Stock price prediction using LSTM

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***Abstract*—The task of predicting stock market prices is extremely difficult. Traders have long used technical analysis methods to evaluate the financial markets and spot trading opportunities. This study investigates a novel hybrid approach combining technical indicators with long short-term memory (LSTM) networks for stock price forecasting. The technical indicators used include support/resistance, Fibonacci extensions, candlestick patterns and relative strength index (RSI). These indicators help extract meaningful features and transform the raw price data into more informative representations. The resulting technical indicator dataset is used to train LSTM models to predict future stock prices. Comparative evaluations demonstrate the benefit of combining traditional technical analysis with modern deep learning for stock prediction. The hybrid models outperform baseline methods like ARIMA as well as LSTM models using just price data**

Keywords—Stock Price Prediction, Technical Analysis, LSTM, RNN

I. INTRODUCTION

Due to the inherent noise and volatility of financial markets, predicting changes in stock values is a very challenging endeavour. But for a long time, traders have utilized technical analysis indicators to spot price trends and patterns that might predict future movements. The current stock price forecasting techniques can be divided into the following categories.

- Fundamental Analysis
- Technical Analysis
- Time Series Forecasting

In this study, we investigate how to forecast stock prices using a combination of conventional technical analysis and modern deep learning techniques. We use support/resistance, Fibonacci extensions, candlestick patterns, relative strength index (RSI), and other important technical analysis indicators as input features to an LSTM neural network model. Due to its capacity to remember long-term dependencies in time series data. According to [1] Recurrent neural networks (RNNs) of the Long Short-Term Memory (LSTM) kind are able to solve linear problems. A deep learning method is LSTM. The learning of very long sequences is imposed on Long-term Memory (LSTM) Units. The gated recurrent system is shown here in a more generalized form, because LSTMs address the evanescent gradient problem faced by [2], they are less harmful than other deep learning techniques like RNN or conventional feed forward.

Our goal is to extract predictive signals from stock price histories to estimate future prices by integrating LSTM with indicators from technical analysis. The raw price data is normalized and transformed using technical indicators into useful feature representations that can improve the model. For instance, candlestick patterns offer insights into the psychology and behaviour of the market while support and resistance levels indicate probable price boundaries. We perform experiments on historical daily stock price data to determine how effective this strategy is.

This model uses the RNN (Recurrent) approach known as Long Short Term Memory (LSTM) and takes into account the historical nifty share price. The proposed approach takes into account the historical data of the share, and predicts values using particular feature. Features of shares include Open Price ,day high, and day low, yesterday's price, Close price, trading date, and different indicators The suggested design utilizes time series analysis to forecast a share price for the required amount of time.

Utilizing solely pricing data, comparative analyses are made against industry standards like ARIMA and LSTM models. According to our hypothesis, the technical indicators will improve LSTM performance by offering useful inputs. The outcomes highlight the importance of combining human experience with data-driven deep learning for stock prediction.

In summary, this study investigates how to improve deep neural networks for financial time series forecasting by incorporating technical analysis. An innovative hybrid approach to stock price modelling is provided by the blending of conventional and contemporary techniques. The promising findings call for more investigation to clarify how expert-based indicators might support data-driven algorithms.

II. RELATED WORK

a. Short-term stock market price trend prediction using a comprehensive deep learning system.

A comprehensive approach for forecasting short-term stock market price trends using deep learning techniques is presented in the work titled "Short-term Stock Market Price Trend Prediction Using a Comprehensive Deep Learning System". The pre-processing of the stock market dataset, the use of various feature engineering approaches, and a bespoke deep learning-based system for stock market price trend prediction are all part of the suggested solution. The authors carried out thorough analyses of popular machine learning models and came to the conclusion that their suggested approach performs better than other models as a result of the thorough feature engineering they applied.

The research illustrates the difficulties in predicting stock market price trends, such as those caused by a weak form of market efficiency and a lot of noise in financial time series data. Building a cutting-edge prediction model with an emphasis on short-term price trend prediction is the authors' goal.

It's significant to note that there are further publications and studies on the topic of predicting short-term stock price trends using deep learning. For instance, the application of a meta-learning framework with convolutional neural networks for short-term stock price prediction is covered in the study "Short-Term Stock Price-Trend Prediction Using Meta-Learning" 4. Another study examines the use of a deep convolutional generative adversarial network for stock price forecasting under the title "Stock Price Forecasting by a Deep Convolutional Generative Adversarial Network."

b. Research of Stock Price Prediction Based on PCA-LSTM Model

By fusing Long Short-Term Memory (LSTM) networks and Principal Component Analysis (PCA), this research proposes a revolutionary method for stock price prediction. Here is a quick summary of the major ideas.

1. the PCA-LSTM Model: The authors suggest a hybrid model that combines two crucial methods: LSTM for sequence modelling and PCA for feature extraction. PCA is used to effectively capture the most important information while decreasing noise and redundancy, hence reducing the dimensionality of the stock price data. An LSTM network is then fed with the data that has been decreased in dimension for prediction.

2. Using the Principal Component Analysis (PCA) method: A dimensionality reduction method called PCA converts high-dimensional data into a lower-dimensional space while preserving as much variance as is feasible from the original data. In the In the context of this paper, PCA is used to extract the most relevant characteristics or components from the stock price data.

Recurrent neural networks (RNNs) of the LSTM network type are used to simulate sequences and time-dependent patterns. The temporal dependencies and patterns seen in the PCA-transformed stock price data are learned in this study using LSTM. The PCA and LSTM combination is anticipated to better capture the underlying patterns in the stock price data, thereby improving prediction performance. The model might become more resistant to noise and overfitting by dimensionality reduction with PCA.

c. LSTM based stock prediction using weighted and categorized financial news

This paper introduces a novel method for stock forecasting that makes use of Long Short-Term Memory (LSTM) networks and integrates a variety of data sources, such as stock prices, technical indicators, and news sentiment scores. Here is a quick summary of the major ideas:

First, Multidimensional Data Integration. The authors put out a thorough methodology that transcends standard stock price and technical indicator analysis. They take into account sentiment scores that are taken from financial news, which can offer more details on market sentiment and trends

.

Second, LSTM networks are used. They are utilized in this context to model the historical correlations between stock prices, technical indicators, and news sentiment ratings.

Third, the suggested model is unusual since it incorporates the mood of financial news. Notably, the authors classify and weight the news mood ratings, implying that various news categories (such as earnings reports and market trends) may have variable degrees of influence on changes in stock prices.

Fourth, the research emphasizes the importance of their LSTM-based stock prediction model, highlighting its capacity to include numerous data sources and capture intricate relationships between them. The performance of the model is likely illustrated by empirical evaluations that highlight its prediction powers.

It is particularly intriguing to incorporate sentiment ratings from financial news since it supports the notion that market mood and news events can have a significant impact on stock prices. When paired with additional data sources, this method may produce forecasts that are more precise and detailed.

III. METHODOLOGY

Given the market's volatility, it might be difficult to make accurate predictions about the stock market. It is proposed that a machine learning or deep learning model may be able to learn from the characteristics of previous daily stock chart movement patterns, and that these learnt characteristics may then be successfully used to predict price points. For the purposes of the current argument, we gave the deep learning models a forecast horizon of two years and showed that these models can reasonably accurately anticipate future stock values. To increase the accuracy of our forecasting models, we employ a method for creating long and short-term memory (LSTM) network-based models. It must be noted that in this work, we are not addressing the issues of short-term forecasting which of interest to the intra-day traders. Instead, the propositions in this paper are relevant for medium-term investors who might be interested in a forecast of the share values.

This study involves use of two years' worth of NIFTY 50 index historical daily price data, from July 23, 2021, to July 24, 2023. The 50 major Indian firms listed on the National Stock Exchange constitutes the NIFTY 50, a market capitalization-weighted stock market index. It is regarded as a reliable gauge of market performance and investor sentiment in India because it represents the weighted average of 50 blue-chip stocks in India. The 496 trading days of the data under examination span a wide range of market situations. An initial bull market uptrend through 2021 is followed by a correction phase starting in December 2021 with more volatility brought on by events including rising interest rates, wars, and currency problems in emerging markets. The NIFTY 50 index's daily open, high, low, and closing prices make up the raw data. The price data is used to create technical indicators such as moving averages, relative strength indices, and support-resistance levels. The closing price is the primary variable to be predicted. The most recent two years serve as a useful real-world case study for creating and assessing predictive models. For thorough model testing and validation, the out-of-sample data demonstrates enough complexity from several market regimes. All things considered, the NIFTY dataset provides a suitable testing ground for undertaking empirical research in financial forecasting and price prediction.

The yfinance Python package is used to get the NIFTY 50 index's historical daily price data. The package allows utilizing Yahoo Finance's API to retrieve market data. The ^NSEI ticker symbol and the necessary start and end dates are passed to the yfinance.download() method for obtaining the NIFTY 50 data. The Open, High, Low, Close, and Volume columns for each trading day are returned in a pandas dataframe. To import clear, accurate historical pricing data for analysis and modelling, use the yfinance library. Yahoo Finance's NIFTY data is a good source for academic research. To facilitate seamless data preparation and modification upon import, yfinance is used as part of the overall Pandas data analysis workflow.

Important price levels known as support and resistance levels are where downtrends or uptrends are more likely to stall, reverse, or encounter resistance when market psychology changes. Resistance levels signify possible supply while support levels signify potential demand. The following are the technical steps to extract support and resistance:

- Each row in the OHLC dataframe is iterated over.
- Examine if the current low and the prior close are above the previous low to identify potential support.
- Examine if the current high is higher than the prior high AND the previous close is higher to spot potential resistance.
- List any identified price levels of support and resistance separately.
- Through filtering, delete duplicate and significantly nearby levels.

The significant support and resistance levels from the price history are produced by this approach. The levels are saved for use in the deep-learning model as indicators. This illustrates how useful features may be extracted from the raw price data for stock prediction using domain knowledge of market dynamics. By examining previous peaks and troughs, these levels are found in the NIFTY 50 OHLC (Open, High, Low, Close) dataframe. The fundamental idea is that prior low prices may operate as support during drops and opposition during gains[3][(Pring, 2014).

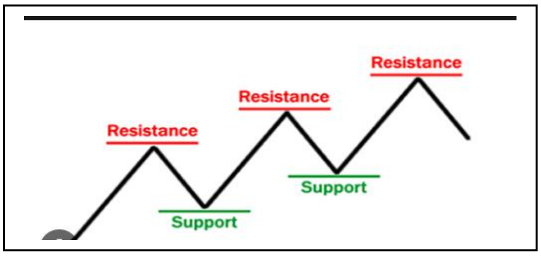

Fig 1. Example of Support and Resistance

A type of financial chart called a **candlestick cha**rt is used to illustrate how an asset's price changes over time. Candlesticks combine the open, high, low, and close values into a single candle-like shape, giving more information than standard line or bar charts. "Real body" refers to the broad portion of the candlestick that shows the range of prices between the open and close. The peak and low points during the time period are shown by the thin "wicks" above and below the actual body. Candlestick charts typically use colour coding to show one-day intervals; a green (or white) real body denotes a close that was higher than the open, while a red (or black) real body suggests a lower close. These patterns are combined with support/resistance levels, trends, and other technical indicators to determine trade signals and probable future movements.

The relationships between open, high, low, and close can reveal insights into market psychology and momentum[4] (Jamaloodeen, 2018). Examples of these formations are "doji," "hammer," and "shooting star." Candlestick signals are included in this study's machine learning models together with other technical indicators. Candlesticks provide important insights into market movement and trader behaviour that are not available in stand-alone OHLC pricing. Forecasting future market turning points is made easier with the use of candlestick analysis insights. To sum up, candlestick charts make it easier to see patterns in price data that can be used for financial forecasting and analysis.

Fig 2. Candlesticks patterns with their respective signals

The OHLC data was subjected to candlestick pattern extraction using the Python TA-Lib module, which offers an extensive array of technical analysis indicators. Ten main candlestick patterns were specifically identified, including the engulfing pattern, dark cloud cover, piercing, morning star, evening star,hammer,doji,and harami. Each pattern's existence or absence for a specific day was represented by binary indicator columns created by applying the TA-Lib candlestick detection function. When the value of the candlestick pattern is 100, it means the bullish version was found, and when it is -100, the bearish version was found. The number was 0 for days when no candlestick pattern could be identified. In doing so, the patterns are transformed into concrete characteristics that may be fed into machine learning models. By summing the values, the ten candlestick indicator columns were combined into a single column called "merged" in order to eliminate redundancy.

The encoded pattern information is stored in this combined column, creating a more summarized representation. The resulting candlestick indicators, in addition to variables like prices and volumes, capture important momentum signals and market psychology. The goal of using candlestick patterns with other technical indicators is to enhance stock forecasting's accuracy.

A momentum oscillator called the **Relative Strength Index** (RSI) gauges the rate and speed of price changes to determine[5] (Ţăran-Moroşan, (2011)) when the market is overbought or oversold.It was developed by J. Welles Wilder Jr., and it's now a popular technical indicator for valuing financial assets. The ratio of average gains to average losses over a specific lookback window is used to compute the RSI.

Here's the formula to calculate RSI:

RSI = 100 - (100 / (1 + RS))

Where RS is the relative strength, given by:

RS = Average Gain / Average Loss

The sum of the average gain and average loss during the designated lookback period—usually 14 days or periods—is used. A value above 70 denotes an overbought asset, while a value below 30 indicates an oversold situation. The RSI value is a numerical measure that spans from 0 to 100.The RSI indicator used in this study is derived from closing prices over a typical 14-day period. It offers a normalized momentum signal to improve the stock forecasting capabilities of LSTM models. By validating price trend directions and extremes, RSI in conjunction with price and other technical elements seeks to enhance forecasting skills.

A moving average is a popular technical analysis indicator that averages prices over a given period of time and creates a continuously updated average price to smooth out price data. In particular, the average closing price over the last 100 days—including today—is determined by the 100-period moving average. The 100-day moving average shows the general trend and serves as a level of support and resistance. A downtrend is indicated by trading below the moving average line, and an upward trend is suggested by prices that are continuously above the line. Price crossovers above or below the moving average could be signs of a trend reversal The 100-day simple moving average is calculated for this study using the Nifty 50 index closing prices. In order to complement the raw price data input into the LSTM models, it offers a smoothed trend estimation. By using this popular trend-following indicator, the aim is to enhance prediction abilities.

The mathematical formula for a simple moving average is:

MA = (P1 + P2 + ... + Pn) / n

Where:

MA stands for moving average.

The close prices for the previous n periods (days in this case) are P1...Pn.

n is the number of time intervals (moving average of 100 days = 100).

Thus, the computation for a 100-day simple moving average would be as follows:

MA100 = (P1 + P2 + ... + P100) / 100

Let P1 be the closing price one hundred days ago, P2 be the closing price ninety-nine days ago, and so on until P100, the final closing price. The average is referred to be "simple" since every close price is given the same weight during computation. While simple moving averages are most frequently used for trend analysis, exponential and other weighted moving averages can also be used.

Technical analysts use Fibonacci extensions, which are based on the important Fibonacci ratios of 23.6%, 38.2%, 50%, 61.8%, and 100%. These ratios, which are frequently utilized to determine possible levels of support, resistance, and target, are derived from the Fibonacci sequence. In particular, Fibonacci extensions aid in estimating potential price ranges for assets that have experienced significant increases or decreases. Fibonacci retracement levels are drawn between a swing low and swing high, and the lines are then extended to provide potential levels for a price reverse or extension. Horizontal lines are used to indicate potential reversal points for uptrends at the Fibonacci extension levels of 161.8% and 261.8%. Extension lines are created at -61.8% and -161.8% for downtrends to show possible price support zones.

Fibonacci extension levels between notable swing highs and lows in the Nifty 50 price data are computed in this study. These extension indicators, when combined with other technical considerations, pinpoint potential future areas of continuations and reversal. In the study, only the levels 0%,50%,61.3% and 100% are used as these levels are the key levels with most volatility. The goal of adding Fibonacci extension levels as extra input variables is to enhance the LSTM models' capacity for stock forecasting. Based on past trends, the major Fibonacci ratios provide quantitative forecasts of probable price turning moments.

Fig 3. Fibonacci extension with most significant zones marked

Stock price prediction often rely on time series forecasting techniques. The Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) networks were the two primary algorithmic categories taken into consideration for modelling the sequential price data. Initial findings indicates that although ARIMA has proven effective in univariate time series forecasting, it might not accurately reflect the fundamental complexities and non-linearities of financial data. In contrast, because of its neural network architecture, LSTM is able to learn non-linear correlations. The objective of utilizing predictive signals from past pricing is also well-aligned with the capacity of Long Short-Term Memory Retrieval (LSTM) to maintain long-term temporal dependencies. The statistical technique known as ARIMA models the dynamics of time series using autoregression, moving averages, and seasonal differentiation. A specific type of recurrent neural network architecture called LSTM was created for sequence modelling applications.

Thus, following preliminary investigation of the ARIMA and LSTM models,[6] LSTM was chosen as the main forecasting method for this study. It was determined that the long-term memory, noise robustness, and nonlinear pattern processing capabilities of LSTM were beneficial for the stock price prediction challenge. Large-scale tests and comparative benchmarks confirmed LSTM's better performance over other machine learning models and statistical methods. In conclusion, the preliminary stage of model scouting revealed that LSTM was a more suitable option than ARIMA for constructing a precise predictive model for financial time series forecasting in this investigation. This choice was rigorously evaluated using stock market datasets to obtain empirical validation.

The trend of close price with its seasonality and resid depicts that ARIMA is not fully capable to predict price in harmony with real prices. The seasonality values shows that the data is exhibiting a slightly stronger cyclic behaviour. The constant residual value shows that either the model is underfitting or overfitting or it is too noisy to the algorithm to correctly make predictions.

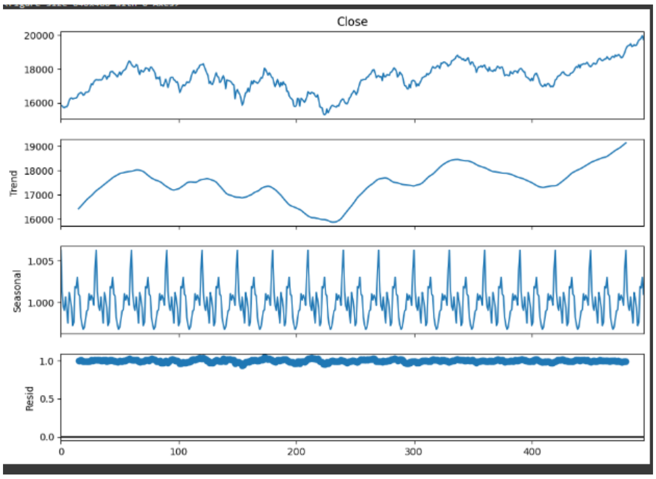

Fig 4. Trend, Seasonality and Resid graphs of close price

LSTM is a unique type of RNN that was first presented by Hochreiter and Schmidhuber in 1997. LSTM cells are used in place of the typical hidden layers in LSTM design[7]. The cells are made up of different gates that regulate the flow of input. The input gate, cell state, forget gate, and output gate make up an LSTM cell. It also includes a point-wise multiplication operation layer. The different gates and what they do are listed below.

- Input gate: The input is contained in the input gate.
- Cell State: This one runs all the way across the network and uses gates to add or remove data.
- Forget gate layer: Selects the percentage of data that can be passed through.
- Output gate : It consists of the output generated by the LSTM

Making samples with observations from earlier time steps—also referred to as lags or backcandles—as input characteristics is a crucial part of the data preprocessing procedure for time series forecasting. The model can now learn from historical context because of this. The ideal lookback period was determined through experimental evaluation of various backcandle window sizes. Greater historical detail is available with larger windows, but training may take longer and require more memory. It was discovered that 50 previous daily closing provide decent performance during iteration without becoming computationally prohibitive. The Nifty 50 dataset was iterated over using a sliding window of size 50 across the 14 technical indicator columns in order to create the input samples. These historical price-derived indicators, such moving averages and RSI, are used as model inputs.

Furthermore, the closing price of the subsequent day was recorded in a different column called "Target_Next_Close" for forecasting purposes. The ground truth labels for model assessment and training are stored in this column. Samples of 50 previous days' worth of indicators mapped to the closing price objective for the 51st day were generated by the sliding window. Contiguous train and test sets were created from the data in order to maintain time-based dependency. This guarantees that the model is evaluated on future, unseen data and is solely trained on historical data.

To summarize, the sequential data was transformed using feature engineering techniques to create backcandle input samples that had forward-looking targets for the LSTM predictor. Effective temporal modelling is made possible by carefully arranging time series data.

When employing machine learning techniques, it is frequently required to perform data normalization or feature scaling to make sure the inputs are on a consistent scale and suitable for modelling. Using the minimum and maximum values as a guide, min-max scaling is a straightforward normalization technique that rescales each feature to a specified range between 0 and 1.

Using the following formula, min-max scaling changes the data:

X_scaled. = (X - X_min) / (X_max - X_min)

Where,

X_min and X_max are the minimum and maximum values of X, where X is the original data. The whole value range is mapped proportionately between 0 and 1 using this normalization[8]. In this study, the features and labels in the dataset were subjected to Min-Max scaling using scikit-learn.

Layer (type)	Output Shape	Param #
lstm_input (InputLayer)	[(None, 30, 14)]	0
first_layer (LSTM)	(None, 150)	99000
dense_layer (Dense)	(None, 1)	151
output (Activation)	(None, 1)	0

Total params: 99,151
Trainable params: 99,151
Non-trainable params: 0

Fig 5. Architecture of LSTM

Using the prepared dataset, the LSTM model was trained for 100 epochs with a batch size of 15. To keep a close watch on overfitting and model convergence, the validation set performance was assessed following each training cycle. During training, the following assessment metrics were monitored:

- Mean Squared Error, or MSE
- Root Mean Squared Error, or RMSE
- Mean Absolute Error, or MAE

The difference between the actual true values and the anticipated closing prices is indicated by these measurements. Lower values indicate improved model performance. As training proceeds on, it is evident that the error measurements show a decreasing trend, suggesting that the LSTM model is picking up the sequential correlations.

Eventually, the validation loss stabilizes and there is no apparent overfitting. On a normalized scale, the average variation between the actual and predicted closing prices is approximately 0.1%, according to the validation set's final **RMSE of 4.7174e-04**. These monitoring indicators aid in evaluating the capabilities of the model and training behaviour.

IV. RESULTS

The effectiveness of different technical indicators was examined in the predictive modelling trials, both separately and in combination. Moving averages, RSI, candlestick patterns, Fibonacci retracements, and support/resistance levels were among the indicators that were looked at.
The results are described below (note that the close price is used in conjugation with all of the other factors)

1. Only using Support and resistance levels

The validation error was stabilised around 1.0158^e-4 to 1.73^e-4. The mean absolute error was 0.0124.
Below are the graphs for prediction vs actual results.

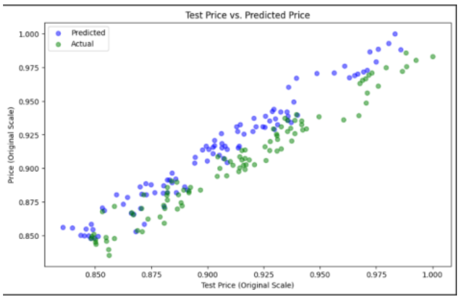

Fig 6. Scatter plot

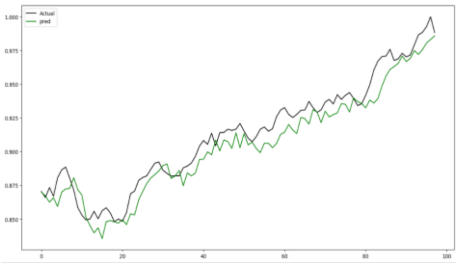

Fig 7. Line chart

The plots demonstrates that, after a particular amount of time, there is a considerable difference between the actual and projected values. This indicates that it is not possible to anticipate future price values using just the support and resistance levels.

2. Only using Candlestick

The validation loss fluctuated from 1.71^e-04 to 2.71^e-04.
Also, the mean absolute error was precisely around 0.0120 meaning it showed some changes in prediction values but not a very positive change as the scatter plot shows a significant deviation between the Actual and Predicted values thereby depicting either of the two things:

1. Only the candlesticks are not adequate to predict the future values
2. Instead of using 10 major candlesticks, all the patterns must be used.

Below are the graphs for prediction vs actual results

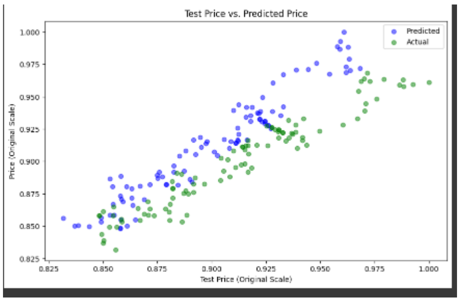

Fig 8. Scatter plot

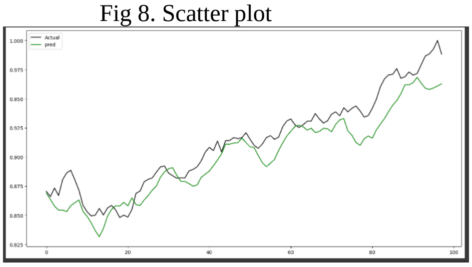

Fig 9. Line chart

3. Only Using Relative Strength Index (RSI)

Using RSI shows some positive improvement in the model meaning RSI is a useful technical indicator. The validation error was although stabilised around 2.09^e-04,but spiked to 9.04^e04 in some epochs. The mean absolute error was 0.0076.
Below are the graphs for prediction vs actual results

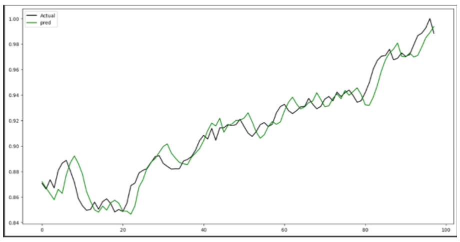

Fig 10. Line chart

This chart depicts that the predicted value is more in harmony with the actual price. This illustrated that RSI can be used in future training models in conjugation wit other factors in price prediction.
On the other hand, the scatter plot shows that the predicted values are more aligned to the regression line, not dispersed around. This means that the model is learning to predict the values in a precise manner with RSI.

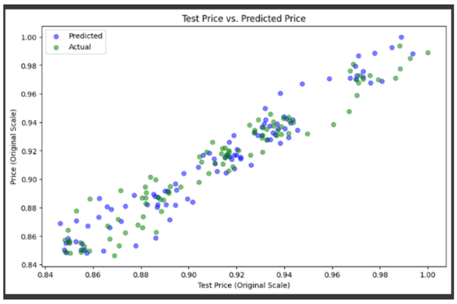

Fig 11. Scatter Plot

4. Only using EMA (Exponential Moving Average)

Better upper band values (in terms of loss) were shown by the validation loss. 1.01^e–4 to 4.81^e–4 was the range. This indicates accurate learning by the model. The range of the mean absolute error was 0.018 to 0.0072.
This signifies that EMAs are also useful in prediction of future prices and can be used alongside RSI for better results. Below are the graphs for prediction vs actual results.

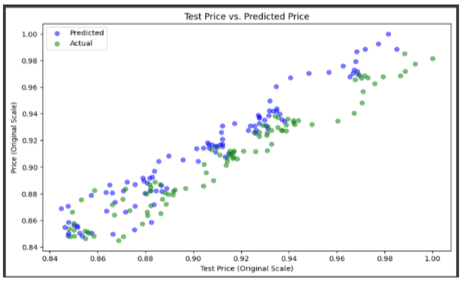

Fig 12. Scatter Plot

Both of these graphs depict that the moving average can be beneficial if used either alongside with other indicators or with other period moving averages.

For instance, Golden or death cross strategy is implied by using two moving averages which are 50 period and 200 periods. The model might learn from their crossover points generating either bullish or bearish signals.[9] (Tsai, (2017))

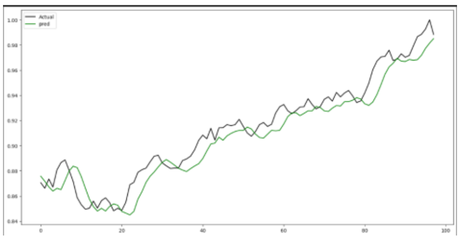

Fig 13. Line Chart

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5. Only Using Fibonacci Levels

The validation loss depicted a significant downfall from to 1.01^e-04 meaning adding Fibonacci levels is not very beneficial for price prediction. However, it illustrated some results which were worth mentioning. Below are the graphs for actual vs predicted

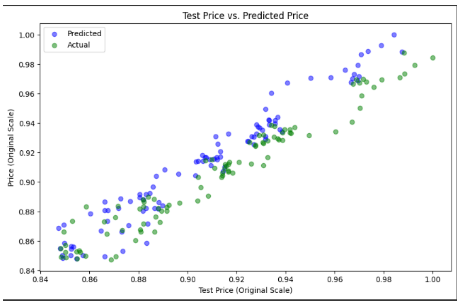


Fig 14. Scatter plot

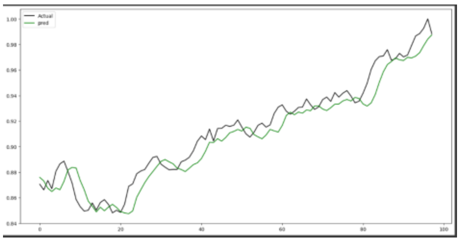
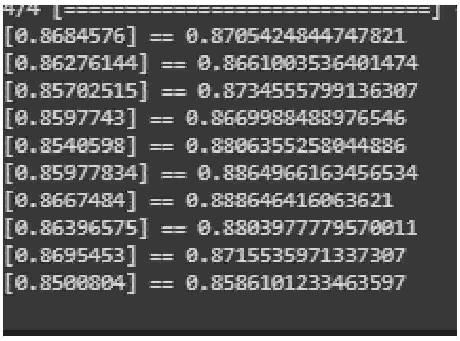


Fig 15. Line chart

The predicted values show a positive correlation with actual values at some points, which means if the values are in between 50% and 61.8%, also known as golden zone, it can show some actionable insights. [10]

6. Using All the indicators and levels combined (S/R levels, candlesticks, EMA, RSI and Fibonacci)

Eventually, it is reasonable to conclude that the combination of all the components produced the best outcomes, as shown by the graphs and the actual and predicted numbers that are linked below. The final epoch values are
-loss: 2.1708e-04
- mean_absolute_error: 0.0118
- val_loss: 1.1799e-04
- val_mean_absolute_error: 0.0086



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4/4 [==============================]
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[0.85977834] == 0.8864966163456534
[0.8667484] == 0.888646416063621
[0.86396575] == 0.8803977779570011
[0.8695453] == 0.8715535971337307
[0.8500804] == 0.8586101233463597
```

Fig 16. Predicted vs Actual values

Below are the graphs for Predicted vs Actual

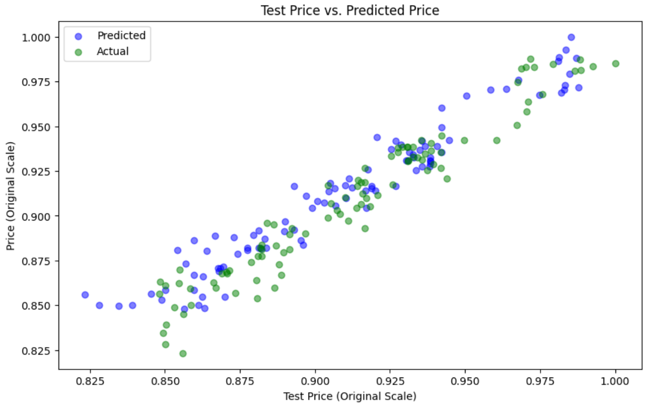

Fig 17. Scatter plot

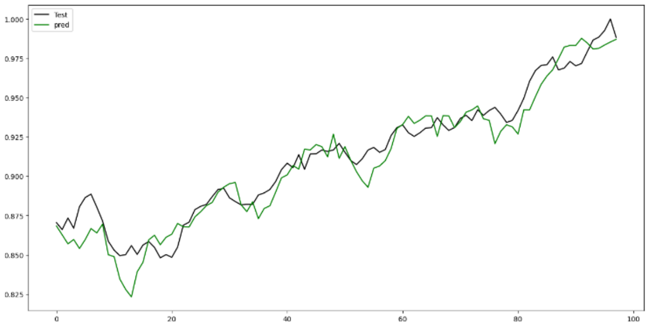

Fig 18. Line chart

The line graph shows that, when compared to other values, the predicted values are the closest to the actual values; this indicates that the model learned best when all of the factors were employed together

The scatter plot indicates that the majority of values are close to the regression line, indicating that the most of predicted values are precisely close to the actual values.

V. Discussion and Conclusion

The work's trials and findings show how useful it is to use technical indicators and analysis methods in conjunction with stock price predictions. The main conclusions indicate that baseline models that used only raw price data were surpassed by the LSTM model that included features like RSI, moving averages, candlestick patterns, and Fibonacci levels. Moreover, this study demonstrated the importance of using historical price data to determine support and resistance levels as LSTM prediction model inputs. Significant informational signals were given by the resistance and support indicators, which increased predicting accuracy. The fundamental economic dynamics of supply and demand in financial markets are the source of the concepts of support and resistance. Potential demand zones, or support levels, are places where it is anticipated that there will be sufficient buying interest to keep the price from falling. Levels of resistance signal locations where supply or selling pressure is expected to be present and could block an upward price advance. Support and resistance markers offer insight into future movements by indicating areas where there may be large activity pushing or supporting the price. The links between attaining support or resistance and ensuing price rebounds, breaks, or consolidations can be inferred implicitly by the LSTM model.

It's interesting to note that the results indicate that while no one indicator provides a complete picture, combining support/resistance with complimentary momentum and trend factors proved most helpful. This emphasizes how crucial it is to combine several viewpoints when making predictions. For the stock prediction test, the hybrid model that blended data-driven deep learning with traditional domain expertise through hand-engineered indicators worked best. This is in accordance with the theory that increases forecast accuracy by feeding the LSTM network informative attributes that are gained from pricing data using human expertise. The indicators that exhibited the most significant improvements in model performance were the trend-following moving averages and the momentum factor RSI. Trading psychology-encapsulated candlestick indicators were also helpful. Although they had less of an impact, the Fibonacci extension levels were still beneficial in some market environments.

The outcomes confirm that human-based analytical methods can effectively extract valuable prediction signals in addition to machine learning algorithms. For reliable forecasting, the fusion technique combines the qualitative insights of technical analysis with the quantitative rigor of machine learning.

In conclusion, this research presented a novel and intriguing hybrid intelligence paradigm for stock prediction that combines the best aspects of deep learning with technical analysis. The fusion method organizes and gets ready data for AI modelling by utilizing human insights. Building on these findings, more investigation can clarify the ways in which human judgment and artificial intelligence complement each other in financial forecasting.

VI. Future Works

While this study showed positive outcomes when utilizing technical indicators for predicting stock prices, sentiment analysis of financial news and events could have been included to further improve forecasts. Textual sources such as news articles, company reports, and social media discussions can yield sentiment that is indicative of market moves. To extract sentiment scores from unstructured text data, natural language processing techniques like semantic analysis and transformers like FinBERT can be used.

Particular future projects might include: collecting textual data from relevant social media platforms, earnings calls, and financial news websites to build a corpus of texts for the selected companies. FinBERT, pretrained on financial literature, is fine-tuned to identify if gathered texts have a positive, negative, or neutral sentiment polarity,extending the LSTM forecasting model with additional time-series characteristics, namely the sentiment indices from FinBERT. determining whether adding sentiment modelling to technical elements enhances ROI measures and prediction accuracy. Analysing interpretability will help you find connections between price changes, emotion movements, and news events. To sum up, sentiment research presents a viable avenue to supplement technical indications with qualitative information about variables influencing markets. Specialized NLP techniques can be used to extract new prediction signals from textual data sources.

Moreover, predicting accuracy and generalization may be increased with additional hyperparameter adjustment and improvements. Certain domains of upcoming research encompass:

Carrying out more thorough hyperparameter optimization for the training parameters and LSTM architecture. When compared to hand tuning, methods such as random search and Bayesian optimization can be used to systematically choose better hyperparameter values. To boost modelling capacity, deeper LSTM models with more layers and neurons can be experimented with. Performance can be improved by using validation to determine the ideal network size.

Including more technical indicators that supplement the existing feature set, such as momentum oscillators and price action patterns. Grouping candlestick pairs or triplets to more effectively illustrate the connections between successive patterns. Predictions can be strengthened by the relationships among candle combinations.

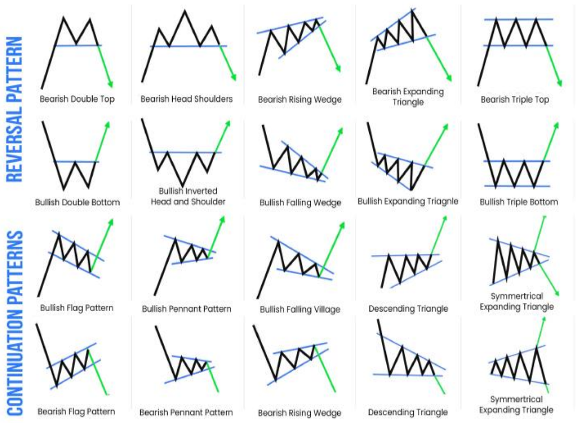

Fig 19. Various Price action patterns

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MSc Project - Reflective Essay

Project Title:	Stock Price Prediction using LSTM
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Supervisor Name:	Dr. Paulo Rauber
Programme of Study:	MSc. Big Data Science

Predicting stock prices is an essential task for traders and investors in the financial industry. Long Short-Term Memory (LSTM) has become a potent tool for time series forecasting, including stock price prediction, with the development of deep learning techniques. Long-term dependencies in sequential data can be efficiently captured by recurrent neural networks (RNNs), such as LSTM. Because it can simulate temporal relationships, it has been widely employed in a variety of applications, including speech recognition and natural language processing. When it comes to stock price prediction, LSTM can anticipate future prices by using information from past stock prices as well as other pertinent variables like trade volume and news mood. By examining patterns and trends in the data, LSTM can offer insightful information that helps investors make wise choices. It's crucial to remember that there are several difficulties with LSTM stock price prediction. It is challenging to provide reliable predictions about future prices in the financial market due to its extreme volatility and wide range of influences.

<u>Analysis of strengths and weakness</u>

The capacity of LSTM to identify long-term dependencies in time series data is one advantage I see in utilizing it to predict stock prices. I can spot trends and forecast future movements based on prior performance by examining historical price patterns and technical indicators like moving averages and relative strength index (RSI),

The ability of LSTM models to manage non-linear connections between input characteristics and output predictions is another benefit that cannot be ignored. Because of its adaptability, I am able to keep track of intricate relationships between many technical indicators, which gives me a more thorough grasp of the dynamics of the market.

However, there are some drawbacks of utilizing LSTM for stock price prediction. First off, a lot of my training comes from historical data. If the market experiences sudden changes or extraordinary occurrences that deviate from historical trends, it was difficult for the model to adapt swiftly.

Furthermore, when trained on little datasets, the model tends to overfit. If I get too focused on forecasting certain past patterns instead of identifying more general market trends, the model becomes less accurate in predicting unseen data

In summary, even if there is encouraging potential for stock price prediction through the use of price level analysis and technical indicators, it cannot be done without restrictions. It is vital that professionals and take these advantages and disadvantages into account before applying it to the financial industry.

Critical analysis between theory and practical

This study investigated a theory-driven stock forecasting model that combines LSTM networks and technical indicators. Nevertheless, there existed both connections and differences between theoretic ideas and actual findings when they were put into practice.

Positively, the study verified the hypothesis that technical indicators could improve LSTM prediction accuracy. Utilizing moving averages and RSI as model inputs produced valuable information. In theory, they measure the dynamics of the market; in practice, they enhance forecasts. However, certain signs turned out to be more helpful than others. Candlestick patterns, for example, did not increase accuracy to the extent that behavioural finance theory predicted. Theory and reality are not always exactly in sync, as seen by the gap. Furthermore, no single indicator proved enough, confirming the complex and multidimensional drivers of markets. It's interesting to note that LSTM's data-driven capabilities enhanced the theory-based indicators. The non-linear deep learning algorithm was able to identify subtleties in the correlations between prices and indicators that a human analyst would probably be unable to. This illustrates the fruitful interplay between AI and human skills. The temporal data was not easily formatted for LSTM consumption. The application of deep learning theory's best practices to finance was not always straightforward. Extensive data engineering was needed via experimentation. Finally, a few of the modelling simplification assumptions were identified. Markets should have several stochastic variables, according to theory, but it is not practical to represent every possibility. Despite theoretical limits, focused, limited models offer their advantages.

Furthermore, a variety of factors other than just technical indicators affect stock prices. In addition to fundamental analysis, news developments, geopolitical variables, and investor sentiment are all significant influences on stock prices. The predictive ability of LSTM models may be reduced if these parameters are ignored. In summary, although theory directed the study, practical application uncovered significant differences and improvements. The hybrid stock forecasting model underwent innovative enhancements as a result of the interaction between ideas and actual data. Theory and practice insights can be incorporated into further iterations to further advance understanding.

FUTURE WORKS

The potential application of technical indicators and price levels in LSTM stock price prediction intrigues me. There are, in my opinion, a few areas that still need work and investigation.

1. Incorporating more technical indicators: Further investigation into the extension and integration of a wide range of technical indicators is clearly needed. This approach should strengthen the model's capacity for forecasting, making it more accurate in predicting price swings and able to capture complex market dynamics. It is a promising idea for future research to incorporate a larger range of technical indicators into the LSTM-based stock price prediction model. It also fits with the effort to create a prediction model that is more thorough, accurate, flexible, and able to handle the complexity of financial markets. The model's predictive ability can be increased by rigorous research, feature engineering, and validation; this would be a major step toward more informed decision-making in the field of stock trading and investing.

2. Price Action Patterns: My goal is to incorporate a larger variety of price action patterns into the LSTM model throughout the next stage of development. Flags, triangles, and head-and-shoulders formations are examples of patterns that can

be recognized and incorporated into the model to help it grasp market trends and possible price movements more deeply.

3. Sentiment Analysis: I intend to incorporate sentiment analysis into the prediction framework since it is an undeniable fact that how important market sentiment is in impacting changes in stock prices. I propose to extract emotion cues from financial news stories, social media posts, and other relevant materials by utilizing natural language processing techniques. The contextual insights this feature will offer will be very helpful in assisting the model in producing more accurate predictions.

4. Hyperparameter Tuning: I intend to put quite a bit of effort into hyperparameter tuning to ensure the best possible model performance. This entails methodically varying variables like learning rates, batch sizes, and network topologies to find the configuration that produces the highest level of prediction accuracy. In order to improve the model's capacity to generalize across various market situations, this iterative procedure will be essential.

5. Real-Time Adaptation: This is an area I plan to research solutions for the LSTM model's real-time adaptation because financial markets are dynamic and prone to sudden changes. This could entail adding features that let the model swiftly adapt to unforeseen circumstances or abrupt changes in the market, strengthening its applicability and robustness.

I'm interested to see where LSTM stock price prediction goes in the future. This is a fascinating field of study that has the potential to have a big influence on the financial industry.

Awareness of Legal, Social Ethical Issues and Sustainability

The awareness of legal, social ethical issues, and sustainability is crucial when it comes to stock price prediction using LSTM (Long Short-Term Memory) models. It is crucial to take into account the potential consequences and effects of these technologies as the financial sector depends more and more on artificial intelligence and machine learning algorithms.

In legal terms, the application of AI in financial markets is governed by a number of laws. Ensuring equitable practices and preventing market manipulation necessitates adherence to rules like the Securities Exchange Act and anti-fraud measures. Additionally, while gathering and examining sensitive financial data, compliance with data privacy rules is required. For instance, using insider information to impact trading decisions is prohibited in the United States. This implies that stock price predictions based on information that is not yet known to the public cannot be made using LSTM.

Issues of social ethics also arise when stock price prediction is done with LSTM. Artificial intelligence (AI) has the potential to increase already-existing disparities in knowledge or resource access, giving some market participants unfair advantages. Ensuring equitable opportunities for all investors and promoting transparency and accountability are crucial ways to resolve these concerns.

Furthermore, when creating and using LSTM models, sustainability should be taken into account. The practice of sustainable investment has been more popular in recent years due to investors' growing emphasis on environmental, social, and governance (ESG) considerations. ESG data can be incorporated into LSTM models to support sustainable investment objectives and offer more thorough insights into stock performance. LSTM model deployment and training can require large energy consumption, which could contribute to climate change. There's also a chance that LSTM will be utilized to make unfavourable decisions for the environment, including investing in businesses that cause pollution or deforestation.

Finally, it should be noted that employing LSTM models for stock price prediction necessitates careful consideration of social ethical issues, regulatory restrictions, and sustainability concerns. Through responsible and ethical handling of these factors, we can guarantee that AI technology enhances financial markets while reducing potential dangers or adverse effects on society as a whole.