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Recognition Character Sanskrit Using Convolution Neural Network

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Abstract—This research presents a pioneering approach using Convolutional Neural Networks (CNNs) for character recognition in Sanskrit, a language renowned for its intricate script and diverse character set. Addressing challenges posed by Sanskrit's complex script and historical variations in writing styles, we developed a CNN-based model that undergoes meticulous preprocessing to enhance image quality and normalize writing styles. Trained on a substantial dataset of annotated Sanskrit characters, our model showcases remarkable accuracy in recognizing Sanskrit characters, even amidst noise and diverse writing styles. This achievement holds significant implications for digitizing ancient manuscripts, aiding linguistic research, and preserving cultural heritage. Automating Sanskrit character recognition accelerates the analysis of Sanskrit texts, offering insights into linguistic evolution, cultural practices, and historical narratives. Moreover, this research lays a foundation for advancing character recognition techniques in complex scripts and languages, fostering opportunities for preserving and exploring diverse cultural heritages worldwide.

Keywords-Sanskrit, character recognition, Convolutional Neural Networks, CNNs, language processing, cultural preservation.

I. Introduction

Character recognition in Sanskrit is a challenging yet essential task in the realm of natural language processing and cultural preservation. Sanskrit, an ancient language with a rich heritage, is characterized by its complex script and diverse set of characters. The intricate nature of Sanskrit script poses unique challenges for automated character recognition systems due to variations in writing styles across different historical periods and regions. As digitization efforts in the realm of linguistic research and cultural preservation gain momentum, the development of robust and accurate techniques for Sanskrit character recognition becomes increasingly crucial.

In recent years, advancements in machine learning, particularly in the field of deep learning, have revolutionized the way we approach character recognition tasks. Convolutional Neural Networks (CNNs) have emerged as a powerful tool in image

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recognition tasks, showcasing remarkable performance across various domains. Applying CNNs to the domain of Sanskrit character recognition presents an exciting opportunity to leverage cutting-edge technology for preserving and studying this ancient language. By training CNN models on annotated datasets of Sanskrit characters and employing sophisticated preprocessing techniques, it is possible to achieve high levels of accuracy and reliability in recognizing Sanskrit characters, even in challenging scenarios with noise and variations in writing styles.

This research aims to explore the effectiveness of CNN-based approaches in Sanskrit character recognition and their implications for linguistic research, cultural preservation, and digital humanities. Through rigorous experimentation and evaluation, we seek to demonstrate the capabilities of CNNs in accurately recognizing Sanskrit characters and contribute to the advancement of techniques for analyzing and digitizing ancient texts, thus fostering a deeper understanding of linguistic evolution and cultural heritage.

II. Literature Study

The field of character recognition has witnessed significant advancements in recent years, driven by the exploration of various algorithms and techniques across different languages and domains.

In [1] Agarwal, Ahmad, and Minakshi conduct a comprehensive survey on handwritten character recognition, addressing the challenges and advancements in this domain. The survey covers various machine learning and deep learning approaches, highlighting the importance of robust algorithms and preprocessing techniques in achieving accurate recognition results. The authors discuss the significance of feature extraction methods, such as wavelet transforms and moments, in capturing essential characteristics of handwritten characters. Additionally, the survey delves into the role of neural network architectures, such as Convolutional Neural Networks (CNNs) and Capsule Networks, in improving recognition accuracy. The study underscores the importance of ongoing research and development in character recognition technologies to address evolving challenges and enhance recognition performance across different languages and writing styles.

In [2] Ni et al. propose an optical character recognition (OCR) algorithm designed specifically for documents with cascading structures. The study addresses the challenges posed by complex document layouts, such as tables, diagrams, and nested structures, which can hinder traditional OCR algorithms. The authors introduce innovative techniques for segmenting and recognizing text within cascading structures, leveraging image processing and machine learning algorithms to improve recognition accuracy. The algorithm demonstrates effectiveness in handling diverse document formats, showcasing advancements in OCR technologies for document analysis and digitization.

In [3]Pial et al. conduct a comparative analysis focusing on Bengali handwritten characters and digits using Capsule Network architecture. The study evaluates the performance of Capsule Networks in recognizing complex Bengali characters, highlighting the network's ability to preserve spatial hierarchies and capture intrinsic features of handwritten characters. The comparative analysis showcases the advantages of Capsule Networks over traditional machine learning algorithms in handling intricate character structures and achieving high recognition accuracy in Bengali script.

In [4]Jayachandran, Kirubasankar, and Varsini explore the enhancement of handwritten character recognition using the XGBoost algorithm, a gradient boosting ensemble technique. The study focuses on improving recognition accuracy and reducing computational complexity through ensemble learning approaches. The XGBoost algorithm demonstrates effectiveness in handling diverse datasets and optimizing feature selection for accurate character recognition. The study highlights the benefits of ensemble learning techniques in enhancing the performance of character recognition systems.

In [5]Sun, Li, and Wu propose an algorithm for handwritten ancient Chinese character recognition based on an Improved Inception-ResNet architecture combined with an attention mechanism. The study addresses the challenges of recognizing complex ancient Chinese characters with varying styles and structures. The proposed algorithm leverages deep learning architectures and attention mechanisms to capture intricate features and improve recognition accuracy. The study contributes to preserving and analyzing historical scripts through advanced recognition technologies.

In [6]Wu, Zhang, and Chen present a method for positioning and segmenting dot matrix characters to improve recognition accuracy. The study focuses on preprocessing techniques to enhance the quality of input images and optimize character segmentation for accurate recognition. The proposed method showcases improvements in character recognition systems by addressing challenges related to noisy input data and complex character structures.

In [7]Raundale and Maredia delve into the analytical study of handwritten character recognition using deep learning approaches. The study explores the advancements in deep learning algorithms, such as CNNs and recurrent neural networks (RNNs), in achieving state-of-the-art recognition accuracy. The authors discuss the importance of data augmentation, model optimization, and hyperparameter tuning in improving recognition performance. The study underscores the role of deep learning techniques in pushing the boundaries of character recognition technologies.

In [8]Wan et al. focus on scene Chinese character recognition based on similar Chinese characters, emphasizing the

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importance of contextual information in character recognition systems. The study explores the use of similarity-based approaches and pattern recognition techniques to enhance recognition accuracy in complex scenes. The authors discuss the challenges of scene-based character recognition and propose innovative methods to address these challenges effectively.

In [9]Bansal, Gupta, and Tyagi review Optical Character Recognition (OCR) systems specifically tailored for vehicular applications. The study discusses the unique challenges of OCR in vehicular environments, such as varying lighting conditions, motion blur, and complex backgrounds. The authors explore adaptive OCR algorithms and real-time processing techniques to improve recognition performance in vehicular applications, highlighting the importance of robust OCR systems for automotive technologies.

In [10]Zheng et al. propose a novel method based on character segmentation for detecting and recognizing slant Chinese screen-rendered text. The study addresses challenges related to slanted text and varying orientations in character recognition systems. The proposed method showcases improvements in detecting and recognizing slant text, contributing to more accurate and robust character recognition technologies.

In [11]Mainkar et al. explore handwritten character recognition for obtaining editable text, emphasizing practical applications in data processing tasks. The study discusses techniques for converting handwritten text into editable digital formats, facilitating data entry and analysis. The authors highlight the importance of accurate character recognition in enhancing data processing efficiency and productivity.

In [12]Mariyathas, Shanmuganathan, and Kuhaneswaran focus on Sinhala handwritten character recognition using Convolutional Neural Networks (CNNs). The study addresses the challenges of recognizing characters in the Sinhala script, leveraging deep learning techniques to achieve high recognition accuracy. The study contributes to language-specific character recognition and showcases the adaptability of CNNs in handling diverse writing systems.

In [13] Ueki et al. tackle the recognition of Japanese connected cursive characters using multiple softmax outputs. The study explores advanced recognition techniques for complex Japanese characters, focusing on enhancing recognition accuracy and handling connected cursive writing styles. The proposed method demonstrates effectiveness in recognizing intricate Japanese characters, contributing to language-specific character recognition technologies.

In [14] Niharika et al. explore character recognition using Tesseract for enabling multilingualism. The study discusses the capabilities of Tesseract OCR software in recognizing characters from multiple languages, facilitating multilingual text processing and analysis. The authors highlight the importance of multilingual character recognition in diverse applications and industries.

In [15] Anuradha et al. focus on deep learning-based Sinhala Optical Character Recognition (OCR), showcasing advancements in deep learning approaches for language-specific character recognition tasks. The study addresses the challenges of recognizing characters in the Sinhala language, leveraging deep neural networks to achieve high recognition accuracy. The proposed deep learning-based OCR system contributes to enhancing language-specific character recognition technologies.

Overall, these studies collectively contribute to the diverse landscape of character recognition, showcasing advancements in algorithmic approaches, neural network architectures, and language-specific techniques for accurate and efficient character recognition across various domains and languages.

III. Proposed Methodology

The proposed classifier model is meticulously crafted within the Anaconda Navigator environment, specifically utilizing the Spider 3.3.6 version of the software. Within this framework, the Variable Explorer feature facilitates the examination of value metrics for various variable parameters, while the Python console window grants visibility into all layers of the Convolutional Neural Network (CNN) architecture that has been meticulously designed.

This classifier model incorporates a CNN architecture characterized by two deep layers. Out of a total of 12,911 images, 80% of the images are allocated for training the neural network, with the remaining 20% reserved for testing purposes. Prior to inputting the images into the CNN, a series of preprocessing steps are undertaken. This includes resizing the images from 28x28x3 to 32x32x1 and converting them from RGB to greyscale. Additionally, several morphological operations are applied, such as filtering using a median filter and segmenting letters from the background through thresholding operations on the images. The dataset employed in this study comprises 58 distinct classes, each representing a single letter or numeric value, with each class containing over 200 images that serve as input data for the neural network.

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 30, 30, 28)	280
conv2d_6 (Conv2D)	(None, 28, 28, 64)	16192
max_pooling2d_3 (MaxPooling2	(None, 14, 14, 64)	0
conv2d_7 (Conv2D)	(None, 12, 12, 64)	36928
conv2d_8 (Conv2D)	(None, 10, 10, 64)	36928
max_pooling2d_4 (MaxPooling2	(None, 5, 5, 64)	0
dropout_2 (Dropout)	(None, 5, 5, 64)	0
flatten_4 (Flatten)	(None, 1600)	0
dense_4 (Dense)	(None, 128)	204928
dense_5 (Dense)	(None, 64)	8256
dense_6 (Dense)	(None, 58)	3770

Figure 1. Proposed CNN Architecture

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In the designed CNN architecture, the activation function employed within the layers is ReLU (Rectified Linear Unit), chosen for its ability to introduce non-linearity into the model. A kernel size of 3x3 is applied to the 32x32 images, initiating the convolution operation between the image matrix and the kernel matrix. This convolutional process, utilizing a ReLU activation function, extracts essential features from the input images. Following convolution, a max-pooling operation is executed using a 2x2 matrix, effectively reducing the dimensionality of the image matrix by half. This reduction, from 28x28 to 14x14, retains crucial information while optimizing computational efficiency.

The subsequent layer within the CNN architecture mirrors this process, applying convolution, activation functions, and max pooling to further refine and extract features from the data. To address the risk of overfitting, a Dropout layer is strategically inserted after the second layer, deactivating approximately 20% of neurons during training to promote generalization and prevent the model from memorizing the training data.

Following these operations, the feature matrices obtained are flattened, converting the multi-dimensional feature maps into a single column. This flattened representation is then passed through two dense layers in the fully connected network. These dense layers, comprising 128 and 64 neurons respectively, establish connections between each output layer and the input layer, facilitating comprehensive information flow and enabling the model to learn complex patterns and relationships within the data.

IV. RESULTS

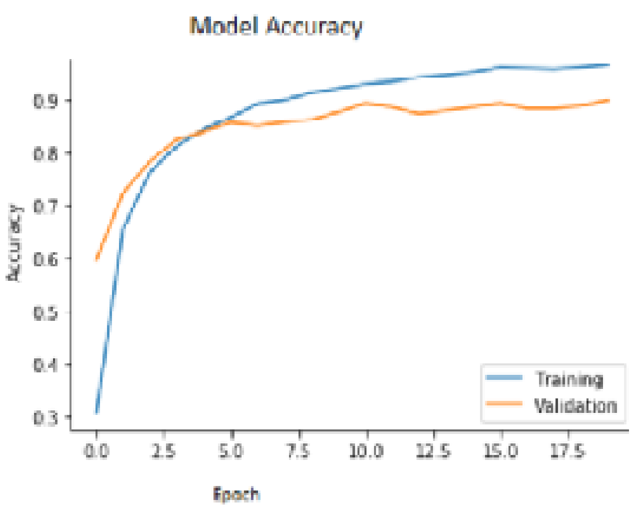

Figure 2. Accuracy of model

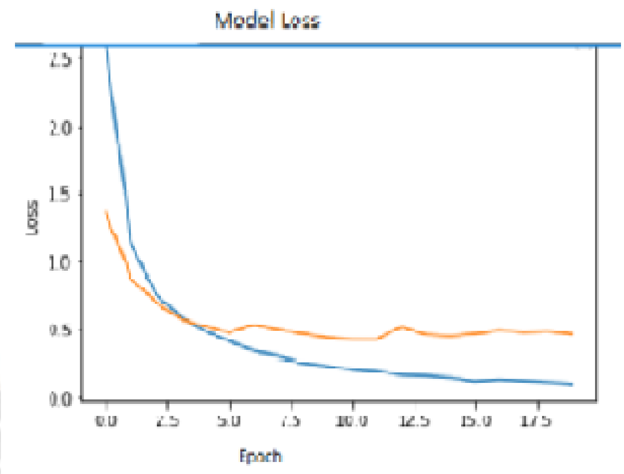

Figure 3. Loss of model

Table I: Time for train/test Models

Classifier	Time Training	Accuracy
SVM		
Wavelet features	6 min 23 sec	72.164%
Wavelet+Moment features	6 min 46 sec	70.368%
CNN		
Epoch:20	23min 04sec	89.74%
Epoch:100	2 hrs 11min	89.956%

The table presented above illustrates the training time and accuracy of two classifiers: one based on a machine learning algorithm, specifically the SVM classifier, and the other utilizing deep learning with a Convolutional Neural Network (CNN) architecture. The SVM classifier is trained using wavelet features, which are a combination of diagonal and vertical feature matrices, as well as a combination of wavelet and moment features. On the other hand, the CNN-based classifier is designed to process more complex features but requires longer training times.

Both classifiers are trained without GPU acceleration, operating on a CPU with a 64-bit i3 processor. The results indicate that the CNN-based classifier achieves higher accuracy compared to the SVM classifier, albeit with a trade-off in training time. This comparison highlights the strengths of deep learning approaches, particularly in handling intricate features and delivering superior classification performance, albeit with increased computational demands during training.

COCNLUSION

Based on the obtained results from different classifiers, it is evident that the Convolutional Neural Network (CNN) based classifier outperforms the SVM classifier in terms of accuracy. This underscores the superiority of Deep Learning over Machine Learning methodologies. While it is acknowledged that training a CNN entails a longer duration compared to SVM, the CNN still yields an impressive accuracy of approximately 89.95%. Thus, in scenarios where speed is crucial, employing a GPU becomes imperative to mitigate training time; however, in cases where cost optimization is prioritized, the use of GPU can be avoided. This observation emphasizes the nuanced trade-offs between computational efficiency and performance excellence when choosing between Machine Learning and Deep Learning approaches.

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