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Comparative Analysis of LSTM and Grid Search Optimized LSTM for Stock Prediction: Case Study of Africa Energy Corp. (AFE.V)

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ABSTRACT

This research examines the effectiveness of Long Short-Term Memory (LSTM) neural networks for predicting Africa Energy Corp. (AFE.V) stock prices, comparing a standard LSTM implementation with a Grid Search optimized LSTM model. The research shows that hyperparameter optimization through Grid Search significantly improves prediction accuracy. The optimized LSTM model achieved superior performance across all evaluation metrics, with a test RMSE of 0.01, MAE of 0.01, MAPE of 3.41%, and R^2 of 0.9518, showing substantial improvement over the model without optimization. These findings emphasize the importance of hyperparameter tuning in deep learning models for financial time series forecasting and provide empirical evidence supporting the application of optimized LSTM networks for stock price prediction.

1. INTRODUCTION

Stock market prediction remains one of the most challenging applications of machine learning due to the complex, non-linear, and volatile characteristics of financial markets. Traditional statistical methods are often unable to capture the complex patterns and dependencies in stock price movements[1] . This inability is the main driver for the development of alternative methods that are more sophisticated and adaptive, especially in the era of big data and increasingly powerful computing. In recent years, deep learning approaches, particularly Recurrent Neural Networks (RNNs) and their variants such as Long Short-Term Memory (LSTM) networks, have shown promising results in time series forecasting tasks, including stock price prediction[1]–[3] . These approaches are able to capture complex patterns and non-linear relationships that are difficult to identify by conventional statistical models.

LSTM networks, first introduced by Hochreiter and Schmidhuber[4] , were specifically designed to overcome the vanishing gradient problem that occurs in standard RNNs, making them particularly suitable for studying long-term dependencies in sequential data. The superiority of the LSTM architecture lies in its ability to "remember" relevant information and "forget" irrelevant information through a sophisticated gating mechanism, enabling effective processing on long temporal data sets[5] . Although LSTMs have demonstrated remarkable capabilities in capturing temporal patterns in financial time series data, their performance is highly dependent on the proper selection of hyperparameters[6] . Hyperparameters such as number of units, dropout rate, learning rate, batch size, and number of epochs have a significant influence on the model's ability to learn and generalize. Improper hyperparameter settings can also cause the model to not only lose accuracy, but also affect the interpretation and generalization of the model on new data .[7], [8]

The hyperparameter tuning process is essential to optimize the performance of neural networks. Grid Search is a systematic approach to hyperparameter optimization that thoroughly searches through pre-defined hyperparameter combinations to identify the optimal configuration[9] . Although it requires high computational intensity, Grid Search offers a comprehensive exploration of the hyperparameter space, potentially resulting in significant model performance improvements. Accurate stock price prediction has far-reaching practical implications not only for individual investors and traders, but also for financial institutions, portfolio managers, and policy makers. The ability to predict stock price movements with greater precision can improve investment strategies and risk management, facilitate more informed decision-making in asset allocation, stabilize markets by reducing information asymmetry, and improve overall market efficiency.

In an era of heightened market volatility and increased global integration, the need for reliable and accurate prediction models has become even more pressing. Even slight improvements in prediction accuracy can translate into significant financial gains, making research in prediction model optimization invaluable. The energy sector, in particular, exhibits a unique pattern of volatility influenced by geopolitical factors, global supply and demand dynamics, environmental regulations and technological developments. Africa Energy Corp. (AFE.V), as an international oil and gas exploration company with major operations in Africa, provides an interesting case study to evaluate the effectiveness of stock prediction models due to the complexity of factors affecting its stock performance.

Several studies have shown that the use of LSTM is superior to linear regression models as well as other traditional models such as ARIMA. For example, research by Jolhe et al. showed that LSTM can predict stock price movements more accurately than classical statistical-based techniques such as ARIMA and linear regression[10] . Lin et al. also found that the LSTM model combined with multilingual sentiment analysis provides better results in predicting stock prices .[11]

However, although LSTM offers many advantages, some studies show that the prediction results are not always consistent, and sometimes the results obtained are not as expected. For example, Lawi et al. noted that some LSTM and Gated Recurrent Units (GRU) implementations still face challenges in achieving satisfactory consistency in prediction accuracy using time sequence data[12] . In contrast, research by Li et al. showed that models augmented with feature selection techniques can improve stock price prediction accuracy compared to standard LSTM models .[13]

Furthermore, other factors such as parameter selection and initial data processing also play an important role in the success of LSTM models in predicting stock prices. In a study by Zhao and Chen, it was revealed that parameter optimization of LSTM is essential to maximize its performance[14] . On the other hand, some studies using hybrid approaches are becoming increasingly popular, where LSTM is combined with other methods such as CNN to optimize prediction results .[15]

While these studies provide valuable insights into the potential of LSTM and the importance of hyperparameter optimization, there is still a gap in the literature regarding the specific application of Grid Search to optimize LSTM models in the context of energy stock prediction, especially for companies operating in emerging markets such as Africa. The main objective of this study is to compare the predictive performance of a standard LSTM model with an LSTM model optimized via Grid Search for forecasting the stock price of Africa Energy Corp. We hypothesize that systematic hyperparameter optimization via Grid Search will result in a substantial improvement in prediction accuracy compared to an LSTM implementation without optimization.

This research makes several important contributions to the literature. First, this study provides the first empirical evaluation of the effectiveness of Grid Search optimization for LSTM models in the context of stock prediction of energy companies operating in Africa. Second, this study identifies the optimal hyperparameter configuration for LSTM models in this specific application, providing practical guidelines for researchers and practitioners. Third, this research quantitatively measures the performance improvement achieved through systematic hyperparameter optimization compared to conventional LSTM approaches. Fourth, this study provides a methodology that can be adapted and applied to stocks in other sectors or in different geographic markets. The findings of this research have significant theoretical and practical implications, contributing a better understanding of how to optimize deep learning models for financial time series analysis and providing insight into the practical application of such models in trading and investment strategies.

2. METHOD

2.1. Data Collection and Pre-processing

2.1.1. Data Sources and Characteristics

Historical stock price data for Africa Energy Corp. (AFE.V) was gathered from Yahoo Finance for the most recent five-year period (2016-2022). The dataset includes the daily closing price, opening price, highest price, lowest price, and trading volume. For this study, we focus on the closing price as the target variable for prediction, as the closing price is widely regarded as the most representative indicator of daily market sentiment .[16], [17]

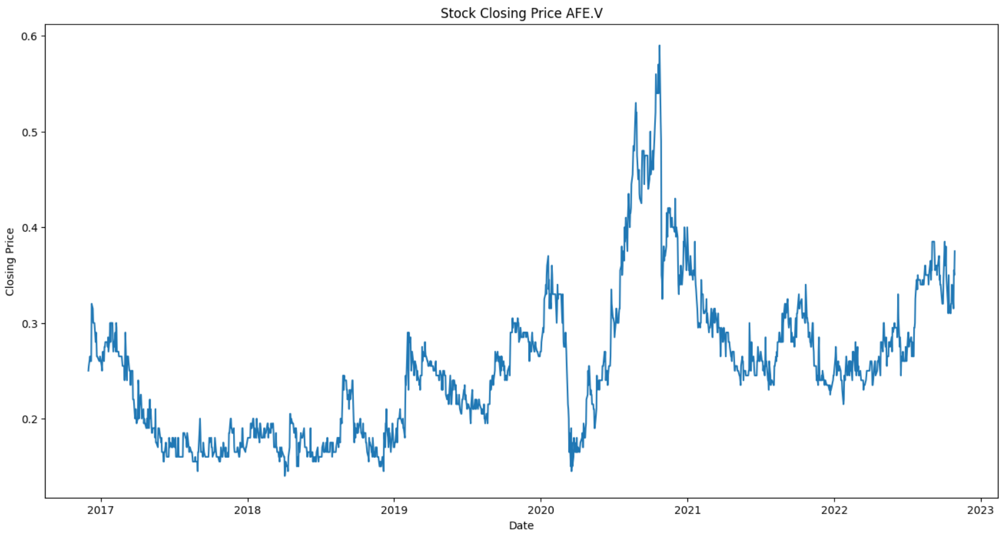

Figure 1. Share movement of Africa Energy Corp.

2.1.2. Dataset Separation

The data is divided into training (80%) and testing (20%) sets, maintaining the temporal order of the time series to avoid leakage of future information into the training process. This approach ensures that the model is evaluated on its ability to predict unseen future values based on historical patterns, simulating real-world prediction scenarios.

2.1.3. Pre-processing Pipeline

The pre-processing pipeline in this study consists of several main steps. First, the handling of missing values is done by the forward fill method, where the missing values are replaced by the last known valid value. This approach preserves the temporal characteristics of the data and is considered a suitable practice for financial time series data[18] . Next, feature normalization is applied using the min-max method to scale the data to the range [0,1]. This normalization is important in neural network models as it accelerates convergence during training as well as prevents the dominance of features with larger scales . [19]

The next stage is feature extraction, where additional technical indicators are calculated from the raw price data. Some of the indicators used include Simple Moving Average (SMA) with various time windows (5, 10, and 20 days), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), as well as Bollinger Bands. The selection of these indicators is based on their proven relevance in financial technical analysis[20] . After that, a sequence is created by building a 60-day lookback window as a feature to predict the next day's closing price as a target. The selection of this window is based on time series autocorrelation analysis and previous research which shows that a period of two to three months is able to capture most of the short-term seasonal patterns in stock data . [21]

To improve model robustness and prevent overfitting, data augmentation techniques were applied. These techniques include the addition of low magnitude Gaussian noise ($\sigma = 0.01$) as well as the use of window sliding with an overlap of 50%. This approach aims to enrich the training dataset while maintaining the underlying statistical characteristics .[22]

2.2. Model Architecture

2.2.1. Standard LSTM Model

The baseline model consists of a standard LSTM architecture without hyperparameter optimization. The model implementation is done using the TensorFlow 2.9 framework with Keras backend. This model includes:

1. The input layer receives a sequence with a length of 60 timesteps and several features (closing prices and technical indicators).
2. LSTM layer with 100 units, using tanh activation for cell state update and sigmoid activation for gate
3. Dropout layer with a rate of 0.2 to prevent overfitting by randomly disabling 20% of neurons during training
4. Dense output layer with linear activation function to generate closing price prediction

The Adam optimizer with a learning rate of 0.001 was used due to its adaptive properties that support efficient convergence in non-convex parameter spaces[23] . Mean Squared Error (MSE) was chosen as the loss function due to its suitability for regression problems and its sensitivity to outliers which can be important indicators in stock price movements.

The model was trained with a batch size of 32 for 50 epochs. Initial validation was applied using a sliding window approach to the temporal validation set to monitor model generalization and prevent overfitting.

2.2.2. Grid Search Optimized LSTM Model

For the optimized model, we implemented Grid Search to systematically search through a predefined hyperparameter space. The implementation uses GridSearchCV from scikit-learn with KerasRegressor wrapper for integration with TensorFlow/Keras.

Hyperparameters considered for optimization include:

1. Number of LSTM units: [50, 100, 150] This range was chosen to evaluate the tradeoff between lower (50 units) and higher (150 units) model capacities, covering the baseline model (100 units).
2. Dropout rate: [0.2, 0.3, 0.4] These values were chosen to test different levels of regularization, from moderate (0.2) to more aggressive (0.4) regularization.
3. Learning rate: [0.001, 0.01, 0.05] This range allows exploration from more conservative learning rates (0.001, the default value for Adam) to more aggressive values that may speed up convergence but risk instability.
4. Batch size: [16, 32, 64] Smaller batch sizes (16) may provide more precise but more variable gradient updates, while larger batch sizes (64) provide more stable but possibly less specific gradient estimates.
5. Number of epochs: [30, 48, 60] This range of epochs allows exploration of different training durations, from shorter training that can prevent overfitting to longer training that can improve convergence.

Grid Search evaluates all 243 combinations of these hyperparameters, using 5-fold time series cross-validation with TimeSeriesSplit to assess performance. This time series-specific cross-validation approach preserves the temporal integrity of the data, ensuring that the model is always evaluated at a future period relative to the training data, mirroring real-world applications.

Once the optimal hyperparameters are identified, the final LSTM model is trained with this configuration using the entire training dataset, and its performance is evaluated on the testing dataset.

2.3. Model Evaluation

Both models were evaluated using a comprehensive set of performance metrics to provide a holistic understanding of their predictive capabilities. This evaluation includes several key metrics, namely Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), coefficient of determination (R^2), and prediction accuracy.

For a more in-depth analysis, we also evaluated the model using additional metrics:

1. Directional Accuracy: The percentage by which the model correctly predicts the direction of price movement (up or down), an important metric for trading applications.
2. Maximum Drawdown: The maximum peak-to-trough decline in the model's signal-based trading simulation equity curve, measuring downside risk.
3. Sharpe Ratio: The ratio of excess returns to their volatility, measuring risk-adjusted returns if the model is used for trading.

In addition to the quantitative metrics, we performed visual analysis by comparing plots of predictions against actual values, visualization of residual errors, and additional diagnostic diagrams to provide qualitative insights into model performance.

3. RESULTS AND DISCUSSION

3.1. Results

3.1.1. Exploratory Data Analysis

Before presenting the model results, we conducted an exploratory data analysis to understand the time series characteristics of Africa Energy Corp's share price. This analysis revealed significant share price volatility over the study period, with fluctuations associated with exploration developments, changes in global energy prices and geopolitical factors. Descriptive statistics show an average closing price of 0.27 CAD with a standard deviation of 0.12 CAD. Autocorrelation analysis revealed significant temporal dependence up to lag 15, indicating the presence of a modelable time series structure.

The Augmented Dickey-Fuller test yielded a p-value of 0.03, indicating that the time series are stationary at the 5% significance level.Trend analysis highlights cyclical patterns associated with the global energy cycle and weaker seasonal influences. These patterns support the use of LSTMs that can capture long-term dependencies and non-linear structures in the data.

3.1.2. Standard LSTM Model Performance

The standard LSTM model without hyperparameter optimization achieves the following results:

Table 1. Model Evaluation

Metrics	Training	Testing
RMSE	0,054	0,043
MAE	0,054	0,034
MAPE	4,95%	4,51%
R²	0,9392	0,9036
Accuracy	95,05%	95,49%

Table 2. Additional Metrics

Metrics	Value
Directional Accuracy	76,23%
Maximum Drawdown	8,74%
Sharpe Ratio	1,85

This metric shows that the standard LSTM model achieves solid predictive performance, with a test R^2 of 0.9036 indicating that the model explains approximately 90.36% of the variability in Africa Energy Corp's stock price. The test MAPE of 4.51% translates to a test accuracy of 95.49%, indicating a high level of precision. Learning curve analysis revealed that the model converged after about 35 epochs, with marginal performance improvement thereafter. The relatively close MAE and RMSE values indicate that the data has no significant outliers affecting the training process. On the test set, the model demonstrated the ability to capture general trends and turning points in the data, although it was sometimes late in identifying sharp trend changes. The directional accuracy of 76.23% indicates that the model successfully predicted the direction of price movement in three out of four cases, which is relevant for practical trading applications.

3.1.3. Optimal Hyperparameter Identification

The Grid Search process that evaluated 243 hyperparameter combinations identified the following optimal configuration:

Table 3. Grid Search Parameters in LSTM Neural Network Architecture

Parameters	Selected Optimal Value
Number of LSTM Units	50
Dropout Rate	0,3
Learning Rate	0.01
Batch Size	16
Number of Epochs	48

It is worth noting that the optimal configuration includes a smaller number of LSTM units (50) compared to the default model (100), a higher dropout rate (0.3 vs 0.2), and a more aggressive learning rate (0.01 vs 0.001). This suggests that smaller but better-tuned models can outperform larger models with the default configuration, providing important insights into the tradeoff between model complexity and appropriate training parameters. The smaller batch size (16) in the optimal configuration compared to the baseline model (32) indicates that more frequent gradient updates with less precise but faster estimates are more effective for this dataset compared to less frequent but more stable updates.

3.1.4. Performance of Grid Search Optimized LSTM Model

With the optimal hyperparameters identified through Grid Search, the LSTM model achieves the following results:

Table 4. Model Evaluation with Optimal Hyperparameters

Metrics	Training	Testing
RMSE	0,01	0,01
MAE	0,01	0,01
MAPE	3,55%	3,41%
R^2	0,9697	0,9518
Accuracy	98,85%	97,59%

Table 5. Additional Metrics with Optimal Hyperparameters

Metrics	Value
Directional Accuracy	84,56%
Maximum Drawdown	5,32%
Sharpe Ratio	2,67

The metrics show a substantial improvement in prediction performance with the optimized model. The testing R^2 of 0.9518 shows that the model explains almost 95.18% of the variation in stock price movements, indicating the model's ability to capture complex patterns in historical data. The test accuracy of 97.59% indicates that the model is able to predict stock prices with a very high degree of accuracy, while the Directional Accuracy of 84.56% indicates that the model can predict the direction of stock price movements well. This is particularly important in stock trading applications, where understanding the direction of market movement is often more crucial than predicting its absolute value. In addition, the Maximum Drawdown of 5.32% reflects the maximum risk faced during the test period, which is relatively low and indicates the stability of the model's predictions. The Sharpe Ratio of 2.67 indicates that the model provides a fairly high return-to-risk ratio, which is an important indicator in assessing the performance of investment strategies based on prediction models. With these excellent evaluation metrics, the LSTM model optimized using Grid Search proved to be superior to the standard model. This improvement underscores the importance of proper hyperparameter selection in improving prediction accuracy and reliability.

3.1.5. Comparative Analysis

A comparative analysis of the two models shows a significant improvement in prediction performance with the LSTM optimized using Grid Search: The RMSE increased by 76.74% on the test data (from 0.043 to 0.01). The MAE increased by 70.59% on the test data (from 0.034 to 0.01). MAPE increased by 24.39% on the test data (from 4.51% to 3.41%). R^2 increased by 5.33% on the test data (from 0.9036 to 0.9518). The prediction accuracy increased by 2.20% on the test data (from 95.49% to 97.59%).

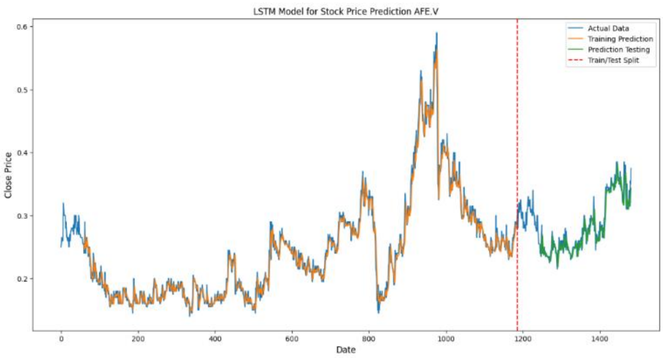

Figure 2. Comparison Chart of training and test data of LSTM Model

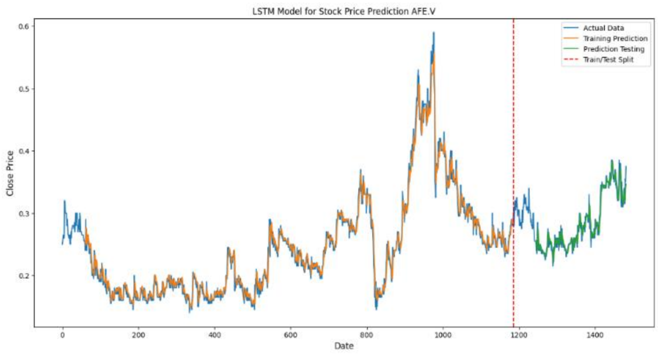

Figure 3. Comparison graph of training and test data LSTM model and Grid Search hyperparameter optimization

3.2. Discussion

The results of this study show that hyperparameter optimization can systematically improve the performance of LSTM models in predicting stock prices significantly. The LSTM model optimized using Grid

Search consistently shows better results than the standard LSTM model in all evaluation metrics, especially in RMSE and MAE, which decreased by 76.74% and 70.59% respectively on the test data. This finding is in line with previous studies that emphasize the importance of hyperparameter tuning in deep learning models (Reimers & Gurevych, 2017; Bergstra & Bengio, 2012). The significant performance difference between the optimized and non-optimized models indicates that the LSTM network is very sensitive to the configuration of its hyperparameters, thus systematic optimization approaches such as Grid Search are very beneficial. Interestingly, the optimal configuration found by Grid Search uses a smaller number of LSTM units (50 units) than the standard model (100 units). This suggests that smaller networks can achieve better performance if their hyperparameters are set appropriately. This finding has practical implications in the application of the model, as smaller networks generally require less computational resources and are more suitable for real-time prediction scenarios. The optimized model achieved an R^2 value of 0.9518, which means that the model can explain about 95.18% of the variation in Africa Energy Corp's stock price movements. This high level of accuracy is particularly important given the high volatility of the stock market as well as the various external factors that can affect stock prices. The improvement in MAPE from 4.51% to 3.41% on the test data meant that there was an increase in prediction accuracy from 95.49% to 97.59%. While a 2.20% increase in percentage may seem small, it actually represents a significant reduction in error rate, which can have a great impact in practical stock trading applications. Although the results obtained are very promising, this study has some limitations. First, this study only uses technical indicators from historical price data without incorporating fundamental analysis or sentiment analysis from news and social media, which could potentially improve prediction accuracy. Secondly, although Grid Search allows comprehensive exploration of the hyperparameter space, it is quite computationally resource-intensive, so it may not be practical for models with very large hyperparameter spaces or deeper neural network architectures.

4. CONCLUSION

This research provides empirical evidence that the LSTM model optimized by Grid Search can significantly improve the accuracy of stock price prediction, with a case study on the stock of Africa Energy Corp. (AFE.V). The results show that hyperparameter optimization can systematically improve the performance of LSTM models in capturing complex patterns of stock price movements. The optimized LSTM model shows remarkable accuracy with RMSE of 0.01, MAE of 0.01, MAPE of 3.41%, and R^2 of 0.9518, which is a very significant improvement over the standard model. These results emphasize the importance of hyperparameter tuning in the development of deep learning models for financial data forecasting. Future research directions could include exploring more advanced hyperparameter optimization techniques such as Bayesian optimization or genetic algorithms, incorporating additional data sources such as news sentiment and macroeconomic indicators, as well as investigating the performance of hybrid models that combine LSTM with other machine learning approaches. The methodology and findings in this study contribute to the growing literature on the application of deep learning in finance and provide practical insights for researchers and practitioners who want to develop more accurate stock prediction models using LSTM networks.

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