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Design and Implementation of Technical Analysis Based LSTM Model for Stock Price Prediction

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Abstract
The paper describes the design and implementation of a Long Short-Term Memory (LSTM) model for stock price prediction based on technical analysis. The model use technical indicators such as moving averages and Bollinger Bands to discover trends in the stock market and forecast future stock values. Historical stock data was used to extract technical indicators for the model. These indicators were then used as input features to train the LSTM model using a supervised learning strategy. Metrics such as mean absolute error, mean squared error, and root mean squared error were used to assess the model's performance. However, as investment became more accessible, the stock market became more difficult and volatile. This paper proposes a stock price prediction system that employs a (LSTM) oriented neural network to forecast the next-day closing price of APPLE shares. Regression and LONG SHORT-TERM MEMORY models are constructed using selected input variables, and their performance is evaluated using RMSE, MAPE, and R squared error metrics to analyze the stock's trend for buying and selling.

Keywords: LSTM, Machine learning, Stock market**,** Regression, Deep learning, Prediction.

I. INTRODUCTION

The general stock-exchange that carries out trading is a platform for purchasing, vending, and supplying shares of widely traded establishments. Transactions can occur through formal exchanges or OTC markets that follow established rules [1]. The objective of investing in shares is to raise incomes by purchasing shares of profitable establishments, and stock values that are determined by supply and demand dynamics. The current stock marketplace is thoroughly tied to the basic level economy, and changes in equity prices heavily influence key economic indicators. Regression analysis, a machine learning method, can be used to make informed predictions of continuous variables based on more than one forecaster variable quantity [2]. This equation can then be used to make predictions of the outcome based on new predictor values. The mathematical equation for regression analysis is usually represented as:

In Regression analysis [3] consists of a set of machine learning methods that allow us to predict a continuous outcome variable (y) based on the value of one or multiple predictor variables (x). Briefly, the goal of regression model is to build a mathematical equation that defines y as a function of the x variables. Next, this equation y = b0 + b*x + e can be used to predict the outcome (y) on the basis of new values of the predictor variables (x). This equation defines the relationship between the predictor variables and the outcome variable, and can be used to make predictions of the outcome based on new predictor values.

In RNN, Long Short-Term Memory (LSTM) [4] is utilized to predict stock prices as it incorporates a retention cell with tanh, +, and - operations at complex gate of network. The past values are stored in a cell having memory capacity make a more accurate prediction. The current paper presents a model for predicting the returns of APPLE stock, which were collected from Yahoo Finance.

The following sections 2 refers to literature review of the connected effort in this mentioned field unit 3 contains technical terms of each process in detail section 4 contains design approach section 5 represents result analysis on graphical representation the model and finally section 6 conclusion and recommendations.

II. LITERATURE SURVEY

In this research paper, multiple references were utilized. Reference [6] predicts the Apple stock prices over 10 years using LSTM. [7] highlights LSTM's ability to process data series quickly and its memory cell for efficient feedback linking. [8] uses ARIMA model to predict stock prices up to 2 years and LSTM and Random Forest to forecast the succeeding day's price. [9] compares LSTM with Generative Adversarial Network for stock value estimation and analyzes the impact of model parameter updates on forecast performance. [10] explores Regression and Classification

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methods for stock price prediction, where Regression predicts the closing price and Classification predicts if the closing price will rise or fall. [11] employs LSTM to predict China stock returns, resulting in a 27.2% accuracy improvement compared to random prediction. [12] uses only fundamental data (open, close, low, and high) to predict stock prices with LSTM in the NIFTY 50 data range. [13] shows LSTM outperforms other models in predicting directional movements of S&P 500 stocks. Karmiani et al. compared different models including LSTM, Back Propagation, SVM for stock value prediction using nine selected companies. LSTM was found to have the highest forecast accuracy and having low variance.

III. TECHNICAL TERMS

In this research, a range of scientific subjects were covered, including technical terms and a design approach section that outlines the mathematical and computer science foundations utilized in constructing the model.

Artificial-Intelligence-AI: This is the reproduction of humanoid intelligence in machineries that are intended to reflect and performance like the humans[14]. It includes generating algorithms and supercomputer systems that can accomplish tasks that naturally need human-like intellect, like recognizing speech, solving problems, and understanding natural language.

Machine-Learning: ML-Machine Learning is a subfield of AI that pacts with the design and expansion of processes that can acquire from and make calculations or conclusions based on information. ML algorithms are capable of improving their performance as they receive more data, making them ideal for tasks where the data is too complex for traditional programming methods.

Regression: This is a kind of statistical oriented analysis procedure that is capable of forecasting an outcome that is derived from one or many parameters of prediction. It involves fitting a mathematical equation to the data that defines the relationship between the predictor variables and the outcome variable, allowing for predictions to be made based on new data.

Recurrent Neural Networks (RNN): These are a kind of neural network that is specifically designed for dispensation sequences of data, like time series or sequences of text. The recurrent connections in RNNs allow for the storage and processing of information over time, making them particularly useful for tasks involving sequences of data with dependencies between time steps. The loss function in a it is a mathematical expression that measures the transformation between the projected output of the RNN and the actual target output. The purpose of the loss function is to minimize the difference, or error, allowing the RNN to learn and improve its predictions over time. One common loss function used in RNNs is mean squared error (MSE), which is defined as:

$$\text{Loss} = (1/n) * \sum (y\_pred - y\_actual)^2$$

Where n is the number of examples in the dataset, y_pred is the predicted output of the RNN, and y_actual is the actual target output. The goal of training the RNN is to minimize this loss function. Other loss functions, such as cross-entropy, can also be used in RNNs depending on the specific task and prediction problem.

Long-Short-Term-Memory (LSTM):

LSTM is a type of RNN that is intended to learn long-term dependencies effectively. LSTM[15] networks are well suited for problems that require capturing and storing relevant info for a historical of time. Unlike traditional RNNs, which have a basic repeating structure, LSTMs have a unique design that allows them to retain important information and not overwrite it. The figure_1 demonstrates the workings of an LSTM network.

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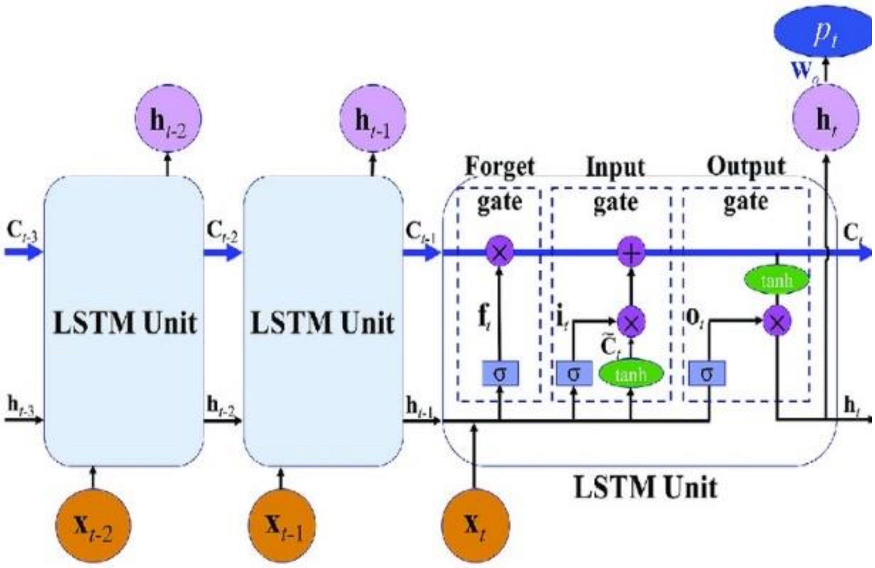

Fig 1: Architecture of LSTM.

At time t, the respective gates and layers compute the following functions:

$$i_t = \sigma(W_i x_t + W_{hi} h_{t-1} + b_i),$$

$$f_t = \sigma(W_f \, x_t + W_{hf} \, h_{t-1} + b_f),$$

$$o_t = \sigma(W_o x_t + W_{h0} h_{t-1} + b_0),\tilde{}$$

$$c_t = \tanh(W_c x_t + W_{hc} h_{t-1} + b_c),$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes c_t \, ,$$

$$h_t = o_t \otimes \tanh(c_t)$$

IV. PROPOSED LSTM ARCHITECTURE

The goal of the projected model for a assumed multivariate monetary time series, information is to forecast the succeeding day closing value using a multivariate categorization of input structures. To achieve this task, the succeeding LSTM operation procedures are considered.

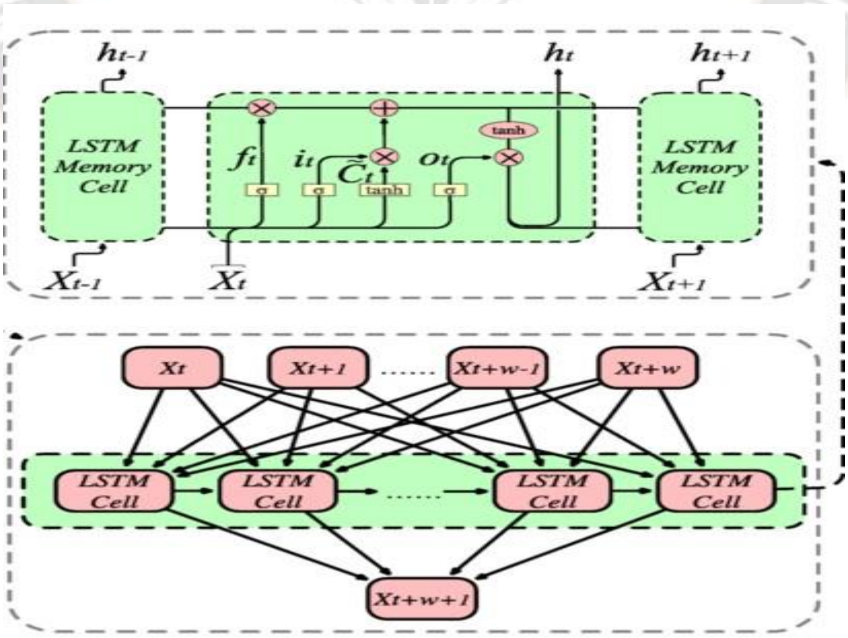

Fig 2: Architecture of TA based LSTM

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The weights (w) of LSTM are learnable limitations. The concluding hidden state (h_f) comprises the most statistics from the input categorization, and is then altered into a vector over a dense layer. LSTM is capable of learning dependencies over extended time intervals, overcoming the vanishing gradient issue faced by regular RNNs through the use of the LSTM unit or block [16]. The operation of LSTM-TA can be summarized by the following equations.

$z_t = \tanh(W^z x_t + R^z h_{t-1} + b^z)$

$i_t = \sigma(W^i x_t + R^i h_{t-1} + b^i)$

$f_t = \sigma(W^f x_t + R^f h_{t-1} + b^f)$

$o_t = \sigma(W^o x_t + R^o h_{t-1} + b^o)$

$s_t = z_t \cdot i_t + s_{t-1} \cdot f_t$

$h_t = \tanh(s_t) \cdot o_t$

V. DESIGN APPROACH

The prediction of APPLE stock price was accomplished using Regression and LSTM models implemented in the Keras framework. The models were trained using a dataset of APPLE stock prices. The close price data was visualized along with the date to provide an overview of the stock price forecast and its comparison with the current price.

Software and Libraries Utilized:

Hardware Supplies: The plan requires a Windows 10 computer with an i3 processor. The Python (3.7) software collection was utilized, besides the libraries used aimed at development were Pandas.

Data Collection: The data for the APPLE stock was obtained from Yahoo Finance in a .csv format and saved in a MS Excel document with 2517 days of data. The dataset comprises fundamental data, including open, high, low, and close prices, as well as technical indicators like Moving Average Convergence Divergence (MACD), Exponential Moving Averages (EMA), and Momentum. Technical indicators are mathematical calculations performed on data such as price or other technical indicators, and are widely used by active traders for analyzing short-term price movements. The dataset covers the period from January 2011 to December 2020.

VI. RESULT ANALYSIS

Predicting the Test Data: Figures 3-4 show the comparison between the stock price and date for both the LSTM-FA and LSTM-TA models, using the same test and train data. The accuracy of the model was determined using the R-square error formula, which is closer to 1, indicating a good fit for the train and test models. Although the mapping of the stock price and predicted prices is not entirely accurate, it serves its purpose for day-to-day predictions. The chart also compares the accuracy of the regression and neural network models.

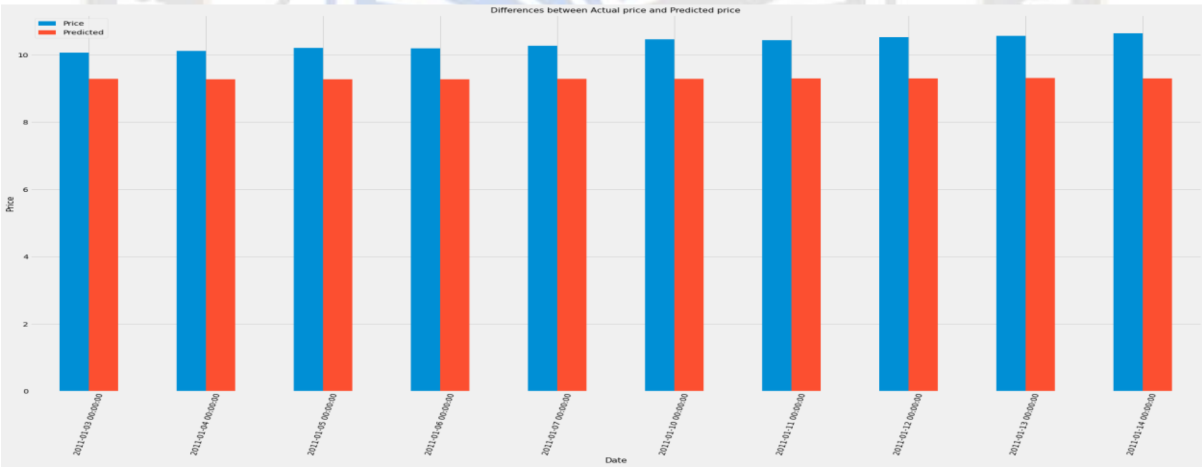

Fig 3: LSTM using Fundamental Analysis

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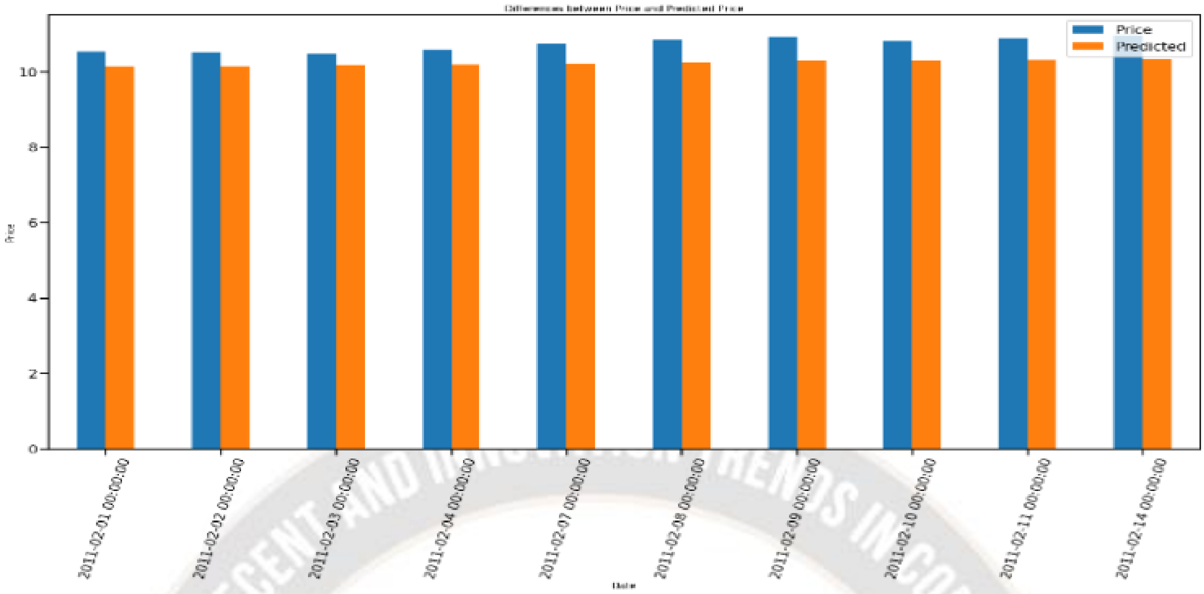

Fig 4: LSTM using Technical Analysis

Table 1: Summary of model accuracies with different epochs

Model	No. of epochs=10	No. of epochs=50	No. of epochs=100
LSTM FI	93.77	94.04	96.29
LSTM TI	94.35	94.82	98.58

Table 2: Result comparison

Model	RMSE	MAE	R-square
LR	0.1609	0.6658	0.9975
RF	1.4251	0.7768	0.9960
SVR	2.0421	0.8713	0.9926
LSTM-FA	0.0783	0.3682	0.9976
LSTM-TA	0.0953	0.5372	0.9983

Table 3: Summary of decisions by different models

Decision	LR	RF	SVR	LSTM-FA	LSTM-TA
SELL	1477	1548	1667	2204	2135
BUY	1031	960	841	353	302

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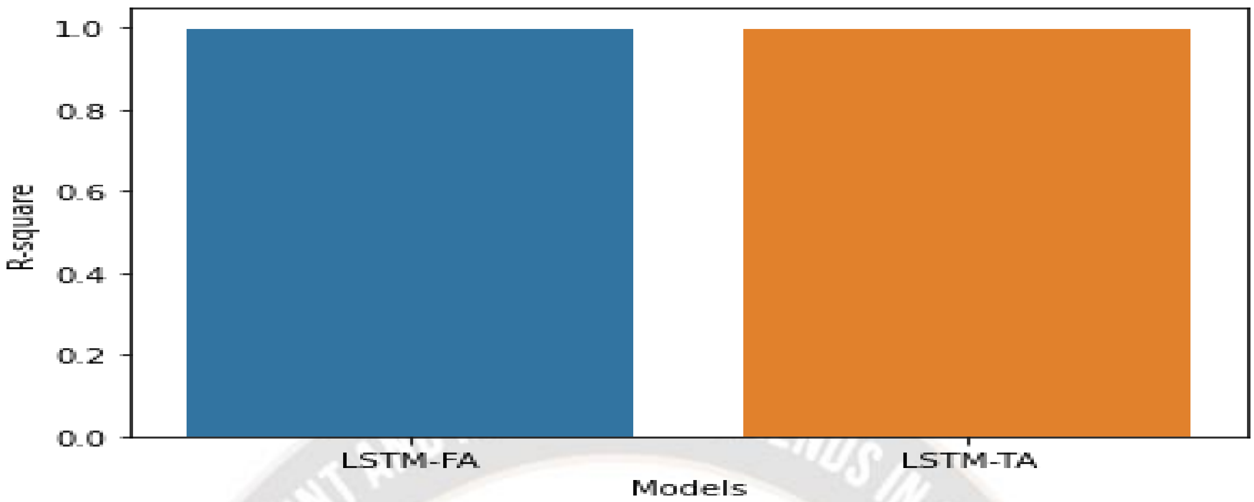

Fig 5: Comparison graph between LSTM-FA and LSTM-TA with R-square

VII. CONCLUSION AND RECOMMENDATION

The results showed that the LSTM-TA architecture was the best model because it made good predictions using information from technical indicators. LSTM-TA did better than other models that also used technical indicators because it could model both short-term and long-term data and catch sudden changes in the stock market. So, it is important to use networks like LSTM-TA, which use both recent and old information, when analyzing this kind of data. In future research, we plan to improve the current method by building the BiLSTM model, which encodes the sequence in both forward and backward directions and combines the results at each step.

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