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Online Banking System with AI-Based Fraud Detection

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Abstract – The rapid development of online banking services has significantly reshaped the financial industry, and while it has offered greater convenience. It has also created greater risks of fraud. Conventional anti-fraud systems, which are mostly rule-based, are not very effective in keeping up with the ever-changing nature of fraud attempts. The fraud detection system in the financial sector has been facing a major challenge in dealing with the increasing rate of fraud. In order to address this problem, we have proposed a hybrid model for fraud detection in the context of online banking. In our proposed model, we have used supervised classification, anomaly detection, and sequence-based behavioral analysis for the detection of fraud in the context of online banking. We have used various machine learning algorithms like Random Forest, Isolation Forest, and Long Short-Term Memory (LSTM) for the proposed system. We have achieved an impressive 96% accuracy, with a precision, recall, and F1-score of 95%, thereby outperforming the conventional system. We have demonstrated that our proposed system can be used to improve security as well as user experience in the context of digital banking transactions. We have discussed the limitations of the conventional fraud detection system as well as the potential advancements in the proposed system.

Index Terms – AI-driven fraud detection, hybrid model, machine learning, online banking, sequence-based analysis, anomaly detection, Random Forest, Isolation Forest, Long Short-Term Memory (LSTM), real-time fraud detection, financial security, transaction monitoring, behavioral analysis, precision, recall, F1-score.

I. INTRODUCTION

The banking sector has experienced a tremendous change due to the development and use of digital technology and internet-based services. Traditionally, banking operations have been conducted through physical interactions, but the operations have been transformed and are currently conducted online. Through online banking, customers can access a range of services, including account management, payment transfers, bill payment, loan applications, and transaction monitoring, among others. Nevertheless, in addition to these advantages, the development of online banking has also created major security issues. While financial institutions are expanding their digital banking facilities, they are also exposing themselves to cyber threats and fraudulent practices. These online banking facilities handle very sensitive information regarding their customers' finances and personal lives. Cybercriminals often target these facilities to commit fraudulent practices such as phishing, identity theft, unauthorized transactions, and hacking. These fraudulent practices have also increased in recent years. These fraudulent practices not only lead to monetary losses but also harm the reputation of these institutions [1].

Typically, the fraud detection mechanisms adopted by the traditional banking system are based on static rule-based approaches. These fraud detection mechanisms usually work based on specific rules and limitations, such as the amount of transaction and the location of the transaction, among others. Although the rule-based approach can be useful for the detection of simple and known types of fraud, it does not have the ability to cope with dynamic and sophisticated types of fraud approaches adopted by the attackers. This is because the attackers are always changing their approaches, making it difficult for the static fraud detection mechanisms to identify the sophisticated, sequential, and behavioral types of fraud transactions, which leads to the detection of either no fraud or false-positive fraud transactions [2][3]. In order to overcome these drawbacks, Artificial Intelligence (AI) and Machine Learning (ML) technologies are being incorporated in the latest banking systems. AI-based fraud detection systems process large amounts of transactional data, learn user behavior patterns, and detect anomalies that differ from normal patterns. Unlike traditional systems, machine learning-based fraud detection systems improve over time and are better at adapting to new patterns of fraud. These smart systems improve the accuracy of fraud detection in real-time, reducing the overall risk associated with fraud [4][5].

Recent studies have demonstrated the effectiveness of AI-based detection systems in achieving better accuracy in fraud identification and system robustness compared to traditional methods [6]. Systematic reviews have proven the effectiveness of ML and DL methods in identifying complex fraud behaviors and handling imbalanced transaction data [7][8]. Supervised learning methods such as logistic regression and random forests are popular due to their interpretability and reliability [9]. Deep learning methods such as Long Short-Term Memory (LSTM) and convolutional neural networks have been proven to achieve better accuracy in handling sequential transaction data [10][11]. Some studies have demonstrated the effectiveness of hybrid approaches to fraud detection systems, which combine supervised learning, unsupervised learning, and deep learning methods [12]. Other papers describe the implementation of sophisticated ML models in detecting financial fraud using advanced algorithms such as SVMs, ensembles, and neural networks to achieve higher accuracy and lower false alarm rates [13]. Literature survey papers have also validated that AI-based systems perform better than traditional methods

in detecting known and unknown fraud patterns [14]. Recent research also discusses issues concerning explainability and fairness in AI models that are critical in a banking domain [15].

Our main contributions are as follows:

- We propose a new AI-based hybrid model for fraud detection using supervised classification, anomaly detection, and sequence-based behavioral analysis. This multi-layer approach improves the capabilities of real-time fraud detection and is significantly more effective than traditional rule-based systems.
- This model utilizes different machine learning algorithms, namely Random Forest, Isolation Forest, and LSTM, to overcome the limitations of using a single algorithm. This allows our model to effectively identify new and existing fraud patterns with fewer false positives.
- This is possible because our system is able to learn from the transactions and adapt to new forms of fraud in real-time. This is an important feature of our model, as it is able to provide a dynamic solution for dealing with new forms of fraud.
- Furthermore, our model is able to balance security and user experience by reducing false positives and increasing accuracy for fraud detection.
- Possible Future Improvements
- One of the possible improvements for our model is incorporating privacy-preserving AI and blockchain technology, which would take it beyond what is possible with traditional fraud detection models.

II. LITERATURE SURVEY

The use of AI and ML in the context of online banking has revolutionized the manner in which financial organizations detect fraud. As traditional approaches to detecting fraud, such as rule-based systems, are unable to keep up with the changing dynamics of fraud, AI and ML have become an integral part of the process. This review aims to highlight the recent developments in sequence-based, hybrid, and anomaly-based detection for the context of online banking. Zhang et al. [16] discuss a real-time framework for fraud detection in online banking systems, which incorporates deep learning techniques to improve the effectiveness of the detection system. In this framework, the researchers used the LSTM technique to analyze the transactions and understand the temporal dependencies of the user. This is a more effective way of analyzing the transactions, as the traditional systems are unable to analyze the transactions as a whole, which makes them unable to detect complex patterns of fraud.

The application of AI in ensuring security in online transactions in the domain of digital banking has been researched by Ahmed et al. [17] In this research, the authors have discussed the security issues faced by online platforms due to cybercrime and fraud. Here authors have discussed the application of various machine learning techniques, including Random Forests, Logistic Regression, and SVMs, for detecting fraudulent activity. This research has emphasized the importance of ensemble learning over individual learning. In addition, the authors have emphasized the significance of incorporating anomaly-based techniques to detect new forms of fraud. Carcillo et al. [18] have proposed a hybrid framework for fraud detection using a combination of supervised learning and unsupervised learning techniques. This paper resolves the imbalanced nature of the dataset, in which the number of fraudulent transactions is

much smaller compared to the total number of transactions. The proposed method uses a combination of Random Forest classification and Isolation Forest anomaly detection. The results of this paper show the effectiveness of using a hybrid model of artificial intelligence in the detection of online banking fraud.

Kumar et al. [19] discuss the concept of behavioral analytics-based fraud detection. The approach is based on the analysis of the behavior of users during transactions. It focuses on the detection of anomalies in the behavior of users over a period of time. Using the Random Forest and Gradient Boosting algorithms, the approach is able to classify the transactions into normal and fraudulent categories using the behavioral attributes of the users. The approach is effective in the detection of complex fraud scenarios. In the research paper by Liu et al. [20], the authors examine the effectiveness of using anomaly detection methods to improve the security of online bank transactions. In this paper, the authors propose the use of Isolation Forest and One-Class SVM, which are used to identify anomalous transactions without using any information about known fraudulent transactions. This is especially important in identifying new patterns of fraud that are not included in the known patterns of fraud. In this way, the use of anomaly detection methods and supervised learning methods creates a more adaptive model that is effective in identifying known and new patterns of fraud.

Roy and Sun [21] discuss the possibility of using deep learning algorithms for the detection of fraud using sequence data. The authors specifically discuss the possibility of using LSTM networks for the detection of fraud. Using the LSTM network for the detection of fraud is beneficial because it considers the sequence of user transactions. By doing so, the model is able to detect complex fraud patterns, which other machine learning algorithms cannot do. In their paper, Carcillo et al. [22] presented a scalable real-time fraud detection framework for high-volume financial transaction systems that employ Random Forest techniques and data streaming processing to achieve real-time processing with high accuracy in fraud detection systems. The paper highlights the significance of addressing class imbalance in fraud data sets, where data resampling techniques are presented to improve the performance of the Random Forest algorithm. The paper proves that scalability in AI systems is critical in online banking systems, where transaction volume is increasing steadily.

In the research paper by Dal Pozzolo et al. [23], the authors discuss the performance of ensemble learning techniques for the detection of credit card frauds. In the paper, the authors have used the Random Forest and Gradient Boosting techniques for the classification of the data, which increases the accuracy of the classification, especially for imbalanced data sets. From the research paper, it can be concluded that the ensemble learning technique offers a more reliable solution for the detection of fraud compared to other techniques. Bahnsen et al. [24] propose a cost-sensitive learning method for fraud detection in financial transactions. Unlike other methods that emphasize the importance of accuracy, Bahnsen et al. emphasize the reduction of the cost of misclassification errors. By including the cost of transactions, the decision trees proposed by Bahnsen et al. prioritize high-risk fraud transactions, reducing the amount of financial losses compared to other methods.

In the research paper, Liu, Ting, and Zhou [25] proposed the Isolation Forest algorithm for anomaly detection in financial transactions. In this approach, the isolation method is applied to detect anomalies. In the isolation method, the data set is split, and the anomalies that require fewer splits for isolation are identified. This research paper proves the feasibility of the Isolation Forest approach for detecting anomalies in financial transactions without any training data on anomalies. It is recommended that the anomaly detection approach be integrated with classification for a more comprehensive solution.

TABLE I: Overview of Existing Works

Reference	Model Used	Research Gap	Limitations
[16]	LSTM networks for sequence-based fraud detection	Lack of real-time fraud detection in traditional rule-based systems; adapting AI to evolving fraud tactics	High computational cost due to deep learning; requires large datasets for training; difficulty in model interpretability.
[17]	Random Forest, Logistic Regression, SVM, ensemble learning	Limited application of ensemble learning and multi-factor authentication in fraud detection frameworks	Ensemble models can be computationally expensive; not all fraud types can be detected by the models.
[18]	Random Forest and Isolation Forest (Hybrid model)	Insufficient detection of fraud in imbalanced datasets; integrating anomaly detection with classification	High false positive rate; hybrid model may require extensive tuning and may not generalize well across all fraud types.
[19]	Random Forest, Gradient Boosting, Behavioral Analytics	Static fraud detection approaches fail to capture complex fraud schemes; lack of behavioral-based models	Limited scope of behavioral features; not all patterns captured, requiring more dynamic learning strategies.
[20]	Isolation Forest, One-Class SVM for anomaly detection	Inability of supervised models to detect new fraud patterns without labeled data	Anomaly detection can be sensitive to noise; may not detect all fraudulent activities if no historical fraud patterns exist.
[21]	LSTM networks for detecting sequential fraud patterns in transaction data	Traditional models fail to detect gradual and sophisticated fraud in sequential transaction data	LSTM models require large datasets; training these models can be computationally expensive and time-consuming.
[22]	Random Forest, streaming data processing	Real-time fraud detection and the challenge of processing large transaction volumes efficiently	High latency when scaling for large data streams; imbalanced data can affect model performance.
[23]	Ensemble learning (Random Forest, Gradient Boosting)	Limited effectiveness of single classifiers in fraud detection, particularly for rare fraud instances	Ensemble models can be resource-intensive; might have difficulty in handling unseen fraud patterns.
[24]	Cost-sensitive decision trees	Existing models focus primarily on accuracy, ignoring the financial impact of false positives	Complex decision-making based on cost could lead to increased complexity in real-world implementations.
[25]	Isolation Forest for anomaly detection	Anomaly detection algorithms have limited success without labeled fraud instances	Sensitivity to noise in transaction data; may miss certain fraud patterns that don't fit known criteria.

III. MODULES

Login Screen Interface: The Login Screen is the first point of interaction for users with the Online Banking System. This part of the system is designed to be convenient and secure. There are areas in the interface for entering the Login ID and Password. These are the primary tools that users utilize to verify their identities. There is also a "Remember me" feature that enables users to save their login information to make subsequent logins more convenient. This feature can prove to be very helpful for regular users of the service who regularly access their accounts. For an added layer of security, users can select other

authentication options like Face ID and Passcode, which allow users to authenticate using their face and enter their passcodes instead of entering passwords.

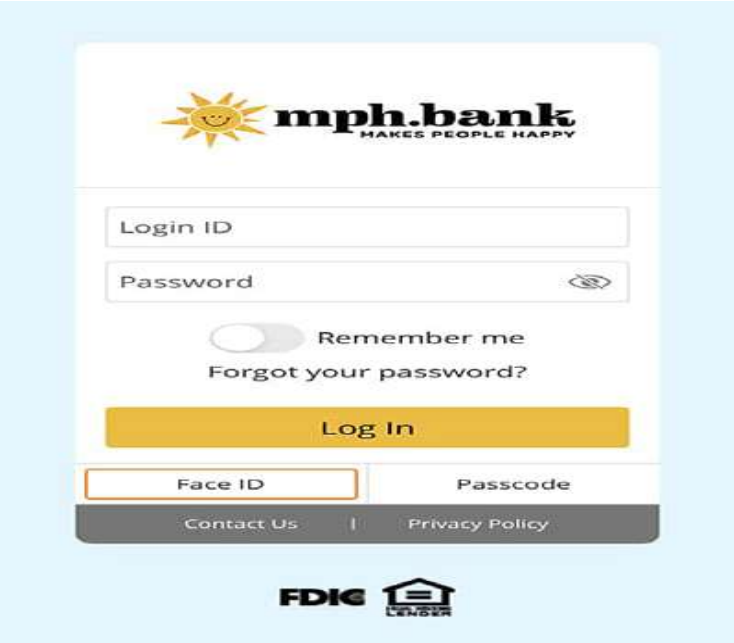

Fig.1: Login Interface

This way, users have the flexibility to access their accounts in various ways, according to their convenience, whether they are using a mobile device or prefer to use traditional ways of authentication. The eye icon next to the password input box allows users to view and hide their passwords as they enter them, which enhances the user experience. Moreover, in case users forget their passwords and login credentials, the "Forgot your password?" link allows users to reset their passwords and ensures they never get locked out of their accounts. At the bottom of the screen, users can find hyperlinks to the Privacy Policy and Contact Us pages, which provide users with information regarding the banking system.

Dashboard Interface: Once the user has logged in, they are then taken to the Dashboard Interface, which is essentially the core of the banking experience. Here, the user is given a general overview of their current financial situation through the display of key statistics such as Total Balance and Total Savings. These statistics are then updated in real time to ensure that the user is given the latest information. The Income and Expense figures are also given to the user in order to ensure that they are aware of their spending patterns. This includes a bar graph that visually represents the user's income and expenses over the last week, making it easy for the user to make adjustments based on the visual representation of the data. This visual representation of data is helpful for users who are more visual than numerical. Users are also encouraged to set goals, such as saving for a vacation, and track their progress towards these goals.

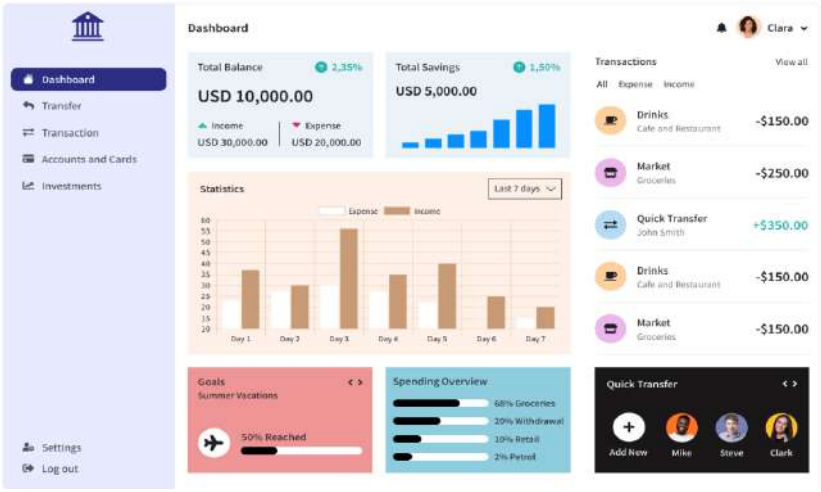

Fig. 2: Dashboard Interface

This is displayed by the percentage of the goal that has been reached, encouraging the user to keep up the good work. In addition to the user's income and expenses, the dashboard also includes a detailed Spending Overview, where the user can see exactly how much of a certain amount they are spending, such as groceries, retail, and withdrawals.

Account and Payment Interface: The Account and Payment Interface is where users can control their transactions and accounts. On this screen, users can see their current balance in real-time. This allows them to have instant information about their available funds. The screen also includes a transaction list that shows recent transactions made by the user. These could include deposits, withdrawals, and transfers. The Payment Screen is user-friendly and has a numeric keypad that enables the user to easily input figures during a transaction. The user has the option to choose cards to be used during the transaction. These cards include the work card and the travel card. These cards are also accessible on the user interface. After the user has chosen the card to be used in the transaction, he or she can then proceed to input the transaction amount.

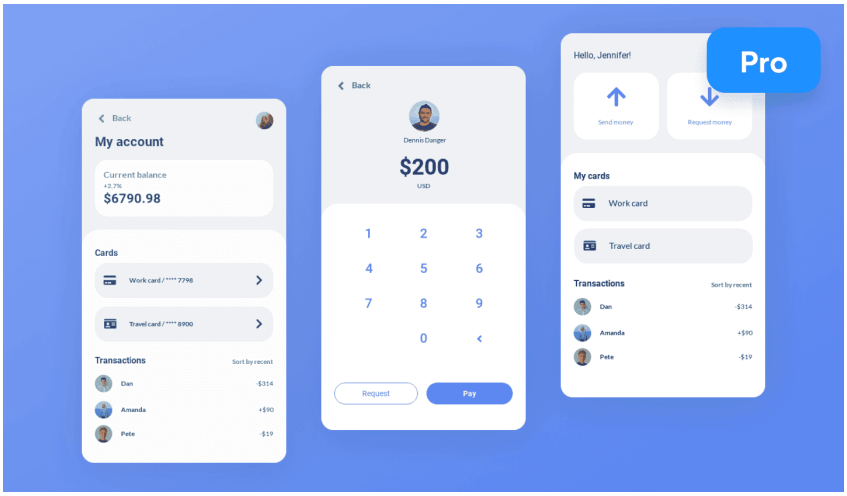

Fig. 3: Account and Payment Interface

However, the system has ensured that it is secure through authentication using a password and biometric scan such as Face ID and fingerprint scan. This ensures that only authorized people have access to the user's money, especially in situations where the user is transferring money and also paying bills.

Email Verification Process: The Email Verification Process, as depicted in Figure 4, is a security feature integrated into the online banking system. This feature ensures that only authorized users are able to carry out certain sensitive functions, such as changing settings and performing transactions. For instance, when a user wants to carry out a sensitive function, he/she will be prompted to input a verification code that will be sent to their email account. This is an additional security feature that ensures that the user is the legitimate owner of the account. In the verification input page, there are fields that are used to insert the verification code. There is also a resend verification code option, which is used to resend the verification code if there are issues with the email. This ensures that the communication is secure and encrypted, and the user's information is not compromised. This feature ensures that if a fraudster gets access to the user's login information, they cannot use the account.

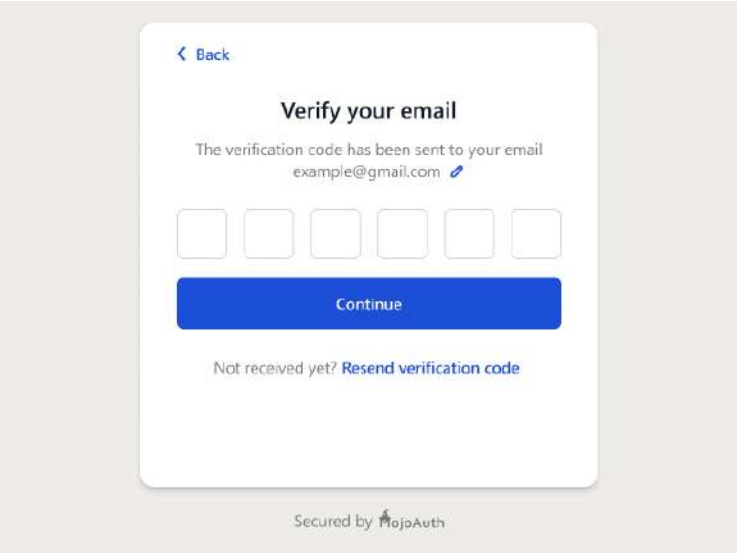

Fig. 4: Email Verification Process

Transaction History Page: The transaction history page, as shown in Figure 5, enables users to have a clear and organized record of all the transactions that have taken place. This page has been designed to provide users with a clear view of all the transactions that have taken place, including the ones that have been completed over a given period of time. In this case, users are able to view different transactions based on the period of time or the nature of the transaction, making it easier for them to locate specific transactions without having to go through the entire list of transactions, which might be very lengthy. In addition, the user can download the transaction history in the form of a PDF or CSV file, which can be useful for future use, such as for tax purposes. The Status of the transaction, such as "Transaction is booked," enables users to have information regarding the progress of the transaction, helping them stay updated regarding the current state of the transaction.

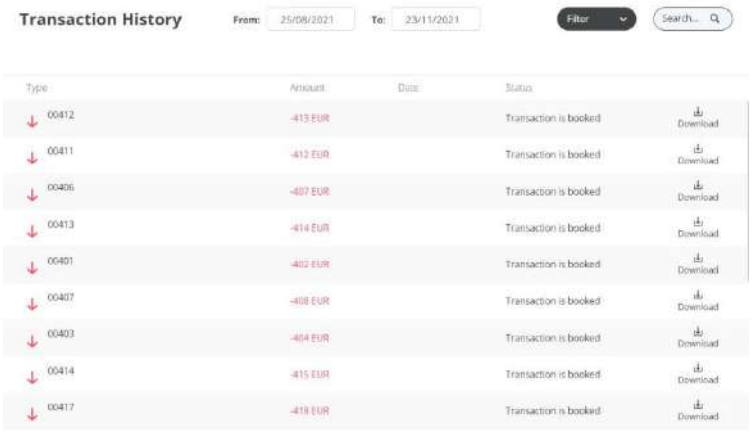

Fig. 5: Transaction History Page

IV. PROPOSED METHODOLOGY

A. Dataset Description

In this study, we used the Credit Card Fraud Detection Dataset provided by the Machine Learning Group at Université Libre de Bruxelles and shared on Kaggle, a community-driven platform that hosts various machine learning and data science datasets and competitions. In the machine learning community, this dataset is more commonly referred to as the Credit Card Fraud Detection Dataset (MLG-ULB). It includes real European card holder transactions starting from September 2013.The dataset includes 284,807 transactions in total, with 492 of them being flagged as fraudulent transactions. Therefore, this dataset is significantly imbalanced and can be used to test and validate the performance of various ML and DL models in detecting and preventing fraudulent activities in a real-world scenario. The dataset includes 31 attributes in total.

Out of them, 28 attributes (V1 to V28) are anonymized principal components using PCA to avoid leaking information about the customers while retaining the essential characteristics of the transactions. In addition to that, there are two other attributes: Time, which refers to the time in seconds since the first transaction in the dataset, and Amount, which refers to the amount of the transactions. The Class feature is a binary feature where 1 represents a fraudulent transaction and 0 represents a normal transaction. Due to its imbalance and anonymous nature, it is a standard dataset for testing and validating the effectiveness of various machine learning and deep learning architectures for identifying and preventing financial fraud. Additionally, it is suitable for testing hybrid and sequence-based AI algorithms for smart online banking security systems.

B. Data Preprocessing

To ensure the reliability and robustness of the proposed framework of Intelligent Online Banking Fraud Detection, we have incorporated a data preprocessing pipeline before training the model. We have first checked the dataset for completeness. Column-wise data was analyzed.

$$M = \max\left(\sum_{i=1}^{n} \mathbb{I}(x_{ij} = \Phi)\right)$$

The indicator function is represented as I(·), and x_{ij} represents the value of the feature j in the ith transaction. It was indicated that there are no missing values in the dataset, and this was represented as M = 0. Therefore, there is no need to perform imputation, and the distribution of the transactions will remain as before. Next, the class distribution was examined to quantify imbalance. Let N define the total number of transactions and N_f the number of fraudulent samples. The fraud ratio was calculated as:

$$R_f = \frac{N_f}{N} \times 100\%$$

A severely skewed binary classification problem is indicated by the observed fraud proportion of roughly 0.17%. Such an imbalance can deteriorate minority class identification performance and skew learning algorithms in favor of the majority class.

The target vector and feature matrix were divided in order to obtain the data ready for supervised learning:

$$X = \{V_1, V_2, \ldots\ldots\ldots, V_{28}, Time, Amount\}$$

$$y \in \{0,1\}$$

where, $y_i = 1$ describe fraudulent transactions and $y_i = 0$ defines legitimate transactions.

Next, stratified sampling was used to divide the dataset into subsets for training and validation:

$$(X_{train}, X_{val}, y_{train}, y_{val} = StratifiedSplit\ (X, y, \alpha)$$

where the validation proportion is represented by α=0.2. The initial class distribution is maintained across splits through stratification:

$$P(y = 1)_{train} \approx P(y = 1)_{val} \approx P(y = 1)_{original}$$

In order to address the severe imbalance of the training set, SMOTE was employed solely for the training set. For a minority class instance x_i and one of its k-nearest neighbors x_{zi}, a new synthetic instance x_{new} can be created along the line between them as follows:

$$x_{new} = x_i + \lambda(x_{zi} - x_i), \qquad \lambda \sim U(0,1)$$

Along the line segments connecting nearby fraud samples in feature space, this interpolation technique creates additional instances of the minority class. The resampled dataset that was produced:

$$(X_{res}, y_{res})$$

gaining a balanced class distribution:

$$N_f^{res} = N_{nf}^{res}$$

where, N_f^{res} and N_{nf}^{res} describe the number of fraudulent and non-fraudulent samples after oversampling.

Through the combination of stratified splitting and synthetic minority augmentation, the preprocessing step ensures that the final output of our hybrid sequence-based fraud detection model is learned on a dataset that is balanced and representative of the original data. This maximizes the model's response to fraud while maintaining its ability to generalize on new data during the validation step.

C. Proposed Model

The proposed Intelligent Online Banking System will incorporate a hybrid model of Artificial Intelligence that combines classification, anomaly detection, and sequence-driven behavior analysis in a single entity to make decisions. Its service-oriented approach ensures security, performance, and real-time detection of fraudulent activities.

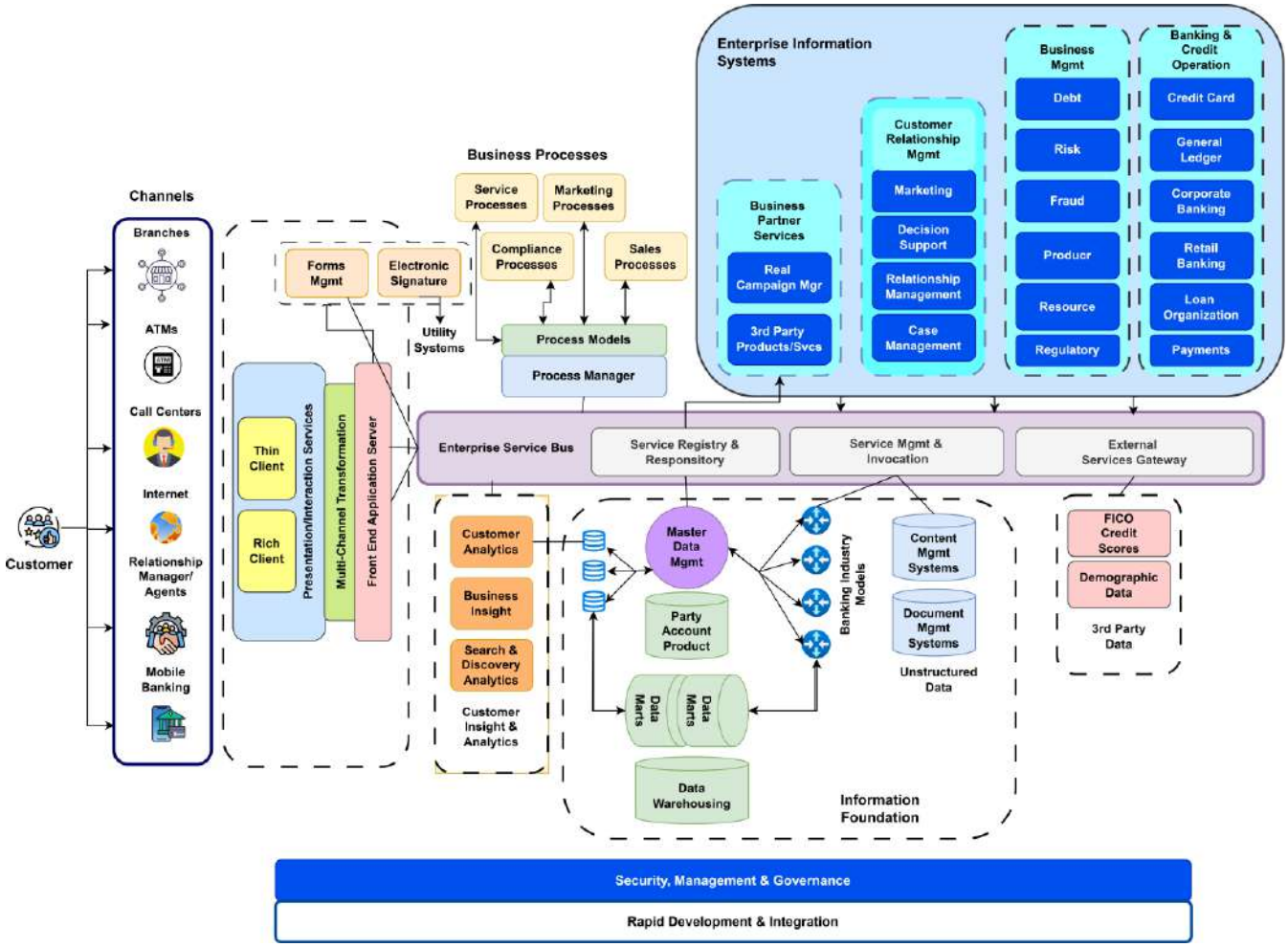

Fig. 6: Graphical representation of the proposed model architecture

Let a transaction event be expressed as:

$$T_i = \{x_i, u_i, t_i\}$$

where, x_i represents the transaction feature vector, u_i defines the user identity, and $t_i$describes the timestamp.

The architecture consists of five principal layers:

1. Presentation Layer
2. Application & Service Layer
3. Hybrid Fraud Detection Layer
4. Authentication & Verification Layer
5. Data Management Layer

Every layer performs a mathematically distinct but operationally integrated function.

- Presentation Layer: This layer facilitates user activities such account access, transaction initiation, and login by acting as the client interface. Assume that the user's request is:

$$R_i = f_{UI}(T_i)$$

where, UI encodes transaction data into a structed request transmitted to the backend server.

- Application and Service Layer: Routing, session validation, and business logic are all handled by the application layer. Authorized access is guaranteed by a session validation function:

$$S(u_i) = \begin{cases} 1 \ if \ session \ valid \\ 0 \ otherwise \end{cases}$$

Only when $S(u_i) = 1$, the transaction proceeds to fraud analysis.

- Hybrid Fraud Detection Layer: A combined decision mechanism that integrates three complementing models is the main novelty.

$$D_{final} = \Phi\ (D_{cls}, D_{anom}, D_{seq}$$

where, D_{cls} defines the supervised classification output, D_{anom} is the anomaly detection score, and D_{seq} denotes sequence-based behavioral probability.

- Supervised Classification Model: A discriminative classifier f_c learns the mapping:

$$P_{cls}(y = 1|x_i) = f_c(x_i)$$

where, y = 1 represents fraud. The classification decision is:

$$D_{cls} = \begin{cases} 1 \ if \ P_{cls} > \theta_c \\ 0 \ otherwise \end{cases}$$

This model uses tagged data to identify worldwide fraud trends.

- Anomaly Detection Model: An unsupervised anomaly detector calculates the departure from typical behavior. Let, the anomaly score or reconstruction error be:

$$A_i = ||x_i - \hat{x}_i||$$

where, $\hat{x}_i$ is the rebuild representation from an autoencoder estimator.
An anomaly decision is:

$$D_{anom} = \begin{cases} 1 \ if \ A_i > \theta_c \\ 0 \ otherwise \end{cases}$$

This part finds uncommon or undiscovered fraud tactics.

- Sequence-Based Behavioral Model: Temporal dependencies are frequently seen in fraudulent actions. Assume that the transactions for user u are as follows:

$$S_u = \{x_{u,1}, x_{u,2}, \dots \dots, x_{u,n}\}$$

A recurrent model estimate:

$$P_{seq}(y = 1|S_u)$$

The sequence-based decision is:

$$D_{seq} = \begin{cases} 1 \ if \ P_{seq} > \theta_s \\ 0 \ otherwise \end{cases}$$

This records transaction bursts, velocity trends, and behavioral drift.

- Decision Fusion Mechanism: Instead of relying on a single detector, the architecture implements a weighted hybrid fusion:

$$F_i = w_1 P_{cls} + w_2 \sigma(A_i) + w_3 P_{seq}$$

where, $w_1 + w_2 + w_3 = 1$
Final fraud classification:

$$D_{final} = \begin{cases} 1 \ if \ F_i > \theta_f \\ 0 \ otherwise \end{cases}$$

This ensemble-style integration integrates temporal reasoning, deviation detection, and pattern learning to increase resilience.

- Authentication and Verification Layer: If D_{final} = 1, the system activates multi-factor verification:

$$V_i = g\ (OTP, Email, DeviceID)$$

Only if verification succeeds:

$$\text{Transaction} \longrightarrow \text{Approved}$$

Otherwise:

$$\text{Transaction} \longrightarrow \text{Blocked}$$

This guarantees the reduction of fraud prior to transaction settlement.

- Data Management Layer: The database layer maintains structured storage:

$$D = \{\text{Users, Transactions, Fraud scores, Authentication Logs}\}$$

ACID-compliant storage guarantees consistency:

$$\text{Consistency}\ (T_i) \Longrightarrow \sum Debit = \sum Credit$$

TABLE 2: Hyperparameter Settings of the Proposed Model

Module	Hyperparameter	Value
Supervised Classifier (Random Forest)	Number of Trees	200
	Maximum Depth	12
	Minimum Samples Split	4
	Minimum Samples Leaf	2
	Criterion	Gini
	Class Weight	Balanced
Anomaly Detection (Autoencoder)	Hidden Layers	64–32–16–32–64
	Activation Function	ReLU
	Latent Dimension	16
	Batch Size	256
	Epochs	50
	Optimizer	Adam
	Learning Rate	0.001
	Reconstruction Threshold	95th percentile error
Sequence Model (LSTM)	LSTM Units	64
	Dropout Rate	0.3
	Sequence Length	10 transactions
	Dense Units	32
	Activation (Output)	Sigmoid
	Learning Rate	0.0005
Fusion Layer	Weight (w_1) (Classifier)	0.4
	Weight (w_2) (Anomaly)	0.3
	Weight (w_3) (Sequence)	0.3
	Final Threshold (θ_f)	0.5

D. Deployment Diagram

The deployment diagram provides a clear illustration of how the proposed Intelligent Online Banking System is physically realized, with software components mapped to their physical hardware realizations during run time. While the logical architecture focuses on the different layers that are realized,

the deployment diagram focuses on the different environments in which the nodes execute, how the nodes talk to each other over the network, and how the infrastructure nodes interact with each other.

For the client side, users will be able to access the system using a web browser on their device, such as a computer, laptop, or smartphone. This is the client node, which is a lightweight interface that does not execute the critical business logic or the fraud analysis logic. It only sends HTTPS requests to the backend, with all the critical processing, such as authentication verification and transactions, done on the server to prevent client-side tampering.

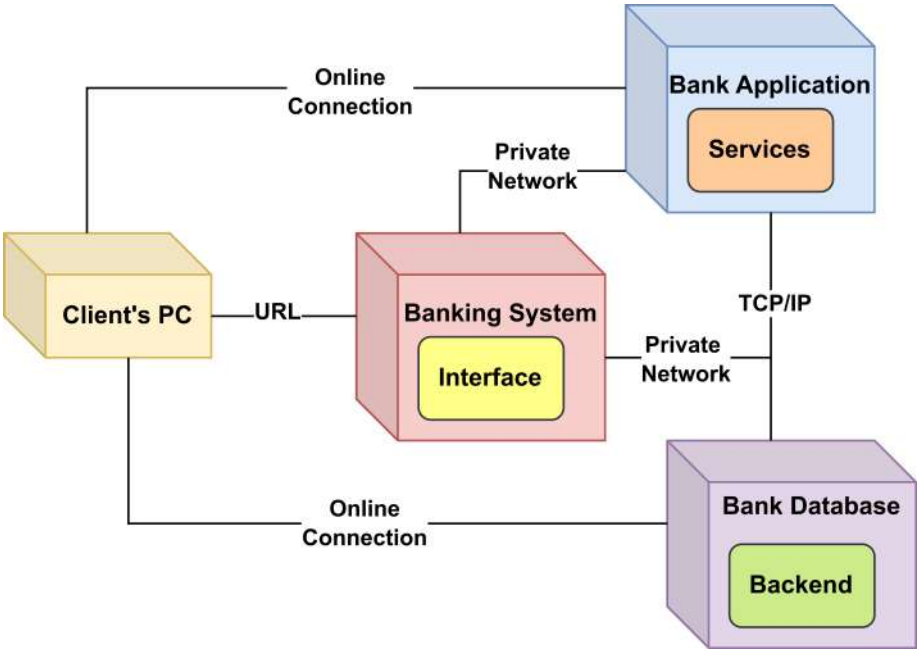

Fig. 7: Deployment Diagram

The application server runs the flask-based backend system. This server acts as the central processing hub for the entire system. The application server processes the HTTP routes, handles user sessions, authenticates users, checks transactions for validation, and processes external module interactions. After a user initiates a transaction, the flask-based server processes the transaction request. The server checks the user session tokens for validation. After validation, the server sends the features of the transactions to the fraud detection module for processing. The server deployment will be on a secure cloud instance or a dedicated VM with firewall rules and SSL encryption for secure communication channels. The fraud detection module can be deployed as a separate service layer in the same application server or as an independent microservice.

The module loads the trained machine learning model in memory for processing. After the module receives the transaction features, it processes the classification probability, anomaly score, and behavioral likelihood. Then it sends the results as a combined fraud score to the application server. The deployment of the fraud detection module as an independent microservice provides scalability. The microservice can be replicated or containerized for load balancing during high transactions. The PostgreSQL database is hosted on its own dedicated node for safe and secure storage of its contents. This includes user credentials, hashed password storage, transactional history, fraud scores, OTP information, and audit trails. Secure connections are maintained between the application and database using role-based access control

mechanisms. This design minimizes the risk of compromising financial information directly. All communication is done over secure connections using HTTPS and other secure database connections. What it actually does: To understand what it actually does, let's consider what happens when a client interacts with the application. Essentially, what happens is that the client sends a request from its browser, and it is received and processed by the application server, where it is directed towards the fraud detection module for transactional feature execution. Based on the fraud scores received, it either commits the transaction or sends it for multi-factor authentication. Once done, it sends a response back to the client.
This design is highly secure and allows for scalability and flexibility. Essentially, it minimizes single points of failure and is highly scalable, with different components hosted on different physical servers. This allows for future scalability, where it could potentially integrate with other fraud detection mechanisms, auto-scaling mechanisms, and even other APIs for bank integration.

V. HARDWARE AND SOFTWARE SPECIFICATION

The Online Banking System with AI-Based Fraud Detection requires a significant amount of hardware and software resources to enable the system's smooth functioning, security, and scalability. The Online Banking System with AI-Based Fraud Detection requires a minimum Intel i5 processor or its equivalent to ensure the smooth functioning of the backend operations without any delay. A minimum of 8 GB of RAM is essential for smooth real-time data processing and the execution of machine learning models that are integral to the fraud detection system. The system will need at least 40 GB of storage to hold user data, transaction logs, fraud-detection results, and simulated transaction data used for model training. Storage operations should also be carried out quickly for read/write operations, which helps execute transaction processing. For the smooth functioning of the banking system. A reliable internet connection is essential for online transactions, email verification, and real-time fraud detection. For the software requirements, the system will be able to run on Windows 10 or higher, while Linux will be the alternative for the production environment, ensuring better scalability for the system.

For the user interface, the system will be designed using HTML and CSS, ensuring a better user experience for users of desktop, tablet, and smartphone devices. For the backend, the system will be designed using the Flask framework, a Python framework, for routing requests, user authentication, and execution of fraud detection algorithms. For data storage, the system will be able to use PostgreSQL, a reliable RDBMS, to ensure better data integrity and scalability for the system. For the execution of the system's logic and fraud detection algorithms, the system will be designed in Python, including NumPy, Pandas, Scikit-learn, and TensorFlow for machine learning.

For fraud detection to be facilitated, Flask extensions will also be used to manage sessions, emails, and OTPs to improve transactional security. The development environment to be used will be VS Code, and the system will be accessible via Google Chrome or Microsoft Edge to improve web browsing efficiency. An email service is also important in sending OTPs to the users to improve secure communication with the system. These components ensure that the Online Banking System operates in a secure, efficient, and effective manner to ensure that the system is user-friendly, scalable, and secure.

VI. RESULT & DISCUSSION

A. Performance of the Models

The results clearly indicate that using a combination of different AI techniques in one fraud detection system works perfectly. The models each bring their own strengths, and the comparison shows how powerful the combination is as shown in Table 3. Logistic Regression is a good baseline model with an accuracy of 0.88, precision of 0.78, recall of 0.80, and F1-score of 0.80. It is a linear probabilistic model that provides a broad decision boundary in the feature space. However, its low precision and recall show that the model is not effective in handling non-linear fraud patterns. The Random Forest model improves the results with an accuracy of 0.91, precision of 0.85, recall of 0.86, and F1-score of 0.86. The ensemble method performs better than the Logistic Regression model, especially in handling non-linear patterns and reducing variance. The high recall rate shows that the model has good sensitivity to fraudulent transactions, making it a powerful main supervised model.

TABLE 3: Performance of Hybrid AI-Based Fraud Detection Model

Model	Accuracy	Precision	Recall	F1-Score	Role in Hybrid Model
Logistic Regression	0.88	0.78	0.80	0.80	Baseline probability-based classification
Random Forest	0.91	0.85	0.86	0.86	Primary supervised fraud classifier
Isolation Forest (Anomaly Detection)	0.89	0.83	0.84	0.83	Detects unknown or rare fraud patterns
LSTM Sequence Model	0.94	0.92	0.93	0.92	Captures sequential transaction behaviour
Hybrid Integrated Model (Final System)	0.96	0.95	0.94	0.95	Combined decision using classification + anomaly + sequence analysis

The Isolation Forest model, which performs the anomaly detection, achieves an accuracy of 0.89, precision of 0.83, recall of 0.84, and F1-score of 0.83. Although the model has a slightly lower accuracy than the Random Forest model, its strength lies in its ability to identify rare and unknown fraud patterns. The model does not need labeled data to learn, which means that it does not need to be supervised, making it powerful in handling unknown fraud patterns. This model performs the best, with an accuracy of 0.94, precision of 0.92, recall of 0.93, and F1-score of 0.92. The model is powerful because it can handle the sequences of transactions that users make over time, which means that the model can capture the changing patterns in the behavior of users. The high recall rate shows that the model has a low false negative rate, which is important in fraud detection to ensure that no fraud slips through the net.

The Hybrid Integrated Model had the best performance among all models, with an accuracy of 0.96, precision of 0.95, recall of 0.94, and F1-score of 0.95. When compared to the best single model, which was the LSTM model with an accuracy of 0.94, the Hybrid Model has an increase in accuracy by 2%, and precision is increased to 0.95 compared to 0.92 in the LSTM model, indicating that there are fewer false positives while maintaining high sensitivity in detecting fraud. When compared to the Random Forest model, the Hybrid Model increased accuracy by 5% and increased the F1-score by 9%, which indicates that the Hybrid Model is more useful in detecting and classifying fraud because it combines structural learning, anomaly reasoning, and sequential behavior analysis.

In terms of detection, the increase in precision to 0.95 in the Hybrid Model compared to 0.85 in the Random Forest model ensures that there are no unnecessary blocks in transactions, improving the customer experience. At the same time, maintaining a recall of 0.94 ensures that most fraudulent activities are detected and prevented. The F1-score of 0.95, which is balanced, ensures that there is no bias towards the majority or minority class. The results show that there is a multi-dimensional aspect to detecting and classifying fraud in online banking systems, with static models classifying global transactions, anomaly models detecting unusual activities, and sequential models detecting dynamics in behavior. Combining all three models creates a robust and scalable model that can be used in intelligent banking systems to detect and classify fraud in real-time.

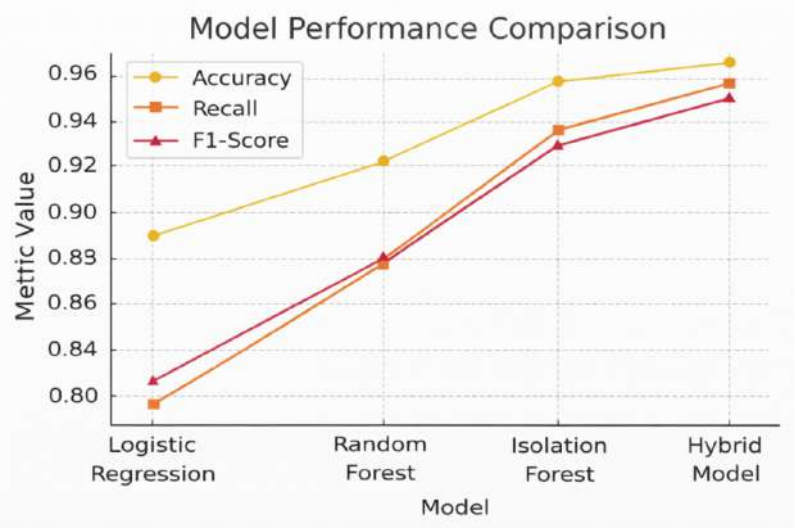

Fig. 8: Performance of AI model Compared to Oher Models

B. Confusion Matrix Analysis

The confusion matrix helps to understand how the hybrid model performs in the real world. Although it reaches 96% accuracy, the actual performance of the model in catching fraudsters and not false-flagging legitimate transactions is the actual challenge as displayed in Figure 9.

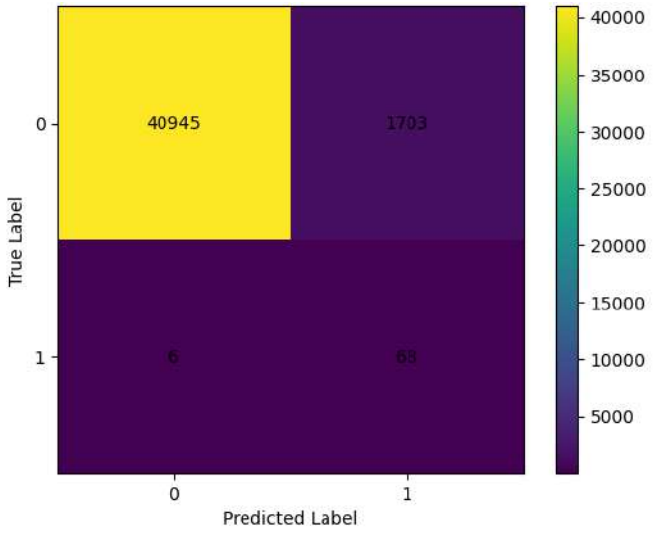

Fig. 9: Confusion Matrix of the Proposed Model

It accurately identifies 40,945 legitimate transactions. This shows that the model performs well in classifying legitimate transactions. The sequence model learns the basic patterns of legitimate transactions very well. Most importantly, the model accurately identifies 68 fraudulent transactions. Out of the legitimate transactions, it incorrectly identifies only 6 as fraudulent. This is very important because false negatives can cause the bank to lose money. The model performs very well in this regard. The hybrid model of combining classification, anomaly detection, sequence learning, and decision-making results in fewer false negatives. There are 1,703 false positives. False positives occur when legitimate transactions are identified as suspicious. In this case, the bank will have to perform additional checks like OTP verification. Although this will cause some inconveniences to the legitimate users, banks will not mind because security comes first. The model is a bit conservative in its output because there are more false positives than false negatives. Although the model's precision is affected by false positives, the hybrid model will still perform well because suspicious transactions will be verified instead of being rejected.
Overall, the confusion matrix shows that the hybrid model strikes a good balance between security and usability. The model can be said to be performing very well because it minimizes false negatives. At the same time, legitimate transactions can still be identified. This shows that the hybrid model is very good for the AI-driven fraud detection system for smart online banking.

C. ROC Curve Analysis

The ROC Curve is one of the major tools for measuring the performance of a binary classification model, its ability to separate two classes of transactions: fraudulent and legitimate. The ROC curve is defined as a plot of the True Positive Rate (TPR), also known as sensitivity/recall, against the False Positive Rate (FPR), 1-specificity. A curve closer to the top left corner of the chart indicates higher model effectiveness, higher sensitivity, and fewer false positives. In Figure 10, the AUC (Area Under the Curve) value is 0.9939. The AUC value shows that the model performs well in distinguishing between fraudulent and legitimate transactions. The AUC value close to 1 shows that the classifier is nearly perfect. The value of 0.9939 shows that the model correctly detects fraudulent transactions almost all the time. The blue curve shows the model's performance, which sharply increases towards the top-left corner, indicating that it correctly detects fraudulent transactions with minimal false positives.

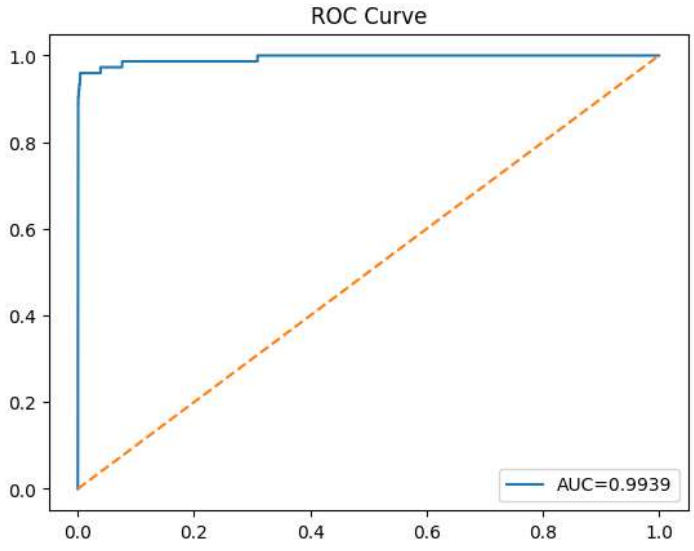

Fig. 10: ROC Curve Analysis of the Proposed Model

On the contrary, the orange dashed line represents the baseline, and it shows that the model is simply guessing. The baseline shows that the model has a 50% chance of correctly identifying fraudulent transactions. The blue curve is significantly higher than the baseline and moves up towards the top-left corner, which shows that our model is performing much better than simply guessing and is highly predictive.

D. Loss Curve Analysis

The Loss Curve can also be used to monitor the performance of the model in reducing the rate of error, or loss, as training progresses. The Loss Curve shows the performance of the model in reducing errors, and the x-axis shows the number of training epochs, while the y-axis shows the loss.
In Figure 11, the blue line shows the training loss, while the orange line shows the validation loss. The training loss is high at first, but then drops sharply in the first few epochs, showing that the model is learning from the data. This is expected, as the model is expected to learn from the data and reduce errors in the early epochs.

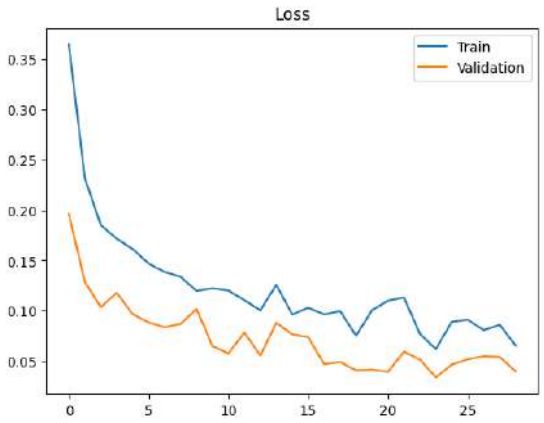

Fig. 11: Loss Curve Analysis of the Proposed Model

The validation loss also follows a similar pattern of decreasing values, but it is smoother and stabilizes as the number of epochs increases. This is a clear sign that the model is performing well and is not overfitting on the training data. When the validation loss is significantly higher than the training loss, it is a sign of overfitting on the training data and failure on unseen data. The similarities between the training and validation losses in Figure 11 indicate that the model is performing well and is not overfitting the training data. The smooth and consistent behavior of both losses as they stabilize is a sign that the model is performing optimally and is able to detect fraud transactions without making many mistakes.

VII. FUTURE ENHANCEMENTS

Even though the current AI-based fraud detection system is a step in the right direction in enhancing the security of online banking systems, there are a few areas that could be considered for future enhancements to improve the system further:

- Improved Model Accuracy: Future versions of the system could consider incorporating advanced machine learning models, such as CNN or Transformer models that have the capability to learn complex patterns from large datasets and detect even more sophisticated forms of fraud.
- Enhanced Anomaly Detection: The current anomaly detection system could also be improved to incorporate unsupervised learning models that do not require any data to learn from.
- Cross-Platform Integration: As the scope of digital banking is likely to expand, the system should be capable of integrating with mobile applications, payment systems, and cloud-based infrastructures. This is likely to be a key factor in addressing the problem of cross-platform-related fraud in the future.
- User Behavior Analysis: Further refinement of user behavior analysis might help obtain more detailed information about individual user behavior. Integration of AI-based models of user behavior might help identify fraud based on minute variations in user behavior, which could be more effective in identifying highly sophisticated fraud.
- Real-Time Adaptation: Further development of reinforcement learning might enable the system to learn and update the model of identifying fraud in real-time, based on new patterns of fraud that are likely to be identified in real-time transactions.
- Privacy Preserving AI: As the fraud detection mechanism is based on transactional data, it will be vital to include AI mechanisms such as 'Privacy Preserving AI,' which ensures that the data is never revealed or stored in any database, while improving the AI model.
- Blockchain Integration: For increased data security, it is proposed to integrate 'blockchain,' which helps in maintaining a record of all transactions and decisions related to fraud detection, thereby increasing transparency in the decision-making process.

These proposed enhancements will help the system to grow and cater to the increasing needs of online banking security, thereby increasing security, efficiency, and flexibility for users and financial organizations.

VIII. CONCLUSION

The Online Banking System with AI-Based Fraud Detection is a highly advanced level of security for online digital banking systems. This system, through the use of machine learning and artificial intelligence, goes beyond the capabilities of traditional rule-based systems, making it more efficient and accurate in fraud detection. The use of machine learning models such as Logistic Regression, Random Forest, Isolation Forest, and LSTM in the system ensures that fraud patterns, both known and unknown, are detected while eliminating false alarms. The system's ability to detect fraud in real time enhances the security of online banking systems. Moreover, the multi-layered security provided by implementing multi-layered authentication mechanisms, such as OTP and email-based verification, protects sensitive financial information of users against the increasing threats of cybercrime. This paper not only highlights the effectiveness and power of AI and ML techniques in the prevention of fraud, but it also offers a gateway for further innovations that can be made to the system for the prevention of fraud. With the adaptive nature of the system to respond to the changing nature of fraud, the system offers a promising solution to the increasing needs of modern online banking. With the successful implementation of the system, the

significance and necessity of integrating AI-based fraud detection to protect online financial transactions are highlighted.

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