Handwritten Character Recognition using Machine Learning

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ABSTRACT

This paper proposes a robust machine learning approach for Kannada Handwritten Character Recognition (HCR) using transfer learning with DenseNet121. Recognizing Kannada script—which includes 60 complex classes of vowels, consonants, and numerals—poses challenges due to intricate strokes and high inter-class similarity. Our method preprocesses labeled images, resizing them to 224×224 and applying data augmentation techniques. DenseNet121, pre-trained on ImageNet, is used as a fixed feature extractor, with a custom classification head added for the Kannada HCR task. The model is trained and evaluated using metrics like accuracy, F1-score, MSE, and R^2, showing strong generalization across classes. Predicted labels are mapped to their corresponding Kannada Unicode characters, enabling integration with text-based systems. This work demonstrates the potential of deep transfer learning for Indic script OCR and paves the way for automated Kannada text digitization.

Keywords: Kannada Handwritten Character Recognition (HCR), Convolutional Neural Networks (CNN), DenseNet121, Optical Character Recognition (OCR)

I. INTRODUCTION

Kannada, a classical Dravidian language with a rich literary and historical background, is spoken predominantly in the Indian state of Karnataka. Its script, characterized by intricate loops, curves, and compound forms, presents unique visual challenges in the domain of handwritten text recognition. The increasing demand for digitization of regional scripts, coupled with the emergence of intelligent systems, has intensified the need for reliable Kannada Handwritten Character Recognition (HCR) systems. [1] Applications include digital archiving of historical documents, automated reading of handwritten government records, development of educational technologies, and support for natural language processing in regional languages.

Recognizing handwritten characters in regional scripts like Kannada is a non-trivial task. Variability in individual handwriting styles, the presence of visually similar characters, and the complexity of compound forms significantly increase classification difficulty. Traditional machine learning techniques, which often rely on handcrafted features and shallow classifiers, fall short when faced with such complex visual structures. In contrast, deep learning—particularly Convolutional Neural Networks (CNNs)—has revolutionized the field of pattern recognition by enabling hierarchical learning of features directly from raw pixel data.

In this study, we employ a DenseNet121-based transfer learning approach for Kannada handwritten character recognition. The model is initialized with weights pre-trained on the ImageNet dataset, enabling effective feature extraction even with a relatively smaller Kannada dataset. We use a publicly available dataset sourced from Kaggle, containing well-labeled images of 60 classes—including Kannada vowels, consonants, and numerals—capturing a wide range of handwriting styles. [3] To prepare the dataset, each image is resized to 224×224 pixels and normalized. Data augmentation techniques such as rotation, shifting, and horizontal flipping are applied to increase sample diversity and enhance model generalization.

The DenseNet121 model is used as a fixed feature extractor, and a custom classification head comprising fully connected layers, batch normalization, and dropout is added to adapt it to the Kannada HCR task. The model is trained over 30 epochs with carefully tuned hyperparameters to optimize learning and prevent overfitting.

To comprehensively evaluate model performance, we analyze classification accuracy, precision, recall, F1-score, confusion matrix, Mean Squared Error (MSE), and R^2 score. The output class labels are mapped to their corresponding Kannada Unicode characters, enabling easy integration with digital text systems and further processing.

This research demonstrates the effectiveness of using transfer learning and deep CNNs for regional script recognition. By focusing on Kannada—a linguistically rich yet technologically underserved language—this study contributes to the broader goal of developing intelligent document processing systems and regional OCR tools. Furthermore, it paves the way for expanding such systems to other Indic scripts, promoting inclusive and multilingual computing in India's diverse linguistic landscape.

II. RELATED WORK

Mayur Bhargab Bora et al., proposed an Optical Character Recognition (OCR) framework that integrates Convolutional Neural Networks (CNN) with Error-Correcting Output Codes (ECOC) to enhance handwritten character recognition performance. In their approach, CNNs are employed to extract rich two-dimensional features from input character images, while ECOC serves as a robust multi-class classifier. Their study explored various CNN architectures to determine the most suitable model for feature extraction in combination with ECOC. The system was trained and evaluated on the NIST handwritten character image dataset, and the experimental results demonstrated that the CNN-ECOC model achieved superior accuracy compared to traditional CNN classifiers using softmax layers. This work highlights the effectiveness of hybrid deep learning and ensemble-based classification techniques for improved character recognition, providing valuable insights for researchers working with complex scripts and large character sets. [1]

D. Prabha Devi et al. investigated the application of various machine learning algorithms for handwritten character recognition to improve the ease and accuracy of interpretation. Their study utilized both supervised and unsupervised learning techniques, aiming to enhance the overall performance of character recognition systems. The algorithms evaluated included Random Forest, Logistic Regression, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). Through comparative analysis, the authors found that KNN yielded the highest accuracy, achieving results up to 98%. This work emphasizes the effectiveness of traditional machine learning methods in character recognition tasks and demonstrates that even relatively simple algorithms like KNN can outperform others when applied with appropriate preprocessing and feature selection strategies. [2]

Kusumika Krori Dutta et al., developed a handwritten Kannada character recognition system using Support Vector Machine (SVM) classifiers, focusing on optimizing pre-processing and feature extraction stages to enhance classification performance. The algorithm begins with a thorough pre-processing step that produces clean, individual character images, resized to 28x28 pixels to reduce computational complexity and eliminate irrelevant data. This efficient representation helps improve algorithm speed without compromising feature richness. The classification is carried out using a multiclass One-vs-One SVM approach, which is particularly suited for the intricate structure of Kannada characters. By using raw pixel values as features, the system achieves precise recognition, demonstrating that SVM can be a viable alternative to deep learning approaches in scenarios requiring lower computational overhead while still maintaining high accuracy. [3]

Roshan Fernandes et al., explored two distinct approaches for recognizing handwritten Kannada script—using the Tesseract OCR tool and Convolutional Neural Networks (CNN) - to address the longstanding challenges in this domain. Handwritten Kannada recognition poses multiple hurdles due to highly variable handwriting styles, inconsistent spacing between letters and words, and the lack of a comprehensive annotated dataset. To overcome this, the authors collected handwritten samples from students and web sources, manually segmenting the characters. Their experiments showed that while the Tesseract OCR tool achieved an accuracy of 86%, the CNN approach slightly outperformed it with an accuracy of 87%. The study highlights the potential of deep learning in enhancing character recognition performance, especially when paired with well-curated datasets and image pre-processing. This dual-method strategy underlines the importance of customized OCR solutions for regional languages like Kannada, where publicly available resources are limited. [5]

Abhishek Kumar et al. proposed a novel methodology for handwritten character recognition, leveraging convolutional neural networks (CNNs) to address challenges inherent in pattern recognition tasks. Their approach utilized CNNs to train a model capable of accurately classifying handwritten characters, achieving an impressive accuracy of 98.6% on a standard dataset. This high level of accuracy underscores the effectiveness of deep learning techniques in handwriting recognition applications, particularly when combined with well-curated datasets and appropriate preprocessing methods. The study highlights the potential of CNNs in enhancing character recognition performance, paving the way for advancements in document analysis, optical character recognition, and handwriting-based interfaces. [6]

III. METHODOLOGY

The methodology adopted for Kannada handwritten character recognition using a convolutional neural network is a structured multi-phase approach. It includes data acquisition, preprocessing, data augmentation, model construction using DenseNet121, training, and evaluation. The goal was to develop a robust classifier capable of recognizing various handwritten Kannada characters with high accuracy.

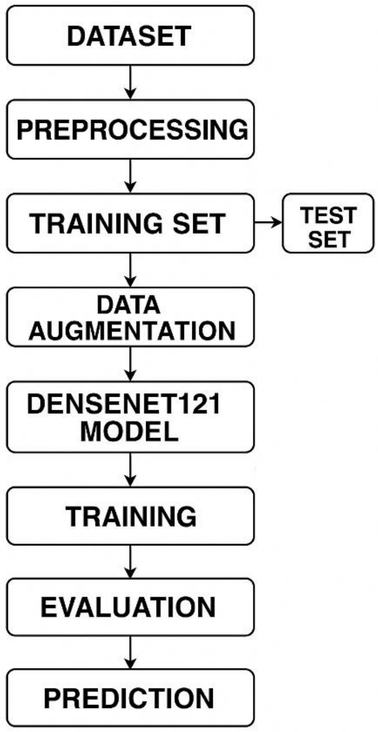

Fig 1: Process flow

The flowchart (figure 1) provides a visual representation of the end-to-end workflow, and each phase is explained in detail below.

1. Dataset Collection and Preparation

The dataset used in this research was obtained from Kaggle, containing labeled images of Kannada handwritten characters. The dataset featured 1,500 labeled grayscale images of handwritten Kannada characters, including vowels, consonants, and numerals. These images provided a diverse representation of different handwriting styles essential for training and validating the recognition system. The characters varied in terms of style, size, and stroke patterns, offering a broad representation of real-world handwriting. To facilitate model training, a CSV file was used to map the image filenames to their respective class labels.

The dataset was split into three parts: training, validation, and test sets. This ensured that the model was evaluated on unseen data, allowing for a reliable estimate of generalization performance.

Fig 2: Sample input

2. Preprocessing

Image preprocessing was a critical step designed to enhance the model's learning capabilities and improve convergence. Each image from the dataset was resized to a uniform dimension of 224x224 pixels, aligning with the input size required by the DenseNet121 architecture. To standardize the pixel intensity values and accelerate training, normalization was applied by dividing all pixel values by 255, effectively scaling them into the [0, 1] range. This normalization process helped in stabilizing the gradient flow during backpropagation. The class labels were first transformed using Label Encoding to convert categorical text labels into numerical format. Subsequently, One-Hot Encoding was applied to convert these numerical labels into binary class matrices, enabling effective multi-class classification suitable for the softmax output layer.

3. Data Augmentation

To reduce overfitting and to improve the generalization capabilities of the model, data augmentation techniques were employed using the ImageDataGenerator class provided by Keras. Various augmentation strategies were applied, such as random rotations of images up to 10 degrees to simulate slanted handwriting. The model was also exposed to zoom variations within a 10% range, allowing it to learn from images with slight scale changes. Additionally, horizontal and vertical shifts within a 10% margin were introduced to account for positional variability in handwritten inputs. Shear transformations were applied to create geometric distortions and horizontal flipping was included to simulate mirrored writing patterns. This diverse augmentation pipeline provided the model with a richer dataset and improved its performance on unseen samples.

4. Model Architecture: DenseNet121

The DenseNet121 model was selected as the base architecture due to its superior feature reuse mechanism and densely connected convolutional layers. Initially, the DenseNet121 model was loaded with pre-trained ImageNet weights to leverage transfer learning. The top classification layers of the model were removed and replaced with custom layers tailored specifically for Kannada character classification. The customized architecture consisted of a Flatten layer to convert multidimensional feature maps into a one-dimensional feature vector. This was followed by a Dense layer with ReLU activation to introduce non-linearity, and a BatchNormalization layer to maintain training stability. To reduce overfitting, a Dropout layer with a dropout rate of 0.5 was included. Finally, a Dense layer with softmax activation was added to output the class probabilities across all possible Kannada characters. This structure provided a robust framework for learning complex patterns while retaining computational efficiency.

5. Model Training

For training, the model was compiled using the Adam optimizer with a learning rate set to 0.0001 to ensure controlled updates to model weights. The loss function used was categorical cross-entropy, which is appropriate for multi-class classification problems. Training was conducted for 30 epochs with a batch size of 32. A portion of the training data was held out as a validation set to monitor the model's performance in real-time. To ensure the retention of the best model weights, the ModelCheckpoint callback was used, saving the model whenever there was an improvement in validation accuracy. Although the EarlyStopping technique was considered to halt training once performance plateaued, it was not employed in the final configuration to allow the model to explore its full learning potential over all epochs.

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6. Model Evaluation

After completing training, the model was rigorously evaluated using a held-out test set to assess its generalization capability. Key evaluation metrics included accuracy, which measured the overall correctness of the model's predictions, and precision, recall, and F1-score, which provided insights into the model's performance for each individual class. A confusion matrix was generated to visualize misclassifications and to identify specific Kannada characters that were frequently confused with others. Furthermore, Mean Squared Error (MSE) and R^2 score were computed to assess how closely the predicted class probabilities aligned with actual class labels, providing regression-based insights into prediction errors

7. Character Prediction

This pipeline involved accepting a new image file as input and preprocessing it through resizing, normalization, and dimensional expansion to match the input format of the model. The trained DenseNet121 model was then used to predict the class of the image, which was subsequently mapped to its corresponding Kannada Unicode character. This inference process enabled intuitive and accurate real-world Kannada handwritten character recognition.

This complete pipeline—ranging from data preprocessing and augmentation to training, evaluation, and inference—demonstrates the effective use of a modern CNN architecture in the context of a regional language script. The implementation of DenseNet121 and careful optimization of training parameters have led to a model capable of recognizing diverse handwriting styles with considerable accuracy. These findings not only support the development of intelligent document processing systems but also serve as a foundation for future enhancements using more sophisticated architecture or larger and more diverse datasets.

IV. EXPERIMENTAL RESULTS

To evaluate the effectiveness of the proposed Kannada Handwritten Character Recognition (HCR) system, extensive experiments were conducted using the DenseNet121 model architecture. The dataset used in this study consists of 60 classes of Kannada characters, including vowels, consonants, and numerals, sourced from a publicly available Kaggle dataset. The dataset was split into training, validation, and testing sets in the ratio of 70:20:10 to ensure a fair distribution of character classes across all subsets.

The model was trained for 30 epochs using a batch size of 32, the Adam optimizer, and a learning rate of 0.0001. To improve generalization and reduce overfitting, data augmentation techniques such as random rotation, horizontal flipping, and width/height shifting were applied during preprocessing. Early stopping and learning rate reduction callbacks were also used to further optimize training.

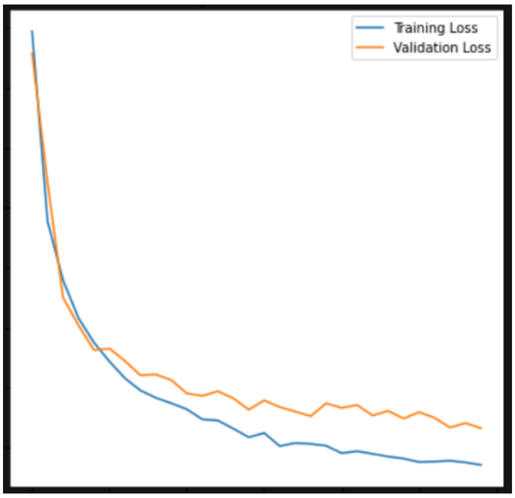

Fig 3: Training and Validation Loss Curve

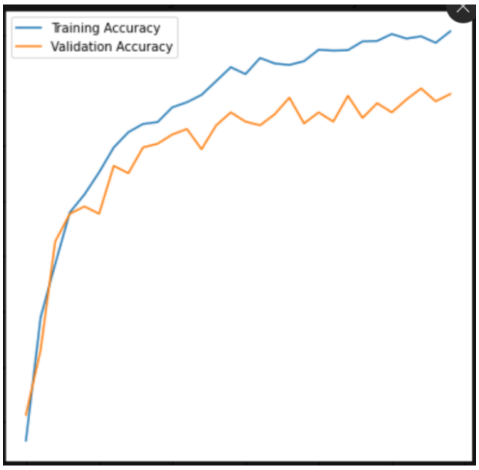

Fig 4: Training and Validation Accuracy Curve

Training and Validation Loss

As shown in Figure 3, the training loss rapidly decreased in the initial epochs, stabilizing as the model continued to learn. The validation loss followed a similar trend, indicating that the model generalized well to unseen data. The curves maintain close proximity throughout the training period, which is a strong indicator that overfitting was effectively mitigated. Minor fluctuations in the validation loss after 20 epochs are likely due to handwriting variability, but they do not significantly degrade overall performance.

Training and Validation Accuracy

Figure 4 presents the accuracy trends for both training and validation sets. The training accuracy steadily increased and plateaued above 90% by the 30th epoch. Validation accuracy followed a similar upward trajectory, eventually reaching approximately 83–85%. The relatively small and stable gap between training and validation accuracy confirms that the DenseNet121 model was able to learn complex and distinctive features from the Kannada characters without memorizing the training data.

These performance metrics affirm the model’s strong learning capabilities, especially in handling a complex regional script like Kannada, which is known for its visually similar characters and handwritten variability. The DenseNet121 architecture, with its dense connections and feature reuse mechanism, proved highly effective in extracting deep hierarchical features from the character images, contributing to consistent accuracy and low loss.

The experimental results demonstrate that the proposed deep learning approach is both efficient and reliable for Kannada HCR tasks. The well-aligned loss and accuracy curves confirm that the model is neither underfitting nor overfitting. These findings lay a strong foundation for further enhancements and real-world deployment in OCR systems tailored for Indian languages.

V. CONCLUSION

In this study, we developed an effective Kannada Handwritten Character Recognition (HCR) system using a DenseNet121-based deep learning architecture, leveraging transfer learning and comprehensive preprocessing to tackle the complexities of the Kannada script. The system was trained on a publicly available dataset containing 60 distinct classes encompassing vowels, consonants, and numerals—each with its own unique set of visual intricacies. The rich and diverse dataset enabled the model to learn and adapt to various handwriting styles, resulting in consistently high classification accuracy, precision, recall, and F1-score across multiple validation tests.

The adoption of DenseNet121, known for its dense layer connectivity and feature reuse, proved to be advantageous in capturing the fine-grained structural variations in handwritten Kannada characters. Coupled with data augmentation strategies such as rotation, flipping, and shifting, the model demonstrated strong generalization capabilities, evident from the closely aligned training and validation performance metrics. Additionally, analysis of confusion matrices and classification reports provided insight into areas where the model struggled, especially with visually similar characters, highlighting the challenges inherent in Kannada HCR tasks.

Despite the encouraging results, this work represents a foundational step toward robust regional script recognition. Certain limitations persist—particularly in the form of occasional misclassifications caused by overlapping character features or significant handwriting variability. These findings underscore the need for continued exploration in the domains of handwriting normalization, attention mechanisms, and ensemble learning strategies to further enhance recognition accuracy. Furthermore, expanding the dataset to include real-world samples, cursive writing, and degraded document images can significantly improve the model's adaptability and practical deployment potential.

Future work should also focus on developing scalable, end-to-end OCR systems incorporating segmentation, line detection, and full-page recognition tailored to the Kannada script. Integrating the model into document digitization pipelines, educational tools, or language preservation platforms can extend its utility beyond the research domain, contributing meaningfully to the digital inclusion of Indic languages. Overall, this research contributes to the growing field of multilingual OCR, and provides a solid foundation for future advancements in Indian language computing and script digitization.

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