DEEP PREDICTION ON FINANCIAL MARKET SEQUENCE FOR ENHANCING ECONOMIC POLICIES

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OUTLINE

- Related work on various financial market predictions, stock prices and method
- Proposed Methology
- Result of Analysis

INTRODUCTION

- Video and image processing has gained significant traction as a study area, developed into a respected career, and made possible by the widespread use of contemporary computer vision technologies.
- Still, effective use of this technology can often increase the effectiveness of problem-solving in various real-world scenarios.
- Classifying time series can be done in various ways. It is possible to categorize an observation sequence into discontinuous and continuous time series based on how constant it is.
- Depending on the exploration variables, it may be split into two categories: adjustable period sequence and multivariable time series.

INTRODUCTION

- Investors might purchase and sell publicly listed company equities on a stock market to make a profit. Due to its reflection on the business climate and performance of businesses, it is a vital amount of a state's financial health.

- Buyers and sellers meet at these markets to trade equities. The rule of source and request, which states that purchasers are prepared to shell out additional for a standard if they believe its value resolve increase and selling are ready to give it less if they believe its value will decrease, determines the pricing of stocks.

- The profitability of companies, political stability, and the economy's overall health are just a few of the variables that may impact the pricing of equities on the stock exchange. Investors can access various tools and techniques for predicting and analyzing stock prices. These include technical evaluation, which takes trading volume and price movements into account, and fundamental evaluation, which looks at a business's financial health and market conditions.

INTRODUCTION

- Applying Transformer's success in modeling sequential information in natural language processing (NLP) to stock marketplace forecast is a simple concept. To the greatest extent of our understanding, few studies assess transformer's accuracy in forecasting stock markets. Most current research focuses on using transformers for sentiment evaluation.

- Based on the transformer architecture, we forecast the equity market index in this study. In contrast to earlier research, we use a direct model of the closing price for the day's data rather than unorganized textual data.

AIMS AND SCIENTIFIC MOTIVATION

- The growing complexity and volatility of the world's financial markets, which pose serious obstacles to economic policy development, served as the impetus for this study.

- Precise forecasting of financial market patterns is essential for decision-makers who must make well-informed choices to maintain economic stability, control risks, and foster sustainable development.

- By utilizing product market danger (i.E. Liquidity) metrics unique to each firm, it turned out that extremely liquid businesses had more erroneous analysts' profit estimates, and performance volatility could not account for the entire discrepancy.

AIMS AND SCIENTIFIC MOTIVATION

- In this work, LSTM-based Artificial Rabbits Optimization Algorithm (ARO) is used to predict financial market sequence.

- The ARO method can be applied to optimize the LSTM network hyperparameters. It can be difficult to optimize an LSTM network's hyperparameters because many variables can be changed, such as the amount of layers, the quantity of neurons per level, and the degree of learning.

- The test findings are gathered, and analysis is done on the financial market prediction sequence's variables framework, asset earnings distribution's fat tails evaluation, economic the marketplace series prediction's variance analysis, and the financial market forecasting impact of the algorithm for deep learning.

ARTIFICIAL INTELLIGENCE

- AI is increasingly mixing with economic processes. Big information circles can be analysed by AI procedures, which can then use the results to forecast the future or make judgments. This can help with tendency analysis, standard value forecast, and savings decision-making.

- AI can also track real-time market circumstances and spot stock buying and selling chances and it has the possible to increase meaningfully the effectiveness and precision of financial decision-making and analysis, which could eventually result in improved investment results for consumers.

LONG SHORT-TERM MEMORY

- A computer program called **Long Short-Term Memory (LSTM)** examines and comprehends data with long-term dependencies. It is frequently applied to the analysis of time series data, including stock prices.

- Because LSTM can handle information with numerous input and output timesteps, it is beneficial for evaluating stock market data.

- The arrangement of historical standard values and other economic information is called time series data. LSTM may use this information to find developments and patterns that can be second-hand to forecast upcoming standard values

PROPOSED METHODOLOGY

- The proposed methodology for predicting financial market sequences to enhance economic policies uses deep learning methods such as the LSTM-based Artificial Rabbits Optimization Algorithm (ARO).

- The proposed method uses image and video processing techniques to generate economic decisions.

- Initially, the information is collected, and then the structures are extracted from the financial market data.

- Next, the features are combined using image processing techniques; then the LSTM-based ARO method is used for the prediction of the financial market price.

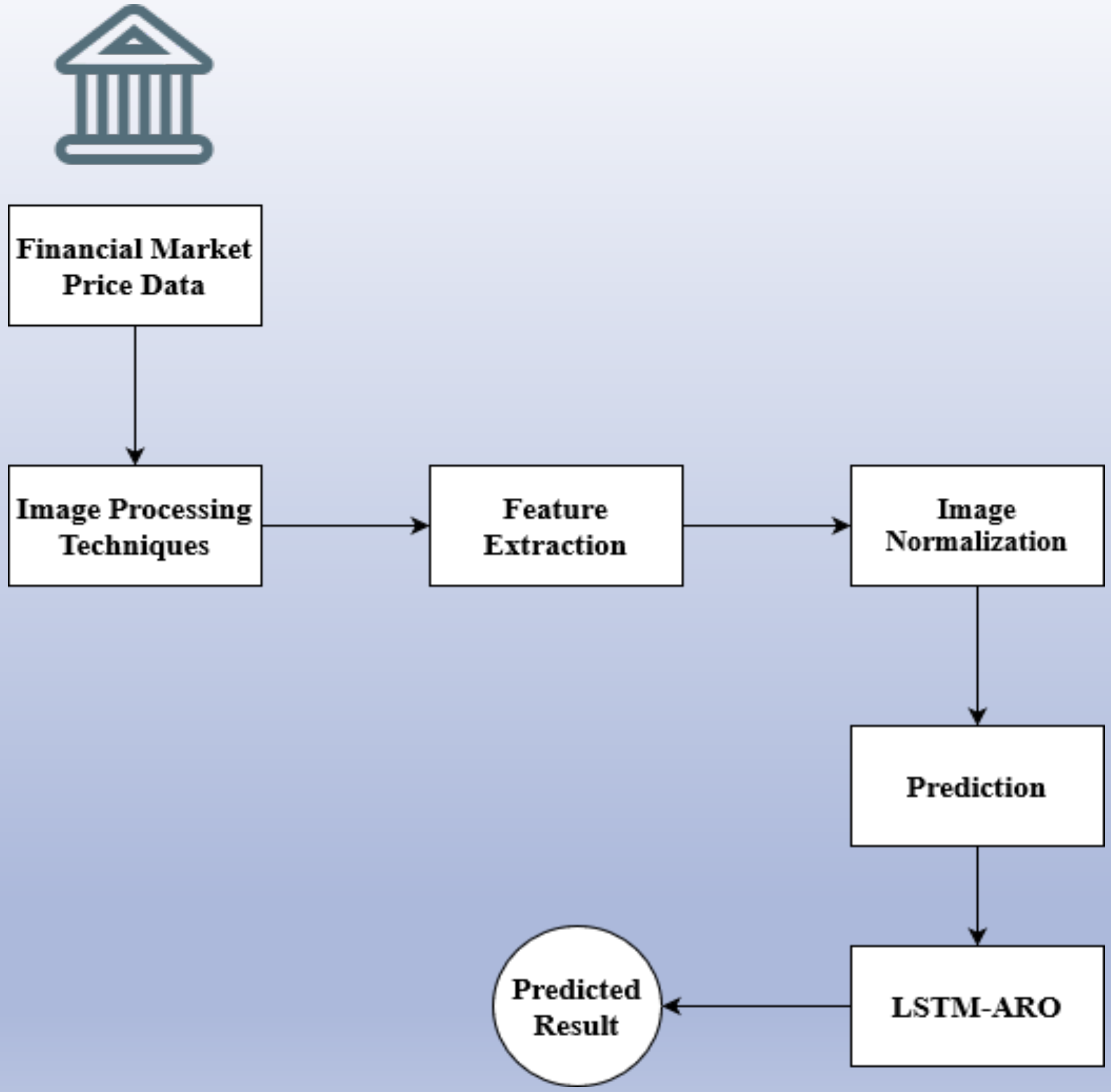


Figure 1.
Architecture Diagram of Proposed Method

DATA COLLECTION USING TIME SERIES DATA

In this work, two different kinds of datasets are used for the prediction of financial market price:

- **DESCRIPTIVE TIME SERIES DATA**: chart observation is typically used in the first examination of a time series to contrast appealing information or identify the series' growth principles. This technique is called descriptive time series analysis. With this straightforward temporal analysis method, unexpected principles are frequently discovered in the realm of natural science (Nile flood law). The natural order states that the creation of suitable policies will advance society's advancement and growth.

DATA COLLECTION USING TIME SERIES DATA

- **STATISTICAL TIME SERIES DATA**

The two primary components of statistical time series analysis are Frequency domain and time domain analysis. The primary technique for discussion is time domain analysis. The process is standard, and it is simple to determine the outcome while Spectral analysis lacks this benefit, and the sequence autocorrelation hypothesis serves as the foundation for this. Data that is fictitious represent events, and momentum is that.

Additionally, the computerized model is reviewed and condensed. The time series information drive be processed with disinterest, and the inertia will persist till the upcoming period swelling.

Owing to its incomparable benefits, the time domain analysis technique has emerged as the greatest generally utilized approach in contemporary time series applicability data, finding widespread application across many domains of civilization.

IMAGE PROCESSING TECHNIQUES

In this technique, initially the images pre-processed and then the images are converted into grey scale image and transformation. Next, the image normalization is used improve the image illumination and the identification of objects.

- **PRE-PROCESSING**

Pre-processing is required to growth the characteristics and excellence of the financial market data picture that is utilized for expert subsequent processing.

The pre-processing steps are as follows:

1. Applying median filter for enhancing the financial data image;
2. The data augmentation is processed;
3. The min-max normalization method is used for normalization process.

1. ENHANCING THE FINANCIAL DATA USING MEDIAN FILTER

Scanning the whole Financial Market data image by means of 4×4 window extent and calculating median rate for the image and replace the centre pixel value by its median value.

$$img[p,q] = median\{img - med[i,j], (i,j) \in P\} \qquad (1)$$

where P signifies a neighbourhood pixel value definite by the user and the centered about site $[m,n]$in the image.

2. DATA AUGMENTATION

To use financial image data augmentation, a higher grade of classification is required. Using rotation and flipping operations, the financial image is transformed. In this piece, the image is rotated by 90 degrees and flipped horizontally.

3. NORMALIZATION AND FEATURE EXTRACTION

To normalize the input financial data image of size 512×512 pixels and by the value of intensity between [0,1] which is evaluated by

$$p_i = \frac{(q_i - min(q))}{(max(q) - min(q))} \qquad (2)$$

Here, p_i is the normalized intensity value of position of image $q_i (1 = 1,2, \dots, n)$ and intensity values of maximum and minimum are represented as $max(q)$ and $min(q)$.

After applying the normalization, the size of image gets resized into 256×256 pixels.

3. NORMALIZATION AND FEATURE EXTRACTION

- In this proposed study, characteristics are extracted from the image using stationary wavelet transform (SWT).
- SWT is a powerful tool for multi-resolution analysis and is particularly effective in capturing both spatial and frequency information. Here, both the low pass filter quantity of low[img] and the high- pass filter values of high[img] are combined with the input signals of the picture in separate subbands, and the factor amount is double.
- Four subbands were identified in the financial data image, img(x,y): LowLow, LowHigh, HighLow, and HighHigh. The vertical, horizontal, and diagonally data in the input image all have the same x * y solution, indicating low variations in quality in these subbands.

- After applying the normalization, the size of image gets resized into 256×256 pixels.

3. NORMALIZATION AND FEATURE EXTRACTION

To obtain the features of the given financial images at the i^{th} level, the following is offered:

- $LowLow_{i+1} = (m,n) = \sum_x \sum_y low_x^i \, low_y^i LL_i(m+x, n+y),$ (3)
- $LowHigh_{i+1} = (m,n) = \sum_x \sum_y high_x^i \, low_y^i LL_i(m+x, n+y),$ (4)
- $HighLow_{i+1} = (m,n) = \sum_x \sum_y low_x^i \, high_y^i LL_i(m+x, n+y),$ (5)
- $HighHigh_{i+1} = (m,n) = \sum_x \sum_y high_x^i \, High_y^i LL_i(m+x, n+y),$ (6)

where $x = 1,2,\ldots,m, y = 1,2,\ldots,n,$ and LL, LH, HL, and HH represent horizontal, vertical, and diagonal subbands, respectively.

3. NORMALIZATION AND FEATURE EXTRACTION

- Therefore, in this study, feature extraction from the financial data image is performed using the Stationary Wavelet Transform (SWT).
- The process involves decomposing the financial data image, into different sub bands: Low Low (LL), Low High (LH), High Low (HL), and High High (HH).
- These sub bands capture low-resolution approximations, horizontal, vertical, and diagonal details of the image, respectively.

FINANCIAL MARKET PRICE PREDICTION USING LSTM BASED ARTIFICIAL RABBITS OPTIMIZATION ALGORITHM (ARO)

- An artificial neural network called an LSTM is made to handle information in sequence, including audio, text, and time series. When information is processed with long-term dependencies (that is, when the outcome at an individual period stage relies on data from previous time steps) it is very helpful.

- LSTM networks employment forget gates, input gates, output gates, and memory cells to let them recall this information over protracted periods of time. By regulating the information entering and leaving the storage cells, these gates enable a network to save and access data on a request basis.

- Functions like language gratitude, translation of languages, and stock price forecasting are regularly achieved with LSTMs.

FINANCIAL MARKET PRICE PREDICTION USING LSTM BASED ARTIFICIAL RABBITS OPTIMIZATION ALGORITHM (ARO)

An LSTM network's mechanisms comprise:

- Data entry into the memory cell is managed by the input gate

$$input = \sigma(W_i * [h_t - 1, x_t] + b_i) \quad (7)$$

- The forget gate regulates the data flow that leaves the memory cell

$$forget = \sigma(W_f * [h_t - 1, x_t] + b_f) \quad (8)$$

- The output gate controls how the memory cell's output is sent to the remaining components of the network

$$output = \sigma(W_o * [h_t - 1, x_t] + b_o) \quad (9)$$

FINANCIAL MARKET PRICE PREDICTION USING LSTM BASED ARTIFICIAL RABBITS OPTIMIZATION ALGORITHM (ARO)

- The memory cell is where the information is stored

$$memory = A = f_t * c_t - 1 + i_t * tan_h(W_c * [h_t - 1, x_t] + b_c \quad (10)$$

- The LSTM unit's output is utilized to generate predictions or transfer data to the following LSTM unit

$$hidden = o_t * tan_h(c_t) \quad (11)$$

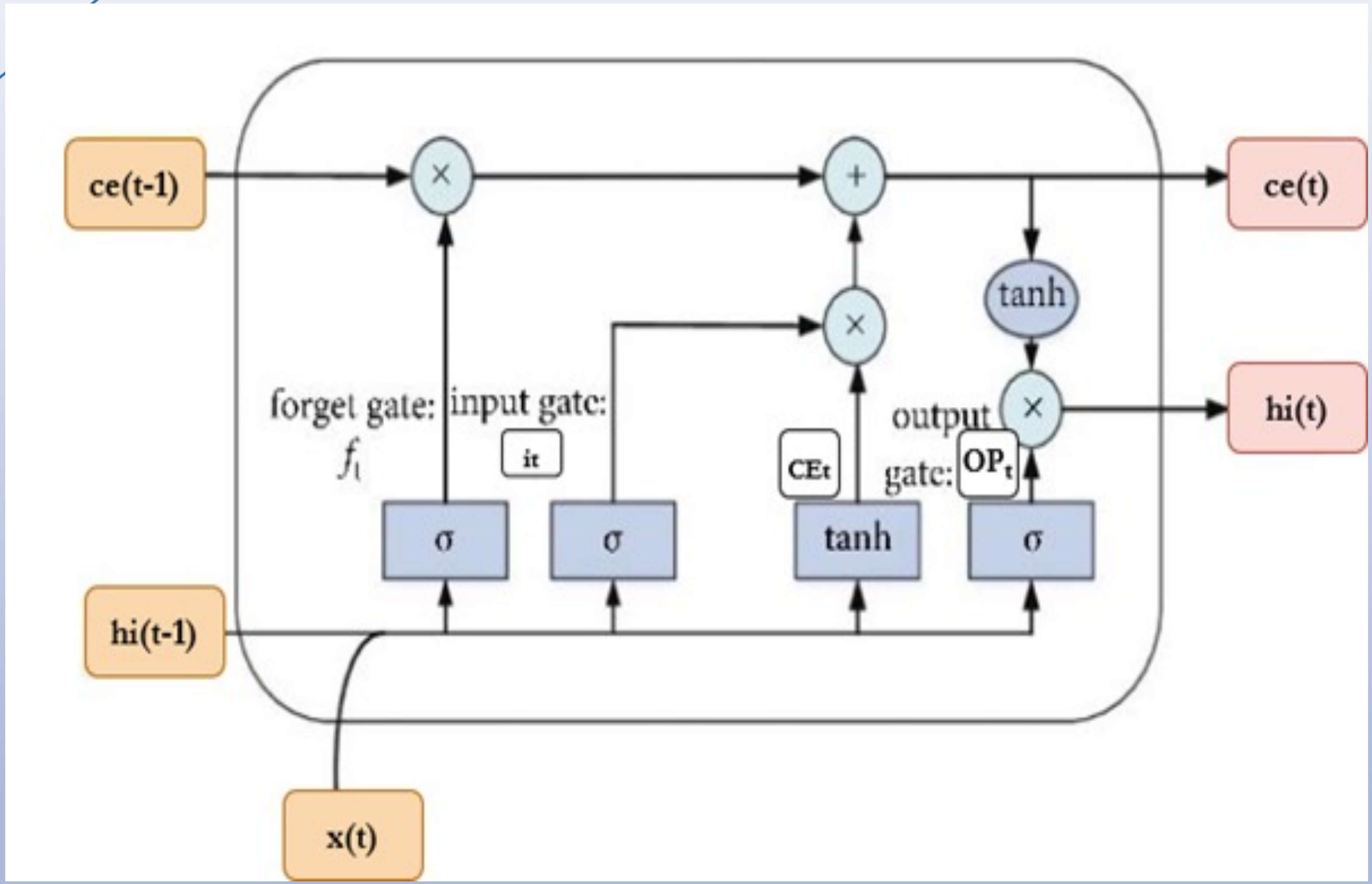


Figure 2.
Structure of LSTM network used for the prediction.

FINANCIAL MARKET PRICE PREDICTION USING LSTM BASED ARTIFICIAL RABBITS OPTIMIZATION ALGORITHM (ARO)

- A specific generous of recurrent neural network (RNN) called long short-term memory (LSTM) is made to deal with the sequential and long-term dependencies that are typical in time series analysis, like financial market data.
- Conventional RNNs are less effective at learning dependencies spanning extended sequences because of the issue of disappearing and explosion gradients.
- LSTMs use a special architecture that combines gates, memory cells, and long-term data retention to address these difficulties. The number of layers, memory cell size, and learning rate are examples of hyperparameters that can have a significant impact on an LSTM network's performance.
- To get the best performance, extensive hyperparameter tweaking is frequently needed, which might take a lot of effort.

ARTIFICIAL RABBITS OPTIMIZATION (ARO)

- A revolutionary algorithm called **ARO** was developed.
- As plant-eating animals, rabbits mostly consume greenery, forbs, and leafy herbs. Over period, they have industrialized a variety of existence techniques. To keep predators from discovering their nests, one of their tactics is to refrain from consuming the grass near their burrows.
- Since much of a rabbit's wide field of vision is used for above perusing, it is informal for them to locate nourishment ended a wide region. This behavior called "foraging" is known as **exploration** and involves moving away from the nests.

ARTIFICIAL RABBITS OPTIMIZATION (ARO)

- A different tactic is to hide randomly. Rabbits are adept at digging tunnels to hide from predators and hunters.

- They excavate many burrows in and around their nest, choosing at random which one to use as a haven from raptors. Rabbits have long back legs and short forelegs, yet their powerful muscles and tendons allow them to run swiftly. They can also turn, pause, or smooth track backward in a wind pattern to complicate their opponents and improve their probabilities of surviving. We refer to this tactic as **exploitation**.

- Rabbits need to preserve energy to survive because they are at the base of the food chain and are frequently preyed upon. To do this, depending on their energy levels, they adaptively alternate between random hiding and detour foraging.

ARTIFICIAL RABBITS OPTIMIZATION (ARO)

ARO is divided into two phases. They are haphazard hiding (exploitation) and detour foraging (exploration).

Rabbits tend to neglect local vegetation and travel great distances in search of food. We refer to this practice as **detour foraging**.

Every rabbit at ARO has a separate area containing grass and tunnels. They may agitate around a food supply and visit each other's areas at randomly to search for food. This implies that they add an interruption and update their position in relation to a different rabbit in the swarm.

ARTIFICIAL RABBITS OPTIMIZATION (ARO)

A model that explains this behavior has been put forth

$$R = L.c \tag{12}$$

$$L = \left(e - e_{\tau}^{(t-1)}\right).sin(2\pi r_2) \tag{13}$$

$$c(k) = \begin{cases} 1 \text{ if } k == g(l) \\ 0\ else \end{cases} \quad k = 1, \ldots., d \text{ and } l = 1, \ldots., [r.d] \tag{14}$$

$$g = randperm(d) \tag{15}$$

$$n_1 \sim N(0,1) \tag{16}$$

ARTIFICIAL RABBITS OPTIMIZATION (ARO)

Each rabbit's position at time t is represented by $x_i(t)$, and its candidate position at time $t + 1$ is $v_i(t+1)$. The population of rabbits size (n), the issue dimension (d), and the maximum number of iterations (T) are additional variables.

Global search is aided by perturbations and running length (L), wherein lengthier step sizes inspire examination and smaller ones encourage manipulation. The assignment of the vector c facilitates the random selection of search subjects for mutation.

By abruptly turning in random directions and probing the exploration space, the consecutively operators (R) imitators the running behavior of a rabbit. Individuals are chosen for mutation during foraging by mapping vector c. Operator R is simulated by moving like a rabbit.

ARTIFICIAL RABBITS OPTIMIZATION (ARO)

This equation

$$c(k) = \begin{cases} 1 & \text{if } k = g(l) \\ 0 & else \end{cases} \quad k = 1, \dots, d \quad \text{and} \quad l = 1, \dots, [r.d] \qquad (14)$$

demonstrates how search individuals investigate by haphazardly looking for food in relation to other bunnies' locations. Their distinct behavior enables them to explore new areas and leave their home range, guaranteeing the ARO algorithm's ability to conduct worldwide searches.

To take advantage of the search space and elude predators, ARO uses random concealment. Every rabbit creates d burrows surrounding its nest in every search space dimensions, then arbitrarily chooses one to hide in. As a result, there is less chance to be preyed upon.

ARTIFICIAL RABBITS OPTIMIZATION (ARO)

The j^{th} hole of the i^{th} rabbit is produced by applying the subsequent formula:

$$H = \frac{T-t+1}{T} . r_4 \tag{17}$$

$$n_2 = N(0,1) \tag{18}$$

$$g(k) = \begin{cases} 1 & \text{if } k = j \\ 0 & else \end{cases} \quad k = 1, \ldots, d \tag{19}$$

As the iterations go on, ARO bunnies transition from random hiding to detour foraging, depending on how energetic they are. This transition from exploration to exploitation is represented by the liveliness component in ARO, which is specified by the following equation

$$A(t) = 4(1 - \frac{t}{T}) ln \frac{1}{r} \tag{20}$$

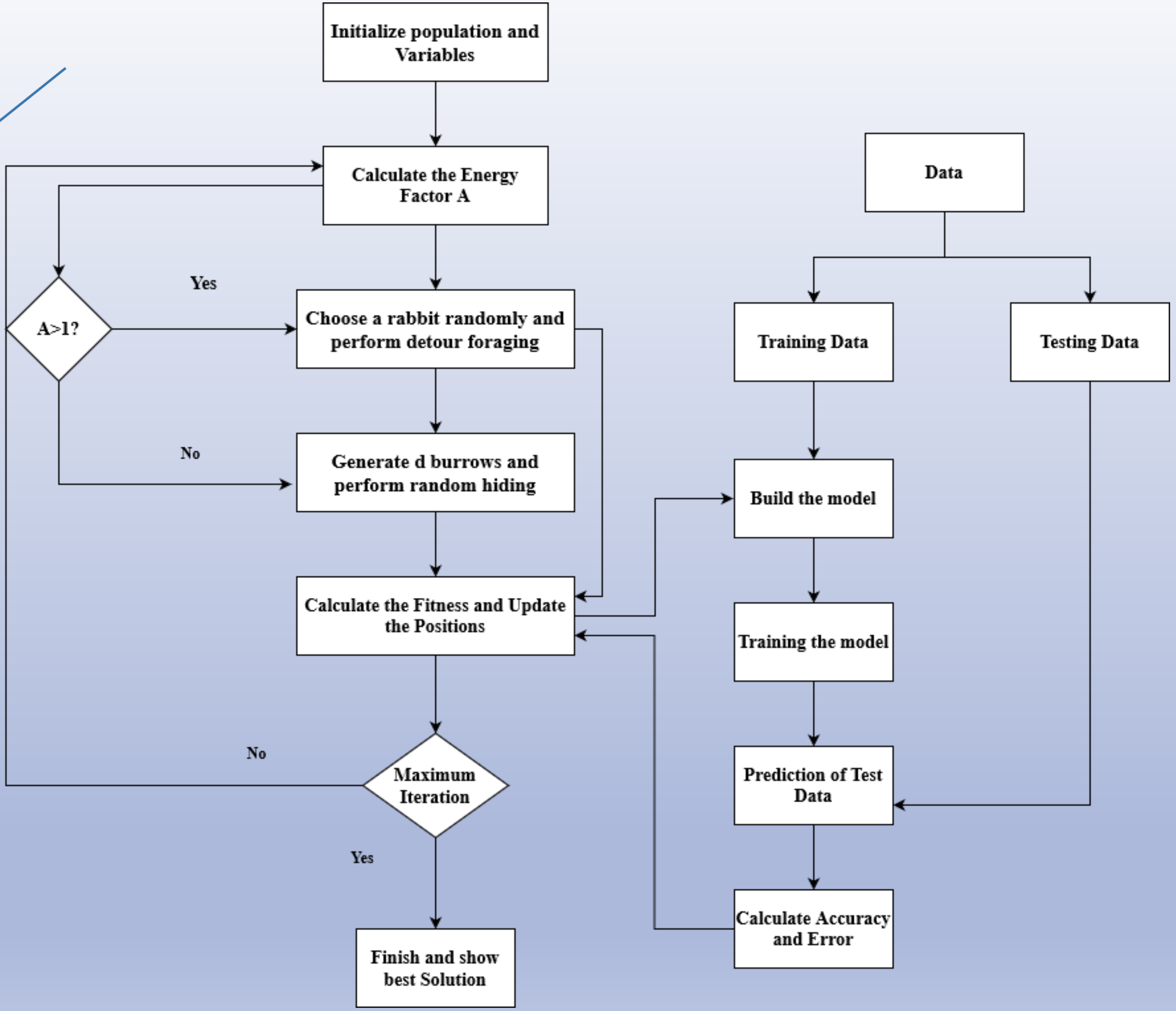


Figure 3.
Proposed LSTM-ARO model

RESULT ANALYSIS

- Using Yahoo Finance (a website that offers a variety of financial statistics, such as exchange rates, stock prices, market indexes, and more), data was collected on the Dow Jones (DJIA).
- It is one of the standard markets in the USA and is part of a network of exchanges that facilitate operations in the stock market, and is one of the markets where buyers and sellers trade shares. DJIA data for time periods can be accessed and downloaded using Python and the Yahoo Finance API.
- A 20-day historical time span was used to estimate prices. The 20-day prices are the input. The price for the following day is the output.

RESULT ANALYSIS

The simulation parameters are shown in the following table:

Hyperparameters	Values
Number of neurons	1,2,3,…..,18,19,20
Layer exists or not	0,1
Dropout Rate	0.3, 0.4, 0.5, 0.6, 0.7
Optimizer Methods	Adagrad, Adam, Adamax, RMSprop, SGD
Learning rate	0.01, 0.001, 0.0001, 0.000001

RESULT ANALYSIS

- The proposed method is evaluated using criteria that quantify how well the model predicts the productivity standards from the input information, as well as how accurate it is.

- The MSE calculates the variation among the actual and predictable standards. The computation involves squaring the disparity among the estimated and real standards, followed by calculating the regular of all these squared disparities. This number is castoff to evaluate the model's correctness; the lower the MSE, the more accurate the model.

$$MSE = \frac{1}{n}\sum_{i}^{n}(y_i - \hat{y}_i)^2 \tag{21}$$

RESULT ANALYSIS

Another way to quantify the variation between predictable and real values is to use the MAE.

It is computed by averaging all the total standards of the disparities that exist among the expected and real standards. The replica's precision is also evaluated using this worth, the lower the MAE, the additional precise the model.

$$MAE = \frac{1}{n}\sum_{i}^{n} |y_i - \hat{y}_i| \qquad (22)$$

RESULT ANALYSIS

A percentage-based metric called MAPE is used to evaluate the accuracy of a predictive tool.

To calculate this, divide the overall disparity between the expected and actual numbers by the actual amount. Then, take the average of each of these fractions. When evaluating a model, the lower the MAPE value, the more reliable its structure is thought to be.

$$MAPE = \frac{100}{n}\sum_{i}^{n}\frac{y_i - \hat{y}_i}{y_i} \qquad (23)$$

RESULT ANALYSIS

- An indicator of the extent to which an equation fits the data is its R^2 score.

- The computation involves calculating the total of the quadrangles representing the variations among the actual and predicted values, multiplying it through the total of the square representing the changes among the real values' mean and the actual numbers, and finally deducting this amount from 1. The representation's precision is strongminded by this worth; the nearer it is to 1, the more accurate the model.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \qquad (24)$$

RESULT ANALYSIS

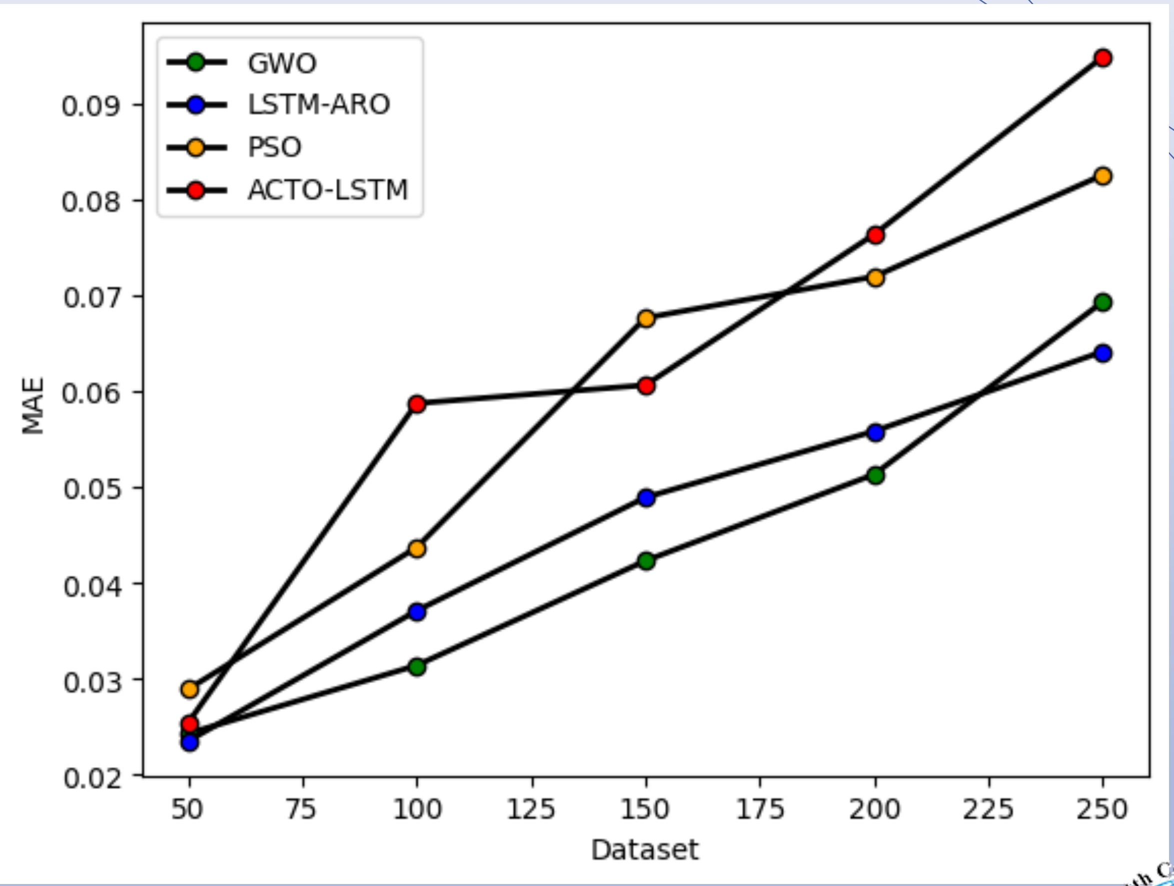
- Every model's prediction accuracy is gauged by the MAE, with a lower value denoting higher accuracy.
- It seems that the LSTM-ARO model is most reliable model overall because it has the least MAE, MSE, R^2 and MAPE across most of the stocks.
- It's crucial to remember that the outcomes differ based on the stock, though. Some models anticipate some stocks more accurately than others.

Methods	MAE	MSE	R^2	MAPE
PSO [37]	0.0825	0.0127	0.0972	1.2986
ACO-LSTM [31]	0.0948	0.0170	0.0953	1.4816
GWO [32]	0.0693	0.0091	0.0917	1.1216
LSTM-ARO	0.0641	0.0079	0.0806	0.9549

Evaluation of MAE, MSE, MAPE and R^2

RESULT ANALYSIS

- The statistic known as Mean Absolute Error (MAE) is regularly working to assess the exactness of an analytical perfect.
- When it comes to financial markets, MAE can be used to evaluate how well an economic model performs when it comes to forecasting the price of stocks or other market indices.
- The projected technique attains healthier presentation likened with traditional methods.



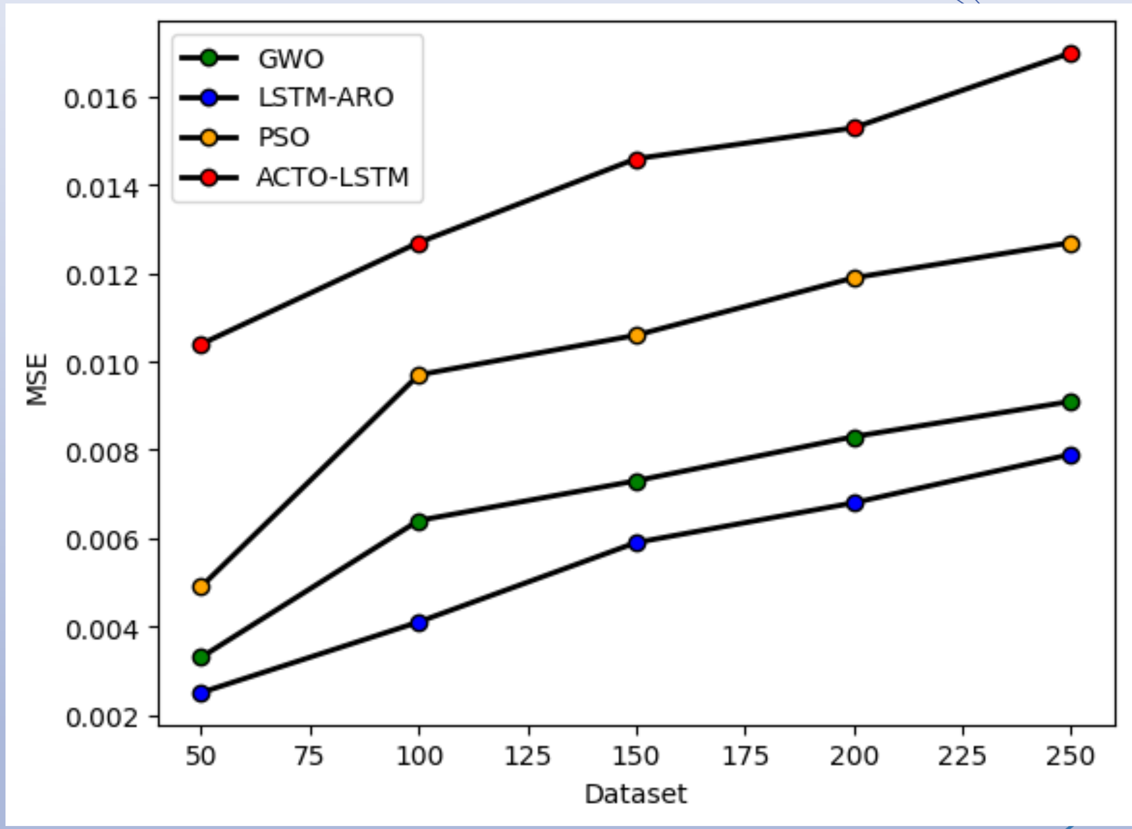
Evaluation of MAE

RESULT ANALYSIS

- The term Mean Squared Error (MSE) refers to a metric that is frequently used in machine learning and statistics to calculate the mean of the squares of errors or variances among actual and anticipated values.

- MSE can be used in financial markets to evaluate a model's forecasting reliability.

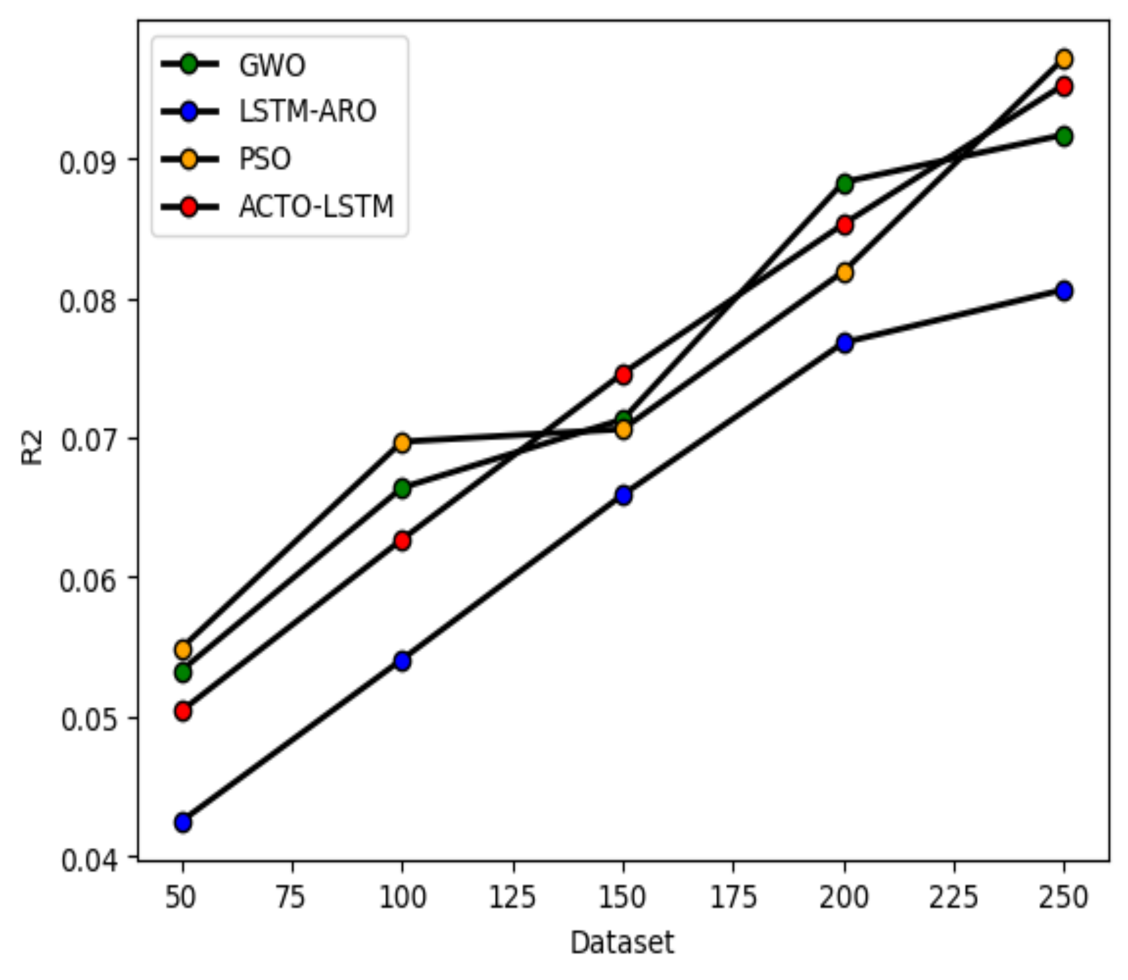
- To measure how far off your forecasts are off reality's stock prices, for example, you could compute the MSE if you had a model that predicted stock prices. Better forecasting accuracy is typically indicated by lower MSE values.



Evaluation of MSE

RESULT ANALYSIS

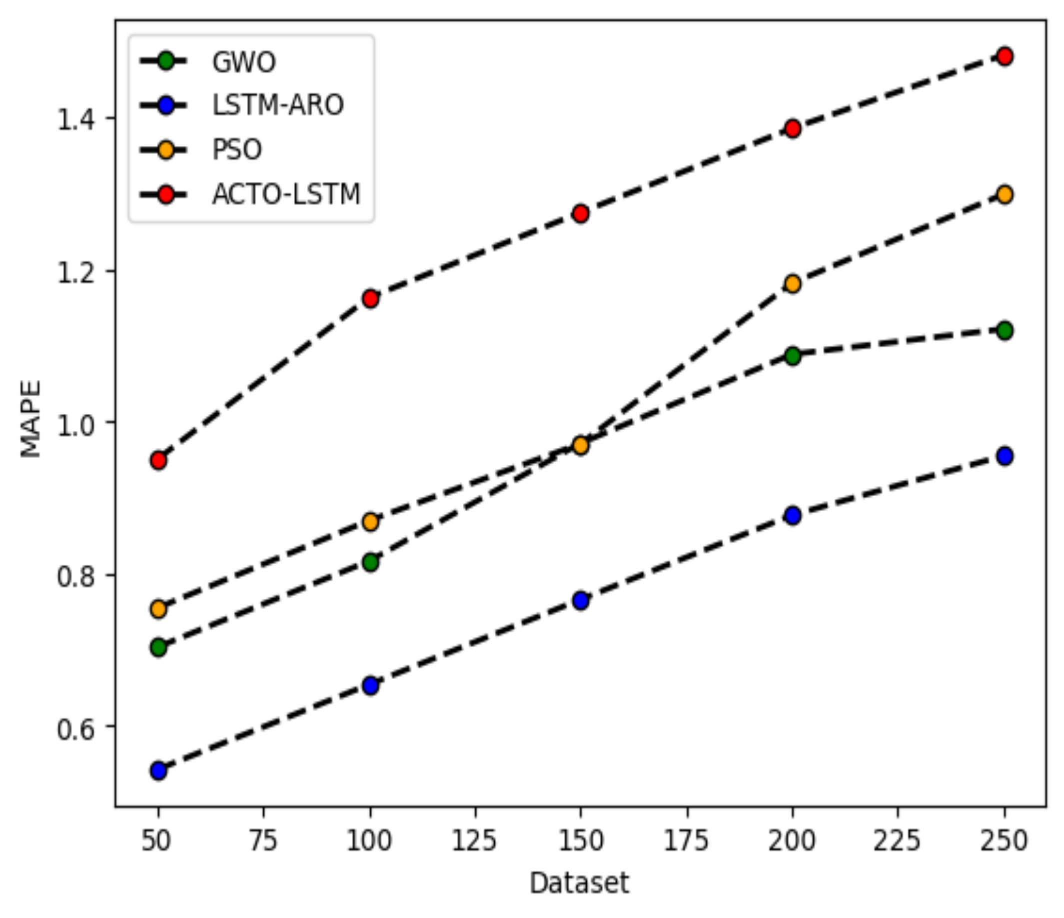
- A measure of statistical significance called R-squared shows how greatly of the difference in the adjustable that is dependent can be predicted based on the independent variable (or variables).
- To evaluate the extent to which the self-governing variable(s) in a regression study describe the difference in the reliant on variable (could be the returns on a financial asset), the financial markets frequently employ R-squared.
- The range of R-squared values is 0 to 1. When the value of the variable that is dependent is 1, it means that all its variability around its mean is explained by the model.
- When the value is 0, it means that no variability is explained by the model.



Evaluation of R^2

RESULT ANALYSIS

- The statistic known as Mean Absolute Percentage Error, or MAPE, is frequently employed to measure the precision of the model used for forecasting. It is especially helpful for assessing the correctness of forecasts or forecasts in the setting of financial markets.
- Financial information can be chaotic and prone to abrupt, erratic fluctuations when using MAPE to financial markets.
- Furthermore, volatility grouping, and non-stationarity are common features of financial time series data, which can complicate forecasting.
- As a result, even while MAPE can be a helpful indicator of accuracy of forecasts, it can only be used when combined with other assessment metrics and a deep comprehension of the qualities of financial data.



Evaluation of MAPE

CONCLUSION

- The rapid growth of image and video processing technologies affects many different sectors. Based on the study and forecast of financial market revenue, investors can make well-informed investment decisions, and the government can design precise regulations for different types of economic control.
- This study examines and forecasts returns on financial markets and other indexes utilizing a deep learning LSTM network and an artificial rabbits optimization technique in image processing technology. This education uses the time series technique to successfully record the regional correlation features of financial market data.
- To anticipate the moment series earnings index for the financial sector, convolution pooling in LSTM is then utilized to extract important information that was previously concealed in the time series data, create a trend curve for the data, and combine the features utilizing image processing technology.

CONCLUSION

- One popular kind of artificial neural network found in time series analysis tools is the Long Short-Term Memory (LSTM) networks. Its accurate estimation of stock prices stems from its capacity to manage information that includes numerous input and output timesteps.
- Financial sector forecasts can be made more accurately by adjusting the hyperparameters of an LSTM model using metaheuristic methods like the Artificial Rabbits Optimization Algorithm (ARO).
- This paper demonstrates the development of an enhanced deep LSTM network with the ARO model (LSTM-ARO) for predicting stock prices. The findings demonstrate the accuracy and effectiveness of the deep learning technique employed in the study for financial sector series predictions. Techniques for analyzing information and image processing offer useful approaches and significantly advance the study of banking.

CONCLUSION

- The work can be expanded in the future by accounting for the additional LSTM hyperparameters, such as learning rate, number of epochs, number of hidden layers and hidden neurons, batch size, time series window length, dropout rate, etc.
- Future research in other financial time series forecasting domains would examine further nature-inspired and evolutionary strategies to optimize the model's hyperparameters.

Thanks for your kind attention

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