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Fraud Signature Detection using Deep Learning

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ABSTRACT **:- Signature verification is one of the most widely used biometric authentication techniques in banking, financial services, and legal documentation. Due to the increasing number of financial fraud cases, traditional manual verification practices have become insufficient. Manual checking is slow, error-prone, and heavily dependent on human skill and experience. This paper presents an automated fraud signature detection system using Convolutional Neural Networks (CNNs). The proposed model extracts spatial features such as stroke width, curvature patterns, writing pressure variations, and structural details of signatures. Through training on genuine and forged samples, the system learns to classify signatures accurately. Experimental results demonstrate that CNNs can effectively improve authentication accuracy, reduce human error, and enhance security in practical applications.**

Keywords :Signature Detection , Deep Learning, CNN, Fraud Detection

I. INTRODUCTION

Signatures remain one of the most accepted forms of verification across industries. Whether it is bank cheques, legal agreements, or identity validation processes, signatures play a crucial role in authentication. However, signature

forgery has become increasingly common due to access to digital scanning tools and advanced editing techniques.

Manual verification, conducted by handwriting experts or employees, is often inconsistent. Human decision-making can be influenced by fatigue, personal judgment, or lack of expertise.

Deep learning, especially Convolutional Neural Networks (CNNs), has emerged as a powerful solution to this problem. CNNs are capable of extracting hierarchical features from images, learning subtle differences between genuine and forged signatures that may not be easily noticeable to humans. This research aims to develop a CNN-based model that can identify fraudulent signatures with high precision.

II. LITERATURE REVIEW

Traditional signature verification methods included handcrafted feature techniques such as:

- SIFT (Scale-Invariant Feature Transform)
- HOG (Histogram of Oriented Gradients)
- Geometric shape-based analysis
- Texture descriptors

While these approaches work for simple tasks, they fail when signature variations are high. Human handwriting differs in pressure, speed, and style, making pre-defined features insufficient.Recent research highlights the advantages of CNNs, which automatically learn relevant features directly from data. Several studies reported:

- Improved accuracy with deep architectures
- Better generalization to unseen signatures
- Successful application of CNNs in other biometrics such as face and fingerprint recognition

This research builds upon previous work and focuses on designing a lightweight CNN architecture specifically for signature verification.

III. METHODOLOGY

A. Dataset

The dataset used in this research consists of multiple classes of signatures, each containing:

- Genuine signatures written by the user
- Forged signatures created by imitators

The dataset was divided into:

- 80% training samples
- 20% testing samples

All images were standardized to maintain uniform size and clarity.

B. Preprocessing

To improve the quality of data and simplify model training, several preprocessing techniques were applied:

1. Grayscale conversion:

Removes unnecessary color information and reduces computation.

2. Resizing to 128×128:

Ensures consistency across samples.

3. Normalization:

Scales pixel values to enhance training stability.

4. Data augmentation:

Random rotation, zooming, shifting, and shearing were used to increase dataset diversity.

This prevents overfitting and improves robustness.

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C. CNN Architecture

The CNN model used in this study contains the following layers:

1. Convolution Layer 1 32 filters, 3×3 kernel Extracts basic edges and simple stroke features

2. ReLU Activation

Introduces non-linearity

Removes negative values

3. MaxPooling Layer (2×2)

Reduces image dimensions

Helps in retaining important features

4. Convolution Layer 2 64 filters, 3×3 kernel

Learns deeper stroke and curvature patterns

5. ReLU Activation + MaxPool

6. Convolution Layer 3 128 filters

Identifies complex signature features such as loops, intersections, and writing pressure

7. Flattening + Fully Connected Layer

Converts extracted features into a 1D vector

Final classification performed here

8. Softmax Output Layer

Produces the probability of genuine vs forged signature D. Training Configuration

The model was trained using the following hyperparameters:

Loss Function: Cross-Entropy Loss

Used because this is a classification task.

Optimizer: Adam

Adaptive optimizer for faster

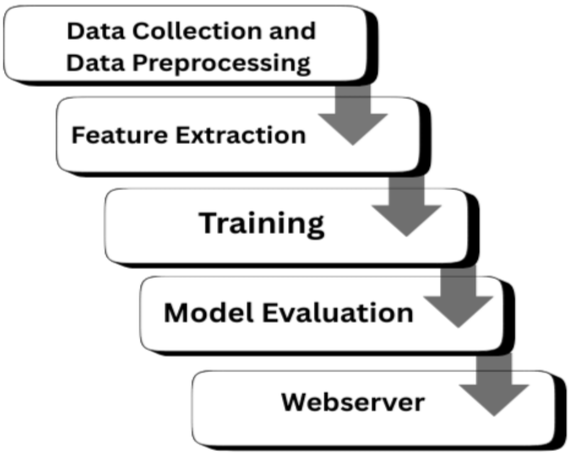

Fig. Architecture diagram

IV. RESULTS

During training, the model showed:

Continuous decrease in training loss

Improvement in validation accuracy

Ability to differentiate between visually similar signatures

The model outputs confidence scores for each prediction. These scores help identify signatures that are uncertain or borderline.

Forgeries that visually looked very similar caused occasional misclassifications. Poor image quality and incomplete signatures also affected performance.

Metric	**Value**
Testing Accuracy	98.21%
Testing Loss	0.0505
False Rejection Rate(FRR)	4.5%
False Acceptance Rate(FAR)	3.8%

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Table 1 : Quantitative Performance of Metrics of Model

V. DISCUSSION

The CNN-based model proves to be an effective technique for signature verification.

Some key observations include:

CNNs automatically extract meaningful features without human intervention

The model is capable of detecting subtle writing differences

Performance depends on the diversity and quality of data

Augmentation helps in reducing overfitting

This approach is highly beneficial for industries such as banking, finance, insurance, and document verification systems where accuracy and speed are critical.

The model demonstrates strong accuracy and reliability by learning writing patterns directly from images. It significantly reduces human workload and provides a scalable, automated solution for signature-based authentication.

VI. FUTURE WORK

To enhance the system further:

Use advanced architectures such as ResNet, VGG16, or

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MobileNet

Train with larger and more diverse datasets

Develop real-time mobile or cloud-based signature verification systems

Incorporate segmentation techniques for complex signature documents

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