IMPRESSION IDENTIFICATION BY USING COMBINATION OF COMBINATION OF CNN AND HOG

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ABSTRACT:

Since the number and calibration of features extracted determine how well these systems can differentiate between real and fake signatures, the feature extraction stage of the offline signature verification system is considered essential and has a major influence on how well these systems perform. This study presented a hybrid approach to feature extraction from signature photos, utilizing a Convolutional Neural Network (CNN) in conjunction with a Histogram of Oriented Gradients (HOG) to find the salient characteristics. Lastly, the CNN and HOG approaches were integrated. With a high accuracy on the ICDAR Dataset, the experimental results showed that our proposed model performed satisfactorily in terms of efficiency and predictive capacity. Given that we examined expertly fabricated signatures, which are more challenging to identify than other types of forged signatures such (simple or opposite), this accuracy is thought to be extremely significant.

INTRODUCTION

Using a person's physiological and behavioral traits, biometrics is the most significant technology technique for identifying them and assessing their power. Individuals in the physiological category are identified by measurements of bodily characteristics including ears, fingerprints, iris, and DNA, while those in the behavioral category are identified by their expression, voice, stride, and signature. Handwritten signatures are among the most widely used biometric verification techniques worldwide. Handwritten signatures serve as distinct behavioral biometrics for financial documents, check processing, passports, banks, and credit cards. Verifying these signatures can be challenging, especially if they are ambiguous. Consequently, to reduce the likelihood of theft or fraud, a system that can differentiate between a real signature and a false one is needed. Many studies have been carried out in this area over the last three decades, ranging from machine learning algorithms to traditional verification based on expert opinions to deep learning algorithms today. However, offline signature verification systems still require a great deal of work and development. Because offline signature photos lack characteristics like pen-tip pressure, velocity, and acceleration, offline signature verification is thought to be more difficult than online verification, according to earlier research [1, 2, 8, 10, 11]. Furthermore, the online technique is inappropriate in practice in a number of instances due to the distinct procedures for acquiring signatures. Here, we combine CNN and HOG algorithms for signature verification to create a hybrid feature extraction method. to get beyond the restrictions on feature extraction.

OBJECTIVE

For a number of retrieved features that may be appropriate for the classification process, this study suggests using the HOG feature extraction technique with a particular cell size. We think that by using this hybrid model, we can increase the accuracy of the verification even more without having to change the system settings for every writer. Thus, in contrast to conventional methods, (HOG-CNN) permits more flexible training. With its strong feature set, the hybrid model could enhance performance when combined with a low-complexity classifier.

PROBLEM STATEMENT

Although offline signature verification is essential for guaranteeing document validity in a variety of fields, it has a difficult time differentiating between real and fake signatures, especially those that are effectively forged. The single-feature extraction techniques used in traditional methods frequently fall short of fully capturing the complex patterns and variances in handwriting styles. Such systems' accuracy and dependability are diminished by this constraint, particularly when handling highly accomplished forgeries. To improve the capacity to identify minute distinctions between authentic and fake signatures, a hybrid feature extraction technique that combines the advantages of cutting-edge techniques like Convolutional Neural Networks (CNNs) and Histogram of Oriented Gradients (HOG) is urgently needed. By filling in the current gaps in feature representation, this method would increase offline signature verification systems' overall efficacy.

EXISTING SYSTEM

The current level of offline signature verification systems has intrinsic challenges with feature extraction, a critical component in determining system performance. Existing systems sometimes employ outdated methods that may not adequately capture the complex distinctions between authentic and fraudulent signatures. Although these techniques are basic, they may not be advanced enough to detect subtle variations in professional forgeries.

Disadvantage of Existing System

- When there is more sound in the data set, such as when target classes overlap, it performs poorly.
- When we have a huge data collection, it performs poorly since it takes longer to train.

PROPOSED SYSTEM

We provide a new approach for the feature extraction stage of our proposed offline signature verification system. We integrate many state-of-the-art techniques to enhance the capacity to differentiate between authentic and fraudulent signatures, realizing how important this stage is in determining the system's overall effectiveness. Our approach combines the Histogram of Oriented Gradients (HOG) technique with a Convolutional Neural Network (CNN) to extract significant features from signature photos.

Advantages of Proposed System

- Resulting in the creation of a more comprehensive and sophisticated feature set for signature verification.
- The ability to accurately differentiate between authentic and fraudulent signatures.

RELATED WORKS

Traditional offline signature verification techniques frequently depended on individual feature extraction techniques, like geometric and statistical features, but because they only focused on global or local characteristics, they were unable to fully capture the complexities of competent forgeries. Though its solo use lacks resilience for complicated forgery detection, Histogram of Oriented Gradients (HOG) is a popular choice for pattern recognition tasks like fingerprint and character recognition since it has demonstrated effectiveness in capturing edge orientations and spatial relationships. Similar to this, Convolutional Neural Networks (CNNs) have shown great promise for global pattern recognition in signature verification by directly learning hierarchical features from visual data. However, CNNs require a lot of processing and rely on big datasets, which might be hard to come by. In order to overcome these drawbacks, hybrid strategies that combine CNN with specialized techniques like HOG have surfaced, effectively utilizing their complimentary advantages to capture both local and global features. When tested on benchmark datasets like ICDAR and GPDS, these techniques have demonstrated promise in enhancing the detection accuracy of even highly skilled forged signatures, which continue to be one of the most difficult parts of signature verification.

METHODOLOGY OF PROJECT

The hybrid model for offline signature verification that has beencreated in this project's implementation phase will make use of both the Histogram of OrientedGradients (HOG) and Convolutional Neural Network (CNN) methods. Users will have anintuitive user interface through which to post signature images. After submission, the system will use the combined CNN and HOG feature extraction techniques to process the input images. Todifferentiate between genuine and fake signatures, the retrieved characteristics will then be included into the classification model. The Flask framework will make it easier for the userinterface and the backend to communicate, offering a smooth and convenient platform forverifying signatures. This user-friendly interface will highlight the system's efficiency andpredictive power, as seen by the trial results, highlighting its usefulness in real-world situations.

MODULE DESCRIPTION:

Gathering the Dataset:

In the first phase of development, the system was designed to get the input dataset for training and testing, with a specific emphasis on verifying signatures. There are 3188 real signature photos in the collection, along with 2983 bogus ones.

Bringing in the Required Libraries:

In the first module, we developed the system to get the input dataset for the training and testing purpose. Dataset is given in the model folder. The dataset consists of 1377 ECG images.

Obtaining the pictures:

The photos are scaled to (224, 224) to guarantee uniformity once the images and their information have been retrieved.

Data Supplementation:

The model's robustness is increased by employing data augmentation techniques with Keras' Image Data Generator. Techniques include zooming, rescaling, shearing, and horizontal flipping.

Model Construction:

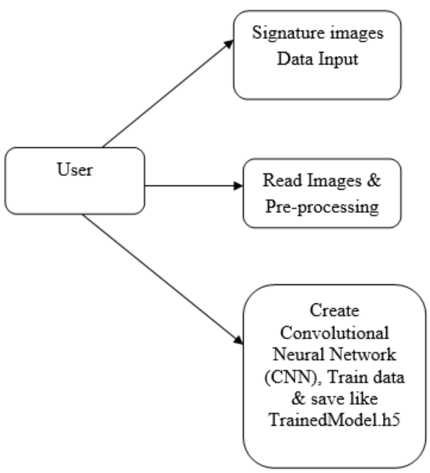
Convolutional Neural Networks (CNNs) are constructed using the Sequential model developed by Keras. The architecture consists of convolutional layers with various filter sizes, a flatten layer, max-pooling layers for dimension reduction, and dense layers. Finally, the last dense layer generates one node with a sigmoid activation function that indicates if the signature is real or not.

Getting the model trained:
The Adam optimizer and binary cross-entropy loss are employed to build the model. It is trained using the fit function with a batch size of 16. Plotting the accuracy and loss of training and validation reveals that the average accuracy of training and validation was 99.99% over 10 epochs.

Reliability on the Test Set:
As demonstrated by its 99.99% accuracy on the test set, the trained model does well in the verification of signatures.

The Trained Model's Preservation:
The final step is to save the trained model as an a.h5 file using the Keras save function. "CNNsignature.h5," a saved model, may be used for real-time signature verification in a production-ready environment.

DATA FLOW DIAGRAM



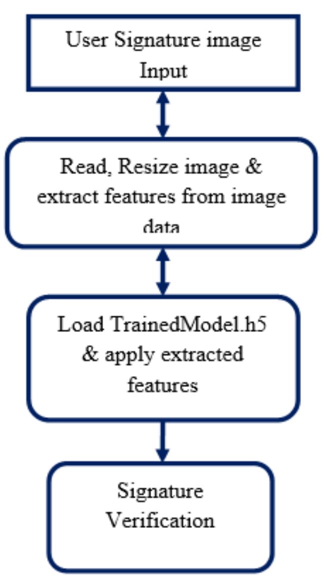


Fig:Flow Diagram

ALGORITHM

Convolutional Neural Network (CNN) and Histogram of Oriented Gradients(HOG):
In this project, offline signature verification was performed using a deep learning technique.A Convolutional Neural Network (CNN) ad hoc model was employed as a deep learning technique. Convolutional Neural Network as a technique for processing images, the three basic layers of a CNN: the convolutional layer, sub-sampling layer(sometimes called the pooling layer), and fully connected layer. CNN use convolutional and pooling approaches to recognize the distinguishing features of images. While the characteristics obtained in the latter layers depict portions of forms and objects, those obtained in the early stages are identified as edges or color information.
Features from the signature images were extracted using the HOG approach.HOG, or Histograms of Oriented Gradients, are mostly employed as person detectors. In this study, HOG was used both alone and in conjunction with the CNN method as a feature extraction approach to detect and recognize signature images. The HOG descriptorapproach hypothetically records events of angle introduction in specific areas of an images or a region of interest (ROI).

SYSTEM ARCHITECTURE

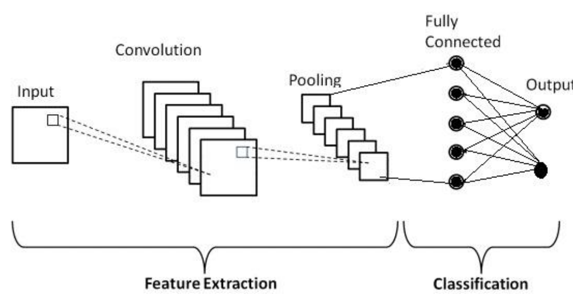


Fig:SYSTEM ARCHITECTURE OF PROJECT

RESULTS

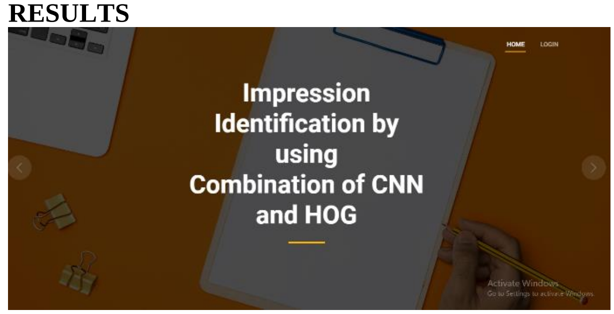


Fig 1: Homepage

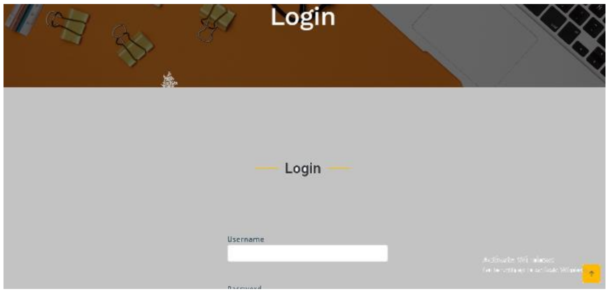


Fig 2: login page

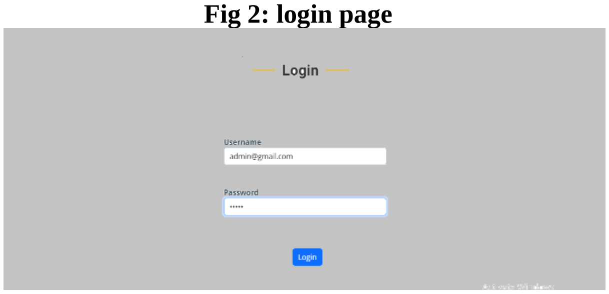


Fig 3:login success page

Fig 4 : Image upload page

Fig 5 : After image uploading

Fig 6: Result page

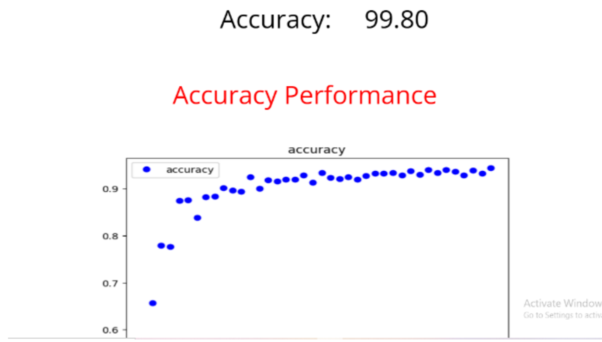


Fig 7: Accuracy page

FUTURE ENHANCEMENT

The project's future scope include continuously enhancing the feature-extraction process to boost forecast accuracy and signature verification efficiency. It is envisaged that modern techniques and dataset expansion would lead to even more dependable model training. In order to overcome new challenges in offline signature verification, ongoing research aims to adapt the hybrid technique, ensuring long-term improvements in flexibility and precision.

CONCLUSION

In order to extract features from signature images, we developed a new method in this study. In particular, we integrated the output of the CNN and HOG approaches, determined the salient features from each, and used probability forecasting to test the retrieved features. On our particular dataset, testing results showed that our suggested model had a high predictive ability and performed well, with a learning accuracy of 99.99%. Because expert forgeries are usually quite close to the actual signatures, they are more difficult to identify than other types of forgeries, such as basic or opposite-hand forgeries. This is particularly significant because we evaluated complex forgeries.

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