Authorship Attribution of Handwritten Kannada Characters via Convolutional Neural Networks

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Abstract—This paper presents a deep learning approach for authorship detection of handwritten Kannada characters. We developed a Convolutional Neural Network (CNN) model to classify handwritten Kannada alphabets based on the author's identity. Our dataset consists of images of handwritten Kannada characters from multiple authors, each assigned a unique identifier. The proposed model achieves 68% accuracy on the test set, demonstrating the potential of CNNs in identifying authorship patterns in Kannada handwriting. This research contributes to the field of digital forensics and handwriting analysis, particularly for Indic scripts, and has potential applications in document verification and historical manuscript analysis.

Keywords—authorship detection, Kannada handwriting, convolutional neural networks, deep learning, character recognition

# Introduction

Authorship detection of handwritten text is a challenging problem with significant implications in various fields, including forensic science, historical document analysis, and digital security. While substantial research has been conducted on authorship attribution for Latin scripts, there is a notable gap in the literature regarding Indic scripts, particularly Kannada. Kannada, an official language of Karnataka, India, presents unique challenges for authorship detection due to its complex character set and the variability in individual writing styles. This research aims to address these challenges by leveraging the power of deep learning, specifically Convolutional Neural Networks (CNNs), to identify authorship patterns in handwritten Kannada characters. The objectives of this study encompass several key goals. Firstly, it aims to develop a Convolutional Neural Network (CNN)-based model specifically designed to accurately identify the author of handwritten Kannada characters. This involves leveraging deep learning techniques to effectively capture and interpret the intricate details inherent in Kannada handwriting styles. Secondly, the study seeks to evaluate the efficacy of these advanced machine learning methods in discerning the subtle nuances that distinguish one author's handwriting from another within the Kannada script. Finally, by focusing on Kannada, a non-Latin script, the research aims to make a significant contribution to the broader field of authorship detection, extending the applicability and understanding of such techniques beyond traditional Latin-based languages.

# Ease of Use

[In this section, provide a comprehensive review of existing literature. Include 3-4 paragraphs discussing previous work on authorship detection, handwriting analysis for Indian languages, and any relevant studies on Kannada script analysis. Cite appropriate sources using IEEE format.]

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# Methodology

## Dataset

Our dataset comprises images of handwritten Kannada alphabets collected from [insert number] unique authors. Each author was assigned a numeric identifier, which serves as the class label for our classification task. The dataset was divided into training (70%), validation (15%), and test (15%) sets.

Data collection process: [Describe how the data was collected, e.g., through a digital writing pad or scanned paper documents]

In preparing our dataset for analysis, several preprocessing steps were implemented. Initially, all images were resized to a standardized resolution of 150x150 pixels to ensure uniformity in our dataset. Following resizing, pixel values were normalized to fall within the range of [0, 1]. Additionally, we conducted [any other specific preprocessing steps that were applied] to enhance data quality and uniformity for subsequent analysis.

Upon completing the preprocessing steps, we gathered dataset statistics for comprehensive insight. The dataset comprises a total of [insert number] images sourced from various authors. Within these images, [insert number] unique authors contributed, each potentially offering distinct perspectives and styles. Furthermore, the dataset encompasses representations of [insert number] distinct Kannada characters, reflecting the diversity and richness of the Kannada script within our dataset.

These preprocessing and statistical insights provide a foundational understanding crucial for further exploration and analysis of the dataset

Dataset structure:

dataset/

├── train/

│ └── images/

├── val/

│ └── images/

└── test/

└── images/

## Model Architecture

We designed a CNN architecture optimized for capturing the intricate features of Kannada handwriting. The model consists of four convolutional layers, each followed by batch normalization and max pooling, and three fully connected layers. The architecture is as follows:

1. Conv2D(64, (3,3), activation='relu')
2. BatchNormalization()
3. MaxPooling2D((2,2))
4. Conv2D(128, (3,3), activation='relu')
5. BatchNormalization()
6. MaxPooling2D((2,2))
7. Conv2D(256, (3,3), activation='relu')
8. BatchNormalization()
9. MaxPooling2D((2,2))
10. Conv2D(512, (3,3), activation='relu')
11. BatchNormalization()
12. MaxPooling2D((2,2))
13. GlobalAveragePooling2D()
14. Dense(1024, activation='relu')
15. Dropout(0.5)
16. Dense(512, activation='relu')
17. Dropout(0.5)
18. Dense(num\_classes, activation='softmax')

This architecture was chosen to progressively extract hierarchical features from the input images, with the later layers capturing more abstract representations of handwriting styles.

## Training Process

We trained the model using the following parameters:

* Optimizer: Adam
* Loss function: Sparse Categorical Crossentropy
* Batch size: 32
* Epochs: 100
* Learning rate: [insert value]

Data augmentation techniques: [Describe any data augmentation techniques used, such as rotation, scaling, or flipping]

Hardware and software environment:

* GPU: [insert details]
* Framework: TensorFlow 2.x
* Programming language: Python 3.x

# Experimental Results

## Model performance

Our model achieved the following accuracies:

* Training set: [insert %]
* Validation set: [insert %]
* Test set: 68%

[Include a figure showing the training and validation accuracy curves over epochs]

Confusion Matrix Analysis: [Provide insights from the confusion matrix, such as which authors or characters were most often misclassified]

## Comparison with Baseline methods

[If applicable, compare your CNN model's performance with traditional machine learning approaches like SVM or Random Forests]

## Figures and Tables

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# Discussion

The achieved accuracy of 68% on the test set demonstrates the potential of CNNs in capturing authorship patterns in Kannada handwriting. This performance is particularly noteworthy given the complexity of the Kannada script and the variability in individual writing styles.

Key observations:

1. [Insert observation about model performance]
2. [Insert observation about challenging cases]
3. [Insert observation about potential biases or limitations]

Limitations:

* [Discuss dataset size limitations]
* [Mention any biases in data collection]
* [Address challenges in generalizing to unseen authors]

Potential applications:

* Digital forensics for Kannada documents
* Historical manuscript analysis
* Automated document verification systems

# Conclusion and future work

This study demonstrates the feasibility of using CNNs for authorship detection in handwritten Kannada characters. Our model's 68% accuracy on the test set provides a strong foundation for further research in this area.

Future work may include:

1. Expanding the dataset to include more authors and a wider variety of writing samples
2. Exploring transfer learning approaches to improve performance
3. Investigating the model's ability to generalize across different Indic scripts
4. Developing ensemble methods to further increase accuracy

By advancing the field of authorship detection for Kannada and other Indic scripts, this research contributes to the broader goals of preserving cultural heritage and enhancing document security in the digital age.

##### Acknowledgment *(Heading 5)*

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