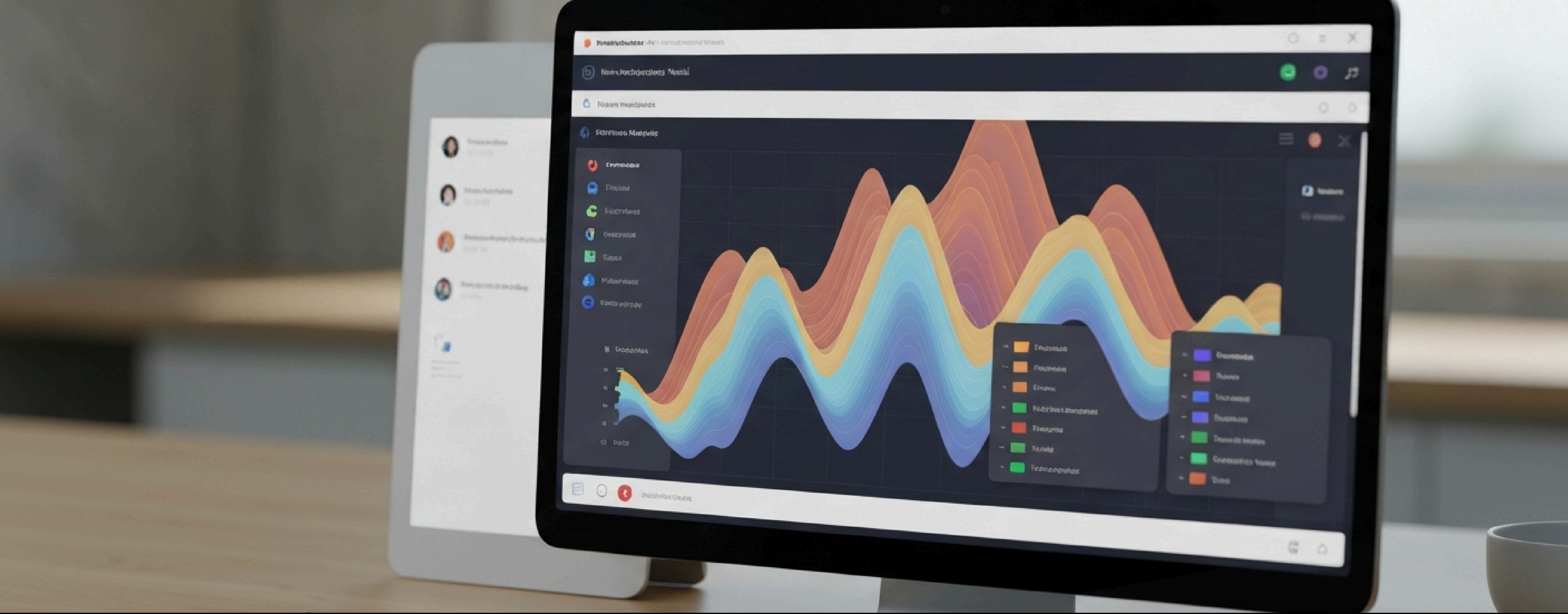

# Enhanced Hybrid Deep Learning Ensemble For Credit Card Fraud Detection

A presentation on optimizing credit card fraud detection using a hybrid deep learning ensemble model.

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# Motivation / Problem Statement

### Credit card fraud is costly and widespread

With highly imbalanced data (492 fraud out of 284,807 transactions)

### Traditional ML models struggle with precision–recall trade-off

High recall models trigger many false positives, leading to operational cost and poor customer experience

### Black-box deep learning models can detect patterns

But often raise even more false alarms

### Problem: Find a model that improves fraud detection

Without overwhelming analysts

### Objective: Build and evaluate a hybrid deep learning ensemble

With reduced false positives and improved overall performance

# Introduction & Literature Review

Hybrid and ensemble models have shown strong performance for credit card fraud detection by combining multiple learners– e.g. hybrid deep learning ensembles for fraud detection (Ileberi & Sun, 2024; Mienye & Sun, 2023).

Class imbalance remains a core challenge and can lead to biased models or misleading performance if not handled correctly (Rtayli & Enneya, 2020; Islam et al., 2023). Sequence-aware models (LSTM, attention/Transformer) can capture temporal and contextual spending patterns that static models miss (Vaswani et al., 2017; Jabeen et al., 2025). Interpretability is important in high-stakes domains like fraud detection; black-box models can be problematic for regulators and analysts (Rudin, 2019).

Contribution: A hybrid deep learning ensemble (CNN + LSTM + Transformer + XGBoost) with imbalance-aware optimisation and threshold calibration for improved operational fraud detection.

# Methodology / Approach

### Dataset

The dataset used is the European Credit Card Fraud dataset, which contains PCA-transformed and anonymized features.

### Preprocessing

The data is preprocessed by scaling, experimenting with oversampling/undersampling techniques, and adjusting class weights to address the class imbalance.

### Model Architecture

The model architecture consists of: - CNN: For feature extraction - LSTM: For modeling sequential spending patterns - Transformer: To incorporate attention mechanism - XGBoost: As the final classification layer

### Training

The model is trained using a loss function with class weighting, early stopping, and threshold tuning to optimize for precision in fraud detection and reduce false positives.

### Baselines

The baseline models used for comparison are Logistic Regression, Random Forest, and a standard Hybrid Ensemble.

# Dataset, Evaluation & Experimental Results

European Credit Card Fraud Dataset: 284,807 total transactions | 492 fraud cases | 284,315 non-fraud cases | 0.172% fraud (imbalance ratio)

| Model | Precision | Recall | F1-Score | AUC-ROC |
|---|---|---|---|---|
| Logistic Regression | 0.0608 | 0.9184 | 0.1141 | 0.9723 |
| Random Forest | 0.9605 | 0.7444 | 0.8398 | 0.9529 |
| Hybrid Ensemble | 0.3320 | 0.8673 | 0.4802 | 0.9523 |
| Hybrid Ensemble (Optimised) | 0.8065 | 0.7653 | 0.7853 | 0.9662 |

***Baseline Hybrid:** FP=171, FN=13, TP=85, TN=56 693
**Optimized Hybrid:** FP=18, FN=23, TP=75, TN=56 846

# Conclusion

### Key Contributions

The optimized hybrid ensemble significantly improves precision and reduces analyst workload while maintaining strong fraud-detection ability.

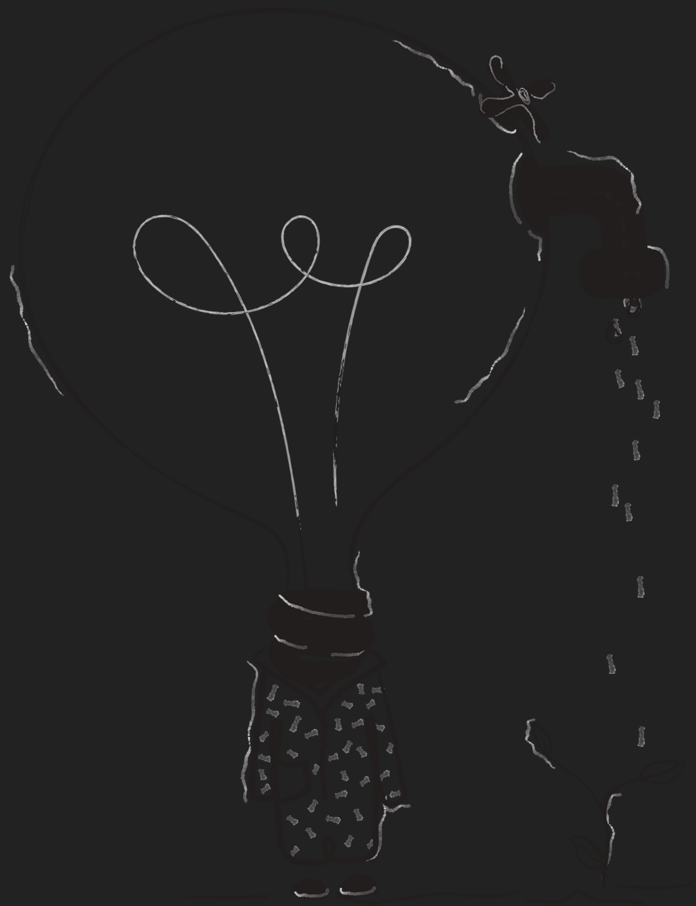
### Limitations

Dataset is from europe; african data is needed for further evaluation.

### Future Research Directions

Model interpretability (e.g., SHAP), real-time detection, custom feature engineering to enhance performance and deployability.

**The optimized hybrid ensemble has made significant contributions to improving fraud detection precision and reducing analyst workload, while maintaining strong overall performance. Future research should focus on enhancing the model's interpretability, real-time capabilities, and leveraging custom features to further optimize the system for practical deployment in real-world banking environments.**



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