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A Deep Learning Model for Kannada Handwritten Optical Character Recognition using MobileNetV2 and CNN

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***Abstract*—Handwritten character recognition remains a complex and vital problem in the domains of computer vision and pattern recognition, particularly for regional languages such as Kannada, which feature intricate character structures and varying handwriting styles. This study presents a deep learning–based approach for the recognition of handwritten Kannada characters using a transfer learning architecture built upon MobileNetV2. The model uses custom dense layers for character classification after extracting high-level visual features using pretrained ImageNet weights. To enhance generalization, a large dataset of handwritten Kannada characters was used, preprocessed using data augmentation and normalization techniques. To address data imbalance, class weighting and adaptive learning techniques were used to train and optimize the model. The suggested MobileNetV2-based model outperforms traditional Convolutional Neural Networks (CNN) techniques in terms of recognition performance and training efficiency, as evidenced by evaluation metrics such as accuracy, precision, recall, and F1-score.**

***Index Terms*—Deep Learning, Convolutional Neural Network, MobileNetV2, Transfer Learning, Optical Character Recognition, Kannada Handwritten Character Recognition, Feature Extraction, and Image Classification.**

I. INTRODUCTION

Handwritten character recognition (HCR) is a key component of OCR systems, especially for diverse languages and scripts [1]. Kannada presents unique challenges due to its curved shapes, complex ligatures, and wide variation in handwriting styles [2], creating a strong need for accurate recognition methods as digital preservation and automation continue to grow [3]. As one of the oldest Dravidian languages with 49 basic characters and several compound forms, its rounded script often reduces the effectiveness of traditional approaches such as rule-based methods, template matching, KNN, and SVM. With the advancements in deep learning, CNN-based models have shown superior performance by learning features directly from images [4], [5].

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In this work, a MobileNetV2-based deep learning model is proposed for Kannada handwritten character recognition, offering high accuracy with low computational cost through depth wise separable convolutions and transfer learning [6]. The model is trained on the Kannada Hand written dataset using preprocessing steps like noise removal, resizing, and normalization, and a Flask-based web interface is developed to facilitate user interaction. This approach enhances the reliability of OCR systems for Kannada while supporting digital accessibility and script preservation [7]. The system workflow includes a Training Pipeline where datasets are loaded, preprocessed, augmented, and used to train a MobileNetV2-based CNN with class weighting and two-phase training. Training progress is monitored through accuracy and loss curves, and the best models are saved in H5 format. In the Testing Pipeline, the trained model is reloaded, with test images resized and normalized for prediction. Final performance is assessed using Accuracy, Precision, and F1-Score to summarize the system's recognition capability.

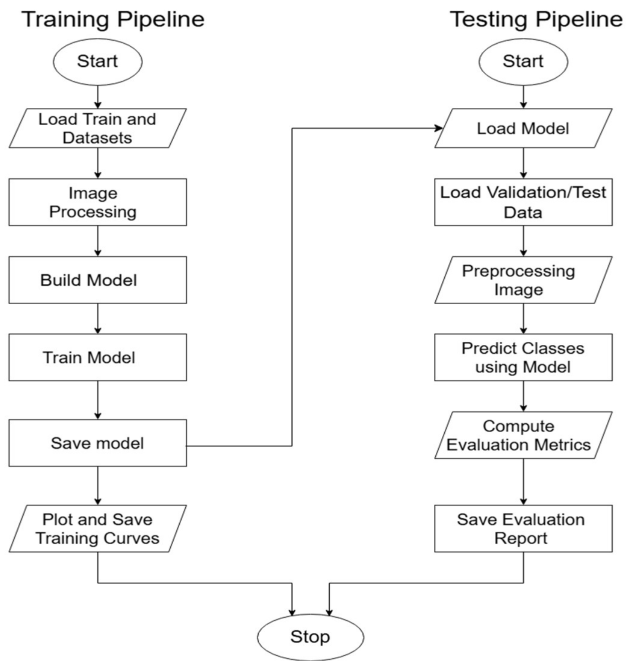


Fig. 1. Training and Testing Pipeline of the Proposed Kannada HOCR System

II. LITERATURE REVIEW

Research on Indic script recognition has grown steadily with the use of deep-learning models. Early approaches focused on character-level recognition, such as the work of Joe et al. [1] on segmented handwritten Kannada characters and Saraswathi et al. [2], who applied machine-learning techniques for Kannada sign-language recognition. Scene-text detection in real environments was explored by Shikha et al. [3], while Hu [4] evaluated deep networks specifically for Kannada handwritten digits. Script identification across multilingual documents has also been studied. Gupta et al. [5] proposed a deep-network framework for script classification, and Siddiqua et al. [6] introduced a lightweight depth wise-separable CNN design for Kannada text classification. Lightweight convolutional models such as MobileNetV2 have become popular due to their efficiency. They have been applied in multiple domains, including music genre classification [7], Gujarati numeral recognition using transfer learning [8], and ancient Brahmi script recognition using modern pre trained models [9]. MobileNet-based methods have also been used for applications such as dysgraphia detection in children's handwriting [10] and improved handwritten-text recognition using transfer-learning-enhanced VGG models [11].Beyond text, MobileNetV2 variants have shown strong performance in other visual tasks such as pest recognition in agriculture [12], watermark-text classification using extended CNN architectures [13], and for low-light signboard text recognition [14]. Additionally, a recently published multilingual OCR system by Dadapeer and Suresh [15] demonstrates the effectiveness of CNN–BiLSTM–CTC architectures for recognizing handwritten English and Kannada word images, further contributing to Indic-script research.

III. METHODOLOGY

The proposed Kannada Handwritten Optical Character Recognition system employs a deep learning-based approach using Convolutional Neural Networks (CNN) and MobileNetV2 through transfer learning. The process involves stages such as dataset collection, pre-processing, model training, evaluation, and deployment.

A. Dataset Collection

The dataset employed in this work is the Kannada Handwritten dataset (KannadaHnd.tgz, 125.8 MB), a subset of the Chars74K collection developed by E. de Campos et al. The dataset includes 657 distinct character classes, covering vowels, consonants, and compound symbols, making it suitable for isolated character recognition tasks.[16]

B. Data Loading

The Kannada handwritten character dataset was arranged in class-wise folders for training and validation and loaded using Tensor Flow's ImageDataGenerator.

C. Data Preprocessing

All images were resized to 224×224 and normalized using MobileNetV2's preprocessing. To artificially expand the training dataset and simulate real-world handwriting variations, several transformations were applied using Tensor Flow's ImageDataGenerator. These included random rotations (±12°), width and height shifts (up to 10%), zooming (up to 8%), shearing, and brightness adjustments (0.8–1.2). The validation pipeline applied only normalization, producing RGB images and one-hot labels for efficient batch processing.

D. Feature Extraction

Feature extraction is essential for identifying strokes, curves, and structural patterns in handwritten Kannada characters, and MobileNetV2 serves as an efficient backbone for capturing these details through depth wise and pointwise convolutions. The model learns hierarchical features automatically, from basic edges to complex character shapes, aided by ReLU activation for non-linearity. Global Average Pooling, Batch Normalization, and Dropout further improve generalization, reduce overfitting, and stabilize training.

IV. MODEL ARCHITECTURE

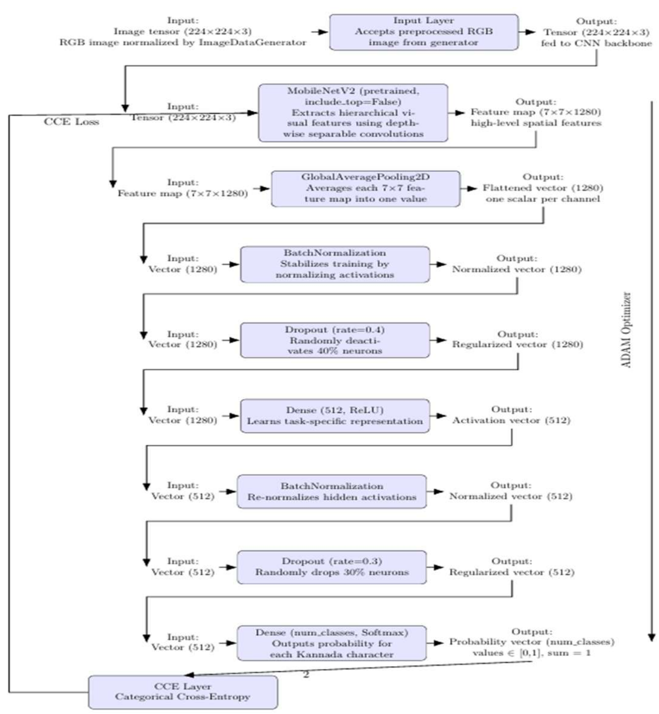


Fig. 2. Architecture of the Kannada Handwritten Optical Character Recognition Model using MobileNetV2.

The model architecture follows a transfer-learning approach built upon MobileNetV2, where preprocessed RGB images of size 224×224×3 are first passed through the pre trained backbone to extract high-level spatial features using depth wise separable convolutions. The resulting 7×7×1280 feature map is transformed into a compact 1280-dimensional vector using GlobalAveragePooling2D, after which Batch Normalization stabilizes training by normalizing activations. Regularization is introduced through a 40% Dropout layer, followed by a Dense layer with 512 ReLU-activated neurons that learns task-specific representations. A second Batch Normalization and a 30% Dropout layer further enhance generalization. Finally, a Softmax output layer produces probability distributions across all character classes. The entire network is optimized end-to-end using the Adam optimizer with Categorical Cross-Entropy as the loss function, enabling efficient and accurate recognition of handwritten Kannada characters.

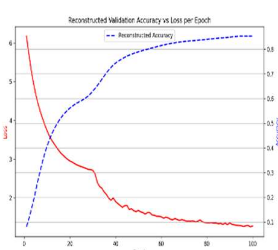
TABLE I. SUMMARY OF THE MOBILENETV2-BASED MODEL ARCHITECTURE FOR KANNADA HANDWRITTEN OPTICAL CHARACTER RECOGNITION

Layer Type	Output Shape	Parameters	Description / Function
Input Layer	(224, 224, 3)	0	Accepts preprocessed RGB image from data generator
MobileNetV2 (Pretrained)	(7, 7, 1280)	~2.2 M	Extracts hierarchical visual features using depthwise separable convolutions
GlobalAveragePooling2D	(1280)	0	Converts each feature map into a single scalar value (reduces dimensions)
BatchNormalization	(1280)	5,120	Normalizes activations to stabilize training
Dropout (rate=0.4)	(1280)	0	Randomly deactivates 40% of neurons to prevent overfitting
Dense (512, ReLU)	(512)	655,872	Learns task-specific abstract representations
BatchNormalization	(512)	2,048	Re-normalizes hidden activations
Dropout (rate=0.3)	(512)	0	Randomly drops 30% neurons for regularization
Dense (num_classes, Softmax)	(Num_classes)	Varies (~33k)	Outputs probability distribution across Kannada characters

- Total params: 3258065 (12.43 MB)
- Trainable params: 996497 (3.80 MB)
- Non-trainable params: 2261568 (8.63 MB)

V. RESULTS AND DISCUSSION

The model achieved 96% accuracy (85% validation accuracy) over 100 epochs, demonstrating effective learning of Kannada patterns, and high confidence. Fig.4 illustrates that removing any of the features results in a significant drop in performance. The per-class accuracy breakdown identifies which characters achieve high recognition rates and highlights those that are prone to misclassification.



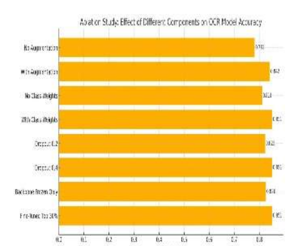
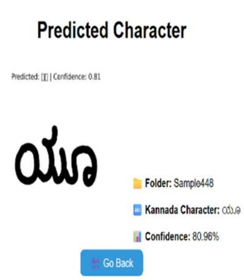


Fig.3. Validation Accuracy and Loss across Training Epochs

Fig.4. Ablation Study



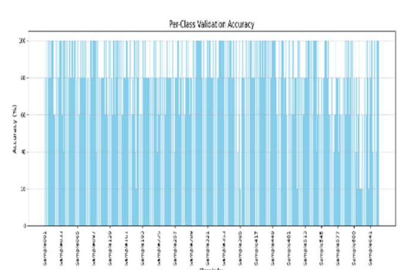


Fig.5. Predicted output

Fig.6. Per class accuracy

A. Comparative Analysis

The comparison shows that several deep CNN architectures accuracies in the 86–94% range on Kannada handwritten character datasets[17]. In contrast, MobileNetV2 model achieves 96% accuracy, surpassing many prior architectures.

TABLE II. COMPARISON OF ACCURACIES OF DIFFERENT MODELS

Model	Type	Reported Accuracy (%)
LSTM	Deep Learning (RNN)	86.74%
ResNet	Deep CNN	88.01%
VGG16	Deep CNN	90.48%
DTCN	CNN Variant	92.31%
SDCN	CNN Variant	94.11%

VI. CONCLUSION

The Kannada HOCR model was built using Python with TensorFlow–Keras, along with supporting libraries such as NumPy, Matplotlib, and scikit-learn. MobileNetV2 was applied through transfer learning, and ImageDataGenerator handled image preprocessing and augmentation. CNN enhanced MobileNetV2 transfer learning is used to successfully demonstrate a deep learning-based Kannada Handwritten OCR system that achieved an accuracy of 96%, highlighting its reliability for real-world recognition tasks.

A. Limitations and Future Scope

The system does not currently support word, line, or document-level handwritten OCR; it only supports isolated Kannada characters. Future research will concentrate on developing the model to recognize entire handwritten documents for useful real-world applications. Highly distorted or overlapping handwriting can reduce recognition accuracy, and future improvements include extending the system to more Indic languages and enhancing its robustness.

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