Stock trend prediction analysis using deep learning

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ABSTRACT

The stock market prediction problem has historically been an arduous one, primarily due to the excessive noise, non-linearity, and non-stationarity that exist within financial time series (FTS) data. The application of deep learning for stock market analysis has made it more common to develop models based on data to predict future stock market trends. Continuing this trend further is the comprehensive evaluation of how well modern deep learning techniques outperform previous standard statistical and machine learning approaches to predicting future stock market price movements presented in this paper.

Based on past stock prices, technical indicators, and potentially news & social media sentiment information will serve as baseline data for this project. Advanced approaches to modeling the data are required in order to achieve the model prediction performance necessary for decision-making. Appropriately designed networks such as the Long Short-Term Memory (LSTM) neural network along with other neural network types (e.g., Gated Recurrent Unit (GRU) and Convolutional Neural Networks) offer potential for identifying local/temporal feature patterns within the stock market.

I. INTRODUCTION

The financial global system is very rapidly changing and very complicated, and is affected by a wide variety of factors. One of the biggest problems associated with financial systems that is of great interest to both researchers and traders is stock price prediction or trends. Traditional techniques for stock price prediction rely on the Efficient Market Hypothesis (EMH), which states that all available information is already reflected in the current stock price, therefore stock prices will behave randomly or unpredictably. However, there has been much empirical research supporting the fact that there are inefficiencies present within the financial market and thus prediction is possible. Tradition stock price prediction techniques are based on Time Series Analysis or ARIMA type models. These types of models work very well for linear systems, whereas the financial systems have nonlinear components, and that presents a real problem for these techniques. Subsequently different prediction techniques such as Decision Trees and SVM has emerged

II. LITERATURE SURVEY

Deep learning is an exciting leap forward for our industry Both long short-term memory (LSTM) and gated recurrent units (GRU) are excellent examples of current advances in applied deep learning. These models can successfully learn from long-term dependency relationships because of how well suited they are for that task. These kinds of models were designed specifically to address some of the limitations of traditional Recurrent Neural Networks (RNNs).

As a result of this, these types of models are well suited for forecasting time series data including predictions about stock market trends. Numerous empirical studies conducted on LSTMs indicate that LSTM-based models perform better than traditional models when learning temporal dependencies and providing accurate forecasts.

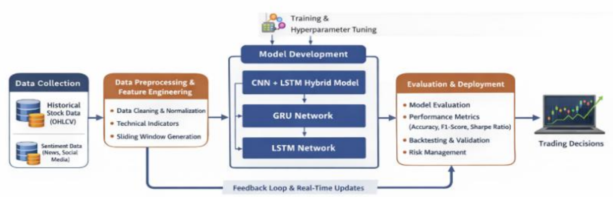
In addition to studying deep learning implementations, research in recent years has also examined a range of hybrid time series forecasting models that combine many different models to produce better forecasting accuracy. The combination of Convolutional Neural Networks, and LSTM networks allows a model to learn both spatial dependencies and temporal dependencies in stock market time series data, thus significantly increasing the accuracy of its forecasts.

III. PROPOSED METHODOLOGY

The main focus of the methodology is to create a model that will allow the prediction of various outcome variables via advanced neural network models. The primary model utilized for this will be an LSTM (long short-term memory) neural network because it is a computationally efficient method of knowing long-term dependencies. Additionally, other neural network models, such as GRUs (gated recurrent units), may also be used for predictions/computational purposes. Separate Convolutional Neural Networks (CNNs) will be combined with the LSTMs to perform feature extraction from the dataset. The CNN model will perform the feature extraction process; subsequently, the LSTM model will model the temporal dependencies of the datasets.

A supervised machine learning approach will develop the model with a dataset that predicts stock price directions (up or down). Splitting the dataset into training, validating and testing portions creates a robust training method for the model. To assist with this training process, the model will use optimizers (e.g., Adam Optimizer) and loss functions (e.g., Binary Cross).

IV. ARCHITECTURE DIAGRAM



V.VARIOUS METHODOLOGY

Temporal sequence learning methods include the use of recurrent networks for forecasting time series data; and the two most common recurrent neural network (RNN) architectures used within this method are Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) RNNs (or similar variants). As the method provides the ability to learn from both long and short-term trends, the method is also better suited for learning longer-term trends than for short-term price fluctuations.

A different method is the hybrid deep learning method. In this case, different models are used together to enhance the accuracy of predictions by combining convolutional neural networks (CNN) and long short-term memory (LSTM).

A) Hybrid CNN-LSTM Methodology

Using both LSTM and CNN allows for the identification of spatiotemporally related features from a dataset that exhibit local trends and patterns as captured by CNN and sequential dependencies as captured by LSTM. The combination of both improves model accuracy.

B)Sentiment-Based Prediction Approach

The incorporation of text and social media into stock forecasting results in predicting stock using text data (NLP) through sentiment analysis. The data extracted will be used on top of existing stock data and is valuable in determining the sentiment of investors, which is a key factor in affecting stock prices.

C) Transformer-Based Methodology A methodology that relies on transformer models and attention techniques to analyse archivegan stocks, will focus on what is important in stock data. This will assist the model in finding long-term relations in the stock archive. This method makes it simple for a model to show its findings, supportable by mathematics as well.

□This method lets you use worldwide dependencies in the data while executing it all at once instead of one piece at a time; as a result, it will work faster and be more efficient.

□This method accomplishes this through self-attention methodologies and measures how much each of the different time periods contributes to the level of importance assigned to future events

D) Reinforcement Learning-Based Approach

In this method, prediction and decision-making are integrated. An agent of reinforcement learning interacts with the stock market environment and attempts to learn to make decisions to buy, sell, or hold based on rewards. This method is used to construct trading strategies.

□ Learning optimal trading rules involves constant interactivity with the environment and receiving feedback (rewards).

□Flexibility: It is capable of adjusting itself in real-time according to the evolving market. Static predictive models have a much harder time doing this.

E) Hybrid Statistical and Deep Learning Approach

Deep learning and statistical methods can be used together through a hybrid of different technique's that take advantage of the best parts of both. Traditional statistical approaches to modelling have benefits in terms of interpretation as well as working with large amounts of structured data.

VI. INPUT

Deep Learning stocks trend prediction relies on historical stock trend data to predict trends using Deep Learning. Stock price predictions use historical data on stock prices, the respective open/high/low/close and volume (OHLCV). OHLCV Data is most important for the stock price. Technical stock indicators such as moving averages, RSI (Relative Strength Indicator) and MACD (Moving Average Convergence Divergence) are also input into Deep Learning models for stock price prediction. Additionally, Natural Language Processing and Sentiment Analysis are also relevant for predicting stock prices using Deep Learning due to investor emotions.

Further macroeconomic variables, such as interest rates and inflation rates can be included to describe the economy overall or to represent today's economic climate.There are also temporal variables in the data, such as dates and habits based on the day of the week, which represent periods of time. Before inputting all of the variables into the model, they are normalized and preprocessed so that they are both consistent and reliable.After preprocessing, these variables have been placed in a time sequence using techniques such as sliding window (fittingly), which makes them suitable for LM and GRU type models.Additionally, temporal variables have also been included (e.g., date and day of the week).

All variables are preprocessed and then normalized before they are put into the model. This makes the model both consistent and reliable. Finally, the variables were arranged in a sequence using a sliding window to make them appropriate for LM and GRU type models.

VII.PSEUDO CODE AND IMPLEMENTATION

BEGIN

1. Load dataset

• Load historical stock data (OHLCV, volume & time)

2. Preprocessing Steps

• Handle missing data

• Normalise data (Min-Max scaling on input variables)

• Create technical indicators (based on user/market criteria)

3. Create sequences of data

• Specify a window size, (e.g. 60 days of data)

• Convert your data to input/output sequences

4. Create training/testing datasets out of your original dataset

5. Create LSTM model

• First, you will create your model with LSTM layers (with optional dropout layers if you want to avoid overfitting)

• Second, you will create a layer to produce outputs from the LSTM network

6. Compile model

• Specify error function (e.g. MSE or BCE)

• Specify optimisation algorithm (e.g. Adam)

7. Train model

• Train your model using your training data set

• Validate your model using a validation dataset (to detect overfitting)

8. Make Predictions

• Make predictions using your test dataset as input to your LSTM model

9. Evaluate Predictions

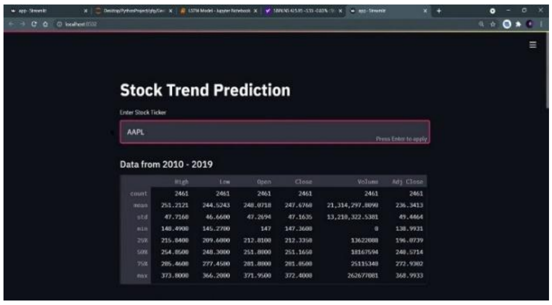
• Determine how accurate your predictions were through accuracy, root mean squared error (RMSE) or mean absolute error (MAE).

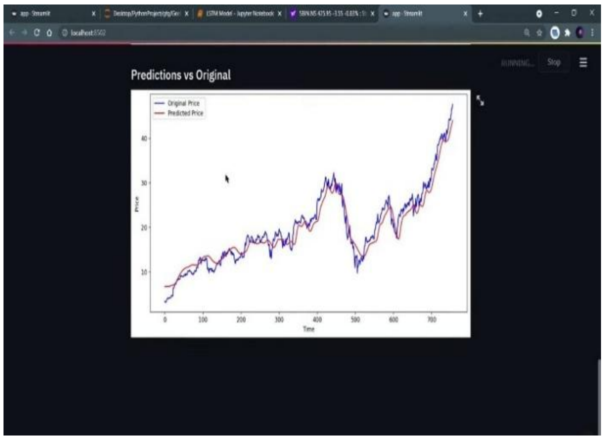
10. Output Predictions

• Visualise the predicted trends (for the next day's predicted stock price) to show whether they are trending upward or downward

END

VIII.OUTPUT





IX.RESULTS AND DISCUSSIONS

The stock trend prediction system that was developed using deep learning techniques produced results which indicate that the system can predict the stock market trends. There was a good agreement between the predicted value of the stocks compared to the original price of the stock, indicating that the model was producing accurate stock prediction and that LSTM is able to learn from previous price data.

In terms of moving averages (100 day and 200 day), both graphs show that the model's moving averages closely correlated to the overall market trends, enabling the model to eliminate noise from the data and achieve a better understanding of the overall direction of the market. Although there are noticeable errors in many cases, particularly during times of extreme market volatility, the model continues to demonstrate a high level of accuracy and correlation with the raw data to the extent that it is experiencing very large price fluctuations on the stock's price, indicating that the overall stock price data has a high degree of variation in prices and therefore, as with the previous experience, the model continues to perform well in an extremely volatile stock market.

X.CONCLUSION

The project has demonstrated that predicting the trend of stocks using Deep Learning is an effective method for modelling and forecasting financial time series. In addition, this project has shown that time series data can be evaluated using Long Short Term Memory Algorithm (LSTM) to understand the temporal relationships and complexities within the data associated with stock prices.

The results also indicated that LSTM could predict stock market trends with a high degree of accuracy; the predicted values were found to be closely correlated with the actual stock market trends. The visualisation of results through moving averages and charts was useful in making informed decisions. However, at the time of conducting the research it was noted that prediction accuracy decreased during periods of extreme volatility in the stock market and that other factors such as economic indicators and stock sentiment were not factored into the predictions. Notwithstanding, the project results indicate that the method proposed represents a significant advancement in the ability to analyse stocks based on Intelligent criteria.Future revisions to this system could enhance overall accuracy by implementing Natural Language Processing for sentiment analysis and hybrid deep learning architectures to improve prediction accuracy in the stock market.

Overall, using deep learning models to predict stock market trends holds much promise in providing methods to collect complex and non-linear patterns that exist in the financial markets. The primary benefit of using this type of approach is that the model effectively utilizes large amounts of data (both past and present) to further refine the accuracy of future value predictions as compared to traditional techniques. However, the issues related to these technologies remain very significant when applying this approach for decision-making purposes.

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