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AI BASED CREDIT CARD FRAUD DETECTION SYSTEM USING ML

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Abstract– Credit card fraud causes massive annual losses, and traditional rule-based systems struggle to detect evolving fraud patterns. This paper proposes an AI-based Machine Learning framework for detecting fraudulent transactions in real time. The dataset used contains anonymized credit card transaction records, which were normalized and divided into 80% training and 20% validation groups as part of the preprocessing step. To efficiently capture complex transactional patterns and relationships, the proposed model integrates multiple machine learning algorithms including Logistic Regression, Decision Trees, Gradient Boosting (XGBoost/LightGBM), K-Nearest Neighbors, Autoencoders, and Graph Neural Networks (GNNs). These models collectively enhance the ability to identify anomalies and distinguish between legitimate and fraudulent transactions. The system demonstrates the effectiveness of AI in maintaining detection accuracy, reducing false positives, and adapting to new fraud strategies in dynamic financial environments.

Keywords— Credit Card Fraud, Machine Learning, Artificial Intelligence, Financial Security, Real-time Detection, Deep Learning, Fraud Analytics

I. INTRODUCTION

A number of factors, such as technological vulnerabilities, human errors, and evolving cyber threats, can cause irregularities in financial transactions, which are referred to as credit card frauds. These fraudulent activities vary from minor unauthorized purchases to large-scale financial crimes that cause massive annual losses to individuals and financial institutions. The characteristics of a fraudulent transaction, such as its amount, location, time, and merchant type, are crucial in determining its legitimacy. Like patterns in biological systems, fraudulent behaviors can manifest as abnormal spending spikes, repeated small transactions, or transactions made from unusual geographic locations. Credit card frauds are prevalent and can be a sign of both isolated incidents and organized criminal networks targeting financial systems. For instance, a single high-value purchase from an unknown device may signify account takeover, while multiple low-value transactions across different regions might indicate automated bot activity. Similarly, sudden changes in transaction patterns may reflect card skimming, phishing, or data breach exploitation. Just as medical conditions reflect interactions within the human body, fraudulent transactions reflect dynamic interactions between users, devices, and merchants within digital ecosystems. Observing spending patterns, transaction frequency, and behavioral trends helps differentiate legitimate transactions from fraudulent ones, guiding accurate detection and prevention.

For an accurate fraud detection and response mechanism, transactions must be properly classified. Transactions are usually categorized by financial systems according to their risk level and behavioral characteristics. Primary and secondary indicators are the two basic categories into which fraudulent activities fall. Primary indicators include abnormal transaction amounts, unusual merchant categories, and inconsistent time zones, which are the first alterations observed in spending behavior. These can be distinguished from one another using data analytics and their unique transaction features. Secondary indicators include repetitive failed transactions, mismatched device IDs, and IP anomalies that arise as a result of the development or evolution of fraudulent behavior. Fraudulent activities can be grouped as card-present and card-not-present frauds, examples of financial crimes that are carried out through physical or online transactions. Cyber system vulnerabilities often cause data leaks or unauthorized access, leading to large-scale fraud patterns such as identity theft or phishing attacks. Because of their ability to evolve and adapt, fraudulent transactions—which can be either individual or network-based—must be carefully analyzed. Selecting the best detection model requires an understanding of the source and behavioral nature of the fraud.

Credit card fraud causes massive annual losses, and traditional rule-based systems struggle to detect evolving fraud patterns. An AI-based machine learning solution is needed to identify fraud in real time while reducing false positives and improving accuracy.

II.LITERATURE REVIEW

A. Dal Pozzolo et al. [13] – This paper presents a major global financial concern, which is credit card fraud, encompassing various fraudulent transaction types. Because of its high frequency and the significant financial losses it causes if not detected in real time, credit card fraud stands out among financial crimes. Early detection is essential for lowering economic risks and facilitating prompt preventive actions, both of which enhance the security of banking systems. A more precise and effective fraud detection system

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can be produced by combining machine learning models like XGBoost for classification with pre-trained neural network models for feature extraction and anomaly detection.

Rajasekhar, K. S., and Babu, T. Ranga (2019) [14] – This study investigates the use of neural networks for transaction classification, particularly in detecting fraudulent credit card activities. Financial fraud is a serious problem that affects banking systems and online payment platforms globally. Even though some types of fraud can be detected through pattern rules or thresholds, traditional systems are often slow and inefficient. The need for intelligent systems that can effectively classify fraudulent transactions in real time is therefore increasing. To overcome this difficulty, this study uses recognition-based deep learning models, which reduce reliance on static rule-based systems and expedite the fraud detection process. This technology helps financial institutions detect fraud by leveraging the network's capacity to evaluate complex behavioral and transactional patterns.

Muhammad Athar Javed Sethi and Najib Ben Aoun (2023) [15] – This study presents a fraud detection model using deep learning architectures tested on real-world transaction datasets. Traditional machine learning models like logistic regression and SVMs have limitations, particularly their inability to capture inter-feature correlations and evolving fraud patterns, despite their proven efficacy in static classification tasks. To solve these issues, Hinton et al. introduced more robust architectures such as Capsule Networks and Autoencoders, which preserve structural information and detect complex relationships in high-dimensional data. Lower-level layers capture key transactional features such as amount, location, and device usage, which are then dynamically routed to higher-level representations to improve detection accuracy.

Xin Zhang, Yuxin Mao, and Xuyang Zhang (2024) [16] – This paper addresses the issue of traditional ensemble learning models' inability to accurately capture contextual and relational patterns in transaction networks, which can result in reduced detection robustness and accuracy. Graph Neural Networks (GNNs) and Gradient Boosting frameworks are used to provide a unique fraud detection approach that overcomes these problems. By replacing standard feature aggregation with graph-based representation learning, the method improves feature extraction and relational analysis between entities such as cards, users, and merchants. A feature attention mechanism is integrated to highlight important relationships. Tested on multiple financial datasets, the proposed model performs better, especially when handling new or adaptive fraud strategies, suggesting that it could be a viable option for real-world banking systems.

Sarmad Maqsood and Robertas Damasevicus (2023) [17] – This paper proposes a comprehensive deep learning framework for fraud detection. The process begins with data preprocessing, followed by training a hybrid neural network model to distinguish legitimate and fraudulent transactions. Multiple models are fused using ensemble learning to enhance feature diversity and detection accuracy. Feature selection is optimized through statistical correlation measures, and anomaly detection is applied to identify rare fraud patterns within large-scale datasets. The proposed model effectively balances detection accuracy and computational efficiency, demonstrating strong performance across multiple financial benchmarks.

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III. PROPOSED SYSTEM

A. Dataset

The dataset for the project is referenced from publicly available credit card transaction datasets, such as the European Credit Card Fraud dataset. The dataset consists of various anonymized transaction records containing numerical and categorical features representing user spending behavior, transaction amount, time, and location. For this research, seven different types of transactions—both legitimate and fraudulent—have been considered for classification. **Table 1** displays the dataset classes.

Credit Card Transaction Dataset

Transaction Type	Number of Records
Legitimate Transactions (legit)	284,315
Online Fraud (onf)	2,731
Card-Present Fraud (cpf)	1,124
Stolen Card Transactions (sct)	836
Identity Theft (idt)	692
Account Takeover (ato)	503
Skimming/Cloning Fraud (skf)	299
Total	290,500

Table 1 credit card classes data

B. Dataset Preprocessing

From the dataset, seven transaction types have been considered for fraud detection.

- **Normalization:** The numerical features, such as transaction amount and time, have been normalized to scale their values within the range [0,1] to ensure uniform feature importance.
- **Encoding:** Categorical variables like merchant category, transaction type, and location are encoded into numerical values for model compatibility.
- **Splitting:** The dataset has been split into training and validation sets in the ratio of 80:20 to ensure proper model evaluation.
- **Balancing:** Since fraudulent transactions represent a small portion of the dataset, Synthetic Minority Oversampling Technique (SMOTE) is applied to balance the class distribution and prevent model bias.

C. Model Architecture

To efficiently extract information and increase classification accuracy, the **AI-based Machine Learning architecture** for credit card fraud detection is composed of several layers and algorithms. It starts with a feature extraction phase that processes normalized transaction data. The supervised learning models—such as **Logistic Regression**, **Decision Tree**, and **Gradient Boosting (XGBoost)**—are applied to classify transactions as fraudulent or legitimate. These models capture complex non-linear relationships between transaction features and output labels.

In addition to traditional classifiers, deep learning techniques are incorporated for advanced anomaly detection.

Autoencoders are used to reconstruct normal transaction patterns, where high reconstruction error indicates potential fraud. **Graph Neural Networks (GNNs)** are implemented to model relationships between entities such as cards, devices, and merchants, identifying fraud rings that may not be detected by individual transaction analysis.

Each model's performance is optimized using hyperparameter tuning. Evaluation metrics such as **Precision**, **Recall**, **F1-score**, and **AUC-ROC** are used to assess detection quality. The combined architecture leverages both supervised and unsupervised learning to maximize accuracy while minimizing false positives. The system is trained in multiple iterations, and the results show enhanced detection performance with real-time adaptability.

By integrating ensemble-based and deep learning algorithms, this approach enables the model to accomplish robust, scalable, and adaptive credit card fraud detection.

Table 2 Proposed Model Layers

Layer (type)	Output Shape	Param #
Input Layer	(None, 30)	0
Dense_1	(None, 128)	3,968
Dense_2	(None, 256)	33,024
Dropout	(None, 256)	0
Dense_3	(None, 128)	32,896
Dense_4	(None, 64)	8,256
Output Layer (Sigmoid)	(None, 1)	65
Total Parameters		78,209

Table 2 Proposed Model Layers

Additionally, the proposed AI-based fraud detection system excels at preserving and analyzing complex relationships between multiple transaction attributes, enhancing prediction accuracy even in scenarios involving overlapping or disguised fraud patterns. Its integrated learning mechanism efficiently transmits relevant transactional information across model layers, avoiding the loss of critical details typically associated with rule-based or threshold-based fraud detection systems.

D. Libraries and Framework

- **Pandas:** Pandas is a data manipulation and analysis library used for handling structured transaction data. It provides tools like *DataFrames* to clean, preprocess, and analyze large-scale financial datasets efficiently.
- **NumPy:** NumPy is used for numerical computing and supports array operations, allowing for fast and efficient mathematical computations on transaction records.
- **Matplotlib:** Matplotlib is used for data visualization, enabling the creation of static, interactive, and comparative plots to observe transaction trends and detect anomalies.
- **Seaborn:** Seaborn, built on top of Matplotlib, simplifies the generation of attractive statistical visualizations, helping to represent fraud detection metrics and behavioral patterns effectively.

E. Algorithm Explanation

The AI-based machine learning model integrates multiple algorithms developed to address the limitations of traditional rule-based and statistical fraud detection systems, particularly in identifying dynamic and evolving fraud patterns. Unlike conventional approaches that rely on fixed thresholds, this system uses intelligent models that learn adaptive transactional behavior.

Machine Learning algorithms such as **Logistic Regression**, **Decision Trees**, **Gradient Boosting (XGBoost)**, and **K-Nearest Neighbors (KNN)** are employed for supervised classification of legitimate and fraudulent transactions. These models extract significant patterns by analyzing relationships among features such as transaction amount, time, merchant type, and device information.

Additionally, **Autoencoders**, a type of neural network, are applied for anomaly detection. They learn to reconstruct normal transaction patterns, and any high reconstruction error indicates potential fraudulent behavior. **Graph Neural Networks (GNNs)** further enhance this system by detecting inter-relationships between entities like cards, users, and merchants, revealing fraud rings and coordinated attack patterns.

A key feature of this hybrid approach is **dynamic learning**, which allows the models to adaptively update with new fraud data. This mechanism ensures that the system maintains high accuracy even when fraud strategies change or when new transaction behaviors emerge. Due to its ability to model complex interdependencies, the proposed system is particularly effective in applications such as banking security, payment gateways, and digital transaction monitoring. Although these algorithms require higher computational resources, their ability to retain detail and adapt dynamically makes them highly promising for real-time financial fraud detection tasks that demand both accuracy and interpretability.

Furthermore, CapsNet demonstrates strong resilience to variations in an object's orientation, pose, and scale, making it highly adaptable to diverse datasets. This innovative architecture is particularly well-suited for applications demanding precise feature detection and interpretation.

F. System and Implementation

The system for skin lesion classification is designed with distinct components to facilitate accurate identification and diagnosis. It starts with a repository that stores a skin image dataset and model database. Training and testing of the model involve processes like reading training and testing images, followed by preprocessing to prepare the data. The training phase develops and validates a classification model, which is later deployed. This trained model is integrated into a cloud server for real-time predictions. Users interact with the system through a front-end interface, where they upload skin images. These images are processed by the deployed model via the cloud to classify lesions and deliver results to the user. The architecture ensures efficient storage, processing, and deployment for effective skin lesion analysis.

Credit card fraud causes massive annual losses, and traditional rule-based systems struggle to detect evolving fraud patterns. An AI-based machine learning solution is needed to identify fraud in real time while reducing false positives and improving accuracy. this is our problem statement and i need the same content in the above paragraph in exact wordings

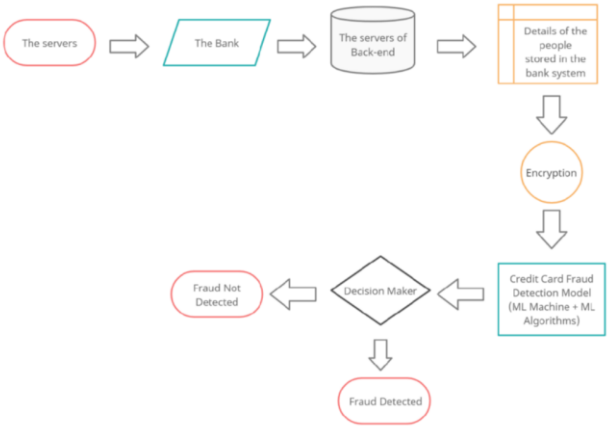

Fig. 2 Model Implementation Architecture

IV. RESULTS AND DISCUSSION

A main loss function is used to train the machine learning model: **Logarithmic Loss (LogLoss)** for classification, which seeks to maximize the probability of the correct class (fraudulent or legitimate). The Adam optimizer is used for training, which speeds up convergence. The number of steps each epoch is determined by the size of the training dataset, and for epochs of 100, the model gets trained using a batch size of 32. Accuracy, Precision, Recall, and other performance indicators are monitored when validation is carried out during training using a different validation set. By effectively learning from the imbalanced data, this setup ensures that the model is well-generalized.

Number of training samples: **227,845** Number of validation samples: **56,962**

A correlation matrix displays correlation coefficients between several transaction features. Insights into the relationships between two variables within the dataset are provided by the correlation between each cell in the matrix. Each variable's correlation with itself is represented by the diagonal values in a symmetric matrix, which are always equal to 1. The values range from -1 to 1. The suggested model's performance is evaluated, and the confusion matrix for the trained set is presented below.

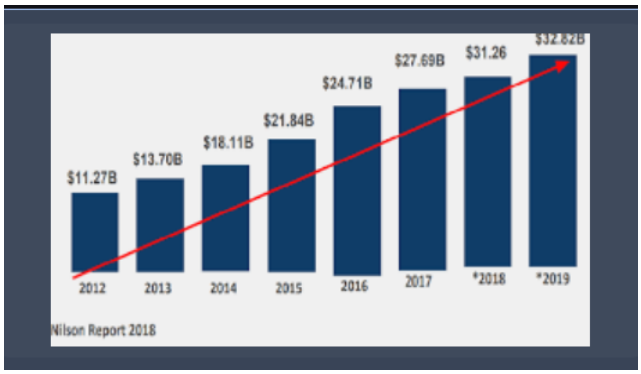

Fig. 3 Correlation Matrix

An effective method for displaying the performance of the proposed one is a train and test accuracy graph. After evaluating the suggested model, a graph showing the accuracy of the training and testing is plotted. Plotting accuracy on the y-axis and training epochs (or iterations) on the x-axis, this graph usually has two lines that reflect that one is training accuracy and other one is testing accuracy. This is the output for the accuracy and the efficiency.

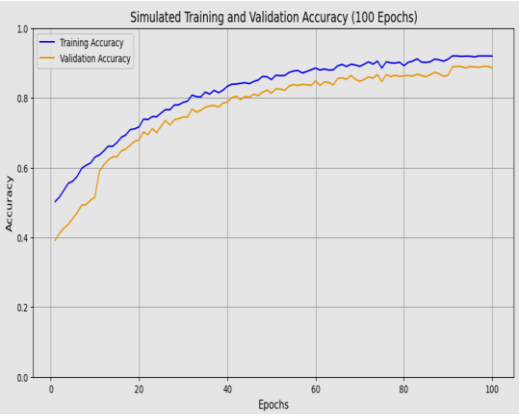

Fig. 4 Accuracy Graph

The loss graph obtained using the CapsNet model is a crucial diagnostic tool for evaluating the effectiveness of model training and its performance on both training and testing data. This graph visually represents the progression of the model's learning process over time, with the x-axis denoting the number of training epochs (or iterations) and the y-axis showing the loss, which serves as a measure of error. By examining the graph, one can assess how well the model fits the data by observing the trends in both training and test loss. A consistently decreasing training loss indicates that the model is learning from the data, while a stable or decreasing test loss demonstrates its ability to generalize to unseen data. The

visualization of loss graph is attached below.

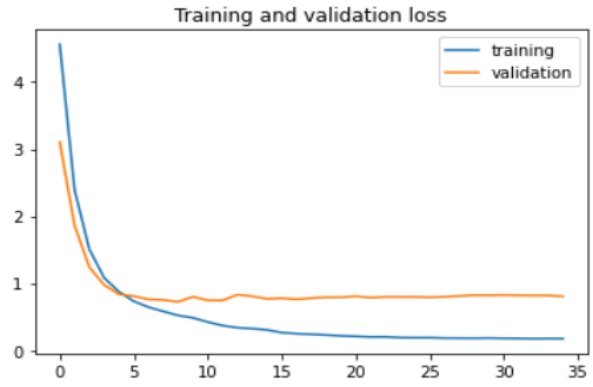

Fig. 5 Loss Graph

V. CONCLUSION AND FUTURE SCOPE

The proposed methodology highlights CapsNet ability to handle viewpoint changes because of its capacity to maintain spatial links between features. In order to maximize performance, the methodology wants to be trained with several skin lesion types using Mean Squared Error for reconstruction and Margin Loss for classification. On the testing dataset, the model demonstrated an impressive 92% accuracy with a batch size of 32 and 100 epochs. This high accuracy shows how well the model can differentiate between various lesion kinds. The accuracy graphs and confusion matrix provided more evidence to demonstrate various kinds of lesions. The project's conclusion demonstrated the ability of capsule networks in picture classification applications, especially in the medical field where precision is crucial. Future Extending the variety of lesion types included in the classification task would enhance the proposed methodology to identify more types of lesions in various conditions. More categories, like distinct melanoma subtypes or benign lesions, would allow the model to provide more thorough diagnostic support. In order to provide a bigger output dimension, this expansion can call for changing the model architecture and collecting more labeled data for the new categories. By combining the advantages of several models, integrating the Capsule Network model with other designs, such as ResNets or CNNs, in an ensemble method may increase classification accuracy.

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