

CALLIGRAPHY IDENTIFICATION OF MULTI-SCRIPT TELUGU DOCUMENTS

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Abstract— The rapid growth of digital document processing and multilingual information exchange has intensified the need for efficient script and calligraphy identification systems. In complex document environments, particularly those containing South Indian scripts such as Telugu, Tamil, and Malayalam, accurate identification of handwritten and printed text remains a challenging task due to variations in writing styles, structural similarities, and noise in scanned images. This work addresses the problem of calligraphy identification in multi-script Telugu documents through an integrated image analysis and deep learning framework. The methodology incorporates systematic pre-processing techniques including noise removal, normalization, and segmentation at multiple hierarchical levels such as text lines, words, and characters. Discriminative statistical and structural features are extracted to capture script-specific characteristics. These features are then utilized by deep learning-based classifiers, particularly convolutional neural networks, to achieve robust and scalable classification performance. The approach effectively handles hybrid documents containing both handwritten and printed content, improving recognition accuracy in diverse real-world scenarios. The proposed framework contributes to the advancement of intelligent Optical Character Recognition systems by enabling reliable script identification, which is a critical prerequisite for downstream text recognition tasks. The results demonstrate improved adaptability, accuracy, and efficiency in multi-script handwritten document analysis.

Keywords— *Calligraphy Identification, Multi-Script Analysis, Optical Character Recognition, Deep Learning, Handwritten Text Recognition, Feature Extraction, Image Pre-processing, Script Classification.*

I. INTRODUCTION

Handwritten Character Recognition (HCR) has emerged as a critical domain within pattern recognition and computer vision, driven by the increasing demand for automated processing of handwritten and multi-script documents. The complexity of recognizing handwritten characters arises from variations in writing styles, character shapes, and document conditions, particularly in regional languages such as Telugu. Unlike printed text, handwritten content lacks uniformity, making feature extraction and classification more challenging. The integration of Optical Character Recognition systems with intelligent learning techniques has significantly improved the ability to convert handwritten content into machine-readable formats, thereby enabling efficient digital archiving and retrieval of information. Early research

demonstrated the feasibility of recognizing cursive handwritten characters using structured segmentation and classification methods [1].

The recognition of handwritten characters in diverse scripts has been extensively explored across different languages, highlighting the need for adaptive and robust models. Techniques such as normalization and transformation-based methods have shown promising improvements in handling distortions and variations in handwritten inputs [2]. In Indian languages, especially Hindi and Telugu, the presence of complex character sets and structural similarities between symbols introduces additional challenges in accurate recognition [3]. Traditional approaches relied heavily on handcrafted features and statistical models; however, advancements in machine learning have shifted focus toward automated feature learning and data-driven methods [4].

Neural network-based approaches have gained prominence due to their capability to model nonlinear relationships and learn discriminative features directly from data [5]. These methods have been successfully applied to various scripts, including Arabic and Kannada, demonstrating improved recognition accuracy and adaptability to different writing styles [6]. Feature extraction techniques combined with classifiers such as Support Vector Machines and K-Nearest Neighbors have further enhanced the performance of recognition systems across multilingual datasets [7]. Additionally, research in Malayalam and Urdu scripts has emphasized the importance of combining structural and statistical features to address the variability in handwritten data [8].

Recent developments in bilingual and multi-script recognition systems have highlighted the necessity of designing unified frameworks capable of handling multiple languages simultaneously [9]. Advanced feature extraction methods, including wavelet transforms and neural-based classifiers, have contributed to improving recognition rates in complex scripts such as Nepali [10]. The integration of deep learning architectures has further accelerated progress by enabling end-to-end learning and reducing dependency on manual feature engineering [11]. Despite these advancements, achieving high accuracy in Telugu handwritten character recognition remains a challenging task due to the large character set and diverse writing patterns [12].

The objective is to develop an efficient system for recognizing handwritten Telugu characters by integrating pre-processing, segmentation, feature extraction, and deep learning-based classification techniques. The contributions include the design of a robust multi-stage recognition framework, effective handling of multi-script and hybrid document scenarios, and improved classification accuracy through deep neural models.

II. RELATED WORK

Handwritten character recognition has been widely explored across different scripts and languages, with significant emphasis on improving feature extraction and classification accuracy. Early work by Arifur Rahaman et al. [13] focused on Bangla handwritten character recognition using Artificial Neural Networks, where a novel feature extraction method based on row and column segmentation was introduced. The approach generated feature matrices representing pixel distribution patterns, enabling effective classification through feed-forward neural networks. This method demonstrated improved recognition performance compared to conventional feature extraction techniques, highlighting the importance of structured data representation.

Advancements in deep learning further enhanced recognition capabilities, particularly through convolutional architectures. Mujadded Al Rabbani Alif et al. [14] proposed a Convolutional Neural Network-based model for isolated Bangla handwritten character recognition. The study incorporated architectural improvements such as dropout layers to enhance generalization and reduce overfitting. The model achieved high accuracy on large-scale datasets, demonstrating the superiority of deep learning approaches in capturing complex visual patterns inherent in handwritten scripts.

In the context of Telugu script recognition, C. Vikram et al. [15] introduced a Multi-Layer Perceptron-based framework that utilized pixel coordinate information for feature extraction. The system transformed handwritten characters into structured numerical representations, enabling efficient classification. The approach effectively handled variations in character shapes and demonstrated the capability of neural networks in distinguishing visually similar characters within the Telugu script.

Further exploration into Telugu character recognition was conducted by Ch. N. Manisha et al. [16], who analyzed multiple recognition methodologies, including both online and offline techniques. Their study emphasized the challenges associated with large character sets, structural complexity, and segmentation issues. Various methods such as pixel distribution analysis and structural feature extraction were discussed, providing a comprehensive understanding of the strengths and limitations of existing approaches in Telugu script recognition.

The use of Support Vector Machines for multilingual handwritten character recognition was investigated by H. Swethalakshmi et al. [17], where stroke-based features were extracted from online handwritten inputs. The system represented characters as sequences of strokes and employed

SVM classifiers for recognition. The results indicated that accurate stroke identification plays a crucial role in improving overall recognition performance, particularly for scripts like Devanagari and Telugu.

Deep learning-based enterprise-level solutions have also been proposed to address large-scale recognition challenges. Khaled Bouaziz et al. [18] presented a comprehensive framework integrating deep learning models with scalable data processing platforms. Their approach emphasized automation, scalability, and real-time processing capabilities, demonstrating the practical applicability of deep learning in industrial environments for character recognition tasks.

Beyond recognition, research has also explored the generation and learning of handwriting styles. Yutian Lei et al. [19] developed a model consisting of classification, generation, and discrimination networks to learn personalized handwriting styles and generate corresponding fonts. This work highlighted the potential of combining recognition and generative modeling techniques to enhance the adaptability of handwriting systems.

The application of deep metric learning in handwritten character recognition was studied by Shah Nawaz et al. [20], where similarity-based learning techniques were employed to improve classification accuracy. The use of Siamese and triplet network architectures enabled the system to learn discriminative feature embeddings, facilitating better comparison between handwritten samples. This approach proved effective in handling intra-class variations and improving recognition performance across complex datasets.

A hybrid deep learning architecture combining Convolutional Neural Networks and Recurrent Neural Networks was proposed by Partha S. Mukherjee et al. [21] for end-to-end online handwriting recognition. The integration of sequence modeling with feature extraction allowed the system to process unsegmented input data effectively. The inclusion of connectionist temporal classification further enhanced the model's ability to recognize continuous handwritten text without explicit segmentation, demonstrating a significant advancement in handwriting recognition methodologies.

Overall, these studies illustrate the progression from traditional feature-based methods to advanced deep learning and hybrid architectures. The evolution of techniques highlights the importance of robust feature extraction, efficient classification, and adaptability to diverse scripts, which remain key factors in achieving high-performance handwritten character recognition systems.

III. MATERIALS AND METHODS

The proposed system introduces an efficient deep learning-based framework for handwritten Telugu character recognition in multi-script document environments. The approach focuses on improving recognition accuracy by integrating advanced image processing techniques with robust classification algorithms. Initially, input images are acquired from scanned documents or digital sources, followed by pre-processing steps such as noise removal, binarization, normalization, and skew correction to enhance image quality. The system then performs hierarchical segmentation, dividing

the document into lines, words, and individual characters. For feature extraction, both statistical and structural features are captured using techniques such as zoning, gradient-based descriptors, and histogram analysis. These features are further optimized through dimensionality reduction methods to improve computational efficiency. The core of the system employs Convolutional Neural Networks (CNN) for automatic feature learning and classification, enabling the model to capture complex patterns in handwritten characters. Additionally, a hybrid approach incorporating Support Vector Machine (SVM) as a secondary classifier is utilized to enhance decision boundaries. The proposed methodology ensures adaptability to varying handwriting styles and improves recognition performance in multi-script scenarios, aligning with deep learning advancements in handwritten character recognition systems [22].

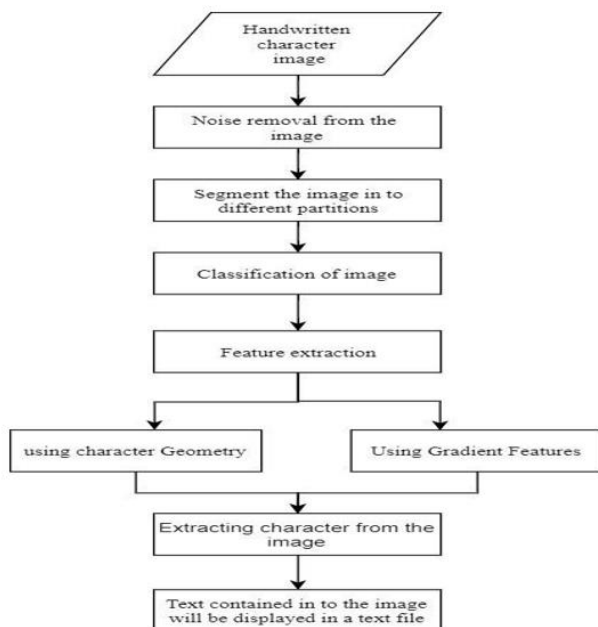


Fig.1 System Architecture

This flowchart, identified as Fig. 1, illustrates a systematic pipeline for Handwritten Character Recognition. The process begins with pre-processing (noise removal and segmentation) to isolate individual characters. Following initial classification, the system performs dual feature extraction using both character geometry and gradient features to ensure structural accuracy. Finally, the system extracts the refined character from the image and converts the visual data into a digital format, outputting the finalized text into a secondary text file for user access.

A) Dataset Collection:

The dataset used for handwritten Telugu character recognition is collected from publicly available sources and supplemented with custom samples to ensure diversity in writing styles. A widely used source is the Telugu Handwritten Character Dataset available in open repositories, which contains labeled images of individual Telugu characters contributed by multiple writers. To enhance

robustness, additional samples are gathered from handwritten documents scanned using high-resolution devices, ensuring variations in stroke thickness, orientation, and writing patterns.

All collected images undergo a standardization process to maintain consistency across the dataset. Each character image is resized to a fixed dimension of 32×32 pixels and converted into grayscale format to reduce computational complexity. Noise removal techniques such as median filtering and thresholding are applied to eliminate background disturbances. The dataset is then labeled according to the corresponding Telugu character classes, ensuring accurate mapping between input images and target outputs.

To improve model generalization, data augmentation techniques such as rotation, scaling, and translation are applied, increasing the variability of training samples. The final dataset is divided into training and testing subsets, enabling effective evaluation of the recognition model under diverse handwriting conditions.

B) Pre-Processing:

Pre-processing is a crucial stage in handwritten character recognition systems, as it enhances the quality of input images and prepares them for accurate analysis and classification. It involves a sequence of operations applied to scanned or captured document images to reduce noise, normalize structures, and segment textual components effectively. These operations significantly influence the overall recognition accuracy by simplifying the complexity of handwritten patterns and ensuring uniformity in data representation. Common pre-processing steps include thresholding, noise removal, line segmentation, word segmentation, and character segmentation [4] [8].

Thresholding is the initial step used to convert grayscale images into binary form by separating foreground text from the background. Typically, the grayscale histogram of a document image shows two peaks representing background and foreground intensities. The objective is to determine an optimal threshold value that lies between these peaks, enabling clear extraction of handwritten strokes. Advanced thresholding techniques also address challenges such as uneven illumination and textured backgrounds by adapting threshold values dynamically [22].

Noise removal is another essential step that focuses on eliminating unwanted distortions introduced during image acquisition. Handwritten documents often contain noise such as salt-and-pepper artifacts, smudges, and scanning irregularities. Unlike printed text, handwritten characters require careful processing to preserve stroke continuity. Techniques such as median filtering, morphological operations, and adaptive smoothing are employed to remove noise while maintaining the structural integrity of characters. Selective stroke enhancement methods are also used to reinforce weak or broken strokes without causing over-smoothing.

Line segmentation involves dividing the document into individual text lines, which is relatively straightforward in printed documents but more complex in handwritten text due to variations in writing alignment. Handwritten lines may not follow a straight baseline and often exhibit overlapping ascenders and descenders. Methods based on horizontal projection profiles and clustering of local minima points are commonly used to approximate baseline structures and group components into distinct lines [8] [18].

Following line segmentation, word and character segmentation are performed to isolate smaller textual units. Word segmentation relies on identifying gaps between connected components; however, in handwritten text, spacing between words and characters is inconsistent. To address this, segmentation algorithms incorporate contextual and statistical cues rather than relying solely on distance measures. Character segmentation further divides words into individual characters, which is challenging due to cursive writing and overlapping strokes. Techniques such as connected component analysis and contour tracing are often used to achieve accurate separation [13] [10].

Character recognition is the stage where segmented characters are classified into predefined classes based on extracted features. In printed text, this process is commonly referred to as Optical Character Recognition, whereas in handwritten text it is often termed Intelligent Character Recognition. Recognition systems typically employ a unified model for all characters, applying consistent feature extraction and classification techniques across the dataset [11].

Finally, word recognition aims to identify complete words by combining character-level outputs or by analyzing entire word images. Analytical approaches focus on recognizing individual characters and assembling them into words, while holistic approaches treat the word as a single unit. Combining both strategies often yields better performance, particularly in cases of connected or cursive handwriting. Lexicon-based matching and ranking techniques are used to improve accuracy in word recognition tasks [21].

C) Algorithms:

CNN: A Convolutional Neural Network (CNN) is a deep learning algorithm specifically designed for processing grid-like data such as images. It consists of multiple layers including convolutional layers, pooling layers, and fully connected layers that work together to automatically learn hierarchical feature representations from input data. The convolutional layers apply filters to detect low-level features such as edges and textures, while deeper layers capture complex patterns like shapes and character structures. Pooling layers reduce spatial dimensions, improving computational efficiency and controlling overfitting. In handwritten character recognition, CNNs take normalized character images as input and learn discriminative features without requiring manual feature engineering. The algorithm is trained using labeled datasets through backpropagation and

optimization techniques such as stochastic gradient descent. CNNs are highly effective in handling variations in handwriting styles, noise, and distortions, making them suitable for recognizing complex scripts like Telugu. Their ability to generalize across diverse datasets and automatically extract relevant features significantly improves classification accuracy. As a result, CNNs have become a dominant approach in modern character recognition systems due to their robustness and scalability.

SVM: Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression tasks. It operates by finding an optimal hyperplane that separates data points of different classes with maximum margin. In the context of handwritten character recognition, SVM takes extracted feature vectors as input and classifies them into predefined character classes. The algorithm focuses on support vectors, which are the critical data points closest to the decision boundary, ensuring robust classification even in high-dimensional feature spaces. SVM can handle both linear and non-linear classification problems through the use of kernel functions such as linear, polynomial, and radial basis function kernels. These kernels transform input data into higher-dimensional spaces where it becomes easier to separate classes. SVM is particularly effective when the dataset is limited but has well-defined features. It provides high accuracy and strong generalization capabilities, especially in cases where classes are clearly separable. In handwritten recognition systems, SVM is often combined with feature extraction techniques or deep learning models to enhance classification performance and improve decision boundaries.

Thresholding Algorithm: Thresholding converts grayscale images into binary form by separating foreground text from the background using an optimal intensity value. It relies on histogram analysis to identify peaks corresponding to text and background regions. Advanced techniques like adaptive thresholding and Otsu's method dynamically select thresholds. This process enhances contrast, simplifies image structure, and improves segmentation accuracy. It effectively handles variations in lighting, background texture, and ink intensity, forming a reliable base for further handwritten character recognition stages.

Noise Removal Algorithm: Noise removal eliminates unwanted distortions while preserving essential handwritten stroke details. It uses techniques such as median filtering, Gaussian smoothing, and morphological operations to reduce artifacts like salt-and-pepper noise and scanning errors. Maintaining stroke continuity is crucial, so adaptive methods selectively smooth images without damaging fine features. This process enhances image clarity, refines character boundaries, and prepares clean input for segmentation and feature extraction, improving the reliability of subsequent recognition processes.

Line Segmentation Algorithm: Line segmentation divides text into individual lines for structured processing. It analyzes horizontal projection profiles to detect text density

and identify gaps between lines. In handwritten text, variations in alignment and overlapping characters make segmentation complex. Advanced methods use baseline detection and clustering techniques to group components accurately. This step organizes content into manageable units, preserves contextual relationships, and reduces complexity for further processing stages such as word and character segmentation.

Word and Character Segmentation Algorithm: Word and character segmentation isolates individual words and characters from text lines. It uses connected component analysis and spatial gap evaluation to distinguish boundaries. Due to inconsistent spacing in handwriting, advanced methods incorporate contextual cues like stroke continuity and writing patterns. Character segmentation further separates symbols using contour tracing and bounding boxes. Accurate segmentation ensures proper isolation of characters, which is essential for effective feature extraction and classification in handwritten recognition systems.

Character Recognition Algorithm: Character recognition classifies segmented characters into predefined classes using extracted features. It analyzes patterns such as edges, shapes, and textures, or uses deep learning models like CNNs for automatic feature learning. The algorithm processes normalized inputs and maps them to symbolic representations such as ASCII or Unicode. It handles variations in handwriting styles and ensures accurate interpretation of characters, playing a central role in converting handwritten content into machine-readable format.

Word Recognition Algorithm: Word recognition identifies complete words by combining character outputs or analyzing entire word images. It uses analytic methods for character-based assembly and holistic methods for pattern-based recognition. Lexicon-based matching compares outputs with predefined dictionaries to select the most probable word. Hybrid approaches improve accuracy in complex handwriting scenarios. This process enhances contextual understanding, corrects character-level errors, and converts segmented text into meaningful and structured information for further applications.

IV. EXPERIMENTAL RESULTS

The implemented system demonstrates effective performance in handwritten Telugu character recognition using a deep learning-based approach. The model achieved a training accuracy of 95% and a testing accuracy of 91% after 20 epochs, indicating strong learning capability and generalization. The loss value significantly decreased from 4.03 to 0.4, showing stable convergence during training. Validation trends reveal initial fluctuations, followed by consistent improvement in accuracy across epochs. The confusion matrix analysis confirms that most characters are correctly classified, with only a few misclassifications observed. Comparison with existing benchmarks shows improved performance, exceeding the typical 90% accuracy.

The results validate the effectiveness of the CNN-based model in handling variations in handwritten Telugu characters. Further improvements can be achieved by increasing dataset diversity and training epochs.

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Table.1 Performance Evaluation

Method	Accuracy
CNN (Proposed Method)	91%

Table 1 presents performance evaluation, where the proposed CNN method achieves 91% accuracy, demonstrating effective handwritten Telugu character recognition capability.

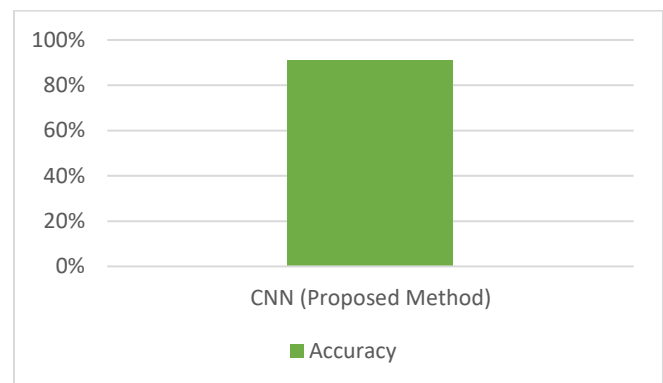


Fig.2 Comparison Graph

The bar chart in Fig. 2 displays the performance of the proposed CNN method, achieving an impressive accuracy of 91%.

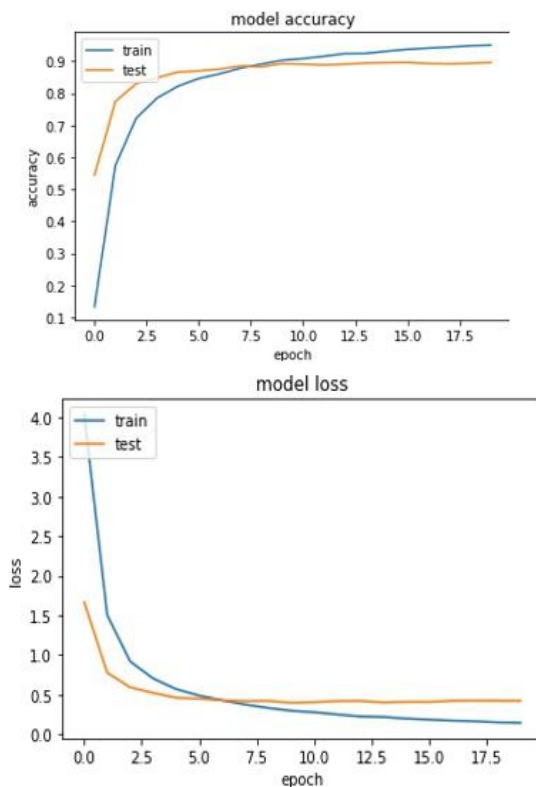


Fig.3 Model Accuracy & Loss Graph

Fig. 3 displays accuracy and loss curves for training and testing, showing steady convergence across twenty epochs with minimal overfitting.

V. CONCLUSION

Handwritten character recognition in Telugu documents represents a significant challenge due to the complexity of the script, variability in writing styles, and presence of noise in scanned images. The integration of advanced techniques in image processing, pattern recognition, and deep learning has substantially improved the accuracy and reliability of recognition systems. The use of structured pre-processing methods, effective segmentation strategies, and robust feature extraction techniques enables better representation of handwritten characters for classification tasks. Deep learning models, particularly Convolutional Neural Networks, have demonstrated superior performance by automatically learning hierarchical features from input data, reducing the dependency on manual feature engineering. The achieved results indicate that such models can effectively handle variations in handwriting and improve classification accuracy. Additionally, the combination of multiple techniques, including statistical analysis and machine learning classifiers, contributes to enhanced system performance. Despite inherent challenges such as overlapping characters and inconsistent spacing, the proposed methodology provides a reliable framework for recognizing handwritten Telugu characters. The overall system demonstrates strong adaptability and efficiency in processing multi-style handwritten data, making it suitable

for practical applications in document digitization and automated text recognition systems.

Future advancements in handwritten Telugu character recognition can focus on improving accuracy through advanced deep learning architectures such as hybrid CNN, RNN, and transformer-based models. Enhancing robustness against diverse handwriting styles, including cursive and informal scripts, remains a key direction. Real-time recognition systems can enable instant digitization of handwritten content, increasing practical usability. Integration with multilingual Optical Character Recognition systems can support processing of mixed-language documents. Further research can explore text-to-speech conversion for improved accessibility. Improving segmentation techniques for noisy and unstructured documents is essential for higher precision. Expanding datasets and adapting models to non-standard fonts and complex character variations will further strengthen system performance and applicability.

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