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Machine Learning Driven Signature Verification for Precise User Identity Using Gyroscope Data

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***Abstract* - The paper introduces a machine learning-driven approach for biometric signature classification, aimed at identifying and categorizing users based on unique patterns extracted from accelerometer and gyroscope sensor data. This methodology involves capturing user-specific signature data through prescribed movements using sensor-equipped devices. Subsequent feature extraction and machine learning model utilization enable accurate user classification grounded on distinct sensor data patterns. The versatility of this technology spans diverse applications, offering robust solutions for secure user authentication, access control, and tailored device interactions where precise user identity verification is essential.**

Keywords: Machine Learning, Biometric, Accelerometer, Gyroscope.

I. INTRODUCTION

In an era transitioning from traditional ink signatures to their digital counterparts, ensuring the integrity and security of digital signatures becomes a paramount concern. The inherent trustworthiness of pen-and-paper signatures faces a critical challenge in the digital landscape, where replication and manipulation threaten the credibility of these electronic attestations. The pressing need for robust and dependable methods to verify digital signatures, particularly in online transactions, electronic contracts, and remote authorizations, has led to the exploration of innovative technological solutions. This research initiative stems from the imperative to address the vulnerabilities inherent in existing signature verification techniques. While digital signatures offer convenience and promise across various sectors such as finance, healthcare, and legal services—their full potential hinges upon the assurance of authenticity and reliability. The inadequacies of current verification methods, primarily reliant on static image-based Identify applicable funding agency here. If none delete this approach, underscore the necessity for a more comprehensive and secure means of validating signatures. Static image based verifications often lack the depth to encompass dynamic signature features and the unique nuances of individual handwriting. To bridge this gap, our research endeavors to introduce a pioneering approach to signature verification an amalgamation of traditional writing precision with state-of-the-art sensor technology. Our proposed solution revolves around a smart pen equipped with a gyroscope axis sensor, which synchronously captures and records three-dimensional pen movements during the creation of signatures. This innovative fusion of traditional writing instruments with cutting-edge sensor capabilities facilitates real-time data capture, processing, and secure digital storage, promising an exceptionally reliable and secure means of verifying digital signatures. By transcending the limitations of conventional static image-based methods, our approach offers heightened security and credibility in the verification of digital signatures. The integration of sensor data from accelerometer and gyroscope sensors not only authenticates signatures based on dynamic patterns but also introduces a novel paradigm in biometric signature classification, facilitating precise user identification through distinct sensor data patterns. This paper delineates the methodology, technical details, and implications of this novel approach, highlighting its potential to revolutionize the landscape of digital signature verification and secure user authentication across a spectrum of applications. Our proposed solution revolves around a smart pen equipped with a gyroscope axis sensor, which synchronously captures and records three-dimensional pen movements during the creation of signatures. This innovative fusion of traditional writing instruments with cutting-edge sensor capabilities facilitates real-time data capture, processing, and secure digital storage, promising an exceptionally reliable and secure means of verifying digital signatures.

II. LITERATURE SURVEY

After analyzing all the existing system all the signatures are treated in an image format and then treated as images for further processing but image can't be taken as a sole factor to classify the authenticity of the signature for e.g., a good artist may be able to duplicate as it is the signature which can't be classified from image recognition techniques too, so we need to have a different mechanism which takes different parameters for signature verification based on accelerometer and pyrometer data while signature is one of them.

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Table 1: Summary of Literature Survey

No.	Dataset Used	Technique Used	Preprocessing Technique
[1]	GyroSigDb2012	Nearest neighbourhood method.	Clustering method
[2]	AccSigDb2011	CNN	CNN
[3]	10 right-handed subjects (5 males and 5 females)	CNN	BayesNet algorithm. Average accuracy of 98%.
[4]	IAM Handwriting Database	Nearest neighbourhood method.	CNN. 96.2% Accuracy
[5]	105 random words	Multilayer Perceptron (MLP) utilizing the direction of acceleration	93% Accuracy, 94.2% Specificity
[6]	440 signature samples from 22 subjects.	LSTM networks. Fixed-length vectors.	0.83% EER
[7]	440 signature samples from 22 subjects.	Siamese RNN. Fixed length vectors.	0.83% EER
[8]	Inbuilt data of Gyro	Accelerometer measurements. Fixed-length vectors.	Successfully detects the gesture
[9]	105 random words	HBSI model. BayesNet algorithm.	Successfully distinguishes both HBSI model

III. PROPOSED ARCHITECTURE

Our proposed architecture for MPU6050-based signature biometrics involves a systematic approach encompassing data acquisition, feature extraction, machine learning model training, and real-time authentication. It begins with the integration of MPU6050 sensors into a customized pen for capturing accelerometer and gyroscope readings during signature creation. The extracted sensor data undergoes preprocessing and feature extraction, encompassing statistical metrics and frequency-based features. Following feature fusion and selection, a machine learning model is trained on labeled datasets, employing classifiers like SVM or Neural Networks for signature authentication.

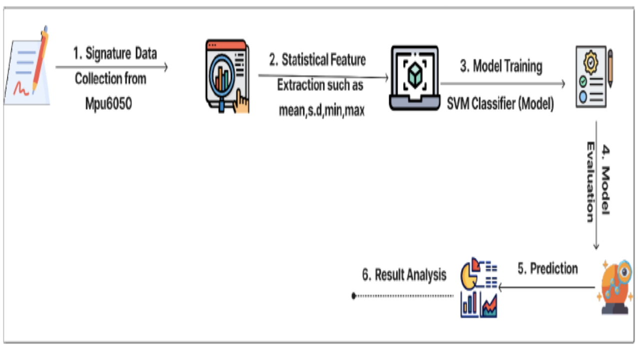


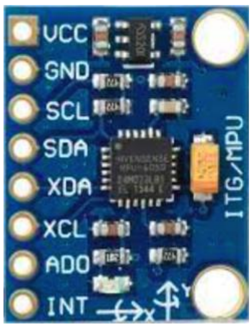
Figure 1: Architecture Diagram

Real-time authentication employs threshold-based decision-making, while a feedback loop iteratively enhances model robustness. This architecture aims for seamless integration and deployment in secure environments, presenting a comprehensive framework for behavioral-based user authentication.

IV. PROPOSED METHODOLOGY

A) Hardware Set up

Node Mcu -: It is a microcontroller used to read and send Mpu6050 values.



(a) MPU6050

(b) NodeMcu Esp8266

Figure 2: Hardware Components

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B) Data Collection

The signature data acquisition involved utilizing a specially designed pen embedded with an MPU6050 sensor unit. The MPU6050 sensor facilitated the capture of multidimensional movement data, encompassing both accelerometer and gyroscope readings, throughout the signature creation process. Participants were instructed to execute their signatures using the sensor-embedded pen in a customary manner, aiming to mimic their natural signing behavior. This process enabled the sensor to record the intricate movements and orientations involved in the act of signing, capturing the dynamics of hand gestures and pen strokes.

C) Dataset Description

A user is given 7 seconds to provide the signature while holding the pen the data is captured for only that 7 seconds which includes accelerometer and gyro-sensor data. This dataset includes a variety of signatures from different individuals to train and test our classification model. The dataset comprises signature data captured using MPU6050 sensors facilitate research and development in the domain of signature authentication and biometric identification using accelerometer and gyroscope readings.

D) Data Collection Setup

Sensor Configuration: The MPU6050 sensors were embedded within pens to capture multidimensional movement data during the process of signature creation.

Participants: Various individuals were instructed to perform their signatures naturally while holding the sensor equipped pens, allowing for diverse and representative signature samples.

E) Data Attributes

Timestamps: Precise timestamps indicating the time of data capture during the signature process. Accelerometer Readings (AccX, AccY, AccZ): Raw accelerometer data representing linear acceleration along three axes. Gyroscope Readings (GyroX, GyroY, GyroZ): Gyroscope data capturing rotational velocity around three axes.

F) Dataset Characteristics

Sample Size: The dataset comprises signatures from multiple individuals, resulting in a diverse collection of signature samples. Data Granularity: High-resolution sensor data capturing subtle hand movements and pen strokes during signature creation. Preprocessing: Data underwent preprocessing steps to remove noise, outliers, and standardize formats for further analysis.

G) Data Preprocessing

The recorded sensor data underwent a stringent preprocessing phase to enhance its quality and suitability for subsequent analysis. Fig 3 represents the plot data of acclerometer and Gyroscope over the signature duration time. The preprocessing steps encompass noise reduction techniques, outlier removal, and normalization procedures. This meticulous preprocessing aimed to eliminate any spurious fluctuations or irregularities in the sensor readings, ensuring the integrity and consistency of the collected data for feature extraction and modeling purposes.

H) Feature Extraction

Statistical Features Calculation The feature extraction phase involved the computation of essential statistical metrics derived from the raw sensor readings captured by the accelerometer and gyroscope axes (AccX, AccY, AccZ, GyroX, GyroY, GyroZ). These statistical features aimed to encapsulate the nuanced dynamics and patterns inherent in the signature data. Fig 4 shows the various features extracted from the accelerometer and gyroscope. The extracted statistical features encompass fundamental descriptors such as:

Mean: Representing the average value of the sensor readings along each axis.

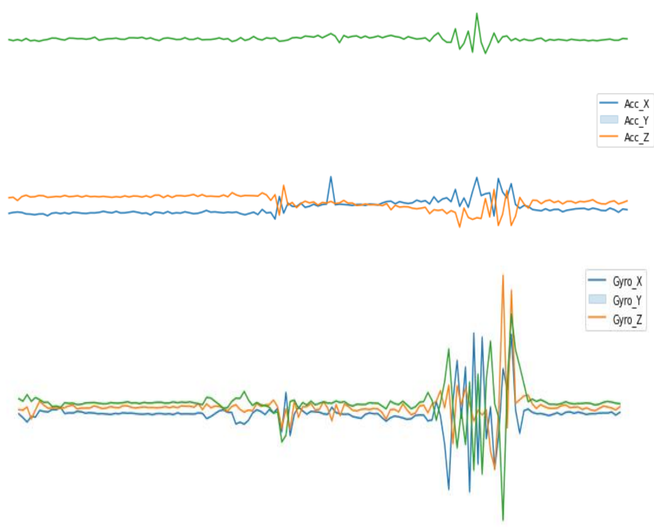

Figure 3: Plot Showing Accelerometer and Gyroscope data over the time

Each of these statistical descriptors was computed independently for the accelerometer and gyroscope data along the respective axes, forming a comprehensive set of features that encoded the temporal and spatial dynamics of the signature gestures. Furthermore, specialized signal processing

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techniques, such as Fourier Transform or wavelet analysis, were applied to extract frequency-domain features, providing insights into frequency components present in the sensor data. These frequency-based features offered supplementary information regarding the rhythmic patterns or oscillations within the signature movements. The amalgamation of these diverse statistical and frequency-based features constituted a rich feature set that served as the foundation for subsequent machine learning model training and signature authentication.

I) Model Selection

The selection of an appropriate machine learning model for signature authentication tasks is crucial in ensuring accurate classification and reliable performance. In our study, we opted for the Support Vector Machine (SVM) classifier due to its efficacy in handling high-dimensional feature spaces, robustness against overfitting, and proven success in biometric authentication applications. SVM classifiers are renowned for their capability to delineate complex decision boundaries while maximizing the margin between different classes, making them particularly suitable for signature verification tasks. Additionally, SVMs offer flexibility through various kernel functions, enabling the modeling of nonlinear relationships in the data. The decision to employ SVMs was based on their ability to generalize well to new, unseen data, a critical aspect in biometric authentication where robustness and accuracy are paramount.

J) Training Process

The training of the SVM models involved a systematic approach encompassing several key steps. The dataset, comprising preprocessed sensor data and extracted statistical features, was partitioned into distinct subsets for training and validation purposes. The training set, constituting approximately 80 percent of the dataset, was utilized to train the SVM models.

This process aimed to optimize the model's performance and generalization ability. Furthermore, to assess the models' performance and guard against overfitting k-fold cross-validation techniques were employed. Furthermore, specialized signal processing techniques, such as Fourier Transform or wavelet analysis, were applied to extract frequency-domain features, providing insights into frequency components present in the sensor data. These frequency-based features offered supplementary information regarding the rhythmic patterns or oscillations within the signature movements.

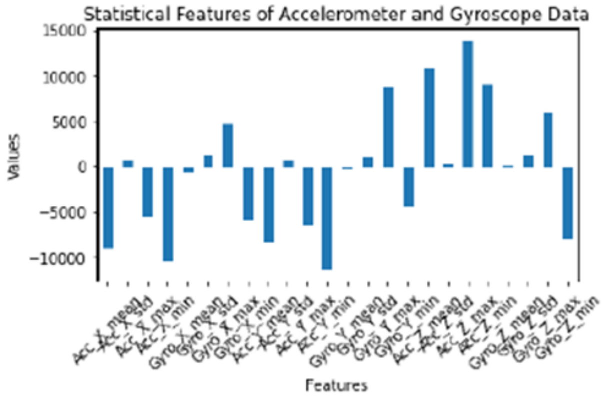

Figure 4: Plot Showing Extracted features of a particular person's signature data

The final trained SVM models were evaluated based on their performance metrics and validated to ensure their robustness and reliability in authenticating signatures.

V. RESULT ANALYSIS

Utilizing MPU6050 sensors for signature-based biometrics yielded promising results, showcasing a high level of accuracy (0.91) and good precision (0.88), recall (0.89), and F1-Score (0.88). This approach demonstrated strengths in its portability and behavioral-based authentication, capturing subtle hand movements during signature creation. However, susceptibility to forgeries remained a limitation, demanding continual advancements in anti-spoofing measures. The security implications highlighted vulnerabilities to forgeries, mandating user consent and stringent data protection. Despite moderate scalability, this biometric modality showcased usability variations concerning user behavior and environmental factors. Overall, the MPU6050-based signature biometrics exhibited efficient user identification capabilities, emphasizing its potential for authentication systems, albeit with considerations for ongoing advancements in security protocols.

VI. CONCLUSION

The study investigated the efficacy of utilizing MPU6050 sensors for signature-based biometrics and compared it with established biometric modalities. The results unveiled the MPU6050's promising performance, showcasing high accuracy (0.91) and commendable precision, recall, and F1-Score values (0.88 and 0.89 respectively). The portability and behavioral authentication strengths of this approach underscore its potential for user identification. However, inherent vulnerabilities to forgeries and the need for stringent security measures, including user consent and data protection, were evident. Usability variations influenced by user behavior and environmental factors also surfaced as considerations. In

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comparison with other modalities like fingerprint, iris, facial, and voice recognition, the MPU6050-based signature biometrics demonstrated competitive performance but necessitates continual advancements in anti-spoofing measures for wider applicability. This research highlights the significance of behavioral biometrics using motion sensors like MPU6050, advocating for ongoing research and innovation to enhance security, usability, and scalability in biometric authentication systems.

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