JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

SIGNATURE FORGERY DETECTION USING NEURAL NETWORK BASED DEEP LEARNING ALGORITHMS

[1]Meduri. Jahnavi, [2] Konakanchi. Vishnu vamsi, [3]Gundavarapu. Divya bhanu, [4] Midde. Bharath Kumar

[1,2,3,4]Student
[1]Department of Electronics and Communication Engineering,
[1] R.V.R & J.C College of Engineering, Guntur, India

Abstract : This paper presents, Signature forgery detection using neural network based deep learning algorithms, aiming to increase the accuracy in training and prediction. The proposed system employs multilayer neural networks. By leveraging the power of deep learning, the model learns complex patterns and variations in signatures, enabling accurate differentiation between authentic and forged signatures. Experimental results demonstrate the effectiveness of the proposed approach in accurately identifying forged signatures with high precision, The proposed implementation of neural network-based deep learning algorithms offers several advantages over traditional methods, including enhanced accuracy, efficiency, and scalability. By automating the signature forgery detection process, the system enables faster decision-making, reduces manual workload, and strengthens document security in digital transactions and administrative workflows. Overall, this project aims to contribute to the advancement of signature verification technologies.

***Index Terms* – Neural networks, deep learning, signature, forgery, multilayer perceptron**

I. INTRODUCTION

Signature forgery detection is a critical task in various domains such as banking, legal, and administrative sectors where document integrity is paramount. Traditional methods of signature verification often rely on manual inspection or rule-based systems, which are time-consuming, subjective, and prone to errors. With the advancements in deep learning and neural network techniques, automated approaches have emerged as a promising solution to address the challenges associated with signature forgery detection.

The implementation of neural network-based approaches involves several key steps. Firstly, a comprehensive dataset comprising genuine signatures and various types of forgeries is collected and preprocessed. The dataset is carefully curated to encompass diverse writing styles, stroke patterns, and levels of forgery sophistication, ensuring robust training and evaluation of the neural network models. Previous studies in signature forgery detection have explored various techniques, which includes photograph processing, function extraction, and system learning. Some studies have targeted on geometric features inclusive of element ratio, centroid, and curvature, even as others have spatial coverage optimization, and interference suppression. However, limited studies have explored the combination of characteristic engineering and MLP models for signature forgery detection.

While dealing with Neural networks, especially deep neural networks like multilayer perceptrons (MLPs), are capable of learning complex non-linear relationships between input features and output labels. This is particularly useful in signature forgery detection where the decision boundaries between genuine and forged signatures may be highly non-linear.

Neural networks can handle large amounts of data efficiently. This makes them suitable for signature forgery detection tasks that involve processing a large number of signature images Neural networks can adapt and learn from new data without the need for manual reprogramming. This allows the signature forgery detection system to continuously improve its performance over time as it encounters new types of forgeries or variations in signature styles. Neural networks are inherently robust to noise and variations in the input data. This is beneficial in signature forgery detection where signature images may contain noise or imperfections due to scanning. The neural network used in the signature forgery detection project, specifically the multilayer perceptron (MLP), works based on the principles of artificial neural networks, which are inspired by the structure and function of biological neurons in the human brain.

II. LITERATURE SURVEY

a) Multi-Layer Perceptron Neural Network for an Offline Signature Verification System

Nuhu, A.S., et al. (2021) proposed a signature verification model using neural networks often involve pre-processing techniques such as normalization, morphological operations, and median filtering. Feature extraction plays a crucial role in enhancing accuracy and reducing training time. This work proposes an offline signature verification method that eliminates the need for extensive trial and error in feature selection by leveraging different feature selection algorithms and pre-processing operations. By selecting the appropriate neural network architecture, each layer can learn specific aspects of the signature, leading to high accuracy in verification. The study emphasizes the importance of automated MLP artificial neural network systems in handling the complex task of signature verification. Through an end-to-end neural network architecture, the system can learn and recognize signature patterns without intervention. Experimentation with various learning rates revealed that a rate of 0.01 yielded the best accuracy 82%.

b) Development of a signature verification model based on a small number of samples

Shyang-Jye Chang, et al. (2023) initially, reviewed the structure and parameters of AlexNet for offline signature recognition. A limited number of samples were then utilized for transfer learning to distinguish between genuine and forged signatures. Data augmentation and pen pressure detection were applied to enhance sample diversity, while transfer learning aimed to improve model generalizability. Due to variations in sample sizes compared to ImageNet, adjustments were made to the network input size and neuron count. Most deep learning architectures utilize ReLU as an activation function, but this can lead to dead neurons hindering further computation. Visual evaluation indicated that a significant portion of neurons lost functionality during transfer, affecting feature transfer effectiveness. To address dead neuron issues, **tanh** activation function was employed instead of ReLU with the model achieving an average accuracy of 90.83%.

c) Digital signature Forgery Detection using CNN

Lakkoju Chandra Kiran et al. (2021) proposed an analysis of methods for ensuring the integrity of visual media, with a focus on detecting manipulated images. They explore active techniques for digital image forgery detection, particularly emphasizing digital signature and watermarking as crucial methods for verifying image authenticity. Signatures, comprising unique features, serve as significant means for authenticity verification, employed through online or offline methods. Offline verification compares current signatures with reference ones, while online verification dynamically assesses script-related knowledge for higher stability and accuracy. The authors develop an online verification system utilizing a dataset of 2000 RGB images of forged and original signatures. Preprocessing involves converting RGB to grayscale, then binary, noise removal, resizing, and feature extraction. A CNN model is trained with three input layers, three hidden layers, and an output layer, distinguishing between Genuine and Forged signatures. Loss minimization and softmax calculation ensure accuracy assessment. Evaluation demonstrates an average accuracy of 97%.

d) Offline Signature Recognition and Forgery Detection using Deep Learning

Poddar, Jivesh, et al. (2020) introduced a method utilizing CNN, the Crest-Through Method, SURF algorithm, and Harris corner detection for offline signature recognition, forgery detection, and verification. CNN and the Crest-Through Method are employed for recognition and verification, while SURF and Harris corner detection are utilized for forgery detection. Pre-processing involves noise removal, scaling, centralization, and rotation using CNN, and length-to-space ratio, width-to-space ratio, and Crest-Through parameter adjustments using the Crest-Through Method. Both methods contribute to signature recognition. Forgery detection entails Harris corner detection for comparing corner points and SURF algorithm for comparing index points with genuine signatures. The system achieves 94% accuracy in signature recognition and 85-89% accuracy in forgery detection. Though not flawless, the system proves to be valuable.

e) Bank Cheque Signature Verification System

Vaibhav Tambade et al. (2018) proposed in the system, that signatures are crucial for verification, particularly in bank cheques and legal documents. Methods were discussed to discern real signatures from duplicates, including feature extraction and comparison techniques. Utilizing Euclidean distance calculation enhances accuracy in determining signature acceptance. Image filtering techniques such as Gaussian and unsharp filters aid in noise reduction and blurriness removal. Neural networks achieve an 85% accuracy rate in processing signature inputs.

III. METHODOLOGY

A. Dataset

We conducted our experiments on a dataset comprising genuine and forged signature images of our team members. The dataset consists of 120 signature samples, with a distribution ratio of 2:1 between genuine and forged signatures.

B. Preprocessing

The first step in preprocessing involves converting RGB color images to grayscale. This conversion simplifies the image representation and reduces computational complexity. The next processing step involves converting gray scale images to binary. This conversion is achieved smoothing the image and then applying Otsu’s method of thresholding. Otsu’s method automatically determines the optimal threshold value to separate the foreground from the back ground.

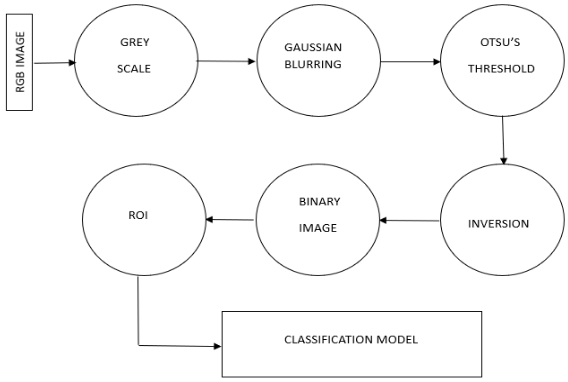

Fig -1: Preprocessing flowchart

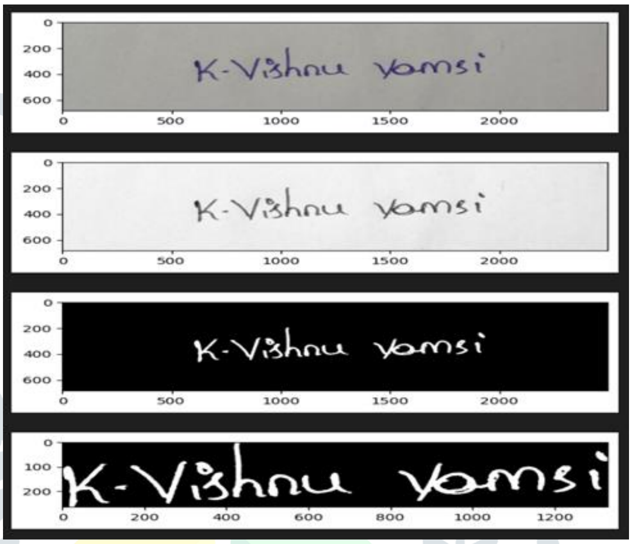

Fig -2: preprocessed signatures

C. Multilayer perceptron implementation

Multilayer Perceptron is like powerful tools for understanding complicated data. They use layers of connected parts called neurons, along with other things like weights and biases, to figure out patterns in information. With this setup, MLPs can learn to make accurate guesses about all sorts of things. Knowing how MLPs are built and how they work is really important for using them to solve real problems and make progress in AI research. Here we have used neural network with three hidden layers. The input layer is fed with the features extracted from the signature dataset. Here the activation function used is tanh and the output layer categorize a signature as either genuine or forged. After the output is produced, the error between the predicted output and the actual output is calculated using a loss function, and the weights of the connections between neurons are adjusted using adam optimization to minimize the error.

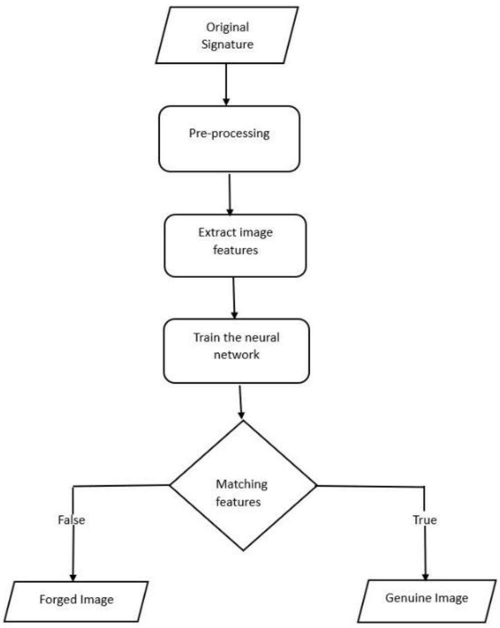

Fig-3: Flow chart

The Adam (Adaptive moment Estimation) optimizer is an adaptive learning rate optimization algorithm commonly used in neural networks, including the multilayer perceptron (MLP) used in the signature forgery detection project. It combines the benefits of two other popular optimization algorithms, namely AdaGrad and RMSProp, to provide efficient and effective optimization.
Adam maintains two vectors m and v. The initial values of two vectors and the time step t are initialized to zero. At each iteration of training Adam computes the gradient g_t.
Mathematically,

$$[g_t = \nabla_\theta f_t(\theta_{t-1})]$$

Where:

- g_t signifies the gradient at iteration t.
- $\nabla\theta$ indicates the gradient for the parameters θ.
- $f_t(\theta_{t-1})$ refers to the objective function being optimized, assessed at the parameter values from the preceding iteration θ_{t-1}.

The first moment vector, denoted as m, is updated. This process involves incorporating both the previous value of m and the most recent gradient. Similarly, the second moment vector, denoted as v, undergoes an update and is a combination of past and present squared gradients. The mathematical expressions for these updates are as follows, respectively:

$$[m_t = \beta_1 . m_{t-1} + (1-\beta_1) . g_t]$$

$$[\vartheta_t = \beta_2 . \vartheta_{t-1} + (1-\beta_2) . g_t^2]$$

Where:

- m_t and ϑ_t signifies the first and second moment vectors at time step t respectively.
- $\beta_1$and $\beta_2$stands for exponential decay rate utilized in estimating the first and second moments.
- g_t represents the gradient observed at time step t.

Since m and v start from a zero initialization, they tend to be biased towards zero, especially in the initial time steps. Adam addresses this bias by adjusting the vectors using decay rates: β_1 for m (first-moment decay rate) and β_2 for v (second-moment decay rate) and can be expressed as below

$$[\hat{m}_t = \frac{m_t}{1-\beta_1^t}]$$

$$[\hat{\vartheta}_t = \frac{\vartheta_t}{1-\beta_2^t}]$$

Where:

- m_t and ϑ_t are the first and second vectors at at iteration t.
- β_1 and β_2 are the decay rates of m and v at time t.

The last stage involves updating the model parameters, constituting the actual optimization process by adjusting the parameters towards minimizing the loss function. This update employs the adaptive learning rates computed in preceding stages and could be expressed as follows

$$[\theta_{t+1} = \theta_t - \frac{\alpha \cdot \hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}]$$

Where:

- θ_{t+1} denotes the parameters after the update
- θ_t signifies the current parameters before the update.
- α serves as the learning rate, a pivotal hyperparameter that determines the size of the step taken towards minimizing the loss function.
- $\hat{m}_t$ represents the bias-corrected first momen estimation of the gradients
- $\hat{\vartheta}_t$ signifies the bias-corrected second moment estimation of the gradients.
- ϵ stands as a small scalar value added to
prevent division by zero and uphold numerical stability.

IV. RESULTS AND DISCUSSION

The experimental results demonstrate the effectiveness of our proposed approach in detecting signature forgeries. Our models achieved an average accuracy of over 95.8% on both training and validation datasets. We evaluated the generalization capability of our models by testing them on unseen datasets with signatures from different individuals and diverse writing styles. Despite the variability in writing characteristics, our accurately detected forgeries with minimal degradation in performance. We meticulously analysed the false positive and false negative rates of our models to assess their reliability in real-world scenarios. The negligible occurrence of false positives and false negatives underscores the robustness and precision of our signature forgery detection system analysis was conducted to evaluate the impact of dataset size and diversity on the performance of our models. We observed that increasing the size and diversity of the training data consistently led to incremental improvements in detection accuracy

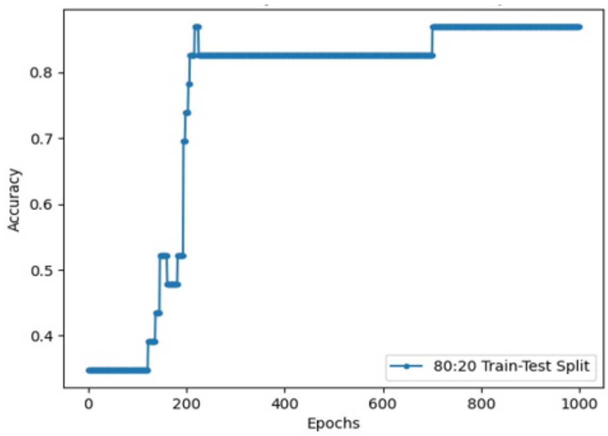

Fig-4: Graph representing accuracy

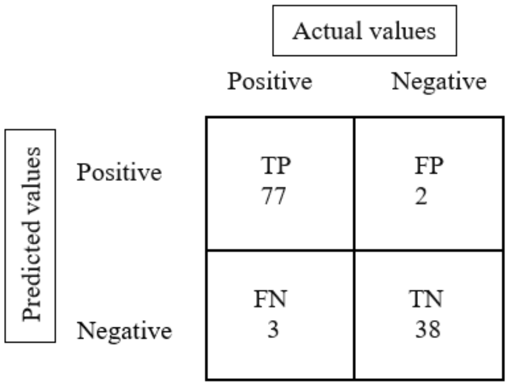

Fig-5: Confusion Matrix

REFERENCES

[1] Sandesh Kandel. 2023 Advancing Security Machine Learning-Based Signature Forgery Detection in Document Authentication Systems. E-ISSN: 2582-2160.

[2] Shyang-Jye Chang, Tai-Rong Wu. 2023. Development of a signature verification model based on a small number of samples.

[3] Shraddha Jagtap, Sejal Kalyankar, Tejal Jadhav and Ashwini Jarali. 2022. Signature Verification And Detection System. International Journal of Recent Scientific Research Vol. 13, Issue, 06 (A), pp. 1412-1418.

[4] Ms. Manjula Subramaniam, Teja E, N Arpith Mathew.2022. Signature Forgery Detection Using Machine Learning. e-ISSN: 2582-5208.

[5] anaz bin ashraf. 2022. signature forgery detection. National College of

[6] Lakkoju Chandra Kiran, Gorantla Akhil Chowdary, Manchala Shalem Raju, Kondaveeti Gopi Krishna. 2021. Digital signature Forgery Detection using CNN. e-ISSN: 2395-0056

[7] Nuhu, A.S., Adam, N., Gadam, A.M. and Dajab, D.D. 2021. Multi-Layer Perceptron Neural Network for an Offline Signature Verification System. Nigerian Research Journal of Engineering and Environmental Sciences 6(1) 2021 pp. 293-298

[8] Jivesh Poddar, Vinanti Parikh, Santosh Kumar Bharti. 2020. Offline Signature Recognition and Forgery Detection Using Deep Learning.

[9] S. Priya, A.K.R.N.Supreeth, K. Somesh, A. Hruday Kumar. 2019. Signature Verification System using Different Algorithms. ISSN: 2278-3075

[10] Vaibhav Tambade, Priyanka Varma, Aditya Sonawale. 2018. Bank Cheque Signature Verification System. ISSN (Online): 2581-5782

[11] Jerome Gideon S, Anurag Kandulna, Aron Abhishek Kujur, Diana A, Kumudha Riamond. 2018. Handwritten Signature Forgery Detection Using Convolution Neural Networks. ScienceDirect Procedia Computer Science 143 (2018) 978–987

[12] Abdul Salam Shah, Masood Shah, Muhammad Fayaz, Fazli Wahid, Hira Khalid Khan and Asadullah Shah. 2017. Forensic Analysis of Offline Signatures Using Multilayer Perceptron and Random Forest. nternational Journal of Database Theory and Application Vol.10, No.1

[13] Sounak Deya, Anjan Dutta, J. Ignacio Toledo, Suman K.Ghosh, Josep Llado´s, Umapada PalSigNet: Convolutional Siamese Network for writer Independent Online Signature Verification. Elsevier Ltd.