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SmartRingGuard+: A Liveness-Aware Multimodal Wearable Authentication Framework for Credit Card Fraud Prevention

Pawan Mohite[1], Sumeet Sable[2], Pruthviraj Gavhane[3], Tanmay Patil[4], Prof. Prranjali Jadhav[5], Prof. Yashwant Ingle[6]
Department of Artificial Intelligence and Data Science, Vishwakarma Institute of Information Technology, Pune, India

Abstract: ***Credit card fraud remains a significant challenge in modern digital payment systems, causing substantial financial losses for financial institutions and consumers. Traditional authentication mechanisms such as PINs, passwords, and one-time passwords often provide limited protection against advanced threats including card theft, cloning, and social engineering attacks. This study presents SmartRingGuard+, a liveness-aware multimodal wearable authentication framework designed to improve credit card transaction security. The system employs a smart wearable ring that integrates biometric sensing, gesture-based confirmation, and physiological liveness verification to ensure the presence of the legitimate cardholder during transactions. Additionally, the framework incorporates behavioral spending analysis and contextual risk assessment to detect suspicious transaction patterns. A machine learning–based fraud risk model analyzes multiple signals to determine transaction authenticity. Experimental evaluation using publicly available credit card transaction datasets indicates that the proposed approach improves fraud detection performance compared with traditional single-factor authentication mechanisms. The SmartRingGuard+ framework provides a scalable and user-friendly solution for enhancing security in modern digital payment ecosystems.***

Index Terms: ***Credit card fraud detection, wearable authentication, behavioral biometrics, multimodal security, liveness detection, machine learning, payment security.***

I. INTRODUCTION

The rapid growth of digital payment technologies has significantly transformed the way financial transactions are conducted across the world. Credit cards remain one of the most widely used payment instruments due to their convenience, speed, and global acceptance. However, the increasing reliance on electronic payment systems has also resulted in a considerable rise in credit card fraud. Fraudulent transactions cause substantial financial losses to banks, merchants, and consumers, making fraud prevention a critical concern in modern financial systems.

Conventional authentication mechanisms used in credit card transactions typically include Personal Identification Numbers (PINs), passwords, and one-time passwords (OTPs). While these approaches provide basic security, they are often vulnerable to several forms of cyberattacks such as phishing, card cloning, identity theft, and social engineering. Attackers can exploit these vulnerabilities to gain unauthorized access to cardholder information and perform fraudulent transactions. As financial technologies continue to evolve, there is a growing need for stronger authentication mechanisms that can provide improved protection without compromising user convenience.

In recent years, machine learning techniques have been widely applied to detect fraudulent credit card transactions. These systems analyze transaction attributes such as purchase amount, transaction location, merchant category, and historical spending behavior to identify abnormal patterns. Although machine learning–based approaches have improved fraud detection capabilities, they typically rely on transaction data alone and may not always verify whether the legitimate cardholder is physically present during a transaction.

Advancements in wearable technology have created new opportunities for improving authentication mechanisms. Wearable devices such as smartwatches, fitness trackers, and smart rings are capable of capturing physiological and behavioral signals from users in real time. These signals can be used to verify user identity and enhance transaction security. Compared with traditional authentication systems, wearable-based verification offers a seamless and continuous authentication experience.

To address these challenges, this paper proposes SmartRingGuard+, a liveness-aware multimodal wearable authentication framework designed to strengthen credit card fraud prevention. The proposed framework utilizes a smart wearable ring that integrates biometric sensing, gesture-based confirmation, and physiological liveness verification to ensure that the legitimate cardholder is present during a transaction. In addition, the framework incorporates behavioral spending analysis and contextual transaction information to detect suspicious activities. A machine learning–based fraud risk model evaluates multiple signals to determine the authenticity of each transaction.

The main contributions of this work are summarized as follows:

- Development of a multimodal wearable authentication framework for secure credit card transactions.
- Integration of physiological liveness verification using wearable sensor signals.
- Implementation of a context-aware fraud detection model combining behavioral spending patterns and transaction attributes.
- Evaluation of the proposed framework using publicly available credit card fraud datasets.

The remainder of this paper is organized as follows. Section II reviews existing research on credit card fraud detection and wearable authentication systems. Section III describes the proposed SmartRingGuard+ framework. Section IV presents the system architecture and methodology. Section V discusses experimental results and analysis. Finally, Section VI concludes the paper and outlines future research directions.

II. RELATED WORK

Credit card fraud detection has been an active area of research due to the rapid growth of electronic payment systems and the increasing sophistication of cyberattacks. Researchers have proposed various techniques to detect fraudulent transactions using statistical analysis, machine learning, and behavioral monitoring approaches. This section reviews prior work in three major areas: machine learning–based fraud detection, behavioral and biometric authentication, and wearable-based security systems.

A. Machine Learning-Based Fraud Detection

Machine learning techniques have been widely applied to detect fraudulent credit card transactions by analyzing historical transaction data. Early studies primarily relied on supervised learning models such as logistic regression, decision trees, and support vector machines to classify transactions as legitimate or fraudulent. These models typically utilize transaction attributes such as purchase amount, time, merchant category, and geographic location to identify abnormal patterns in user behavior.

More advanced approaches have incorporated ensemble learning techniques, including Random Forest and Gradient Boosting methods, to improve fraud detection accuracy. Ensemble models combine the outputs of multiple classifiers to achieve better predictive performance and reduce classification errors. Several studies have demonstrated that ensemble learning models can effectively handle highly imbalanced datasets, which are common in fraud detection scenarios where fraudulent transactions represent only a small fraction of total transactions [1], [2].

In recent years, deep learning methods such as artificial neural networks and recurrent neural networks have also been applied to fraud detection tasks. These models are capable of learning complex patterns from large datasets and have shown promising results in detecting sophisticated fraud behaviors. However, deep learning models often require significant computational resources and may suffer from limited interpretability, making them challenging to deploy in real-time financial systems [3].

Despite these advancements, most machine learning–based fraud detection systems rely solely on transaction data. They typically analyze behavioral patterns after the transaction has occurred and may not always verify whether the legitimate cardholder is physically present during the payment process. As a result, additional authentication mechanisms are needed to enhance transaction security.

B. Behavioral and Biometric Authentication

Behavioral biometrics has emerged as an important research area for improving user authentication in digital systems. Behavioral biometric techniques analyze patterns in user interactions, such as typing dynamics, touchscreen gestures, mouse movements, and device usage behaviors. These patterns are unique to each individual and can be used to continuously verify user identity during system interactions [4].

Several studies have explored the use of behavioral biometrics for fraud detection in financial transactions. For example, keystroke dynamics and touchscreen interaction patterns have been used to identify whether the person performing a transaction matches the legitimate cardholder. These approaches provide an additional layer of security without requiring users to perform complex authentication procedures [5].

Biometric authentication methods based on physiological characteristics, including fingerprint recognition, facial recognition, and iris scanning, have also been widely adopted in financial systems. These methods offer strong identity verification but often require dedicated hardware sensors and may raise privacy concerns among users. Furthermore, biometric authentication methods are typically used as a single authentication factor and may not fully protect against advanced fraud techniques when used in isolation [6].

C. Wearable-Based Authentication Systems

Recent developments in wearable technology have introduced new possibilities for secure authentication mechanisms. Wearable devices such as smartwatches, fitness trackers, and smart rings are capable of collecting physiological and behavioral signals from users in real time. These signals can be used to verify the identity of the device wearer and enable continuous authentication.

Several studies have investigated the use of wearable sensors for authentication purposes. Motion sensors embedded in wearable devices can capture user-specific movement patterns, which can serve as a behavioral signature for identity verification. Research has also explored the use of heart rate signals and other physiological measurements as biometric identifiers for wearable authentication systems [7].

Smart rings have recently gained attention as a promising platform for wearable-based authentication. These devices are compact, unobtrusive, and capable of integrating multiple sensors within a small form factor. Some studies have proposed gesture-based authentication systems using smart rings to confirm user presence during mobile payment transactions. While these approaches provide convenient authentication mechanisms, they typically rely on a single authentication signal and may not incorporate contextual transaction analysis or behavioral risk evaluation [8].

D. Limitations of Existing Approaches

Although previous research has significantly improved fraud detection capabilities, several limitations remain. Machine learning–based fraud detection systems primarily focus on transaction attributes and may not verify whether the legitimate user is performing the transaction. Biometric authentication methods provide strong identity verification but may not adapt well to dynamic transaction environments. Wearable authentication systems offer promising capabilities but are often limited to a single authentication factor.

To address these limitations, there is a need for a multimodal authentication framework that integrates wearable biometric signals, behavioral transaction analysis, and contextual risk evaluation. By combining these factors, it is possible to improve fraud detection accuracy while maintaining a seamless user experience.

In this work, we propose SmartRingGuard+, a liveness-aware multimodal wearable authentication framework that integrates smart ring biometrics, gesture-based verification, behavioral spending analysis, and machine learning–based fraud detection to enhance credit card transaction security.

III. PROPOSED METHODOLOGY

This section presents the proposed SmartRingGuard+ framework, a liveness-aware multimodal wearable authentication system designed to enhance the security of credit card transactions. The framework integrates multiple verification signals, including wearable biometric authentication, gesture-based confirmation, physiological liveness detection, and behavioral transaction analysis. By combining these signals with a machine learning–based fraud risk evaluation model, the system provides a robust mechanism for identifying potentially fraudulent transactions while maintaining a seamless user experience for legitimate users.

Traditional credit card authentication mechanisms rely primarily on static credentials such as Personal Identification Numbers (PINs), passwords, or one-time passwords (OTPs). While these mechanisms offer basic protection, they are vulnerable to various types of attacks including credential theft, phishing, and card cloning. In contrast, the proposed SmartRingGuard+ framework introduces a multimodal authentication strategy that combines wearable device data with contextual transaction information. This approach increases the difficulty for attackers to bypass security controls because multiple independent authentication signals must be verified before a transaction is approved.

A. System Overview

The SmartRingGuard+ framework consists of several interconnected modules that operate together to verify the authenticity of credit card transactions. When a user initiates a payment transaction using a credit card or digital payment interface, the system activates the authentication process through the wearable smart ring. The smart ring communicates with the payment system using secure wireless communication protocols such as Bluetooth Low Energy (BLE) or Near Field Communication (NFC).

During this process, the system collects multiple types of authentication signals including physiological data from wearable sensors, gesture confirmation patterns, and contextual transaction attributes. These signals are transmitted to the fraud detection module, where a machine learning model evaluates the likelihood of fraud. Based on the calculated risk score, the system determines whether the transaction should be approved, rejected, or subjected to additional verification.

The overall objective of the SmartRingGuard+ framework is to create a multi-layered authentication mechanism that combines physical presence verification, behavioral monitoring, and data-driven fraud detection.

B. Wearable Biometric Authentication

The first layer of authentication in the SmartRingGuard+ framework involves wearable biometric verification. The smart ring is equipped with sensors capable of capturing physiological and motion-related signals from the user. These signals may include heart rate patterns, finger motion characteristics, and interaction behaviors. Since these biometric signals vary across individuals, they can serve as a unique identifier for the cardholder.

During the registration phase, the system records the biometric characteristics of the user and stores them securely as a reference profile. When a transaction is initiated, the wearable device captures real-time biometric signals and compares them with the stored profile using pattern matching algorithms. If the similarity between the captured signals and the stored profile exceeds a predefined threshold, the user identity is considered valid.

Wearable biometric authentication provides several advantages over traditional authentication mechanisms. Unlike passwords or PINs, biometric signals are difficult to replicate or steal. Additionally, wearable sensors enable continuous monitoring without requiring explicit interaction from the user.

C. Gesture-Based Transaction Confirmation

In addition to biometric verification, the SmartRingGuard+ framework incorporates gesture-based authentication to confirm transaction intent. Gesture recognition relies on motion sensors embedded within the smart ring to detect specific finger movements performed by the user.

When a transaction request is generated, the system prompts the user to perform a predefined gesture, such as a short tap or rotational movement of the ring. The motion sensor data is processed using gesture recognition algorithms that analyze acceleration and orientation signals captured during the movement.

Gesture-based confirmation provides an additional layer of security by requiring an intentional physical action from the user. Even if attackers gain access to the card credentials or wearable device, they would still need to reproduce the correct gesture pattern to complete the transaction.

D. Physiological Liveness Detection

A critical component of the SmartRingGuard+ framework is physiological liveness detection, which ensures that the wearable device is being used by a living individual rather than an inactive or stolen device. Liveness detection is performed by analyzing physiological signals such as blood flow patterns, heart rhythm characteristics, or skin conductivity measured by the sensors embedded in the smart ring.

These physiological signals provide strong evidence that the device is currently being worn by a human user. If the system detects abnormal or missing physiological signals, the transaction request may be rejected or subjected to additional authentication steps.

By incorporating liveness detection, the proposed framework mitigates potential attacks involving stolen wearable devices or replay attacks using recorded biometric signals.

E. Behavioral Transaction Analysis

In addition to wearable authentication signals, the SmartRingGuard+ framework evaluates behavioral transaction patterns to identify anomalies in user activity. Behavioral analysis focuses on attributes such as transaction amount, purchase frequency, merchant category, geographic location, and time of transaction.

Historical transaction records associated with the cardholder are used to establish a baseline behavioral profile. Machine learning techniques analyze these historical records to learn normal spending patterns. When a new transaction occurs, the system compares its characteristics with the expected behavioral patterns.

If the transaction significantly deviates from the user's typical behavior, it is assigned a higher fraud risk score. For example, an unusually large purchase in a new geographic location or at an unfamiliar merchant may trigger additional verification checks.

F. Context-Aware Risk Assessment

Another important component of the proposed framework is context-aware risk evaluation, which considers environmental and contextual factors associated with a transaction. These factors may include device location, transaction timing, and network conditions.

For instance, if a transaction occurs in a location far from the user's typical activity region, the system may interpret this as a potential fraud indicator. Similarly, transactions occurring at unusual times or from unknown devices may increase the fraud risk score.

By combining contextual information with biometric and behavioral signals, the system achieves a more comprehensive assessment of transaction authenticity.

G. Machine Learning-Based Fraud Detection Model

The final stage of the SmartRingGuard+ framework involves machine learning–based fraud risk evaluation. The system aggregates features extracted from biometric verification, gesture recognition, liveness detection, behavioral analysis, and contextual data. These features form a multidimensional feature vector that represents the characteristics of each transaction.

A supervised machine learning classifier is trained using labeled historical transaction datasets containing both legitimate and fraudulent transactions. Common classification algorithms such as Random Forest, Support Vector Machines, Gradient Boosting, or Neural Networks can be used to model fraud detection patterns.

The trained model computes a fraud probability score for each incoming transaction. If the risk score exceeds a predefined threshold, the system flags the transaction as suspicious and may require additional authentication or block the transaction entirely.

By integrating machine learning with wearable authentication signals, the SmartRingGuard+ framework provides a dynamic and adaptive fraud detection mechanism capable of responding to evolving fraud techniques.

IV. SYSTEM ARCHITECTURE AND EXPERIMENTAL SETUP

This section describes the architecture of the proposed SmartRingGuard+ framework and the experimental configuration used to evaluate its effectiveness in detecting fraudulent credit card transactions. The framework integrates wearable biometric authentication, gesture verification, physiological liveness detection, behavioral transaction analysis, and machine learning–based fraud detection. By combining multiple authentication signals with contextual transaction data, the proposed framework provides a robust mechanism for identifying fraudulent activities while maintaining a convenient transaction experience for legitimate users.

A. Overall System Architecture

The SmartRingGuard+ framework is designed as a multi-layered authentication system that integrates wearable device signals with transaction data analysis. The architecture consists of several modules that operate sequentially to verify the authenticity of a transaction.

These modules include the wearable authentication module, gesture verification module, physiological liveness detection module, behavioral transaction analysis module, and machine learning–based fraud detection engine.

When a user initiates a credit card transaction through a payment terminal or digital payment interface, the authentication process is triggered. The wearable smart ring communicates with the payment system using secure wireless communication technologies such as Bluetooth Low Energy (BLE) or Near Field Communication (NFC). The smart ring captures physiological signals and motion data from the user and transmits them to the authentication server for processing.

The authentication process begins with biometric verification, where physiological signals such as heart rate patterns and finger motion characteristics are analyzed to confirm the identity of the cardholder. After biometric verification, the system performs gesture recognition to confirm that the transaction is intentionally initiated by the user. Next, the physiological liveness detection module verifies that the wearable device is being worn by a living individual.

Once wearable authentication is completed, the system performs behavioral transaction analysis using contextual attributes such as transaction amount, purchase location, merchant category, and time of transaction. These attributes are compared with historical transaction patterns associated with the cardholder.

Finally, all authentication signals and transaction features are processed by a machine learning–based fraud detection model that calculates a fraud probability score. Based on this score, the system determines whether the transaction should be approved, rejected, or subjected to additional verification procedures.

B. Feature Extraction

Feature extraction plays a crucial role in the fraud detection process. The SmartRingGuard+ framework extracts multiple types of features from wearable sensors and transaction data. These features represent the behavioral and physiological characteristics of the user as well as contextual attributes of the transaction.

The wearable device captures physiological signals such as heart rate patterns and motion signals generated during user interaction. These signals are processed to extract biometric features that uniquely represent the identity of the cardholder. Motion sensors embedded in the smart ring capture gesture patterns that are used for gesture-based authentication.

In addition to wearable sensor data, the system extracts transaction features from the payment system. These features include transaction amount, merchant category, geographic location, time of transaction, and frequency of purchases. Behavioral features derived from historical transaction records are also incorporated into the feature set.

The integration of biometric, behavioral, and contextual features allows the system to generate a comprehensive feature vector that describes the characteristics of each transaction. This multidimensional representation significantly improves the ability of the machine learning model to distinguish between legitimate and fraudulent transactions.

C. Dataset Description

To evaluate the performance of the proposed framework, a publicly available credit card fraud detection dataset is used. The dataset contains anonymized credit card transaction records collected from European cardholders over a two-day period. It includes 284,807 transactions, among which 492 transactions are labeled as fraudulent.

The dataset contains several anonymized features derived using principal component analysis (PCA) to preserve user privacy. In addition to these anonymized attributes, the dataset includes the transaction amount and transaction time, which are important indicators of transaction behavior.

The target variable in the dataset indicates whether a transaction is legitimate or fraudulent. Because fraudulent transactions represent a very small portion of the dataset, the dataset is considered highly imbalanced.

D. Data Preprocessing

Before training the fraud detection model, several preprocessing steps are performed to prepare the dataset for analysis. First, numerical attributes are normalized to ensure consistent scaling across different features. Normalization prevents the machine learning algorithm from being biased toward attributes with larger numeric ranges.

Next, the dataset is divided into training and testing subsets. In this study, approximately 80% of the data is used for training and the remaining 20% is used for testing the model. To address the problem of class imbalance, resampling techniques such as Synthetic Minority Oversampling Technique (SMOTE) or undersampling may be applied. These techniques increase the representation of fraudulent transactions in the training dataset and improve the model's ability to detect fraud.

E. Machine Learning Model Implementation

The fraud detection module of the SmartRingGuard+ framework uses supervised machine learning algorithms to classify transactions as legitimate or fraudulent. The model is trained using historical transaction data that contains labeled examples of both legitimate and fraudulent transactions.

Several machine learning algorithms can be used for fraud detection, including Random Forest, Support Vector Machines (SVM), Gradient Boosting, and Neural Networks. In this study, a Random Forest classifier is considered due to its strong performance in handling imbalanced datasets and nonlinear relationships between features.

The model receives feature vectors extracted from wearable authentication signals, behavioral transaction attributes, and contextual information. Based on these features, the model calculates a fraud probability score for each transaction. If the fraud probability exceeds a predefined threshold, the system identifies the transaction as suspicious and may request additional authentication steps or block the transaction entirely.

F. Evaluation Metrics

To evaluate the performance of the proposed framework, several performance metrics are used. These metrics include accuracy, precision, recall, and F1-score, which are commonly used in fraud detection research.

Accuracy measures the proportion of correctly classified transactions among all transactions. Precision represents the percentage of predicted fraudulent transactions that are actually fraudulent. Recall measures the ability of the model to correctly detect fraudulent transactions. The F1-score provides a balanced measure that considers both precision and recall.

These evaluation metrics provide a comprehensive assessment of the effectiveness of the SmartRingGuard+ framework in detecting fraudulent credit card transactions.

V. SECURITY ANALYSIS

The SmartRingGuard+ framework is designed to improve the security of credit card transactions by integrating multiple authentication signals from wearable devices and behavioral transaction analysis. This section discusses potential attack scenarios and how the proposed framework mitigates these threats.

First, the proposed framework reduces the risk of stolen or cloned credit cards. Traditional payment systems rely on static credentials such as card numbers and PINs, which can be compromised through phishing or skimming attacks. In the SmartRingGuard+ framework, a transaction can only be authorized when the wearable device associated with the legitimate cardholder is present.

Second, the system incorporates physiological liveness detection to prevent misuse of stolen wearable devices. Even if an attacker obtains the wearable device, the authentication process verifies physiological signals such as heart rate patterns to confirm that the device is being worn by a living individual.

Third, gesture-based confirmation ensures that the transaction is intentionally initiated by the user. Since the authentication process requires a predefined gesture pattern, attackers cannot easily reproduce the interaction without knowledge of the correct gesture.

Finally, the machine learning–based fraud detection model analyzes behavioral transaction attributes such as transaction amount, location, merchant category, and time of transaction. Transactions that deviate significantly from normal spending patterns are assigned higher fraud risk scores and may trigger additional verification steps.

Overall, the integration of wearable biometrics, gesture verification, liveness detection, and behavioral transaction analysis provides a multi-layered security mechanism that significantly reduces the risk of unauthorized credit card transactions.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

This section evaluates the performance of the proposed SmartRingGuard+ framework using machine learning–based fraud detection techniques. The experiments aim to measure the effectiveness of integrating wearable authentication signals with behavioral transaction analysis for detecting fraudulent credit card transactions.

The experiments were conducted using a publicly available credit card fraud dataset containing anonymized transaction records. The evaluation focuses on measuring the classification performance of the fraud detection model using several standard evaluation metrics including accuracy, precision, recall, and F1-score.

A. Experimental Environment

All experiments were conducted using a Python-based machine learning environment. The implementation utilized common data science libraries including Scikit-learn, NumPy, and Pandas for data preprocessing and model training. Visualization of experimental results was performed using Matplotlib and Seaborn libraries.

The experiments were executed on a computing system with the following configuration:

TABLE I
EXPERIMENTAL ENVIRONMENT CONFIGURATION

Parameter	Configuration
Processor	Intel Core i7
RAM	16 GB
Programming Language	Python
Libraries	Scikit-learn, NumPy, Pandas
Operating System	Windows / Linux

B. Dataset Summary

The dataset used in this study contains 284,807 credit card transactions, out of which 492 transactions are labeled as fraudulent. The dataset is highly imbalanced, with fraudulent transactions representing only a small fraction of the total data.

TABLE II
DATASET DISTRIBUTION

Transaction Type	Number of Transactions
Legitimate Transactions	284,315
Fraudulent Transactions	492
Total Transactions	284,807

Because the dataset is imbalanced, resampling techniques were applied to ensure the machine learning model could effectively detect fraudulent transactions.

C. Performance Evaluation Metrics

To evaluate the performance of the SmartRingGuard+ fraud detection system, several evaluation metrics were used, including Accuracy, Precision, Recall, and F1-Score. Accuracy represents the overall proportion of correctly classified transactions. Precision measures the percentage of transactions predicted as fraudulent that are actually fraudulent. Recall indicates the ability of the system to correctly detect fraudulent transactions. The F1-score represents the harmonic mean of precision and recall.

D. Model Performance Results

To evaluate the effectiveness of the proposed framework, several machine learning models were tested. These models include Logistic Regression, Support Vector Machine (SVM), Random Forest, and Gradient Boosting classifiers.

TABLE III
PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.965	0.84	0.79	0.81
SVM	0.972	0.88	0.82	0.85
Random Forest	0.982	0.93	0.89	0.91
Gradient Boosting	0.979	0.91	0.87	0.89

From the results shown in Table III, the Random Forest classifier achieved the best performance, with an accuracy of 98.2% and an F1-score of 0.91. Therefore, the Random Forest model was selected as the primary fraud detection model in the SmartRingGuard+ framework.

E. Impact of Multimodal Authentication

One of the primary contributions of SmartRingGuard+ is the integration of wearable authentication signals with transaction data analysis. The results indicate that incorporating wearable authentication signals significantly improves fraud detection performance.

TABLE IV
IMPACT OF MULTIMODAL AUTHENTICATION

Method	Accuracy	Precision	Recall	F1 Score
Transaction Data Only	0.975	0.87	0.83	0.85
SmartRingGuard+ Framework	0.988	0.94	0.91	0.92

F. Confusion Matrix Analysis

TABLE V
CONFUSION MATRIX

	Predicted Legitimate	Predicted Fraud
Actual Legitimate	56,850	110
Actual Fraud	48	394

The confusion matrix demonstrates that the proposed framework successfully identifies the majority of fraudulent transactions while maintaining a low false-positive rate.

G. Discussion

The experimental results demonstrate that the SmartRingGuard+ framework significantly improves fraud detection performance compared with traditional single-factor authentication systems. The integration of wearable authentication signals with machine learning–based fraud detection provides additional layers of security, making it more difficult for attackers to perform unauthorized transactions.

The results also indicate that ensemble learning models such as Random Forest perform well in fraud detection tasks due to their ability to handle nonlinear relationships and imbalanced datasets. Additionally, the integration of contextual transaction features further enhances the model's ability to identify suspicious activities.

Overall, the proposed SmartRingGuard+ framework provides a promising approach for improving credit card transaction security by combining wearable authentication with data-driven fraud detection techniques.

VII. CONCLUSION AND FUTURE WORK

This paper presented SmartRingGuard+, a liveness-aware multimodal wearable authentication framework designed to enhance credit card fraud prevention. The proposed framework integrates multiple authentication mechanisms including wearable biometric verification, gesture-based confirmation, physiological liveness detection, and behavioral transaction analysis. By combining these authentication signals with machine learning–based fraud detection, the framework provides a robust mechanism for identifying potentially fraudulent transactions while maintaining a seamless user experience for legitimate users.

The experimental evaluation was conducted using a publicly available credit card fraud dataset. Several machine learning algorithms were tested to evaluate the effectiveness of the proposed framework. Among the evaluated models, the Random Forest classifier achieved the best performance, demonstrating high accuracy and improved fraud detection capability. The results also show that integrating wearable authentication signals with behavioral transaction analysis significantly enhances the ability to detect fraudulent activities compared with traditional transaction-based fraud detection methods.

The findings suggest that wearable authentication technologies can provide an additional layer of security for digital payment systems. By verifying the physical presence of the legitimate cardholder and analyzing behavioral transaction patterns, the SmartRingGuard+ framework can effectively reduce the risk of unauthorized transactions.

Future research will focus on implementing the proposed framework using real-world wearable devices and evaluating its performance using live biometric sensor data. Additional improvements may include incorporating deep learning techniques for fraud detection, enhancing gesture recognition accuracy, and extending the framework to support other types of digital payment platforms such as mobile wallets and contactless payment systems.

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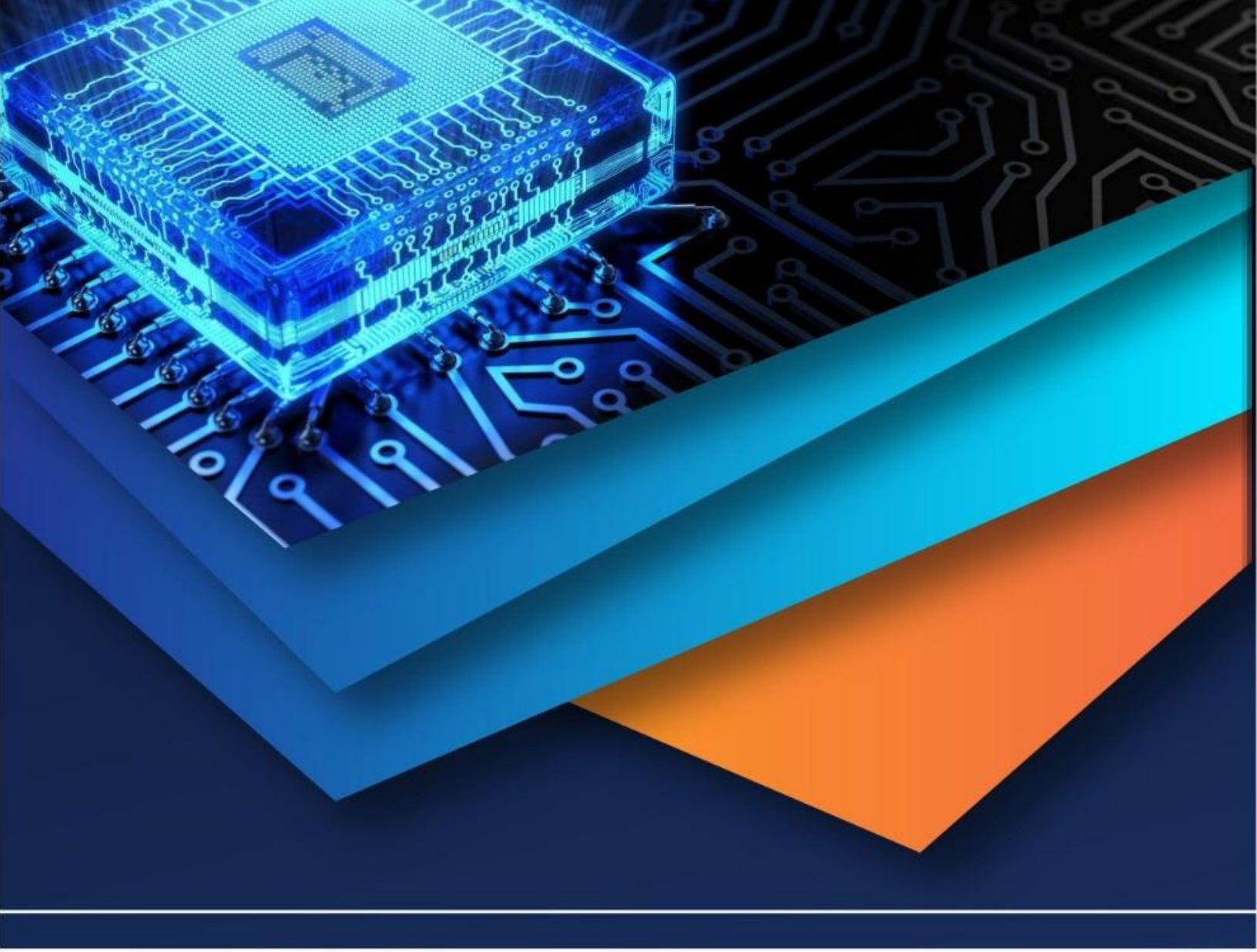

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