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Fraud Detection using Risk Based Binary Classification

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Abstract: A Google Pay fraud detection system is proposed in this research, implemented in C++, which detects fraudulent transactions through a risk-based binary classification framework. The system analyzes key factors such as transaction amount, transaction frequency, device trust, and location mismatch to determine transaction legitimacy
A binary output is generated by the system, with 0 denoting legitimate transactions and 1 denoting fraudulent transactions. The study highlights how machine learning–inspired approaches can be applied to real-time payment systems to improve security and prevent financial losses.
Keywords: legitimate, fraudulent, probability, possibility.

I. INTRODUCTION

The rapid proliferation of digital payment platforms, including Google Pay, has been widely acknowledged in the literature as a key driver of efficiency and convenience in modern financial transactions.
However, several studies have highlighted that the increased adoption of such platforms has also contributed to a corresponding rise in fraudulent activities. Prior research indicates that cybercriminals employ increasingly sophisticated techniques to exploit vulnerabilities within digital payment infrastructures, thereby posing significant security threats to both users and financial institutions.
These threats manifest in various forms, including unauthorized access, financial losses, and diminished user trust in digital financial services. Consequently, existing literature emphasizes the necessity of implementing robust security frameworks and advanced fraud detection mechanisms to mitigate fraud risks and enhance the overall resilience of digital payment ecosystems.

II. WORKING OF MODEL

The Google Pay Fraud Detection System is designed to assess the legitimacy of digital payment transactions by systematically analyzing multiple transactional and contextual attributes. At the initial stage, the system acquires essential transaction-related information from the user, including the monetary value of the transaction, the total number of transactions performed by the user within the same day, the trust status of the device used to initiate the transaction, and the presence of any discrepancies between the current transaction location and the user's historical location patterns. These features collectively capture both behavioral and contextual risk indicators associated with fraudulent activity.
Each extracted feature is assigned a predefined weight that reflects its relative significance in contributing to the overall transaction risk. Features such as unusually high transaction amounts, elevated transaction frequency, usage of untrusted devices, and location inconsistencies are typically associated with higher fraud susceptibility and are therefore assigned greater weights. A composite risk score is then calculated through a weighted linear combination of the selected features, enabling the aggregation of diverse risk factors into a single quantitative measure.
To facilitate probabilistic interpretation and binary classification, the computed risk score is subsequently passed through a sigmoid activation function. This transformation maps the unbounded risk score to a normalized probability value within the range of 0 to 1, representing the likelihood that a given transaction is fraudulent. A fixed decision threshold of 0.5 is employed to classify transactions, wherein probability values equal to or exceeding the threshold are categorized as fraudulent, while values below the threshold are classified as legitimate.
Finally, the system outputs the computed risk score and corresponding probability value, thereby providing a transparent and interpretable basis for fraud detection decisions.

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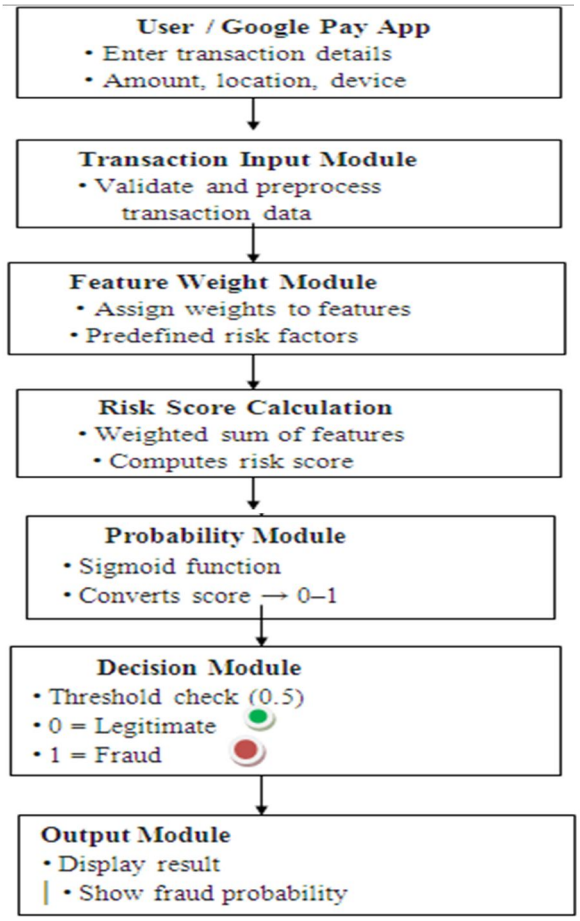
Figure 1. How The System Works



Below is an example dataset suitable for producing the output of the described Google Pay Fraud Detection model**. This aligns with a** literature-style / experimental setup, where inputs, computed risk scores, and final classifications are reported.

Figure 2 .Sample Dataset Structure (Model Output)

Transaction ID	Amount (₹)	Transactions per Day	Device Trusted (1=Yes, 0=No)	Location Mismatch (1=Yes, 0=No)	Risk Score (Weighted Sum)	Fraud Probability	Classification
T001	500	2	1	0	0.85	0.30	Legitimate
T002	12,000	8	0	1	2.10	0.89	Fraudulent
T003	3,500	5	1	1	1.45	0.81	Fraudulent
T004	1,200	1	1	0	0.60	0.35	Legitimate
T005	9,000	7	0	1	1.95	0.87	Fraudulent

Mathematical Representation

- Risk Score

$$R = w_1 \cdot Amount + w_2 \cdot Transactions + w_3 \cdot Device + w_4 \cdot Location$$

- Fraud Probability (Sigmoid Function)

$$P = \frac{1}{1 + e^{-R}}$$

. Decision Rule

$$\text{Fraudulent if } P \geq 0.5$$

III. CONCLUSION

The Google Pay detection system illustrates the effectiveness of risk-based classification in identifying fraudulent transactions. It delivers accurate results while requiring minimal resources and has the potential for further enhancement to support real-world deployment. This work underscores the critical role of fraud detection in digital payment systems and lays the groundwork for more advanced security solutions.

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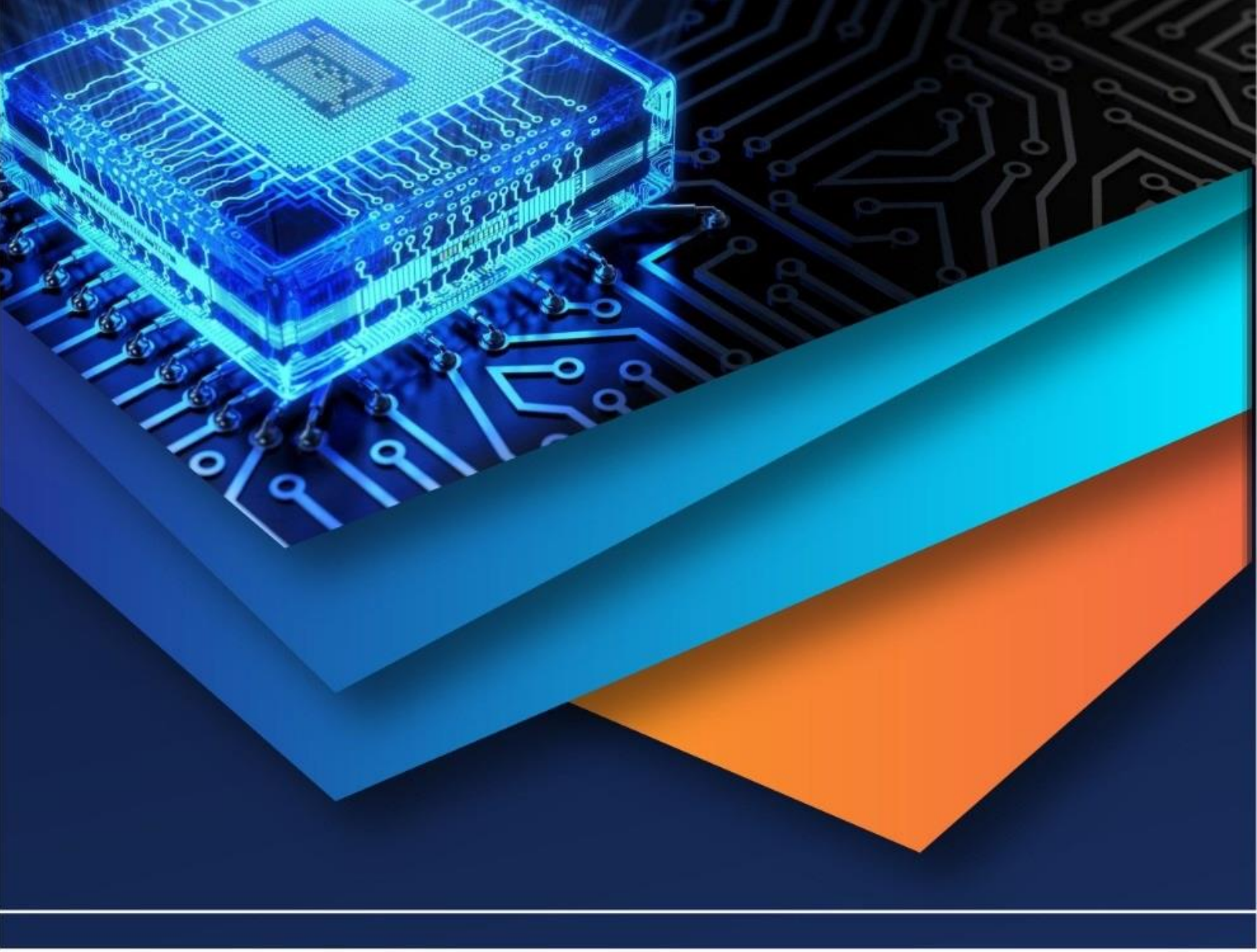

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