Signature Recognition Using Convolutional Neural Networks and Feature Extraction Techniques

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***Abstract*—This report presents the development of a signature recognition system using Convolutional Neural Networks (CNN) and manual feature extraction techniques, such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT). The task involves recognizing signatures from 159 classes, each containing only four samples, which posed challenges related to data scarcity. The performance of the CNN and manual methods is evaluated, and their training and test accuracies are compared.**

I. Introduction

Signature recognition is a challenging problem, especially in situations where the dataset is limited in terms of samples per class. In this assignment, we developed a signature recognition system using CNNs and compared it with traditional manual feature extraction methods such as HOG and SIFT. Given the small number of samples per class (159 classes, with only four samples per class), the models struggled to generalize, which is reflected in the large difference between training and testing accuracies. The goal of this assignment is to compare CNNs with manual feature extraction techniques for signature recognition.

II. Methodology

A. Dataset

The dataset consists of images from which we had to extract the classes and the samples for each class. Using Contours and OpenCV, 159 classes were found each representing a unique individual's signature. Each class contains only four samples, with three used for training and one reserved for testing. The limited number of samples per class made it difficult for the models to generalize effectively.

B. Preprocessing

After extracting four signatures of each class using OepnCV and Contours, each signature image was preprocessed by converting it to grayscale, resizing, and normalizing the pixel values. These steps ensured uniformity in the data fed into the CNN.

C. Model Architecture

For the CNN, we used a straightforward architecture consisting of several convolutional layers followed by pooling layers, culminating in fully connected layers for classification. In contrast, HOG and SIFT used traditional feature extraction techniques where key features were extracted manually from the signature images and passed through a classifier.

D. Training

Due to the small number of samples, the CNN model showed a clear overfitting trend, achieving high training accuracy but low test accuracy. The HOG and SIFT methods also suffered from limited generalization ability due to the dataset's constraints.

III. Results

A. CNN Results

Training accuracy for the CNN model was significantly higher than the test accuracy, indicating overfitting. Figures 1 illustrate the training and test accuracies, respectively.

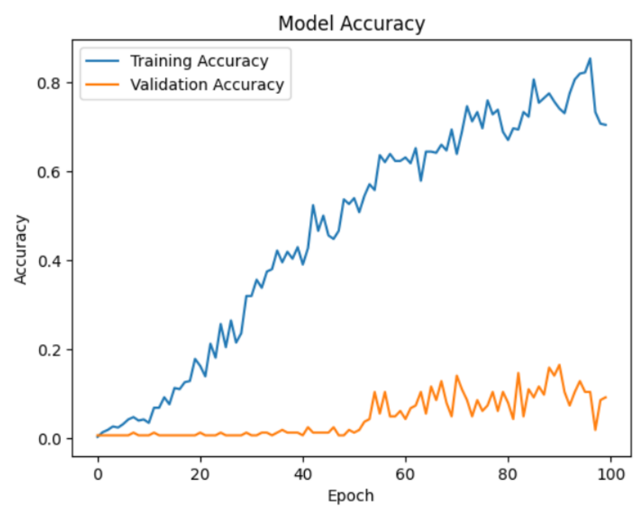

Fig. 1. CNN Training vs Testing Accuracy.

B. HOG and SIFT Results

Similar trends were observed for HOG and SIFT, where the models performed well on the training set but failed to generalize on the test set due to the small number of samples per class. Figures 2 and 3 show the training and test accuracies for these methods.

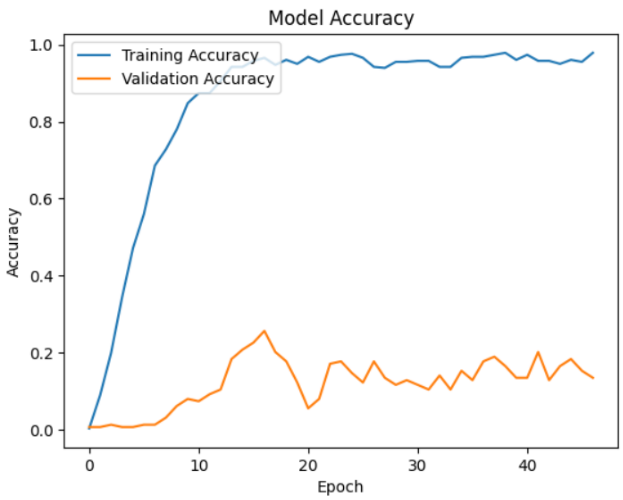

Fig. 2. HOG Training vs Testing Accuracy.

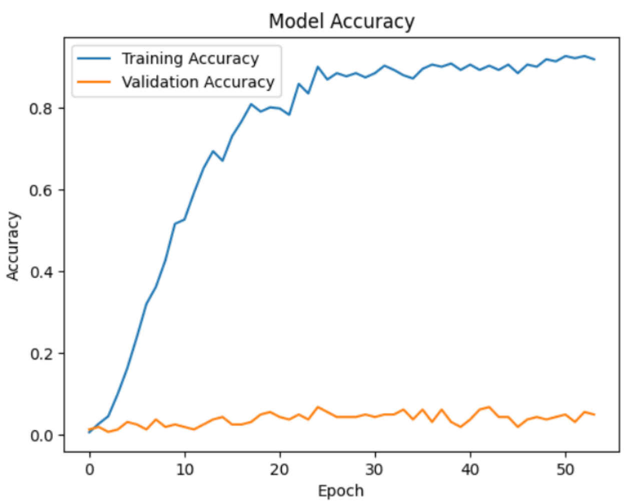

Fig. 3. SIFT Training vs Testing Accuracy.

IV. Discussion

The results highlight the limitations posed by the small dataset. The CNN model, while capable of learning complex patterns, could not generalize effectively due to the lack of sufficient training data. Overfitting was a significant issue, and the test accuracy remained low compared to the training accuracy. Manual feature extraction methods like HOG and SIFT faced similar challenges, with the model unable to differentiate between classes effectively.

To address these challenges in future work, data augmentation techniques could be employed to artificially increase the number of training samples. Additionally, more sophisticated CNN architectures with regularization techniques such as dropout could help mitigate overfitting.

V. Conclusion

In this project, we implemented a signature recognition system using CNN, HOG, and SIFT. Due to the limited number of samples per class, all methods exhibited high training accuracy but low test accuracy, indicating overfitting. Data augmentation and more advanced architectures could help improve generalization in future experiments.