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Time Serial-Driven Risk Assessment in Trade Finance: Leveraging Stock Market Trends with Machine Learning Models

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Abstract

There is a lot of power in the Stock Market over both national and global markets. What affects stock prices? The performance of the industry, the news and success of the company, the confidence of investors, and both small and large-scale economic factors such as wage rates and employment rates. Trends in stock prices can be figured out by looking at the things that cause them and how the stock has done in the past. This research suggests using Long Short-Term Memory (LSTM)-based deep learning to evaluate risk in trade finance. It does this by using Yahoo Finance data from the stock market. The suggested LSTM model takes advantage of temporal correlations in sequential financial data to get an F1-score of 96.32%, an accuracy of 96.17%, a precision of 96.89%, a recall of 95.76%, and an accuracy of 96.17%. Compared to other machine learning models, the suggested model works better because it gets 91.2% accuracy for Support Vector Machine (SVM) and 88.72% accuracy for Random Forest (RF). The suggested model shows that it is strong and dependable by looking at its accuracy and loss curves along with its confusion matrix results. Improving the way trade finance evaluates stock price risk by using an LSTM model that is better at finding complicated patterns and long-lasting connections in market data makes the process more efficient.

Keywords: *Stock Market Trends, Trade Finance, Risk Assessment, Financial Technology (FinTech), Stock Market Prediction, Machine Learning, Financial Forecasting, Stock Data.*

INTRODUCTION

The financial industry functions as one of the vital core systems of worldwide development because it directs capital flows while encouraging investments and enabling worldwide trading activities. The elaborate trading system functions with trade finance mechanisms which fill the financial gap between goods delivery and payment collection. Trade finance provides temporary loans to exporters and importers that ensures operational continuity of international trade transactions [1]. Global trade expansion leads to increased requirements for innovative risk assessment methods which must adapt in the trade finance sector [2].

Stock markets hold essential economic understanding potential that many businesses fail to utilize [3]. The markets depict information about investor feelings together with business outcomes and worldwide economic performance as they provide instantaneous financial industry updates. The stock market trends provide specific data about both economic stability and upcoming threats. The market indicators maintain direct significance in trade finance since alterations in sentiment levels combined with organizational performance predict future disruptions affecting trades and related changes in creditworthiness before major economic declines [4]. Stock market trends enable more detailed and present-minded analysis to support trade finance risk evaluation [5].

Stock market trends when employed for trade finance risk evaluation create an innovative strategic foundation which builds upon conventional risk management systems. The standard risk assessment practices use historical financial records and pre-established business risk guidelines. Financial institutions that integrate stock index data signals into their operations can take proactive steps to identify emerging risks thus making better-decision making possible [6]. Such an approach enables financial organizations to deploy a data-driven risk evaluation system that corresponds with global market speed and volatility.

The complete utilization of stock market trends depends on advanced analytical tools which ML provides as an exceptional solution. The combination of ML models suits analysis of secret complex patterns running throughout big time series stock price data structures. The models achieve outstanding stock market forecasting success through their ability to extract knowledge from past trends and automatically identify current market changes in real-time [7]. Through their persistent learning abilities and prediction capabilities these systems are suitable solutions for updating trade finance risk assessment systems [8]. The approach seeks to decrease trade risk evaluation uncertainty while enhancing financial operation speed and resilience by merging stock market prediction methods with practical business imperatives in a changing global market.

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Motivation and Contribution of Paper

The motivation of this study arises from a growing demand for accurate and timely risk assessment in the sensitive trade finance sector where market volatility and economic fluctuations take place from time to time. But traditional assessment methods tend to lack in-depth addressing of dynamic nature of the trends in the stock market. As ML and DL models such as LSTM networks get ML and DL models, especially LSTM networks become popular, there is a great chance to improve the predictive ability. In pursuit of this, this research tries to aid financial institutions with robust tools for reducing risk and making more informed trade finance decisions by virtue of integrating stock market indicators, making use of them in data-driven models. Below are outlined how the following contribution of paper are:

- Integrated historical stock market data as key indicators to enhance the accuracy of risk forecasting.
- Developed an automated pre-processing pipeline for consistent and reproducible data preparation.
- Conducted feature engineering to extract relevant patterns and trends from raw financial inputs.
- Applied normalization and scaling methods to improve LSTM model convergence and performance.
- Developed a predictive model using LSTM to assess trade finance risk based on stock market trends.
- Utilize the model's performance by checking its F1-score, accuracy, precision, memory, and the confusion matrix's inaccurate information.

Structure of Paper

Below is the format of the rest of the paper. Information about the stock market is given in Section II. It's all explained in Section III. It compared in Section IV. There is a conclusion to the study and ideas for more research in Section V.

LITERATURE REVIEW

The current work is conducted by filtering and analyzing some significant research on risk assessment in trade finance in the stock market. Table I provides the background study for Trade Finance in the stock market, including its dataset, models, performance, and contribution.

Wang, Guo and Chen (2019) collects relevant material on Sina Finance, then uses sentiment analysis to extract and obtain the time series of the financial sentiment index using three indexes. In order to build a prediction model, this research uses LSTM NN, taking into account the long-term latency of financial time series. The model's testing and training showed that as the text mood index went up, the MSE of the LSTM prediction model's results went down from 74.57 to 19.06 and the MAE went down from 5.96 to 3.14. This happened with both the CNN and the PSO-BP algorithms. The prediction model is less accurate than the predicted results. The precision has increased, and the inaccuracy is little [9].

Coelho (2019) show that adding mood analysis to the text linked by the URL doesn't make the model work better when all the tweets from a given day are considered, since the model only figures out the direction of change and not the level of change. The model for predicting stocks is 65% accurate, which is better than the base case accuracy of 44%. Adding mood analysis to the model did not change the accuracy [10].

Baek and Kim (2018) suggested model is tested against two sets of sample stock market data: the S&P500 and the KOSPI200. It's very good at making guesses based on the data when the model is used. The test error for ModAugNet-c is less than that for SingleNet, which doesn't have an LSTM part that stops overfitting. For the S&P500, the test showed that SingleNet's mistakes dropped to 54.1% for MSE, 35.5% for MAPE, and 32.7% for MAE. The KOSPI200 went through the same thing: SingleNet's mistakes dropped to 48%, 23.9%, and 32.7%, in that order. To see if the forecast LSTM module is the only thing that makes the test work, look at the learnt ModAugNet-c [11].

Xu and Kešelj (2014) suggest a way to use collective mood analysis to guess what will happen in the stock market and see how accurate it is at guessing how a stock's price will change the next day. Finding mood was easiest with the SVM method, which got 71.84 and 74.3% for positive and negative emotion, respectively. Stock price changes (up or down) can be predicted using sentiment analysis. they discovered that overnight activity on Stock Twits is linked to stock trading the next business day in a good way [12].

Yu, Chen and Zhang (2014) introduces a support vector machine-based ML method for building a stock selection model that can classify stocks in a way that is not linear. Although, the training set's quality has a big impact on how well SVM classification works. It is not necessary to use complicated and high-dimensional financial measures directly. Instead, principal component analysis (PCA) is added to the SVM model to get useful feature information that is low-dimensional. This improves the accuracy and speed of training while keeping the original data's traits. That model works 75.4464% of the time in the training set and 61.7925% of the time in the test set. It uses a support vector machine and PCA after norm-standardization [13].

Table 1. Overview of Recent Studies on Stock Market Trends with Machine Learning Models

Author	Proposed Work	Dataset	Key Findings	Challenges/Gaps
Wang, Guo, and Chen (2019)	Integrated sentiment analysis from Sina Finance with stock index time series; built an LSTM-based prediction model.	Financial sentiment index (text from Sina Finance) and Shanghai Stock Exchange (SSE) Index	Improved LSTM model accuracy; MSE decreased from 74.57 to 19.06, MAE from 5.96 to 3.14; outperformed CNN and PSO-BP models.	Financial sentiment may not capture all market dynamics; limited to Chinese stock market data.
Coelho et al. (2019)	Stock market prediction model incorporating Twitter data and sentiment from URLs.	Twitter posts referencing financial content	Achieved 65% prediction accuracy over 44% baseline; sentiment from URL-based text did not enhance model performance.	Model did not account for sentiment magnitude; only predicted direction.
Baek and Kim (2018)	Proposed ModAugNet-c with LSTM for S&P500 and KOSPI200 forecasting; evaluated with and without overfitting prevention.	S&P500 and KOSPI200 historical stock data	Significant reduction in MSE, MAPE, and MAE; enhanced accuracy when overfitting prevention was applied using LSTM modules.	Model performance highly dependent on LSTM tuning; possible overfitting in small datasets.
Xu and Kešelj (2014)	Two-stage stock market prediction model using sentiment analysis and SVM classification; analyzed overnight sentiment impact.	StockTwits messages + stock price data for 15 companies	SVM achieved 71.84–74.3% accuracy in sentiment detection; overnight sentiment correlated with next-day stock price in 9/15 stocks.	Limited to short-term daily prediction; subjective sentiment interpretation; does not generalize to all stocks.
Yu, Chen, and Zhang (2014)	Used PCA to reduce financial data dimensionality and applied SVM for stock classification.	Financial indicators for stock performance	Achieved 75.45% training and 61.79% testing accuracy; PCA improved efficiency and reduced complexity.	SVM model sensitive to training data quality; lacks interpretability in real-time decision-making.

RESEARCH METHODOLOGY

The methodology for Stock Market Trends with ML Models involves a comprehensive pipeline starting with data collection from Yahoo Finance, capturing critical stock attributes. Following this, rigorous data preprocessing steps are applied, including handling missing values using statistical imputation, tokenization, and stop word removal (for any embedded textual data), and feature selection through correlation analysis and the Select Best technique, ultimately selecting the top 20 features, including stock prices, technical indicators, and major indices. Scaling all features to a range of [0,1] using min-max normalization. A ratio of 80:20 is then used to divide the information between training and testing. For learning about temporal dependencies in financial time series, the memory cell and gate processes of a Long Short-Term Memory (LSTM) model are used. This model works well with sequential data. Accuracy, precision, recall, and the F1-score, which is based on the confusion matrix, are some of the common classification metrics used to judge the model. Figure 1 shows the next steps of a plan.

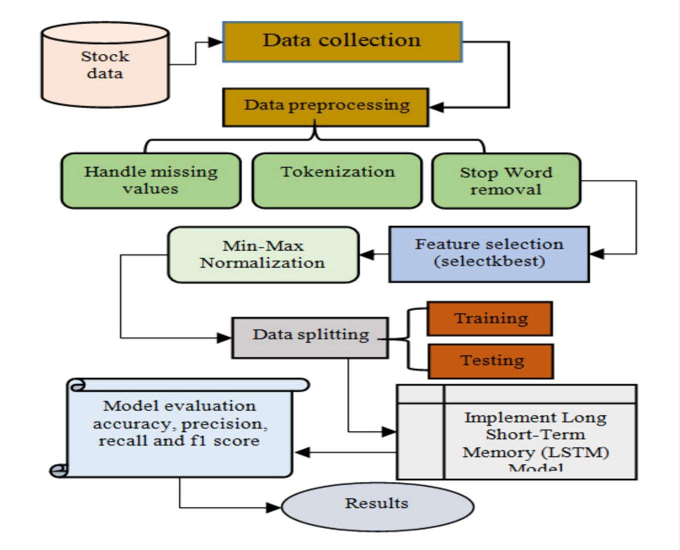

Fig 1. Proposed flowchart for the Stock Market trends

Each step of the proposed flowchart for the Stock Market is provided below:

Data Collection

Stock data from Yahoo Finance was used to figure out whether the price of a stock went up or down on a certain day. The information was in Excel format and had the following fields: adjust close, initial price, low and high price, volume, and end price.

Data Preprocessing

Processing data is an important part of making accurate predicting models. The program also makes sure that the data are properly organized and cleaned, which improves the model's accuracy and makes it more stable and useful overall. For pre-processing, the steps below are mentioned:

- **Handle missing value:** Numeric columns that are missing values are filled in with the column's mean value, which keeps the central trend. Whereas classification columns are filled with mode, which means the most common category is used to fill the column, and the original distribution of categories is kept as close to possible.

- **Tokenization:** Tokenization is one of the first steps in getting data ready for NLP. This is the process of cutting text into smaller pieces, which are known as tokens. But tokens don't have to be words or sentences. They can be more than that. Breaking up a piece of text into useful pieces is called tokenization. In this case, it might split a block of text into words or lines.

- **Stop Word removal:** In data processing, stop word removal refers to the act of removing common words, which are often meaningless words, such as these ('the,' a, is) to make the efficiency and accuracy of natural language processing (NLP) better. The focus is on the meaningful words and the noise is reduced in the data during this process.

Feature Selection

Feature selection is an important part of preparing data because it helps models work better, avoid overfitting, and be easier to understand. It involves finding and choosing the most important features (variables) from a dataset. The top 20 features were selected for predicting Apple's Adjusted Close price using correlation analysis and the SelectkBest method. These include four stock price variables, 12 technical indicators (five SMAs and seven EMAs), and four major indices (IXIC, GSPC, DJI, NYA). The strong correlation and high importance scores of these features justified their inclusion in the final model.

Max-Min Normalization

This work used min-max normalisation, which changes the value of each feature to a number between 0 and 1. The formula for this method is written as Equation (1):

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

X is the current value of the data feature, and X_{min} and X_{max} are its lowest and highest values, respectively.

Data Splitting

There are two sets of data: a training set and a test set. The training set is used train the data and testing set used for evaluate the model efficiency. The ratio of data are 80:20.

Long Short-Term Memory (LSTM) Model

There is a great way for LSTM to sort text: it can learn over time how words are related [14]. In this case, it's a RNN, which is a stacked network that feeds the outputs of one layer into the next [15]. LSTM has feedback links that let it work with groups of data instead of just single data points. A cell, an input gate, an output gate, and a forget gate make up an LSTM node. The three gates in the cell decide how data goes through it and store values that have been saved over time. Each LSTM layer has three multiplicative gates and a memory block that is connected to many other memory blocks. Writing, reading, and refreshing temporary data all the time is how gates make sure it is used for a certain amount of time. x_t, h_{t-i}, c_{t-i}, and h_t, c_t, both go into and out of the unit in the following ways: The hours of Equation (2 to 7):

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (2)$$

$$f_t = \sigma(W_f x_t + U_i h_{t-1} + b_f) \quad (3)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (4)$$

$$g_t = tanh(W_g x_t + U_g h_{t-1} + b_g) \quad (5)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \quad (6)$$

$$h_t = o_t \odot \tanh(c_t) \quad (7)$$

The logistic sigmoid function is shown by σ and $\odot$ element-wise multiplication is shown by in the above formulae. At time step t, the LSTM unit is made up of an input gate i_t, a forget gate f_t, an output gate o_t, a hidden unit h, and a memory cell c_t. Learnt factors are W and U, and extra bias is b. How much of the internal memory information is shown is controlled by the input gate, and how much is saved is controlled by the output gate.

Evaluation Metrics

The forecast model has reached its last step. Here, you should rate the accuracy of the predictions using different measures, such as the confusion matrix, f1-score, and classification accuracy. There are statistical numbers for each metric that come from a confusion matrix class. The following instances of confusion matrix are:

- **TP (True Positive):** The number of right types of tuples that the classifier sorts.
- **FP (False Positive):** The quantity of negative pairs that the classifier believes to be positive.
- **FN (False Negative):** Number of positive tuples that the algorithm thinks are negative.
- **TN (True Negative):** Number of negatively ordered tuples that the algorithm sorts properly into groups.

Accuracy: Accuracy is measured by the ratio of the number of right guesses to the total number of predictions in the testing set. Accuracy Equation is (8)-

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+l} \quad (8)$$

Precision: Precision is the number of guesses for positive classes that turn out to be true predictions for positive classes. Number of successfully forecast positive explanations divided by the total number of positive observations that were expected. This phrase is Equation (9)-

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

Recall: Consider recall as the sum of all the correct positive statements. It is written as Equation (10)- in mathematically.

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

F1 score: Taking the harmonic mean of a model's precision and recall gives you the F1 score, which shows how well the model fits the information. Mathematically, it's written as Equation (11)-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (11)$$

Combined these metrics give insights on the accuracy and effectiveness of the model in predicting the target variable.

RESULTS AND DISCUSSION

The results of performance evaluations were presented for this section of experiments. All this was done on a multi core computer with Intel Core i7 CPU at clock speed of 3.4 GHz, nVIDIA Geforce GTX 980M graphics GPU of memory 8 GB, and other components. The result of the proposed LSTM model is given in Table II. With an impressive accuracy of 96.17%, the model demonstrates its effectiveness in correctly identifying both positive and negative instances. The precision of 96.89% indicates a very low rate of FP, meaning that the majority of predicted Risk Assessments in Trade Finance are indeed actual Stock Market. The F1-score of 96.32% shows that the model is good at predicting Risk Assessment in Trade Finance in the stock market, with a recall of 95.76% and a performance mix between precision and recall.

Table 2. Experiment Results of Proposed Models for Risk Assessment in Stock Market

Performance matrix	Long Short-Term Memory (LSTM)
Accuracy	96.17
Precision	96.89
Recall	95.76
F1-score	96.32

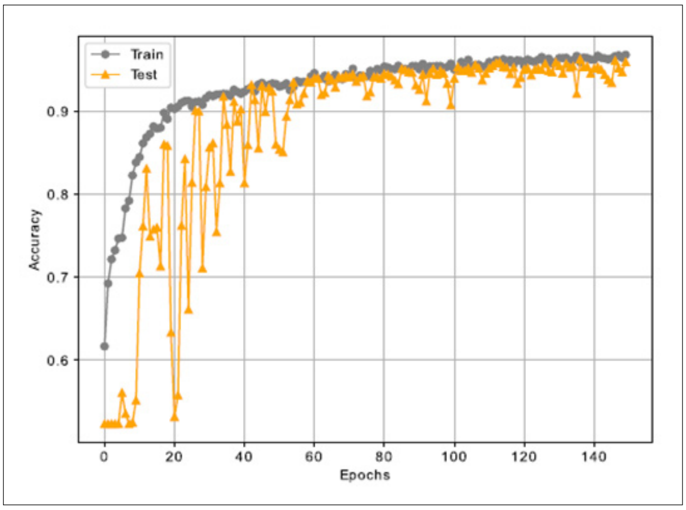

Fig 2. Accuracy curve for LSTM

During training and testing over 150 epochs, Figure 2 shows how accurate a model was. The number of epochs is shown on the x-axis, which ranges from 0 to 150, and the accuracy is from 0.5 to 1.0 on the y-axis. The gray line with circular markers represents the training accuracy, which generally increases and plateaus around 0.95 after approximately 60 epochs. The orange line with triangular markers represents the testing accuracy, which exhibits more fluctuation, initially increasing but then showing significant drops and rises before generally stabilizing around 0.93 after about 100 epochs, with some continued minor variations.

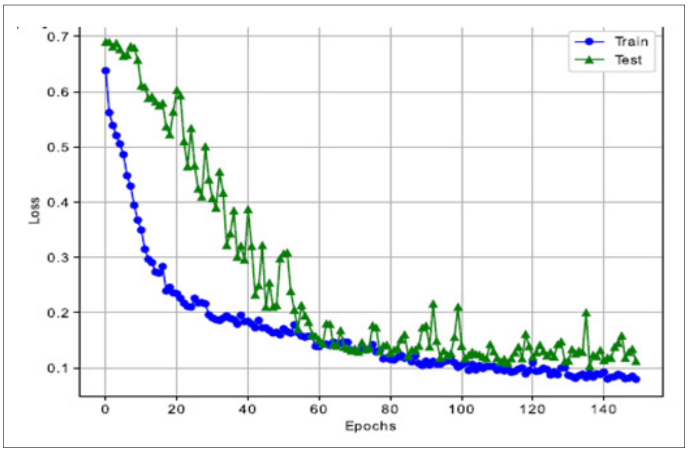

Fig 3. Loss Curve for the LSTM

Figure 3 displays a line graph that displays the amount of effort a model lost over 150 iterations of training and testing. For each stage, the y-axis shows the number of times the process happened, and for each loss, the x-axis shows the amount of loss. There are 150 epochs, and the blue line with round marks shows the training loss. It goes down steadily over the epochs, from above 0.6 to below 0.1 by the end. The green line with triangular markers represents the testing loss, which initially decreases alongside the training loss but exhibits more fluctuation. After around 40 epochs, the testing loss shows several peaks and valleys, generally staying between 0.1 and 0.2, with some higher spikes, while maintaining a lower overall trend compared to its initial values.

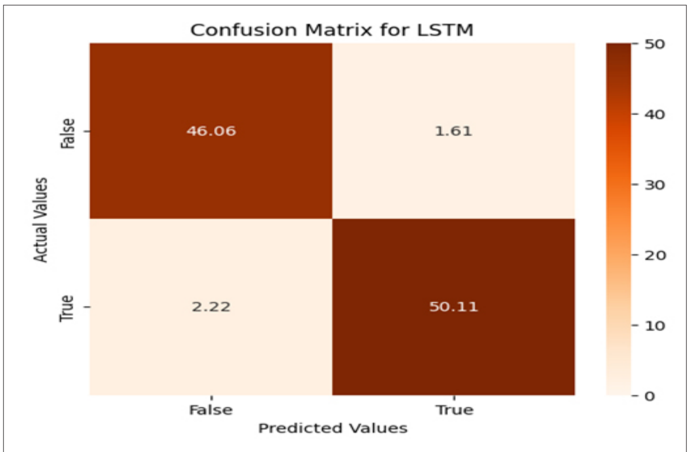

Fig 4. Confusion Matrix for LSTM

Figure 4 shows the LSTM model's confusion matrix, which shows how well it can sort stock market movements based on the features that are fed into it. The matrix shows that the model properly forecasted 50.11% of the real positive cases (True Positives) and 46.06% of the real negative cases (True Negatives), which shows that it is very good at effective the difference between the two groups. The False Positive rate stands at 1.61%, while the False Negative rate is 2.22%, both relatively low, signifying minimal misclassifications. These results suggest that the LSTM model is highly operative in capturing the underlying patterns of the dataset and demonstrates strong predictive capability for stock market-based risk assessment in trade finance.

Comparison with Discussion

Table III gives the comparative analysis for stock market forecasting between ML and DL models on stock data shown here. The LSTM model among the models evaluated turns out to have the highest prediction of 96.89% accuracy, which indicates the best potential of LSTMs in producing prediction for the financial time series data. SVM then comes with 91.2% accuracy, which shows its capability to work well with classification tasks that have clear margins. Although slightly worse at an accuracy of 88.72%, the RF model's result still demonstrates its robustness through ensemble learning. The same comparison highlights the appropriateness of the DL techniques like the LSTM in the dynamic, volatile domains like stock market risk assessment.

Table 3. Comparison between ML and DL models for Risk Assessment on Stock Data

Models	Accuracy
RF [16]	88.72
SVM [17]	91.2
LSTM	96.89

A key point in performing stock market risk assessment in trade finance is the proposed LSTM based model, which brings several advantages. The accuracy of market risks reflected by high precision and recall scores of its accuracy in predicting market risks are because it has the ability to effectively learn and model long term dependences in Sequential Financial data. As opposed to the traditional ML models, LSTM can capture the intricate temporal patterns as well as the nonlinear trends are present in stock market behavior.

CONCLUSION AND FUTURE STUDY

Random walks and number predictions were used in the first studies to try to guess how stocks would move. But after behavioural finance became popular, it was also studied how people's emotions and intuitions affected the movement of stock markets. The suggested LSTM model did a great job of evaluating trade finance risk based on the stock market, with an F1-score of 96.32% and top scores of 96.17% for accuracy, 96.89% for precision, and 95.76% for recall. Traditional ML models like SVM and Random Forest are not only much worse than these. They also show that the model can handle the complex temporal relationships in financial time series data. However, it is not completely stable in testing loss, thus might be overfitting. Future work will be devoted to the improvement of the generalization of the model in the hybrid DL architectures with the attention mechanisms and also to the test of the model on non-standard financial datasets and make sure that the model is robust and scalable in real world applications.

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