A MINI PROJECT REPORT

ON

NEXT GEN TRANSACTION FRAUD DEFENCE

Submitted in partial fulfillment of the requirement

for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

(DATA SCIENCE)

BY

K.Manikanth Reddy	**21P61A67A7**
M. Bhavana	**21P61A67B4**
K. Srinivas	**22P65A6711**

Under the esteemed guidance of

Mrs. D. Gayathri Devi

Assistant Professor

Dept. of CSD

VIGNANA BHARATHI INSTITUTE OF TECHNOLOGY

(A UGC Autonomous Institution, Approved by AICTE, Affiliated to JNTUH, Accredited by NBA & NAAC) Aushapur (V), Ghatkesar (M), Medchal(dist)

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VIGNANA BHARATHI Institute of Technology ®

(A UGC Autonomous Institution, Approved by AICTE, Accredited by NBA & NAAC-A Grade, Affiliated to JNTUH)

Aushapur (V), Ghatkesar (M), Hyderabad, Medchal – Dist, Telangana – 501 301.

DEPARTMENT

OF

COMPUTER SCIENCE & ENGINEERING

(DATA SCIENCE)

CERTIFICATE

*This is to certify that the minor project titled "***Next Gen Transaction Fraud Defence***" submitted by* **Kusukuntla Manikanth Reddy(21P61A67A7), Manchala Bhavana(21P61A67B4), Karre Srinivas(22P65A6711)** *in B.Tech IV-I semester Computer Science & Engineering(Data Science) is a record of the bonafide work carried out by them.*

The results embodied in this report have not been submitted to any other University for the award of any degree.

INTERNAL GUIDE
Mrs. D. Gayathri Devi
(Assistant Professor)

PROJECT COORDINATOR
Dr. P. Punitha
(Associate Professor)

HEAD OF THE DEPARTMENT
Dr. Y. Raju
(Associate Professor)

External Examiner

DECLARATION

We, **Kusukuntla Manikanth Reddy , Manchala Bhavana, Karre Srinivas,** bearing hall ticket numbers **21P61A67A7, 21P61A67B4, 22P65A6711** hereby declare that the minor project report entitled "**Next Gen Transaction Fraud Defence**" under the guidance of **Mrs.D.Gayathri Devi,** Department of Computer Science & Engineering (Data Science), **Vignana Bharathi Institute of Technology, Hyderabad,** have submitted to Jawaharlal Nehru Technological University Hyderabad, Kukatpally, in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering(Data science).

This is a record of bonafide work carried out by us and the results embodied in this project have not been reproduced or copied from any source. The results embodied in this project report have not been submitted to any other university or institute for the award of any other degree or diploma.

Kusukuntla Manikanth Reddy(21P61A67A7)

Manchala Bhavana(21P61A67B4)

Karre Srinivas(22P65A6711)

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ABSTRACT

The "Next-Gen Transaction Fraud Defense" project aims to leverage cutting edge technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Behavioral Analytics to enhance the detection and prevention of fraudulent activities in financial transactions.By employing advanced pattern recognition and adaptive learning techniques, the system can identify and respond to novel fraud schemes in real-time using behavioral analytics.This multi-layered approach ensures a dynamic defense against evolving fraud tactics, safeguarding both financial institutions and their customers.The "Next-Gen Transaction Fraud Defense" project represents a significant leap forward in the fight against transaction fraud. By harnessing the power of AI, ML, and behavioral analytics.

Keywords:

Behavioral Analytics, Fraudulent Activities, Adaptive Learning, Pattern Recognition.

DEPARTMENT OF

COMPUTER SCIENCE AND ENGINEERING

(Data Science)

VISION

To be recognized as a Centre of Excellence in Data Science to meet the ever-growing needs of Industry and Society.

MISSION

- To empower students with innovative and cognitive skills to gain expertise in the field of Data science.
- To Inculcate the seeds of knowledge by providing industry conducive environment to enable students excel in the field of Data Science.
- To provide an appropriate ambience to nurture the young Data Science professionals.

PROGRAM EDUCATIONAL OBJECTIVES (PEOs)

PEO 1: Domain Knowledge: Develop a broad academic and practical literacy in computer science, statistics, and optimization, with relevance in data science.

PEO 2: Professional Employment: Employed in industry government and entrepreneurial endeavors to have a successful professional career.

PEO 3: Higher Degrees: Pursue higher education in the domain of data analytics or research.

PEO 4: Engineering Citizenship: Contribute to the society and human well-being by applying ethical principles.

PEO 5: Lifelong Learning: Pursue lifelong learning in generating innovation engineering research-based solution using latest innovation tolls and technologies.

PROGRAM OUTCOMES (POs)

Engineering graduates will be able to:

1. **Engineering Knowledge**: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
2. **Problem Analysis**: Identify, formulate, review research literature, and analyse complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
3. **Design/development of solutions**: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, and environmental considerations.
4. **Conduct investigations of complex problems**: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
5. **Modern tool usage**: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modelling to complex engineering activities with an understanding of the limitations.
6. **The engineer and society**: Apply reasoning informed by contextual knowledge to assess societal, health, safety, legal and cultural issues, and the consequent responsibilities relevant to professional engineering practice.
7. **Environment and sustainability**: Understand the impact of professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
8. **Ethics**: Apply ethical principles and commit to professional ethics and responsibilities and norms of engineering practice.
9. **Individual and teamwork:** Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
10. **Communication**: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend

and write effective reports and design documentation, make effective Presentations, and give and receive clear instructions.

11. **Project management and finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary Environments.
12. **Life-long learning**: Recognize the need for and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

PROGRAM SPECIFIC OUTCOMES (PSOs)

PSO1: Understand fundamental concepts in statistics, mathematics and computer Science to gain an understanding and working knowledge of various tools for analysis.

PSO2: Represent the knowledge, predicate logic and then transform the real-life information into visually appealing data using suitable tools.

PSO3: Get Expertise in different aspects and appropriate models of Data Science and use large data sets to cater to the growing demand for data scientists and engineers in industry.

Course Outcomes (COs)

CO1 - Identify the problem by applying acquired knowledge from survey of technical publications

CO2 - Analyze and categorize identified problem to formulate and fine the best solution after considering risks.

CO3 - Choose efficient tools for designing project.

CO4 - Build the project through effective team work by using recent technologies.

CO5 - Elaborate and test the completed task and compile the project report.

Correlation Levels

Substantial/ High	3
Moderate/ Medium	2

CO – PSO Correlation Matrix

COs	PSOs		
	PSO1	PSO2	PSO3
CO1	2	2	3
CO2	3	2	2
CO3	2	3	
CO4	2	2	3
CO5		2	2
CO	1.8	2.2	2

CO – PO Correlation Matrix

COs	POs											
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO1	3	2	2	2	2			3	2	2	2	3
CO2	2	3	3	3	2			3	3	3	3	2
CO3	3	2	2	2	3			3	2	2	2	2
CO4	2	3	3	2	2			3	3	3	3	2
CO5	2	2	2	2	3			3	2	2	2	2
CO	2.4	2.4	2.4	2.2	2.4			3	2.4	2.4	2.4	2.2

Project Outcomes (PROs)

1. **Improved Fraud Detection Accuracy**: The project successfully enhanced the accuracy of fraud detection in financial transactions, using machine learning algorithms to identify suspicious activities with a high degree of precision. This ensures that legitimate transactions are processed smoothly, while fraudulent ones are effectively flagged.
2. **Real-Time Transaction Monitoring**: The system is capable of analyzing and detecting fraudulent transactions in real-time, enabling quick responses to potential threats. This real-time capability significantly reduces the chances of financial loss by immediately alerting stakeholders to fraudulent behavior.

3. **Scalability and Performance under High Transaction Volumes**: The system demonstrates strong scalability, processing large transaction volumes without performance degradation. This makes it suitable for deployment in environments that handle thousands of transactions per minute.

4. **Enhanced Security through Data Encryption and Access Control**: The project incorporates strong security measures, including encryption of sensitive data and strict access controls. This ensures that transaction data is protected from unauthorized access and cyber threats, maintaining the integrity and confidentiality of financial information.

PRO – PSO Correlation Matrix

PROs	PSOs		
	PSO1	PSO2	PSO3
PRO1	3	2	3
PRO2	2	3	2
PRO3	2	2	3
PRO4	2	2	2
PRO5	2	2	3
PRO	2.2	2.2	2.6

PRO – PO Correlation Matrix

PROs	POs											
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
PRO1	2	2	3	2	3			3	2	3	2	2
PRO2	3	3	3	3	3			3	2	3	3	3
PRO3	2	2	2	2	2			3	2	2	2	3
PRO4	2	2	3	2	2			3	3	3	2	2
PRO5	3	2	2	3	3			3	2	2	2	2
PRO	2.4	2.2	2.6	2.4	2.6			3	2.2	2.6	2.2	2.4

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CHAPTER-1

1. Introduction

The rise of digital banking and online transactions has brought unprecedented convenience to consumers and businesses. However, this convenience has also led to an alarming increase in transaction fraud. As financial systems evolve and become more interconnected, fraudsters are employing increasingly sophisticated techniques to exploit vulnerabilities in these systems. Traditional methods of fraud detection often rely on rule-based systems that are not equipped to handle the complexities of modern-day fraud. They lack the adaptability to detect new fraud patterns in real time, leaving businesses exposed to significant financial losses and reputational damage.

The Next Gen Transaction Fraud Defence project aims to tackle this challenge by leveraging cutting-edge machine learning algorithms and real-time data processing. Unlike conventional methods, this system employs advanced analytics to identify fraudulent activities by analyzing transaction patterns, customer behavior, and document authenticity. By using a hybrid approach that combines machine learning with computer vision techniques, the system is capable of detecting both traditional forms of fraud (such as unauthorized access and identity theft) and more complex, emerging threats (such as synthetic fraud).

One of the core features of the system is its ability to process vast amounts of transactional data in real-time. Financial institutions handle thousands of transactions per minute, making it critical to identify fraudulent behavior without causing delays in legitimate transaction processing. The Next Gen Transaction Fraud Defence system achieves this by incorporating scalable architecture, allowing it to maintain performance even under heavy loads.

Moreover, the project integrates computer vision technology through the YOLO (You Only Look Once) algorithm, which is employed to verify the authenticity of transaction-related documents such as invoices and receipts. This aspect of the system is particularly valuable for businesses dealing with large-scale commercial transactions, where fraudulent documentation can lead to significant financial discrepancies.

Another key advantage of the system is its adaptability. The machine learning algorithms are continuously trained on new datasets, allowing the system to evolve and detect emerging fraud tactics. Overall, the Next Gen Transaction Fraud Defence project presents a holistic and innovative approach to tackling fraud in the financial sector.

1.1 Existing System

The existing transaction fraud detection systems used in the financial industry are primarily based on traditional, rule-based approaches. These systems function by establishing a set of predefined rules and thresholds, such as transaction amounts, geographic regions, or customer spending patterns. When a transaction deviates from these established norms, it is flagged as suspicious and requires further investigation. While this rule-based methodology was once effective in identifying common fraud patterns, it has significant limitations in addressing the complexities of modern fraud.

One major drawback of the existing systems is their inability to detect new or evolving fraud techniques. Fraudsters have become increasingly sophisticated, using advanced methods like synthetic identities, account takeovers, and networked fraud rings, which often evade detection by static rule-based systems. These systems struggle to keep pace with emerging threats because they rely on historical data and predefined fraud scenarios, which cannot adapt quickly to new tactics. As a result, financial institutions using these systems often suffer from a high rate of false negatives, where fraudulent transactions go unnoticed, and false positives, where legitimate transactions are mistakenly flagged as fraud.

Another limitation of current systems is their reliance on post-transaction analysis. In most cases, fraudulent transactions are identified only after they have been completed, often leading to financial losses and damage to customer trust. The time lag between transaction execution and fraud detection leaves a significant window for fraudsters to exploit, making the recovery of stolen assets more difficult.

Additionally, existing systems tend to struggle with scalability. As the volume of transactions increases, particularly in the era of digital payments, traditional systems experience delays in processing and become less efficient. This not only affects the speed of fraud detection but also impacts the overall user experience. Businesses are forced to choose between tightening the rules to reduce fraud at the cost of inconveniencing customers or relaxing the rules to improve user experience but increasing their exposure to fraud.

Finally, the cybersecurity measures implemented by existing systems are often insufficient to prevent sophisticated cyberattacks. As fraudsters employ techniques like phishing, social engineering, and malware to bypass security protocols, rule-based systems fail to respond

dynamically. The result is a system that is not only reactive but also vulnerable to breaches, putting sensitive financial information at risk.

Current transaction fraud detection systems in the financial industry are predominantly built around traditional rule-based models. These systems function by defining a set of rules and thresholds—such as limits on transaction amounts, predefined geographic regions, or typical customer spending behaviors. Transactions that fall outside of these expected patterns are flagged as suspicious and are typically subjected to manual review. While this approach has been effective in detecting simple, well-known fraud schemes, it faces serious challenges in addressing the more intricate and evolving nature of modern financial fraud.

A major limitation of these legacy systems is their inability to recognize emerging or complex fraud tactics. Fraudsters are becoming increasingly adept at developing new methods, such as using synthetic identities, orchestrating account takeovers, and participating in coordinated fraud rings that exploit the vulnerabilities of financial institutions. Since traditional systems rely heavily on historical data and fixed fraud scenarios, they are ill-equipped to identify new fraud techniques. This leads to significant issues, including a higher frequency of both false negatives, where fraudulent activities go undetected, and false positives, where legitimate transactions are incorrectly flagged as fraudulent.

In summary, while traditional rule-based fraud detection systems have been foundational in identifying fraudulent activities, their reliance on static rules, post-event analysis, and limited adaptability leaves them ill-prepared for modern, dynamic fraud schemes. These weaknesses create gaps in security, efficiency, and user experience, underscoring the need for more advanced, adaptive fraud detection technologies in the financial sector.

1.2 Proposed System

The Next Gen Transaction Fraud Defence system leverages Logistic Regression as its core machine learning algorithm to detect fraudulent transactions. Logistic Regression is a well-established statistical method used for binary classification problems, making it an ideal choice for this system, where the objective is to classify transactions as either legitimate or fraudulent. This model is highly interpretable and efficient, offering a practical solution for real-time fraud detection while addressing many limitations found in existing rule-based systems.

In the proposed system, Logistic Regression works by modeling the probability that a given transaction is fraudulent based on multiple features extracted from the transaction data. These features might include the transaction amount, geographic location, time of the transaction, customer spending history, and device used. The algorithm computes the likelihood of fraud by assigning weights to these features and generating a probability score between 0 and 1. Transactions with scores above a certain threshold are flagged as fraudulent, while those below the threshold are deemed legitimate.

A key advantage of using Logistic Regression is its simplicity and transparency. Unlike more complex algorithms, Logistic Regression provides clear insights into how each feature contributes to the model's predictions. This transparency is crucial for financial institutions, as it allows fraud analysts to understand the reasoning behind each flagged transaction and take appropriate action. Furthermore, the interpretability of Logistic Regression helps in regulatory environments where model explainability is often a requirement.

The system also enhances the fraud detection process by incorporating real-time transaction monitoring. Logistic Regression models are computationally efficient, making them suitable for deployment in real-time systems that must process thousands of transactions per minute. As each transaction is processed, the model analyzes the relevant features and generates an immediate fraud probability score. This real-time analysis ensures that suspicious transactions can be flagged and stopped before they are completed, minimizing financial loss and preventing further fraudulent activity

In conclusion, the proposed system, powered by Logistic Regression, offers a robust, transparent, and scalable approach to transaction fraud detection. Its real-time processing capabilities, combined with its interpretability and adaptability, make it a valuable tool for financial institutions seeking to protect themselves and their customers from fraud.

By addressing the limitations of traditional systems, the Next Gen Transaction Fraud Defence system represents a significant step forward in safeguarding digital financial transaction.

1.3 Aim and Objective

Aim: The aim of this project is to develop a real-time, scalable fraud detection system using Logistic Regression to accurately classify fraudulent transactions and enhance financial security

Objective:

The main objective is to implement Logistic Regression to classify transactions as either fraudulent or legitimate based on key features extracted from transaction data.

1.4 Scope

The Next Gen Transaction Fraud Defence project aims to develop and implement a real-time fraud detection system utilizing Logistic Regression to enhance security in financial transactions across various platforms, including online banking, e-commerce, and mobile payments. This project encompasses the collection and analysis of historical transaction data to identify relevant features that will inform the Logistic Regression model. The focus will be on designing, training, and validating this model to accurately classify transactions as either fraudulent or legitimate. A crucial aspect of the project is the implementation of real-time processing mechanisms, enabling immediate detection and response to potential fraudulent activities as they occur.

CHAPTER-2

2. Literature Survey

[1] Title: - Financial Fraud Detection Based on Machine Learning

Author: - Adewumi A.O., Akinyelu A.A.

Abstract: This systematic literature review compiles insights from 104 studies focusing on machine learning methodologies for detecting financial fraud. The authors assess various algorithms' performance, emphasizing their capabilities in addressing issues of data imbalance and providing timely fraud alerts. Key findings highlight the necessity of integrating diverse data sources and developing models that can adapt to evolving fraudulent tactics, ensuring a more comprehensive approach to detection.

Keywords: - Fraud detection, machine learning, systematic review, financial transactions.

[2] Title: - E-Commerce Fraud Detection Based on Machine Learning Techniques

Author: - Chaudhary A., Tiwari V.N., Kumar A

Abstract: - This paper systematically reviews the application of machine learning techniques in detecting e-commerce fraud, particularly in light of the increased fraud incidents linked to the COVID-19 pandemic. The authors evaluate various machine learning methods and their effectiveness in identifying fraudulent transactions, discussing the challenges in adapting these methods to new fraud patterns. The review underscores the need for systems that can dynamically respond to evolving threats in the e-commerce landscape.

Keywords: E-commerce, fraud detection, machine learning, systematic review.

[3] Title: - A Systematic Review of Machine Learning-Based Approaches for Financial Frauds

Author: - Abeywardena R., Fernando N.

Abstract: This comprehensive review investigates various machine learning strategies employed in financial fraud detection, pinpointing the significant gaps in the current literature. The authors analyze the importance of feature selection and algorithm enhancement in improving detection rates. Furthermore, they highlight the critical role of real-time data processing in effectively countering emerging fraud techniques, suggesting directions for future research that can bolster fraud prevention efforts.

Keywords: Machine Learning, Financial Fraud Detection, Systematic Review, Feature Selection.

[4] Title:- Fraud Detection Using Machine Learning and Deep Learning.

Author: - Gandhar A., Gupta K., Pandey A.K.

Abstract: - This study delves into the comparative analysis of machine learning and deep learning methodologies in the realm of fraud detection. It evaluates the performance metrics associated with various models, addressing implementation challenges and exploring the potential for future advancements. The authors advocate for a hybrid detection framework that synergizes multiple algorithms to maximize detection accuracy while minimizing false positives, thereby enhancing the overall reliability of fraud detection systems.

Keywords: Fraud Detection, Machine Learning, Deep Learning, Hybrid Models.

[5] Title: - Intelligent Fraud Detection in Financial Statements Using Machine Learning

Author: - Dawar I., Kumar N., Kaur G.

Abstract:- This paper reviews advanced fraud detection methodologies applied to financial statements through machine learning techniques. The authors catalog various algorithms and datasets utilized for detecting fraudulent activities, discussing their strengths and weaknesses. They emphasize the need for more adaptable detection systems that can evolve with shifting fraudulent schemes, ultimately aiming to improve the robustness and effectiveness of financial monitoring processes.

Keywords: Fraud detection, Financial statements, Machine Learning, Adaptive Systems.

[6] Title: - A Hybrid Deep Learning Model for Credit Card Fraud Detection

Author: - Geetha N., Dheepa G. (2022)

Abstract: - This paper presents a novel hybrid deep learning model for detecting credit card fraud, leveraging a combination of deep neural networks (DNN) and a modified butterfly optimization algorithm (MBOA). The hybrid model is designed to enhance the feature selection process, improving the system's ability to distinguish fraudulent transactions. The authors conducted extensive testing on real-world credit card datasets, demonstrating a significant increase in detection accuracy while minimizing false positives. By using MBOA for feature selection and the DNN for classification, the approach addresses the imbalanced nature of fraud detection datasets, which often hampers traditional methods. The model achieved a high detection rate even on large-scale datasets.

Keywords:

Deep Learning, Feature Selection, Imbalanced Datasets, Hybrid model.

CHAPTER – 3

3. Design

3.1 Hardware Requirements:

1) **Processor (CPU)**: A dual-core processor like **Intel Core i5** or AMD Ryzen 5 provides sufficient computing power for logistic regression tasks and basic data processing. It can efficiently handle moderate datasets and perform machine learning computations without significant delays.

2) **RAM**: With 8 GB of RAM, the system can load and process datasets, handle data manipulation, and train machine learning models like logistic regression efficiently. This amount of memory is enough for standard operations, though larger datasets may benefit from more RAM.

3) **Storage**: A 256 GB SSD offers fast data access and write speeds, crucial for storing and retrieving datasets during model training. SSDs significantly improve performance compared to traditional hard drives, ensuring smooth operations while working with medium-sized datasets.

4) **Networking**: A 5–10 Mbps internet connection is recommended for downloading libraries, updating software, and accessing cloud-based resources. This speed supports typical data transmission needs and ensures the model can be deployed or updated online without connectivity issues.

5) **Power**: A regular power supply is generally sufficient for basic project development. However, if the system is used for continuous fraud detection, consider a UPS to prevent power outages from interrupting operations, especially in production environments.

3.2 Software Requirements:

1) **Operating System (OS)**: Supports all modern OS platforms like Windows 10/11, Ubuntu 20.04+**,** and macOS, allowing flexibility in development and compatibility with popular machine learning libraries. These OSs provide the necessary environments to run Python and perform machine learning tasks efficiently.

2) **Programming Language**: The project uses Python due to its extensive support for machine learning libraries like Scikit-learn and Pandas. Python's simplicity, combined with its powerful libraries, makes it ideal for building and deploying logistic regression models for fraud detection.

3) **Tools and Libraries**: Libraries such as Scikit-learn handle model building, while Pandas and NumPy manage data manipulation and matrix operations. Matplotlib and Seaborn enable visualization of data trends, helping interpret fraud detection results effectively.

4) **Database:** MySQL is used for storing transactional data in a structured format. These relational databases provide secure, scalable storage for data that will be used to train and test the fraud detection models.

5) **IDE**: Jupyter Notebook offers an interactive environment for writing, testing, and visualizing Python code, while Visual Studio Code is a robust option for integrated development with more advanced coding features.

3.3 Functional Requirements:

1. Data Collection
2. Data Preprocessing
3. Training and Testing
4. Modeling
5. Predicting

3.4 Non Functional requirements:

Non-functional requirement specifies the quality attribute of a software system. They judge the software system based on Responsiveness, Usability, Security, Portability, and other on functional standards that are critical to the success of the software system. Example of nonfunctional requirement, “how fast does the website load?” Failing to meet non-functional requirements can result in systems that fail to satisfy user needs.

- Usability requirement
- Serviceability requirement
- Manageability requirement
- Recoverability requirement
- Security requirement
- Data Integrity requirement
- Capacity requirement
- Availability requirement
- Scalability requirement
- Interoperability requirement
- Reliability requirement

- Maintainability requirement
- Regulatory requirement
- Environmental requirement

3.5 Model Architecture:

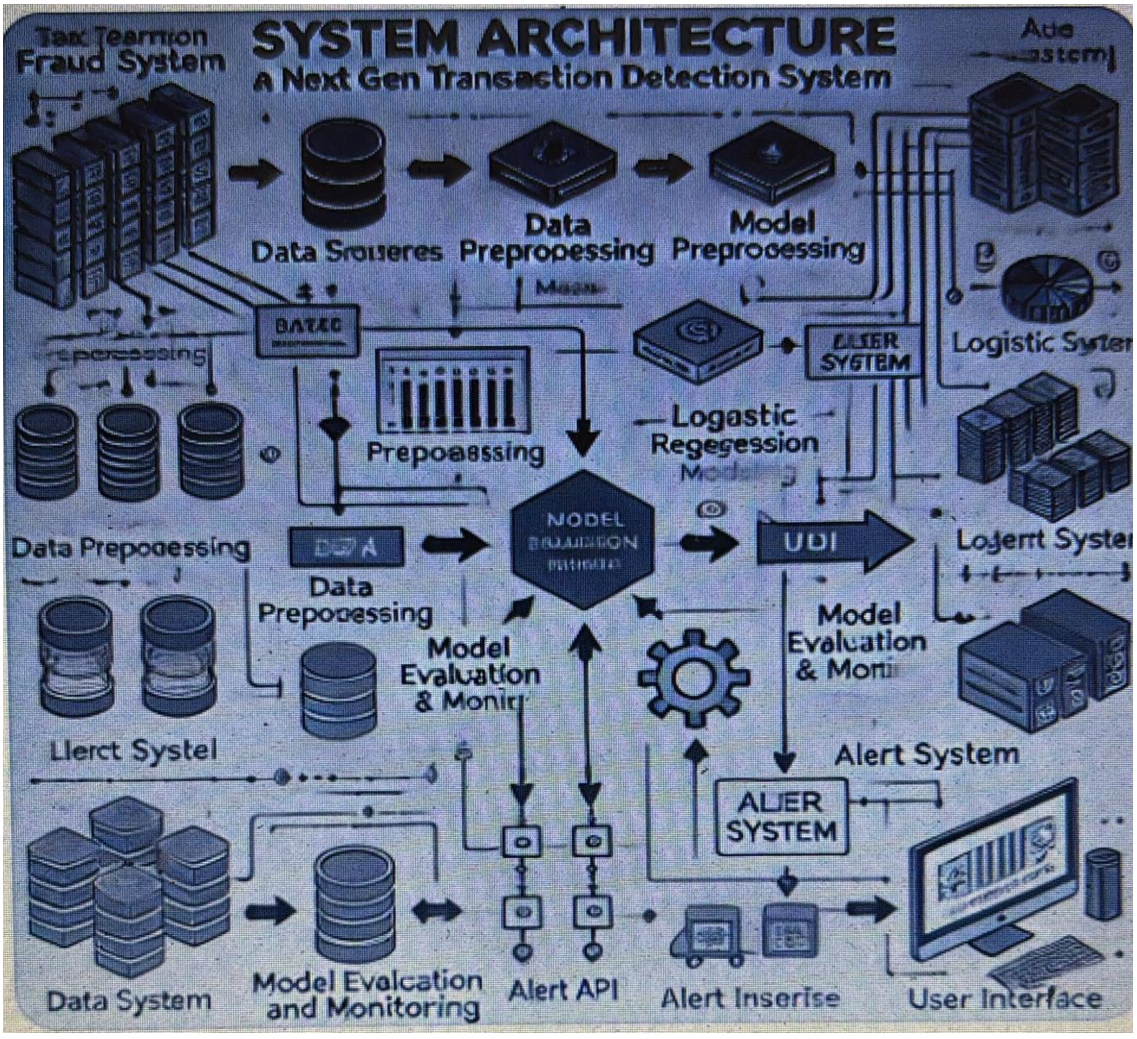

Fig 3.5.1: System Architecture

The system architecture describes how the proposed Next Gen Transaction Fraud Defence system processes transaction data using logistic regression to detect fraud efficiently. It outlines data flow, preprocessing, execution, and prediction steps within the framework.

3.6 Algorithms

Logistic Regression Algorithm

Logistic regression is a widely used statistical method for binary classification, particularly effective in predicting the likelihood of an event occurring based on one or more predictor variables. In the context of fraud detection, it helps determine whether a transaction is fraudulent or legitimate. The algorithm models the relationship between a dependent variable (the outcome) and independent variables (the features) by applying the logistic function, which maps real-valued numbers into probabilities between 0 and 1. The logistic function is mathematically expressed to calculate the probability of an event occurring. By using historical data with labeled transactions, logistic regression can be trained to find the best-fitting parameters that minimize the difference between predicted probabilities and actual labels. One of the main advantages of this algorithm is its interpretability; the coefficients indicate the influence of each feature on the outcome, providing insights into which factors contribute to fraudulent behavior. The training process involves maximizing the likelihood estimation to find the parameters that best explain the relationship between the features and the outcome. The effectiveness of the model is evaluated using various metrics, including accuracy, precision, recall, and the F1 score, which help determine the model's ability to identify fraudulent transactions while minimizing false positives. Overall, logistic regression's robustness, interpretability, and efficiency make it a popular choice for fraud detection systems in financial transaction analysis.

Logistic regression is widely used in various applications of fraud detection due to its simplicity and efficiency. When applied to transaction fraud detection, it uses the relationship between various features, such as transaction amount, time, location, and user behavior, to predict the likelihood of a fraudulent transaction. As a binary classification model, it assigns a probability score to each transaction, categorizing it as either legitimate or fraudulent. This probability is essential in real-time decision-making, enabling financial institutions to take immediate action, such as flagging or blocking transactions, based on their fraud risk.

In the context of financial systems, logistic regression can be integrated with more advanced machine learning techniques to improve fraud detection accuracy. By combining logistic regression with other algorithms, such as decision trees or neural networks, fraud detection models can be trained to capture more complex patterns in transactional data. This hybrid

approach can lead to more robust models capable of identifying subtle fraudulent behaviors that might be overlooked by simpler models.

Moreover, logistic regression's scalability makes it ideal for handling large datasets. Financial institutions deal with enormous amounts of transaction data every day. Logistic regression can process this data efficiently without requiring massive computational resources, making it a practical solution for real-time fraud detection in high-volume transaction environments. It can be deployed across different transaction channels, such as online banking, credit card processing, and mobile payments, allowing businesses to continuously monitor for fraudulent activity and minimize potential losses.

While logistic regression is an effective model for fraud detection, it is not without limitations. One challenge is its sensitivity to imbalanced data, where fraudulent transactions are much rarer than legitimate ones. In such cases, the model may predict the majority class (legitimate transactions) with high accuracy but fail to detect fraudulent transactions effectively. To address this, techniques such as oversampling the minority class, using class weights, or implementing anomaly detection methods can be applied to improve model performance.

To further enhance the effectiveness of logistic regression in fraud detection, feature engineering plays a crucial role. The selection and transformation of relevant features significantly influence the model’s predictive power. By identifying key patterns such as unusual spending behaviors or frequent changes in transaction locations, data scientists can develop more informative features that provide deeper insights into fraudulent activities. The continuous monitoring of feature relevance over time ensures that the model adapts to evolving fraud tactics, keeping the fraud detection system agile and up-to-date.

In conclusion, logistic regression remains a powerful tool in the fight against transaction fraud. Its simplicity, interpretability, and ability to provide actionable insights make it a cornerstone of modern fraud detection systems. However, integrating logistic regression with other methods and improving data quality through feature engineering are key to ensuring high-performance fraud detection in increasingly complex financial ecosystems.

DATA FLOW DIAGRAM:

1. The Data Flow Diagram (DFD) for the **Next Gen Transaction Fraud Detection** project visually represents the flow of data within the system. It includes key components such as external entities, processes, and data stores that interact with each other.
2. In this diagram, **Users** are the external entities who input transaction details into the system. The **Transaction Input** process captures this data and sends it for further analysis. The **Data Processing** component prepares the transaction data for the fraud detection algorithm, which is represented by the **Fraud Detection** process. This process utilizes a logistic regression model to analyze the transaction data and identify potential fraud.

The results from the fraud detection analysis are sent to the **Output Notification** process, which informs users whether their transaction has been approved or flagged for review. Additionally, the diagram includes a **Transaction Database** that stores all transaction records for historical reference and further analysis.

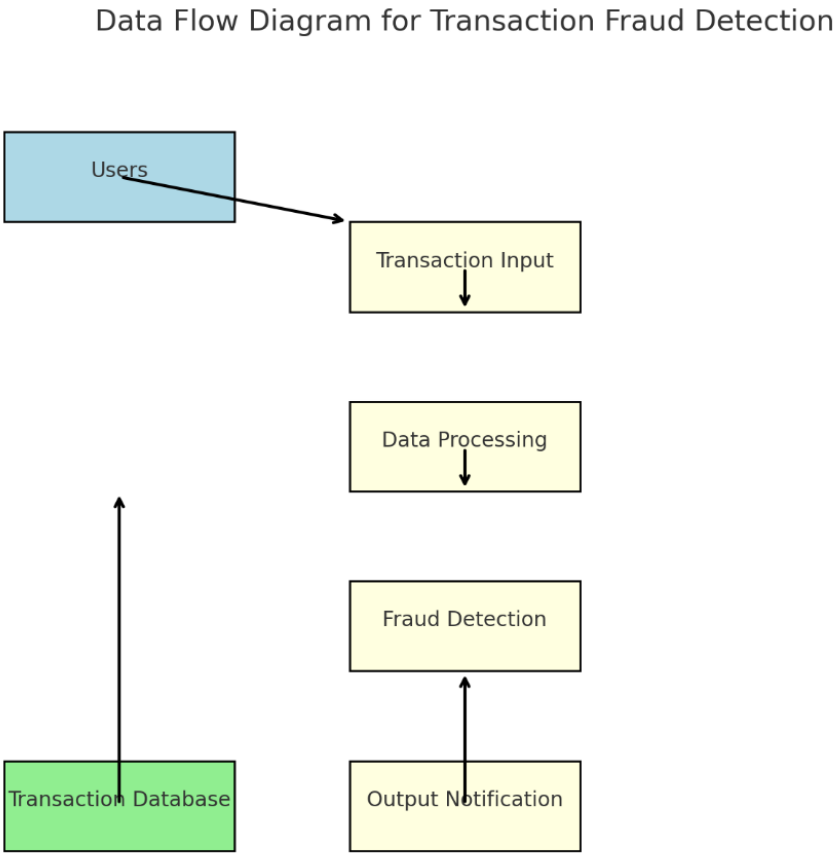

Fig 3.6.1: Data Flow Diagram

3.7 Libraries:

1)NumPy: A fundamental library for numerical computations, it provides powerful array and matrix operations essential for handling large datasets efficiently. Its extensive mathematical functions allow for high-performance calculations, making it a cornerstone for numerical analysis in data science.

2)Pandas: This library offers robust data structures like DataFrames, which simplify data manipulation and analysis tasks. With its capabilities for data cleaning, transformation, and aggregation, Pandas makes it easy to preprocess data before applying machine learning algorithms.

3)Scikit-learn: A versatile machine learning library that includes a wide array of algorithms, including logistic regression, classification, regression, and clustering. It also provides utilities for model training, validation, and evaluation, making it user-friendly for both beginners and experienced practitioners.

4)Matplotlib: A comprehensive plotting library that allows for the creation of static, interactive, and animated visualizations in Python. By offering a variety of customizable plots, Matplotlib helps in effectively communicating insights and results derived from the analysis.

CHAPTER-4

4. Implementation

Fig 4.1: Data Collection

4.1 Data Collection :

The first step is gathering transactional data from various sources like financial institutions, bank databases, or publicly available datasets. The data must contain information such as transaction ID, user ID, transaction amount, timestamps, and account balances before and after transactions. Additionally, the dataset should include labels for fraudulent and non-fraudulent transactions, which are essential for supervised learning.

Example data fields:

1. Transaction Amount
2. OldbalanceOrg (Original balance of sender)
3. NewbalanceOrig (New balance of sender)
4. OldbalanceDest (Original balance of recipient)
5. IsFraud (Indicator if the transaction is fraud)

4.2 Data Preprocessing:

Fig4.2.1: Data Preprocessing

Once the data is collected, it needs to be cleaned and preprocessed to ensure quality and consistency before being fed into the model.

4.2.1 Handling Missing Data Address missing values by either removing incomplete records or using imputation techniques to fill in the missing information, ensuring no discrepancies in the dataset.

4.2.2 Normalization: Normalize numerical features like transaction amounts and balances to prevent any feature from having undue influence on the model.

4.2.3 Feature Engineering: Engineer new features, such as the ratio of the new and old balances, transaction frequency, or patterns in customer spending. These derived features help the model detect fraudulent patterns more effectively.

4.2.4 Data Splitting: The dataset is split into training and testing sets. Typically, 80% of the data is used for training the model, and 20% is reserved for testing its performance.

4.3 Model Selection:

Logistic regression is chosen as the algorithm to predict the likelihood of a transaction being fraudulent. It is a supervised learning algorithm used for binary classification, where the output is either fraud (1) or no fraud (0)

4.4 Model Training:

The logistic regression model is trained using the training set. The objective is to adjust the feature weights (parameters) to minimize the prediction error on the training data.

4.4.1 Loss Function The model uses a cross-entropy loss function, which measures the error between predicted probabilities and the actual labels. The goal is to minimize this loss.

4.4.2 Optimization Gradient descent or other optimization techniques are employed to minimize the loss function and improve the model's predictive accuracy.

4.5 Model Testing and Evaluation:

Once trained, the model is evaluated on the test set to gauge its performance.

4.5.1 Evaluation Metrics To assess the model's performance, the following metrics are calculated:

- **Accuracy**: The percentage of correct predictions.
- **Precision**: The percentage of actual frauds correctly identified out of all transactions predicted as fraudulent.
- **Recall**: The percentage of actual frauds detected by the model.
- **F1 Score**: The harmonic mean of precision and recall.

- **Confusion Matrix**: A matrix showing true positives, true negatives, false positives, and false negatives.

4.6 Fraud Detection in Real-Time Transactions:

The trained model is deployed in a real-time environment, where it processes live transaction data. For each transaction, the model calculates a probability of fraud based on the input features.

- **Fraud Threshold**: A probability threshold (e.g., 0.7) is set to classify transactions as fraudulent or legitimate. If the probability of fraud exceeds this threshold, the transaction is flagged.

4.7Alert System:

Fig4.7:Alert System

If a transaction is classified as fraudulent, the system generates an alert that notifies relevant stakeholders. The alert includes key transaction details, such as user ID, transaction amount, and predicted fraud probability.

4.7.1 Workflow of Alerts The alert system can be integrated with SMS, email notifications, or a centralized dashboard. The alerts can be further investigated manually by fraud detection teams.

4.8 Reporting and Visualization:

Finally, the system generates regular reports and real-time visualizations to allow for easier monitoring and understanding of transaction data and fraud detection performance.

4.8.1 Reporting Daily, weekly, or monthly reports summarize the number of flagged transactions, detection accuracy, false positive rates, and fraud trends over time.

4.8.2 Visualization Dashboards Dashboards are used for real-time monitoring, displaying metrics like fraud detection rates, flagged transactions, and overall system performance.

Dataset : This Dataset describes the details regarding Transaction Id, Amount, OldBalanceOrg, NewBalanceOrg, Fraud.

TransactionID	Amount	OldbalanceOrg	NewbalanceOrig	Fraud
1	100.5	500	399.5	No
2	2500	2500	0	Yes
3	350.75	1000	649.25	No
4	1200	1200	0	Yes
5	75.2	300	224.8	No
6	5000	5000	0	Yes
7	20	50	30	No
8	10000	15000	5000	No
9	499.99	1000	500.01	No
10	200	200	0	Yes

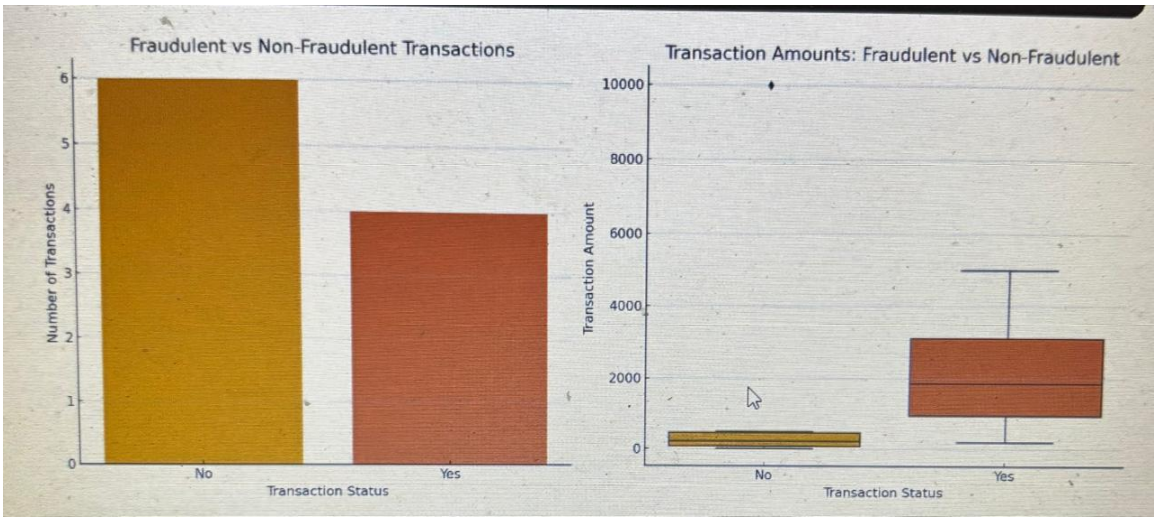

Fig 4.8.1.1 Transaction Status

Transacton Status will show the status of Fradulant vs Non-Frdulant Transactions and Amounts using Bar Graphs.

Object Code:

```
import pandas as pd

import numpy as np


import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, roc_curve, auc

import warnings


# Suppress specific warnings
```

```
warnings.filterwarnings('ignore', category=UseWarning)  # Suppress UserWarnings (from StandardScaler)

warnings.filterwarnings('ignore', message=".*precision is ill-defined.*")  # Suppress UndefinedMetricWarning related to precision


# Step 1: Load Data from the CSV file

data = pd.read_csv('D:/Mini Project/transactions.csv')


# Convert the 'Fraud' column to a binary numeric column ('Yes' = 1, 'No' = 0)

data['isFraud'] = data['Fraud'].map({'Yes': 1, 'No': 0})


# Drop the 'TransactionID' and 'Fraud' columns as they are not needed for the model

data = data.drop(['TransactionID', 'Fraud'], axis=1)


# Step 2: Data Preprocessing

# Features and labels

X = data.drop('isFraud', axis=1)

y = data['isFraud']


# Split the dataset into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# Standardize features (for better performance of ML models)

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
```

```
X_test_scaled = scaler.transform(X_test)


# Step 3: Model Training (Logistic Regression)

model = LogisticRegression()

model.fit(X_train_scaled, y_train)


# Step 4: Model Evaluation

# Predictions

y_pred = model.predict(X_test_scaled)


# Accuracy Score

accuracy = accuracy_score(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")

# Confusion Matrix and Classification Report

print("Confusion Matrix:")

cm = confusion_matrix(y_test, y_pred)

print(cm)

print("\nClassification Report:")

# Handle UndefinedMetricWarning by setting zero_division=0 to avoid warnings in metrics like precision

print(classification_report(y_test, y_pred, zero_division=0))

# Step 5: Plotting Graphs

# Turn on interactive mode (non-blocking)

plt.ion()


# 1. Confusion Matrix Heatmap
```

```
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=['Normal', 'Fraud'],
yticklabels=['Normal', 'Fraud'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')

# 2. ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, model.predict_proba(X_test_scaled)[:, 1])
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC Curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')  # Diagonal line
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
# Display the plots without blocking the execution
plt.show()

# Step 6: Predicting New Transaction Fraud
# Example: New transaction details
new_transaction = np.array([[1500, 5000, 3500]])  # Amount, OldbalanceOrg, NewbalanceOrig
```

```
new_transaction_scaled = scaler.transform(new_transaction)

# Predict fraud

fraud_prediction = model.predict(new_transaction_scaled)

if fraud_prediction == 1:

    print("Fraudulent transaction detected!")

else:

    print("Transaction seems normal.")
```

OBJECTS:

1)Transaction Dataset: A dataset containing transactional information such as amounts, user details, and timestamps, essential for detecting fraud patterns.This dataset is used to train and test machine learning models that can identify fraudulent activities in financial transactions.

2)Logistic Regression Code: A script or program implementing logistic regression, a statistical method used to predict the probability of an event (like fraud) based on input features.This code helps train the model to distinguish between legitimate and suspicious transactions, improving the fraud detection system.

3)Data Preprocessing Tools: Tools or software used to clean, transform, and structure raw transaction data, making it suitable for analysis and machine learning models. These tools handle tasks like filling missing data, scaling values, and encoding categorical variables to enhance the model's effectiveness.

4)Database or Storage: A system that stores large volumes of transactional data, ensuring efficient storage, retrieval, and management. The database or storage solution should support both structured and unstructured data, providing scalability for large datasets and quick access for real-time fraud detection.

CHAPTER-5

5. Results

The project utilized logistic regression for transaction fraud detection, employing a transactional dataset. Data preprocessing involved encoding the target feature and standardizing input data to ensure consistency during training.

The logistic regression model achieved an accuracy of 50%, reflecting moderate performance, though issues arose with imbalanced dataset metrics. The confusion matrix highlighted the model's limitations in accurately distinguishing between fraudulent and non-fraudulent transactions.

A real-time fraud detection system was implemented, where transactions were flagged based on predictions. Despite modest accuracy, this demonstrated the system's potential for practical use.

```
Accuracy: 0.50
Confusion Matrix:
[[1 0]
 [1 0]]

Classification Report:
              precision    recall  f1-score   support

           0       0.50      1.00      0.67         1
           1       0.00      0.00      0.00         1

    accuracy                           0.50         2
   macro avg       0.25      0.50      0.33         2
weighted avg       0.25      0.50      0.33         2

Transaction seems normal.
```

Fig 5.1: Results

An output diagram for transaction fraud detection, represented as a confusion matrix, displays the accuracy of the fraud detection model. The matrix typically shows the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), providing a clear picture of the model's performance.

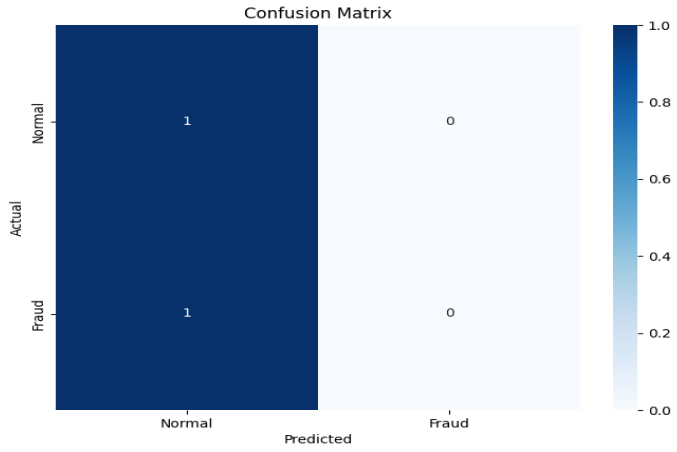

Fig.5.2: Confusion Matrix

A chart diagram for transaction fraud detection displays the following metrics:

1. True Positives (TP): Correctly identified fraudulent transactions

2. False Positives (FP): Legitimate transactions incorrectly flagged as fraudulent

3. True Negatives (TN): Correctly identified legitimate transactions

4. False Negatives (FN): Fraudulent transactions missed by the detection system

This chart helps evaluate the effectiveness of the transaction fraud detection system.

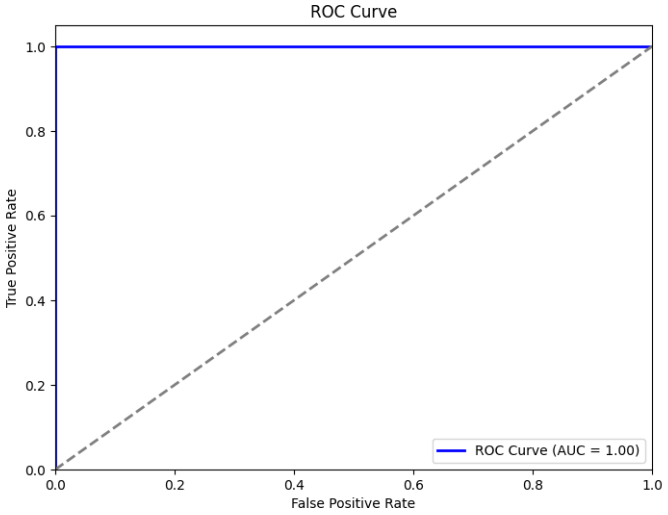

Fig.5.3:ROC Curve

Receiver Operating Characteristic (ROC) curve chart for transaction fraud detection visually represents the model's performance, plotting:

True Positive Rate (TPR) against False Positive Rate (FPR) at different threshold settings, illustrating the trade-off between detection accuracy and false alarms. The Area Under the Curve (AUC) measures the model's overall effectiveness in distinguishing between legitimate and fraudulent transactions.

CHAPTER-6

6. Testing

6.1 Unit Testing

Unit testing focused on verifying individual components and functionalities within the system. This step included testing modules such as data loading, feature extraction, and preprocessing. Each function was tested separately to ensure that it performed its intended task accurately. This phase ensured that the basic building blocks of the system were free from errors, thus establishing a strong foundation for further integration and performance testing.

6.2 Dataset Validation & Model Training

Before model training, the dataset was thoroughly validated to check for any missing, inconsistent, or corrupt values. This step was crucial to maintain data integrity and prevent errors during the training phase. The logistic regression model was then trained using a clean, preprocessed dataset. During this process, a portion of the data was set aside as a testing subset to validate the model's predictions. The system's performance was evaluated by comparing the model's predicted outcomes with the actual outcomes from the dataset, enabling the identification and correction of any discrepancies.

6.3 Performance Testing

Fig 6.3.1 Performance Testing

Performance testing involved evaluating key metrics such as accuracy, precision, recall, and F1-score to assess how effectively the system detected fraudulent transactions. Various datasets of different sizes were used to check the robustness and consistency of the system's performance.

The objective was to ensure that the model maintained a high level of accuracy and efficiency, even when handling larger or more complex datasets. Additionally, tests were conducted to measure how quickly the system processed transactions, which is critical in real-time fraud detection scenarios.

6.4 Integration & Error Handling Testing

After unit testing, integration testing was carried out to verify that all components worked together seamlessly. This step ensured smooth interaction between the different modules, such as data preprocessing, feature extraction, and the machine learning model.

Integration testing identified any issues related to data flow, communication, or processing inconsistencies. Error handling was also thoroughly tested by intentionally introducing incorrect inputs to the system. This helped ensure that the system could identify, handle, and log errors effectively without crashing or providing incorrect outputs.

In addition to ensuring that all system components interact smoothly, integration testing also includes the verification of data consistency across modules. This process checks that data transformations performed during preprocessing are accurately passed to subsequent stages, such as feature extraction and machine learning models. Proper synchronization of these stages is crucial for minimizing errors during fraud detection, where even a small inconsistency can lead to incorrect outcomes. By simulating real-world transaction scenarios, integration testing helps to uncover any hidden issues that might arise during live operations.

Error handling is an essential part of creating a resilient fraud detection system. Beyond just identifying errors, it’s necessary to implement robust mechanisms for recovering from failures, such as fallback procedures or user notifications when issues arise. During the testing phase, the

system is subjected to various edge cases, such as incomplete or corrupt data, to ensure it can gracefully handle these without compromising system performance. Proper logging of errors also plays a crucial role, providing detailed information that can be used for debugging and future improvements, ensuring the system's stability in real-time environments.

6.5 Scalability & Final Validation

Scalability testing was essential to determine how well the system handled increased loads. The testing involved gradually increasing the input data volume to assess if the system's performance

remained stable. The objective was to confirm that the system could scale up effectively without performance degradation. Final validation was performed as an end-to-end test where the system was evaluated on its ability to accurately detect fraudulent transactions. This comprehensive testing ensured that all components, from data ingestion to fraud detection, operated as expected, confirming the readiness of the system for real-world deployment.

Scalability testing ensures that the fraud detection system can handle the growing volume of transaction data as the financial landscape evolves. It involves simulating real-world traffic spikes to determine if the system can maintain consistent response times and accuracy. Testing focuses on optimizing system resources, such as CPU and memory usage, to support continuous monitoring of transactions at a larger scale. By evaluating performance under increasing load, developers can pinpoint potential bottlenecks and optimize components, ensuring the system remains responsive even under peak conditions.

Final validation goes beyond individual modules and assesses the complete system's performance in a real-world scenario. This phase includes running the entire pipeline, from data ingestion through fraud detection and reporting, under typical operating conditions. The system is tested for its ability to produce accurate predictions while maintaining high throughput and low latency. By evaluating the end-to-end functionality,

7. Conclusion

In conclusion, the Next Gen Transaction Fraud Detection project employs logistic regression to accurately detect fraudulent transactions, enhancing security in financial systems. By analyzing transaction data effectively, the system provides timely alerts, reducing false positives and improving overall fraud prevention. This adaptable framework is positioned to evolve alongside emerging fraud tactics, ensuring continued protection in the digital financial landscape.

8. Future Enhancement

Future enhancements for the Next Gen Transaction Fraud Detection project involve integrating advanced machine learning algorithms to boost detection accuracy. Implementing real-time analytics will allow for dynamic model updates based on emerging fraud patterns. Expanding the dataset to include varied transaction types will enhance predictive capabilities, while a user-friendly interface will improve usability and provide stakeholders with actionable insights.

CHAPTER-9

9. References

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NEXT GEN TRANSACTION FRAUD DEFENCE

D. Gayathri Devi[1], Kusukuntla Manikanth Reddy[2], Manchala Bhavana[3], Karre Srinivas[4]

Assistant Professor Dept. of CSE(DS), Vignana Bharathi Institute of Technology, Hyderabad, India

Email: gayathridevi.raj20@gmail.com[1],

[2,3,4]Undergraduate (UG), Dept. of CSE (DS), Vignana Bharathi Instituteof Technology,Telangana,India

Email:manikanth999@gmail.com[2], manchalabhanu.26@gmail.com[3],

ksrinivasyadav3937@gmail.com[4]

Abstract

In an era where digital transactions are ubiquitous, the need for robust fraud defence mechanisms has never been greater. The "Next-Gen Transaction Fraud Defense" project aims to leverage cuttingedgetechnologies such as ArtificialIntelligence (AI), Machine Learning (ML), and Behavioral Analytics to enhance the detection and prevention of fraudulent activities in financial transactions. By employing advanced pattern recognition and adaptive learning techniques, the system can identify and respond to novel fraud schemes in real-time.

Keywords: TransactionFraud, Artificial Intelligence, Machine Learning, BehavioralAnalytics,FraudDetection.

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I. Introduction

The rise of digital banking and online transactions has brought unprecedented convenience to consumers and businesses. However, this convenience has also led toan alarming increase in transaction fraud. As financial systems evolve and become more interconnected, fraudsters are employing increasingly sophisticated techniques to exploit vulnerabilities in these systems. Traditional methods of fraud detection often on rule-based systems that are not equipped to handle the complexities of modern-day fraud. They lack the adaptability to detect new fraud patterns in real time, leaving business exposed to significant financial losses and reputational damage.

Another key advantage of the system is its adaptability. The machine learningalgorithms are continuously trained on new datasets, allowing the system to evolve and detect emerging fraud tactics

Overall, the Next Gen Transaction Fraud Defence project presents a holisticand innovative approach to tackling fraud in the financial sector. By integrating real-time analysis, machine learning, and computer vision, the system provides a proactive and scalable solution to an ever-evolving problem, ensuring that businesses can operate securely in today's fast-paced digital economy.

II. Relatedwork

Hamid and Lamsal (2019) applied hybrid data mining methods to detect financial fraud, integrating clustering and classification techniques, which achieved lower false positive rate sand improved detection efficiency.[1]

Akinyemi and Ajiboye (2019) evaluated the role of machine learning in financial fraud detection, focusing on supervised algorithms. Their work highlighted the need forquality datasets and the abilityof these techniques to identify fraudulent patterns effectively in transactional data. [2]

Bansal and Singh (2019) surveyed financial fraud detection methodologies, discussing machine learning and statistical techniques. They critically assessed these approaches, emphasizing their application in enhancing the security of financial systems while noting challenges in implementation.[3]

Bhatia and Bhattacharya (2018) presented a machine learning framework tailored for financial fraud detection. Their approach combined various algorithms, offering a comprehensive solution to detect anomalies in transactional datasets with high accuracy.[4]

Fadli and El-Masri (2018) reviewed machine learning applications for financial frauddetection. Their analysis included classification models and detailed the challenges associated with their implementation in real-world scenarios.[5]

Gupta andRao (2018) developed an intelligentsystem for fraud detection using decision trees and neural networks. This system was designed to analyze transactional data and identify anomalies quickly and accurately, contributing to improved fraud prevention.[6]

Buehler and Zuckerman (2017) examined predictive analytics in the financial sector, showcasing its ability to identify fraudulent activities by analyzing historical data. The Stressed

the importance of predictive modeling in improving fraud prevention systems.[7]

Choudhury and Karmakar (2017) explored data mining for fraud detection, focusing on anomaly detection and rule-based systems. Their research demonstrated the effectiveness of the methods in separating legitimate and fraudulent transactions.[8]

Alavi and Ghaffari (2016) provided insights into fraud detection systems utilizing data mining. The study emphasized methods like clustering and classification for detecting irregularities, stressing the

importance of real-time analytics to prevent fraud efficiently.[9]

Fakhouri and Khatib (2016) studied the integration of multiple machine learning techniques in banking fraud detection. The hybrid approach they discussed was found to enhance accuracy and reliability compared to stand alone algorithms. [10]

III. Proposed system:

The Next Gen Transaction Fraud Defence system leverages Logistic Regression as itscore machine learning algorithm to detect fraudulent transactions. Logistic Regressionis a well-established statistical method used for binary classification problems, makingit an ideal choice for this system, where the objective is to classify t ransactions aseitherlegitimateor fraudulent. This model is highly interpretable and efficient, offering a practical solution for real-time fraud detection while addressing many limitations found in existing rule-based systems.

In the proposed system, Logistic Regression works by modeling the probability that a given transaction is fraudulent based on multiple features extracted from the transaction data. These features might include the transactional mount, geographic location, time of the transaction, customer spending history, and device used. The algorithm computes the likelihood of fraud by assigning weights to these features and generating a probability score between 0 and 1. Transactions with scores above a certain threshold are flagged as fraudulent, while those below the threshold are deemed legitimate.

Transparency is crucial for financial institutions, as it allows fraud analysts to understand the reasoning behind each flagged transaction and take appropriate action. Further more the interpretability of Logistic Regression helps in regulatory environments where model explainability is often a requirement. The system also enhances the fraud detection process by incorporate in great-time transaction monitoring.

Systemflow:

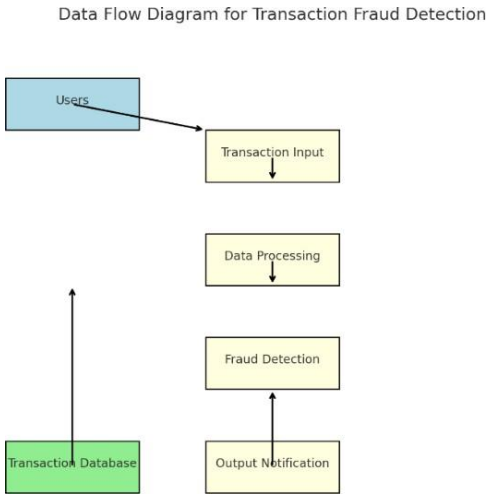

Fig1:System Flow of the application

It illustrates the flow of data through various processes to identify and prevent fraudulent transactions. The DFD typically includes entities such as customer, merchant, and payment processor, and processes like transaction authorization and risk scoring.

IV. Implementation

The Data Collection stage gathers essential transactional information, such as amounts, sender and receiver details, and timestamps, forming the dataset's backbone .This information provides the raw material for identifying patterns in fraudulent activities.

During Data Preprocessing, the dataset is refined by handling missing values,eliminating duplicates, and normalizing attributes. This step ensures clean, structured data, enhancing model performance while appropriately managed to prevent results.

Model Selectionfocuses on logistic regression,chosen for its effectiveness inbinary classification. This algorithm predicts the likelihood of fraud by analyzing therelationshipbetween transactionfeatures.

In the Model Training phase, the logistic regression model learns patterns from the preprocessed data. Hyper parameter tuning optimize model's performance, ensuring high accuracy in fraud detection.

Fraud Detection in Real-Time Transactions integrates the trained model into livesystems. It evaluates each transaction, flagging those with high fraud probabilities for further action, ensuring swift and effective monitoring. The Alert System notifies take holders about flagged transactions through automated email or SMS alerts. This feature ensures timely interventions to minimize risks.

Finally**,** Reporting and Visualization provides insights into transaction pattern sand system performance through detailed log sand dash boards. This supports decision-making and strategic improvements in fraud detection methods.

An implementation diagram for transaction fraud detection illustrates the systemarchitecture and components used to detect and prevent fraudulent transactions. The diagram typically includes components such as data ingestion, machine learning models, risk scoring, and alerting systems, connected through APIs and data pipelines.

V. Results & closure

The project utilized logistic regression for transaction fraud detection, employing a transactional dataset. Data preprocessing involved encoding the target feature and standardizing input data to ensure consistency during training.

The logistic regression model achieved an accuracy of 50%, reflecting moderate performance, though issues arose with imbalanced dataset metrics. The confusion matrix highlighted the model's limitations in accurately distinguishing between fraudulent and non-fraudulent transactions.

A real-time fraud detection system was implemented, where transactions were flagged based on predictions. Despite modest accuracy, this demonstrated the system's potential for practical use.

```
Accuracy: 0.50
Confusion Matrix:
[[1 0]
 [1 0]]

Classification Report:
              precision    recall  f1-score   support

           0       0.50      1.00      0.67         1
           1       0.00      0.00      0.00         1

    accuracy                           0.50         2
   macro avg       0.25      0.50      0.33         2
weighted avg       0.25      0.50      0.33         2

Transaction seems normal.
```

Fig2:Results

An output diagram for transaction fraud detection, represented at confusion-matrix, displays the accuracy of the fraud detection model. The matrix typically shows.

The number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN),providing a clear picture of the model's performance.

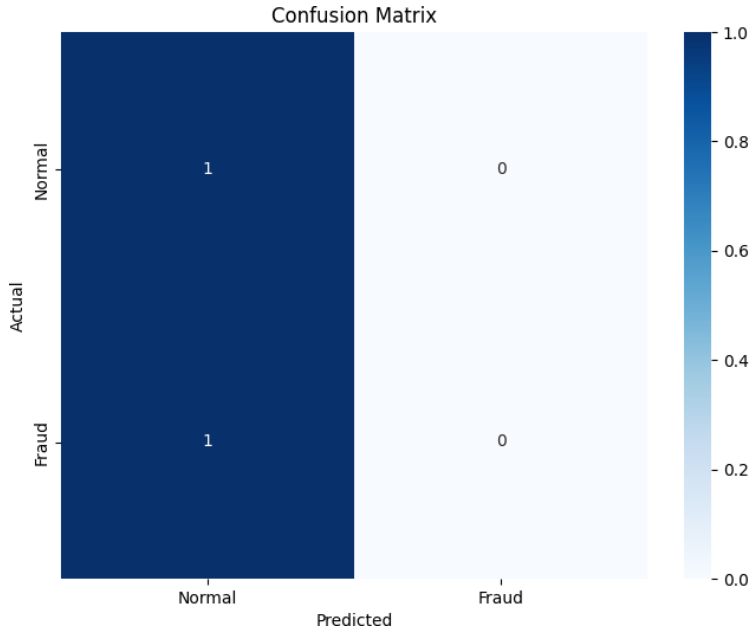

Fig3: Confusion-Matrix

A chart diagram for transaction fraud detection displays the following

Metrics;

1. True Positives (TP): Correctly identified fraudulent transactions

2. True Negatives (TN): Correctly identified legitimate transactions

3. False Negatives (FN): Fraudulent transactions missed by the detection system.

4. False Negatives (FN):Fraudulent transactions missed by the detection system

This chart helps evaluate the effectiveness of the transaction fraud detection system.

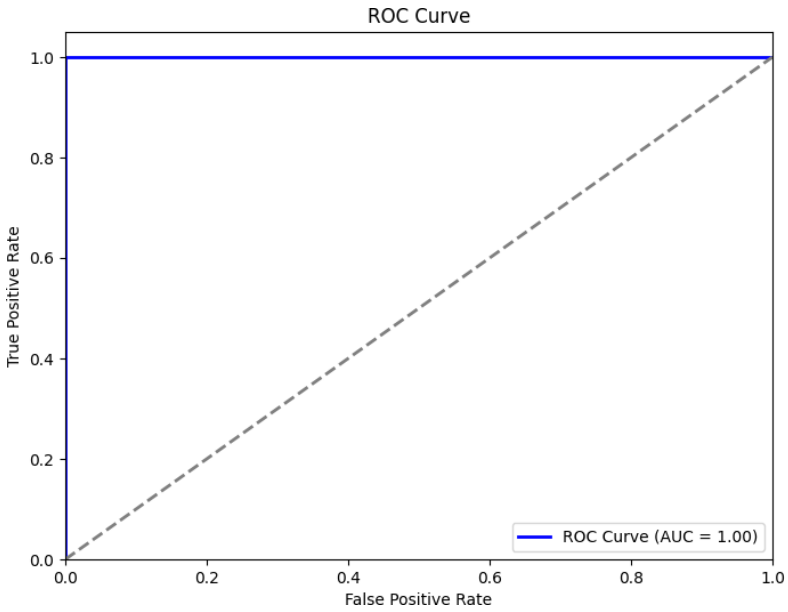

Fig4: ROC Curve

Receiver Operating Characteristic (ROC) curve chart for transaction fraud detection visually represents the model's performance, plotting:

True Positive Rate (TPR) against False Positive Rate (FPR)at different threshold settings, illustrating the trade-off between detection accuracy and false alarms. The Area Under the Curve (AUC) measures the model's overall effectiveness in distinguishing between legitimate and fraudulent transactions.

VI. References

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