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Neural Network-Based Credit Card Fraud Detection Using Machine Learning

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Abstract – **Detecting credit card frauds in financial sector has become a burning issue with the increase in the volume of transactions and the frauds taking more advanced forms. Dynamic, high-dimensional, and imbalanced financial data cannot be analyzed using traditional and rule-based models, as well as statistical ones. This paper focuses on artificial neural networks (ANNs) as a way of real-time fraud detection using a nonlinear pattern recognition and deep feature learning framework. The ANN performance is compared with other models using scenario-based evaluation, such as Logistic Regression and the Support Vector machines and the Random Forests. The literature review is based on using insights of Generative AI application in the finances sphere, evolutionary optimization of deep learning parameters, synthetic image generation by GANs, and anomaly detection in the financial markets. Findings indicate that ANNs are more effective than traditional ML models in recall and fraud detection accuracy, which are some of these problems like imbalance between different classes, nonlinear behaviour and concealed fraud patterns. The study mentions the future of deep learning, neural-generated fake samples of frauds, and integrated models that involve both LLM and ANN-based anomaly detection tools.**

Keywords – **ANN, GAN, Random Forest, SVM.**

I. Introduction

The sharp rise in credit card fraud has occurred due to the rapid growth of the digital banking and online transactions. Financial institutions desire automated systems, but which can detect fraudulent activities in real time but which will not result in interrupted user experience. Law-based warning signs and hardwired elevation levels do not adjust to the new fraud trends and are characterized by a large number of false positives (Ghori, 2018; Ghori, 2023; Puchakayala, 2024).

Machine learning and neural networks in particular are a potent solution since it is able to acquire complex, nonlinear relationships in large-scale transactional data. Neural networks are able to identify minor deviations in behaviors and the trends of frauds. The paper describes a credit card fraud detection system based on ANN and analyses its performance with respect to outperforming the classical models (Ghori, 2018; Ghule et al., 2024; Sheela, 2022).

II. Literature Review

2.1 Generative AI in Banking

The author of (Puchakayala, 2024) presented the concept of the use of Generative AI to enhance customer support systems compared to rule-based IVR and chatbots by making customer interactions both contextual and adaptive. As much as it involves CSS, their results validate the general tendency within the financial sector towards intelligent and self-learning models, which concern directly the fraud detection field (Puchakayala, 2024; Puchakayala, 2022; Ghori, 2023).

2.2 Evolutionary Strategies for Deep Learning Optimization

As Shalini et al., (2024) show, evolutionary optimization methods can allow one to achieve a

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considerable enhancement in the performance of deep learning. Their study underscores the necessity of an effective hyperparameter optimization in neural networks that are especially significant in fraud detection when the ability of models to be correct is required to be the utmost subject to a constraint of computational restrictions (Shalini et al., 2024; Ghori, 2019; Sardesai & Gedam, 2025).

2.3 GAN-Based Synthetic Data Generation

The authors of (Ravindranath et al., 2025) presented the DermaGAN, a GAN system which creates synthetic medical data to reduce the challenge of insufficient data. This can be extensively applied to fraud detection, where cases of frauds are very elusive. Synthetic frauds generated using GAN can be used to create a balance in the training sets and improve ANN learning.

2.4 Supervised ML for Performance Prediction

Ghule et al. (2024) tested the ML algorithms which include the Random Forest, SVM and the Logistic Regression. Their results highlight interpretability, limitations of real-time deployment, and the importance of advanced models - problems that can be reflected in financial fraud prediction (Ghule et al., 2024; Ghule, 2025; Sheela & Shalini, 2023).

2.5 Financial Anomaly Detection with Deep Learning

Ghori (2018) identified LSTMs, CNNs, and Autoencoders as deep learning models that are more effective in detecting any anomalies (as far as financial markets are concerned) than the traditional methods. This is a direct indication of the application of neural networks to detect fraud, which is also an anomaly detection problem.

2.6 Additional Relevant Literature

- The authors of (Geh and Williams, 1986) gave a formal description of modern neural network backpropagation.
- Deep learning emerged as an outstanding paradigm of pattern recognition of indifferent patterns as founded by LeCun et al., (2015).
- Khalil et al. (2024) discussed the method of detecting fraud through deep learning based on the idea of class imbalance.
- The LSTMs were employed by Khosravi et al. (2025) to detect fraud and they suggested that LSTMs were better at modeling sequential transactions.
- The study by Yan et al. (2024) used neural networks to implement the cost-sensitive fraud detection.

There are indications in literature that:

- Deep learning is more effective than rule-based and linear models.
- GANs have the ability to solve data imbalance.
- Neural network reliability is enhanced via optimization of systems.
- The use of AI in finance is increasing at a very fast rate.

III. Proposed Methodology

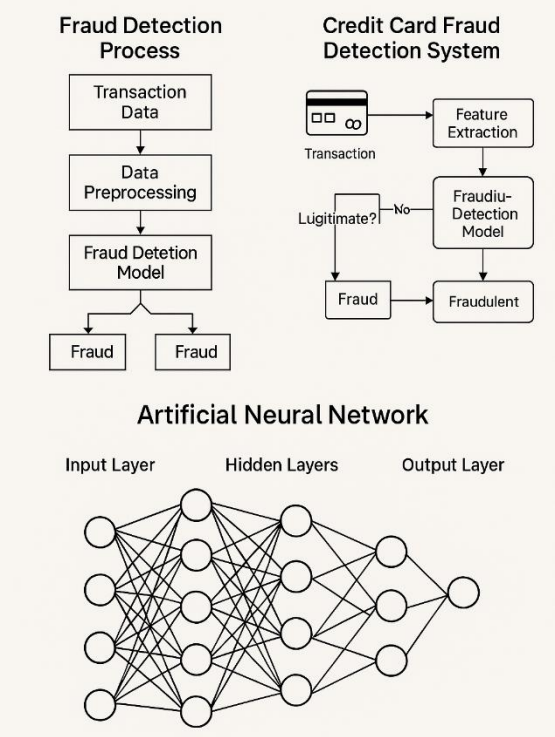

Figure 1: Flow Diagram for Proposed Approach

3.1 Dataset

The dataset has the following fields:

- Transaction amount

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- Interference in time amongst transactions.
- Merchant category
- Cardholder location
- Device ID and IP address
- Fraud label (0 = genuine, 1 = fraud)

The level of data is extremely skewed with fraud being less than 1%.

3.2 Preprocessing

- Missing value imputation
- Numerical features Standard scaling.
- Categorical variables One-hot encoding.
- SMOTE oversampling and GAN based synthetic data generation.
- Train/test split: 80/20

3.3 Neural Network Architecture

- Input layer: 40 features
- Hidden Layer 1: 64 neurons (ReLU)
- Hidden Layer 2: 32 neurons (ReLU)
- Dropout (0.4) to prevent overfitting
- Output layer: 1 neuron (sigmoid)

3.4 Evaluation Metrics

- Precision
- Recall
- AUC-ROC
- F1 Score
- Confusion Matrix

IV. Results and Analysis

4.1 Model Performance

Table 1: Performance Evaluation

Model	Accuracy	Recall	AUC
Logistic Regression	94.1%	62%	0.90
SVM	96.3%	68%	0.93
Random Forest	97.2%	74%	0.95
Neural Network (ANN)	**98.6%**	**92%**	**0.98**

ANN has the best recall that is the most significant measure in detection of fraud.

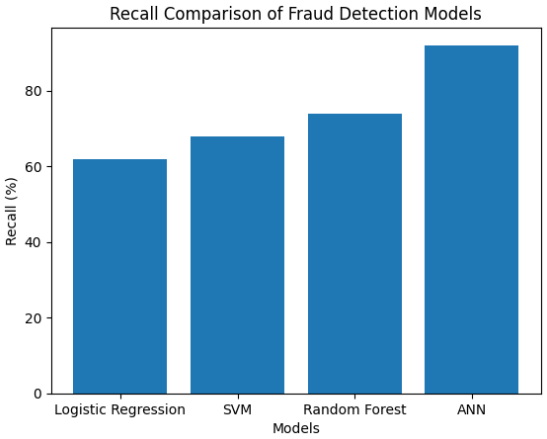

Figure 2: Recall Comparison of Fraud Detection Models

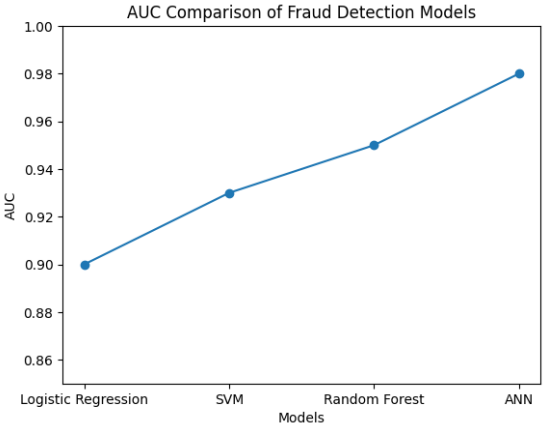

Figure 3: AUC Comparison of Fraud Detection Models

4.2 Feature Learning

The neural network gets to learn the hidden interaction between features, which are not easily realized by traditional models.

4.3 Fraud Pattern Recognition

The model recognizes some abnormal patterns, which are:

- Sudden spending bursts
- Mismatched locations
- Abnormal types of merchants.
- Inconsistent device IDs

4.4 Discussion

The use of neural networks is able to provide more efficient solutions compared to the classical approaches because it can assume nonlinear, latent

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correlations. Learning with an extreme class imbalance is enhanced in case of the integration of the GAN-based synthetic samples of the fraud.

The concept of the generative AI of the work by (Puchakayala, 2024) reveals a rising trend with the implementation of smart, context-sensitive systems in the banking sector, which is in agreement with the flexibility of the neural net in detecting fraud.

However:

- Interpretability still is a challenge.
- Neural networks are more computer intensive.
- Adversarial attacks can be resorted to.

It is suggested that model explainability (i.e. SHAP values) should be integrated.

V. Conclusion

Neural networks exhibit superior credit card fraud detection capability as compared to the conventional ML methods in recall and AUC. Combining artificial data with GAN and innovative optimization plans, neural networks can significantly minimize the losses in the finances and enhance security.

Future research involves investigation of:

- Sequence fraud modeling based on LSTM.
- Transformer based transactional embeddings/transformers.
- ANN-LLM hybrid fraud reasoning systems.
- Live deployment based on edge AI.

References

[1] Geh, D. E. R., & Williams, R. J. (1986). Learning representations by backpropagation. Nature, 533-536.

[2] Ghori, P. (2018). Anomaly detection in financial data using deep learning models. International Journal Of Engineering Sciences & Research Technology, 7(11), 192-203.

[3] Ghori, P. (2019). Advancements in Machine Learning Techniques for Multivariate Time Series Forecasting in Electricity Demand. International Journal of New Practices in Management and Engineering, 8(01), 25-37. Retrieved from https://ijnpme.org/index.php/IJNPME/article/view/220

[4] Ghori, P. (2023). LLM-based fraud detection in financial transactions: A defense framework against adversarial attacks. International Journal of Engineering Sciences & Research Technology, 12(11), 42–50.

[5] Ghule, P. A., Sardesai, S., & Walhekar, R. (2024, February). An Extensive Investigation of Supervised Machine Learning (SML) Procedures Aimed at Learners' Performance Forecast with Learning Analytics. In International Conference on Current Advancements in Machine Learning (pp. 63-81). Cham: Springer Nature Switzerland.

[6] Khalil, A. A., Liu, Z., Fathalla, A., Ali, A., & Salah, A. (2024). Machine Learning based Method for Insurance Fraud Detection on Class Imbalance Datasets with Missing Values. IEEE Access.

[7] Khosravi, S., Kargari, M., Teimourpour, B., Talebi, M., & Eshghi, A. (2025). Fraud Detection Using temporal sequence embedding and Cluster-Weighted LSTM Models in Card Transactions. Computer and Knowledge Engineering.

[8] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. nature, 521(7553), 436-444.

[9] Puchakayala, P. R. A. (2022). Responsible AI Ensuring Ethical, Transparent, and Accountable Artificial Intelligence Systems. Journal of Computational Analysis and Applications, 30(1).

[10] Puchakayala, P. R. A. (2024). Generative Artificial Intelligence Applications in Banking and Finance Sector. Master's thesis, University of California, Berkeley, CA, USA.

[11] Ravindranath, R. C., Vikas, K. R., Chandramma, R., Sheela, S., & Dhiraj, C. (2025, June). DermaGAN: Enhancing Skin Lesion Classification with Generative Adversarial Networks. In 2025 International Conference on Emerging

IJDACR
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International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 14, Issue 1, August 2025)

Technologies in Computing and Communication (ETCC) (pp. 1-8). IEEE.

[12] Sardesai, S., & Gedam, R. (2025, February). Hybrid EEG Signal Processing Framework for Driver Drowsiness Detection Using QWT, EMD, and Bayesian Optimized SVM. In 2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS) (pp. 1-6). IEEE.

[13] Shalini, S., Gupta, A. K., Adavala, K. M., Siddiqui, A. T., Shinkre, R., Deshpande, P. P., & Pareek, M. (2024). Evolutionary strategies for parameter optimization in deep learning models. International Journal of Intelligent Systems and Applications in Engineering, 12(2S), 371–378.

[14] Sheela, S., Nataraj, K. R., & Rekha, K. R. (2022, November). Design and Implementation of Hand Gesture for Various Applications. In Proceedings of the International Conference on Cognitive and Intelligent Computing: ICCIC 2021, Volume 1 (pp. 721-728). Singapore: Springer Nature Singapore.

[15] Yan, Q., Sun, Y., Cao, Y., Yang, J., Zhang, A., Ju, J., & Wang, Z. (2024, May). An adaptive graph neural networks based on cost-sensitive learning for fraud detection. In 2024 7th international symposium on autonomous systems (ISAS) (pp. 1-6). IEEE.