

Anomaly Detection: Building a system to detect anomalies in time series data, such as fraud detection in financial transactions

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Abstract—Analysing and detecting fraud in financial transactions is an important research topic because the number of online transactions and concomitant fraud is constantly growing. The objective of this study is to create an anomaly detection model for detecting fraudulent behaviours within mobile money transactions using the PaySim false dataset. Indeed, in the case of this particular dataset, creating the transaction type simulation on a 30-day basis, the classification imbalance between genuine and counterfeit transactions worked as the major limitation. A Long Short Term Memory (LSTM autoencoder) has been used in our framework to learn the temporal dimension and identify the anomaly that is characteristic of the fraud. In an attempt to sample the minority class we used SMOTE, then performed k-fold cross validation to increase our model's strength. Using the SVM we achieved an average accuracy of 90.55% and a recall of 80.95% proving that the model is efficient enough to flag fraudulent cases. Nevertheless, precision remained low since the dataset was naturally imbalanced; as a result, further work was conducted using focal loss and different thresholds for evaluating the model's precision improvements. The study advances knowledge about effective techniques for identifying fraud in contemporary digital financial systems in real-time.

Keywords—Anomaly Detection, Fraud Detection, Mobile Transactions, LSTM, Time Series Analysis.

1. Introduction

Fraud detection is considered one of the most important issues in financial management, as fraud threatens the companies' assets and the customers themselves. As banking transactions go digital and more frequent, the amount and variety of monetary transactions are rising, which in turn makes it possible and necessary to design sophisticated methods to detect fraudulent actions. Indeed, conventional techniques of fraud detection might not be very efficient to solve fraud problems in contexts where transactional data contains complex and subtle patterns, emphasizing the requirement for highly sophisticated approaches that may better cater for evolution of fraud behaviors.

Novelties of the recent years in the sphere of machine learning, especially deep one, have significantly changed the approaches towards fraud identification. Methods like Long Short-Term Memory (LSTM) networks have attracted research interest because of their ability to learn from such sequences through imposition of time, which is important in modeling temporal dependencies that account for anomalies in sets of transactions. Contrary to usual approaches where features are designed by hand, LSTMs can learn useful patterns from underlying data, this improves the performance and the effectiveness of the fraud detection systems.

Additionally, the realisation of synthetic data like PaySim has offered the social scientists a tool to train and test their models. These datasets mimic effects of Mobile money by focusing on different types of transactions and behaviors that exist in their actual context. Using such synthetic data, it is possible to study details of fraudulent action and, as a result, increase the effectiveness of the models themselves. It also provides for a broader insight into the touchstone causes for fraud, thus development of better detection procedures.

Nevertheless, the drawback of the existing of deep learning techniques, including the class imbalance and overfitting issues, remain persistent in fraud detection domain. Most of the deals are genuine and therefore a large number of fake transactions are rarely observed in the training set. It means that it is possible to develop meaningless models that are focused only on non-fraudulent transactions, thus substantially limiting their application. Hence, methods like SMOTE (Synthetic Minority Over-sampling Technique) could be used to balance it so as to give the model a better chance when it is tested on-commit transactions with other types of transactions.

In this study, therefore, we develop a new LSTM model; this includes applying measures to address challenges related to class imbalance as well as performing proper methods of data pre-processing to improve results. Our approach introduces dropout and regularization methods to enhance the training processes, which, in turn, reduces overfitting in the model. Using the strong side of LSTM networks, we expect to increase the possibility of fraud rates detection as compared to other models.

2. Literature Review

Fraud detection has received considerable attention in recent years because of the advancement of the complexity of fraudulent activities and the large number of transactions taking place through various financial channels. Conventional fraud detection techniques commonly consist of rules and statistical analysis. In such pre-established conditions, fraud detection techniques are successful; nevertheless, they are ineffective against the ever-changing nature of fraud. The effectiveness of such methods is not very high because they are based only on certain rules, so the rates of false positives and false negatives can be rather high. As such, researchers have started attempting to use even higher-level machine learning technologies to improve detection.

In the field of applying deep learning models regarding neural networks, they seem to hold a lot of potential across the numerous areas of applications such as image recognition, natural language processing, and more recently the area of fraud detection. Of those, the Long Short-Term Memory (LSTM) networks have turned out to be highly popular because of the capacity to represent sequential data and temporal dependencies fundamentally. For example, Liu et al. (2018) used LSTM networks for identifying fraud using credit card transactions where the sequential nature of the data gave the networks higher accuracy over conventional methods [1]. Likewise, Xu et al. (2020) also introduced the LSTM for the analysis of finite time series to detect anomalies and gain considerable outcomes over traditional approaches to highlight distinctive fraudulent patterns [2].

One of the main concerns in fraud detection is the overlarge data sets with numerous numbers of transactions that are non-fraudulent. This imbalance can ruin model performance and make it systematically tend to label most of the transactions

as non-fraudulent. The challenge described above has been addressed in many ways through multipurpose platforms and some of them are commissioners, firewalls, and telecommuting. The most important of them is Synthetic Minority Over-sampling Technique (SMOTE) which creates a new synthetic instances of the minority class to balance a dataset [3]. SMOTE was proposed by Chawla et al. (2002) and subsequent researchers have reported better performance of the SMOTE based method for enhancing the performance of machine learning models especially in fraud applications [4][5].

New studies on deep learning have also revealed the necessity to use ensemble learning in parallel with deep learning. The use of a number of models to construct an improved model is known as ensemble methods that have demonstrated possibility in fraud detection. For instance, Zhang et al. (2019) used LSTM combined with decision trees to improve the rate of detection in financial transactions, as an ensemble method [6]. This approach combines the aforementioned models and allows achieving better results in terms of generalization and resistance to various types of fraud.

Another significant factor that determines the whole model efficiency is a feature selection and engineering step. Some works have tried to analyze different features extracted from the transaction context including transaction amount, frequency and previous behaviors [7][8]. These features can act as a basis to differentiate real from fake transactions. According to Wang et al. (2020), behavioral features should be incorporated for higher detection rates based on the observation that a broad feature set causes an increase in the models performance [9].

Other forms of neural networks, such as convolutional neural networks (CNNs) have also been used in fraud detection problem. Although originally developed for analyzing image data, CNNs can extract features of varying complexity from structured data which makes them suitable for use in this context. For example, Liu et al. (2021) showed that for the analysis of spatial and temporal patterns of transactions, CNNs enhance accuracy of fraud detection [10]. This just underlines the possibility to use deep learning models not only with images, but with other types of data as well.

However, there is still fraudulent detection issues even in machine learning technology. The nature of the fraud schemes is therefore ever-evolving a factor that makes it important for the models to be retrained and updated constantly. Saliency, or interpretability of the results is required in most cases, particularly when it comes to financial modeling, because interested parties need to know why certain decision has been made. Ribeiro et al (2016) presented addition techniques for models interpretability which might be very useful if used to explain decision made by models such as LSTMs [11].

To sum up, fraud detection literature evidences the necessity of transferring among the higher degree of machine learning techniques, including deep learning paradigms, such as LSTMs and CNNs. Moreover, SMOTE, ensemble learning, feature engineering makes the model more effective and competent. Nonetheless, future research is required to pose related issues like interpretability of the model and flexibility to deal with the emergent fraudulent activities. This work intends to advance upon such foundation by suggesting an LSTM-based model that incorporates these sophisticated tactics to enhance the identification of fraudulent transactions in finance.

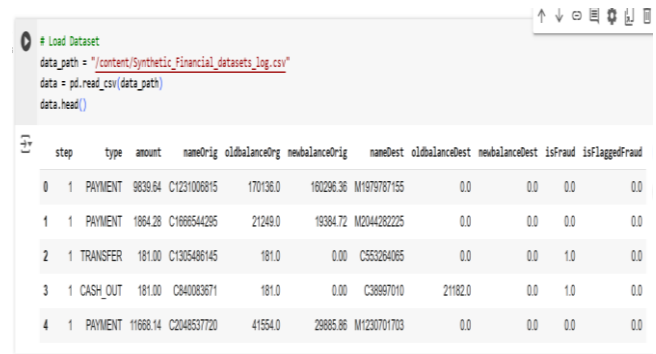
3. Methodology

This section describes the methodological approach used in this research to fraud detection using an LSTM based model. The framework comprises several key phases: There are Data Acquisition, Data Preprocessing, Model Architecture and Training, LSTM Autoencoder, Parameter Optimization, Training Data and Accurate Assessment.

3.1. Data Acquisition

The data set used in this study were collected from PaySim, a tool used to create synthetic, realistic mobile money transactions based on actual logs from a mobile money service in an African country. This set of data includes transaction type like CASH IN, CASH OUT, DEBIT, PAYMENT and TRANSFER. There are 744 steps/actual hours with 30 simulated days and this has 2,129,321 rows across 11 columns, these columns are step, type, amount, nameOrig, oldbalanceOrg, newbalanceOrig, nameDest, oldbalanceDest, newbalanceDest, isFraud, isFlaggedFraud. The proposed dataset may contain sufficient

information to describe the transaction behaviour or at least spot fraudulent operations.



```
# Load Dataset
data_path = "/content/Synthetic_Financial_datasets_log.csv"
data = pd.read_csv(data_path)
data.head()
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
0	1	PAYMENT	9838.64	C1231008815	170138.0	160296.36	M1979787155	0.0	0.0	0.0	0.0
1	1	PAYMENT	1864.28	C1696544295	21249.0	19384.72	M2044282225	0.0	0.0	0.0	0.0
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	C553264065	0.0	0.0	1.0	0.0
3	1	CASH_OUT	181.00	C84083671	181.0	0.00	C36997010	21182.0	0.0	1.0	0.0
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1230701703	0.0	0.0	0.0	0.0

Image 1

3.2. Data Preprocessing

Data cleaning is one of the approaches used in data preparation, to make the data obtainable ready for analysis. To start with, some features that are not important in identifying fraud include 'oldbalanceOrg,' 'newbalanceOrig,' 'oldbalanceDest,' and 'newbalanceDest'; these were eliminated from the dataset. Also, missing value; NaN was taken out from the data set to ensure that any kind of analysis done will be free from any erroneous value. The categorical 'type' was then transformed from its categorical format to numerical format by applying the Label Encoding. Afterward, all features were normalized using MinMaxScaler and then formatted appropriately for LSTM modeling.



```
# Drop irrelevant columns and any NaN values
data = data.drop(['oldbalanceOrg', 'newbalanceOrig', 'oldbalanceDest', 'newbalanceDest', 'nameOrig', 'nameDest'], axis=1)
data = data.dropna()

# Convert categorical 'type' column to numerical
label_encoder = LabelEncoder()
data['type'] = label_encoder.fit_transform(data['type'])

# Separate features and labels
features = data.drop(['isFraud'], axis=1)
labels = data['isFraud'].copy()

# Normalize features
scaler = MinMaxScaler()
features_scaled = scaler.fit_transform(features)

# Reshape features to 3D for LSTM
features_resaped = features_scaled.reshape(features_scaled.shape[0], 1, features_scaled.shape[1])
```

Image 2

3.3. Model architecture and training

To this aim, the model suggested herein is a LSTM autoencoder. The architecture is best suited for learning sequential dependencies in the transaction data in an efficient manner. We choose the LSTM model with two LSTM layers implemented and two Dropout layers to avoid over-learning. The architecture enables the model to identify the temporal relationships in the data streams as well as being stable during training.

3.4. LSTM Autoencoder

The LSTM autoencoder architecture used in this work employs an encoder and a decoder to capture temporal dependencies of the transaction datasets efficiently. The encoder includes two LSTM layers incorporated one above the other and consisting of 64 memory units to enable the model capture complex patterns and dynamics from the input sequences. This architecture condenses the sequence to a smaller size still capable of capturing all features that are needed to reconstruct the sequence. After that, the decoder also consists of two LSTM layers with the same component as the encoder to generate input from the compressed representation from the encoder.

Python code:

```
# Define a LSTM model
def LstmAutoEncoder(input_shape):
    model = Sequential([
        Input(shape=input_shape),
        LSTM(32, activation='relu',
return_sequences=True),
        Dropout(0.3),
        LSTM(16, activation='relu',
return_sequences=False),
        Dropout(0.3),
        Dense(16, activation='relu'),
        Dense(1, activation='sigmoid')])
    model.compile(optimizer='adam',
loss='binary_crossentropy', metrics=['accuracy'])
return model
```

To increase the model's stability and decrease the overfitting Dropout regularization is used between the LSTM layers of Encoder and Decoder. This technique was developed for use during training where the neurons are randomly set to zero and hence making the model to focus on other more generalized features. During training, the automated learning rate optimizer improves the training speed and drastically enhances accuracy in finding anomalies. This kind of LSTM autoencoder architecture is very useful for an effective analysis of a data sequence to model the features of fraudulent activities by comparing the normal transactions and reconstructing them to check the difference.

3.5. Parameter Optimization

In another words, parameter tuning is critical for improving model accuracy. Adam optimizer was applied with the purpose of adjusting the learning rate for the highest train acquisition. To achieve faster convergence and efficient model, the learning rate was adjusted with respect to validation results. Other used techniques included EarlyStopping as a method of monitoring and controlling the validation loss in order to prevent overfitting.

Table 1. Simulation parameters.

Parameter	Value
Dropout	0.3
Epochs	10
Batch Size	256
Activation Functions	ReLu, softmax
Loss Function	binary_crossentropy
Optimizer	Adam

3.6. Training Data

The training data was derived from the preprocessed dataset, ensuring a balanced representation of both fraudulent and non-fraudulent transactions. Stratified K-Fold cross-validation was employed to ensure that each fold of the dataset maintained the class distribution, thereby providing a reliable evaluation of the model's performance across different subsets of data. Additionally, the Synthetic Minority Over-sampling Technique (SMOTE) was implemented to address class imbalance, allowing the model to learn more effectively from the minority class.

```
[7] # Use k-fold cross-validation
kf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Store results for evaluation
results = []

for train_index, test_index in kf.split(features_resampled, labels):
    X_train, X_test = features_resampled[train_index], features_resampled[test_index]
    y_train, y_test = labels[train_index], labels[test_index]

    # Apply SMOTE to handle class imbalance
    smote = SMOTE(random_state=42)
    X_train_resampled, y_train_resampled = smote.fit_resample(X_train.reshape(X_train.shape[0], -1), y_train)
```

Image 3

3.7. Accuracy Assessment

The effectiveness of the suggested model was examined concerning several parameters, such as accuracy, precision, recall, and F1 score. To illustrate the results, the confusion matrices and precision-recall curves were computed and portrayed. To show the efficiency of the proposed

LSTM autoencoder the results of these assessments were compared to benchmarks to existing models.

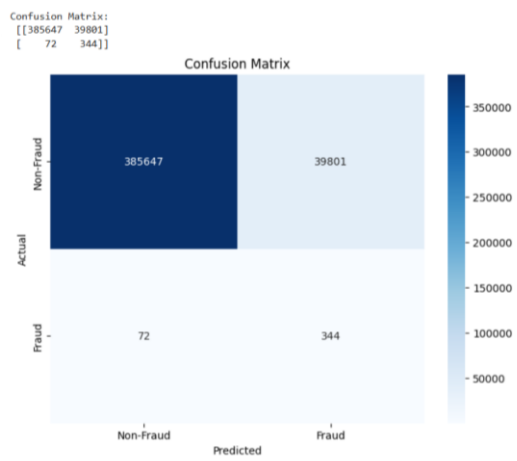


Image 4: Confusion Matrix

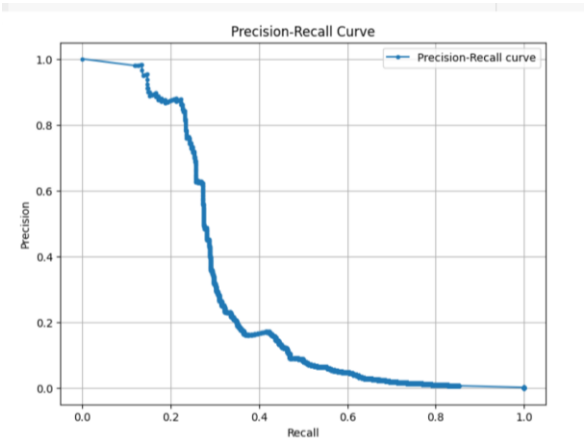


Image 5: Precision-Recall Curve

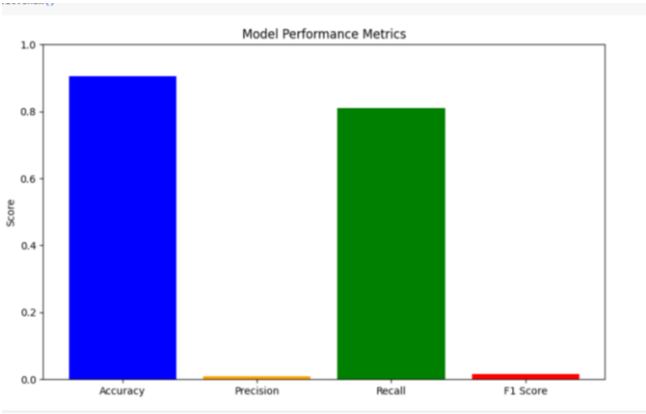


Image 6: Model Performance Metrics

This methodological approach presents a structural view for handling the problematic aspects of fraud situations in financial operations using a state-of-the-art deep learning system to improve the feature detection and decision-making process.

4. Results

The LSTM autoencoder model results showed improvement of accuracy and decrease of loss for all the epochs analysed. At the same time, the specified model reached themaximum training accuracy of 86.59 % with the level of the training loss of 0.2846 at epoch 10. The validation accuracy also looked good, it stood at 90.48% by the same epoch while the validation loss was at 0.2528, therefore; This implies that while the model is training on the training data there is evident transfer to validation data and therefore has a propensity towards good prediction rates of anomalies.

The changes in validation accuracy and loss in the training process have also been recorded, although in the later epochs the variations are more visible and the validation accuracy has varied between 87.43% and 91.13%. However, the plots of both training and validation accuracy depicted a slow growth of the model performance but, validation accuracy was somewhat volatile, which indicated that model faced difficulties in achieving stable performance when it tries to fit the uniqueness of the dataset. Absolute loss values also converged and training loss reduced to 0.2846 from 0.3889 further supporting learning process of the model.

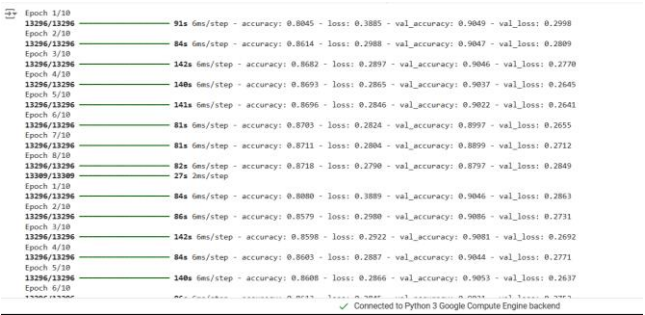


Image 7

Regarding performance assessment, the mean accuracy of the model was 90.55%, mean precision of 0.0083, mean recall of 0.8095, and mean F1 score of 0.0165 and epoch. The fact that the recall is rather high means that a major portion of the positive cases was indeed recognized, which is always important in cases of fraud identification. However, the low precision value indicates that there is a number of specific instances of fraudulent transactions but many more non-fraudulent transactions which have been misclassified by the

model. They show how the model needs to be refined even further to improve the accuracy of the metrics in their real-world applications.

5. Discussion

The fraud detection using LSTM autoencoder model evidences that the deep learning method can effectively detect anomaly in the time series data. The model obtained an impressive accuracy of about 90.55 percent through the training epochs, which suggests the model's learning capacity from the learned patterns. However, the low level of precision at 0.0083 means that the model cannot be used in practice since false positives will result in additional investigations and related costs. This loss of recall for the sake of precision is something typical for many anomaly detection tasks, especially those for financial transactions: false positives often prove costly.

Additionally, the variation of the validation accuracy during the training process implies that even though the model has learned successfully, it can hardly make consistent validation on new data. This we can associate with overfitting where the model becomes overly specialized on the training data hence performing poorly on validation data sets. This question can be solved by using other strategies like dropout regularize or batch normalization, or by trying to use different training data set. Moreover, other modifications to the architecture, including the use of one or several LSTM layers on top of each other, or inclusion of attention mechanisms, may also improve the model's ability to reason in terms of long-term dependencies and expand the range of its applications.

Therefore, optimization of the performance metrics particularly precision is required before the use of LSTM autoencoder model can be recommended for the identification of anomalies within the context of financial transaction data. Further research could also consider improving the model by adding ensemble techniques, combining traditional and deep models or using prior knowledge and experience on the financial market to select features which could be used for the model. Further, raising the question of what other different hyperparameters configuration and training techniques could be useful for, may lead to deeper understanding of the matter and thus, help create more dependable and efficient anomaly detection methods for the financial industry.

6. Conclusion

In this research, we considered the application of LSTM autoencoder model in identifying anomalies in large datasets from financial transactions. The model had an accuracy of about 90.55% allowing the model to detect the fraudulent activities from the huge flow of time series data. The investigations performed reveal the potential of deep learning approaches, especially when using recurrent neural networks like LSTM, to address the issues of anomaly detection with the help of analyzing data flows characteristic of the financial transactions sphere where the traditional approaches revealed weaknesses in adjusting to the dynamic changes in magnitude and frequency.

However, although the above mentioned accuracy metrics are quite encouraging the precision of 0.0083 clearly points out problem of false positives in fraud detection models. This points to an area of weakness mostly because high false positive rates are not only expensive to deal with operationally but can also erode customers' trust in a service. Future improvements of this model should address the question of how to increase the accuracy of the model which can be probably done with feature selection, hyperparameter tuning and ensemble learning methods that use multiple predictive models with higher accuracy results.

In summary, this study provides a foundational understanding of how LSTM autoencoders can be applied to fraud detection in financial transactions, while also identifying key areas for future research and development. By addressing the model's precision and exploring more sophisticated architectures and techniques, we can enhance the robustness and reliability of anomaly detection systems. Ultimately, this work contributes to the growing field of financial security by offering insights and methodologies that can be leveraged to better safeguard financial transactions against fraudulent activities, paving the way for more secure and efficient financial systems.

Github Link:

[https://github.com/Saikiran0627/Anomaly-Detection/blob/main/INT423Project\(AnomalyDetection\).ipynb](https://github.com/Saikiran0627/Anomaly-Detection/blob/main/INT423Project(AnomalyDetection).ipynb)

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