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MACHINE LEARNING-DRIVEN ANALYSIS OF AMERICAN STOCK DATA: ENHANCING PREDICTIVE CAPABILITIES IN U.S. DIGITAL FINANCE

Odubajo Adeyemi Julius
Dept. MoMo Payment Service Bank
Lagos, Nigeria
yemiodubajo@yahoo.com

Abstract

The US stock market and real estate prices have been high for a few years now. For the economy to grow in a healthy way, the link between real estate prices and stock prices needs to be carefully looked into. Made for predictive purposes, it is important to predict mutual fund as well as Exchange Traded Fund performance. This study suggests using a Long Short-Term Memory (LSTM) neural network to predict how well U.S. funds will do based on data from those funds. Then the dataset is chronologically split to preserve temporal integrity and the LSTM model is trained to learn time series patterns. The model shows low prediction errors on the test set with RMSE of 0.0547 and MSE of 0.0030, as experimental results show. Performance of the proposed LSTM against baseline models (SVR, GAN) is also tested and show better accuracy and reliability. The results show that deep learning models, especially LSTM, can help us understand and learn how financial data changes over time. They could also help us come up with a new investment plan and make predictions about the future of the economy.

Keywords: Stock Price Prediction, American Stock Market, Digital Finance, Machine learning, US Funds dataset.

I. INTRODUCTION

Its financial systems are often as robust as a nation's economic strength. Financial markets are key to the resources channeling and the business growth and economic development [1]. There is a stock market among these. Companies need to sell shares to get money, and people who buy them hope that their money will go up in value [2]. Therefore, stock markets simultaneously reflect the underlying economic activities and have investment signals and risk assessment influences on future economic directions. In this global economy, the American Stock Market is in a unique prestigious position. The NYSE and NASDAQ are the two biggest stock exchanges in the world, so the U.S. stock market is an international business center. In particular, its performance affects domestic and global economies as a key proxy of investor confidence, corporate performance, and policy performance [3]. The American market is at the center of the financial world due to the amount of high-frequency data generated each day, which has become a subject of economic analysis and investment strategy [4].

Digital finance links technology to the performance of financial services, which has made the huge amount of data available even more important [5]. Mobile banking, online trading platforms that use robots as financial advisors, and algorithmic trading that is based on real-time financial data are all part of the American digital finance business [6]. American stock data functions as a vital resource for developing innovative and swift financial services that can customize services to client needs. Processing digital finance has not only made it easier and more efficient, but has laid the groundwork for the use and easier detection of advanced data analytics and predictive modeling in more occurrences. Predictions of stock market prices have become a vital industry application which focuses on forecasting both opening and closing costs of equities. Stock price forecasts provide useful inputs to institutional and retail investors who use them to manage their portfolios while decreasing financial vulnerability [7]. Unfortunately, given the complexity and volatility of the stock markets (driven by macroeconomics, news from the companies, market sentiment, and unforeseen events), stock market movements can hardly be predicted.

To address this, researchers and financial technologists are using ML and DL models which are apt at capturing non-linear and temporal pattern found in data, [8]. Stock market forecasting has been shown to be very well served by algorithms such as DT, RFs, SVRs, and ANNs and advanced DL architectures such as RNNs, LSTM, and GRU. Instead, these techniques deliver accurate predictions while promoting the broader objectives of U.S. digital finance through making intelligent and data driven investments.

A. Motivation and Contribution of the Study

This study arises from the fact that the demand for financial forecasting has grown largely and especially in Mutual Funds and ETF cases where investors want to optimize their portfolios to provide for better returns and reduce risk. In the context of growing market complexity as well as increasing availability of large amounts of data in the financial markets, conventional methods may not suitably handle temporal patterns or finer details in the way market behavior evolves. It is proposed to leverage XGBoost as a powerful ensemble learning model to enhance fraud detection by improving the prediction performance while handling important issues including class imbalance and building a better and diversified features set. The following things are added by this study:

- It planned the use of LSTM networks in order to predict the performance of U.S. funds into the future.
- It removes duplicate records, keeps the data integrity and increases accuracy in the model by addressing missing data using forward fill and interpolation techniques.
- Effectively select, reduce dimensionality and preserve important info using Applied Principal Component Analysis (PCA).
- It integrates financial indicators along with the historical data to predict U.S. funds more accurately using LSTM.
- Evaluation measures like RMSE and MSE were used to check the model's performance and accuracy.

B. Justification and Novelty

This study justifies the use of LSTM networks in this study as such networks are capable of memorizing relational and temporal dependencies as well as complex temporal patterns, which are important for financial prediction tasks. Compared with conventional machine learning models, LSTMs are suitable for handling sequential data, which makes them useful for predicting the performance of U.S. funds depending on historical financial indicators. This method is unique because it combines LSTM networks with PCA, which helps lower the number of dimensions in the data without losing any important information. Furthermore, the incorporation of full financial data, such as ESG scores and key financial ratios, integrated with the LSTM model makes for a more appropriate, data-led process to inform financial investment decisions for superior forecasting abilities in active markets.

C. Structure of the paper

The structure of this paper as follows: Section II talks about basic information on U.S. fund performance prediction and automated learning methods. The study method is explained in Section III, which includes data collection, preprocessing, model implementation, and evaluation. The experimental results and analysis of how well the LSTM model predicted fund events are shown in Section IV. This paper's last section, V, talks about possible paths for future work.

II. LITERATURE REVIEW

This section examines at earlier research on stock prices, finds gaps in the existing literature, and compares research results that are similar to those of this study. Table I shows a comparison of the background study based on its results, flaws, and suggestions for future work.

Chang and Zhang (2023) In the stock market, investing based only on human experience has been slowly replaced by methods that use both past stock data and machine learning. a mixed Generative Adversarial Network that was built on a model that was already trained. This network looks closely at the features of stock trends and is better at reading stock data than older methods. Some models in this work are pre-trained and some are deep-trained. The Generative Adversarial Network, ARIMA-Lasso units, and filters are all parts of the deep training model. When they use past data from the last three years of the American stock market, they find that their model is most accurate more than 84% of the time [9]

Kumbure et al. (2022) Computer-based ways to guess what will happen in the stock market that kind of stock market has been looked at before, along with the things that were used to teach computer programs how to guess these markets. 138 journal papers from 2000 to 2019 were looked at. The main things this review adds are a thorough look at the data, especially the markets and stock indices that were predicted, as well as the 2173 different factors that were used to make those predictions, such as technical indicators and macro-economic variables [10]

Risman et al. (2021) Digital payments are a part of digital finance, and they are becoming more important as e-commerce and financial technology grow. They help keep money safe and digital. The study used the Multiple Linear Regression Model and MRA to look at 120 sets of panel data from 2010 to 2019. The numbers show that market risk can make the good things that digital banking does for the economy less safe. This means that the good effects of digital finance on financial stability will be weaker because of higher systematic risk [11].

Wei and Chaudhary (2020) In terms of money, the direction of price change is the most important thing about a stock time series. The neural network's prediction mistake only shows how close the model was to nailing the price on the market. Something very important to investors is that it doesn't show which way the stock price goes up and down. As an example, the annualized return rate for the Chinese stock 600275 is -59.49%, and the annualized return rate for the American stock AMZN is +26.49%. Just 0.0152 separates their forecasts. If the prediction mistake doesn't go up or down with the stock price, that means the issue is with the absolute value limit on the same scale [12].

Moni (2019) guessing the annual S&P 500 stock market measure is a good way to see how stable world politics are. Using genetic programming and machine learning to make a pattern for an algorithm that looks at history of the S&P 500 stock index, gold prices, U.S. war deaths, crude oil prices, the Dow Jones Industrial Average, and inflation rates in the U.S. About 14% of the time, this algorithm's guess was very close to the truth [13].

Achkar et al. (2018) ANN are one of the most advanced ideas in AI because they can figure out hard computer problems and guess how the stock market will move. Both BPA-MLP and LSTM-RNN are looked at in terms of their pros and cons. Blockchain stocks, Google stocks, and Facebook stocks were some of the types of data that were used in the tests. The best case for the MLP algorithm is that it works 97% of the time [14].

Xu (2020) The American stock market is built on a system with many dimensions. Cooper et al. came up with the idea that this study is based on. These ideas come from the fact that the American stock market gained a lot between 1968 and 2003. Because of this, Cooper's test method is also looked at in detail in the study. Based on Cooper's test method, the study ranks the rate at which the assets of American businesses gained each year from 2001 to 2003. Naturally, this research can look at how the US stock market has grown over time and attempt to understand why it has grown so quickly [15].

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TABLE I. A Comparison of Different Machine Learning Methods for Figuring Out Stock Prices Expert Prediction

Author	Dataset	Methodology	Findings	Limitations	Future Work
Chang and Zhang (2023)	American Stock Market (last 3 years)	Composite Generative Adversarial Network (GAN) with pre-training and deep training models	Optimal accuracy of the model exceeds 84% in stock prediction experiments.	The model may require further testing on other market conditions.	Explore more financial indicators and extend to other markets.
Kumbure et al. (2022)	138 journal articles (2000-2019)	Literature review of machine learning techniques for stock market prediction	Extensive examination of markets, stock indices, and 2173 unique variables for stock prediction.	Does not focus on the actual performance of specific machine learning models.	Application of machine learning to a broader range of stock markets.
Risman et al. (2021)	120 panel data samples (2010-2019)	Multiple Linear Regression Model and MRA	Market risk moderates the influence of digital finance on financial stability.	The study focuses on a limited set of variables and countries.	Investigate more diverse regions and the impact of digital finance.
Wei and Chaudhary (2020)	Chinese Stock 600275, American Stock AMZN	Neural network for stock prediction	Neural networks' prediction error does not account for the direction of stock price movement.	Prediction error does not incorporate stock price movement directionality.	Develop methods that better account for stock price movement direction.
Moni (2019)	S&P 500 Stock Index, Gold Prices, Dow Jones, Oil Prices	Genetic Programming approach to predict S&P 500 based on global indicators	High prediction accuracy (within 14%) for the S&P 500 index using global indicators.	The model's scope is limited to S&P 500 and a few global indicators.	Extend the algorithm to other financial indices and include more variables.
Achkar et al. (2018)	Facebook, Google, Bitcoin stocks	Neural Networks (BPA-MLP and LSTM-RNN) for stock market prediction	Achieved best-case accuracy of 97% for MLP algorithm in stock prediction.	Performance may vary with different stock types or conditions.	Experiment with other stock datasets and fine-tune the models.
Xu (2020)	U.S. Stock Market (1968-2003)	Multidimensional system analysis based on Cooper's theory	The research identifies key predictors for abnormal returns in the U.S. stock market over several decades.	Limited to historical data from 1968 to 2003.	Apply the model to more recent data and test its relevance today.

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III. METHODOLOGY

The methodology of this study involves several key steps to process and analyze, as illustrated in Figure 1. The U.S. Funds dataset for predicting mutual fund and ETF performance. First, the data is collected from Yahoo Finance, which includes key attributes such as fund family, historical returns, and financial ratios. Then, data preprocessing is performed, where missing values are handled using forward fill and interpolation techniques, and duplicate records are removed to ensure data integrity. Next, the dataset is normalized using a scaling method to bring all features to a consistent range of 0 to 1. This is followed by Principal Component Analysis (PCA), which cuts down on the number of variables in the data while keeping the important ones. The teaching process then uses 80% of the data, while the testing process barely touches 20%. It is then separated into training and testing sets and put back together correctly to avoid losing any data. Additionally, the training set teaches the LSTM model how to guess what will happen with the fund in the future. Lastly, MSE, MAE, and RMSE are used to evaluate the model's performance and ascertain the precision and dependability of its predictions.

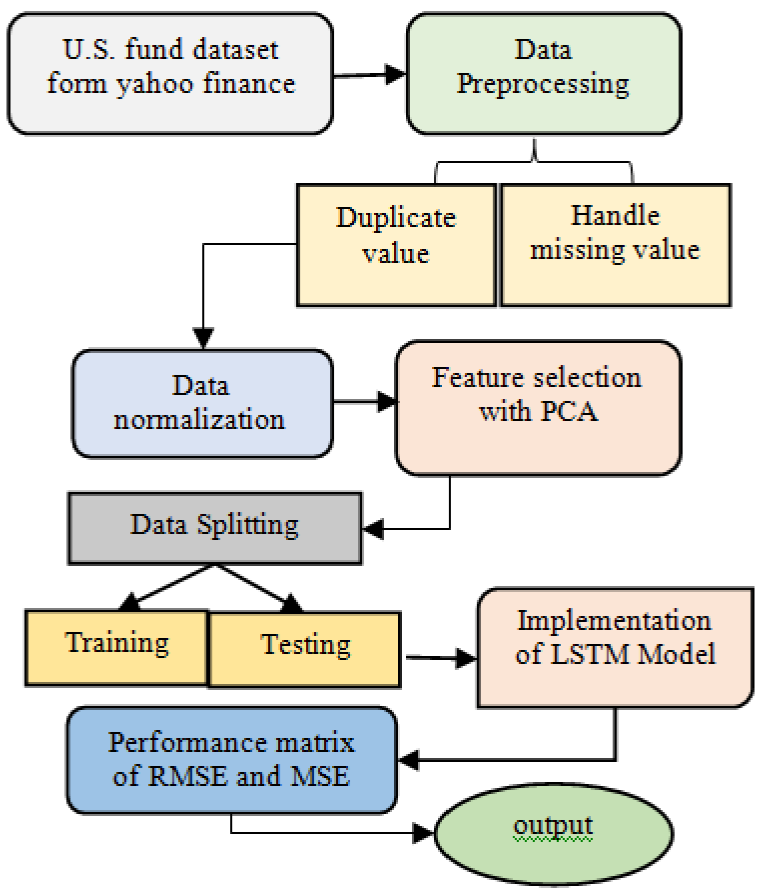

Fig. 1. Proposed Flowchart for American Stock Price Prediction

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In below Flowchart providing the following steps and process of system implementation:

A. Data Collection

Yahoo Finance crawls the web to find the 23,783 Mutual Funds and 2,310 ETFs in US Funds. It has general fund details like the total net assets, the family of funds, the start date, and portfolio indicators like cash, stocks, bonds, and sectors. It also shows past results (year to date, one year, three years, etc.), financial ratios (P/E ratio, Treynor ratio, Sharpe ratio, alpha, beta), and ESG scores. Figure 2 shows the prices at which the data began and ended.

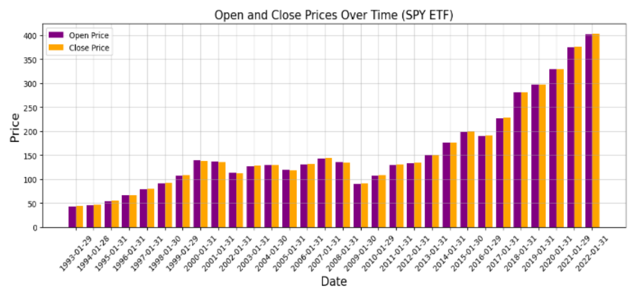

Fig. 2. Open and Close Price Over US Market

Figure 2 shows how the open and close prices of the SPY Exchange-Traded Fund (ETF) change over time. In the United States, the SPY ETF is a well-known way to measure the stock market. It comes after the S&P 500 average did well. On the x-axis are the times, and on the y-axis are the prices in USD. Each time point has two bars: a purple bar indicating the open price and a orange bar representing the close price. The chart demonstrates a general upward trend over time, with notable price increases in recent years, reflecting the historical growth of the U.S. equity market.

Fig. 3. Scatter Plot for US Fund Dataset

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Figure 3 visualizes the relationships between Morningstar ratings (overall, return, and risk), net annual expense ratio (for the fund and its category). The diagonal shows the distribution of each variable, while the off-diagonal plots display pair wise scatter plots illustrating the correlation between variables, with correlation coefficients provided in the upper triangle to quantify linear relationships. Thus, it becomes possible to approximate the relationship between these key fund characteristics with one another.

B. Data Preprocessing

Several preprocessing steps were taken on the dataset to make it a good, consistent dataset. To handle the duplicate data, the duplicates were eliminated, and to handle the missing values, the forward fill and interpolation was used. Normalization was used on all variable to bring them into a common scale, which is known as feature scaling. Listed below are the following steps performed in pre-processing steps followed by Principal Component Analysis (PCA) for feature selection:

- Handling Missing Values: Stock dataset was dealt with missing values: forward fill to maintain temporal continuity and linear interpolation to estimate value between gaps. To ensure the data quality, rows or features which contain a lot of missing data were dropped and it ended up a clean and reliable dataset for training the model.
- Duplicate Removal: The dataset was also scanned for duplicate records which might skew the statistical analysis and mess up the machine learning model. It was found that the rows across to them were identical and removed to make sure integrity and uniqueness of each data point in a more accurate and rewarding way of training.

C. Data Normalization

Normalization is a technique initiating data to fit in a scale of 0 to 1. By subtracting the smallest value from each data points, and dividing by range of values, as specified in Equation (1).

$$X_{scaled} = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad (1)$$

X_{scaled} is the normalized value X, X represents the normalized value, X_{min} and X_{max} represent the feature's lowest and highest values.

D. Feature Selection with PCA

The US Funds dataset has a lot of dimensions, so PCA was used to pick out the most important features. This was done to handle the dimensions and make the prediction models work better. As well as fund attributes and portfolio compositions, past returns, financial ratios (like P/E, Sharpe, Treynor, alpha, beta), and ESG scores are all part of it. By turning correlated factors into a smaller set of uncorrelated principal components while keeping most of the variance, PCA helps get rid of unnecessary data. This decrease in dimension makes the model more useful and easier to understand without losing a lot of information.

E. Data Splitting
Training and testing sets were made from the processed data. Some data was set aside for testing (10%), training (70%), and validation (10%).

F. Performance with LSTM Model
The LSTM layout Within the RNN's secret layer, data can go either way because the nodes are constantly interacting with each other. [16]. The RNN's output can be seen as a response to both the input layer and the state of each secret unit before it was fed in. The state of the node that came before it can be thought of asthe input. In the LSTM's "gate" structure, the RNN's hidden layer nodes are changed into special memory cells (blocks) that change data and states from earlier periods. For example, Figure 4 shows that this makes the RNN work better.

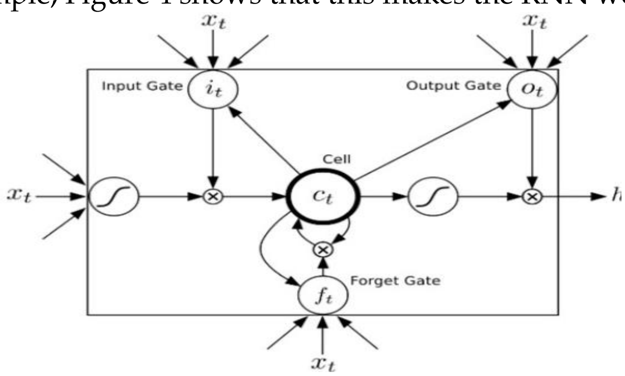

Fig. 4. Structure of LSTM Model

A simple way to see how memory cells are put together is in Figure 4. There are three gates that make up a memory cell. They are the input gate (it), the forget gate (ft), and the output gate (o). The input gate knows how much data is in the cell right now because of a recent timestamp. The remember gate's job is to decide what to keep and what to delete from the last cell state. This stops the numbers inside the cells from rising too quickly. Because of how it's made, the output gate can handle the new state and send the filtered data. The LSTM network method is shown below in steps. To begin, the first gate sorts and takes out extra data from the input that is present at time t. It also finds the memory cell ' value so that the state can be changed. The next two Equations are (2) and (3).

$$i_t = \delta[Z_i \cdot [h_{t-1}, x_t] + a_i) \qquad (2)$$

$$\tilde{c}_t = \tanh\,(Z_c \cdot [h_{t-1}, x_t] + a_c \qquad (3)$$

In Equation (4), find the forget gate's f_t value. In order to depict long-term trends and remove extraneous information, the forget gate further refines and retains the previous data.

$$f_t = \delta\left(Z_f \cdot [h_{t-1}, x_t] + a_f\right) \qquad (4)$$

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Equation (5) shows that the old cell state c_{t-1} is changed to the new cell state $\tilde{c}_t$ by taking away some information and adding the filtered candidate value to it.

$$c = f_t * c_{t-1} + i_t * \tilde{c}_t \qquad (5)$$

The last expression's mathematical sign * is known as the dot product between matrices. The updated state $\tilde{c}_t$ is screened by the output gate ot. The updated state and the output gate state decide what the output is.

G. Performance Metrics

RMSE and MSE were used to compare and rate the LSTM US fund forecast model's performance and find out how well it worked in this study [17]. All of the success metrics can be shown mathematically. The following measures are used to judge how well each algorithm works:

RMSE: A different method, the RMSE, was also used instead of the MSE. The RMSE is found by taking the square root of the MSE. It is a scale that looks like real numbers and shows how big the average prediction mistakes are. For better understanding and comparison, the RMSE is given in the same unit as the real values. It comes up as Equation (6).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \qquad (6)$$

MSE: MSE is another popular way to judge how well regression models work. It figures out the average of the squared differences between what the model said would happen and what actually did. Since the errors are squared before they are averaged, this metric is sensitive to values that are out of the ordinary. It gives more weight to bigger errors than to smaller ones. In Equation (7), it stands for.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \qquad (7)$$

The real values are shown by xi, the expected values by y_i, and the number of observations by n. These factors show how well the model works compared to other models for American stock data.

IV. RESULT AND DISCUSSION

A PC with an Intel Core i7 VPro processor running at 2.2 GHz, Microsoft Windows 10 installed, and 16 GB of RAM memory was used in a series of tests to see how well the suggested model could predict the price of American stocks. There is a bar graph in Table II that shows how well the trial LSTM model did on the U.S. funds dataset. On the training set, the seen model has an

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RMSE of 0.0617, on the validation set it is 0.0458, on the testing set it is 0.0547, and on the training set it is 0.0021. It's also worth noting that the MSE for training was 0.0038 and the MSE for testing was 0.0030. They got low error values, which means the LSTM model was able to find the trend in the dataset. This is usually possible in a field called "financial domain time series forecasting."

TABLE II. EXPERIMENTAL RESULTS OF THE LSTM MODEL ON THE U.S FUNDS DATASET FOR AMERICAN STOCK

Matrix	Training	Validation	Testing
RMSE	0.0617	0.0458	0.0547
MSE	0.0038	0.0021	0.0030

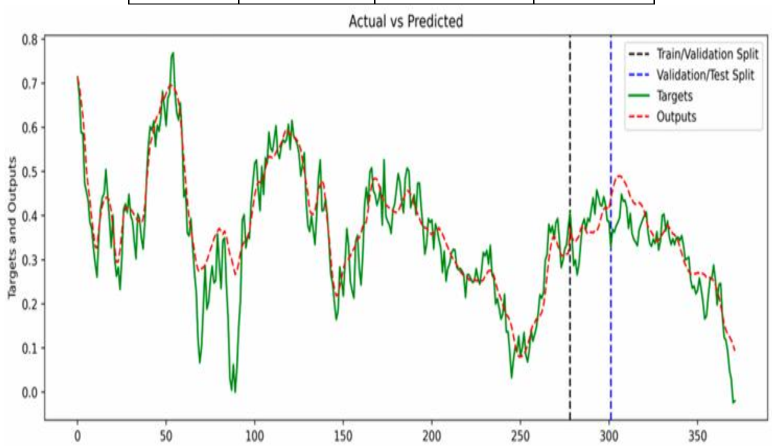

Fig. 5. Actual and Predicted price for LSTM

Figure 5 shows Actual vs Predicted values for the LSTM model on U.S. funds dataset. The actual target values are represented by green line, while the red dashed line shows the predicted output to LSTM model. Vertical lines with dotted black and dotted blue lines split the data into train/validation (black dotted line) and validation/test (blue dotted line) sections, allowing to observe the behavior of the model with respect to different sets of data. This shows that the model can learn and generate patterns well from time series data and achieve strong predictive accuracy over U.S financial time series data.

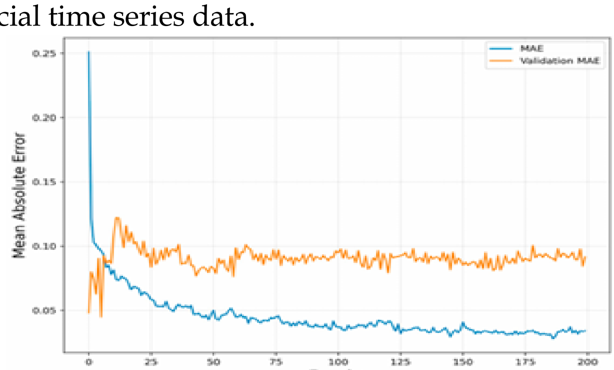

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Fig. 6. Plot for MAE LSTM Model

The MAE of the LSTM model over 200 training epochs on the U.S. funds dataset is shown in Figure 6. The blue curve shows the MAE for the training data, and the orange curve displays the MAE for the confirmation data. Both measures, however, go down a lot in the first few epochs, which shows that the model is learning pretty well. The validation MAE levels off after about 30 epochs, with only small changes, while the training MAE levels off, drops, and then stays at a low number. These results also show that the LSTM model is stable and can accurately predict how US stock funds will behave with little mistake.

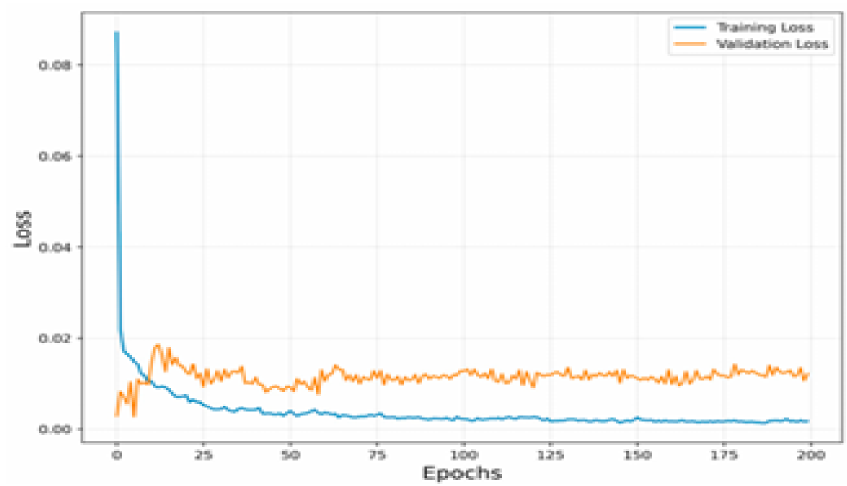

Fig. 7. Plot for Loss Curve of LSTM

Loss curves of the LSTM model are presented on the U.S. funds datasets over 200 epochs in Figure 7. The training loss shown with the blue line, and the validation loss by the orange line. And both losses are very flat for the first couple of epochs, which indicates that learning is fast. Validation loss begins to flatten out around 25 epochs and training loss keeps on declining smoothly and reach a very low value. One can see from the very small gap between these two curves and lack of any significant divergence that the model is very well generalized and not overfitting.

A. Comparative Analysis

This section looks at the suggested LSTM model in contrast to other models, like SVR and GAN. Table III shows how well each model did by combining MSE and RMSE. However, the LSTM model does better than the best model because it gets rid of the MSE of 0.0030 and the RMSE of 0.0547. This shows that the predictions are very accurate and there isn't much difference between them and the actual stock price, while the SVR is 46.72 MSE and 6.82 RMSE. GAN does better than SVR, but not when compared to LSTM.

TABLE III. COMPARATIVE ANALYSIS BETWEEN PROPOSE AND BASE MODEL FOR AMERICAN STOCK PRICE DATA

Model	MSE	RMSE
SVR[18]	46.72	6.82
GAN[19]	11.49	3.39
LSTM	0.0030	0.0547

Multiple benefits are available for the suggested LSTM-based model for predicting financial time series. By detecting long-term relationships in sequential data, it improves the accuracy of forecasting compared to older machine learning models. The use of PCA for dimensionality reduction improves computational efficiency without significant information loss. Compared to baseline models demonstrates superior performance with lower RMSE and MSE values, highlighting its robustness, generalization capability, and suitability for real-world financial forecasting tasks.

V. CONCLUSION AND FUTURE WORK

Investing in stocks is a demanding and demand-driven way to make money. So, studying stock predictions, or more specifically, predicting stock prices, is a very important part of the stock market. Getting share price predictions wrong has a big effect on global finance, so they need a good way to guess how share prices will change. One way to guess what the stock price will be is to use machine learning. This article showed an LSTM model that can be used to guess how well mutual funds and ETFs will do by looking at data from U.S. funds. The model did a good job of capturing how financial time series data changes over time. It got an RMSE of 0.0617 on the training set, 0.0458 on the validation set, and 0.0547 on the testing set. The Mean Squared Error (MSE) numbers that went with them were 0.0038, 0.0021, and 0.0030. Comparative study showed that the LSTM model did much better than baseline models like SVR (MSE: 46.72, RMSE: 6.82), and GAN. This shows that it is more accurate and can generalize better. Despite its strong performance, the model is limited by its reliance on historical data and exclusion of external market factors, which may reduce accuracy during unexpected economic events. Future work will aim to enhance the model by integrating macroeconomic indicators, financial sentiment analysis, and advanced architectures like Transformers to improve adaptability and prediction accuracy.

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