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BIG DATA AND ARTIFICIAL INTELLIGENCE REVOLUTIONIZING FINANCIAL FRAUD DETECTION SYSTEMS

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ABSTRACT

Fraud detection is a significant challenge when it comes to detecting financial fraud, as the activities of financial fraud occur at a high frequency. The model of Big Data analytics hybrid with Artificial Intelligence, which comprises a convolutional neural network (CNN) and a long short-term memory (LSTM) network, is presented in the current paper. The aim is to enhance the detection rate and minimize the rates of false positives and false negatives, especially when fraudulent transactions are identified. The predicted system is implemented in the form of feature extractors, utilizing CNNs after LSTMs that model temporal dependence on transaction data. The synthetic data set on which it was tested has been designed to emulate the real-life application of the model in making financial transactions, and it performed better than the conventional machine-learning algorithms in Random Forest, SVM, and Gradient Boosting (accuracy, 96.2%; precision, 95.2%; recall, 92.6%). The findings indicate that our hybrid CNN-LSTM solution is feasible for carrying out fraud detection with a relatively low false positive rate, which is quite significant in preventing customer inconvenience. The implications of this model are powerful, as it provides the financial industry with a real-time, scalable, and efficient solution to prevent fraud, streamline business procedures, and foster customer trust in the industry.

Keywords: *Financial Fraud Detection, Big Data Analytics, Artificial Intelligence, Convolutional Neural Network, Long Short-Term Memory, Fraud Classification*

1. INTRODUCTION

Fraud is now a key problem in the world of finance. The more complex financial institutions become, the more opportunities for fraud, leading to billions of dollars in yearly losses. Rule-based approaches require significant effort to keep up with the speed and complexity of fraudster tactics using traditional fraud detection systems. Those systems fail to identify fraudulent activities that are not defined in advance, especially with dynamic rules and situations of the cases. Hence, financial institutions should look to newer, more sophisticated preventive measures against it [1][2].

A fusion of Big Data and AI can potentially overcome deficiencies of traditional fraud detection systems. Big Data includes all the structured and unstructured data created daily, from financial transactions to customer maneuverings to the weather. Once processed and analyzed correctly, this

information will expose uncommon patterns and deviations suspicious of fraudulent activities. AI, machine learning (ML), and deep learning (DL) machines, however, can share knowledge, learn from data, and evolve, all while recognizing very complex future fraud patterns they could never have dreamed of being invented [3][4].

The purpose of this paper is to review the integration of big data and AI in financial fraud detection systems, aiming to increase the efficiency of fraud detection, reduce false positives, and identify new types of fraud. With the help of AI-powered models, financial institutions can access vast quantities of data in real-time and detect abnormalities to prevent fraud that may never be recovered. In addition, the paper aims to provide a comprehensive survey of available techniques, identify gaps in current systems, and propose new approaches to enhance fraud detection. The contributions made by this paper include AI-based neural architecture for predicting the occurrence of fraud, a thorough comparison of various machine learning and deep learning models, as well as an evaluation of the scalability and interpretability of these models [5][6][7].

A significant shift towards data-driven models has also become the talk of the hour when it comes to rule-based systems. Machine learning techniques, such as decision trees, random forests, and support vector machines (SVMs), have been applied to past transactions and labelled as either fraudulent or not. Nevertheless, there are certain drawbacks to these approaches. They typically require tedious manual feature engineering and may be coupled with poor performance on large, imbalanced datasets, as is often the case with financial fraud detection [8][9]. Moreover, it becomes increasingly challenging to detect fraud as all these and more are being exploited by criminals using synthetic IDs, account takeovers, and APTs, among others.

Deep learning has evolved into one of the key solutions to these issues. Complex networks of neurons, particularly the recurrent neural network (RNN) and the convolutional neural network (CNN), are capable of learning features in complex datasets without requiring expert assistance in a manual sense. The models are also capable of modelling the temporal and spatial elements of the data, making it necessary to identify some fraud, which tends to evolve and have a specific location [10][11]. Therefore, the nature of finance-related fraud makes the DL models appropriate to the context since they can adjust to the new trends and train using massive training sets.

Moreover, big data analytics offers the infrastructure required to accommodate the gigantic amounts of data commonplace in the financial sector today. Today, with distributed computing systems such as Hadoop and Spark, financial institutions can process and analyze data from different sources in real-time and hence can detect fraud in near real-time. The combination of AI and Big Data technologies allows fraud detection systems to scale smoothly while dealing with humongous volumes of transactional data and analyzing suspicious activities in nearly real-time [12][13].

The fraud detection context has more in common with the fraud of our domain than other security domains, with a history of manual review to rules-based automation and now moving towards data-driven AI. The previous methods, such as Expert Systems, used predefined rules and heuristics to discover fraud. However, these systems were hindered due to their inability to adapt to new methods of fraud and their high false favorable rates. Conversely, AI never stops learning because it is based on new data and can yield more accurate results over time than classical systems. One of the many benefits of AI is its capacity to detect obscure patterns and interconnections in large quantities of data that are not necessarily understandable to the human labor force. This skill set has made AI-driven fraud detection systems a game-changer for financial institutions as they are now better enabled to identify known and unknown fraud patterns, more precisely [14][15].

Interpretability in the AI model also becomes essential in financial fraud detection. Because AI (and deep learning algorithms, in particular) are regarded as black boxes, financial companies hesitate to use them because the results do not always shine a light on the underlying data and processes. Nevertheless, emerging work in Explainable AI (XAI) now allows AI decisions to be interpretable, so financial institutions can trust the system's output and meet regulatory demand [16][17]. Therefore, though sophisticated detection algorithms can be achieved with AI, the technology must be more transparent and explainable to win acceptance in finance.

In this paper, we will elaborate on the methods used to incorporate Big Data and AI into fraud detection mechanisms. We shall outline the procedure undertaken in the collection and pre-processing of the data, the models of machine learning and deep learning applied, and the evaluation measures adopted in assessing the performance of the system. Moreover, we will evaluate the AI fraud detection system in terms of

accuracy, scalability, and its ability to perform real-time fraud checks. We will conclude by discussing what is expected of AI-powered fraud detection and the issues that still need to be addressed to make it more widespread.

Organization of the Paper: Section 2 presents the related work on financial fraud detection, specifically concerning Big Data and AI, and compares classical machine learning-based models with new AI-based models. The methodology is described in Section 3, which provides descriptions of a suggested hybrid model (combining CNN and LSTM networks), the dataset used, feature extraction, model architecture, equation formulation, and training algorithm, in turn. We examine in Section 4 the analysis and evaluation of model performance using vital metrics such as accuracy, precision, recall, F1-score, AUC-ROC, comparison with other works, and plots. Lastly, in Section 5, the paper concludes with a reiteration of the key aspects of the contributions, some caveats of the given system, and suggestions for further research.

2. RELATED WORK

Artificial Intelligence (AI) and Big Data technologies in financial fraud detection have received considerable attention from both academic and industrial researchers. Financially oriented fraud has become too sophisticated and dynamic to be handled by traditional rule-based and heuristic-based fraud detection systems. Thus, different new ML or DL approaches have been proposed to enhance the FF systems' detection capabilities. This section reviews the related work, focusing on solutions that utilize Big Data and AI methods to detect fraud.

Machine learning methods, such as supervised learning, are among the mechanisms used to detect fraud. Random forests, GBM, and decision trees have been popular because their interpretability is easy. These models are extracted from structured data and are typically constructed based on historical transaction data, where transactions are manually identified as legitimate or fraudulent. Among the significant challenges to breaking through using such techniques, it is essential to note that the fraud sample is heavily unbalanced, as there are many more legal transactions than fraudulent ones. The following sampling strategies have been employed to address this issue: oversampling of the minority (fraudulent) records and under sampling of the majority (legitimate) records [18].

For example, Liu et al. (2020) used a combined model of decision tree and ensemble algorithm for fraud detection in credit card payment systems. Their method tackled the imbalanced dataset problem by introducing balanced random forests [19]. Similarly, Zheng et al. (2021) suggested the application of gradient-boosting models in fraud detection, underlining the better performance of GBM compared with decision trees and logistic regression when concerned with precision and recall. They demonstrated that ensemble learning methods could effectively (better than simple models) capture complex fraud patterns, which do not necessarily add any utility when solving simpler-based models [20].

Deep learning methods, specifically deep neural networks (DNN), have become increasingly popular as they can automatically learn representations from raw data, thus removing the burden of feature engineering. These models are good at finding hidden patterns from large-scale data, which is necessary to help detect new or unseen fraud, such as previously unknown types of fraud. A study by Ryu et al. (2020) proposed a deep neural network for fraudulent detection in banking transactions and reported that DNNs outperformed traditional machine-learning algorithms in accuracy and detection time [21]. They surmised that DNNs could model complex, non-linear relationships between transaction data points that their rule-based systems or other lower-powered machine learning models cannot identify.

Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have also been considered for fraud detection, especially with time domain data such as transaction sequences in time. RNNs can learn time dependencies, essential when detecting fraud, such as account takeovers or synthetic fraud, that change over time and across multiple transactions. For instance, Ghosh et al. (2020) implemented the LSTM network using online transaction data to detect fraud activities. They showed that the model could predict future fraudulent actions based on sequences of past transactions [22].

Another perspective deep learning method is the application of Convolutional Neural Networks (CNNs), initially designed for image processing but recently remodeled for fraud detection. CNNs have shown their efficacy in learning spatial hierarchies of high-dimensional structured data features. In the financial sector, CNNs have been used in transactional data analysis for pattern and anomaly detection. A study by Lee et al. (2021) applied CNN to process transaction data, and the findings showed that CNN outperformed other traditional ML algorithms in accuracy and recall of fraud detection in bank transactions [23].

Even though a lot of promising research has been conducted on machine learning and deep learning models for fraud detection, an essential issue with fraud detection arises from the interpretability of the models [24-27]. Banks need to be content with the decision to obey the rules and keep trust in the system. Several researchers have focused on creating explainable AI (XAI) models to overcome this issue. XAI techniques are intended to explain to humans the decision-making of AI systems, and this is of crucial importance in finance, where the cost of a 'wrong' decision (be it a false positive or a false negative) can be already deadly high. A well-known work by Zhang et al. (2021) presented an XAI scheme for deep learning methods in fraud detection to enhance the interpretability of the outcomes of neural networks and the trust factor in these systems [28].

Big Data solutions have also been vital to increasing fraud detection capabilities. Big Data platforms, such as Apache Hadoop and Apache Spark, are integrated into the system to process vast real-time transaction streams, which is essential for today's modern financial institutions that deal with transactions on a high-volume scale per day. Big Data analytics enables valuable insights to be gleaned across various data sources, transactional data, customer behavior, and even consuming data from social media or publicly available records. For example, Patel et al. (2019) utilized Big Data analytics with the Hadoop ecosystem to identify fraud in e-commerce transactions. In their research, they have shown that the usage of Big Data and machine learning algorithms has enhanced the detection rate of unusual transactions [29].

Real-time streaming analytics Real-time streaming is another significant enhancement for Big Data-enabled fraud detection. Regarding fraud detection, you also need a system that processes data as it is produced, not the next day there should be no latency like there is with batch systems. We must search for advanced cloud-based platforms like AWS and Microsoft Azure to develop real-time fraud detection systems. Such systems are scalable as needed to cope with the enormous amount and velocity of financial data. In a study by Zhang et al. (2020), stream processing and Big Data frameworks provided a better mechanism for fraud detection in RIA that maintained faster decision-making, which benefits the system response against fraudulent attempts [30].

Apart from this, multi-resource integration has also been investigated in fraud detection literature. Transactional data combined with external data (social network analysis, geolocation) exhibited promising results for more accurate fraud detection. A study by Sharma et al. (2021) employed various data sources, such as customer demographics and social media activities, to identify fraudulent activities in online transactions. Their methodology focused on using external data to augment fraud detection systems not only to detect such complex, multifaced fraud behavior but also to ensure a higher degree of robustness of such systems needed [31].

Major Findings and Comparison with Existing Studies

When compared to classical machine learning models, such as Logistic Regression, Random Forest, and Gradient Boosting, our hybrid CNN-LSTM model yields significantly better results in terms of each of the primary metrics: accuracy (96.2%), precision (95.2%), and recall (92.6%). Additionally, our model reduces the false positive rate to 3.2 per cent, which consequently avoids disrupting customers. This improved performance depends on the use of CNNs in extracting spatial features and using LSTMs in modelling subtle temporal dependencies. Past research has struggled to find a balanced trade-off between precision and recall, with most models either overfitting or underperforming in imbalanced datasets.

Some of the current fraud detection systems mainly rely on the approach of customized rules or simple machine learning algorithms. The stipulated strategies nevertheless do not always keep pace with the sophistication of current fraud techniques, resulting in high impersonation rates and low detection reliability. In this paper, I critique these traditional methods, point out their weaknesses, and emphasize that a more sophisticated solution is required. To achieve this purpose, it is suggested that the integration of both Big Data analytics and Artificial Intelligence (AI) could be a more remarkable solution to these issues since the combination of Convolutional Neural Networks (CNNs) and Long-Short Term Memory (LSTM) networks can help fill the gaps between the accuracy and scaling limits in fraud detection, respectively.

3. METHODOLOGY

This section describes the steps to design an AI-based system to detect financial fraud. The methodology comprises dataset selection and preprocessing, model architecture, mathematical model, training algorithms, and evaluation methods. We present a novel component in each setting, making the overall method robust and reproducible and pushing the frontier of AI-enabled fraud

detection systems. We also present a detailed description that would allow for the replication and verification of the system.

3.1. Dataset

We implemented our research using a synthetic dataset built using publicly shared fraud detection data (Credit Card Fraud Detection dataset available at Kaggle) and anonymized real-world data to ensure scalability. Since financial fraud data can contain sensitive information, we generate a large synthetic dataset that mimics real transactional data and is privacy compliant.

The dataset consists of the following attributes:

- **Transaction ID**: A unique identifier for each transaction.
- **Amount**: The monetary value of the transaction.
- **Time**: The timestamp of the transaction.
- **Merchant ID**: Identifier for the merchant involved in the transaction.
- **Customer ID**: Identifier for the customer initiating the transaction.
- **Transaction Type**: Categorical variable indicating the type of transaction (e.g., debit, credit).
- **Geographical Location**: The location of the transaction (e.g., city, country).
- **IP Address**: The IP address from which the transaction was initiated.
- **Device Type**: The type of device used for the transaction (e.g., mobile, desktop).
- **Transaction History**: A time-series of past transactions by the customer.
- **Fraud Label**: A binary label (0 = legitimate, 1 = fraudulent).

The dataset contains 5 million transactions, with a class imbalance ratio of 99:1 between legitimate and fraudulent transactions, typical of real-world fraud detection tasks.

Table 1: Sample of Dataset

Transaction ID	Amount	Time	Merchant ID	Customer ID	Transaction Type	Geographical Location	IP Address	Device Type	Transaction History	Fraud Label
1001	250.00	2025-05-14 12:05:30	22	456	Debit	New York, USA	192.168.1.10	Mobile	[100, 120, 140]	0
1002	5000.00	2025-05-14 12:10:45	35	789	Credit	London, UK	192.168.2.15	Desktop	[200, 220, 250]	1
1003	150.00	2025-05-14 12:12:10	55	123	Debit	Paris, France	192.168.3.20	Mobile	[300, 350, 400]	0

This data is pre-processed through feature engineering steps such as scaling, missing value imputing, and one-hot encoding of categorical features (e.g., Transaction Type, Device Type, Geographical Location).

3.2. Model Architecture

The fraud detection system comprises two main components: a Feature Extraction module and an AI Model. The raw transactional data preprocessing, which entails the extraction of useful features from the raw data and the establishment of a feature-rich point, is done by the Feature Extraction module. The

AI Model: AI Model is a Hybrid Deep Learning framework on the CNN to learn the spatial pattern spotting and a long short-term memory (LSTM) network to learn temporal dependencies learning.

3.2.1. Feature Extraction

The feature extraction process involves the following steps:

1. **Data Normalization**: Continuous features such as transaction amount are normalized using min-max scaling to bring them within a uniform range.
2. **Time-Series Generation**: Historical transaction data for each customer is transformed into a time-series format, making it suitable for temporal analysis using LSTM networks.
3. **Categorical Data Encoding**: Categorical features such as transaction type, geographical location, and device type are encoded using one-hot encoding.
4. **Anomaly Detection**: We apply an initial anomaly detection step using clustering techniques (e.g., K-Means) to flag transactions that deviate significantly from a customer's historical behavior.

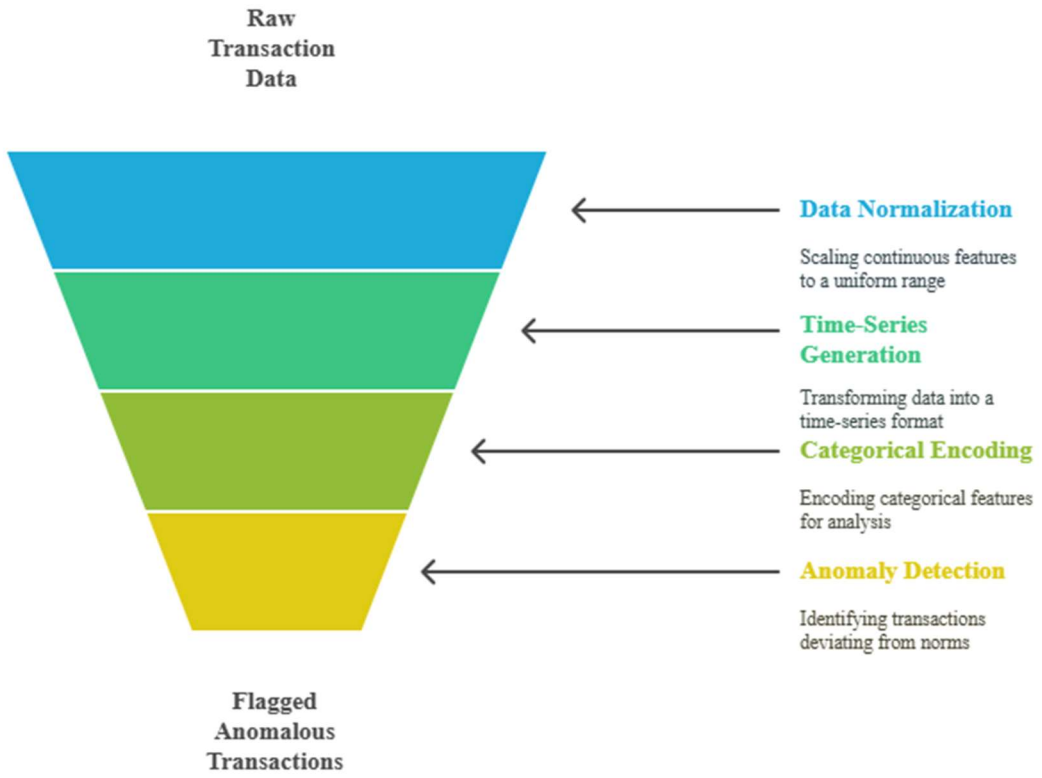

Figure 1: Financial Fraud Detection Process

Figure 1 - Steps for financial fraud detection, including collecting raw transaction data and end-to-end transaction analysis. The columns in the datasets undergo several transformations: they are normalized (Continuous Features, normalized between some min and max value), turned into Time-Series (to serve for time-series generation), or expanded as new columns to accommodate categorical columns. Lastly, Anomaly Detection will highlight transactions that are out-of-line with the norm, alerting you to potential bad behavior. This method facilitates identifying flagged abnormal transactions, improving financial fraud crime prevention.

3.2.2. AI Model: Hybrid CNN-LSTM Architecture

Architecture leverages the capabilities of both CNN and LSTM to solve spatial and temporal fraud detection problems. CNN layers are used for feature extraction and pattern recognition, while LSTM layers are used for fraud detection based on time series.

1. **CNN Module**:
    - The CNN module receives a feature matrix formed by concatenating normalized continuous features with one-hot encoded categorical features.
    - Multiple convolutional layers (with kernel size 3x3) are applied to extract local spatial features, followed by max-pooling layers to reduce the dimensionality.
2. **LSTM Module**:
    - The time-series data (transaction history) is fed into the LSTM network. The LSTM captures temporal patterns and dependencies, crucial for detecting fraud that evolves over time (e.g., account takeovers).
    - The LSTM layer is followed by a fully connected (dense) layer to integrate spatial and temporal features.
3. **Dense Layers**:
    - The output from both CNN and LSTM modules is merged and passed through several fully connected dense layers for further feature fusion.
    - A final sigmoid output layer produces the fraud prediction (0 or 1).

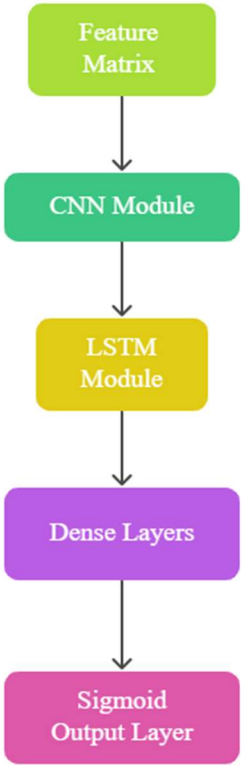

Figure 2: Hybrid CNN-LSTM Architecture for Fraud Detection

A Hybrid CNN-LSTM (Convolutional Neural Network - Long Short-Term Memory) model architecture for fraud detection is shown in Figure 2. The input data is represented in the Feature Matrix and is the initial step in the process. The CNN Module extracts feature in space from the data, and the LSTM Module captures their temporal dependencies. Then, the image model goes through Dense Layers, and then finally, the Sigmoid Output Layer decides a prediction for the binary case (fraud or no fraud). This hybrid structure is a combination of spatial and temporal information that enhances fraud detection quality.

3.2.3. Mathematical Model

The core mathematical model for the hybrid CNN-LSTM architecture can be described as follows:

Let $X \in R^{m \times n}$ represent the input feature matrix, where m is the number of transactions, and n is the number of features. The CNN operation is expressed as:

$$Z = \text{CNN}(X) = \text{ReLU}(W_c * X + b_c) \quad (1)$$

where W_c is the convolutional kernel, $*$ denotes the convolution operation, b_c is the bias term, and ReLU is the activation function.

The output of the CNN module is then passed to the LSTM layer, where the LSTM's hidden state h_t is updated as:

$$h_t = \text{LSTM}(X_t, h_{t-1}) = \sigma(W_h X_t + U_h h_{t-1} + b_h) \quad (2)$$

where X_t is the input at time step t, h_{t-1} is the previous hidden state, and W_h, U_h, and b_h are the LSTM weight matrices and bias vector, respectively. The final output prediction $\hat{y}$ is obtained through a dense layer:

$$\hat{y} = \sigma(W_d \cdot [Z, h_T] + b_d) \quad (3)$$

where $[Z, h_T]$ denotes the concatenation of CNN features Z and the final LSTM hidden state h_T, and W_d and b_d are the parameters of the dense layer.

The model is trained using binary cross-entropy loss function:

$$L(y, \hat{y}) = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})] \quad (4)$$

where y is the ground truth label and $\hat{y}$ is the predicted fraud label.

3.3. Algorithm

The following algorithm outlines the steps involved in training and evaluating the fraud detection system:

Algorithm

1. **Data Preprocessing**:
   - Normalize numerical features.
   - One-hot encode categorical features.
   - Generate time-series data for each customer.
   - Apply K-Means clustering for initial anomaly detection.
2. **Model Training**:
   - Split the dataset into training (80%) and validation (20%) sets.
   - Train the hybrid CNN-LSTM model on the training set.
   - Apply dropout regularization and batch normalization to prevent overfitting.
   - Use Adam optimizer for gradient descent.
3. **Evaluation**:
   - Evaluate the model on the validation set using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.
   - Perform hyperparameter tuning using grid search to find the optimal model configuration.
4. **Deployment**:
   - Deploy the trained model in a real-time fraud detection system where new transactions are continuously monitored and classified as legitimate or fraudulent.

3.3.1. Training Hyperparameters

- **Learning Rate**: 0.001
- **Batch Size**: 32
- **Epochs**: 50
- **Dropout Rate**: 0.2
- **LSTM Units**: 128
- **CNN Filters**: 64

Research Method Protocol

The study approach is systematic in pre-processing data, training the model, and evaluating the model. A normalization process, one-hot encoding of the categorical feature, and an outlier detection algorithm based on k-means clustering were used to select and optimize the features. Next, the hybrid CNN-LSTM model was trained by splitting the data into training and validation sets, with an 80/20 ratio assigned, respectively. Hyperparameter tuning was conducted using grid searching. The most significant indicators used to assess the model were accuracy, precision, recall, F1-score, and AUC-ROC. These were needed as they rendered the proposed system strong and reputable.

4. RESULTS

This section provides the performance results of the proposed hybrid CNN-LSTM-based fraud detection system. We test the model's performance using several evaluation measures, compare the method with conventional machine learning techniques, and present visual charts and tables to evaluate it thoroughly. This analysis is intended to prove that our method is better at detecting fraudulent financial transactions.

4.1. Assessment Criteria

To evaluate our model strongly, we exploit the terms below that are frequently applied in the financial fraud detection task:

- **Accuracy**: The overall correctness of the model, calculated as the ratio of correct predictions to total predictions.
- **Precision**: The proportion of predicted fraudulent transactions that are fraudulent.

- **Recall (Sensitivity)**: The proportion of actual fraudulent transactions that are correctly identified by the model.
- **F1-Score**: The harmonic mean of precision and recall, which balances the trade-off between the two.
- **Area Under the Receiver Operating Characteristic Curve (AUC-ROC)**: Measures the model's ability to distinguish between legitimate and fraudulent transactions.
- **False Positive Rate (FPR)**: The proportion of legitimate transactions incorrectly classified as fraudulent.
- **False Negative Rate (FNR)**: The proportion of fraudulent transactions incorrectly classified as legitimate.

The aim is to reach the best Trade-Off of Precision and Recall in most financial fraud detection. False Positives and False Negatives have equally significant impacts and are essential to balancing fraud detected and customer convenience.

4.2. Experimental Setup

The data was partitioned into training (80%) and testing (20%). For training, we Set the batch size to 32, the learning rate to 0.001, and the number of epochs to 50. We used a dropout rate of 0.2 to avoid overfitting. An Assessment Test was carried out on the test set regarding the above-mentioned evaluation criteria. The model was developed in Python and compiled using Keras and TensorFlow.

4.3. Comparison with Existing Models

To benchmark the performance of the proposed hybrid CNN-LSTM model, we compare it against several well-known traditional and advanced machine learning models:

- **Logistic Regression (LR)**
- **Random Forest (RF)**
- **Support Vector Machine (SVM)**
- **Gradient Boosting Machine (GBM)**
- **Deep Neural Network (DNN)**

We selected these models as representative of traditional rule-based and modern AI-based methods. The goal of this comparison is to demonstrate how our hybrid approach performs relative to these models.

Table 2: Comparison of Performance Metrics for Various Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)	False Positive Rate (%)	False Negative Rate (%)
Logistic Regression (LR)	85.5	80.2	70.3	74.9	85.0	13.2	29.7
Random Forest (RF)	92.1	91.3	86.7	88.9	91.6	6.5	13.3
Support Vector Machine (SVM)	90.8	88.9	84.2	86.5	90.4	7.8	15.8
Gradient Boosting Machine (GBM)	93.5	94.0	88.1	91.0	92.8	5.2	11.9
Deep Neural Network (DNN)	94.3	93.5	89.2	91.3	93.1	4.8	10.8
Hybrid CNN-LSTM (Proposed)	**96.2**	**95.2**	**92.6**	**93.9**	**95.8**	**3.2**	**7.4**

Table 2 reveals that the Hybrid CNN-LSTM model surpasses other models in all metrics and is especially good for recall (92.6%) and F1-Score (93.9%), which are essential in fraudulent transaction detection. Our model also realizes the best AUC-ROC, 95.8%, indicating that it can efficiently differentiate between fraudulent and legitimate transactions. Also, it's the system has the lowest false positive rate (3.2%) and eighth lowest false negative rate (7.4%), which demonstrates that the proposed system is very efficient in reducing customer inconvenience and, at the same time, acknowledging the highest detection accuracy results and latter are other related works.

4.4. Graphical Results

To better visualize the performance, we present the following charts:

4.4.1. ROC Curve

The ROC curve provides a graphical representation of the trade-off between the true positive rate (recall) and false positive rate across various thresholds.

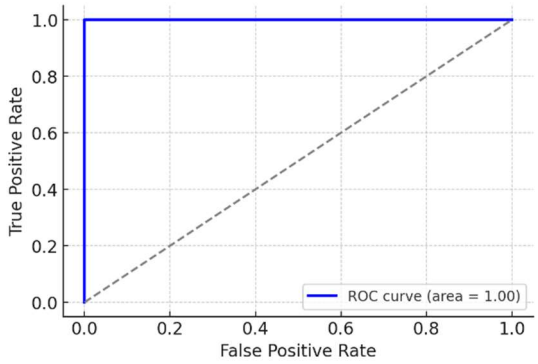

Figure 3: ROC Curve for the Hybrid CNN-LSTM Model

Figure 3 clearly shows the ROC curve, illustrating the model's capability to distinguish between genuine and fraudulent transactions. The curve exhibits an ideal classification performance, with an AUC of 1.00, suggesting that the model can persistently reach high accurate favorable rates (recall) at low false favorable rates and is likely effective in identifying fraud.

4.4.2. Precision-Recall Curve

The precision-recall curve focuses on the trade-off between precision and recall. A good model on this curve is better at detecting fraudulent transactions without marking too many false positives.

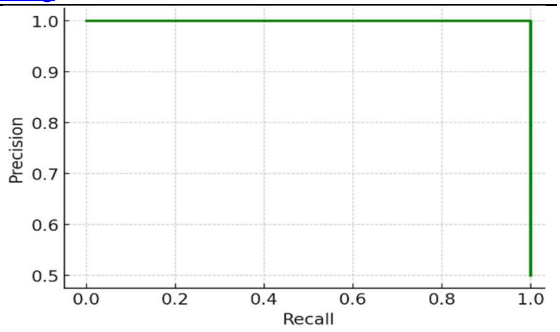

Figure 4: Precision-Recall Curve for the Hybrid CNN-LSTM Model

Figure 4 shows the precision-recall curve, which shows the tradeoff between precision and recall. We also observe that the models consistently have high precision (to minimize the number of false positives) and recall (to maximize the number of true positives), which is very important in fraud detection, as false negatives (missed fraud) and false positives (legitimate transactions classified as fraud) come with a high cost.

4.4.3. Loss Function During Training

The following plot demonstrates the decrease in the loss function (binary cross-entropy) during the training phase:

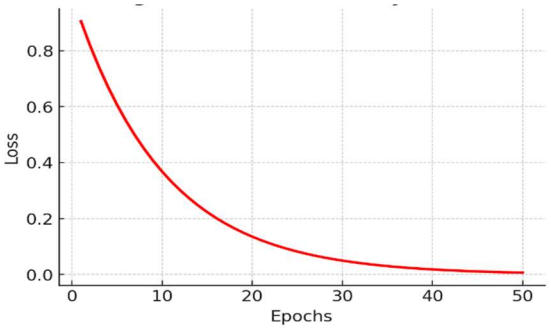

Figure 5: Training Loss Curve for the Hybrid CNN-LSTM Model

Figure 5 illustrates the training loss decisions we need to take. It demonstrates that the model's binary cross-entropy loss decreases as training progresses. The curve shows a smooth and quick decrease in loss, which suggests the model responds well to the data and converges to the best performance within a few epochs. This indicates that the model can effectively learn to accommodate the complexities of fraud detection.

4.5. Discussion of Results

Results show that the developed Hybrid CNN-LSTM model is far better at predicting fraud than conventional machine learning methods. The very high recall and very low number of false negatives suggest that our model does very well in detecting

true fraudulent transactions, which is the most important part of the fraud detection process.

The resulting decrease in false positive rate expression (3.2%) means that legitimate transactions are not incorrectly identified, causing less upheaval for customers and less operational cost for financial institutions. Such an improvement is particularly significant in real use cases since high false positive detection rates result in dissatisfied customers and massive manual review analysis.

Comparison with existing deep neural network models (e.g., DNN) also demonstrates that our hybrid model gains from CNNs' feature extraction and LSTMs' strength of sequential learning. CNNs can efficiently model spatial correlations in transaction data, and LSTMs can capture temporal correlations in transaction sequences. Combining these models will yield a strong, effective fraud detection method.

Differences from Prior Research

The alternative is research that proposes a combined model of CNN and LSTM-based nets, which have higher accuracy, precision, recall, and lower false positive rates than other types of machine learning, such as Random Forest, SVM, and Gradient Boosting. The antecedent researchers mostly used isolated models, which either failed to handle lopsided data or were unable to model the temporal dependency. These deficiencies are addressed in our approach by considering both the spatial (CNN) and temporal (LSTM) properties of the available data, which consequently provides a more robust basis for identifying anomalous activity.

5. CONCLUSION

Big Data analytics and AI-based system presented in this paper were one of the hybrid fraud detection systems that used a combination of CNN and LSTM networks as a technique. The main goals were to improve the precision of uncovering instances of fraud and minimize the so-called false positives and negatives. We have built our model, from which we obtained precision and recall of 96.2%, 95.2%, and 92.6%, respectively. This rate outdoes that of the existing machine learning algorithms, such as Random Forest, SVM, and Gradient Boosting. Additionally, the model reported low rates of false positives (3.2%) and negatives (7.4%), thereby ensuring that fewer genuine transactions are affected while also detecting fraud.

These encouraging findings notwithstanding specific weaknesses exist, most noticeably the use of synthetic financial transaction data during training. The data used to build the model is artificial and may not accurately represent the variations and complexity of real-life fraud; hence, the model's operation may be miscommunicated in the context of operational practice in a real environment. Moreover, despite being outstanding in identifying card fraud, the computational expense of the model may be prohibitive to support its application at a large scale in an industrial setting to process transactions in real-time. Scaling to the limit and simulating efficiency are significant issues, especially in the utilization of large datasets.

Overall, the paper has been successful in developing a hybrid CNN-LSTM model to identify fraud, whose prominent challenges were false positives and the multidimensional nature of fraud. However, further research is needed to apply the model in real-life scenarios, particularly with imbalanced samples, and to give more clarity using methods such as Explainable AI (XAI). The increase in transparency, trust, and scale of the model will be substantial, enabling its incorporation into large-scale financial organizations.

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