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Forecasting the Movement of Renewables Stocks Using BSE Energy Index[1]

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ABSTRACT

Coincident to the dip in the demand of conventional sources of energy like coal, oil and gas as the pandemic progressed has been a surge in the global demand for environment friendly practices, putting the spotlight on energy generated from renewable sources. The Renewables sector has found favor and is witnessing steady rise on a global level. Though a minor contributor to the power generation in India, this sector is deemed to grow in the coming years as India strives to reduce its CO_2 emissions, making the related instruments lucrative investment options. Stock exchanges are critical to the economic health of a nation and the pandemic led to major crashes in several exchanges around the world. Investment firms can employ deep learning models to forecast the movement of the market and thus assure their customers of high returns in the high-risk environment, cutting through the general pessimism pervading the investment sphere post-pandemic. This work builds forecasting models for two such stocks using neural networks. Selecting the BSE as the universe of study, two companies are selected and modelled across two techniques: LSTM and Bidirectional LSTM, employing three different feature sets. The inclusion of BSE Energy Index in the models alongside the historical prices enables capturing the influence of external elements on the energy market.

Keywords: *Stock market, COVID, March market crash, LSTM, Renewables*

1. Introduction

Importance of sectoral analysis. When the WHO declared COVID-19 a pandemic on the 11th of March 2020, subsequent panic selling led to crashes in several major stock exchanges around the world. A study of the impact of the crash (Mazur, Dang & Vega, 2021) on the firms covered by S&P1500 shows that not all sectors nosedived, rather some found favor, such as healthcare. Their results emphasize the contribution of sectoral analysis in presenting a fine-grained picture of the economic crisis. The non-uniformity of the economic impacts of any global or regional phenomenon is common knowledge. This forms the basis of Sector rotation, a popular investment strategy to maximize returns and minimize risks in the highly volatile stock exchanges. It capitalizes on the cyclical (and often predictable) rise and fall of different sectors in the economy. Investors dynamically shift their assets from sectors heading saturation or downfall, to sectors of the rise. (Zhu, Yi & Chen, 2020) utilize macroeconomic variables like GDP and inflation to build a portfolio optimized for sector rotation. Detailed sectoral analysis of market related investments can uncover peculiarities invisible in aggregate studies.

Renewables Sector. One of the sectors which is performing well after the onset of the pandemic, globally as well as nationally, has been power generation from Renewables. Renewable sources of energy encompass myriad sources like solar, hydro, wind and bioenergy. Market related instruments, Renewable Energy Certificates (RECs), are traded as

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an energy commodity. Steady growth in this sector is being witnessed (REN21, 2020), which is foreseen to grow further as the world shifts away from fossil fuels. The 2021 United Nations Climate Change Conference, organized in Glasgow at the beginning of November, 2021 is expected to draw additional attention (and trade) towards this sector. Power generation from renewables is still a minor contributor to the coal dominated energy sector of India. However, as through renewables the country can actively reduce its dependency on crude oil (which forms a large part of its imports) and coal powered power plants (which are responsible for high CO_2 emissions) in meeting its ever-increasing energy demand, the National Action Plan for Climate Change (NAPCC) has been supporting and promoting advancement in this sector. The International Energy Agency (IEA) shows that contrary to conventional energy sources, renewables were the only source that experienced a growth in demand in the aftermath of COVID-19 pandemic. In comparison to the Morgan Stanley Morgan Stanley Capital International (MSCI) All Country World Index (ACWI) Energy Index, MSCI Global Alternative Energy Index was less affected by the pandemic, as found by (Czech & Wielechowski, 2021). Besides being instrumental in mitigating climate change, projects in renewables promote local employment for the skilled as well as the unskilled, encourage the adaptation of technology to local needs, and ensure energy security in the long run. These multifaceted benefits have reinforced positive perception about renewable energy, which has translated into positive sentiments in the investors' community.

Forecasting Tools. As investment decisions are easily swayed by panic and greed, even with access to vital information, investors side with dubious companies (Chakraborty, 2021) in riding the wave. Other biases, like overconfidence, the illusion of control, loss aversion and herd mentality, lead even experiences investors to loss making ventures (Althelaya, El-Alfy & Mohammed, 2018). To ensure high returns and minimize risks, forecasting models based on such sectoral information come handy in making investment decisions. Though a huge body of literature can be found on stock forecasting, perhaps it is the non-linearities and irregularities in stock data that sustain interest in this domain. Though the Efficient Market Theory forwards the belief that none of technical analysis and fundamental analysis is sufficient in ensuring risk adjusted excess returns consistently, the existing research of forecasting has proven both of these techniques useful, an idea central to the vast literature available on stock exchange related forecasting, also demonstrated by (Althelaya, El-Alfy & Mohammed, 2018). The work of (Siami-Namini, Tavakoli & Namin, 2019) is a comparative analysis of the ARIMA, LSTM and Bidirectional LSTM (Bi-LSTM) techniques on a multitude of stock price series recorded at different granularities. Employing the Root Mean Square Error (RMSE) as the assessment metric, they find the prediction of Bi-LSTM superior to the others.

On similar lines, this work integrates a range of technical indicators to the historical data of aforementioned stocks, and models them using stacked LSTM and stacked Bi-LSTM. In addition to RMSE, three other metrics are used for the assessment. The time span of this data includes the market crash of March, 2020 and thus demonstrates high volatility.

2. Materials And Methods

Data. The Bombay Stock Exchange, now BSE (www.bseindia.com) was established in 1875 and is Asia's first stock exchange. Thus, this exchange has a history of 145 years. BSE SENSEX is India's widely traded stock market index and is internationally traded in EUREX and BRCS countries. As of date BSE does not maintain an index dedicated to renewable energy, thus an equivalent of the MSCI Global Alternative Energy Index is absent. The BSE Energy Index, which quantifies the stock movements of the companies in the energy sector listed with BSE, has been considered. Its calculation includes several companies as listed in (MoneyControl.com, n.d.).

Two companies listed with the BSE, corresponding to symbols NHPC and SURANASOL, have been considered for this work. NHPC Limited (BSE: NHPC) is the largest hydropower development organization in India. It has also diversified to include solar and wind-based projects. Currently it has an installation base of 7071 MW. Nine projects are under construction. Surana Solar Limited (BSE: SURANASOL) is one of the leading manufacturers of solar photovoltaic modules. It has four grid connected Solar Power Plants commissioned in Gujarat and Telangana of 5MW each, with several upcoming projects in the Southern region of the country. These entities are not among the components of BSE Energy Index.

The historical data obtained on BSE (www.bseindia.com) includes multiple fields besides the open-close-low-high (henceforth referred to as OHLC) and volume. These are named as trades, turnover, deliverable quantity, the weighted average price, and the spreads i.e., differences for high-low and close-open. A trade refers to the transfer of the share from seller to buyer. The number of trades carried out in the business day, the number of shares marked for delivery and their percentage of the total number of shares traded, are recorded for each business day. Share turnover is a metric associated with the liquidity of the stock. Weighted Average Price, or WAP, is calculated as the average share purchase price weighted by the number of shares purchased at that price.

The data used for this work spans 2 years, from the 14th August, 2019 till 13th August, 2021.

Figure 1 charts the daily closing prices of the selected stocks.

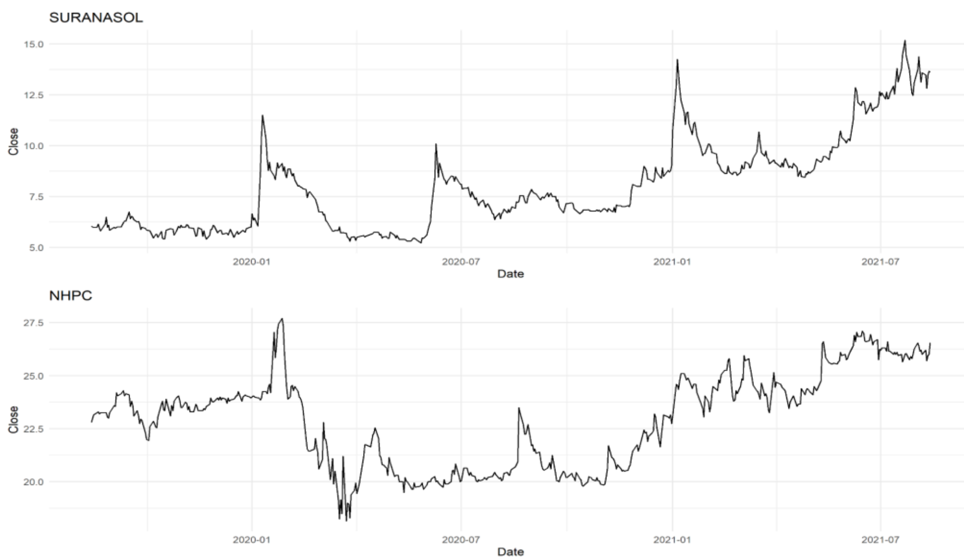

Figure 1.Closing Prices

Figure 2 shows the volatility of the two series, calculated as per the classical close-to-close method (Vințe, Ausloos & Furtună, 2021), using a window of 20 days.

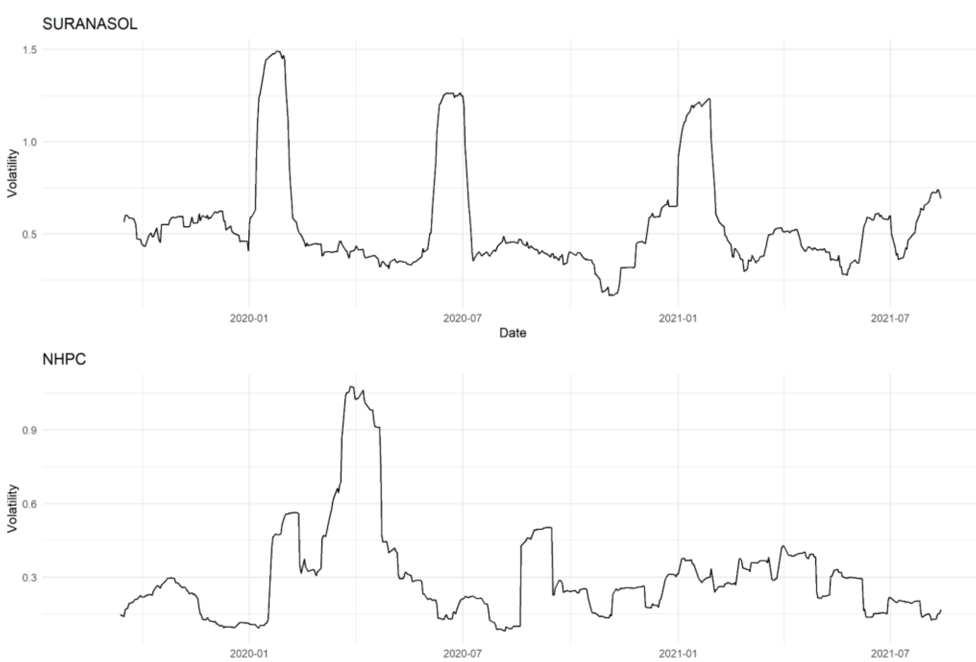

Figure 2. Closing Prices Volatility

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As can be observed from Figure 2, the prices for SURANASOL demonstrate higher volatility compared to those of NHPC. While the volatility of NHPC peaks around the market crash, for SURANASOL we see peaks appearing cyclically, every 4-5 months.

The typical prices of the BSE Energy Index, sourced from the BSE website, has been included as a predictor. Currently, the energy sector in India is dominated by conventional sources like oil and coal. Visual comparison of the BSE Energy Index with the MSCI ACWI Energy Index, presented in Figure 3, highlights their similarities. The sharp dip in the month of March 2020, and the subsequent steady rise is evident. The period of study includes this crash, thus makes for an interesting study of a period characterized by uncertainty and volatility in the market.

Figure 3. Visual Comparison of MSCI ACWI and BSE Energy Index

Feature generation. Technical indicators are derived from the OHLC and Volume to assist buy-sell-hold decisions. These are overlaid on the OHLC data, or charted as complementary information. A total of 40 indicators are used, some described as follows.

Trend following indicators follow the past price action. Two of those, the simple moving average and the Exponential volume weighted moving average, each with a window of 20 business days, have been included. Momentum based indicators such as Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) add information about the speed of price change. Trading bands and envelopes, such as Bollinger Bands, enrich the feature set. The classical volatility (Vințe, Ausloos & Furtună, 2021), referred to as the close-to-close method, is measured as the standard deviation of the log returns. However, over decades of research, alternate measures have been suggested. While the Parkinson estimator employs just the high and low prices, the Garman-Klass estimator, Rogers- Satchell estimator and Yang-Zhang estimator include OHLC prices as well. The Chaikin volatility indicator includes the information on volume into the calculation.

Data Scaling. The feature sets have been scaled using the Absolute Maximum Scaling, wherein values of each column are divided by its respective maximum. The purpose of this operation is to make the data suited to neural networks.

Feature Selection. (Haq, Zeb, Lei & Zhang, 2021) discusses 44 indicators and (Peng, Albuquerque, Kimura & Saavedra, 2021) use 124. While numerous technical indicators are available, simplicity and parsimony of the model enhances its reliability and performance. Therefore, the Boruta algorithm, also used in (Lee, Kim & Yoon, 2021) is employed to prune any unnecessary features. As part of the Boruta procedure, (Kursa, Jankowski & Rudnicki, 2010) describe, replicas of each feature variable are included

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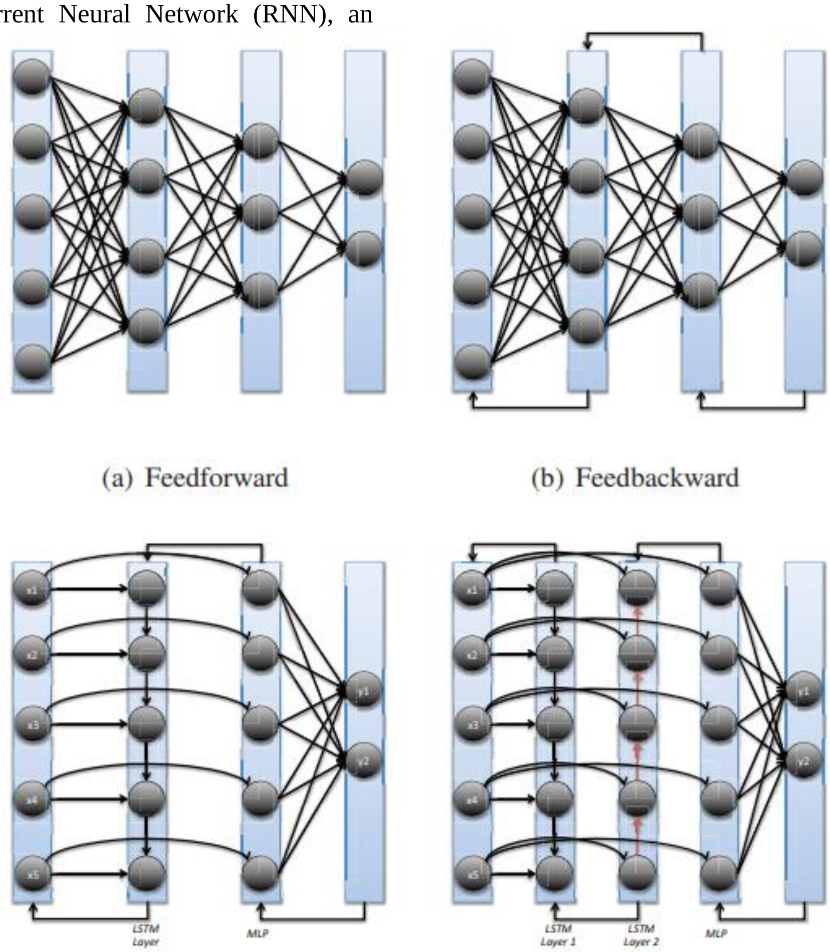
in the model and randomly shuffled. The importance of each variable is recorded over a series of random forests. The proportion of runs which found a feature statistically important determines the final result of approving or rejecting the feature, or leaving it undetermined.

Model. Traditionally forecasting models employed statistical techniques like ARIMA, GARCH, EGARCH et cetera. Techniques based on spectral decomposition were borrowed from the domain of signal processing. However, with the advancement in machine learning, forecasting has been dominated by algorithms often such as Support Vector Machines (Vo, Nguyen & Le, 2020; Lee, Kim & Yoon, 2021) and Deep Neural Networks (Shah, Campbell & Zulkernine, 2018). As the dependency of future occurrences on past observations cannot be overlooked, Recurrent Neural Network (RNN), an artificial neural network architecture which incorporates memory units, has been especially successful for modelling time series. The LSTM model is a variant of RNN that was proposed to solved the issue of vanishing gradient. (Lee, Kim & Yoon, 2021), and has proved to a promising model for long term forecasts, as reported by (Shah, Campbell & Zulkernine, 2018). LSTM has the characteristic of selectively retaining and forgetting information, making it effective in modelling sequences with dependency on a long train of past values without the requirement of a large memory.

A picture is worth a thousand words. (Siami-Namini, Tavakoli & Namin, 2019) presents the popular architectures of neural networks as diagrams, presented here in Figure 4.



(a) Feedforward (b) Feedbackward

(c) LSTM (d) BiLSTM

Figure 4. Neural Network Architectures (Siami-Namini, Tavakoli & Namin,2019)

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In Figure 4(a), the flow of information is from input layer to output layer. In Figure 4(b), there are links passing information in the reverse direction. Both of these are fully connected networks, as can be observed from the dense net of edges. As can be observed from Figure 4 (c) and 4(d), Bi-LSTM has an extra layer where information flows in the reverse direction, indicated by a layer marked with red arrows. Bi-LSTM has a set of two LSTM layers traversing the data in opposite directions, one reading the values left to right, and the other right to left (Althelaya, El-Alfy, & Mohammed, 2018). In several works, Bi-LSTM generates better forecasts, some of which are (Siami-Namini, Tavakoli & Namin, 2019; Vo, Nguyen & Le, 2020). The bidirectional processing often leads to slower convergence to equilibrium when compared to that of LSTM (Yıldırım, Toroslu & Fiore, 2021). The current work implements LSTM and Bi-LSTM, with a stack of two layers.

Assessment. This section presents four metrics used for assessment of forecasting models. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), as used in (Ding & Qin, 2020), are popular for measuring the goodness of the forecast.

$$MAE = \max\left(|Close_{actual} - Close_{predicted}|\right)$$

$$RMSE = \sqrt{\frac{\sum_{1}^{n}(Close_i - \widehat{Close}_i)^2}{n}}$$

However, as (Yıldırım, Toroslu & Fiore, 2021) places emphasis on the prediction of the direction of movement, the standard Directional Accuracy and Profit Accuracy are also used. They are elaborated as follows.

Directional accuracy, used in (Shah, Campbell & Zulkernine, 2018), takes the difference between prices on consecutive trading days and categorizes them into increases and decreases, without taking into consideration the absolute magnitude of the change. Thus, four terms are created.

Table 1. Directional Accuracy Calculation Terms

Term	**Description**
$True_{increase}$	The count of increases correctly predicted as increases
$True_{decrease}$	The count of decreases correctly predicted as decreases
$False_{increase}$	The count of increases incorrectly predicted as decreases
$False_{increase}$	The count of decreases incorrectly predicted as increases

$$Directional\ Accuracy = \frac{True_{increase} + True_{decrease}}{True_{increase} + True_{decrease} + False_{increase} + False_{decrease}}$$

DA is similar to a binary evaluation because it compares the direction of each prediction against the direction of true data for a specified time period i.e., 7 days and takes an average across all predictions.

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(Yıldırım, Toroslu & Fiore, 2021) define an alternate measure for directional accuracy, christened profit accuracy. While directional accuracy takes into consideration the increase and decrease between consecutive prices, this measure finds a threshold and marks all the changes below this threshold value as "no action". Thus, this measure is less sensitive to minor fluctuations in the prices.

Determining the threshold value consists of two steps. The first involves taking the differences between prices on consecutive trading days and through the inspection of histogram find a value T such that the interval [0, T] contains 85% of these differences. The second step involves calculating the number of differences corresponding to increases, decreases and no action for all potential thresholds in this interval and finding the one value which yields the maximum entropy, as calculated by the following formula. This value is taken as the threshold.

$$Entropy = -\sum P_i * \log(P_i)$$

The profit accuracy takes into account the actual differences labelled as increase, decrease and no action, and compares the same in the predicted data. This yields nine terms as listed below.

Table 2. Profit Accuracy Calculation Terms

Term	**Description**
$\text{True}_{\text{decrease}}$	The count of decreases predicted correctly
$\text{True}_{\text{increase}}$	The count of increases predicted correctly
$\text{False}_{\text{noact->decrease}}$	The count of no action in actual data predicted as decreases
$\text{False}_{\text{noact->decrease}}$	The count of no action in actual data predicted as increases
$\text{False}_{\text{increase->decrease}}$	The count of increases in actual data predicted as decreases
$\text{False}_{\text{decrease->increase}}$	The count of decreases in actual data predicted as increases
$\text{True}_{\text{noact->noact}}$	The count of no action predicted correctly
$\text{False}_{\text{increase->noact}}$	The count of increases in actual data predicted as no action
$\text{False}_{\text{decrease->noact}}$	The count of decreases in actual data predicted as no action

The last two terms, $\text{False}_{\text{increase->noact}}$ and $\text{False}_{\text{decrease->noact}}$ have been merged with the $\text{True}_{\text{increase}}$ and $\text{True}_{\text{decrease}}$, respectively.

$$Profit\ Accuracy = \frac{True_{increase} + True_{decrease}}{\sum all\ terms}$$

Software Tools. Open-source software tools R and Python have been utilized for this work. The generation of technical indicators and the visualization of the data has been carried out on R. The LSTM and Bi-LSTM models are developed using the Tensorflow library on Python. The assessment of the results has been carried out on R.

3. Results And Discussion

The Boruta Feature Selection marked all features important, so none was dropped. The results obtained under each scenario has been presented as follows. The graphical representation of the actual and forecasted values for each of the two series has been presented. This is followed by the tabulated values of RMSE and MAE, and values of Directional Accuracy and Profit Accuracy.

From Figure 5, the forecasts generated by LSTM and Bi-LSTM are close. In Figure 6, the inclusion of technical indicators generates spikes in the forecast. For NHPC, LSTM overestimates while Bi-LSTM underestimates.

The simplest models, with OHLC and the BSE Energy Index as feature sets, demonstrate the lowest RMSE and MAE, when Tables 3, 5 and 7 are compared. However, when compared on the metrics of Profit Accuracy and Directional Accuracy, inclusion of the technical indicators proves useful. The feature set 3 gives the best results based on profit accuracy and directional accuracy, as can be observed from Tables 4, 6 and 8.

Feature Set 1: Using BSE Energy and OHLC only,

Figure 5. Actual vs Forecasted (Feature Set 1)

Table 3. Assessment of Feature Set 1 (MAE and RMSE)

Symbol	**MAE**		**RMSE**	
	LSTM	**Bi-LSTM**	**LSTM**	**Bi-LSTM**
SURANASOL	0.35	0.30	0.47	0.38
NHPC	0.31	0.22	0.38	0.27

Table 4. Assessment of Feature Set 1 (Directional Accuracy and Profit Accuracy)

Symbol	**Directional Accuracy**		**Profit Accuracy**	
	LSTM	**Bi-LSTM**	**LSTM**	**Bi-LSTM**
SURANASOL	68.75%	70.42%	57.5%	59.17%
NHPC	59.03%	63.89%	56.17%	60.45%

Feature Set 2: Using OHLC and technical indicators

Figure 6. Actual vs Forecasted (Feature Set 2)

Table 5. Assessment of Feature Set 2 (MAE and RMSE)

Symbol	MAE		RMSE	
	LSTM	**Bi-LSTM**	**LSTM**	**Bi-LSTM**
SURANASOL	1.03	0.87	1.12	0.98
NHPC	0.40	0.87	0.47	0.92

Table 6. Assessment of Feature Set 2 (Directional Accuracy and Profit Accuracy)

Symbol	Directional Accuracy		Profit Accuracy	
	LSTM	**Bi-LSTM**	**LSTM**	**Bi-LSTM**
SURANASOL	72.26%	80.33%	58.80%	60.46%
NHPC	67.54%	68.55%	57.66%	58.06%

Feature Set 3: Using OHLC, BSE Energy Index and technical indicators

Table 7.Assessment of Feature Set 3 (MAE and RMSE)

Symbol	MAE		RMSE	
	LSTM	Bi-LSTM	LSTM	Bi-LSTM
SURANASOL	1.18	0.69	1.26	0.78
NHPC	0.19	0.74	0.27	0.82

Table 8. Assessment for Feature Set 3 (Directional Accuracy and Profit Accuracy)

Symbol	Directional Accuracy		Profit Accuracy	
	LSTM	Bi-LSTM	LSTM	Bi-LSTM
SURANASOL	73.75%	81.04%	58.96%	61.25%
NHPC	70.59%	70.71%	60.65%	60.95%

4. Conclusion

The comparative analysis in this work compares the forecasts generated by LSTM and Bi-LSTM on two volatile renewable energy stocks. Starting with data collection from the BSE website, the steps of feature generation, feature selection, data scaling, modelling, and assessment was carried out. The choice of span included the market crash caused by the pandemic. The three feature sets and 2 models (LSTM and Bi-LSTM) create six scenarios. The Feature Set 3, including 40 technical indicators and the BSE Energy Index generates the best outcomes, however, the improvement moving from LSTM to Bi-LSTM is minor and doesn’t justify the extra computation that Bi-LSTM needs. Thus, LSTM with BSE Energy Index and the technical indicators will serve as a good forecasting model. With machine learning tools flooding the market, comparative studies aid in model selection to optimize computation while ensuring high performance in for real time applications.

5. Future Work

The current work gives a maximum profit accuracy of 71 per cent. It might be a case of overfitting, which can be investigated and corrected with dropout and associated networks, such as those in (Ding & Qin, 2020). Optimizing the feature set can be attempted by inclusion of other technical indicators and pruning for parsimony. (Vințe, Ausloos & Furtună, 2021) recommends the use of intrinsic entropy model as a substitute of volatility (Yıldırım, Toroslu & Fiore, 2021; Zhu, Yi & Chen, 2020) include macroeconomic factors. The works of (Challa, Malepati & Kolusu, 2020) and (Althelaya, El-Alfy & Mohammed, 2018) describe forecasting models for the returns instead of prices. This transformation can be included to enhance the forecast.

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