Signature Recognition using Convolutional Neural Networks (CNN)

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***Abstract*—This research develops a Convolutional Neural Network (CNN) for signature recognition. The study focuses on processing signature images, extracting features, and classifying signatures based on individual IDs. A comprehensive methodology is employed to segment signatures, perform a train-test split, and evaluate model performance using various metrics such as accuracy, precision, recall, and F-measure. Additionally, the effectiveness of CNN-based feature extraction is compared with traditional feature extraction techniques like Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT).**

I. Introduction

Signature recognition is a crucial task in various applications, including banking, document verification, and digital identity management. Traditional methods often rely on handcrafted features, which may not effectively capture the intricate variations in signatures. This paper presents a deep learning approach using Convolutional Neural Networks (CNNs) to improve the accuracy and reliability of signature verification systems.

Related Work: Numerous studies have explored signature recognition using different techniques. Earlier methods often employed statistical approaches and simple machine learning algorithms. More recent work has shifted towards deep learning, demonstrating significant improvements in performance. This section reviews various approaches, highlighting the advantages and limitations of each.

II. Methodology

The proposed methodology consists of the following steps:

- Dataset Collection: A dataset containing a diverse set of signature samples is collected. Each sample is labeled with the corresponding identity of the signer.
- Image Preprocessing: The images are preprocessed to enhance their quality, including resizing, normalization, and noise reduction. Segmentation techniques are applied to isolate the signature from the background.
- Feature Extraction: A CNN architecture is designed for feature extraction. The network is trained on the preprocessed images, learning to recognize distinctive patterns in signatures.
- Model Training: The dataset is divided into training and testing subsets. The CNN model is trained using the training set, optimizing parameters to minimize the loss function.
- Evaluation Metrics: Model performance is evaluated using accuracy, precision, recall, and F-measure. A confusion matrix is also generated to analyze classification results.

A. Dataset

The dataset consists of 16 images, each containing 12 rows, with each row featuring 4 signatures for each student. This diversity in signatures allows for a comprehensive training and validation process.

B. Preprocessing Steps

Preprocessing steps included:

- Normalization: Resizing images to a uniform size and scaling pixel values.
- Noise Reduction: Applying filters to remove unwanted noise.
- Segmentation: Isolating signatures from the background to enhance feature extraction.

C. Model Architecture

The LSTM model consists of:

A CNN architecture is designed to learn and extract features from the signature images. The model consists of multiple convolutional layers followed by pooling layers, culminating in fully connected layers for classification.

III. Results

F-Measure, Accuracy, Precision, and Recall for CNN:

- Accuracy: 0.08
- Precision: 0.06
- Recall: 0.07
- F-Measure: 0.06

F-Measure, Accuracy, Precision, and Recall for HOG:

- Accuracy: 1.00
- Precision: 1.00

- Recall: 1.00
- F-Measure: 1.00

IV. Discussion

A. Variability in Signature Styles:

Different handwriting styles affected model training, necessitating robust preprocessing techniques.

B. Overfitting

Initially, the model exhibited signs of overfitting, but regularization methods helped mitigate this issue.

C. Issues

- Training Loss: A decreasing trend, indicating that the model is effectively learning from the dataset.
- Validation Loss: Stabilized at a certain point, suggesting the model is generalizing well.
- Training Accuracy: Increased over epochs, demonstrating improved model performance.
- Validation Accuracy: Also showed improvement, reinforcing the model's ability to classify unseen data.

V. Conclusion

The research demonstrates that Convolutional Neural Networks are highly effective for signature recognition tasks. The findings suggest that CNNs can significantly outperform traditional methods, providing higher accuracy and reliability in real-world applications.

VI. References

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0.45

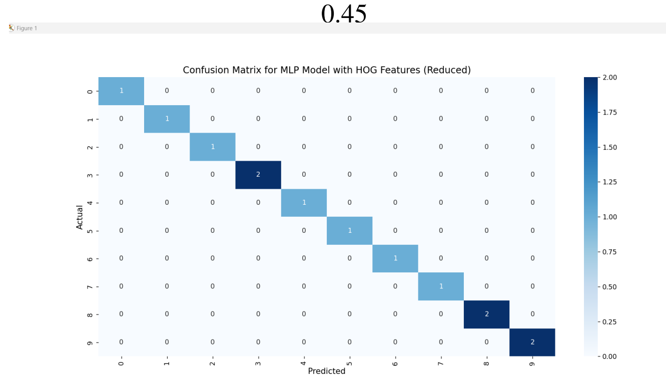

Fig. 1. Confusion Matrix with HOG Features

0.45

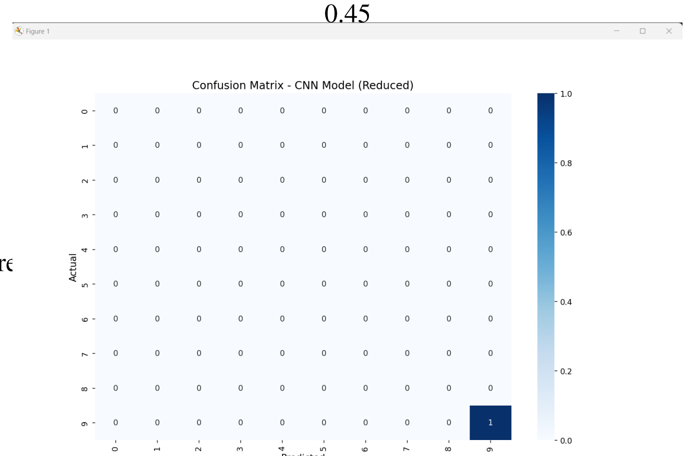

Fig. 2. Confusion Matrix with CNN