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A Survey on Long-Short-Term-Memory Networks and its Applications

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Abstract - Long Short-Term Memory (**LSTM**) Network, a category of Recurrent Neural Networks (RNN) is effective for time series data as it maintains information for a longer time in the memory and resolves gradient problems. It is proficient in learning the past stages information and utilizing the same in future predictions. Two major applications Stock price prediction and financial fraud detection are considered in the paper for evaluating the performance of LSTM .Experimental results reveal that, for stock price prediction, the model achieves least MAPE 1.603 for the Bank of Baroda dataset and Minimum MAE value of 1.421 for the Punjab National Bank dataset. In fraud detection system, LSTM achieves the performance accuracy of 99.98% in a short time using Adam optimizer.

***Key Words*: Stock Market Prediction, Financial Fraud Detection, Time series Data, LSTM, RNN**

1.INTRODUCTION

Time series is a sequence of observations of numeric variables indexed by date or timestamp. The most common application of time series analysis is forecasting future values of a numeric value using the temporal structure of the data. The available observations will be appropriate to predict values from the future. In statistics, a moving average is a calculation used to analyze data points by creating a series of averages of different subsets of the entire dataset. LSTMs can be used to model univariate time series forecasting problems**.** The paper discusses application of LSTM on two major applications (Stock price prediction and Financial fraud detection) that makes use of time series data

1.1 Financial fraud detection

Online transactions brought the great danger of unauthorized payments, which are known as financial frauds. These can be banking transaction fraud, online identity theft, insurance fraud, payment card fraud, and money laundering. The fraudulent activities in finance are very sophisticated and very complicated to identify. As the use of the internet is growing exponentially, more and more businesses such as the financial sector are operationalizing their services online. Nowadays, financial fraud is increasing in number around the world. Unauthorized access and unusual attacks are recognized based on LSTM Financial fraud detection model. The model is to identify suspicious financial transactions and alert the relevant authorities about them to take appropriate action. As a result, the proposed model may constitute a utility tool for the commercial sectors to reduce their potential losses.

1.2 Stock price prediction

Stock market prediction is the process of taking actions to identify the future value of company stock or other financial traded on an exchange. The accurate prediction of a share price movement could yield significant profit for the investors. Many factors impact the value of stocks, including national politics, market indicators, and trading aspirations. Although stock trading heavily depends on numerous advanced technologies to make buying and selling choices. Accurate forecasts are difficult to obtain since financial sector patterns are complex, dynamic, and non-linear. There are typically two primary approaches to forecast the stock value. The first approach focuses on strategic and business activities like business revenue, investments, and estimates growth figures. The second approach is the strategy for technical assessment based on past asset performance. In Stock Market Prediction, the goal is to accurately predict the future value of the financial stocks of a company. Deep learning approaches can detect structure and trends in time-scale predictions such as non-linearity and complexity. LSTMs are very powerful in sequence prediction problems because they can store past information. It is essential in our case because the previous stock price is crucial in predicting its future price.

2. Related Works

Lindemann et al. [1] present Recurrent neural networks and exceedingly Long short-term memory (LSTM) has been investigated intensively in recent years due to their ability to model and predict nonlinear time-variant system dynamics. A categorization in LSTM with optimized cell state representations and LSTM with interacting cell states. LSTM networks solve multidimensional problems by dividing the problem into sub-problems and organizing them in a hierarchical structure. The investigated approaches are evaluated against defined requirements being relevant for an accurate time series prediction. These include short-term and long-term memory behavior, the ability for multimodal and multi-step ahead predictions, and the according to error propagation.

Vijh et al. [2] carried out a daily stock price dataset from the Bloomberg website. Over the most recent two decades determining stock, returns have become a significant field of research. The aim is to predict the next-day stock price and a long-term stock price using a support vector machine (SVM) algorithm. Features like PF ratio, PX volume, 10-day volatility, 50 days moving average, etc. The accuracy ratio is the number of days that the model correctly classified the testing data over the total number of testing days. The Quadratic Discriminant Analysis is the best among all models, and it scores an accuracy of 58.2%. With the long-term model predicting the next n days stock prices, the longer the time frame, the better the accuracy for SVM. With a time window of 44 days, the SVM model accuracy reached 79.3%. If the number of features increases, then the accuracy is also increased. The model produces an accuracy of 79% for all 16 features and 64% for only 8-features, and 55% for 1-feature.

Lai et al. [3] work on New York Stock Exchange dataset with 1000 data rows. They used 70% of the training data to predict the stock prices for the next 60 days and project-tested predictions over 3- months (the next 60 days predictions) from the remaining pool of 30% data. Through optimizations, they predict the actual closing prices within 0.71% mean absolute percentage error (MAPE), with the highest variance -3.2% among all of the 62 days. The model demonstrated a high potential for using an Artificial Neural Network (ANN) to predict stock prices accurately.

Naik et al.[4] carried the study on 10-years of the historical dataset from the Bombay Stock Exchange (BSE) to predict the stock price index movement. They conducted experiments using ten stock price indicator signals as inputs. The prediction model decides whether the stock will go up or down in the coming ten days. Stock price analysis indicators include SMA, EMA, Momentum, Stochastic SK, Stochastic SK, MACD, RSI, etc. The prediction models they have used include Artificial Neural Network (ANN), Support Vector Machine(SVM), Random Forest, and Naive Bayesian models. The model outputs "up" or “down” movement signals. The result reveals that the random forest scored the highest performance with 83.56% accuracy with their inputs.

Rana et al. [5] work on the Formosa Taiwan Cement Company dataset from the Taiwan Stock Exchange (TSE). LSTM model used the average of the previous five days' stock market information (open, high, low, volume, and close) as the input value. The prediction was then used as part of the average stock price information for the next five days through the ARIMA method. The results showed that the Root Mean Square Error (RMSE) value was above 1.3.

Ghosh et al. [6] work on the TCS stock price dataset from National Stock Exchange (NSE) using RNN with the LSTM model. The model could keep the memory of historical stock returns to forecast future stock return output. The related stock information was stored and used. The RNN with LSTM model deployed on stock closing prices, and results showed that the Root Mean Square Error (RMSE) value was below 25.09.

Patel et al. [7] work on a historical stock price dataset from the Spanish Stock Company to analyze future market/stock values. Linear Regression (LR), Support Vector Regression (SVR), and Long Short Term Memory (LSTM) were used to predict stock market prediction. And also compared the different activation functions with various optimizers and concluded that the tanh activation with the Adam algorithm performs best with an accuracy of 98.49%. The results reveal that the performance of the LSTM model was better than the other models.

Yuning Zhang et al.[8] proposed a methodology that aims to predict the next-day closing price of the stock using Artificial Neural Network (ANN) and Random Forest (RF) algorithms. The historical stock price of the top 5 companies took from the Yahoo finance dataset. The model uses standard strategic indicators: Mean Absolute percentage Error (MAPE) and Root Mean Squared Error (RMSE) for evaluation. The results showed that the best values obtained by the ANN model give Root Mean Square Error (0.42) and Mean Absolute Percentage Error (0.77).

VadalaChakshu et al. [9] proposed a statistical method, the Naive Bayes algorithm for classification. It selects a decision that has maximum probability. Naive Bayes classifier depends upon two predictions. The assumption is that all features which had to be labeled should evolve in the decision. A hybrid approach of under-sampling and over-sampling kept on unlabeled datasets for SVM and LR. The dataset consists of 284,807 transactions in 2 days by European Cardholders in September 2013 with 492 fraud transactions. It shows that the dataset is very imbalanced. Accuracy, precision, F1-Score, and Recall are the evaluation parameters for finding fraud. Based on the accuracy, Naïve Bayes yields 90.61%, SVM yields 96%, and LR produces 85.2%. By comparing the results, SVM gives high accuracy of 96%. It is the best algorithm for detecting fraud.

Li et al. [10] exploit the static and dynamic behavior of customers in a unified framework. Firstly, address and explore the information in continuous time-spaces. Then propose to use time attention-based recurrent layers to embed the detailed data of the time interval, such as the duration of specific actions, time differences between various measures and sequential behavior patterns, etc., in the same latent space. Then combine the learned embeddings and static profiles of users altogether in a unified framework. Extensive experiments validate the effectiveness of the proposed methods over state-of-the-art methods on various evaluation metrics, especially on recall at top percent, which is an essential metric for measuring the balance between service experiences and the risk of potential losses. Compare the algorithm such as Time Attention-RNN, LSTM, and GRU on the Alipay dataset. AUC, F1-Score, and RATP are the performance metrics to find the best algorithm. Among the above algorithms, LSTM provides the highest RATP and, it is the best for detecting fraud.

Jha et al. [11] use Artificial Neural Networks (ANN) by Genetic Algorithms (GAs) to detect fraud. The International credit card dataset has 13 months, from January 2006 through January 2007, of about 50 million (49,858,600 transactions) credit card transactions about one million (1,167,757 credit cards). Name the panel dataset of all transactions in this period as dataset A. B has 2,420 known fraudulent transactions made with 506 credit cards. Logistic Regression(LR) is to show the enhanced performance to create appropriate derived features. A comparison done on the average values of derived and primary features for the two datasets reveals differences in purchase behavior between fraudulent and legitimate transactions. Consider the overall correct classification with sensitivity and specificity measures. The lower specificity of the model means that more legitimate transactions will get flagged as fraudulent triggering, potential loss of sales, and unhappy customers. However, models with high sensitivity may find use with risk-averse merchants, who would prefer to catch more fraudulent transactions even at the expense of losing some potential sales by stopping legitimate transactions.

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Wang et al. [12] introduced the attention mechanism based on the LSTM neural network. The attention mechanism calculates the importance of the LSTM output at different times and extracts more critical information. The Event2vec model was constructed that transforms each event into a vector. Use Adam's (Adaptive Moment Estimation) optimizer to train the deep learning models. Dropout was an effective method to prevent over-fitting and improve the model effect in deep learning. It is a method of discarding neural units from the network according to certain probability during training of the neural network. BOA-XGBoost, LSTM, BLSTM-Meanpool algorithms were compared. From the results, the low dimension of the embedded space will harm the prediction effect.

Shirgave et al. [13] use the paysim synthetic dataset for processing the model. Machine Learning is considered one of the most successful techniques for fraud identification. It uses a classification and regression approach for recognizing fraud in credit cards. A supervised learning algorithm uses labeled transactions for training the classifier. An unsupervised learning algorithm uses peer group analysis that groups customers according to their profile and identifies fraud based on customers spending behavior. A model with two types of the classifier using random forest was used to train the behavior features of transactions. Comparing the two random forests and have analyzed their performance on fraud identification in credit cards. Compare the algorithms such as Logistic regression, SVM, Decision Tree, Naive Baive, and KNN. Hence, the proposed system using random forest will show better accuracy for training data.

Maniraj et al. [14] proposed a model that detects frauds. Credit Card Fraud Detection is a typical sample of classification. The process focused on analyzing and pre-processing the datasets. The deployment of multiple anomaly detection algorithms such as Local Outlier Factor and Isolation Forest algorithm on the PCA transformed Credit Card Transaction data. Class 0 denotes a valid transaction, and 1 represents a fraudulent one. Compare the output of the above algorithms to determine their accuracy and precision for testing purposes. While the Local Outlier Factor algorithm does reach over 99.6% accuracy, its precision remains only at 28%. However, when feeding the entire dataset into the algorithm, the precision rises to 33%.

3. Materials and methods used

The Long-Short Term Memory model has pertained to stock price market and financial fraud detection. The LSTM architecture allows learning through long dependency on sequences prediction issues. It is an extension for Recurrent neural networks (RNNs), which are forms of deep learning neural networks with memory. It is well suited for prediction due to prior knowledge and the relation between prediction results and historical input data. The LSTM architecture allows learning through long dependency on sequences prediction issues. It is helpful for longer-term patterns and can maintain a long memory. Besides, it has a default behavior that keeps information for a long-term period.

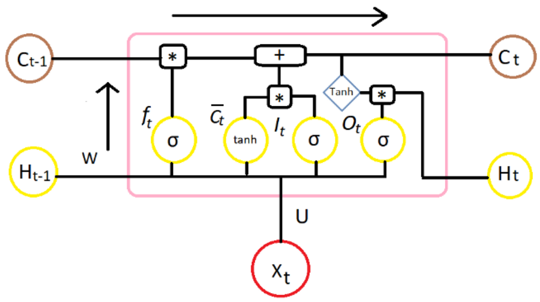


Figure3.1 LSTM Internal cell structure

As shown in Figure 3.1, the structure of The LSTM network includes memory blocks (cells) has several states and gates. The cell state is the vital chain of information flow. It allows the information to flow forward unaltered. The forget gate (ft) determines what information must be removed or kept. Data from the previous hidden state (ht-1) and current input (Xt) executes the sigmoid function. The sigmoid function (r) determines the values between 0 and 1. The hidden state, *ht*, at each memory cell is decided based on theupdated C*ell state*, *Ct*, and the output vector O*t*.

3.1 LSTM for Stock Price Prediction

Long Short Term Memory (LSTM) model is used to predict an increase or decrease in future stock prices. The experiments have been performing using historical datasets of the Bank of Baroda (BOB) and Punjab National Bank (PNB). The introduced new variable or feature named OHLC (open, high, low, and close) average in the proposed model for improving performance. It also compared and analyzed the performance of different epochs for training data with the discrete batch sizes and finally obtaining the most accurate one.

3.1.1: Data Collection

Day-wise past stock prices of two banking and financial services companies in the Indian Stock Exchange NIFTY 50(Bank of Baroda (BOB) and Punjab National Bank (PNB). It will be extracted from yahoo finance for the BOB data series cover the period from 1/04/2018 to 31/03/2020, and the PNB data series covers the period from 3/1/2017 to 31/12/2019.

The data contains information about the stock such as,

- Date: Specifies trading date
- High: Maximum price during the day
- Low: Minimum price during the day
- Open: Open price of the day
- Close: Close price of the day
- Volume: The number of shares that changed hands during a given day

3.1.2 : Pre-processing

i. Data cleaning: Dropping the unwanted attributes and empty rows.

ii. Data integration: After the dataset is transformed into a clean dataset, then calculating the moving average. Moving average is used to analyze the time-series data by calculating averages of different subsets of the entire dataset. The reason is to calculate the moving average of a stock is to help smooth out the price data over a specified period by creating a constantly updated average price. Then data set is split into training and testing data with respective percentages of 75% and 25%

iii. Feature Scaling: Normalization is performed to scale the stock prices between (0, 1) to avoid intensive computation.

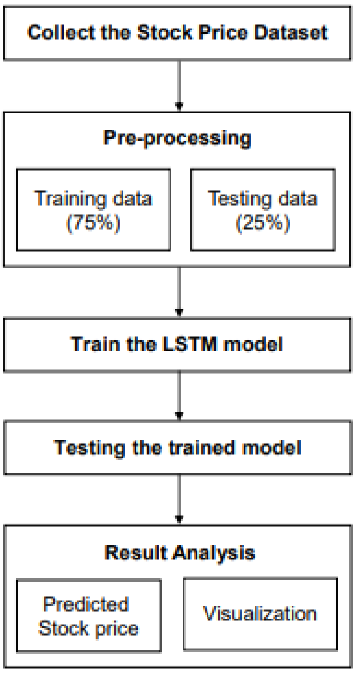


Figure 3.2 System workflow of the stock price prediction model

Step 3: Train the LSTM Model

LSTM model consists of a sequential input layer followed by 3 LSTM layers, with few dropout layers to prevent over-fitting, and then a dense layer with activation. Add the LSTM layer with the following arguments: 50 units which is the dimensionality of the output space. The Return sequences = true, which determines whether to return the final output in the output sequence or the entire sequence. Input shape as the shape of our training set. Then compile the model using the 'adam' optimizer and set the loss as the mean squared error function. Compile and fit the training set to run on different epochs with different batch sizes.

3.1.2 Performance metrics

3.1.2.1 Mean Absolute Error (MAE):

MAE is the absolute difference between the model predictions and the actual values.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |x_i - x|$$

Where 'x_i' refers to the actual price value, 'x' refers to the predicted price value, and 'n' refers to the total window size.

3.1.2.2 Root Mean Squared Error (RMSE):

RMSE is a standard way to measure the error of a model in predicting quantitative data.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - F_i)^2}{n}}$$

where 'O_i' refers to the actual price, 'Fi' refers to the predicted price, and 'n' refers to the total window size.

3.1.2.3 Mean Absolute percentage Error (MAPE):

MAPE can be considered as a loss function to define the error termed by the model evaluation. Estimation of accuracy is differences in the actual and estimated problems.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{(O_i - F_i)}{O_i} * 100$$

where 'O_i' refers to the actual price, 'F_i' refers to the predicted price, and 'n' refers to the total window size.

3.2 Financial Fraud Detection Application

3.2.1 Proposed System

Figure 3.3 shows the proposed methodology for financial fraud detection. The model is divided into three modules preprocessing, LSTM model, and evaluation.

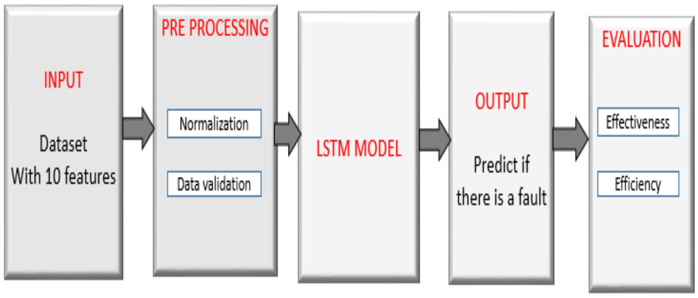


Figure 3.3 Architecture of financial fraud detection model

3.2.2 Dataset

The dataset "Synthetic financial datasets for fraud detection" is taken from Kaggle datasets, and it contains ten columns and 66543 entries. PaySim uses aggregated data from the private dataset to generate a synthetic dataset that resembles the usual operation of transactions and injects malicious behaviour to evaluate the performance of fraud detection methods.

Step 1: **Preprocessing**

Dataset samples are prepared to train and test the model. Data validation and normalization are the essential steps to be done before training and testing. It removes null, empty, and negative values in the dataset. Dividing the data samples into training and testing is essential for getting a realistic assessment of the performance. The proposed model has allocated 80% of the dataset for the training and the residual 20% for testing.

Step 2: Training the LSTM model

Creation of the LSTM structure and setting up value for the parameters are the two substages involved in this stage. The prepared data in the processing stage is fed into the model and processed by the layers that contain LSTM cells. The structure of The LSTM network includes memory cells that have several states and gates. To improve the results of the work, the model uses several parameters called hyperparameters. The parameters include optimizer, batch size, epochs, and matrix are used to measure the performance.

Attribute	Description
step	maps a unit of time in the real world. In this case, 1 step is 1 hour time. Total steps 744 (30 days simulation).
Type	CASH-IN, CASH-OUT, DEBIT, PAYMENT, and TRANSFER.
Amount	amount of the transaction in local currency
nameOrig	customer who started the transaction
oldbalanceOrig	initial balance before the transaction
newbalanceOrig	the new balance after the transaction
nameDest	customer who is the recipient of the transaction
oldbalanceDest	initial balance recipient before the transaction
newbalanceDest	new balance recipient after the transaction.
isFraud	identifies a fraudulent transaction (1) and non-fraudulent (0)

Table 3.1 Attributes and their description of Synthetic financial datasets for fraud detection

Step 3: Output and Evaluation

Then, the results obtained from the LSTM model will be analyzed and evaluate whether it is fraud or not. The evaluation will be estimated using different parameters like loss rate, accuracy, and execution. Further, number of layers and the number of iterations are tested to provide the best results. Adam optimizer is used to determine hyper parameters for best prediction and execution time.

3.2.3 Adam Optimizer

Adaptive Moment Estimation is an algorithm for optimization technique for gradient descent. The method is efficient when working with big problems involving a lot of data or parameters. It requires less memory and is efficient.

3.2.4 Performance metrics

3.2.4.1 Accuracy

The accuracy metric is a statistical calculation of how a model predicts correctly. The aim of calculating the accuracy is to achieve the model's efficiency.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

TP denotes a true positive that indicates a suspicious transaction
TN denotes a true negative that indicates the original transactions
FP denotes false positive that indicates non-suspicious transactions wrongly identified as suspicious transactions
FN denotes a false negative that indicates the suspicious transactions wrongly identified as original transactions.

3.2.4.2 Loss rate

The loss rate is a function that measures the difference between the actual output and predicted output during training to speed the process of learning. It is for evaluating the model performance and minimizing the error.

$$Loss = Y - Log(Y_{Pred}) + (1 - Y) - Log(1 - Y_{Pred})$$

Where Y denotes the actual output and Y_{Pred} denotes the predict output.

4. Result Analysis
4.1 Stock price prediction system

The results obtained based on the LSTM model for the Bank of Baroda (BOB) and Punjab National Bank (PNB) datasets are shown in Figure 4.1 and 4.2 respectively. The Bank of Baroda dataset achieved a Mean Absolute Error of 1.935, a Root Mean Squared Error of 2.516, and a Mean Absolute percentage Error of 1.603. The Punjab National Bank dataset achieved a Mean Absolute Error of 1.421, a Root Mean Squared Error of 1.901, and a Mean Absolute Percentage Error of 1.688. So the overall performance shows better results for both datasets for stock prediction.

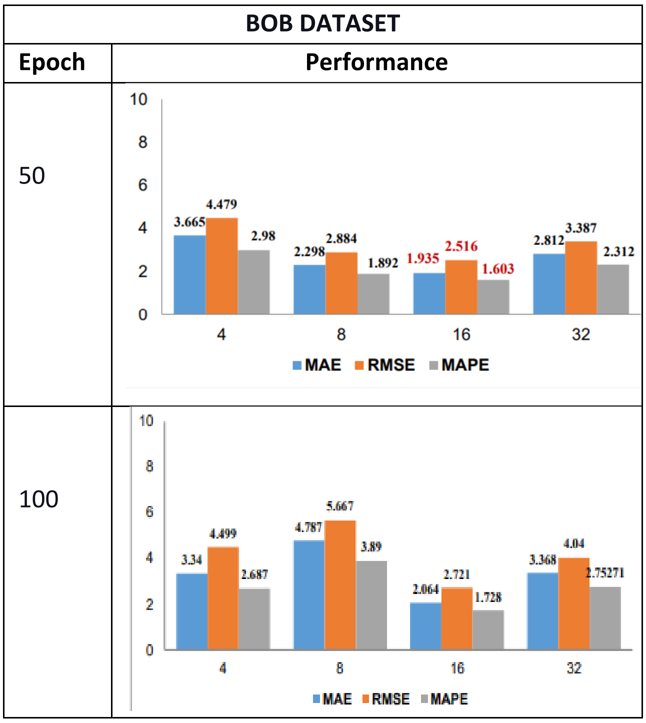
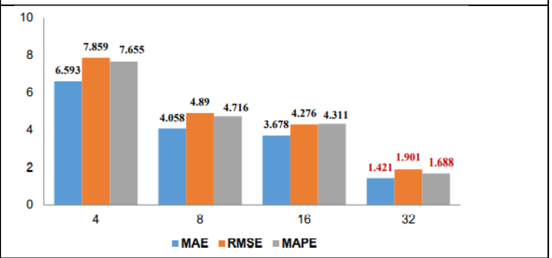


Figure 4.1 Performance of LSTM on for different batch size (4, 8, 16 and 32) for 50 and 100 epoch on BOB dataset

4.2 Financial fraud detection system

The LSTM model will detect the accuracy in light of big data. It addressed the problem of detecting unknown and sophisticated fraud detection by using deep learning techniques to identify patterns quickly and with high accuracy. It is known that Adam optimizer can deal with big data, does not require a huge memory space, and is computationally efficient. Adam optimizer achieved good results on several layers and a different number of iterations. Results of LSTM in terms of accuracy and loss for each epoch is depicted in Figure 4.3. The model obtained an accuracy of 99.98%.

<table>
<tr><th colspan="2">PNB DATASET</th></tr>
<tr><th>Epoch</th><th>Performance</th></tr>
<tr><td>50</td><td>


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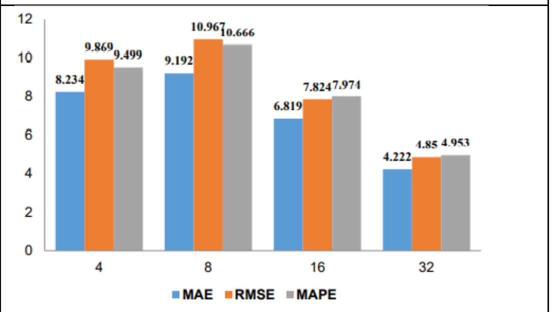
<tr><td>100</td><td>


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Table 4.2 Result of metrics and performance of PNB dataset for 50 and 100 epochs

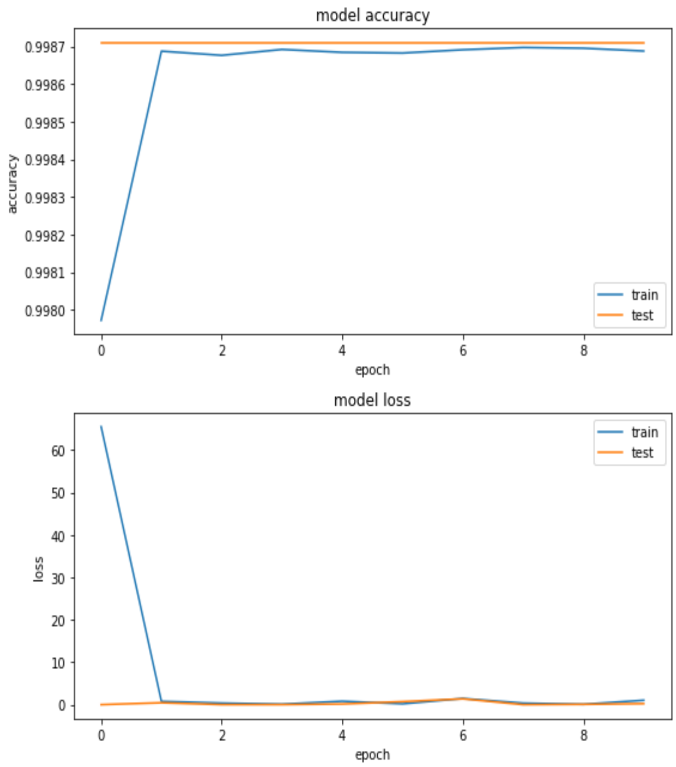

Figure 4.3 Epoch versus model loss and model accuracy

5. CONCLUSIONS

The Long Short Term Memory architecture was motivated by an analysis of error flow in existing RNNs which found that long time lags were inaccessible to existing architectures because back propagated error either blows up or decays exponentially. The improved learning of the LSTM allows the user to train models using sequences with several hundreds of time steps. LSTMs have the promise of being able to learn the context required to make predictions in time series forecasting problems. The applications of LSTM in stock price prediction and financial fraud detection give the best results compared to other models. The model compared and analyzed the performance of different epochs for training data with the various batch sizes. The results for stock price market prediction show that the best values obtained by the LSTM model give 1.935 (MAE), 2.516 (RMSE), 1.603 (MAPE) for the Bank of Baroda dataset, and 1.421 (MAE), 1.901 (RMSE), 1.688 (MAPE) for Punjab National Bank dataset. The LSTM technique achieves the performance accuracy of 99.98% in a short time by using Adam optimizer for detecting financial fraud.

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