Maharshi Karve Stree Shikshan Samstha's
Cummins College of Engineering for Women, Pune
(An Autonomous Institute affiliated to Savitribai Phule Pune University)

23PCCE501L – Artificial Intelligence and Machine Learning Laboratory

TY BTECH COMP DIV A

Group 4

Transaction Fraud Detection Using Machine Learning Techniques

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Introduction

- Financial transactions have increased massively through online banking, UPI, e-commerce, wallets, etc.
- Along with this growth, fraudulent transactions have also increased.
- Manual rule-based systems often fail to detect evolving fraud patterns.
- Machine Learning helps identify fraud by learning patterns from historical data.
- This project uses Logistic Regression & Random Forest models to classify transactions as fraud or normal
- Our project adds an extra layer of intelligence: Location-based behavior analysis.

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Objective

- Build a reliable ML system to detect fraudulent transactions.
- Train and compare Logistic Regression & Random Forest on a real transactions dataset.
- Preprocess data: scaling, handling imbalance, stratified split.
- Evaluate using Accuracy, Precision, Recall, F1-score, ROC-AUC.
- Build a Gradio-based user interface to test fraud risk in real-time.
- Analyze model behavior, outcomes, and challenges.
- Integrate user location + transaction location similarity

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Problem Statement

To develop an efficient and scalable machine learning model capable of detecting fraudulent financial transactions using supervised learning techniques and deploy it with an interactive interface.

Challenges Addressed:

- Real-time decision requirements
- Evolving fraud patterns
- Need for accurate + interpretable predictions
- Existing datasets do not contain location information, limiting fraud analysis.
- Need a system that combines transaction patterns + location behavior.

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Market Analysis

- Digital payments in India grew over 50% yearly due to UPI and online banking.
- Fraud cases such as phishing, unauthorized transactions, OTP theft, and merchant scams are rising.
- RBI reports growing financial cybercrime cases every year.
- Businesses require:
    a. Real-time fraud detection
    b. Explainability
    c. Scalability
    d. High fraud recall (avoid missed frauds)

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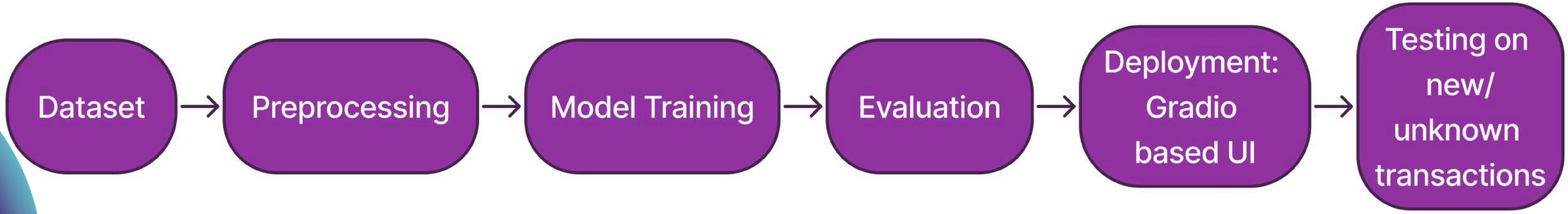
Methodology



Outcomes

- Models trained successfully on anonymized transaction dataset
- Random Forest performed best in terms of recall & AUC
- Generated Confusion Matrix, ROC Curve, Accuracy Table
- Created a working Gradio app for predicting fraud probability
- Created a donut chart showing contribution of the features

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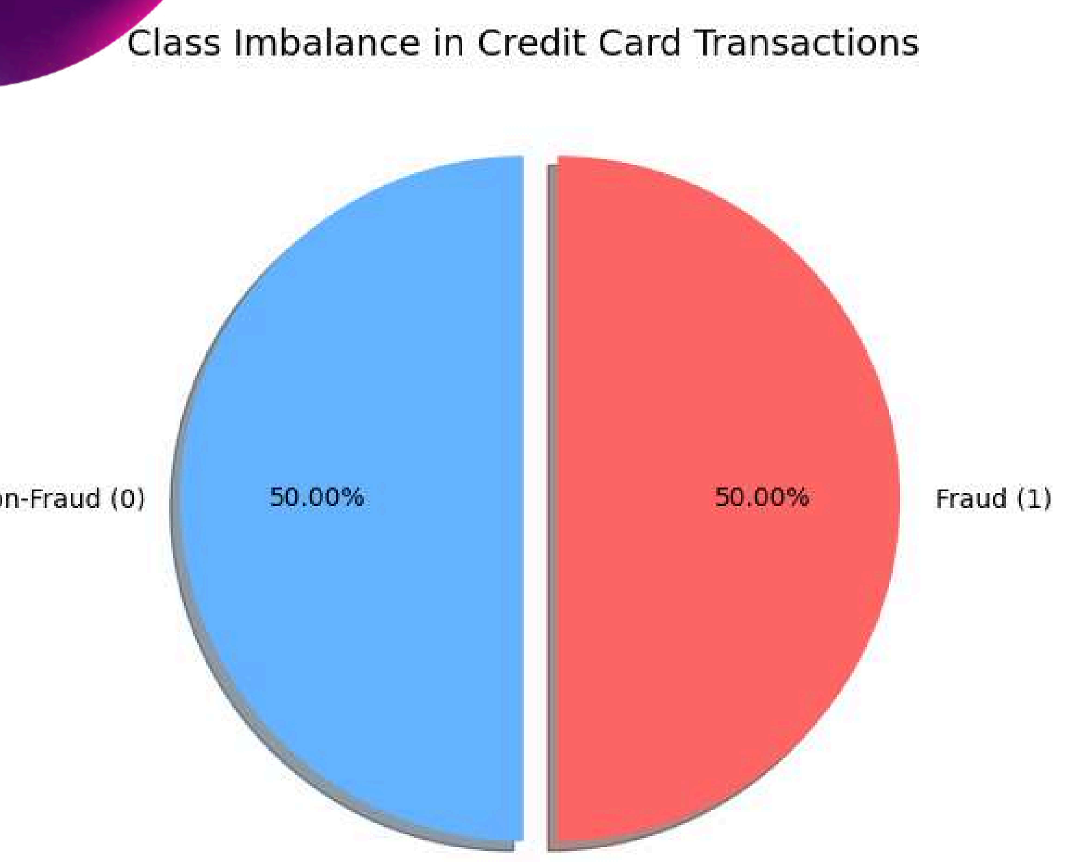
Results

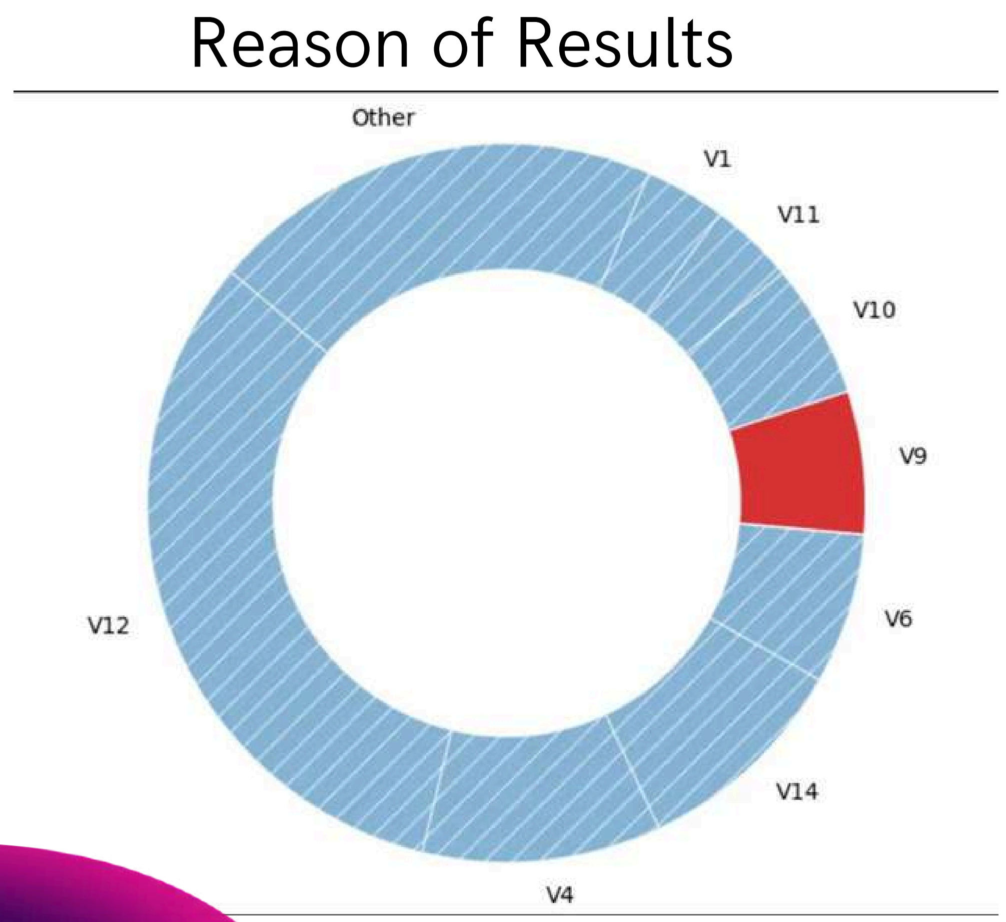
```
==============================================================
Model: Logistic Regression
==============================================================
              precision    recall  f1-score   support

           0     0.9976    0.9990    0.9983     56863
           1     0.9990    0.9976    0.9983     56863

    accuracy                         0.9983    113726
   macro avg     0.9983    0.9983    0.9983    113726
weighted avg     0.9983    0.9983    0.9983    113726

Confusion matrix:
  TN: 56,805   FP: 58
  FN: 137   TP: 56,726
```

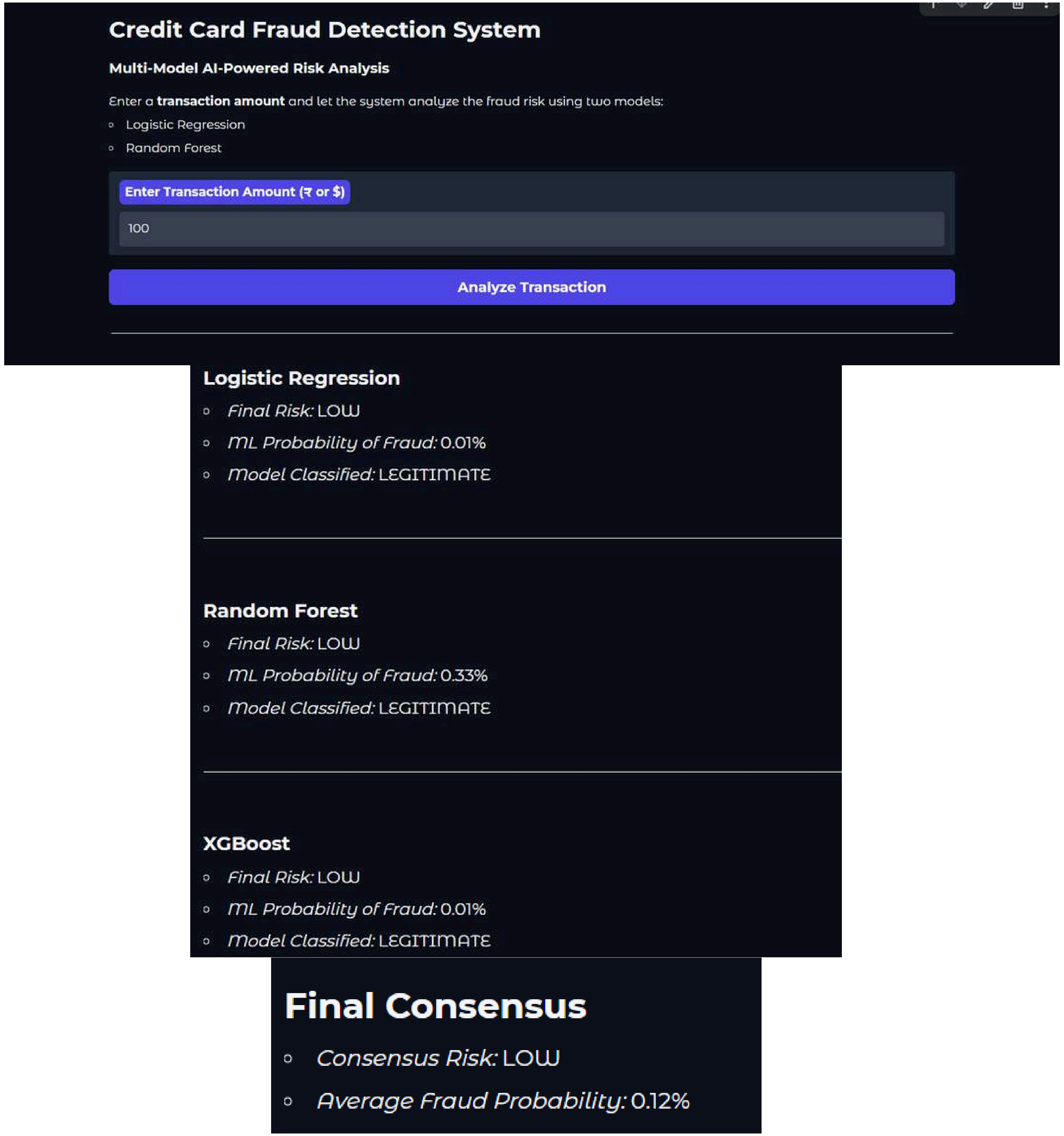
```
==============================================================
Model: Random Forest
==============================================================
              precision    recall  f1-score   support

           0     0.9997    0.9998    0.9998     56863
           1     0.9998    0.9997    0.9998     56863

    accuracy                         0.9998    113726
   macro avg     0.9998    0.9998    0.9998    113726
weighted avg     0.9998    0.9998    0.9998    113726

Confusion matrix:
  TN: 56,852   FP: 11
  FN: 16   TP: 56,847
```

```
==============================================================
Model: XGBoost
==============================================================
              precision    recall  f1-score   support

           0     0.9996    0.9999    0.9997     56863
           1     0.9999    0.9996    0.9997     56863

    accuracy                         0.9997    113726
   macro avg     0.9997    0.9997    0.9997    113726
weighted avg     0.9997    0.9997    0.9997    113726

Confusion matrix:
  TN: 56,855   FP: 8
  FN: 23   TP: 56,840

==============================================================
```

```
Overall comparison:
              Model  Accuracy  AUC-ROC  True Positives  False Negatives  False Positives
Logistic Regression  0.998285 0.999807           56726              137               58
      Random Forest  0.999763 0.999996           56847               16               11
            XGBoost  0.999727 0.999977           56840               23                8

Best model by AUC-ROC: Random Forest (AUC: 1.0000)
```


Class Imbalance in Credit Card Transactions
n-Fraud (0)
50.00%
50.00%
Fraud (1)


Reason of Results
Other
V1
V11
V10
V9
V6
V14
V4
V12


Credit Card Fraud Detection System
Multi-Model AI-Powered Risk Analysis
Enter a transaction amount and let the system analyze the fraud risk using two models:
Logistic Regression
Random Forest
Enter Transaction Amount (₹ or $)
100
Analyze Transaction
Logistic Regression
Final Risk: LOW
ML Probability of Fraud: 0.01%
Model Classified: LEGITIMATE
Random Forest
Final Risk: LOW
ML Probability of Fraud: 0.33%
Model Classified: LEGITIMATE
XGBoost
Final Risk: LOW
ML Probability of Fraud: 0.01%
Model Classified: LEGITIMATE
Final Consensus
Consensus Risk: LOW
Average Fraud Probability: 0.12%

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Conclusion

- Developed an end-to-end Transaction Fraud Detection system.
- Compared LR and RF and XGBoost .
- Achieved extremely high accuracy due to clean anonymized dataset.
- Demonstrated real-time prediction using Gradio.
- System can be extended for banks, wallets, e-commerce, and merchant fraud protection.

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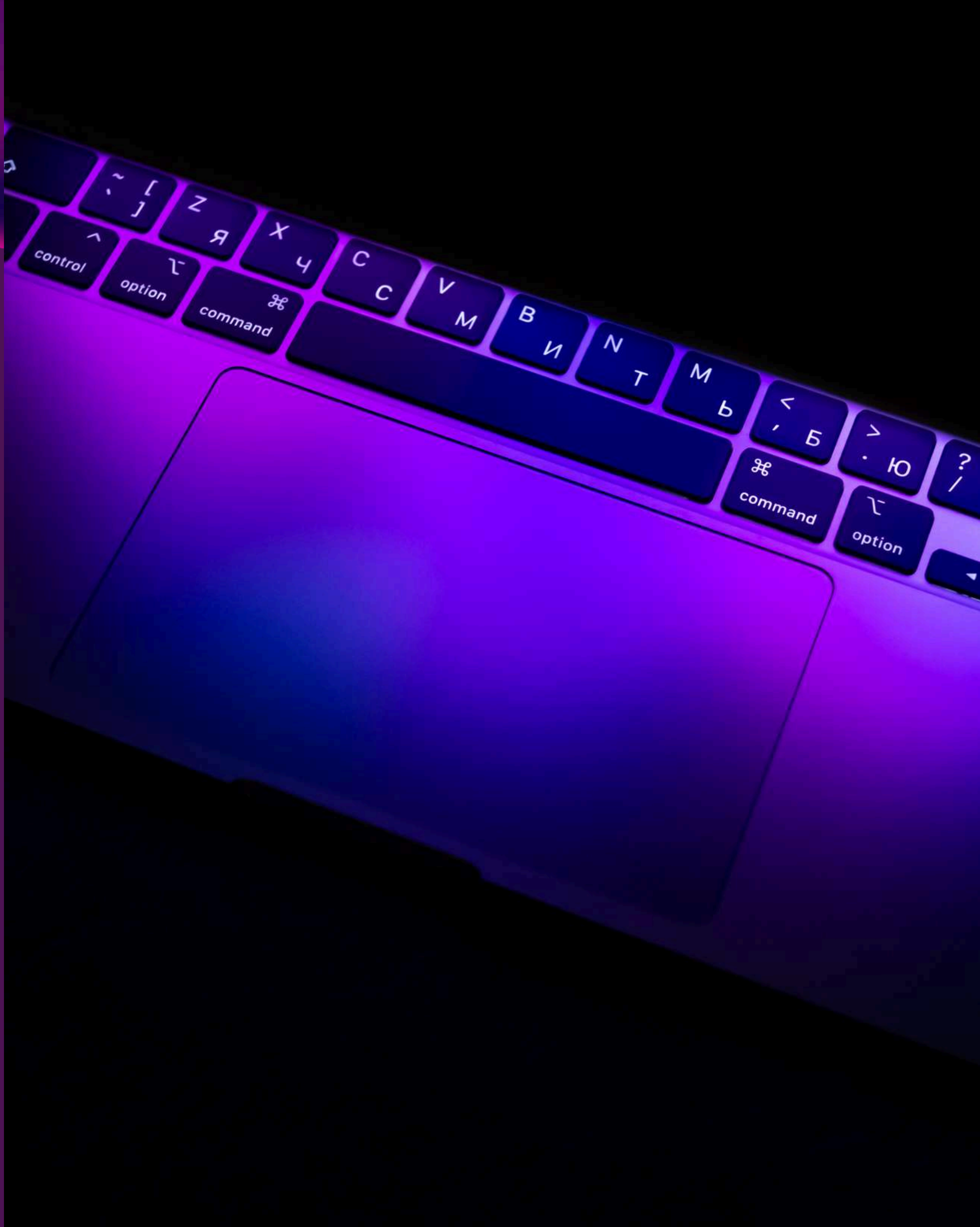
Future Scope

- Add SHAP explain-ability
- Deploy model as API or web service
- Integrate deep learning or anomaly detection
- Add real-time streaming data
- User behavior profiling
- Adaptive retraining pipeline



Acknowledgement

We sincerely thank:

- Our project guide :
  - Varsha Pimprale
  - Dr. Sandhya Arora
- Open-source contributors of datasets/tools
- Kaggle for providing dataset access

References

- Gradio documentation
- Kaggle: Fraud Transaction Dataset
- West, Bhattacharya. “Intelligent financial fraud detection”

THANK YOU