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Applying Predictive Modelling Techniques for Stock Market Prediction

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Abstract*— As analysts in the financial business, calculating stock prices has never been an easy assignment. Research in the literature has shown that stock price movements can be predicted with the appropriate level of accuracy if the right variables are chosen and the right predictor models are created, refuting the Efficient Market Hypothesis' assertion that it is impossible to predict stock prices with any degree of accuracy. people with flexibility. Studies conducted in the literature have shown that stock price variations may be predicted with an appropriate degree of accuracy if the necessary variables are selected and appropriate predictor models are constructed. people with flexibility. In addition to economic factors, stock values are impacted by a wide range of significant psychological, intellectual, physical, and other factors. Facebook Prophet is employed in this study to predict stock prices. Stock price prediction algorithms have been developed and tested using publicly available stock data from Yahoo Finance. Prophet may generate seasonality on a daily, monthly, and annual basis, including with holiday impacts, by employing regression models. The results of the experiment indicate that Facebook Prophet is a useful tool for long-term stock price prediction.

***Keywords*—Stock Prediction, data preprocessing, regression, time-series analysis, ANN, Neural networks.**

I. INTRODUCTION

The main stock market in India, National Stock market of India Ltd. (NSE), is supported by a number of local and foreign financial institutions in addition to publicly traded and privately held enterprises. Based on the amount of contracts traded, NSE was the largest derivatives exchange globally in 2021, according to data released by the Futures Industry Association (FIA). The World Federation of Exchanges' figures from 2021 show that NSE was rated fourth globally in terms of cash equities. Predicting stock prices is challenging since the investment is routed through several investors, causing changes in the supply and demand chain. But knowing the underlying dynamics as an investor might help you trade more profitably.

People today are highly interested in putting their money in the stock market in order to increase their earnings quickly. Any company's stock, which may be purchased privately, is the foundation of any portfolio. Such transactions must be governed by certain legal guidelines in order to prevent any more illegal activity. One kind of security that indicates ownership in the issuing company is a stock. Stocks are available to the public in a variety of ways and have withstood the test of time.

People who trade stocks on the stock market can make or lose a fortune in this incredibly difficult and sophisticated system, which calls for expertise and experience. This work attempts to forecast stock values by utilizing sophisticated machine learning principles like LSTM (Long Short Term Memory) and Recurrent Neural Networks. This model uses these ideas in conjunction with a company's past equity share price to produce its findings. Stock market shares have several characteristics, such as opening price, day high, day low, trading date, total trade quantity, and total trade turnover. The suggested approach retrieves historical and real-time data from Yahoo Finance, cleans and transforms it, and then feeds it into the Keras model to get the desired outcome.

II. LITERATURE SURVEY

A. Pedictive models : LSTM and CNN

With the use of add-on models that produce nonlinear patterns from seasonal, weekly, daily, and holiday results, LSTM models are used to forecast time series data. When there are several seasons of historical data and several time periods with significant seasonal outcomes, it performs well. The prophet is good on missing data and trend changes and often works with outsiders. This model takes extremely minimal computing time as compared to others.

In the context of stock prediction, CNN usually refers to Convolutional Neural Networks, a kind of deep learning model frequently employed in image recognition applications, rather than the news network. However, because market data is sequential and time-dependent, directly using CNNs to stock prediction is not simple.

B. Related Work

[7] When investing in stock markets, stock prices serve as the investor's first point of reference. However, only glancing at the price is insufficient. Investors must possess the

fundamental information necessary to analyze stock prices in order to make wise investment choices that will optimize their returns. There are essentially two approaches to stock analysis and price prediction. There are two ways that are frequently used to analyze stock prices i.e. Top-Down and Bottom-Up Approach. In a top-down approach the industrialist starts with the general state of economy, then focuses on the industries poised to perform well depending on the various factors at play in the market (for example, the pharmaceutical industry was anticipated to perform well as the covid-19 pandemic spread), before picking individual stocks from the industries that have been focused on. Whereas the bottom-up approach is the opposite of top-down approach. Here, you begin by locating a business that you would want to invest in before moving upward. Look at the industry it is in, then assess the overall state of the economy in the nation or areas the company operates in. According to the author, commonly used metrics in fundamental analysis include earnings per share, price to earnings ratio, return on equity, price to earnings to growth ratio and price to book ratio. The measures such as simple moving averages, exponential moving averages, candlesticks patterns, volume breakouts and momentum indicators are used more often in technical analysis.

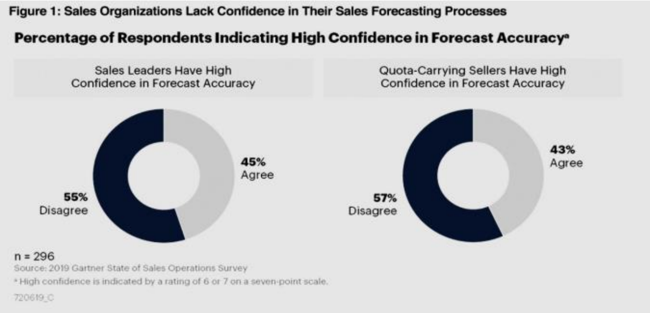

Fig.1 Sales organizations' confidence for their forecasting methods

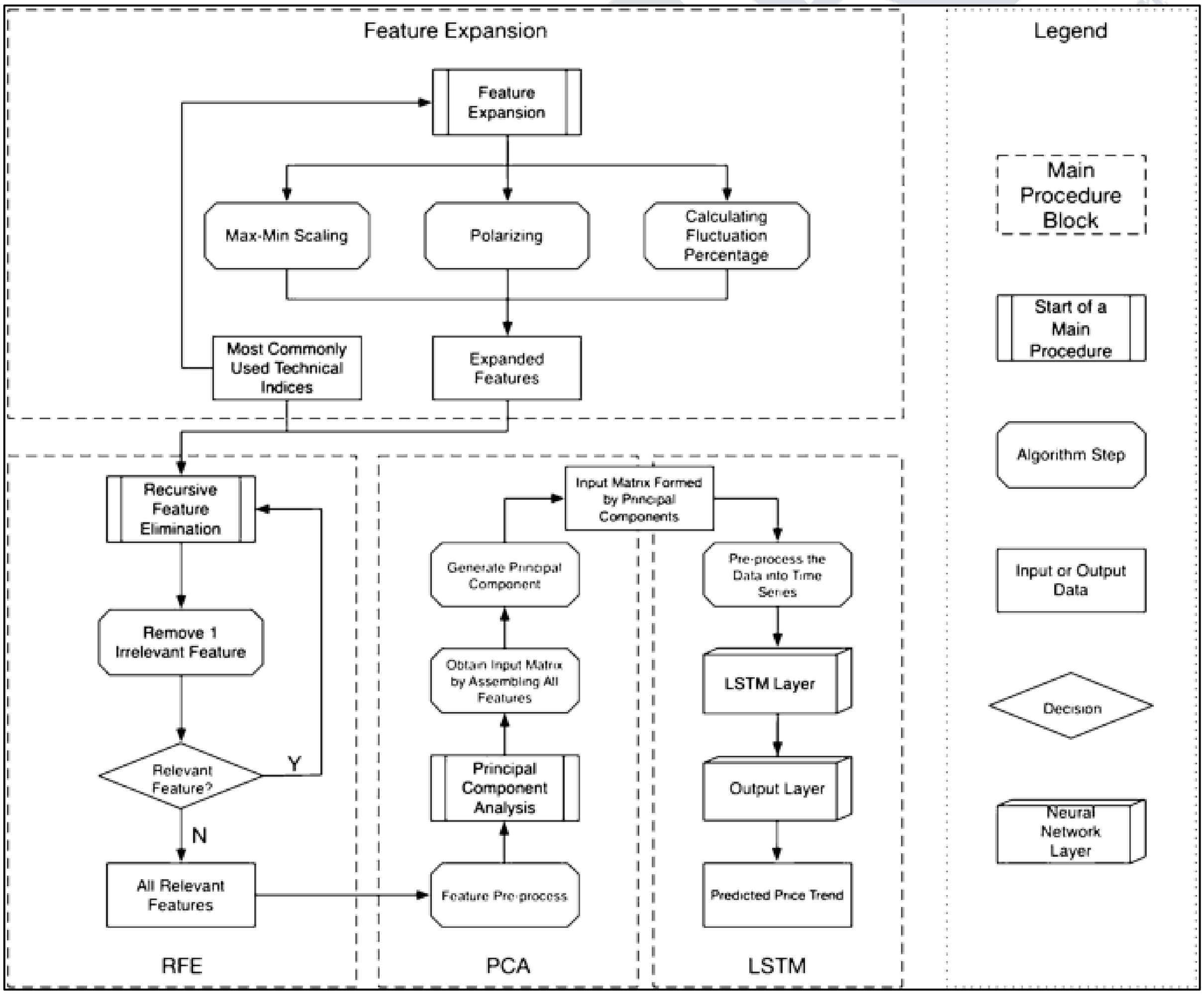

Fig.2 Feature expansion using RFE, PCA, LSTM

Prediction is done using regression algorithms. Therefore, RMSE (root mean squared error) and MAPE (mean absolute percentage error %) are used as evaluation metrics. Forecast accuracy is being obtained through these methods.

$$M = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$

where A_t is the actual value, F_t is the forecasted value and n is the total number of observations.

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

Fig.3 Formula for calculating RMSE

While MAPE (%) assesses this difference in relation to the genuine values, RMSE provides the disparities between anticipated and actual values. For instance, a MAPE score of 12% means that there is a 12% average discrepancy between the projected and actual stock prices.

Now, let's talk about the LSTM model. Long Short-Term Memory, or LSTM, is a powerful time series algorithm. It has the ability to record past trend patterns and predict values with accuracy. To put it simply, the key to understanding an LSTM model is to understand the Cell State (Ct), which represents the innate short- and long-term memory of a cell.

While P/E and P/B ratios are commonly utilized by traders and fund managers to predict market movements, other indicators that are being investigated are not well-known to many regular investors. Dividend given is one example of a fundamental indicator. Dividend yield is calculated by taking the current share price and dividing it by the yearly dividend paid on each share.

Dividend is equivalent to (annual dividend / current price) × 100.

(Annual dividend / current price) x 100 equals dividend yield.

For example, if a company paid an annual dividend of Rs 22 and its current market price was Rs 440, its dividend yield would be 5%. What therefore does dividend yield reveal about the prospective future price of a stock?

The company could be overpriced if the dividend yield is low since the share price is more than the dividend that is paid out. This implies a possible decline in the future.

Conversely, a high dividend yield suggests that the corporation is trying to draw in investors by raising dividends and that there isn't much interest in the stock. This results in an undervaluation of the stock price.

In their study, D. Selvamuthu et al. [10] employed several ANN versions to anticipate stock prices. However, they noted that the accuracy of the forecast is contingent on the learning technique employed to train the ANN.

This is how a structure of a neural network looks like.

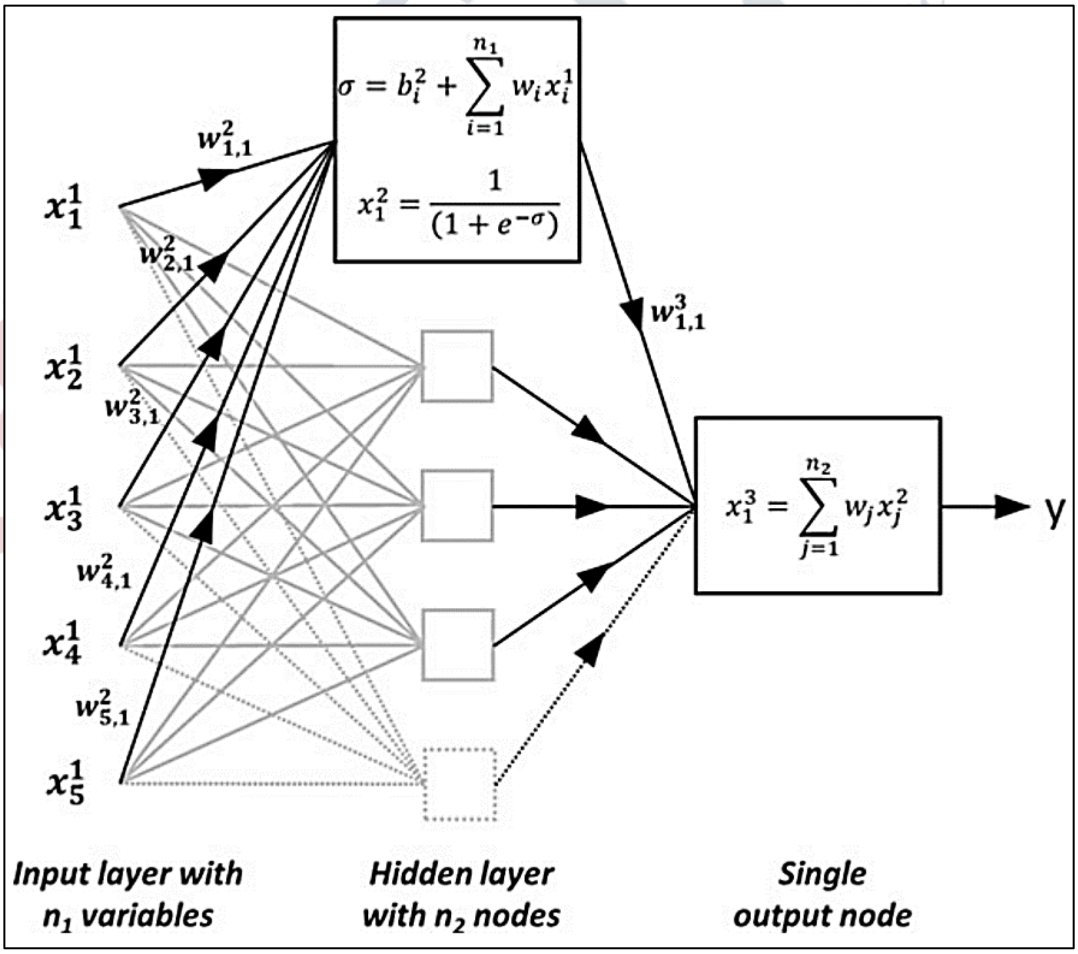

Fig.4 Structure of a Neural Network

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Initial point $\mathbf{w}_0$, update frequency T, strong Wolfe line search parameters c_1 and c_2, $\alpha_{min} > 0$, $\alpha_{max} > 0$, threshold parameter $\epsilon > 0$.
Compute the initial batch gradient and initialize $\mathbf{h}_0 \leftarrow \nabla f(\mathbf{w}_0)$.
for $k = 0, 1, \ldots$ **do**
  Compute the batch gradient $\mathbf{u}_k \leftarrow \nabla f(\mathbf{w}_k)$.
  Initialize $\mathbf{x}_0 \leftarrow \mathbf{w}_k$.
  Initialize $\mathbf{g}_0 \leftarrow \mathbf{h}_k$.
  Initialize $\mathbf{d}_0 \leftarrow -\mathbf{g}_0$.
  for $t = 0, 1, \ldots, T-1$ **do**
    Randomly choose a subset $\mathcal{S} \subseteq \mathcal{D}$.
    Determine the learning rate α_t satisfying the strong Wolfe line search

$$\begin{cases} f_S(\mathbf{x}_t + \alpha_t \mathbf{d}_t) - f_S(\mathbf{x}_t) \le c_1 \alpha_t \nabla f_S(\mathbf{x}_t)^T \mathbf{d}_t, \\ |\nabla f_S(\mathbf{x}_t + \alpha_t \mathbf{d}_t)^T \mathbf{d}_t| \le -c_2 \nabla f_S(\mathbf{x}_t)^T \mathbf{d}_t. \end{cases} \quad (3.2)$$

    Set $\alpha_t \leftarrow \min(\alpha_{max}, \max(\alpha_t, \alpha_{min}))$.
    Set the new iteration as $\mathbf{x}_{t+1} \leftarrow \mathbf{x}_t + \alpha_t \mathbf{d}_t$.
    Compute the variance reduced gradient $\mathbf{g}_{t+1} \leftarrow \nabla f_S(\mathbf{x}_{t+1}) - \nabla f_S(\mathbf{w}_k) + \mathbf{u}_k$.
    Compute conjugate parameter $\beta_{t+1} \leftarrow -\frac{|\mathbf{g}_{t+1}^T \mathbf{d}_t|}{\mathbf{g}_t^T \mathbf{d}_t} \times \frac{\|\mathbf{g}_{t+1}\|^2}{\|\mathbf{g}_t\|^2}$.
    if $\beta_{t+1} > \epsilon$ **then**
      set $\beta_{t+1} \leftarrow 0$.
    end
    Update the search direction $\mathbf{d}_{t+1} \leftarrow -\mathbf{g}_{t+1} + \beta_{t+1} \mathbf{d}_t$.
  end
  Set $\mathbf{h}_{k+1} \leftarrow \mathbf{g}_T$.
  Choose t randomly from $\{1, \ldots, T\}$ and set $\mathbf{w}_{k+1} \leftarrow \mathbf{x}_t$.
end

Fig.5 Levengerg-Marquardt with new line search

They further compared three different algorithms to compute the accuracy. First was Levenberg-Marquardt algorithm. To avoid computing the Hessian matrix and to approximate the second-order training speed, the Levenberg-Marquardt algorithm was created. It is used to resolve non linear least squares problems.

Input: $x_0 \in \mathbf{R}^n$, $\mu > 0$, $\gamma > 0$, $\varepsilon > 0$, $\epsilon > 0$, $\sigma_1, \sigma_2 > 0$, $r, \rho \in (0, 1)$ and the sequence $\{\epsilon_k\}$ satisfying in (8).
Step 0 Set $k := 0$.
Step 1 Compute $F_k = F(x_k)$ and $J_k = J(x_k)$.
  If $\|J_k^T F_k\| \le \varepsilon$, stop. Otherwise compute λ_k by (14).
Step 2
  (a) Obtain d_{1k} by solving the following linear system

$$(J_k^T J_k + \lambda_k I)d = -J_k^T F_k. \quad (15)$$

  (b) Solve the linear system

$$(J_k^T J_k + \lambda_k I)d = -J_k^T F(y_k), \quad (16)$$

  to obtain d_{2k}, where $y_k = x_k + d_{1k}$.
  (c) Solve the linear system

$$(J_k^T J_k + \lambda_k I)d = -J_k^T F(z_k), \quad (17)$$

  to obtain d_{3k}, where $z_k = y_k + d_{2k}$.
  (d) Set $d_k = d_{1k} + d_{2k} + d_{3k}$.
Step 3 If

$$\|F(x_k + d_k)\| \le \rho \|F_k\|, \quad (18)$$

  then take $\alpha_k = 1$ and go to step 5. Otherwise go to step 4.
Step 4 Set

$$d_k = \begin{cases} d_{1k} + d_{2k} + d_{3k} & \text{if } F_k^T J_k(d_{1k} + d_{2k} + d_{3k}) \le -\gamma, \\ d_{1k} & \text{otherwise.} \end{cases} \quad (19)$$

  Compute $\alpha_k = max\{1, r^1, r^2, \ldots\}$ $with$ $\alpha = r^i$ $satisfying$

$$\|F(x_k + \alpha d_k)\|^2 \le (1 + \epsilon_k)\|F_k\|^2 - \sigma_1 \alpha^2 \|d_k\|^2 - \sigma_2 \alpha^2 \|F_k\|^2, \quad (20)$$

  where the positive sequence $\{\epsilon_k\}$ satisfies (8).
Step 5 Set $x_{k+1} = x_k + \alpha_k d_k$. Set k=k+1 and goto step 1.

Fig. 6 Theory of Bayesian regulation

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Theory of scaled conjugate gradient was the second. When the performance function quickly declines, the backpropagation algorithm changes its weights in the direction of the sharpest drop (negative of the gradient). Nevertheless, fast convergence in this direction is not always a corollary of fast lowering of the performance function. The conjugate directions are searched in conjugate gradient algorithms, which usually lead to a faster convergence than the steepest-descent approach. Most algorithms calculate the updated weight step size duration based on a learning rate. However, most conjugate gradient algorithms alter the step size following each iteration.

The third algorithm on which they worked was Theory of Bayesian regulation.

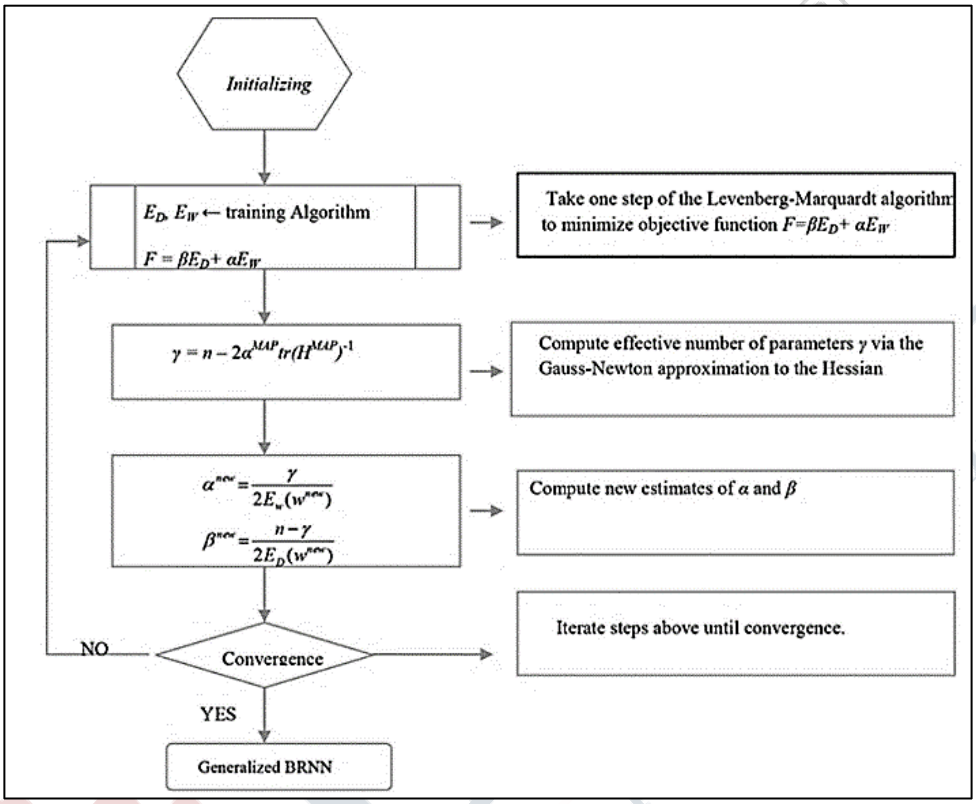

Fig.7 BRANN Flowchart

The Artificial neural networks using Bayesian regularization lowered or eliminated the requirement for time-consuming cross-validation (BRANNs). perform more steadily as a result than traditional backpropagation. A nonlinear regression is transformed into a "well-posed" statistical issue akin to ridge regression by the use of a mathematical approach known as Bayesian regularization. One of the main benefits of this approach is that it takes into account the probabilistic nature of the network weights related to the given data set.

We may ascertain the number of iterations (or "epochs") at which the mean squared error is at its lowest or shows the least variance with the use of the performance charts. As we can see, on the tick dataset (15-min dataset), Scaled Conjugate Gradient delivers the best validation in 103 (54) iterations, whereas Levenberg-Marquardt provides the greatest validation in 10 (13) iterations. On the other hand, in both datasets, Scaled Conjugate Gradient requires less time than Levenberg-Marquardt. Scaled Conjugate Gradient has the second-best overall performance across all datasets, whereas Bayesian Regularization outperforms Levenberg-Marquardt in terms of least mean squared error. However, Scaled Conjugate Gradient performs better than the competition when test dataset performance is the only factor considered.

Studies show a positive correlation between mutual fund inflows and market performance. Momentum has a role in investment decisions; when more people invest, the market rises and draws in additional buyers. Positive feedback is included in the cycle.

Experienced investors have seen many market ups and downs and feel that the market will ultimately level out. These people have previously been discouraged from investing by high market prices, but historically low prices might offer a chance.

The tendency of a variable, such a stock price, to progressively converge on an average value over time is known as mean reversion. Numerous significant economic indicators, including GDP growth, interest rates, unemployment, and currency rates, have all shown signs of the pattern. A mean reversion can also be the source of business cycles.

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The idea that past performance is meaningless is another theory. When Paul Samuelson studied market returns in 1965, he came to the conclusion that an efficient market should not have an impact like this since past pricing patterns should not affect current prices. He concluded that market prices are martingales.

The current number in a martingale is the strongest predictor of the number that comes next. Probability theory uses the concept to evaluate the results of random motion. For instance, let's say you decide to wager $50 total on a coin flip. When the coin is tossed, how much cash will you have? You may end up with $100 or nothing at all after the toss, but statistically, your best bet is $50, which is your starting position. After the coin toss, a martingale is employed to predict your luck.

A helpful tool that allows you to examine your earnings in a certain company if you would have invested in it five years ago is the simulator available on their website.

III. IMPLEMENTATION

For forecasting, the CNN and LSTM models, which are implemented in Python and R, were utilized. It is fast and provides fully automatic predictions that analysts and data scientists may manually modify. It is a technique for forecasting time series data that adapts an additive model to seasonality in non-linear patterns that happen on a daily, weekly, monthly, and holiday basis. It works well with highly seasonal time series and numerous seasons of historical data. Prophet is often good at handling anomalies and resilient to missing data and trend fluctuations. Prophet is available as open-source software and was developed by Facebook's core data science team.

Time series forecasting may be challenging due to the range of approaches and hyperparameters available for each method.

A. Installing and importing necessary dependencies

Library modules pandas and prophet are being used for this model. Pandas allows us to bring in the tabular data. Prophet module contains the model and can be used to train our dataset in the later stages if this implementation. Prophet can only operate on a very particular kind of data frame.

B. Retrieving the data into our notebook

The dataset was read and characterized its datatypes using the pandas module before starting our analysis. This stage is essential for determining the preprocessing activities that need to be carried out in order to guarantee that the data is clean and prepared for analysis. Handling missing numbers, adjusting data types, and normalizing or modifying the data as needed are some examples of preprocessing. For any data-driven study to produce accurate and trustworthy results, proper preprocessing is necessary.

To guarantee thorough coverage and robustness, the data for this study is carefully gathered from a wide range of sources. Prominent financial databases that offer comprehensive and in-depth financial information, including Bloomberg and Thomson Reuters, are among the key sources. These databases form the foundation of financial data analysis and are well known for their dependability.

The data was also collected from stock exchange websites, which provide up-to-date information on stock prices, trading volumes, and other relevant metrics, in addition to financial databases. These websites are a great resource for learning about the dynamics and trends in the industry.

Additionally, company websites were an essential source of information, especially when trying to get straight answers from press releases, corporate announcements, and comprehensive financial statements. These records give an accurate picture of the performance, market positioning, and strategic direction of an organization.

In addition, the analysis of financial statements and reports yielded both quantitative and qualitative information on the operational effectiveness, market strategies, and financial well-being of the firms. These studies are frequently thorough and offer a close examination of several financial indicators.

Examination of publications and news stories was done from reliable financial news sources to supplement the quantitative data. These articles can provide background information and in-depth analyses of investor mood, market developments, and overall economic conditions that could affect our research.

Finally, in order to obtain insightful viewpoints and professional opinions, interviews with investors and financial professionals were undertaken. These interviews offered insightful information and aided in more precise data interpretation, ensuring that our study is comprehensive and supported by industry knowledge.

Our goal was produce a strong and comprehensive dataset that will enable an in-depth and perceptive financial analysis by combining data from these diverse sources.

C. Data preprocessing

Data preprocessing can be done through cleaning which includes removing null values from the data, removing and inconsistencies and filtering the useful data out of outliers. Data cleansing is done to improve the quality of results which the model is supposed to display. This is usually done by ignoring the tuples (ignoring the rows which have extremely large number of values), performing regression, by clustering.

When working with time-series data, it is critical to have a date or time stamp column. The prophet model demands that to predict the trends. After the conversion we'll need to drop store nbr column. Moreover, the model only needs two columns to work with. So, we'll rename transactions and date columns to y and ds respectively. The axis = 1 argument tells

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pandas to drop the columns and not the rows.

D. Training the model and making predictions and evaluation of performance

Before LSTM and CNN objects can be fitted to a dataset using the fit() function and supplying the dataset, they need to be defined and setup. To set up the desired model's growth, seasonality, and other properties, pass arguments to the model object. By default, the model will work very hard to automate almost everything.

```
Epoch 21/30
129/129 [==============================] - 4s 29ms/step - loss: 1.2765e-04
Epoch 22/30
129/129 [==============================] - 4s 28ms/step - loss: 1.2460e-04
Epoch 23/30
129/129 [==============================] - 4s 28ms/step - loss: 1.2409e-04
Epoch 24/30
129/129 [==============================] - 4s 28ms/step - loss: 1.5360e-04
Epoch 25/30
129/129 [==============================] - 4s 28ms/step - loss: 1.1619e-04
Epoch 26/30
129/129 [==============================] - 4s 30ms/step - loss: 1.2326e-04
Epoch 27/30
129/129 [==============================] - 4s 27ms/step - loss: 1.2586e-04
Epoch 28/30
129/129 [==============================] - 4s 28ms/step - loss: 1.2285e-04
Epoch 29/30
129/129 [==============================] - 4s 27ms/step - loss: 1.2068e-04
Epoch 30/30
129/129 [==============================] - 4s 29ms/step - loss: 1.1156e-04
Out[14]: <keras.src.callbacks.History at 0x28f0b5009d0>
```

Fig.7 training of data onto the model

The internal_width option, which we have set to 0.92, is used to estimate the uncertainty interval based on the number of samples utilized. For a sub-daily time series, the daily seasonality = True argument fits the daily seasonality. If you leave this option unset, the default seasonality will be weekly and yearly. Since the values are dynamic, they may be altered to suit the analytical context.

Fig. 8 Tested and predicted value

IV. RESULTS AND CONCLUSION

In order to anticipate stock prices for the next five years, a reliable system has been built using Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN). By giving investors comprehensive projections, this predictive technology can greatly improve their ability to make informed investment decisions by enabling them to choose firms that are most likely to provide the best returns over a certain period of time. By incorporating these cutting-edge machine learning algorithms, the prediction process is improved in accuracy and dependability, which helps investors make more thoughtful and calculated investment decisions.

Furthermore, by adding more characteristics, the system's prediction accuracy may be raised even higher. These could include other pertinent financial measurements, market sentiment assessments, and more detailed economic data. By doing this, the system becomes more engaging and user-friendly and provides investors with a more complete tool. Increasing the size of the dataset that was used to train the model will also improve its prediction ability. More accurate and reliable projections may be produced by using a larger, more diversified dataset that captures a greater variety of market circumstances and trends.

The results of this investigation are consistent with earlier studies that emphasize the significance of many variables in stock market return prediction. This research validates that investor sentiment, industry performance, and economic variables are important determinants of stock market returns, which is in line with previous studies. A wider range of significant factors are also identified by this study, such as market indices, volatility, insider trading, sector rotation, trend following, smart money movements, insider trading, technical and fundamental analysis, short interest, and options activity. When taken as a whole, these variables offer a thorough understanding of the processes affecting stock market performance.

The outcomes highlight the intricacy of the stock market and the wide range of factors that influence its movements. Regression study showed that a number of factors had a major influence on stock market returns, including investor sentiment, industry performance, economic circumstances, and geopolitical concerns. The research also discovered that a number of other important factors influence market performance, including market indices, short interest, options activity, insider trading, sector rotation, trend following, smart money movements, technical and fundamental analysis, market mood, and volatility. Strong correlations between these factors and stock market returns were validated by the correlation study, demonstrating their importance in predicting market movements.

These results imply that whether choosing investments or creating economic policies, both investors and policymakers have to use a comprehensive approach. Taking a broad view guarantees a deeper comprehension of market dynamics and can result in more successful tactics. To help investors make informed investment decisions, this entails broadening their analytical tools and taking into account a number of indications. It entails developing policies that take into account the complex structure of the market, maintain stability, and encourage long-term economic progress.

In summary, this research offers insightful information on the variables influencing stock market returns and the efficacy of sophisticated prediction models like CNN and LSTM. The study emphasizes the necessity of a thorough strategy that considers a wide range of important issues when making decisions on investments and policies. Policymakers may create stronger economic plans and investors can make better-informed judgments by utilizing these information.

V. FUTURE SCOPE

This study's conclusions have important ramifications for investors and governments alike. The report emphasizes to investors how crucial it is to diversify their holdings by making investments across a variety of markets and asset types. This strategy aids in reducing the risks brought on by fluctuations in the market and downturns in certain industries. Investors might possibly increase profits and better protect their wealth by diversifying their assets. Diversification lowers the chance of significant losses by acting as a buffer against erratic market swings.

The findings of the study underscore the need for policymakers to take into account the wider consequences of economic policies on the stock market and the economy at large. Fiscal and monetary economic policies may have a significant impact on investor confidence and market stability. The possible effects on the economy should be recognized by policymakers, who should work to develop measures that support both growth and stability in the economy and a favorable investment environment. Economic policies and market performance interact in a complicated way, and developing successful policies requires a knowledge of this interaction.

The study also emphasizes how crucial it is to consider a wide range of variables when choosing investments or creating economic strategies. To make wise investment decisions, investors must take into account a variety of elements, including macroeconomic statistics, industry trends, and the state of the world economy. In a same vein, to guarantee that their choices promote economic development and resilience, officials should include thorough economic data and market input into their decision-making procedures.

All things considered, this study offers fresh perspectives on the numerous variables affecting the stock market and how they interact. The results highlight the need for a comprehensive strategy in both investment selection and the formulation of economic policies. This entails developing a diverse investment plan and keeping up with changing market dynamics for investors. This means that policymakers must create measures that promote both long-term market stability and growth in addition to addressing the current economic issues. The report essentially urges a thorough and knowledgeable approach to negotiating the intricacies of the stock market and the larger economic environment.

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