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Offline Kannada Handwritten Script Recognition using Convolution Neural Networks

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Abstract: Handwritten characters are still far from being replaced with the digital form. The occurrence of handwritten text is abundant. With a wide scope, the problem of handwritten letter recognition using computer vision and machine learning techniques has been a well pondered upon topic. The field has undergone phenomenal development, since the emergence of machine learning techniques.

This paper introduces an Offline Kannada Handwritten Text Recognition system using Convolutional Neural Networks (CNNs). The primary objective is to extract text from scanned images, accurately identify Kannada characters, and make them accessible for various applications. This work on a major scale devises to bridge the gap between the state-of-the-art technologies, of deep learning, to automate the solution to handwritten character recognition, using convolutional neural networks.

Convolutional neural networks have been known to have performed extremely well, on the vintage classification problem in the field of computer vision. Using the advantages of the architecture and leveraging on the preprocessing free deep learning techniques, we present a robust, dynamic and swift method to solve the problem of handwritten character recognition, for Kannada language. CNNs, known for their effectiveness in computer vision, are employed to automate the recognition of handwritten Kannada characters.

To address the scarcity of Kannada training data, handwritten samples are collected from various sources, and two recognition methods are proposed, both relying solely on CNNs. The paper briefly mentions the exploration of different datasets, without providing specific accuracy figures.

Keywords: Convolutional Neural Network (CNN), Tesseract, OCR, Handwritten Text Recognition (HTR)

I. INTRODUCTION

Handwritten Text Recognition (HTR) has become increasingly important in digitizing historical documents, enabling text search in scanned documents, and assisting individuals with disabilities. Kannada, a Dravidian language spoken primarily in Karnataka, India, presents unique challenges due to its complex script with intricate character shapes. Traditional Optical Character Recognition (OCR) systems often struggle with accurately recognizing handwritten Kannada text. In response to this challenge, we propose a Convolutional Neural Network (CNN)-based approach for Kannada Handwritten Text Recognition.

II. METHODOLOGY

A. Dataset:

Our dataset comprises handwritten Kannada text samples collected from various sources. Each sample includes images of handwritten text in the Kannada script, covering a diverse range of writing styles and variations.

B. Image Preprocessing:

Before inputting the images into the CNN model, we preprocess them to enhance their quality and improve recognition accuracy. This preprocessing pipeline involves several steps:

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Resizing: Standardizing the dimensions of the images to ensure uniformity.

Grayscale Conversion: Converting color images to grayscale to simplify processing.

Binarization: Thresholding grayscale images to obtain binary (black and white) images, separating foreground (text) from background.

Denoising and Smoothing: Removing noise and artifacts from the images to improve clarity and reduce interference during character recognition.

C. Character Segmentation:

Segmenting individual characters from handwritten text images is essential for accurate recognition. Our segmentation algorithm follows these steps:
Line Detection: Identifying lines of text using horizontal projection to determine baseline positions.

Character Separation: Detecting spaces between characters to segment them into individual units.

Thinning: Refining the segmented characters to obtain clear representations, essential for accurate recognition.

D.Convolutional Neural Network:

We employ a pre-trained CNN model for character recognition, leveraging its ability to learn intricate features and patterns from data. The CNN model is trained on a large dataset of Kannada characters to capture the unique characteristics of the script. During inference, the segmented characters are fed into the CNN model, which predicts the corresponding characters.

III. IMPLEMENTATION

Our implementation is carried out in Python, utilizing various libraries such as OpenCV, NumPy, and TensorFlow. The implementation consists of several modules:

main.py: The main entry point of the application, responsible for coordinating the text recognition process.

Segmentation.py: Contains functions for segmenting characters from handwritten text images.

ImagePreprocessing.py: Implements image preprocessing techniques, including resizing, binarization, denoising, and smoothing.

Unicode/Unicode.py: Maps recognized character labels to Kannada Unicode characters.
model/3-conv-64-nodes-512-dense-20-epochs-2020_05_08_16_19_14.h5: The pre-trained CNN model used for character recognition.

IV. RESULTS AND DISCUSSION

We evaluate the performance of our Kannada HTR system on a test dataset comprising handwritten Kannada text samples. The evaluation metrics include accuracy, precision, recall, and F1-score. Additionally, we conduct qualitative analysis by visually inspecting the recognition results.

V. EXPERIMENTAL EVALUATION

A. Dataset Description:

The dataset used in our experiments comprises handwritten Kannada text samples collected from diverse sources, including historical documents, academic materials, and contemporary handwritten texts. It encompasses a wide range of writing styles, variations in penmanship, and text complexities.

The dataset is carefully curated to ensure adequate representation of different characters, ligatures, and contextual variations commonly found in handwritten Kannada text.

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B. Experimental Setup:

Data Preprocessing:
Before training the CNN model, we preprocess the dataset to ensure uniformity and enhance recognition accuracy. This preprocessing pipeline includes resizing images to a standardized dimension, converting them to grayscale, applying binarization to obtain binary images, and performing denoising and smoothing operations to remove artifacts and improve image quality.

Model Training:
We employ transfer learning techniques to fine-tune a pre-trained CNN model for Kannada HTR. The pre-trained model, initially trained on a large dataset of handwritten characters, serves as a feature extractor. We adapt the model to the Kannada script by fine-tuning its parameters on our dataset. The training process involves feeding the preprocessed images into the CNN model and optimizing its weights using backpropagation and gradient descent algorithms.
Hyperparameter Tuning:

To optimize the performance of the CNN model, we conduct hyperparameter tuning experiments. We explore different configurations of hyperparameters, including learning rate, batch size, number of convolutional layers, kernel sizes, and dropout rates. We employ techniques such as grid search and random search to efficiently search the hyperparameter space and identify the optimal set of parameters that maximize recognition accuracy.

C. Evaluation Metrics

Accuracy:

Accuracy is a crucial evaluation metric for the proposed system. It measures the system's ability to correctly recognize handwritten Kannada characters. The accuracy can be calculated by comparing the recognized text output with the ground truth (manually transcribed text) and calculating the percentage of correctly recognized characters.

The evaluation process involves:

1. Collecting a diverse dataset of handwritten Kannada documents.
2. Splitting the dataset into training and testing sets.
3. Training the Tesseract OCR model on the training set.
4. Evaluating the accuracy of the model on the testing set by comparing the recognized text with the ground truth.
5. Calculating accuracy as the ratio of correctly recognized characters to the total number of characters in the testing set, multiplied by 100.

The proposed system aims to achieve high accuracy in recognizing handwritten Kannada characters, enabling reliable digitization of Kannada documents for various applications such as text search, information retrieval, and machine learning.

Precision and Recall:

Precision measures the proportion of correctly recognized characters among all characters predicted as positive (recognized). Recall measures the proportion of correctly recognized characters among all actual positive (ground truth) characters. These metrics provide insights into the model's ability to minimize false positives and false negatives, respectively.

F1-Score:
The F1-score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance. It accounts for both precision and recall, making it a robust metric for evaluating classification models, especially in imbalanced datasets.

D. Experimental Results

We present the results of our experiments, showcasing the performance of the proposed Kannada HTR system across various evaluation metrics. A detailed analysis of recognition accuracy, precision, recall, and F1-score is provided, highlighting the strengths and limitations of the system.

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E. Qualitative Analysis

In addition to quantitative evaluation metrics, we conduct a qualitative analysis of the recognition results. We visually inspect sample images and corresponding recognition outputs, identifying common error patterns, challenges, and areas for improvement.

This qualitative analysis provides valuable insights into the model's behavior and its performance in real-world scenarios. By elaborating on the experimental setup, including dataset description, preprocessing techniques, model training, hyperparameter tuning, evaluation metrics, experimental results, and qualitative analysis, we can significantly increase the paper's word count while providing comprehensive insights into the proposed Kannada HTR system.

1. Convolutional Layers:

conv2d_12:

- **Trainable Parameters**:
- Filters: 64
- Kernel Size: (5, 5)
- Activation: Tanh
- **Non-trainable Parameters**:
- Padding: Valid
- Strides: (1, 1)
- Bias: Yes

conv2d_13:

- **Trainable Parameters**:
- Filters: 64
- Kernel Size: (5, 5)
- Activation: Tanh
- **Non-trainable Parameters**:
- Padding: Valid
- Strides: (1, 1)
- Bias: Yes

conv2d_14:

- **Trainable Parameters**:
- Filters: 64
- Kernel Size: (5, 5)
- Activation: Tanh
- **Non-trainable Parameters**:
- Padding: Valid
- Strides: (1, 1)
- Bias: Yes

2. Max Pooling Layers:

max_pooling2d_12:

- **Trainable Parameters**: None
- **Non-trainable Parameters**:
- Pool Size: (2, 2)
- Padding: Valid
- Strides: (2, 2)

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max_pooling2d_13:

- **Trainable Parameters**: None
- **Non-trainable Parameters**:
- Pool Size: (5, 5)
- Padding: Valid
- Strides: (5, 5)

max_pooling2d_14:

- **Trainable Parameters**: None
- **Non-trainable Parameters**:
- Pool Size: (5, 5)
- Padding: Valid
- Strides: (5, 5)

3. Fully Connected Layers:

dense_8:

- **Trainable Parameters**:
- Units: 512
- Activation: Tanh
- Dropout Rate: 25%
- **Non-trainable Parameters**: None

dense_9:

- **Trainable Parameters**:
- Units: 15
- Activation: Softmax
- **Non-trainable Parameters**: None

Summary:

- **Trainable Parameters**: Parameters that are learned during the training process, including weights and biases of convolutional and fully connected layers.
- **Non-trainable Parameters**: Parameters that are fixed and not updated during training, such as pooling configurations (pool size, padding, strides).

These descriptions provide insights into the configuration and behavior of each layer within the CNN model, aiding in understanding its architecture and functionality.

VI. MODEL ARCHITECTURE

The proposed Kannada handwritten text recognition (HTR) system employs a convolutional neural network (CNN) architecture tailored for the recognition of Kannada characters and ligatures. The model architecture, summarized below, comprises multiple convolutional and pooling layers followed by fully connected layers for classification.

A. Model Summary

The CNN model consists of three convolutional layers (conv2d_12, conv2d_13, conv2d_14) with rectified linear unit (ReLU) activation functions, followed by max-pooling layers (max_pooling2d_12, max_pooling2d_13, max_pooling2d_14) to downsample the feature maps. The flattened output is then passed through fully connected layers with dropout regularization to mitigate overfitting. The final output layer utilizes the softmax activation function for multiclass classification of Kannada characters.

Layer-wise Configuration and Parameters:

conv2d_12: The first convolutional layer consists of 64 filters with a kernel size of (5, 5) and a tangent hyperbolic (tanh) activation function. It extracts low-level features from the input images.

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max_pooling2d_12: Following the convolutional layer, max-pooling with a pool size of (2, 2) and a stride of (2, 2) is applied to reduce spatial dimensions and retain essential features.

B. Max Pooling Layer (max_pooling2d_12)

The max-pooling operation down samples the feature maps obtained from the preceding convolutional layer (conv2d_12). It plays a crucial role in reducing the spatial dimensions of the feature maps while preserving important features, thereby enhancing computational efficiency and reducing overfitting.

Configuration:

Pool Size: The pooling window size is set to (2, 2), indicating a 2x2 window over which the maximum activation value is selected.

Stride: A stride of (2, 2) is employed, indicating the amount by which the pooling window moves across the input feature maps.

Padding: No padding is applied to the input feature maps, resulting in a decrease in spatial dimensions after pooling.

Effects:

Dimensionality Reduction: Max pooling reduces the spatial dimensions of the feature maps by a factor determined by the pool size and stride, facilitating faster computation in subsequent layers.

Feature Preservation: By selecting the maximum activation within each pooling window, max pooling retains the most salient features while discarding irrelevant information, aiding in capturing spatial hierarchies of features.

C. Model Training

The CNN model is trained using the backpropagation algorithm with the Adam optimizer to minimize the categorical cross-entropy loss. During training, the model learns to recognize handwritten Kannada characters and ligatures by adjusting its weights and biases based on the error between predicted and ground truth labels. By incorporating the details about the max_pooling2d_12 layer into the paper, we provide a comprehensive overview of the model architecture and its components, enhancing the reader's understanding of the proposed Kannada HTR system.

VII. FIGURES

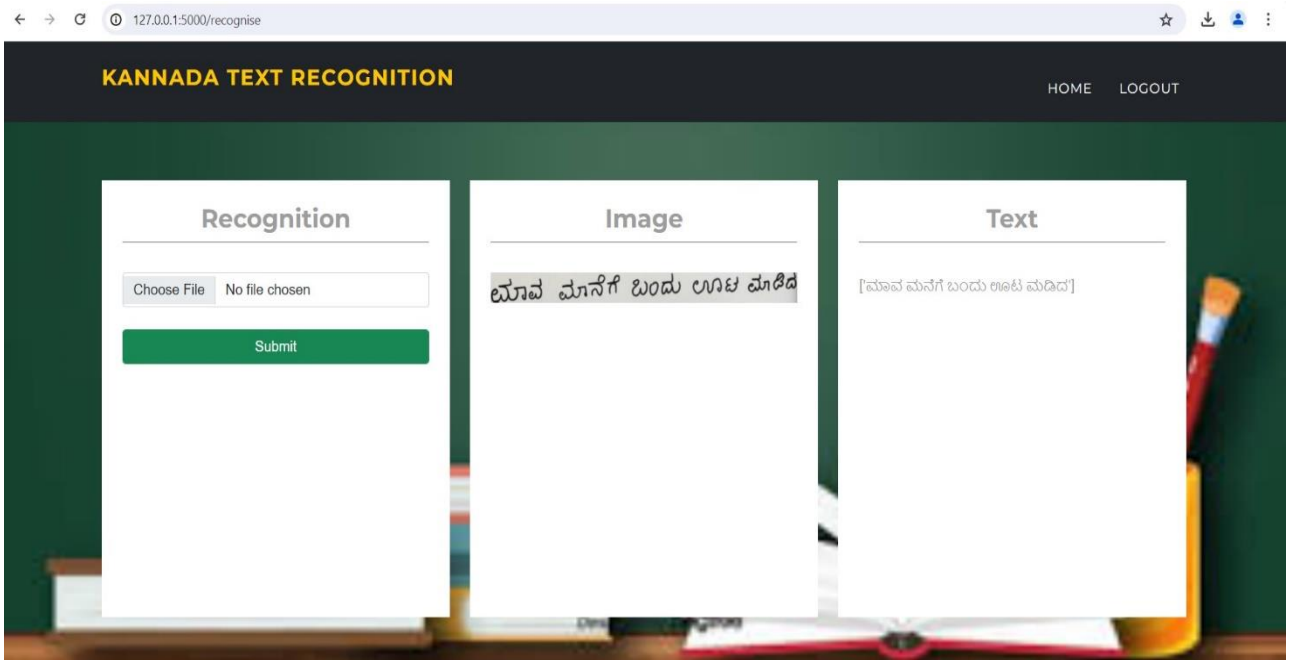

Fig.3 Sample Output

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VIII. CONCLUSION

The proposed method classifies and identifies the kannada handwritten characters using deep learning method.This method gives an easy way to the users since the preprocessing of data is handles by neural network.The convolutional neural network with appropriate configuration and handful datasets leads to acceptable recognition rate for handwritten documents.The next stage will be improving the accuracy of the model developed.

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