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Beyond Fundamentals Or Technicals: Unveiling Synergies Through Linear And Non-Linear Models For Stock Index Predcition

[1]A. R. Aruna, [2]Dr. Sreeya B

[1]Research Scholar (Assistant Professor), Department of Management Studies,
Saveetha School of Law, Saveetha Institute of Medical and Technical Sciences, Chennai
arunaar.ssl@saveetha.com
[2]Associate Professor (Research Supervisor), Department of Management Studies,
Saveetha School of Law, Saveetha Institute of Medical and Technical Sciences, Chennai
sreeyab.ssl@saveetha.com

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Abstract
Stock market prediction is a debatable area of research since many decades and various studies have been done to predict the returns and movement of stock prices which will help the investors to take long or short positions in their portfolio. The main objective of the study is to understand the efficacy of fundamental, technical indicators and combined (technical and fundamental) in prediction of CNX Nifty 50 Index employing Linear regression, Random forests, Decision trees, Support Vector regression and Feed forward neural networks. Required data for analysis are collected from NSE website and time frame of the data collected is from 01-Jan-2018 to 31-Dec-2021. It was found from the analysis that feed neural networks outperform other models and linear model also provide equally good results with technical indicators and hybrid indicators. Even though technical analysis and combined approach have good performance metrics, combined approach has lower error metrics such as MAD and SSR than technical analysis

Keywords: Fundamental Analysis, Technical Analysis, Nifty 50, linear models, FNN

1. INTRODUCTION

Stock markets plays a vital role in the growth of any industry which in turn have impact on the economy of the country. It acts as "financial barometer and development indicators of national economy of the country, industrial growth and stability is reflected in the index of stock exchange" (Naved, 2014) .It is for this reason, government, industry, and the central banks of the country keep close watch on the happenings in the stock market. Stock market is an investment avenue for professional investors and the public. Also, India has been recently ranked as the second most preferred equity investment destination among the emerging markets in 2019 after Brazil, according to a survey conducted by Bloomberg (Sanchi Padia, 2019). So, it becomes necessary that investors make informed investments in stocks that meet their investment need. Also understanding stock predictions helps investors to strategically allocate funds. It helps the investors the optimal entry and exit points resulting in minimization of risk and maximizing the profits.

There are diverse approaches used for providing insights into stock market behaviour. First one, fundamental analysis attempts to find intrinsic value of a security using publicly available financial information about the company and also related economic factors. Buy or sell decisions are made based mispricing of the security. Secondly, technical analysis, which studies the past prices and other trading activity data trends, to predict the price of the security. Recently, Sentiment analysis, which focuses on the emotions of the investors for making buy/ sell decisions.

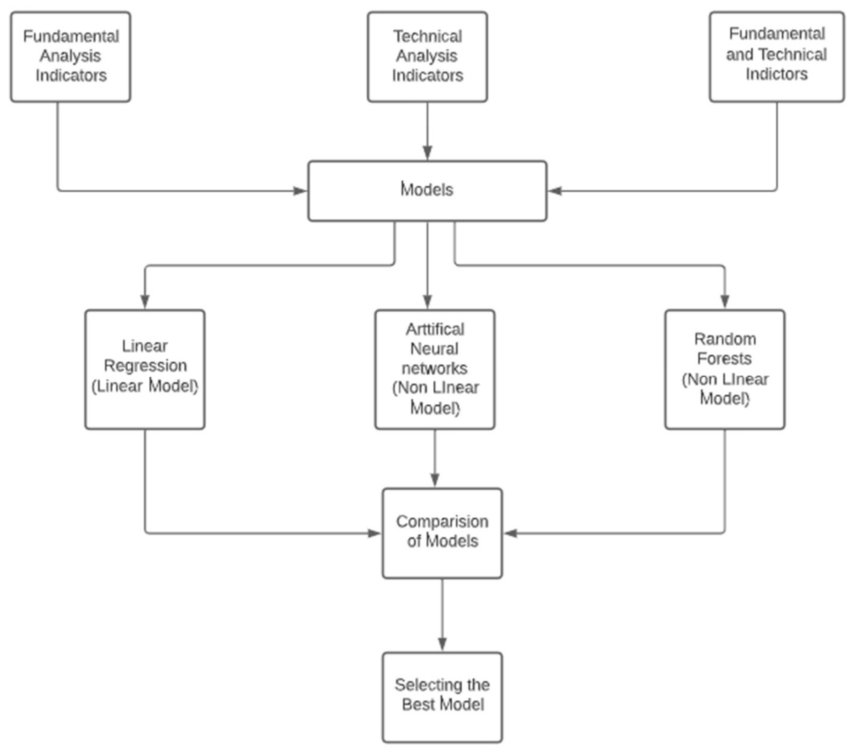
Consistent evolution of the techniques used for each of these approaches, where traditional regression methods have been employed (Suryanto, 2010) followed by using time series analysis methods such as ARIMA (Meher et al., 2021; Tamamudin & Rusyida, 2022). These traditional techiques assume linear dependence between variables. Machine learning algorithms helped the researchers to overcome this assumption and various studies explored applications of various machine learning algorithms in stock market predictions.(Jabbari & Fathi, 2014)(Al-Thelaya et al., 2019) (Adebiyi et al., 2012)

Extensive review of literature reveals that there are many studies related to predicting the stock market returns or direction of movement of individual stocks (Wijaya & Nugroho, 2023)
(Kaur & Dharni, 2023) but limited studies were available in the prediction of stock index (Aguirre et al., 2020) (Ayala et al., 2021) in Indian context (M. Kumar & M., 2006)(Singh, 2022). Also, such studies used either fundamental or technical indicators but not combination and comparative analysis of hybrid models.
Hence, the main purpose of this study can be seen from two perspectives

- First one is, whether the fundamental analysis or technical analysis or combination of both technical and fundamental analysis can better predict the stock market index movement?
- Secondly, Linear Models or Non-linear (Machine learning) models can better predict the Stock market movement?

The diagrammatic representation of the paper is as given below

Figure 1 : Structural Outline of the study



2. REVIEW OF LITERATURE

(Kaur & Dharni, 2023) examined the accuracy of stock market predictions of 381 companies from National Stock Exchange of India's CNX 500 index using fundamental and technical indicators. The results shows that the hybrid model produce better stock returns than buy and hold strategy**.** (Wijaya & Nugroho, 2023) employed fundamental and technical indicators of 30 banking companies listed in Indonesia Stock Exchange, to predict stock returns of the banking companies. Time frame for the study is from 2017 to 2021. It was found that Earnings Per share, Debt equity ratio, stock price, trade volume and Current ratio have significant impact on stock returns.(Singh, 2022)attempted to predict stock markets employing machine leaning models. The researcher used 8 supervised machine learning models using the historical data of Nifty 50 Index from 22/04/1996 to 16/04/2021 spanning 25 years. It was found that Support Vector Machines performed better among all the models followed by Artificial Neural Networks. Stochastic Gradient Ascent performed better with increase in size of dataset**.** (Fathali et al., 2022) employed three different deep learning algorithms (RNN, LSTM, and CNN) to predict the stock returns of the NIFTY 50 index and daily prices of Nifty 50 during the time period of 01/01/2014 to 31/12/2018 is considered with combination of daily Open, High, Low, Close and Volume as input parameters for feature selection. The performance metrics indicate that LSTM model is better compared to RNN and CNN models. (Ajinkya Rajkar, 2021)used technical and sentiment analysis to predict closing prices of selected stocks from NSE using RNN. A system was built to give Buy/Sell or Hold signals when live prices were fed to the system. LSTM was used for forecasting of prices using two years of historical data. (M et al., 2018) used deep learning models for NSE stock market prediction. Linear models (AR, MA, ARIMA, ARMA) and non-linear models (ARCH, GARCH, Neural Network) were employed for prediction. Highly traded stocks from different sectors in NSE and NYSE were selected and the closing prices of stocks during the period of 01 Jan, 1996 to 30th June, 2015 were used for analysis. It was found from analysis that neural networks performed better than linear models. (M. Kumar & M., 2006)employed multiple machine learning models to predict the direction of CNX Nifty Index. Authors used 12 technical indicators collected for the time period from 1st January 2000 to 31st May 2005. The results indicate that SVM have the highest hit ratio.

3. METHODOLOGY

3.1. Data

The study employs both technical indicators and fundamental indicators for stock index prediction using linear and nonlinear models. CNX Nifty50 index values during the time frame from 01-Jan-2018 to 31-Dec-2021. Price to Earnings Ratio (P/E), Price to Book ratio (P/B) and Dividend Yield were used as fundamental indicators for valuing the Nifty 50 index (Varsity, Zerodha) and Relative strength index of 14 days (RSI), 14-day Stochastic Oscillator, Stochastic moving average, Simple Moving average of 21 days and Exponential Moving average of 21 days and 14-day Williams %R were used as technical indicators (D. Kumar et al., 2016).

3.2. Normalization of data

All the collected data are pre-processed using Min Max Normalization method. All the variables are scaled between the values 0 and 1 using the formula

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

Where,

- X is the original value,
- X_{norm} is the normalized value,
- X_{max} and X_{min} a are the minimum and maximum values of X respectively.

Normalization ensures that all the variables contribute equally to the dependent variable.

3.3. Models used

Linear regression model is used to understand the linear relationship between the variables Numerous studies were conducted using models used CART, Feed Forward Neural networks, Support vector Regression and Random forests (M. Kumar & M., 2006). CART, FNN and Random forests were used in this study to test the non-linear relationship between the variables and linear regression is used to study linear relationship. Dataset is partitioned in the ratio 70/15/15 (Training/ Testing/Validation).

3.4. Model Evaluation

Pseudo $R^{2,}$ Mean Absolute Deviation (MAD), Root Mean Square of Error (RMSE) and Sum of Square of residuals (SSR) were used for evaluation of models. A brief description of the evaluation metrics is given below.

- **Coefficient of determination (R^2)** is a statistical measure of predictability of the model and it indicated the proportion of variance in outcome variable (dependent variable) that can explained by the predictor variables (independent variables). It can have values between 0 and 1. Higher the value of R^2, greater is the predictive ability of the model.

- **Mean Absolute Deviation (MAD)** is the statistical measure that provides insight on spread of data around the mean. MAD is always positive and smaller MAD indicates less variability of data around the mean. It is calculated using the formula,

$$MAD = \frac{\sum |x_i - \overline{x}|}{n}$$

Where,
Σ denotes the mean.
n is the total number of observations
x̄ denotes the mean.
xi is each individual value

- **Sum of Squared Residuals (SSR)** assesses the capability of regress Sum of Squared Residuals (SSR) formulaion model to capture the variations in data. Lower the value of SSR, better fit is the model. It is also called as Residual Sum of Squares (RSS) or Sum of Squared Estimate of Errors (SSE). It is calculated using the formula

$$RSS = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n \text{ are predicted values}$$
$$y_1, y_2, \ldots, y_n \text{ are observed values}$$
$$n \text{ is the number of observations}$$

- **Root Mean Square Error (RMSE)** is used to evaluate how well the model performs in prediction of values. Lower RMSE indicates better fit of the model. RMSE of test partition is used for ranking the models.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

$$\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n \text{ are predicted values}$$
$$y_1, y_2, \ldots, y_n \text{ are observed values}$$
$$n \text{ is the number of observations}$$

4. RESULTS AND DISCUSSION

4.1. Fundamental Analysis

Ranking of models for stock index prediction using fundamental indicators as predictors are detailed in the following table

Model	MAD	R^2	RMSE	SSR	Rank
Random Forests	0.014	0.974	0.034	0.166	II
FNN	0.028	0.968	0.038	0.209	III
Decision trees	0.022	0.984	0.028	0.101	I
SVM	0.083	0.837	0.093	1.116	V
Linear Regression	0.064	0.867	0.077	0.854	IV

Decision trees perform the best among the models with RMSE of 0.028 followed by FNN (RMSE 0.038). With respect to comparison with linear regression, all the non-linear models except SVM, perform better than linear regression. The findings of this study follow (Metsomäki et al., 2020) where the author attempted to find relation between accounting ratios and stock return and (Gu et al., 2020).

4.2. Technical Analysis

Stock index prediction done with technical indicators as input variables with various models shows that Feed forward Neural networks perform better among all models with least RMSE of 0.008. But it was found that linear regression showing better performance metric than other non-linear model considered for the study. SVM is the least performer with high RMSE of 0.043. These results matches with findings of (Nair et al., 2010) where the author used technical indicators to produce trading signals and (Fangqiong Luo et al., 2010) but contradicts findings by (Bustos et al., 2017) where SVM performs better than Artificial Neural Networks.

Table 1: Evaluation metrics for Nifty50 prediction using Technical indicators

Model	MAD	R^2	RMSE	SSR	Rank
Random Forests	0.015	0.984	0.027	0.096	III
FNN	0.006	0.998	0.008	0.010	I
Decision trees	0.025	0.974	0.038	0.218	IV
SVM	0.036	0.964	0.043	0.229	V
Linear Regression	0.007	0.998	0.010	0.012	II

4.3. Combined Analysis (Fundamental and Technical indicators)

The models are fed with the both fundamental and technical indicators are given as input to predict the stock index, the results are as follows.

Table 2: Evaluation metrics for Nifty50 prediction using both Fundamental and Technical indicators

Model	MAD	R^2	RMSE	SSR	Rank
Random Forests	0.006	0.998	0.009	0.010	II
FNN	0.005	0.998	0.008	0.008	I
Decision trees	0.021	0.982	0.030	0.135	IV
SVM	0.042	0.974	0.041	0.215	V
Linear Regression	0.008	0.998	0.012	0.017	III

The results indicate good performance by FNN, random forests and Linear regression model with same high R2 value of 0.998 but small differences in error related parameters such as RMSE, MAD and SSR. It is evident from the table that FNNs perform better than all model with least RMSE of 0.010 followed by linear regression with RMSE of 0.010. SVM shows poor performance among the models with high RMSE of 0.043.

The results contradict with (Emir et al., 2012) where SVM gave superior results and (Nicholas & Sikha, 2021), whose findings shows that random forests are better model than ANNs.

For comparing the performance of the various approaches, RMSE value of models were taken and it was found that technical and combined/hybrid approach have same RMSE of 0.008.

Approach	Model	RMSE
Fundamental analysis	Decision trees	0.028
Technical analysis	FNN	0.008
Combined approaches (Fundamental and Technical analysis)	FNN	0.008

Since the value of RMSE of the two approaches are same, other performance metrics were taken for ranking. Coefficient of determination values are also same (R^2=0.998) for both the approaches but MAD and SSR values are lower for combined/hybrid approach than technical analysis approach. So, it can be concluded that combined approach provides better predictions than technical or fundamental analysis taken in isolation and FNN provides better performance than other models. Similar findings were given by (Kaur & Dharni, 2023), (Tan et al., 2020) and (Suryanto, 2010)

5. CONCLUSION

The study of stock market trends highly influences the country's growth trends on a macro level and investor's investment decisions in a micro level but perfect accuracy is elusive due to the market's inherent complexity. This study used both fundamental and technical indicators to predict Nifty 50 index employing linear model and non-linear models (machine learning models). It was found from the analysis that feed neural networks outperform other models and linear model also provide equally good results with technical indicators and hybrid indicators. Even though technical analysis and combined approach have good performance metrics, combined approach has lower error metrics such as MAD and SSR than technical analysis. It becomes evident for investors/ equity analyst to have careful analysis of the market in both fundamental and technical aspects to earn better returns and can also adopt non-linear models for prediction purpose. This research work can be extended to inclusion of indictors that reflect investor sentiments and their impact can also be studies. Also, various other models like LSTM and other ensemble approaches can also be employed to build a better predictive model.

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