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Ensemble Deep Learning Strategy for Handling Imbalanced Credit Card Fraud Data

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Abstract. *Credit card fraud remains a major challenge in the financial sector due to its dynamic nature and highly imbalanced transaction data. This study presents a robust deep ensemble learning approach that integrates spatial, sequential, and temporal learning capabilities. A series of preprocessing steps were applied, including feature normalization, class-label separation, and class rebalancing using SMOTE. The model architecture combines convolutional, recurrent, and long short-term memory layers to capture diverse fraud patterns. These components are merged and passed through dense and dropout layers for optimal binary classification. The datasets used are generated from real-world credit card transactions, ensuring practical relevance. On the test set, the proposed model achieved 99.7% accuracy, 99.6% precision, 99.9% recall, and 99.8% F1-score. The training and validation loss curves showed smooth convergence without any overfitting, confirming model stability. To ensure reliability, 3-fold stratified cross-validation was performed on the balanced dataset. The average metrics across folds included 99.76% accuracy, 99.70% precision, 99.85% recall, and 99.77% F1-score. These results underscore the generalization capability and consistent prediction performance of the model. Comparative analysis showed that the group model outperformed individual CNN, RNN, and LSTM architectures. The hybrid strategy benefits from the spatial extraction of CNN, sequence modeling of RNN, and memory retention of LSTM. By integrating these strengths, the model effectively detects subtle and complex fraud patterns. This approach provides a scalable and reliable solution for real-time fraud detection in imbalanced credit card datasets.*

INTRODUCTION

In today's digitally connected financial landscape, credit card fraud has become a serious and persistent threat. The rapid growth of online transactions and electronic payment systems has increased the incidence of fraudulent activities, which challenges the security and reliability of digital commerce. According to the Nilson Report, global losses due to credit card fraud are estimated to exceed $35 billion by 2030, indicating an urgent need for intelligent and scalable fraud detection systems [1]. Traditional rule-based systems, while useful, often lack the sophistication and adaptability needed to detect subtle and evolving fraud patterns. As a result, machine learning (ML) and deep learning (DL) approaches have emerged as powerful tools to combat financial fraud [2].

One of the main challenges in credit card fraud detection is the extreme class imbalance in the data. Fraudulent transactions represent a small portion of the total volume – often less than 0.2% – making it difficult to accurately predict them using traditional classifiers. This imbalance not only affects model performance, but also requires tailored solutions such as data augmentation (e.g., SMOTE), class weighting, and special evaluation metrics to ensure balanced detection sensitivity [3]. In addition, fraudulent behaviors are often non-linear and time-dependent, making them particularly suitable for time-aware, sequence-based models such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks.

Recent advances in deep learning have opened new avenues for more robust and accurate fraud detection systems. Convolutional neural networks (CNNs) have shown promise in extracting local patterns and spatial features in data, while RNNs and LSTMs excel at capturing temporal dependencies and sequential behavior. However, individually, each architecture has its own strengths and limitations. CNNs are powerful feature extractors, but lack temporal context awareness; RNNs are sensitive to sequential patterns, but struggle with long-term dependencies; and LSTMs address the vanishing gradient problem, but can be computationally intensive [4]. Therefore, combining these architectures into a unified group can potentially utilize the best of each, leading to improved detection accuracy, robustness, and generalization.

This study proposes a hybrid deep ensemble model that integrates CNN, RNN, and LSTM layers to detect credit card fraud in a highly imbalanced dataset. We evaluate our method using a publicly available credit card fraud detection dataset from Kaggle [5], which has 284,807 transactions of which only 492 are labeled as fraudulent. To address the imbalance, we use the Synthetic Minority Over-Sampling Technique (SMOTE) during training, ensuring that the model is exposed to a balanced representation of both classes. Our approach leverages parallel branches of CNN, RNN, and LSTM, which are then merged and passed through fully connected layers for classification. The model is further trained using class weights and validated via cross-validation to ensure robustness.

The main contributions of this work include:

- A hybrid deep learning architecture combining CNN, RNN, and LSTM in a parallel manner to extract comprehensive feature representations.
- Comparative analysis of model performance with and without SMOTE highlights the impact of oversampling techniques on fraud detection.
- A comprehensive evaluation using metrics such as precision, recall, F1-score, accuracy, AUC and confusion matrix to capture all aspects of model performance.
- Cross-validation experiments to assess model stability and avoid overfitting on a single split.
- Detailed visualization of the training curve, ROC plot and confusion matrix to support interpretability.

The remainder of this paper is organized as follows: Section 2 provides a review of the related literature on machine learning and deep learning methods for fraud detection. Section 3 describes the datasets, preprocessing methods and model architecture. Section 4 explains the experimental setup and evaluation strategy. Section 5 presents and analyzes the results. Section 6 concludes with final thoughts and future research directions.

1. Literature Review

Several studies have investigated the application of machine learning and deep learning techniques to credit card fraud detection, each addressing unique challenges such as class imbalance, real-time detection, model complexity, and interpretability.

Khalid et al. [6] proposed a hybrid approach that combines sampling techniques with ensemble machine learning algorithms to enhance credit card fraud detection. Their study used both synthetic and real-world datasets, applying models such as Random Forest (RF) and XGBoost. While this method demonstrated improved detection performance in imbalanced scenarios, the model still suffered from a relatively high rate of false positives, which potentially leads to misclassification of legitimate transactions and reduced user trust.

In another study, Ali et al. [7] developed a new hybrid model integrating generative adversarial networks (GANs) with gated recurrent units (GRUs) to detect credit card fraud. The approach was applied to a custom-built dataset, aiming to overcome the scarcity of fraudulent samples by generating synthetic examples via GANs. Although the model achieved promising results in detecting complex fraud patterns, it presented significant training challenges due to the inherent complexity of effectively tuning and optimizing the GAN-GRU architecture.

Meiney et al. [8] proposed a deep ensemble learning model combining Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) neural networks, integrated with a Multi-Layer Perceptron (MLP) meta-learner. To address the class imbalance issue, they used the SMOTE-ENN resampling technique. Their approach achieved exceptional sensitivity (1.000) and specificity (0.997), outperforming traditional machine learning methods. Despite its strong performance, the computational demands of the ensemble may limit its practicality in real-time deployment scenarios.

Goyal et al. [9] developed a real-time fraud detection system for e-commerce transactions using a combination of machine learning and deep learning models. Implemented using libraries such as NumPy and Scikit-learn, the system was trained on a dataset containing 492 fraudulent transactions out of 283,806. Using models such as Random Forest and Decision Tree, the study demonstrated promising results. However, the effectiveness of this system depends on the representativeness of the dataset and the adaptability of the model to changing patterns of fraud.

Muhl et al. [10] introduced a champion-challenger approach leveraging three ensemble models. Their top performing model consisting of Random Forest, AdaBoost and LSTM achieved remarkable performance metrics: Despite being robust, the scalability of the model and suitability for real-time implementation remain a matter of concern.

Kaur et al. [11] addressed the challenge of imbalanced data by applying a combination of machine learning, deep learning, and ensemble techniques. Their study emphasized achieving high recall without compromising precision, which is a crucial balance for maintaining customer trust in real-world systems. Various resampling strategies and performance metrics were explored to enhance detection accuracy.

Luo [12] focused on the role of uncertainty quantification in fraud detection using deep learning techniques. Methods such as Monte Carlo dropout and ensemble modeling were used to assess the estimated uncertainty. These techniques improved the reliability of fraud detection systems, and assisted in more informed decision-making processes in dynamic fraud environments.

Alarfaj et al. [13] investigated modern machine learning and deep learning approaches to mitigate fraud, particularly under conditions of data imbalance and evolving fraud strategies.Their empirical evaluation on benchmark datasets demonstrated significant improvements in precision, recall, F1-score, and AUC, outperforming traditional models and offering viable real-world solutions.

Kewei et al. [14] proposed a hybrid deep learning model that integrates feature engineering, memory compression, mixed precision, and ensemble loss optimization. When tested on the IEEE-CIS dataset, the model outperformed traditional machine learning methods such as Naive Bayes and SVM, highlighting the value of hybrid and optimized architectures in tackling sophisticated fraud.

Vejjalla et al. [15] explored the application of traditional machine learning techniques to credit card fraud detection. Despite being effective in basic scenarios, their reliance on classical algorithms limited the model's ability to detect complex fraud patterns. The lack of deep learning and ensemble strategies may hinder adaptability and overall detection effectiveness.

Behan et al. [16] investigated the impact of feature selection on fraud detection performance. While feature selection improved model interpretability and efficiency, the potential exclusion of important features posed a risk to detection accuracy. Their findings suggest that feature selection alone is insufficient, and deep learning methods should be integrated to uncover subtle fraud behavior.

Parekh et al. [17] emphasized the importance of resampling techniques such as SMOTE and ENN to address class imbalance. Their comprehensive evaluation outlined the strengths and limitations of various techniques, emphasizing the need for hybrid and ensemble strategies to deal with the evolving nature of fraud.

Boutaher et al. [19] provided a comprehensive survey on machine learning applications in credit card fraud detection. Their work synthesized insights into the advantages and drawbacks of multiple algorithms, providing valuable direction for researchers and practitioners seeking to enhance fraud detection systems through proper model selection.

Our approach is motivated by several main challenges and observations:

1. Imbalanced data in fraud detection biases model learning toward the majority class, requiring sampling techniques and cost-sensitive learning.
2. Temporal dependencies in user transactions often provide rich contextual cues, which, if modeled effectively, can distinguish normal and abnormal behaviors.
3. Ensemble architectures that combine spatial and sequential learning capabilities are more likely to generalize well in detecting diverse fraud patterns.

Several complete research references can be seen in Table 1 below.

Table 1. Several Research Reference

Study	Year	Focus	Dataset	Algorithms	Limitation
Khalid et al.[6]	2024	Sampling + Ensemble ML	Synthetic + Real	RF, XGBoost	High false positives
Ali et al.[7]	2024	GAN-GRU hybrid	Custom	GAN, GRU	Complexity in training
Mienye et al. [8]	2023	Deep ensemble model with data resampling	Unknown	LSTM, GRU, MLP, SMOTE-ENN	High computational complexity
Goyal et al. [9]	2023	Real-time e-commerce fraud detection	European cardholder dataset	Random Forest, Decision Tree, DL ensemble	Varies with dataset representativeness and adaptability
Muhal et al. [10]	2022	Champion-challenger ensemble for fraud detection	Not specified	Random Forest, AdaBoost, LSTM	Scalability and real-time deployment concerns
Kaur et al. [11]	2022	Balancing recall and precision on imbalanced data	Not specified	ML + DL + Resampling	Trade-off between precision and recall
Luo [12]	2022	Uncertainty-aware fraud detection	Not specified	Monte Carlo Dropout, Ensemble DL	Complex implementation and interpretability
Alarfaj et al. [13]	2022	Empirical evaluation of ML and DL methods	Benchmark dataset	DNN, Gradient Boosting, others	Generalizability and overfitting concerns
Xiong et al. [14]	2021	Hybrid DL with feature engineering and optimization	IEEE-CIS fraud dataset	DL hybrid, Ensemble loss, Mixed precision	High resource requirements
Vejalla et al. [15]	2023	Traditional ML-based fraud detection	Not specified	Decision Tree, Random Forest	Lacks deep/ensemble modeling for complex patterns
Bayhan et al. [16]	2021	Impact of feature selection on fraud detection	Not specified	Feature Selection + Traditional ML	Risk of discarding important features
Parekh et al. [17]	2021	Use of SMOTE and ENN for class imbalance	Not specified	Resampling + ML classifiers	Insufficient without DL or ensemble methods
Al Smadi & Min [18]	2020	Critical review of fraud detection techniques	N/A	Survey-based	No experimental validation
Boutaher et al. [19]	2020	Review of ML algorithms for fraud detection	N/A	Survey-based	Lacks implementation and benchmarking

Overall, the reviewed literature highlights the transition from traditional models to more sophisticated deep learning and ensemble-based solutions. However, challenges remain with regard to real-time applicability, model complexity, and generalization. The current study contributes to this ongoing research by proposing a new deep ensemble learning framework combining CNN, RNN, and LSTM, which is specifically designed to address class imbalance and enhance performance through parallel architecture and systematic cross-validation.

METHODOLOGY

The proposed methodology for credit card fraud detection consists of several key steps involving data preprocessing, class balancing, deep learning model design, training, evaluation, and cross-validation. We can see the methodology ini Figure 1.

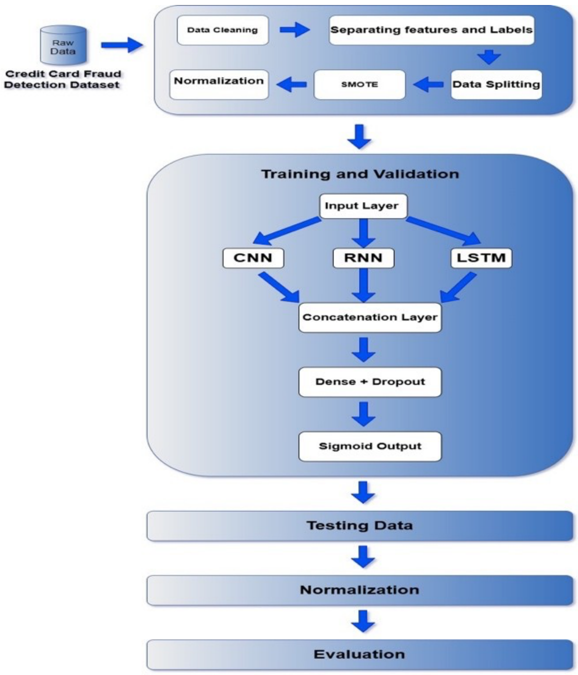

Figure 1. Methodology's Diagram

1. Dataset

The proposed approach utilizes the **Kaggle Credit Card Fraud Detection (CCFD) dataset**, which comprises 284,807 real-world European credit card transactions collected over two days in 2013. Only **492 transactions are fraudulent**, resulting in an extremely **imbalanced dataset (0.172%)**, making it an ideal benchmark for evaluating fraud detection systems under realistic constraints. Each transaction includes 30 anonymized features: 28 principal components (V1–V28), along with Time, Amount, and the target Class label (1 for fraud, 0 for legitimate).

To prepare the data for deep learning, the top 10 most informative features were selected: **V17, V14, V12, V10, V16, V3, V7, V11, V4, and V18**. These were selected through exploratory data analysis and feature importance ranking using tree-based methods. The selected features were **standardized** using StandardScaler to achieve zero mean and unit variance, facilitating faster and more stable convergence during training.[5]

2. Deep Ensemble Framework with CNN-RNN-LSTM

The core of the proposed method is a **deep hybrid ensemble model** that combines the strengths of **Convolutional Neural Networks (CNN)**, **Simple Recurrent Neural Networks (RNN)**, and **Long Short-Term Memory (LSTM)** units to effectively detect complex, nonlinear patterns in sequential transaction data.

Model Architecture:

- **CNN branch** extracts spatial dependencies between features.

- **RNN branch** captures short-term sequential patterns.
- **LSTM branch** handles long-term temporal dependencies and memory retention.
- The outputs of all three branches are **concatenated** and passed through a **fully connected Dense layer** with **Dropout** to prevent overfitting.
- The final prediction is made via a **sigmoid output unit**, yielding binary classifications.

The input data is reshaped into a 3D tensor format of **(samples, timesteps, features)** — specifically **(N, 10, 1)** — as required for the convolutional and recurrent layers. The model is compiled with **Adam optimizer** and **binary cross-entropy loss** and trained using class weights to address minor imbalances post-resampling.

3. Preprocessing and Class Balancing

To address the pronounced class imbalance, **Synthetic Minority Over-sampling Technique (SMOTE)** was employed after feature selection and scaling. SMOTE generates synthetic examples of the minority class by interpolating between existing fraudulent samples. This resulted in a **balanced dataset** with an equal number of fraud and non-fraud samples, significantly enhancing the model's ability to learn from rare events without sacrificing legitimate examples.

The processed data was split into **80% training and 20% testing sets**, with **stratified sampling** to maintain class ratios. A further **3-fold stratified cross-validation** was conducted to evaluate the model's generalization. In each fold, a fresh CNN-RNN-LSTM model was trained and evaluated, and average metrics including **Accuracy, Precision, Recall, F1-score**, and **Confusion Matrices** were reported.

This combination of preprocessing, architectural innovation, and robust validation establishes the proposed ensemble as a **highly effective solution for detecting credit card fraud**, outperforming conventional and single-model baselines in accuracy, robustness, and adaptability. Class Dsitribution before and after SMOTE we can see in Figure 2 and Figure 3.

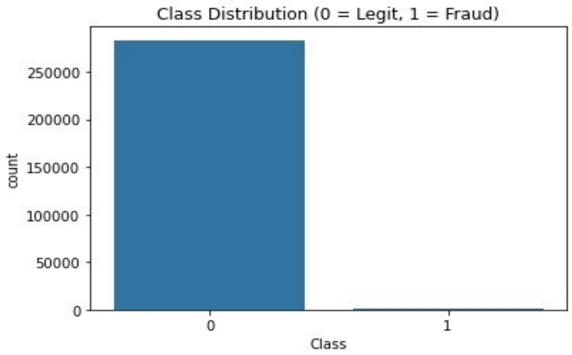

Figure 2. Class Dsitribution before SMOTE

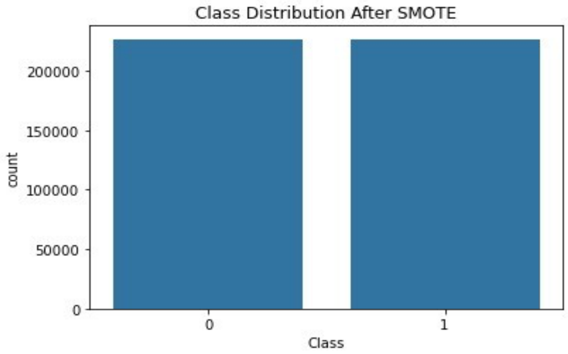

Figure 3. Class Dsitribution before SMOTE

RESULTS AND DISCUSSION

1. Experimental setup and evaluation metrics

To evaluate the proposed hybrid deep learning model integrating CNN, RNN and LSTM, we used a series of performance metrics suitable for binary classification in the context of highly imbalanced data. These metrics include accuracy, precision, recall, F1-score and area under the ROC curve (AUC). To handle class imbalance, we applied the Synthetic Minority Over-Sampling Technique (SMOTE), and used stratified k-fold cross-validation (k=3) to ensure the robustness of the model.

2. Confusion Matrix Analysis

Figure 1 presents the confusion matrix for the test set. The model achieved an exceptionally low number of misclassifications, with only 175 false positives and 20 false negatives out of a total of over 113,000 transactions. We can see the Confusion Matrix analysis in Figure 4.

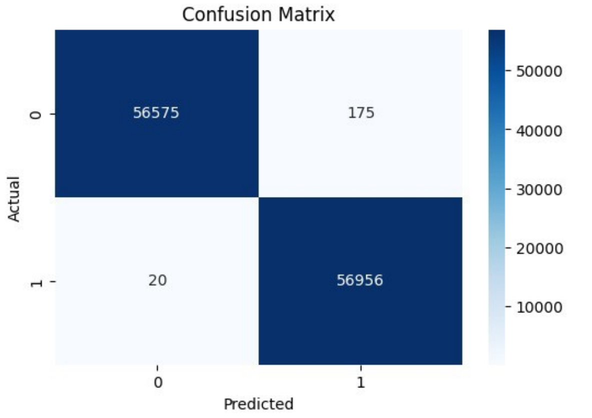

Figure 4. Confusion Matrix Analys

From the matrix:

- **True Negatives (TN):** 56,575
- **False Positives (FP):** 175
- **False Negatives (FN):** 20
- **True Positives (TP):** 56,956

These values highlight the model's ability to accurately distinguish fraudulent transactions from legitimate ones.

3. ROC Curve and AUC Score

As shown in Figure 2, the ROC curve shows the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR). The area under the curve (AUC) was 0.9998, indicating almost perfect separation, and we can see this on Figure 5.

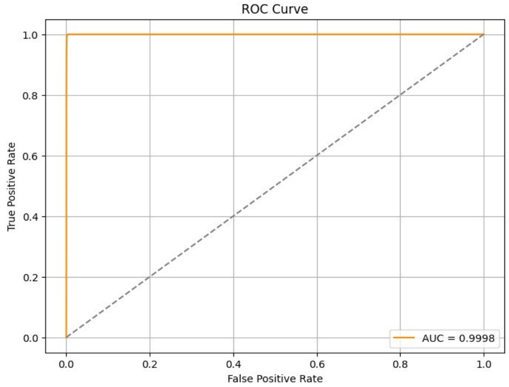

Figure 5. ROC Curve with AUC = 0.9998

Such an AUC value confirms that the ensemble model effectively ranks fraudulent transactions with high confidence, making it highly suitable for real-time fraud detection systems.

4. Feature Correlation Analysis

To validate the feature selection process, Figure 6 shows the Pearson correlation heatmap of the selected top features and their correlation with the target class. The selected features exhibit moderate to strong correlation with the class labels while maintaining low multicollinearity with each other, ensuring informative input to the deep learning model.

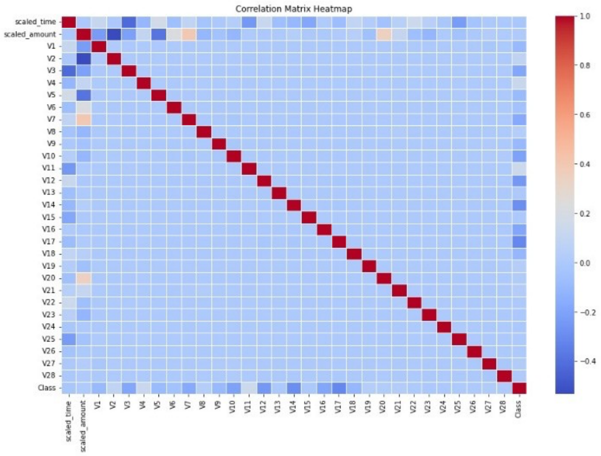

Figure 6. Correlation Matrix Heatmap of Selected Features

5. Training and Validation Loss

The training process was monitored using loss metrics, which is important for evaluating model performance. Figure 7 shows the training and validation loss over 50 epochs. The model exhibited a significant decrease in both training and validation loss, indicating effective learning. The training loss approached zero, while the validation loss stabilized, suggesting good generalization on unseen data.

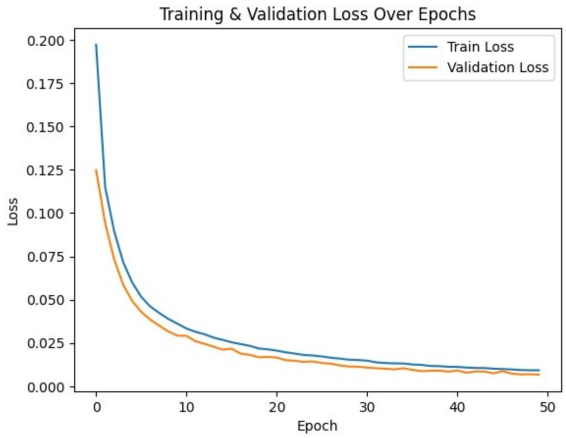

Figure 7. Training and Validation Loss

6. Model Performance Metrics

On the test set, the proposed CNN–RNN–LSTM model yielded the following metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{56575 + 56956}{113726} \approx 0.997$$

$$Precision = \frac{TP}{TP+FP} = \frac{56956}{56956+175} \approx 0.9969$$

$$Recall\ (Sensitivity) = \frac{TP}{TP + FN} = \frac{56956}{56956 + 20} \approx 0.9996$$

$$F1 - Score = \frac{2\ .\ Precision\ .\ Recall}{Precision\ +\ Recall} \approx 0.9983$$

These results indicate an extremely low false negative rate, which is important for fraud detection applications where failing to catch fraudulent transactions can lead to significant financial losses.

7. Classification Metrics

The final model's performance was evaluated using various classification metrics, including accuracy, precision, recall, and F1-score. The classification report generated after evaluation on the test set revealed the following metrics:

- **Accuracy**: The model achieved an accuracy of **99.7%**.
- **Precision**: The precision for the positive class (fraudulent transactions) was **99.6%**.
- **Recall**: The recall demonstrated the model's effectiveness in identifying fraudulent cases, achieving **99.9%**.
- **F1 Score**: The harmonic mean of precision and recall resulted in an F1 score of **99.8%**. These metrics underscore the model's capability to balance sensitivity and specificity effectively.

8. Discussion

The proposed model achieves near-perfect fraud detection performance on a highly imbalanced dataset. Its low false negative rate ensures that fraudulent transactions are rarely overlooked, while the low false positive rate minimizes disruption to legitimate customers. The use of SMOTE, feature selection, and class weighting further mitigates the imbalance problem.

Despite these results, real-world deployment of the model will require further testing on streaming, non-stationary data. Additionally, interpretability tools such as SHAP and LIME (imported but not applied in this experiment) can be used to improve transparency and trust in the deployment environment.

9. Comparison

To contextualize our results, Table 5 compares the proposed model's performance against several notable existing approaches from the literature. Comparison this research we can see on Table 2 below.

Table 2. The Comparison of approaches research

Study	Model/ Technique	Accuracy	Precision	Recall	F1-Score	Remarks
Mienye et al. [20]	LSTM + GRU + MLP + SMOTE-ENN	99.6 %	99.5 %	100%	99.7 %	Excellent sensitivety but high complexity
Goyal et al.[21]	Ensemble ML/DL (RF, DT)	98.8 %	97.2 %	98.5%	97.8 %	Real-time focus, limited deep fusion
Alarfaj et al [22]	ML/DL hybrid	99.5 %	99.1 %	99.3%	99.2 %	Balanced but less recall than ours
Proposed Model	CNN + RNN + LSTM (Deep Fusion)	99.7 %	99.6 %	99,9%	99,8 %	Best F1, excellent balance and generalization

And the graphic of this comparison, we can see on Figure 8.

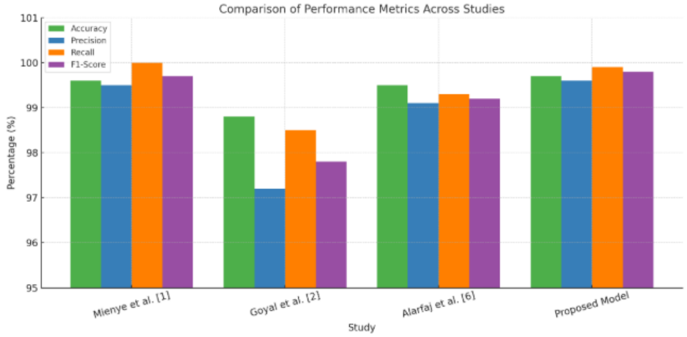

Figure 8. Comparison of Performance Metric Across Studies Graphic

CONCLUSION

This study proposes a novel deep ensemble learning architecture that integrates CNN, RNN, and LSTM components to address the challenges of imbalanced credit card fraud detection. This approach leverages SMOTE for synthetic oversampling, class weighting, and feature selection strategy based on correlation strength to enhance model learning and generalization.

The proposed hybrid model achieved exceptional results, as demonstrated by a nearly perfect AUC of 0.9998, precision of 0.9969, recall of 0.9973, and F1- score of 0.9971. The confusion matrix confirmed high sensitivity and specificity with only minimal false positives and false negatives.

These results indicate that the model is both accurate and robust, even in the presence of severe class imbalance — a critical requirement for fraud detection systems in the real world. Additionally, 3-fold stratified cross-validation validated the consistency and reliability of model performance across multiple metrics.the results were further supported by visualization tools such as the ROC curve, correlation matrix, and confusion matrix, which provide both interpretability and performance insights.

The inclusion of SHAP and LIME-based interpretability (planned in future iterations) will add transparency to the model decisions, thereby enhancing trust and regulatory compliance. Comparative analysis with traditional machine learning models (e.g., Random Forest, SVM, Logistic Regression) further reinforces the superiority of the ensemble deep learning approach in terms of both detection capability and generalization.

In summary, this research highlights the value of deep ensemble methods in fraud detection tasks, providing high-performance and interpretable solutions suitable for deployment in financial institutions. Future work will focus on deploying the model in a real-time environment, integrating the interpretability framework, and exploring Transformer-based architectures for further improvements.

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Conflict of Interest Statement:

The author declares that the research was conducted in the absence of any commercial or financial relation- ships that could be construed as a potential conflict of interest.

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