forward and backward directions, which helps to understand the context of each character about its neighbors, which is crucial for accurate recognition. CNN, on the other hand, deals with variations in writing styles and quality of handwritten samples.

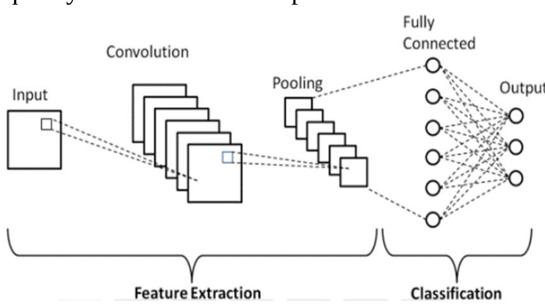


Fig. 3.6. Architecture of CNN

A specific type of neural network known as a convolutional neural network (CNN) consists of multiple layers, including the pooling or sub-sampling layer, convolution layer, non-linearity (ReLU) layer, and fully-connected layer. A common filter among several neurons is present in every convolution layer. These filters extract details from the input image by being smaller than the original. The receptive field is the region of the picture from which the filter extracts features; the features that are extracted are referred to as feature maps. The output of these dot products is stored in different neurons of the convolution layer after the filter does a dot product operation with the previous layer.

Every neuron in the pooling layer makes use of the output from the convolution layer that came before it. Reducing the dimensionality of the input is the pooling layer's main objective since it makes the network easier to control and more computationally efficient. There are two methods for pooling: average pooling and maximum pooling. When using max pooling, the highest value in the feature map is chosen, and this maximum value is used to replace all other pixels. The process of average pooling involves calculating the feature map's average value and replacing the impacted pixels with it. The final output is a condensed version of the original image, which is then used as input for the following convolution layer.

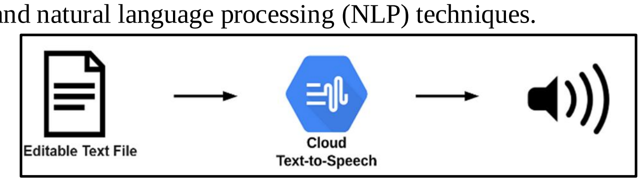
The fully connected layer, also known as the output layer, is the last layer of a CNN. With every neuron in this layer coupled to every other neuron in the layer before it, classification is handled by this layer. The retrieved features are combined by the fully connected layer, which then uses these features to categorize the input. CNNs may be tailored to a wide range of tasks due to their flexible number of layers, which makes them effective tools for pattern recognition applications such as image recognition.

5) Module 5 Recognition and post-Processing

Identifying and classifying items, patterns, or information from input data—such as pictures, audio, text, or other types of data—is a common task for a recognition module in a system. As was previously noted, in the context of handwritten recognition, it explicitly refers to the module in charge of recognizing and translating handwritten text or symbols into digital text or characters. A recognition system must include post-processing and correction algorithms, particularly for jobs like handwriting recognition where the input data may contain errors, noise, and variances. Following the first recognition, these methods are used to hone the findings and raise the output's accuracy. Using contextual analysis and linguistic models, correctly identify text. Use strategies for correcting grammar.

6) Module 6 Text to speech Conversion

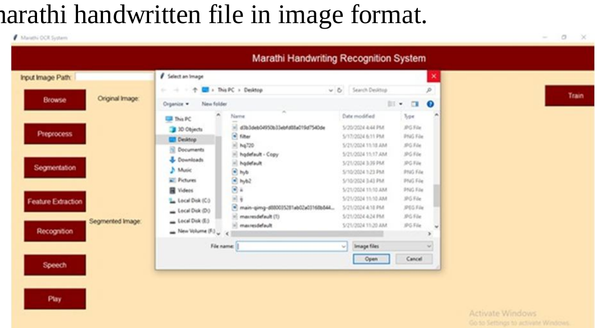
The Google Text-To-Speech API is a useful tool for developers and organizations as it provides numerous benefits and use cases for turning detected text into speech. Developers can use this service from Google Cloud to turn text into spoken audio. The content, complete with formatting, special characters, and punctuation, must be sent to the API. Together with the audio format and quality, specify the voice parameters for the created speech. To produce speech that sounds realistic and is of excellent quality, this procedure combines voice synthesis and natural language processing (NLP) techniques.

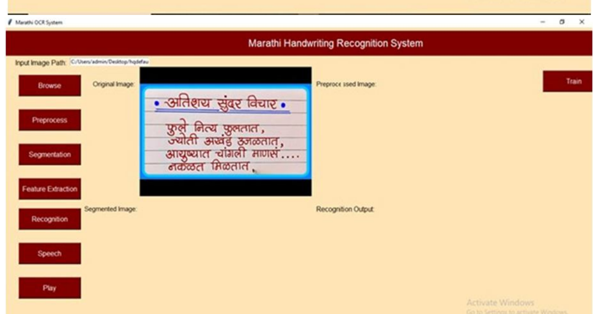


V. IMPLEMENTATION OF SYSTEM

A. Input Image File

In this system first we have to insert a marathi handwritten file in image format.





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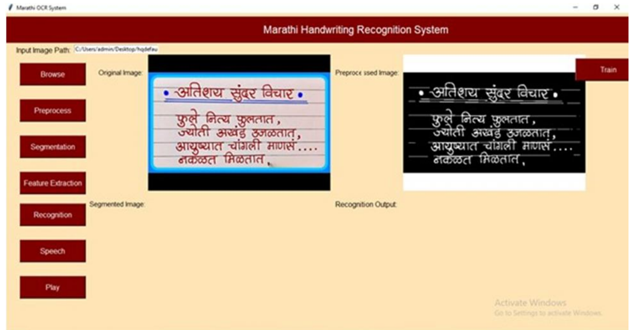
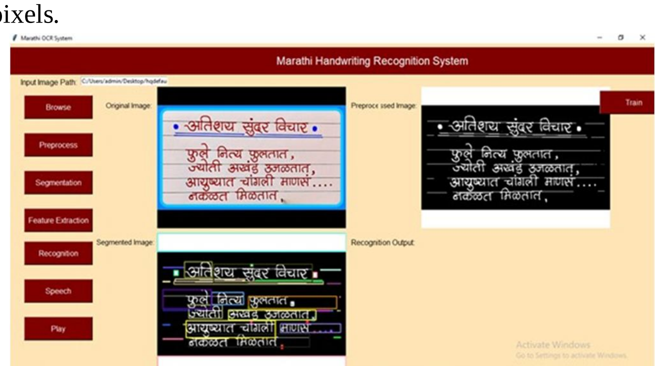
B. Image Preprocessing

The next step is to preprocess the data to enhance quality and remove noise. Common preprocessing techniques include resizing the images to a consistent size, converting them to grayscale, and applying filters to eliminate background noise. Additionally, use image enhancement techniques such as sharpening, noise reduction, smoothing, and blurring to improve image quality.



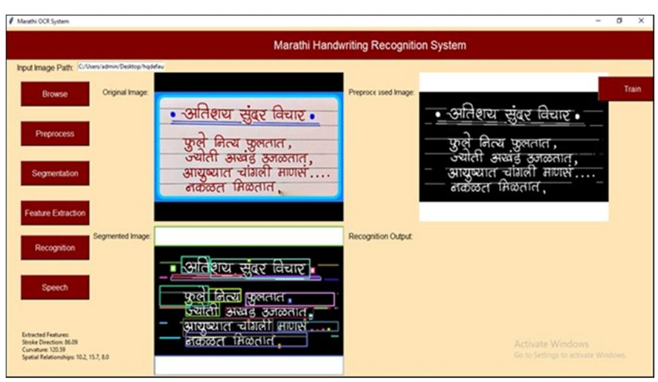
C. Segmentation

It is a fundamental step in the process of handwritten character recognition. This step involves partitioning the input image into multiple segments or regions based on specific criteria. Segmentation is crucial because it isolates individual characters from the background and other surrounding elements, enabling the recognition system to accurately identify and extract each character. The segmentation process typically employs techniques such as thresholding, edge detection, and contour detection. Thresholding is commonly used to convert a grayscale image into a binary image by selecting a threshold value that separates the foreground (characters) from the background. Pixels with intensity values above the threshold are classified as foreground pixels, while those below are considered background pixels.



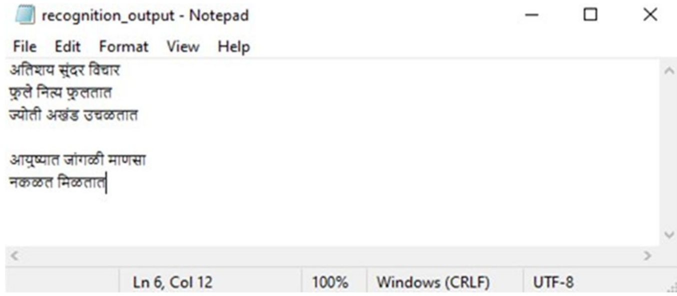
D. Feature Extraction

Feature extraction plays a critical role in handwritten character recognition, involving the extraction of essential attributes from each segmented character to capture its distinctive characteristics. These extracted features act as inputs for the recognition algorithm, enabling accurate character identification and classification. Techniques for feature extraction encompass a range of methods such as statistical descriptors, structural features, transform-based approaches, and advanced methodologies like convolutional neural networks (CNNs).



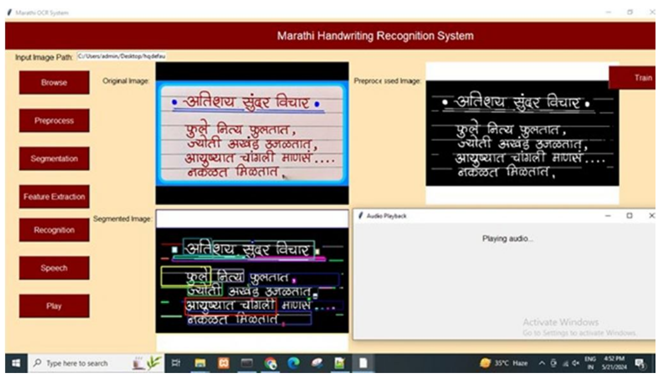
E. Marathi Text Recognition

Converting Marathi handwritten characters into text files, as depicted in Figure 4.6, enhances efficiency in data entry, document processing, and language analysis across domains where Marathi text is widely used. This digital transformation of handwritten Marathi text improves accessibility, usability, and integration with other text-based applications.



F. Text to Speech Conversion

After recognizing and converting Marathi text into a text file, the system can utilize text-to-speech (TTS) libraries or APIs to generate audio output. This synthesized speech can be played using audio playback software or seamlessly integrated into the user interface of the recognition system.



VI. ACCURACY COMPARISON

Below is a table displaying the accuracy of current and proposed methods for recognizing handwritten Marathi letters and numbers across five datasets.

Dataset Type	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5
Existing Handwritten (Alphabets)	94.5 %	94.3 %	94.2 %	94.1 %	94.0%
Existing Handwritten (Numerals)	98.4 %	98.3 %	98.1 %	98.0 %	97.9%
Proposed Handwritten (Alphabets)	97.6 %	97.5 %	97.4 %	97.3 %	97.2%
Proposed Handwritten (Numerals)	99.4 %	99.3 %	99.2 %	99.0 %	98.9%

VII. CONCLUSION AND FUTURE WORK

Creating a Marathi handwriting recognition system using machine learning offers substantial advantages in terms of accuracy, efficiency, customization, scalability, and automation. Machine learning algorithms excel in identifying intricate patterns and features in handwriting that may challenge human perception, thereby facilitating the creation of highly precise handwriting recognition systems. These systems streamline the process of transcribing handwritten documents, significantly reducing time and effort compared to manual transcription.

The development methodology for a Marathi handwriting recognition system using machine learning includes several critical steps: data preprocessing, feature extraction, model training, evaluation, optimization, and deployment. These steps involve preparing and refining the data, extracting relevant features that characterize handwriting styles, training a machine learning model on a dataset of handwritten samples, assessing its performance, optimizing its parameters for enhanced accuracy, and finally, deploying it in a production environment for real-time handwriting recognition.

A Marathi handwriting recognition system utilizing machine learning offers a versatile tool for various applications involving the processing of handwritten documents and data. These include tasks such as digitizing historical documents, real-time recognition of handwritten notes, and improving accessibility for individuals with disabilities.

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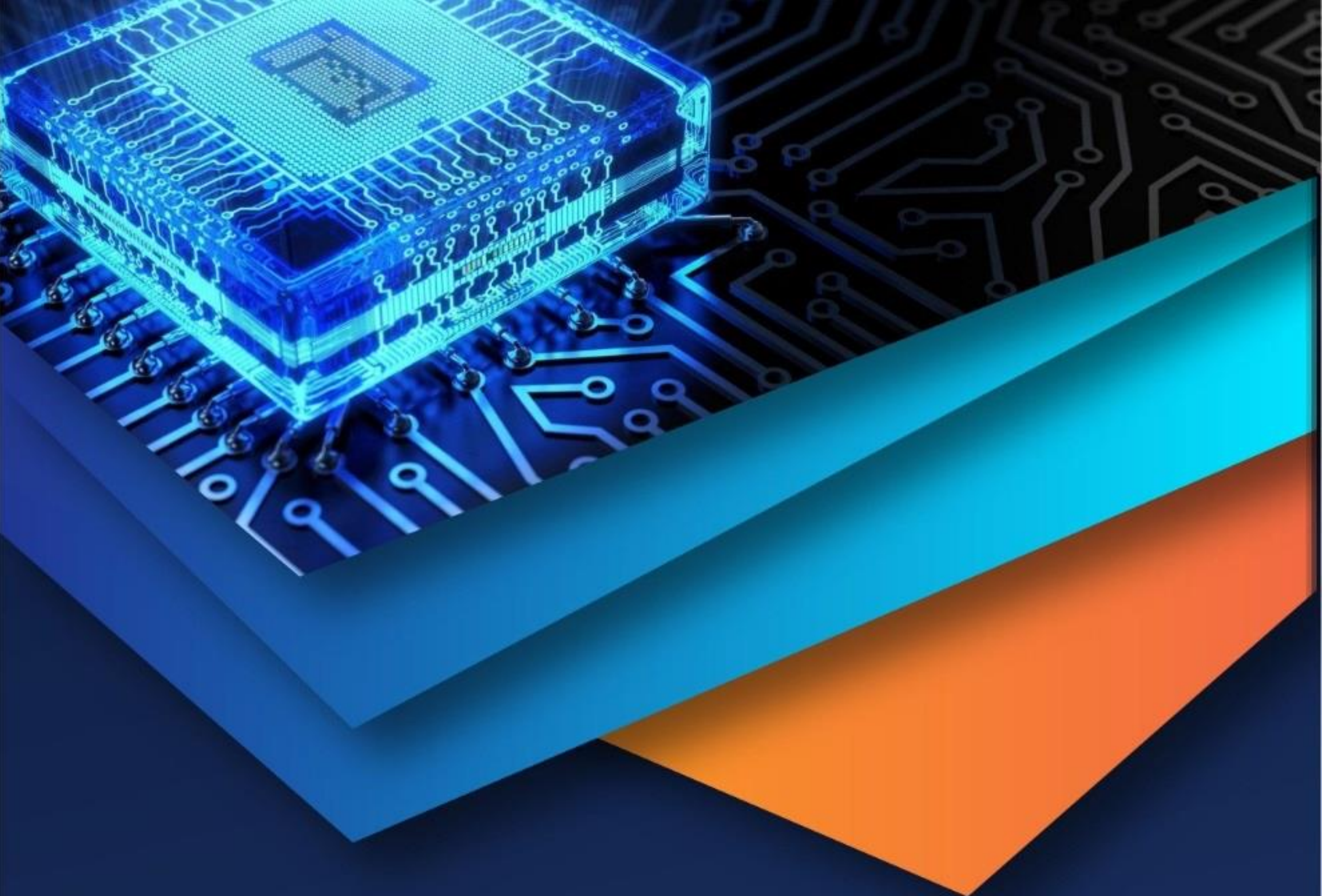

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