International Journal of Research and Development in Engineering Science
ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/
Regular Issue, Vol. 7, Issue.3 (May – June), 2025 , Pages: 13 - 18
Received: 25 August 2024 ; *Accepted:* 31 January 2025 ; *Published:* 07 April 2025
https://doi.org/10.63328/IJRDES-V7RI3P3
Original Paper : Classification Research – Experimental Research Paper

Digital Signature Recognition Using Mobile NET

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Abstract: Handwritten signature classification stands as a fundamental aspect in document verification systems. The paper develops a stable handwritten signature classification framework based on Convolutional Neural Networks (CNN), the lightweight Mobile Net architecture and Alexnet for optimizing signature verification precision and operation speed. Handwritten signature classification represents an intricate process because writing styles consistently exhibit distinct individual characteristics hence requiring systems with sophisticated understanding capabilities. The model design implements CNN extraction of hierarchical image features and Mobile Net structure to achieve both performance excellence and operational compatibility across devices independent of their computing power. The present approach applies data augmentation together with transfer learning methods which improve both the generalization performance and unseen data accuracy of the model. Breeding from our signature classification framework yields promising outcome.
Keywords: Deep Learning, Convolutional Neural Networks (CNN), Mobile net, Image Processing.

1. Introduction

Handwritten signatures operate as an essential universal approach toward personal identification when performing secure document verification and identity authentication tasks. The extensive utilisation of handwritten signatures creates analytical classification problems because human factors such as mood and health and aging affect signature content. [1] Digital platform expansion creates an urgent requirement for systems which effectively classify handwritten signatures with precision. Traditional approaches fail to address these variations so developers require adopting deep learning technologies for advanced implementation. Networks (CNNs) deliver superior performance in all image recognition applications. Standard deep learning systems demonstrate too much complexity for real-time implementation especially when running on limited resources.[2] This research develops an efficient handwritten signature classification system through combining CNNs with MobileNet and AlexNet structures while employing transfer learning and data augmentation techniques.

1.1. Scope of the Study

The work explores the development of signature classification models through deep learning techniques. The scope includes: This research combines CNNs with MobileNet and AlexNet architectures to develop a signature classification model which achieves optimal performance. The implementation of transfer learning methods together with data augmentation techniques elevates model performance specifically for dealing with multiple signature formats and variations. [3] A performance evaluation of the model will include accuracy checks that contrast with traditional signature classification approaches. A real-time system evaluation under development aims to run on low- resource devices while examining deployment potential. This study develops a dependable method to verify documents and authenticate identities across legal, banking and digital platforms with secure operations.

1.2. Problem Statement

The proper recognition of signatures by hand continues to be a persistent problem for secure document authentication and identity verification because human signatures present unique patterns from both individual characteristics and surrounding conditions. Standard methods and less complex machine learning models fall short when seeking high accuracy levels during signature classification tasks involving multiple signature styles

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alongside minimal signature variations. Current deep learning models face deployment obstacles because of their challenging computational requirements for real-time applications on low- processing power devices. The world requires an advanced simple framework for handwritten signature classification which achieves high accuracy when deployed across practical scenarios including diminish power systems. [4]

1.3. Objective of the Study

This research develops a handwritten signature classification system that merges Convolutional Neural Networks (CNNs) with MobileNet and AlexNet architectures to work as one unified structure. Handwritten signature classification can achieve both increased accuracy and improved efficiency by utilizing transfer learning frameworks which enhance feature extraction capabilities. The system needs to reduce its computational demands for deployment on mobile devices with edge processing needs while upholding significant classification precision. The model needs to incorporate data generation methods to improve its generalization capacity across different signature forms while accepting a range of hand-written signatures. The research will compare the proposed system to standard classification approaches by illustrating its superior precision and performance speed and instant feature use ability.

2. Related Work

The investigation involves building a system for handwritten signature verification which depends on deep convolutional neural networks (CNNs). This research evaluates the ability of CNN- based architectures to extract advanced features from signature pictures that lead to discrimination between real signatures and forged signatures. Research deals with training deep learning models to boost verification precision because deep learning outperforms traditional signature recognition applications. Deep learning approaches to all the demonstrate major improvements in signature verification systems operations according to research findings. [5]

The research examines deep learning applications for the analysis of handwritten signatures and develops methods to distinguish real signatures from forged ones. Several deep learning architectures are examined including CNN (Convolutional Neural Networks) and LSTM (Long Short-Term Memory networks) for extracting sequential patterns in handwritten signatures. The research tackles handwriting style variability issues through convolutional layers that perform feature extraction then relies on recurrent layers to track signature temporal relationships. This method enables the recognition system to detect signatures with greater accuracy. [6] This study examines deep learning models including MobileNet along with ResNet50 and Inceptionv3 and VGG19 to perform handwritten signature verification tasks. The research integrates YOLOv5 with these models to achieve superior performance for detecting signature forgeries in handwritten signatures. A robust signature system development strategy aims to process signature variations effectively while maintaining extreme precision when identifying signatures. Seven shows how multiple deep learning systems create better verification outcomes when integrated for signature authentication.[7]

This work examines how convolutional neural networks function in tasks that verify handwritten signatures stored offline. The research team created a deep learning model which demonstrated 99.70% accuracy in signature verification tasks while showing CNNs' efficiency for real forged signature differentiation. The model improves its signature processing capabilities through its multi-layer CNN architecture by recognizing key features in signature images which increases both verification accuracy and system speed. Current research applies deep learning technology to signature verification systems which now provides faster more reliable authentication capabilities for banking environments alongside legal document verification tasks. [8]

3. Proposed System

A new system aims to establish an effective and precise model to distinguish real signatures from forged signatures. The deep learning CNN together with AlexNet and MobileNet architectures support the development of this robust solution to meet requirements and across high-performance systems as well as constrained-resource environments.

3.1. Dataset

The dataset used in this study consists of images of handwritten signatures, categorized into two classes: Forgery and Real. The selection of images represents training material and ensures model evaluation takes place. The data distribution consists of training groups alongside testing groups to validate model generalization across unseen datasets. The implementation of this technique blocks neural net overfitting while also guaranteeing optimal performance during real-world deployments.

3.2. Preprocessing Steps

Image data requires essential data preprocessing to become fit for training purposes. This includes the following steps: Image training becomes more effective by subtracting the

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pixel values from 0 and then dividing them by 1. The standardized input accelerates training convergence while improving its running efficiency. Splitting the Dataset: A training subset merges with a validation subset which combines with a testing subset to divide the whole dataset. The distribution of available data uses 70% for training purposes while validation occupies 15% along with testing which also comprises 15%. This measure allows the model to receive adequate training with image data consisting of three distinct evaluation sets.[9] Data Augmentation: To expand the training data diversity the model receives data augmentation methods include image rotations with flips and sizing adjustments. Improving model generalization across signature styles and variations becomes essential due to this step in the process.

3.3. Model Training

The model training involves using three different deep learning architectures: The general-purpose architecture CNN automatically extracts hierarchical features from input images to perform its functions. CNNs have become a standard choice for image classification work while providing exceptional performance for signature verification tasks. AlexNet: The deeper architectural system of CNN demonstrates advanced capabilities in the identification of complex image patterns. By having extra layers than typical CNNs AlexNet achieves superior capacity to extract sophisticated elements from signature images. MobileNet:

The CNN architecture stands as a compact design optimized for use on mobile platforms as well as edge systems. MobileNet operates with optimal computational efficiency to run signature classification on devices needing minimal power usage. [10] This architecture provides suitable precision alongside optimal computational performance making it an optimal solution for this research.

3.4. Model Evolution

The model evaluation system relies on multiple accuracy metrics for measuring its operational effectiveness after the training process. Key metrics include: The model achieves Accuracy by distinguishing between real or forged signatures among total predicted observations. [11] The classification task utilizes this evaluation technique as its primary assessment metric. Precision, Recall, and F1-Score: The model evaluation metrics perform an assessment of signature discrimination accuracy by analyzing false positive and false negative outcomes in real versus forged signature identification tasks. The experiment compares various architectures (CNN, AlexNet, MobileNet) to find which configuration achieves maximum operational efficiency with minimal accuracy loss.

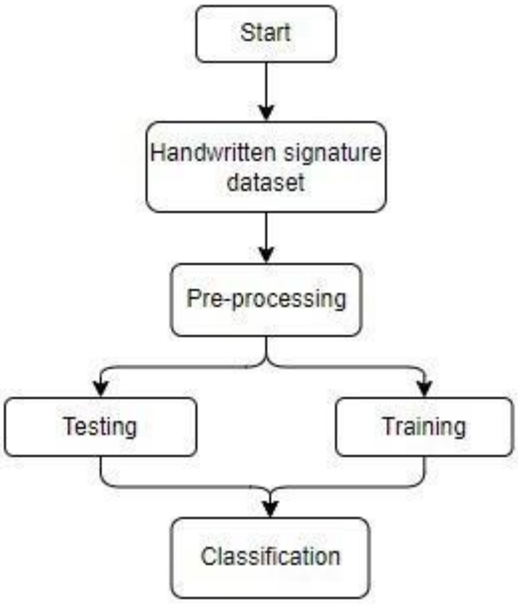

Figure.1 Proposed System Flow Chart

4. Methodology

4.1. CNN

Convolutional Neural Networks (CNNs) function as deep learning models which excel at detecting images together with patterns in their input data. Through convolutional layers these networks learn hierarchical features found in input data. [12] The convolutional layers use their filters to notice edge and texture patterns when processing simple input features while locating more intricate patterns as the layers grow deeper. The model reaches greater computational efficiency when pooling layers follow convolutional layers because these layers reduce the quantity of elements in the feature maps. CNNs serve handwritten signature classification tasks through automatic extraction of key image elements that eliminates manual feature engineering requirements.

The predictive output layer in these models employs softmax or sigmoid functions for binary or multi-class classification purposes while full connected layers perform the actual predictions. The CNN demonstrates strong potential for image classification because it detects spatial patterns effectively while operating with a basic structure which proves beneficial but also requires extensive computation for real-time processing. [13]

4.2. AlexNet

The deep neural network architecture name AlexNet achieved fame during the ImageNet competition of 2012. Unlike traditional CNNs, AlexNet is deeper, consisting of eight layers: Five convolutional layers lead to three fully

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connected layers in this model architecture. The framework contains larger convolutional filters and implements local response normalization (LRN) to achieve better generalization through adjacent neuron activation normalization.

AlexNet mitigates overfitting with dropout functioning in its fully connected layers through this mechanism that disables random neuron subsets during training to ensure model independence from individual features. [14] With its strong capability to study complex patterns within big datasets AlexNet proves effective for difficult tasks including handwritten signature classification.

The model requires powerful computation capabilities for its operation although it remains most effective in resource-heavy systems. Because AlexNet operates using multiple processing layers it extracts advanced signature features that basic recognition systems cannot capture thus providing better accuracy in handwritten signature identification.

4.3. MobileNet

MobileNet stands as a light-weight deep learning architecture optimized to work on mobile equipment and embedded systems although CPU resources remain restricted. Unlike traditional convolutional layers, MobileNet uses depthwise separable convolutions, which break down the convolution process into two smaller steps:

MobileNet performs a depthwise convolution operation then finishes with pointwise convolution logic. [15] Many training parameters and theoretical costs decrease substantially through this compression method while retaining excellent operational performance levels.

The MobileNet framework serves such real-time picture categorization duties as handwritten signature examination due to its need for quick response time and its capability to function with limited hardware resources. The architecture utilizes ReLU6 which serves hardware implementation needs through its restricted output boundaries.

The MobileNet architecture replaces standard fully connected layers with global average pooling to achieve more efficient model design. The balance between performance output and computational efficiency of MobileNet makes it suitable for mobile signature verification systems that require both online and offline signature classification.

5. Results And Discussion

Training Accuracy and Validation Accuracy: The training accuracy increases steadily from around 75% to nearly 100% over 9 epochs, while the validation accuracy remains consistently high around 95%. This indicates that the model is learning well during training and performs consistently on the validation set.

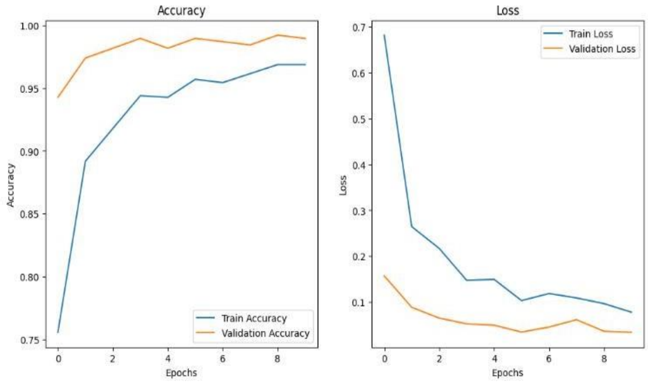

Figure.2 AlexNet accuracy and loss graphs

Training Loss and Validation Loss: The training loss decreases sharply from around 0.7 to below 0.1 over the same period, and the validation loss also shows a decreasing trend, though at a slower rate. This signifies that the model is effectively minimizing the error during training.

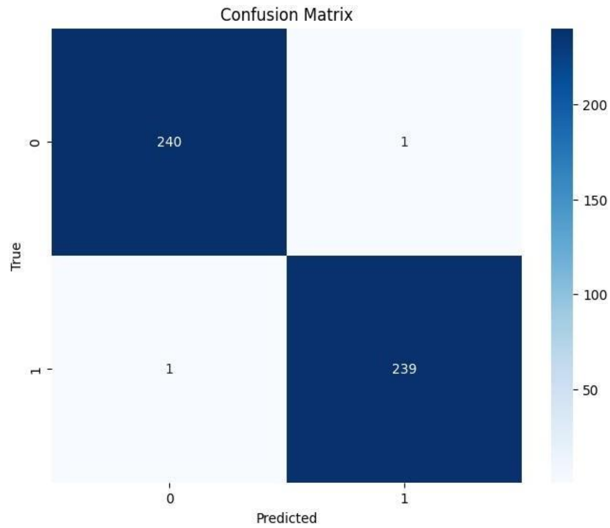

Figure.3 Confusion Matrix for AlexNet

Accuracy and Loss Trends: Training accuracy increases steadily, while validation accuracy remains high; both training and validation loss decrease over time, showing effective learning.

Performance Indication: The small gap between training and validation accuracy highlights that the model isn't overfitting, with slightly lower validation loss hinting at underfitting or an easier validation set.

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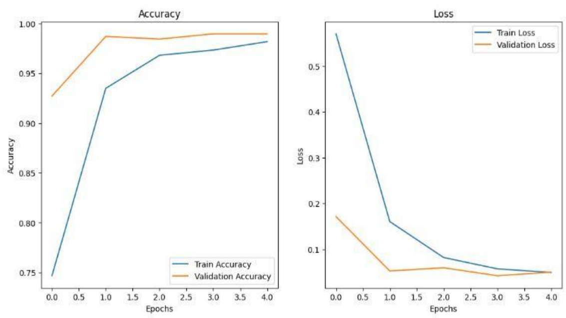

Figure.4 CNN Accuracy and Loss graphs

Accuracy Trends: Training accuracy steadily increases from 0.75 to nearly 1.0, while validation accuracy remains stable around 0.98.

Loss Trends: Training loss decreases sharply from above 0.5 to nearly 0.05, with validation loss stabilizing around 0.05.

Model Performance: The model exhibits high accuracy and low loss for both training and validation sets, suggesting effective learning and minimal overfitting.

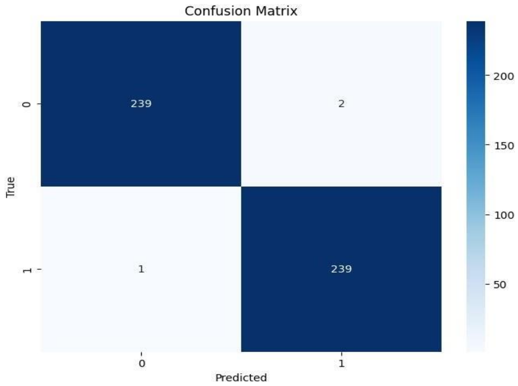

Figure.5 CNN Confusion Matrix

Accuracy Overview: The confusion matrix indicates the model has high accuracy with 239 true positives and 239 true negatives, with only 3 errors (2 false positives, 1 false negative). Model Performance: The model effectively distinguishes between the two classes, showing minimal misclassifications.

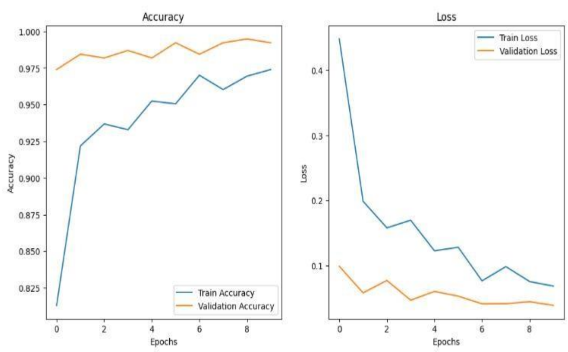

Figure.6 Mobilenet accuracy and loss graph

Accuracy Trends: Training accuracy increases steadily, reaching around 97.5%, while validation accuracy remains stable at about 97.5% throughout the epochs.

Loss Trends: Training loss decreases significantly from approximately 0.45 to below 0.05, with validation loss also reducing but at a slower rate, stabilizing around 0.05.

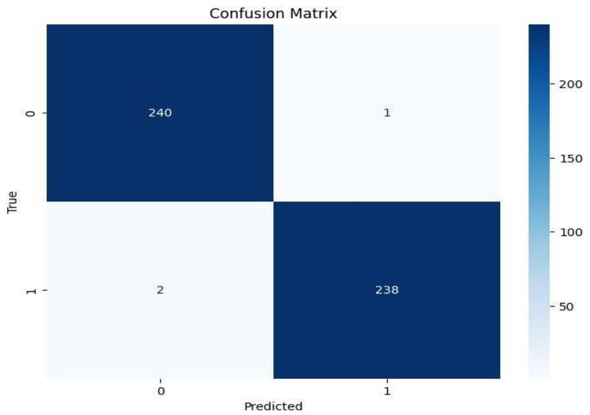

Figure.7 MobileNet Confusion Matrix

High Accuracy: The model shows high accuracy with 240 true negatives and 238 true positives, indicating strong performance.

Minimal Misclassifications: With only 1 false positive and 2 false negatives, the model is well-calibrated and effective in distinguishing between classes.

6. Conclusion and Future Scope

This project demonstrates the potential of generative AI in converting textual prompts into realistic images and creating short videos efficiently with high quality by leveraging stable diffusion.Through experimentation with text-to-image and text-to-video synthesis, the project showcases how diffusion models can be adapted for dynamic content generation. The integration of deep learning models, pre-trained diffusion networks, and efficient processing pipelines ensures that the generated images and videos maintain coherence, quality, and alignment with the input prompts.This project paves the way for applications in educational content creation, creative storytelling, digital marketing and more, demonstrating the transformative impact of AI-driven media synthesis. Future research can focus on extending the project to effectively support VR and AR environments,generating 360 degrees panoramic videos for reality applications. Implementing speech-to-image/video technology allowing users to generate required images and video through spoken inputs. These enhancements will significantly improve the efficiency, usability, and scalability of the system, making it a powerful tool for AI-driven content creation

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