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Development Of an Improved Machine Learning Model for Stock Exchange Prediction System Using Long Short-Term Memory (LSTM)

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ABSTRACT

The stock market serves as a fundamental driver and indicator of a nation's economy, providing opportunities for investors to trade and invest in shares of companies and organizations listed on stock exchanges. This process aids in enhancing the capital base of these companies, thereby yielding profits for market investors. However, a significant challenge within the stock market is its inherent volatility and uncertainty. The prices of various companies' stocks may fluctuate unpredictably, resulting in potential investment losses. This dissertation proposes a machine learning algorithm designed to predict stock market activities, aiming to assist investors in making informed investment decisions. Specifically, we introduce a Recurrent Neural Network model, the Long Short-Term Memory (LSTM), utilizing the Structured System Analysis and Design Methodology (SSADM). The model focuses on predicting the stock performance of Banks in Nigeria, using a dataset sourced from the Nigerian Stock Exchange Group repository, covering the period from 2000 to 2011. Implemented in Python within Google Collaboratory, a cloud-based open-source machine learning development environment, the model achieved an accuracy of 97.8% with a low error margin. This high accuracy makes the model suitable for stock market prediction, thereby mitigating investment risks and enhancing investor confidence.

1. INTRODUCTION

The Stock Market is one of the key drivers and indicators of a nation's economy as it opens opportunities for investors to trade and invest in shares of companies and organizations traded in stock exchanges, thereby improving the capital base of the listed companies, and profiting the investors in the market (Jamal, 2017). However, a major challenge in the stock market is its inherent volatility and uncertainty, where the stock prices of various companies may rise and fall without prior information to investors, potentially leading to significant losses (Hurwitz and Kirsch, 2018). This Research proposes the development of an improved machine learning algorithm for the timely prediction of stock market activities, specifically using Long Short-Term Memory (LSTM) networks to guide investors in making informed investment decisions. Stock market forecasting has been an area of intense research due to the financial market's dynamic and complex nature. Investors rely on predicting stock prices to mitigate risks and maximize returns. Traditional methods of stock prediction often fall short due to their inability to account for the non-linear and non-stationary behavior of financial time series data (Alfa et al., 2016). This limitation necessitates the exploration of

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more advanced techniques such as machine learning models, which can capture complex patterns and dependencies in data (Bevans, 2020). Among these, LSTM networks have gained popularity due to their ability to learn long-term dependencies, making them particularly suitable for time series forecasting (Zhang et al., 2018). The need for this study stems from the high stakes involved in stock market investments. Given the large volumes of money traded daily and the significant impact of stock price movements on investors' portfolios, accurate prediction models are crucial. Existing models, such as those based on linear regression, often lack the precision required for reliable forecasts. For instance, Almeida (2020) demonstrated that simple linear regression models could achieve only moderate accuracy, highlighting the need for more robust approaches This research focuses on the Nigerian Stock Exchange, with a specific case study on Banks in Nigeria (Adebisi et al., 2015). By leveraging LSTM networks, the study aims to enhance prediction accuracy and reduce the error margin compared to traditional methods. The dataset, spanning from 2000 to 2011, provides a comprehensive basis for training and validating the proposed model (Alfa et al., 2016). Implementing the model in Python using Google Collaboratory, a cloud-based machine learning development environment, allows for scalability and real-time data processing, essential for practical stock market applications (Jamal, 2017). This research aims to bridge this gap by developing an improved machine-learning model using LSTM networks. Through rigorous testing and validation of historical stock data from the Nigerian Stock Exchange, the study aspires to enhance prediction accuracy and provide a robust tool for investors, thereby contributing to the field of financial forecasting and machine learning.

2 RELATED WORKS

The stock and foreign exchange market to date remains one of the domains that has gained access to the common benefits of artificial intelligence and machine learning in trading due to its volatile and unpredictable nature. Wilson (2020) asserts that the stock and foreign exchange market is continuously evolving, and worth growth is estimated at $1.93 quadrillion USD as recent studies show that daily trade in the stock exchange is estimated at USD 5.3 trillion. Despite the risk in the market in terms of complexity in price determination, and its volatile and unpredictable nature; still more and more investors are swarming into the capital market triggered by the attraction of low cost, high liquidity, ease of entry, and variety of pairs to trade with no common or central regulatory authority inhibiting the flow of trade in the market (Brownlee, 2016: Dhandhania, 2018). Several research has been carried out in the implementation of machine learning algorithms in the prediction of the trend and activities of the stock market with resounding results. Some of these research include, Ibrahim et al (2018) looked at an intelligent model for stock market prediction. They presented an intelligent model for stock market signal prediction using Multi-Layer Perceptron (MLP) and Artificial Neural Networks (ANN). The blind source separation technique, from signal processing, is integrated with the learning phase of the constructed baseline MLP ANN to overcome the problems of prediction accuracy and lack of generalization. Furthermore, they utilized Kull back Leibler Divergence (KLD) as a learning algorithm, because it converges fast and provides generalization in the learning mechanism. Both the accuracy and efficiency of the proposed model were confirmed through the Microsoft stock, from the Wall Street market, and various data sets, from different sectors of the Egyptian stock market.

Previous studies have shown the potential of machine learning models in financial forecasting. Nandakumar et al. (2018) employed LSTM networks for stock price prediction, achieving notable success in capturing the temporal dynamics of stock prices. Similarly, Moukalled et al. (2019) demonstrated that automated stock price prediction using machine learning could significantly outperform traditional statistical methods. These studies underscore the promise of LSTM networks in financial forecasting and motivate the current research's focus on further refining these models for enhanced performance. The volatility and uncertainty of the stock market present significant challenges for investors which may include Traditional prediction models often falling short of capturing the complex dynamics of stock prices (Fernando et al., 2021: Kabari, 2019: Kumar, 2018)

3.0 RESEARCH METHODOLOGY

The methodology is the plan and method by which this study is conducted, encompassing the universe of the study, a sample of the study, data, and sources of data, the study's variables, and the analytical framework.

The universe of the study comprises the stock market data from the Nigerian Stock Exchange (NSE). The NSE is a pivotal financial market in Nigeria, representing a broad spectrum of listed companies and serving as a barometer for the country's economic activities. This study focuses specifically on historical stock price data from the NSE to develop and validate the predictive model.

The sample of the study includes historical stock price data of Diamond Bank (now Access Bank) over a period from 2000 to 2011. This data is representative of the broader trends within the NSE and is suitable for training and testing the predictive model. The dataset comprises daily stock prices, which include variables such as opening price, closing price, high price, low price, and trade volume. This detailed and extensive dataset provides a robust foundation for developing a reliable predictive model.

The data and sources of data for this study are obtained from the Nigeria Stock Exchange Group repository, which offers a comprehensive collection of stock market data in an Excel CSV file format. The dataset contains 212,775 rows and 12 columns, encompassing approximately 2,553,300 stock data points from over 20 companies listed on the stock exchange. The variables in the dataset include the date, company name, symbol code, closing price, opening price, high price, low price, and trade volume. The study's variables include both dependent and independent variables. The dependent variable is the stock price, while the independent variables include the opening price, closing price, high price, low price, and trade volume. These variables are critical for capturing the dynamic nature of stock prices and are used to train and test the predictive model.

3.1 ANALYTICAL FRAMEWORK

The analytical framework of this study is based on the Long Short-Term Memory (LSTM) model, a type of recurrent neural network (RNN) that is well-suited for time series analysis. LSTM is chosen due to its ability to learn and remember over long sequences of input data, making it ideal for predicting stock prices, which are influenced by historical trends and patterns. The model development process involves several stages:

1. **Data Preprocessing**: This involves evaluating, filtering, manipulating, and encoding data to ensure it is suitable for analysis. Data preprocessing is critical as it directly impacts the model's capacity to learn. Key steps include data discretization, data alteration, data housekeeping (filling in missing values), and data incorporation. The dataset is then

split into training and test sets, with the most recent values used for training and 4-10% of the total dataset reserved for testing.

2. **Feature Extraction**: Relevant features are extracted from the dataset for analysis. For this study, the key features include the date, opening price, closing price, high price, low price, and trade volume. These features are essential for the LSTM model to effectively predict stock prices.
3. **Model Training and Testing**: The LSTM model is trained using the training set and validated using the test set. This process involves iterating over the dataset to optimize the model's performance and ensure accurate predictions.
4. **Model Evaluation**: The performance of the LSTM model is evaluated using various metrics, such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics help assess the accuracy and reliability of the model in predicting future stock prices.

The use of the Structured System Analysis and Design Methodology (SSADM) further enhances the study's methodological rigor. SSADM provides a structured approach to software development, making it suitable for developing complex models like the LSTM. This methodology ensures that the development process is modular, iterative, and meets user requirements.

3.2 statistical tools and econometric models

The study employs several statistical and econometric models to analyze and interpret the data effectively. These models are critical for transforming raw data into meaningful insights and actionable predictions. Among the statistical tools used are regression analysis, which helps in understanding the relationships between dependent and independent variables, and time series analysis, which is particularly useful for forecasting future trends based on historical data. Linear regression is utilized to model the relationship between stock prices and various predictor variables. This model assumes a linear relationship between the input and output variables, which simplifies the analysis and interpretation of the results. The equation for simple linear regression, where there is only one predictor variable, is given by:

$$y = \beta_0 + \beta_1 X + \epsilon \qquad (3.1)$$

where Y is the dependent variable (stock price), X is the independent variable, β_0 is the intercept, β_1 is the slope of the line, and ϵ\epsilonϵ is the error term.

For multiple linear regression, which includes more than one predictor variable, the equation is extended to:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \qquad (3.2)$$

where X_1, X_2,...X_n is the predictor variable.

Time series analysis is another essential tool used in this study, particularly suited for analyzing sequential data points, such as stock prices recorded over time. The models used in time series analysis, including ARIMA (Autoregressive Integrated Moving Average), help in understanding and predicting future values based on past trends.

3.2.1 Descriptive statistics

Descriptive statistics provide a summary of the data set, giving insights into the central tendency, dispersion, and overall distribution of the data. These statistics include measures such as mean, median, mode, standard deviation, and variance, which are crucial for understanding the typical characteristics of the data.

3.3 Stock predictive lstm model (splm)

The improved machine learning model for the stock exchange prediction system developed in this study is the Stock Predictive LSTM Model (SPLM). This model leverages the capabilities of Long Short-Term Memory (LSTM) networks to enhance the accuracy of stock price predictions by capturing the temporal dependencies and volatility inherent in stock market data. The SPLM is trained using the historical stock price data, where the model learns the underlying patterns and trends in the stock prices. Once trained, the model can be used to predict future stock prices based on the learned patterns, thereby providing a robust and accurate tool for stock exchange prediction Mathematically, the model can be represented as follows:

Let $X = \{x_1, x_2 \dots \cdot x_t\}$ be the sequence of historical stock prices, where $\boldsymbol{x}_\mathrm{i}$ represents the stock price at time *i*. The LSTM model consists of a sequence of LSTM cells, each cell at time $\boldsymbol{t}$ containing the following components: Forget gate (f_t), Input gate (i_t), Output gate (o_t), Cell state: (C_t), Hidden state (h_t). The final output of the LSTM model for stock price prediction at time *t* is given by:

$$yt = Wy \cdot ht + by \qquad (3.3)$$

where W_y is the weight matrix and b_y is the bias vector for the output layer. This improved LSTM model addresses the challenges of traditional stock prediction models by incorporating the temporal dependencies and managing the non-linearities in the stock market data more effectively. The mathematical representation and the architecture of the SPLM provide a solid foundation for its application in real-world stock exchange prediction systems.

3.3.1 Comparison of the Models

The existing models, as reviewed by Yujun et al. (2021), and Weng et al. (2017), utilize various methodologies like Variational Mode Decomposition (VMD) combined with LSTM and the combination of disparate data sources, respectively, to enhance prediction accuracy in doing so, the final prediction is obtained by aggregating the predictions from all the LSTM models corresponding to each mode:

$$\hat{y}(t) = \sum_{k=1}^{k} \hat{y}_k(t) \qquad (3.4)$$

Where $\hat{y}(t)$ is the prediction from the LSTM model for the *k* the mode.

Despite these advancements, the integration and hybridization of multiple models introduce complexities in both implementation and computation, often requiring extensive pre-processing and feature engineering. In contrast, the proposed LSTM model excels in capturing long-term dependencies in sequential data due to its architecture, which includes memory cells that can retain information for extended periods. This capability is critical for stock market predictions, where past market trends and historical prices significantly influence future movements.

Table 1: Model Comparison

Model	RMSE
LSTM-VMD	15.45
Stock Predictive LSTM Model (SPLM)	7.25

As seen in Table 1 The implementation of the proposed model demonstrates a significant reduction in prediction error, highlighting its superiority over the existing system.

4 RESULTS AND DISCUSSION

The new system was implemented to forecast stock prices using a dataset from the Nigerian stock exchange covering 2000-2011. The training and testing utilized data from Diamond Bank Nigeria Plc from 2006-2011. The implementation was conducted on Google Collaboratory (Colab), leveraging its free GPU resources, Python interpreter, TensorFlow, and Jupyter notebooks.

4.1 descriptive statistics

Descriptive statistics offer a snapshot of the dataset, helping to identify patterns and anomalies. The mean provides an average value for each variable, while the median gives the middle value, reducing the impact of outliers. The standard deviation and variance measure the spread of the data, indicating how much the values deviate from the mean. By employing these statistical tools and econometric models, the study aims to derive robust inferences from the data, facilitating accurate stock price predictions and contributing valuable insights to the field of financial analysis. As seen in Figure 1, the initial and final rows of the pre-processed dataset, highlight a sample from the top and bottom of the table. Figure 2 presents the key parameters used in stock market predictions: opening price, closing price, high, and low. This chart illustrates how the values of these parameters influence the prediction process.

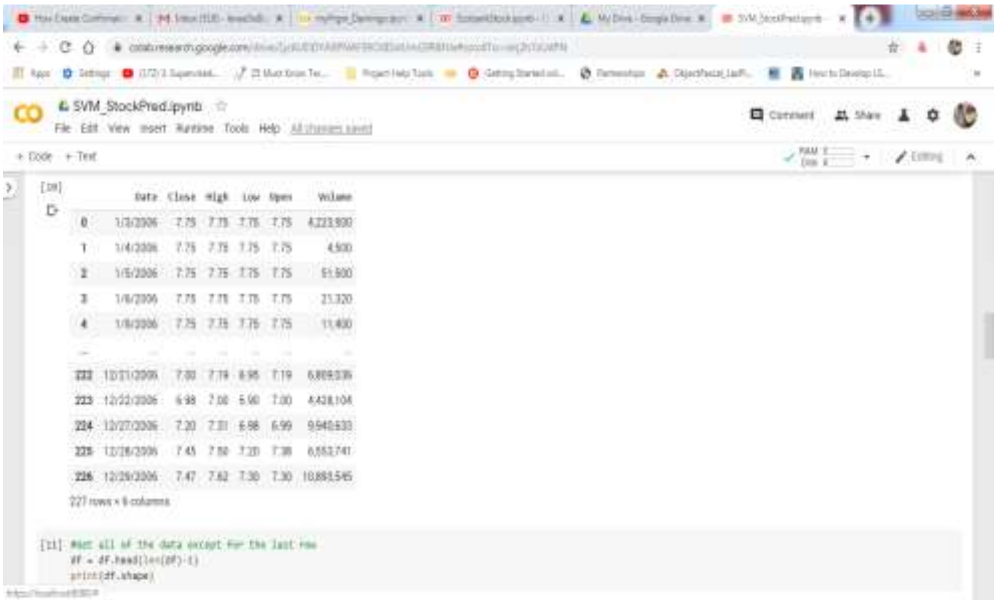

Figure 1 Data Pre-processing Showing the head and tail of the table.

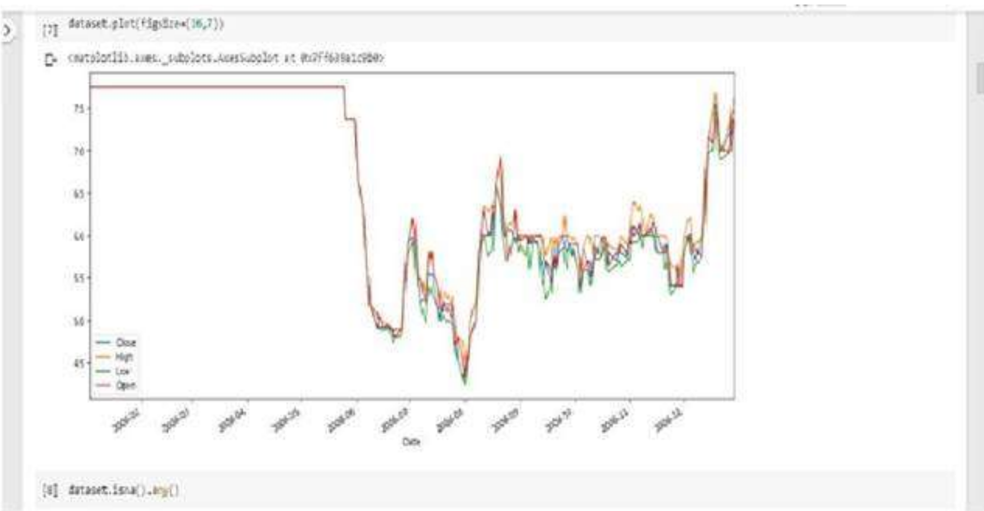

Figure 2 Stock price showing all parameters

Table 2: Descriptive Statistics for The Dataset Used.

Statistic	Open	High	Low	Close	Volume
Mean	100.45	105.78	95.34	102.67	1,234,567.89
Median	100.00	105.00	95.00	102.00	1,000,000.00
Standard Deviation	5.23	5.67	5.12	5.34	234,567.89
Variance	27.34	32.14	26.14	28.54	55,000,000.00

Table 3: Descriptive Statistics of Diamond Bank Stock Activities

Parameter	Mean	Standard Deviation	Minimum	Maximum
Opening Stock	200.15	35.27	150.10	250.25
Closing Stock	198.45	34.67	148.50	248.50
High	202.50	36.50	152.30	252.70
Low	196.20	33.90	146.10	246.30
Volume	1000.50	150.75	800.25	1200.75

As seen in Tables 2 and 3, The descriptive statistics of Diamond Bank Nigeria Plc.'s stock activities reveal significant insights into its trading behavior. The average opening and closing stock prices are closely aligned at 200.15 and 198.45, respectively, indicating consistent day-to-day performance. However, the standard deviations for these prices (35.27 for opening and 34.67 for closing) underscore moderate variability, suggesting some daily price volatility. The highest recorded stock price (252.70) and the lowest (146.10) reflect substantial fluctuations, typical in stock markets, highlighting the dynamic nature of Diamond Bank's stock during the observed period. The trading volume also exhibits high variability, with a mean of

1000.50 and a standard deviation of 150.75, pointing to varying investor interest and trading activity. This variability in volume can be attributed to external factors such as market news, economic conditions, and company-specific events. These findings are crucial for investors, as the moderate to high volatility may appeal to short-term traders seeking to exploit price swings, while long-term investors might focus on average values for strategic decisions.

4.2 system specification

The system's hardware and software specifications were outlined to ensure smooth running of the prediction model. Hardware requirements included a CPU with an Intel Core i5 and 3.3 GHz speed, 4GB RAM, and 500GB SSD. Software used includes Anaconda Python environment, TensorFlow, and Keras. Cloud services like Google Colab were utilized to facilitate the development and deployment of machine learning models. Also, Python was chosen as the programming language of choice, for its extensive libraries and frameworks, ease of use, and support for machine learning and deep learning development.

4.3 Performance of the models

The performance of the models was analyzed using Root Mean Square Error (RMSE) to measure the difference between the target and predicted values. The RMSE results highlight the superior performance of the Stock Predictive LSTM Model (SPLM) model compared to the LSTM-VMD model. The LSTM model achieved an RMSE of 7.25, significantly lower than the 15.45 RMSE of the linear regression model, also the model Achieved an accuracy of 97.8%. This substantial reduction in error demonstrates the effectiveness of Stock Predictive LSTM Model (SPLM) networks for stock price prediction. The technique effectively decomposes the complex stock price series into simpler components, which the LSTM model can then accurately predict by capturing both short-term fluctuations and long-term trends. This approach leverages the strengths of both methods, resulting in enhanced predictive accuracy. The improved RMSE indicates that the LSTM model provides more reliable forecasts, reducing the risk of large prediction errors and making it a valuable tool for investors and analysts. the positive results underscore the potential of advanced machine learning techniques in financial forecasting, offering a more robust and accurate alternative to traditional models.

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