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STOCK PRICE PREDICTION USING DEEP LEARNING TECHNIQUES

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ABSTRACT

There are two commonly held beliefs when it comes to picking stocks. Fundamental analysis is the initial step in making an investment decision, while technical analysis is the process used in making that decision. Investing involves using two separate analytical tools: fundamental analysis and technical analysis. Fundamental analysis and technical analysis can both tell whether an investment in a company is appealing or unattractive, and then go on to speculate on what the future trends of stocks will be. The combination of fundamental and technical research may provide a complete trading strategy. Artificial recurrent neural network (RNN) architecture, long short-term memory (LSTM) networks. The large-sequence-processing capabilities of LSTMs apply to many data sets. The vast quantity of data that is produced every day in the stock market is ideal for use in artificial intelligence applications. We want to use LSTM to build a financial market forecasting network that uses Technical and Fundamental analysis of businesses to predict the stock prices the next day. To do both kinds of analysis, the input data is pre-processed to contain necessary variables and then trained on LSTM& GRU. In this work we proposed Clustered Gradient Descent Adam optimizer usually perform better than models with Adam optimizer. The GRU model beats the LSTM model when it comes to overall accuracy.

Keywords: *Long Short-Term Memory (LSTM) networks, Deep Learning, Fundamental Analysis, Technical Analysis, Financial Markets.*

1 INTRODUCTION

Today's trading started with the trade of shares in the East India Company in London in the mid-1600s. In a public market, shares may be bought and sold, traded on a stock exchange, or privately transferred in the form of an over the counter (OTC) transaction. Equities are known as stocks. Fractional stock ownership of a business represents ownership interests in the company. A stock market is a marketplace where investors may purchase and sell these ownership interests. Without an efficient stock market, businesses are unable to obtain money rapidly from the public, limiting their potential to grow. On most markets, such as the Bombay Stock Exchange (BSE) or the NASDAQ, shares are exchanged. A stock exchange is an important component of the stock market and provides a platform for people to purchase and sell equities. To ensure investors are protected from financial fraud, government authorities supervise stock exchanges, keeping the exchange market running efficiently [8]. The primary goal of the stock market is to act as a source of cash for growing businesses. Investing in publicly listed businesses is a secondary goal since it gives the public and affluent investors a chance to benefit from the earnings of the company. The stock market serves as the primary driving force behind this endeavor. The history of the stock market shows that it has been a rewarding place for investors to put their money, but it has also been a place of adversity. An investor may get gains solely by chance in the stock market, therefore they must do rigorous study into every element of the investment before putting money into it[1]. Before investing, the investor will do fundamental and technical research of the business. Investing in the stock market is now the most profitable investment choice. The return is consistently high, which reflects the success of their strategy. However, high rates of return also come with the potential for significant losses. When it comes to stocks, historical returns exceed most other investment options. Based on Vanguard's analysis, the historical average return for stocks over the last twenty-six years has been 10.3%. Bonds pay an average of 5.4% while the stock market return over the same time was only 5[2]. Stocks are a good way to increase the money over the long run. Investing in dividends and share repurchases is an excellent strategy to use, because this also boosts the total return on investment. On the whole, investors want to avoid uncertainty and thus will often experience a panic in the face of it[3]. Panic is followed by errors, which may then lead to further losses. In order to overcome these disadvantages, investors must comprehend how to overcome the problems of stock market investment.

An artificial recurrent neural network (RNN) architecture [1] is utilized in the area of deep learning in order to deal with LSTM problems. Due to the delays of undetermined length, LSTM networks are great for categorizing, analyzing, and generating predictions based on time series data. The time series stock market data is an example of this kind of data. Recurrent neural networks use a GRU mechanism as a gating mechanism. LSTM with a forget gate is similar to the GRU, but with a lower number of parameters; GRU does not include an output gate. While investing in the stock market is like playing the lottery, one should not invest based only on lottery tickets. In order to discover a successful stock, the must conduct research and investing analysis. For many investors, it is a time-consuming, complicated job to invest in the stock market. Monitoring the price movement of the stock is necessary even after the have found a stock to purchase [4]. While long-term investors hold for the long run, knowing when to leave a stock position if it turns out to be a poor investment decision is essential. Market prediction offers great profit avenue and is a fundamental incentive for most researchers in this part. To predict the market, most researchers use either technical or fundamental analysis. Technical analysis focus on analyze the direction of prices to predict upcoming prices, while fundamental analysis depends on analyze shapeless textual information like financial news and earn reports. In this work we work on the both technical and fundamental analysis .In contrast to the other current review articles that concentrate on discussing many methods used for forecasting the stock market, this study aims to compare many deep learning (DL) methods used for technical and fundamental analysis to find which method could be more effective in prediction and for which types and amount of data. The study also clarifies the recent research findings and its potential future directions by giving a detailed analysis.

The current research is organized into four sections, the section 2 given to a literature review. Section 3 describes the proposed method. The section 4 contains the conclusion.

2 LITERATURE SURVEY

According to academic scholars, there are two basic schools of thinking when it comes to investing: fundamental analysis and technical analysis. To establish a sound strategic investment strategy, these two assessments must be used. The studies vary in several ways, notably how the tool functions and how it is executed, the time period during which analysis is performed, and the types of cells studied. Multiple critical evaluations have been done on them to assess their combined capability [5]. FA is a technique of determining the intrinsic value of a security by analyzing economic and financial variables that are correlated with it. The researchers that developed the framework are also researchers interested in microeconomic and

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macroeconomic security issues. To comprehend if the stock is cheap or overpriced, the main objective of the study is to be completed. Typically, before doing a fundamental study of the stock, researchers investigate the broader economy and the health of the industry. In basic analysis, most of the ratios rely on publicly accessible data. Stocks are analyzed most often using fundamental analysis, although it is valuable in other securities, including bonds and derivatives. Fundamental Analysis is often used to find out if a company's stock is a good investment. To choose the investment companies in which to deposit their money, investors must first decide when to buy the shares. With respect to stock investment, as well, timing is critical. In this case, the technical indicators may assist [6]. In technical analysis, an investor does technical computations to identify technical indicators. The following indications may help an investor know whether to purchase or sell shares. Investors have a broad range of technical indicators at their disposal. Our aim is to choose a few stocks that match investors' trading styles and market circumstances at the moment. A number of indicators may make a chart messy and distract from the signal. When using technical indicators, OHLCV data is often used. In addition to the technical indications, there are many to select from. Several kinds of technical indicators exist, including Momentum Indicators, Volume Indicators, Volatility Indicators, Trend Indicators, and Other Indicators.

2.1 Existing Work

The Prophet library is an open-source toolkit made for univariate time-series datasets to predict trends. This algorithm makes finding appropriate hyperparameters for the model a hands-off experience. The default settings attempt to predict data with trends and seasonal structure by default. Using a time series forecasting model called a "additive" implementation Prophet employees predict trends, seasonality, and vacations. That has been made to be as simple and effortless as possible, for example, pointing it at a time series and getting a prediction. Internal usage, such as predicting sales, capacity, and the like, is what this software is designed for.

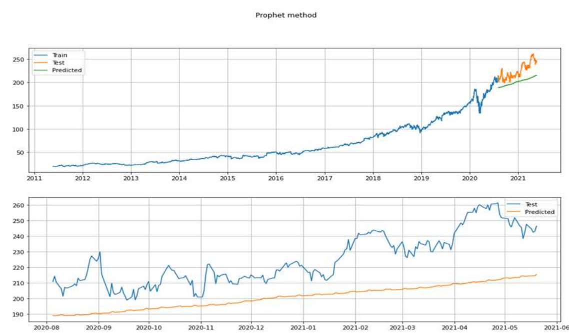

Figure 1: Training vs testing vs predicted graph of Facebook's prophet for Microsoft's adj closing price

Fig 1 shows the difference between the training and testing data and the predicted value. The difference is prominent and shows a wide gap in learning. Autoregressive integrated moving average, or ARIMA, is a statistical analysis model that may be used to better understand a dataset or to make predictions about future trends. If a statistical model predicts future values based on previous values, it is autoregressive. A good example is an ARIMA model, which attempts to predict the future price of a stock based on its historical price movements or make profits projections by using previous financial results. Moving average smoothing is used in ARIMA models. In technical analysis, they are often used to predict future securities prices[7]. In the absence of knowledge about the future, these models presume that the future will be like the past. Therefore, this means that when market circumstances are right, such as financial crises or times of fast technological development, their predictions may be incorrect.

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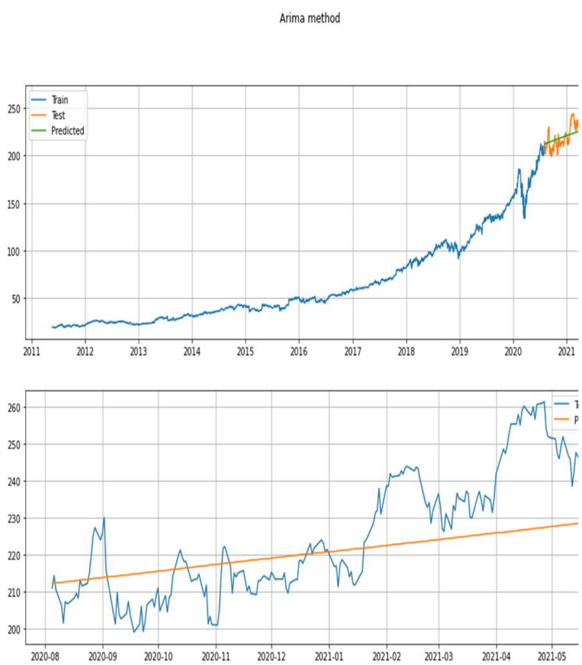

Figure 2: Training vs testing vs predicted graph of auto ARIMA for Microsoft's Adj closing price

In figure 2, the training and testing data are shown as well as the estimated values for the auto ARIMA model. Auto ARIMA outperforms Facebook's Prophet, although their forecast does not agree completely with the facts. It's also known as the coefficient of determination, R2, or r2 and is pronounced "R squared" (s). It uses the model's explained variance to help gauge how effectively the model observes outcomes. [5] Below is a table displaying the r2 scores that were calculated using the training of three models: an auto ARIMA model, a Facebook Prophet model, and an LSTM. Most often, the coefficient of determination will vary between 0 and 1.

Table 1 Comparison of r2 scores of various models

MODEL	R2 SCORE
Auto ARIMA	-6.695536832725067
Facebook Prophet	-1.8375445714799845
LSTM	0.7718175925776691

From Table 1 we can conclude that LSTM outperforms both auto ARIMA and face book Prophet and hence is a suitable choice for the proposed system.

3. PROPOSED WORK

Two typical methods are used to choose a stock. The first is an essential analysis and the second is a study of technical aspects. Basic analysis and technical analysis, however, use totally distinct ways to collect stocks. Fundamental analysis and technical analysis may be used to evaluate whether or not an investment in the stock is lucrative and to predict future stock trends further the entire results will show in experimental results refer as 4.the figure 3 shows the proposed method block diagram.

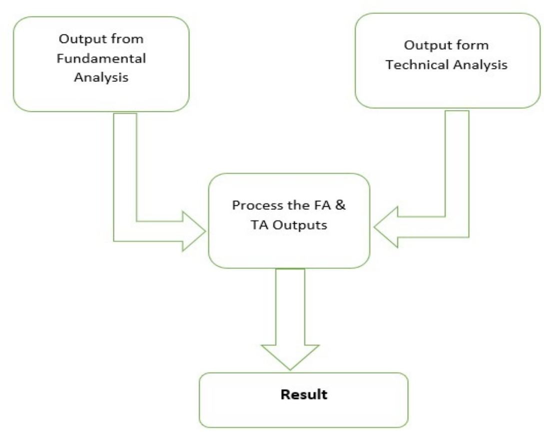

Figure 3: Proposed method block diagram

Methodology

1. Explanation of Data:

The ancient data for the five companies takes been collected from Yahoo Finance. The dataset included. The dataset includes 10 year data from 4/5/2011 to 4/5/2021 of Infosys, D-mart and Dr. Reddy, SBI, TCS. The data comprisesinfo about the stock such as High, Low, Open, Close, Adjacent Close and Adjacent Volume. New Variables

Ten new variables have been produced for the prediction of stock final price. Thes-e variable have been used to train the model.

The new variables are as follows:

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1. Stock High minus Low Price (H-L)
2. Stock price’s 10 day’s Exponential Moving Average (EMA)
3.
tock price’s 20 day’s Simple Moving average(SMA)
4.
tock price’s 30 day’s Simple Moving average(SMA)
5.
tock price’s 50 day’s Simple Moving average(SMA)
6.
tock price’s 14 Days RSI (Relative Strength Index)
7.
tock price’s 20 Day’s Bollinger Bands
8.
tock price’s 12 Day’s Exponential Moving Averages(EMA)
9.
tock price’s 26 Day’s Exponential Moving Averages(EMA)
10.
tock Price 9 Day’s Signal line(MACD)

Results:
To estimate the effectiveness of the models, a contrast is made between the two techniques on five different sector companies namely, Infosys, D Mart, Dr. Reddy using both LSTM and GRU models along with Clustered Gradient Descent with Adam Optimizer. Predicted closing prices are subjected to R squared value for finding the final minimized errors in the predicted prices

Clustered Gradient Descent with Adam Optimizer.
Assuming that the complete data set is denoted as D[] and each attribute in the data set is assumed [Spot trading dataset, Future trading dataset & Optional Trading Dataset]. Here, each and every attribute is considered to have their own domain with m number of records. The Manhattan distance between the data points can be considered as the similarity measure and the total distance set is represented as

$$\lambda[\,] = \int_{i=1}^{n} |D_i - D_{i+1}| \quad (1)$$

Manhattan distance of the similarity measures of the all distances, the final centroid can be calculated as,

$$C[\,] = D_k[\,] = \frac{D_k[\,]}{|D_i - D_{i+1}|_{i=0}^{n}} \quad (2)$$

The D[] set defined the relation between elemens based on their similarities (Spot trading elements, future trading elements and option trading elements apply on the LSTM and GRU networks

Adam Optimizer
Adaptive Moment Estimation is an algorithm for optimization technique for gradient descent. The technique is really effective when working with big problem involving a lot of data or parameters. It requires less memory and is effective. Spontaneously, it is a combination of the ‘gradient descent with momentum’ and Root Mean Square Propagation algorithm.

Momentum:
This algorithm is used to rush the gradient descent algorithm by taking into deliberation the ‘exponentially weighted average’ of the gradients. Using averages makes the algorithm converge towards the minima in a faster pace.

m_t= Gradients of cumulative at time t [current] (initially, $m_t = 0$)
m_{t-1} =Gradients of cumulative at time t-1 [previous]
W_t = weights at particular time t
W_{t+1} = weights at particular time t+1
α_t = learning rate at particular time t
∂L = Loss of derivative technique
∂W_t = wieghts of derivative at time t
β = Moving average (const, 0.9)

Root Mean Square Propagation (RMSP):
Root mean square prop or RMSprop is an adaptive learning algorithm that tries to improve AdaGrad. Instead of taking the cumulative sum of squared gradients like in

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AdaGrad, it takes the ‘exponential moving average’.

W_t = weights at particuletime t
W_{t+1} = weights at particular time t+1
α_t = learning rate t
∂L = Loss Function of derivative
∂W_t = Weights of derivative time t
V_t = squares of sumof past gradients. [i.e sum($\partial L/\partial Wt-1$)] (initially, $V_t = 0$)
β = Moving average (const, 0.9)
ϵ = positive constant (10^{-8})

Mathematical Part of Adam Optimizer

Taking the parameters used in the above two methods, we get

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\left[\frac{\delta L}{\delta w_t}\right] v_t = \beta_2 v_{t-1} + (1-\beta_2)\left[\frac{\delta L}{\delta w_t}\right]^2$$

(3)

This Optimizer hits this problematic by computing ‘bias-corrected’ m_t and v_t. This is also done to control the weights while reaching the global minimum to prevent high oscillations when near it. The formulas used are:

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} \hat{v}_t = \frac{v_t}{1-\beta_2^t} \tag{4}$$

Automatically, we are familiarizing to the gradient descent after every repetition so that it remains controlled and unbiased through the process, henceforth the name Adam.

Clustered gradient descent after every repetition so that it remains controlled and balanced throughout the course, hence the name Clustered Gradient Descent with Adam Optimizer

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} + C[] = D_k[] = \frac{D_k[]}{\left|D_i - D_{i+1}\right|_{i=0}^{n}}$$
$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} + C[] = D_k[] = \frac{D_k[]}{\left|D_i - D_{i+1}\right|_{i=0}^{n}}$$

(5)

The gating mechanism of LSTMs suppresses memorization. LSTMs include gates that can store, produce, or retrieve information. These gates use element-wise multiplication by sigmoid ranges between 0-1 to store the memory. Analog is suited for backpropagation since it is differentiable. The GRU has two main gates It may be reset or updated. Just as a neural network is a network of neurons, each gate is composed of a network of weights and biases. GRU's and LSTMs are very similar, with one major difference; they are all designed to deal with the vanishing gradient issue. Gates 2 on LSTMs GRU has a smaller gate than the output gate of the forget gate. Our idea is to use a variety of LSTM models to study how different hyperparameters affect task performance. The figure 4 shows the Flowchart of the proposed work

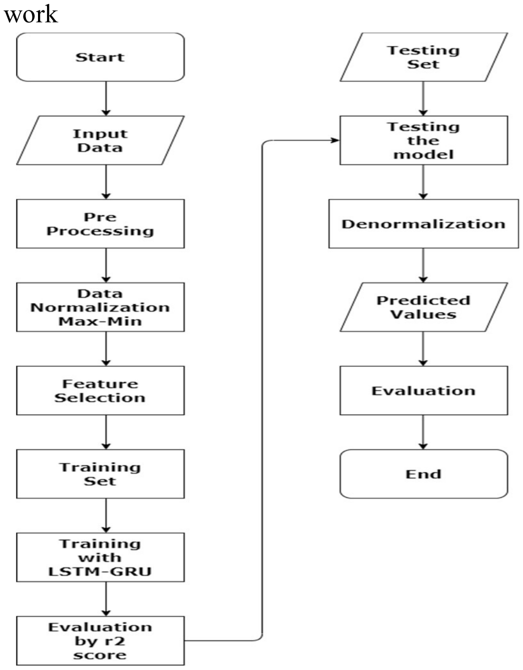

Figure 4: Flowchart of the proposed work

3.1Long Short-Term Memory- (LSTM)

The idea of the cell state and its numerous gates lies at the heart of LSTM. In the cell state, the sequence chain's relative information is distributed along the whole chain. The memory of the network may be described as being similar to that. in principle, the cell state may convey important information as the operation proceeds Thus, the previous temporal steps are not completely isolated from each other, resulting in less short-term memory problems. Information is being added or deleted to the cell state as the cell state progresses through the various states. The

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neural gates enable for various information to be sent to the cell states. The gates are able to store and access information during training to aid recall. Sigmoid activations are seen in Gates. The tanh activation is comparable to a sigmoid activation. Instead of squeezing values between negative numbers and positive numbers, it squeezes values between zero and one. Any integer being multiplied by 0 is 0, leading values to be "lost" or vanish. Multiplying any integer by 1 will always give the same result, thus the value stays the same or is “kept.” The network learns whether data is unimportant, which means that it may be discarded or preserved. Squishes values between 0 and 1, producing Sigmoid. In LSTM cells, three distinct gates control the flow of information. A gate to forget information, a gate to enter information, and a gate to output information. Forgetting involves throwing out unnecessary knowledge, and the forget gate determines what is to be discarded or retained. During a hidden state, the information that is transferred from the previous state and the information from the current input are used to generate a sigmoid function. The will find that values tend to land between between 0 and 1. The closer to 0 indicates to have forgotten something, and the closer to 1 means to be concerned about something.

We first feed the prior concealed state and the current input through a sigmoid function to apply the cell state. When the values to be transformed are between 0 and 1, the updated values will be those given by the transformation. A number between 0 and 1 indicates something is either unimportant or significant. To aid in regulating the network, the feed the hidden state and current input into the tanh function, which squishes values between -1 and 1. To calculate the final result, the next multiply the tanh output with the sigmoid output. In other words, the sigmoid output will prioritize which data will be retained from the tanh output. The cell state gets pointwise multiplied by the forget vector to get its state value. When it's multiplied by values approaching 0, this has the potential to reduce the values in the cell's state. We apply a pointwise addition to the input and produce the output of the pointwise addition. We then feed this into the neural network, which uses the updated cell states to make a prediction. That new cell state is ours. The output gate determines which of the concealed states is to be revealed next. Don't forget that concealed state information is made up of prior input data. It's useful for making predictions as well, because of the concealed state. To begin, we feed in the concealed state that we've just revealed and the current input. After passing the new cell state to the tanh function, we apply the operation. To determine what information the hidden state should contain, we multiply the tanh output with the sigmoid output. The concealed state is the output. In order to account for the new cell state and the new hidden, they are transferred to the next time step.

3.2 Gated recurrent units – (GRU)

In theory, recurrent neural networks with gated recurrent units plan from their history of input data to get target vectors. There is not much difference between LSTMs and these unsupervised learning algorithms. The GRU does not have a cell state, using a concealed state instead. Two more gates, all of which are reset and update gates, are also included. The may use the Gated Recurrent Unit to increase the memory capacity of a recurrent neural network, or it can make training a model a whole lot easier. To solve the vanishing gradient issue in recurrent neural networks, the hidden unit may be utilized. An update gate works similarly to an LSTM's forget and input gates. The decision is made on what to throw away and what to add. Another gate used to forget how much previous knowledge the reset gate lets the forget. Nonlinearity is introduced using the Current Memory Gate, which is found in the Reset Gate, and in order to create the input Zero-mean. Past information has less of an impact on future information as a result. The figure 5 shoes architecture diagram for LSTM

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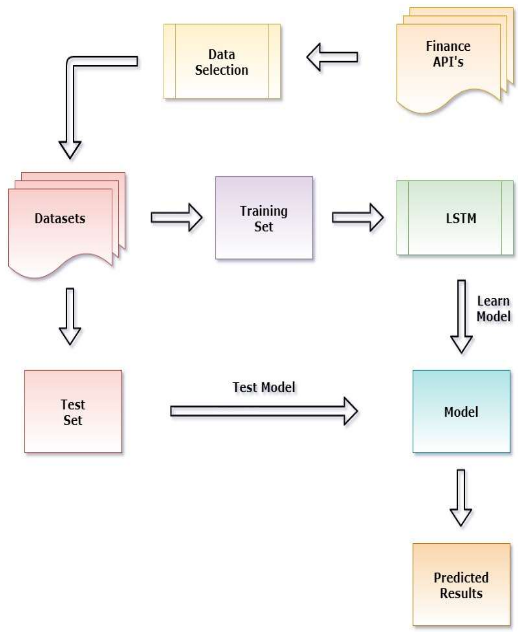

Figure 5: Architecture diagram for LSTM

4. EXPERIMENTAL RESULTS

LSTM networks with recurrence. Because of these loops, information may last longer. Long Short-Term Memory (LSTM) networks are a specific kind of recurrent neural network (RNN) designed to learn long-term dependencies. By using special structures called gates, the LSTM may perform operations like adding or removing information to the cell state, depending on the specific application. Gates are a method to allow information to flow while users are not searching for it. A normal Sigmoid Neural Net layer is joined with a pointwise multiplication procedure to form this neural network. It specifies how much of each ingredient is acceptable. To regulate and safeguard the cell state, there are three of these gates in an LSTM. An LSTM network has multiple layers and each layer has multiple memory blocks. The smallest memory block in an LSTM network is referred to as a memory block. Each memory block stores one or more memory cells and has a pair of adaptive, multiplicative gating units that control input and output of all cells in the block. A recurrently self-connected linear unit known as the constant error carousel (CEC) sits at the heart of each memory cell. We call the CEC's activation the cell state. The CECs avoid vanishing errors since they are unable of responding to additional input or errors from the cell. Hence, their error flows stay constant regardless of the condition of the cell. Both forward and reverse flows are guarded by the CEC. The cells of a multiplicative gate unit are opened and closed by multiplicative gate units learning how to do it. With regards to the learning method used by LSTM, it is both local in space and time and computationally intensive (1). It may tackle difficult, long-term problems that were never before addressed by any of the RNN algorithms. [4]

There are three distinct parts to the project. Fundamental analysis is applied to the chosen businesses during the first phase, termed Fundamental Analysis. The second phase, which is known as Technical Analysis, analyzes the stocks on the list to come up with trends and possible movements. LSTM and GRU models are trained to predict healthy investment decisions from segments 1 and 2 in the third category, which is termed models.

Table 2: Financial Analysis output table

	RELIANCE.NS	INFY.NS	SBI.NS	DMART.NS	DRREDDY.NS	TCS.NS
Current Ratio	Low	High	Low	High	High	High
Operating Profit Ratio	Unhealthy Company	Unhealthy Company	Unhealthy Company	Unhealthy Company	Unhealthy Company	Unhealthy Company
PE Ratio	Good	Bad	Good	Bad	Bad	Bad
Dividend Yield	Low dividends	Low dividends	Low dividends	No dividends	Low dividends	Low dividends
Earnings per share	High	High	High	High	High	High
Net Profit Ratio	High	High	High	High	High	High

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Output Screens:

	RELIANCE.NS	INFY.NS	SBIN.NS	DMART.NS	DRREDDY.NS	TCS.NS
Current Ratio	Low	High	Low	High	High	High
Operating Profit Ratio	Unhealthy Company	Unhealthy Company	Unhealthy Company	Unhealthy Company	Unhealthy Company	Unhealthy Company
PE Ratio	Good	Bad	Good	Bad	Bad	Bad
Dividend Yield	Low dividends	Low dividends	Low dividends	No dividends	Low dividends	Low dividends
Earnings Per Share	High	High	High	High	High	High
Net Profit Ratio	High	High	High	High	High	High

RSI Strategy

It is overbought when the RSI rises over 70 percent. When a stock's price rises quickly, it is said to be overbought. If a stock is overbought, it usually suffers a price decline. Oversold RSI occurs when the RSI goes below 30 percent. An oversold stock price drops quickly, suggesting that it is oversold. The price of a stock tends to increase when a stock is oversold.

Many systems use the RSI indicator, and they tend to be ineffective. When the RSI goes over 70%, it's time to sell. Buying may be an excellent strategy when the RSI goes below 30%. Alternative parameters may be used. To modify the parameters to match our trading style, market circumstances, and the stock we're interested in, the keys are knowing how to adjust the settings and not making any drastic changes. The figure 6 shows RSI output for Infosys

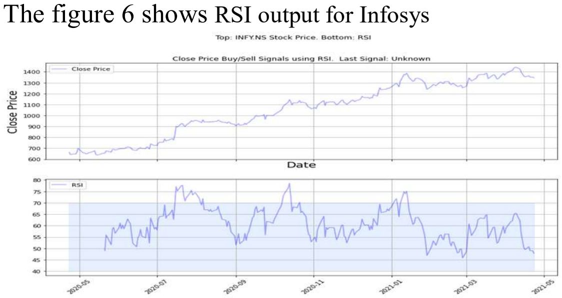

Figure 6: RSI output for Infosys

MACD Strategy

By combining the MACD with the Signal Line, we can construct a simple trading strategy. At this intersection, the MACD line and the signal line cross each other. The MACD line falls below the signal line when this happens, which means the should consider selling.

The MACD line is above the signal line when this occurs, which means it indicates a buying opportunity. If the MACD and Signal lines are both negative, then the market is bearish. Nike used the term "Bullish" to describe a situation when the MACD and Signal lines are both above zero. Moving averages show that previous events have the potential to affect the future. These things don't always happen. Additionally, the lag from the moving averages is added, meaning that generated signals come after the market move has started. 12- and 26-period EMAs have different MACD settings. In more sensitive equity situations, we might use MACD(5,35,5), which would be useful for weekly charts, while MACD(12,26,9) may be better for weekly charts. The outcome of this investment is completely reliant on the investor. Keeping in mind the long-term price patterns as well as other factors is a critical aspect to have in mind. Bear in mind that a stock may continue to rise even if it seems to be over bought. The figure 7 shows MACD output for Infosys.

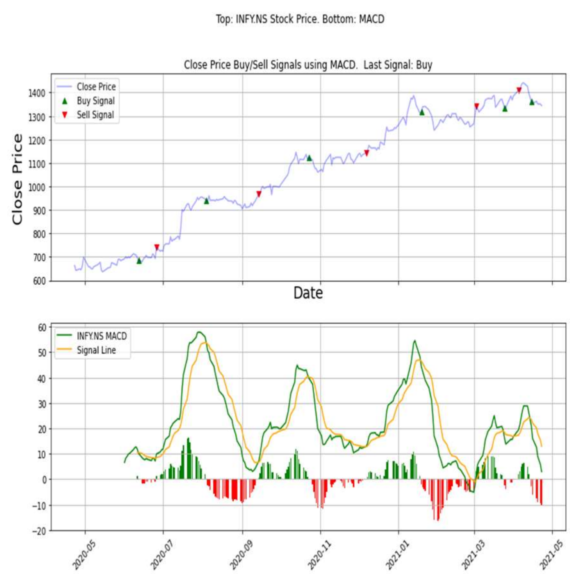

Figure 7: MACD output for Infosys

Bollinger Bands Strategy:

If the market price is in the upper Bollinger band, sell it. When the market price is between the lower Bollinger band and the upper range band, it is time to purchase. The notion that the stock price would ultimately fall off the uptrend and hit the bottom band is why this trade is based on a bearish breakout strategy. When it comes to the Bollinger Band, we may use it to predict whether we should purchase a company, but bad

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news about the market might have an effect on the stock's price. Treating the signal as an indication of occasional inaccuracy is important. The figure 8 shows Bollinger Bands output for Infosys

R2 scores GRU:
company: Infosys, model0: r2 = 0.920323460436326
company: Infosys, model1: r2 = 0.9257339400666886
company: D-mart, model0: GRU0, r2 = 0.9311232058448095
company: D-mart, model1: GRU1, r2 = 0.9264546378238229
company: Dr.Reddy, model0: GRU0, r2 = 0.9797232487665207
company: Dr.Reddy, model1: GRU1, r2 = 0.9925243144853353

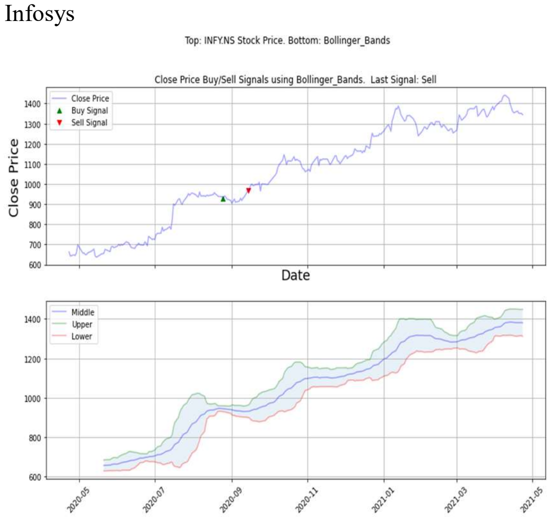

Figure 8: Bollinger Bands output for Infosys

Models

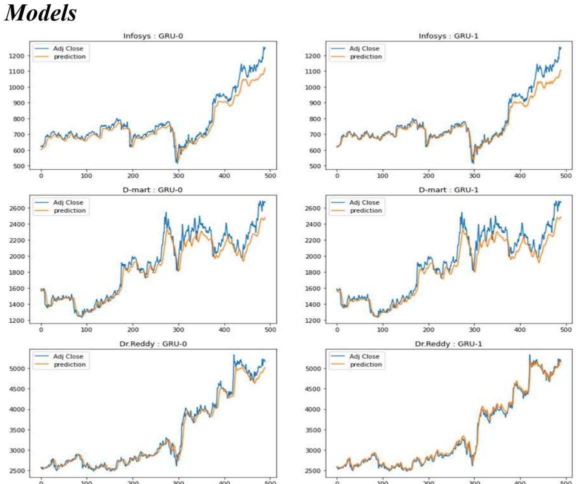

Figure 9: GRU model 1 vs GRU model 2 (Infosys, D-mart and Dr. Reddys)

In the above graphs in figure 9 , we can see plots of Infosys, D-mart and Dr. Reddy stocks. We have considered the adjacent closing prices. The graphs show the actual adjacent closing prices vs the prices predicted by the GRU models.

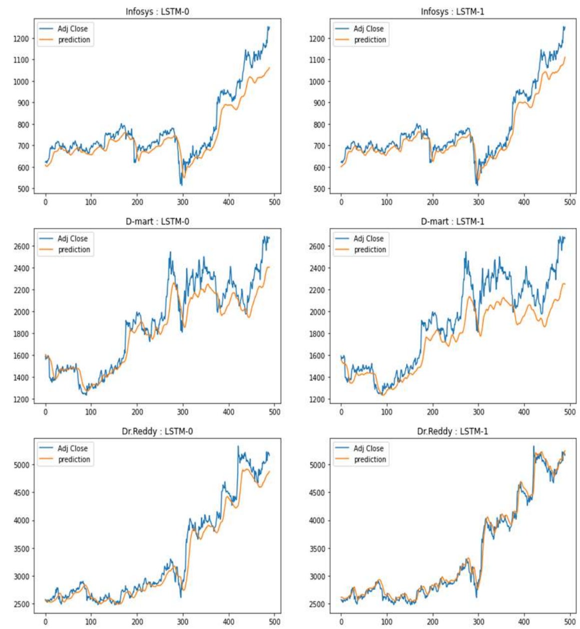

Figure 10: LSTM model 1 vs LSTM model 2 (Infosys, D-mart and Dr. Reddys)

In the above graphs in figure 10, we can see plots of Infosys and Dr. Reddy stocks. We have considered the adjacent closing prices. The graphs show the actual adjacent closing prices vs the prices predicted by the LSTM models.

R2 SCORES LSTM VS GRU

R2 scores LSTM:
company: Infosys, model0: LSTM0, r2 = 0.8438915832027458
company: Infosys, model1: LSTM1, r2 = 0.9045737873317453
company: D-mart, model0: LSTM0, r2 = 0.871551101620503
company: D-mart, model1: LSTM1, r2 = 0.7223963230934076
company: Dr.Reddy, model0: LSTM0, r2 = 0.949420636639756
company: Dr.Reddy, model1: LSTM1, r2 = 0.986113309728188

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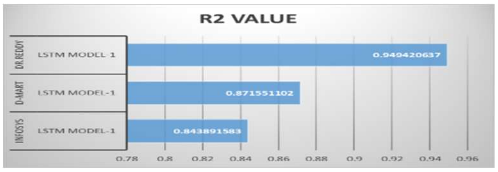
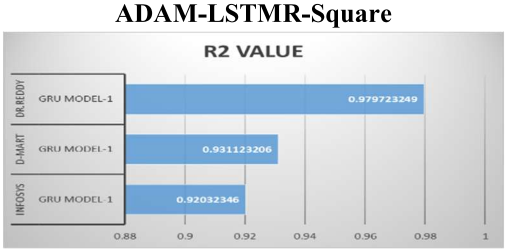
GRUMODEL-1R2



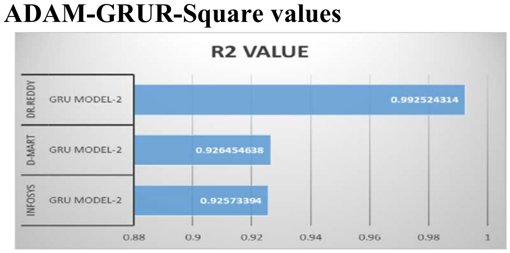
Terms Representation

Gru0 or model 0	Adam Optimizer
Gru1 or model1	Clustered Gradient Descent with Adam Optimizer
Lstm0 or model 0	Adam Optimizer
Lstm1 or model 1	Clustered Gradient Descent with Adam Optimizer

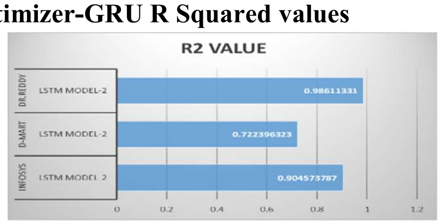
ADAM-LSTMR-Square



ADAM-GRUR-Square values



Clustered Gradient Descent with Adam Optimizer-GRU R Squared values



Clustered Gradient Descent with Adam Optimizer-LSTM R Squared Valuess

Result Analysis

Infosys seems like a profitable investment from the fundamental analysis table above. While fundamental analysis has no guarantee of success, like any other investing strategy or method, it is possible to use fundamental analysis to generate positive results. Although fundamental value indicates that a company is cheap, this does not ensure that the firm's shares will increase to their intrinsic value at any point in the future. The situation is far from straightforward. While basic analysis may provide accurate information, in practice, actual price behavior is affected by many variables, some of which might invalidate this approach. When investors and analysts take a closer look at a business, they will usually employ a mix of fundamental, technical, and quantitative studies to determine how promising that company's future may be.

This time the RSI readings obtained from the screen output are about 30% of their total possible values, and the MACD line is under the signal line. This reveals that the best moment to buy into Infosys is now. While technical indicators provide many indications, the signals they generate are entirely theoretical. While the accuracy of the signals can never be guaranteed, 100 percent of the time, the signals are generally correct. The market may react in ways that are both unpredictable and unexpectable. Caution is required when using indicators since investors risk losing part, if not all, of their money. It is important to keep in mind that stock trading is a serious undertaking. The market is often unpredictable. Most of the time, technical indicators are used in combination to provide a more accurate assessment. There are, for example, many tools that use the Bollinger Bands and MACD indicators such as the RSI to decide whether or not it is a good moment to buy or sell. The factors and strategies used in trading should be modified based on the market outlook, trading style, and investment portfolio. The should always do a back test on the trading technique before using it. Based on the four models described above, it can be deduced that models using Clustered Gradient Descent Adam optimizer usually perform better than models with Adam optimizer. The GRU model beats the LSTM model when it comes to overall accuracy. Market prediction offers great profit avenue and is a fundamental incentive for most researchers in this part. To predict the market, most researchers use either technical or fundamental analysis. Technical analysis focus on analyze the direction of prices to predict upcoming prices, while fundamental analysis depends on analyze shapeless textual information like financial news

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MODEL (Dr.Reddy)	R2 SCORE
Auto ARIMA	-2.695536832725067
Facebook Prophet	-5.8375445714799845
LSTM	0.6218175925776691
GRU Adam Optimizer	**0.9797232487665207**
GRU –Proposed Model	**0.9925243144853353**

and earn reports. In this work we work on the both technical and fundamental analysis .In contrast to the other current review articles that concentrate on discussing many methods used for forecasting the stock market, this study aims to compare many deep learning (DL) methods used for technical and fundamental analysis to find which method could be more effective in prediction and for which types and amount of data. The study also clarifies the recent research findings and its potential future directions by giving a detailed analysis.

Comparative Analysis:

MODEL-INFOSYS

MODEL (Infosys)	R2 SCORE
Auto ARIMA	-6.695536832725067
Facebook Prophet	-1.8375445714799845
LSTM	0.7718175925776691
GRU Adam Optimizer	**0.920323460436326**
GRU –Proposed Model	**0.9257339400666886**

MODEL-D-MART

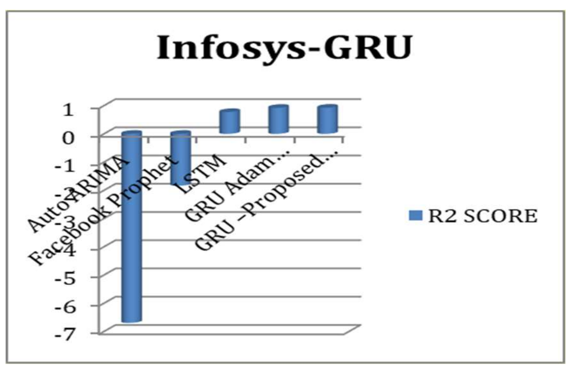
MODEL (D-Mart)	R2 SCORE
Auto ARIMA	-3.695536832725067
Facebook Prophet	-2.8375445714799845
LSTM	0.5518175925776691
GRU Adam Optimizer	**0.9311232058448095**
GRU –Proposed Model	**0.9264546378238229**

MODEL (Infosys)	R2 SCORE

Auto ARIMA	-7.695536832725067
Facebook Prophet	-3.8375445714799845
LSTM	0.4418175925776691
LSTM Adam Optimizer	**0.8438915832027458**
LSTM –Proposed Model	**0.9045737873317453**

MODEL (D-Mart)	R2 SCORE
Auto ARIMA	-3.695536832725067
Facebook Prophet	-2.8375445714799845
LSTM	0.5518175925776691
LSTM Adam Optimizer	**0.871551101620503**
LSTM –Proposed Model	**0.7223963230934076**

MODEL (Dr.Reddy)	R2 SCORE
Auto ARIMA	-2.695536832725067
Facebook Prophet	-5.8375445714799845
LSTM	0.6218175925776691
GRU Adam Optimizer	**0.9797232487665207**
GRU –Proposed Model	**0.9925243144853353**



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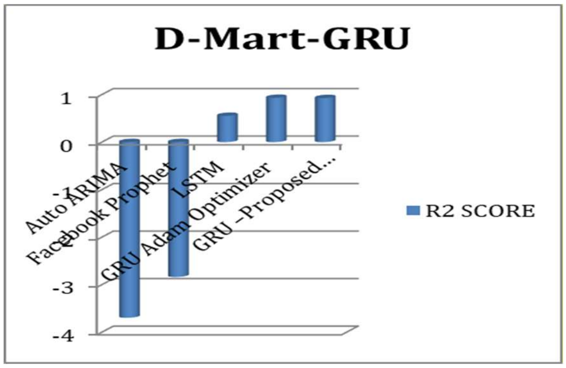

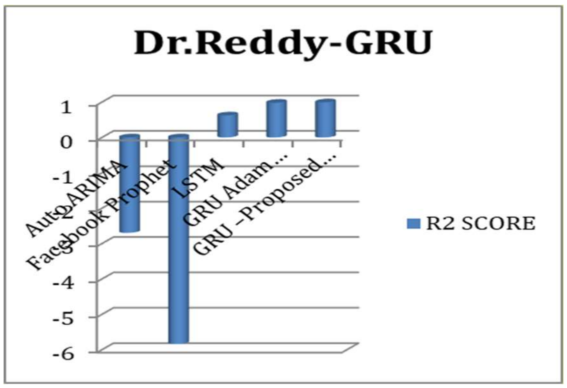

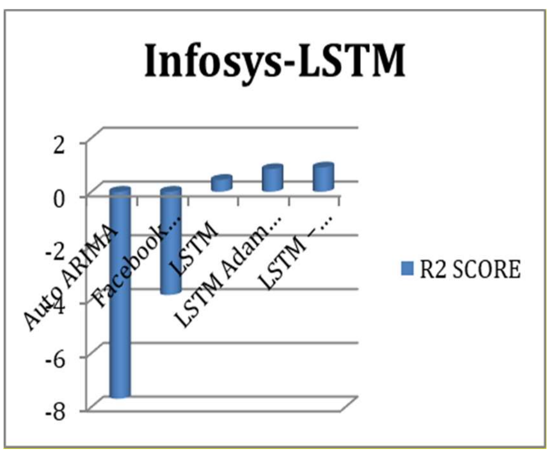

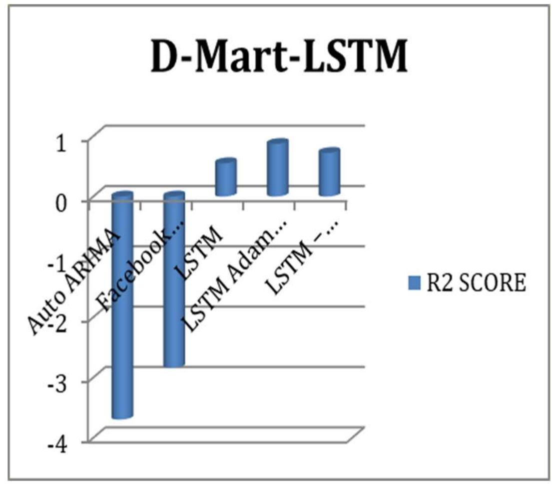

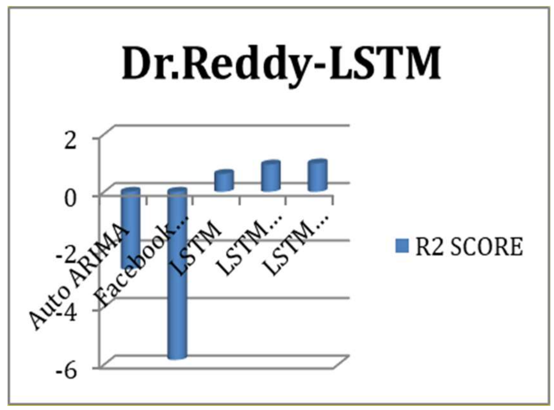

Figure 11: Different models with R2 score

4 CONCLUSIONS

Deep learning algorithms when paired with the right fundamental analysis ratios and technical indicators can be a strong addition to an investor's toolkit. Fundamental analysis is key in understanding the economy in which the company operates and the strength of the industry it lies in. Technical analysis is utilized to analyze the strength and weakness of the stock and aids in future stock purchase decisions. LSTM and GRU provide a suitable architecture to attempt to predict future stock prices. Fundamental and technical analyses have both yielded impressive returns to the dataset, they are completely distinct from each other and are used together to choose a healthy company in addition to using LSTM- GRU.We hereby conclude that LSTM and GRU perform better on time-series data like stocks when compared to other preexisting models. Thiswork can be developed into a web application that applies these techniques to analyze real-time stock data and make predictions. Hybrid models incorporating both LSTM and GRU algorithms can be developed for faster and more accurate prediction of stock prices. Further, these models can be enhanced to predict based on sentiment changes about a stock. Furthermore, as future work, different techniques like clustering and deep learning techniques can be included to enhance accuracy. And also retrieve news-based system, public media-based opinion analysis approach can extract sentiments about a specific stock. The different trading models can also be tested to get a better accuracy rate(combination of technical , Fundamental and Sentimental Analysis).

REFERENCES

[1] G. Bathla, "Stock Price Prediction Using Lstm And Svr," 2020 Sixth International Conference On Parallel, Distributed And Grid Computing (Pdgc), 2020, Pp. 211-214, Doi: 10.1109/Pdgc50313.2020.9315800.

[2]. Z. H. Kilimci And R. Duvar, "An Efficient Word Embedding And Deep Learning Based Model To Forecast The Direction Of Stock Exchange Market Using Twitter And Financial News Sites: A Case Of Istanbul Stock Exchange (Bist 100)," In Ieee Access, Vol. 8, Pp. 188186-188198, 2020, Doi: 10.1109/Access.2020.3029860.

[3] M. Faraz, H. Khaloozadeh And M. Abbasi, "Stock Market Prediction-By-Prediction Based On Autoencoder Long Short-Term Memory Networks," 2020 28th Iranian Conference On Electrical Engineering (Icee), 2020, Pp. 1-5, Doi: 10.1109/Icee50131.2020.9261055.

[4] K. Ullah And M. Qasim, "Google Stock Prices Prediction Using Deep Learning," 2020 Ieee 10th International Conference On System Engineering And Technology (Icset), 2020, Pp. 108-113, Doi: 10.1109/Icset51301.2020.9265146.

[5] J. Arosemena, N. Pérez, D. Benítez, D. Riofrío And R. Flores-Moyano, "Stock Price Analysis With Deep-Learning Models," 2021 Ieee Colombian Conference On Applications Of Computational Intelligence (Colcaci), 2021, Pp. 1-6, Doi: 10.1109/Colcaci52978.2021.9469554.

[6] Z. D. Akşehir And E. Kılıç, "Prediction Of Bank Stocks Price With Reduced Technical Indicators," 2019 4th International Conference On Computer Science And Engineering (Ubmk), 2019, Pp. 206-210, Doi: 10.1109/Ubmk.2019.8906999.

[7] A. Namdari And Z. S. Li, "Integrating Fundamental And Technical Analysis Of Stock Market Through Multi-Layer Perceptron," 2018 Ieee Technology And Engineering Management Conference (Temscon), 2018, Pp. 1-6, Doi: 10.1109/Temscon.2018.8488440.

[8] Manish Agrawal, Asif Ullah Khan, Piyush Kumar Shukla," Stock Price Prediction Using Technical Indicators: A Predictive Model Using Optimal Deep Learning," 2019international Journal Of Recent Technology And Engineering (Ijrte) Issn: 2277-3878, Volume-8 Issue-2, July 2019, Doi: 10.35940/Ijrteb3048.078219

[9] Jaideep Singh And Matloob Khushi, "Feature Learning For Stock Price Prediction Shows A Significant Role Of Analyst Rating," 2021 . Appl. Syst. Innov. 2021, 4, 17. Https://Doi.Org/10.3390/ Asi4010017

[10] Andrea Picasso, Simone Merello, Yukun Ma, Luca Oneto, Erik Cambria,"Technical Analysis And Sentiment Embeddings For Market Trend Prediction,"Expert Systems With Applications,Volume 135,2019,Pages 60-70, Issn 0957-4174.