Enhancing Stock Price Prediction Accuracy Using ARIMA and Advanced Greylag Goose Optimizer Algorithm

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Abstract

This paper applies ARIMA and the Greylag Goose Optimizer (GGO) algorithm, among others, for pre-trending the stock market prediction. This study aims to improve stock price forecasting using proper feature selection methods and time series modeling. The dataset encompasses historical pricing data that was scraped from Yahoo Finance in January 2019. There were many models for feature selection applied in the data preprocessing phase, such as bGGO, bGWO, bGWO_PSO, bPSO, bWAO, bBBO, bMVO, bSBO, bGWOGA and bFA. The model's performance was judged on metrics based on average error, select size and fitness; the GGO (Greylag Goose Optimizer) algorithm had the best performance rating, with an Average error equal to 0.36455. The ARIMA model was used to predict future stock prices based on the selected features, with the lowest MSE being 0.001367831 and an RMSE of 0.0369842, evidencing powerful forecasting ability. This outcome proves the reliability of integrating feature selection approaches with ARIMA for stock price prediction; it helps improve forecast accuracy and provides valuable insights for investors and analysts. The final point indicates the importance of powerful optimization tools in decision-making.

Keywords: Stock Prices; Feature Selection; ARIMA; Greylag Goose Optimizer; Financial Data; Machine Learning.

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1. Introduction

Stock price prediction stops at the gates of the financial markets, influencing the investors and analysts' decisions regarding the anticipated price movements. Concisely and correctly pegged stock prices can yield substantial gains in financial terms, bolster risk management, and bring about superior portfolio management. The age-long stock price forecasting done by statistical methods of linear regression, moving averages, and autoregressive model is used by traditional stock price prediction methods. Nevertheless, as a rule, they do not replicate the intricate, non-linear relationships bear in mind when predicting financial data. In the last few years, the developments in AI (artificial intelligence) and machine learning algorithms have been significant, especially in stock price predictions. These sophisticated algorithms can handle massive data sets and discover multidimensional patterns. Among the techniques are the neural networks, the SVM, and ensemble methods, which have been proven effective in improving performance and robustness [1-4].

It is the most critical stage in the predictive modeling process. Still, feature selection is crucial when dealing with high-dimensional datasets, which are common in financial markets analysis. Feature selection plays a vital role in choosing the most significant variables that directly impact the target variable. In this way, feature selection leads to the reduction of high-dimensional data, which is much better than the models that have obscure interpretations. Effective feature selection can lead to several benefits: through this approach, it decreases computational cost by eliminating redundant and non-relevant features, improves the accuracy of model building by focusing on the most critical variables, and reduces the risk of overfitting as well (which occurs when the model learns noise present in data). Different classifiers of features, including filter sorting, wrapper sorting, and embedded method, will help to decide the best subset features. In this paper, we conduct the effectiveness studies of different feature selection approaches (bGGO, bGWO, bGWO_PSO, bPSO, bWAO, bBBO, bMVO, bSBO, bGWO_GA and bFA) in the framework of stock market prediction [5-8].

The ARIMA (Auto Regressive Integrated Moving Average) model is a standard tool in the domain of statistical methods of the analysis of time series data. As developed by Box and Jenkins, the ARIMA model is preferably used to fit the series data into the time series category because it helps capture the underlying patterns and traits [9-11]. The ARIMA model combines three components: AR, I, and MA terms, which are used to characterize the relation between observations and several lagged observations, the model applied to them, and the residual errors of a moving average. The ARIMA model flexibility permits its application to different time series data with various figures, such as seasonality and trends, which leads to the focus model being a sound mechanism for financial prediction [12-14].

This research aims to improve the efficiency level of stock price prediction by combining the time series forecasting model with advanced feature selection techniques. Specifically, the study aims to achieve the following objectives:

1. Evaluate the performance of various feature selection algorithms: Implementing the feature selection models, which include bGWO, bGWO_PSO, bPSO, bWAO, bBBO, bMVO, bSBO, bGWO_GA, and bFA, is an essential stage in determining the relevant features for effective stock price prediction.

2. Identify the most compelling feature selection algorithm: The purpose of the paper is to observe which algorithms perform better in the specified data using metrics such as mean error, feature size, and fitness.

3. Integrate the selected features with the ARIMA model: With features that get the output of the most effective algorithm, the ARIMA model will be trained to generate a forecast for stock prices in the future.

4. Assess the predictive performance of the combined approach: The investigation will assess the technical capabilities of the ARIMA model through the use of MSE, RMSE, MAE, and other pertinent indicators.

5. Provide valuable insights for investors and analysts: The research will provide practitioners with practical decision-making approaches and tools that may transform them into wise finance decision-makers.

The structure of this paper is organized as follows: Section 2 discusses the reviewed literature from the past studies conducted on stock price prediction, feature selection models, and the ARIMA model of finance forecasting. We report our details on the dataset in Section 3. These involve the source, characteristics and preprocessing methods that we have applied. Section 4, the methodology part, explains the types of feature selection models and the ARIMA model implementation in detail. Section 5 is dedicated to the outcome of the feature selection and ARIMA model, exiting their success. Section 3 provides a final point that summarizes the main idea of the piece by including details on implications, limitations, and recommendations for further research.

2. Literature Review

AI and ML are the two related technologies that have been among the most discussed topics in finance learning. Nevertheless, a comprehensive meta-reflection of what we learned during the research is yet to be provided in this review. This gap has been bridged by conducting surveying AI and ML research related to finance [15]. Through co-citation and bibliometric-coupling analysis, we intend to determine how the thematic structure of AI and ML research will be performed from 1986 to 2021. Through uncovering nine specific clusters via co-citation and eight through bibliometric coupling, three overarching groups of finance scholarship have been identified: (1) building and assessing investment portfolios, as well as investor attitude study; (2) analysing bankruptcy fraud and distress; lastly, (3) sentiment inference, outlook, and plan formulation. Moreover, the joint textual analyses and content reviews have brought out the trends and focus areas of the subject matter related to AI and ML in finance. Outcomes comprise AI and ML evaluation for that particular project.

A review of AI and Machine Learning in the finance field was done by [16]. When a bibliometric method was employed, 348 articles were published from 2011 to 2021 in journals indexed in the SCImago database. A set of programs and tools, including Rstudio, VOSviewer, and Excel, was used to carry out the analysis. It was found that the most active scientists and scientific institutions came from the selected countries, including sources, documents, and writers. The analysis showed a steady rise in publishing starting in 2015. AI/ML research fields included insurance payment prediction, gold price prediction, portfolio management, oil price prediction, AML, behavioural finance, big data analytics, and blockchain. The US, China and the UK lead the overall publishing volume, and technological advances are better showcased. Those results help provide implementable tips to the players involved in the market, mostly fintech and finance companies, on how AI and ML can be incorporated into their total decision-making strategy.

One of the most intriguing things in the last years is the swift progress in machine learning technologies, which has allowed us to solve many problems in various areas. Average forex is one of the widespread financial products used by corporations, institutional investors, and individuals to hedge their exposure and investment objectives. They are the most popular because they are cheap and pay at a rate tied to the underlying asset and behaviour at the due date; therefore, this avoids market price manipulations. Hence, numerical approaches involving averaging prices of arithmetic average options require repetitive calculations of large numbers, which is very expensive and involves unrealistic assumptions about the model. To price the arithmetic and geometric average options, [17] provided an accurate and fast machine-learning technique. The approach, a model-free one, was rigorously checked via real-world scenarios and simulations.

The bibliometric methods were utilized by [18] the survey of the literature on machine learning, artificial intelligence, and deep learning mechanisms within the financial spectrum. The thought about the publishing platform in ML, AI, and DL in finance and making it easier to understand the work of researchers, the research development and the continuous growth of the field was examined. We observed a surge in Reddit publication trends within this research area, with the USA and Chinese universities leading other posts. The new theme of study, namely ESG (environment, social, and governance) with the help of ML (machine learning) and AI (artificial intelligence), was unveiled. Yet, such a gap was observed without controlled and scrutinized academic research on the use and effectiveness of these cutting-edge automated technologies in the financial sector. It was discovered that algorithm biases became the main barrier to the model prediction accuracy in regions such as the insurance, credit rating, and mortgage systems. This study shows the future direction might be in ML and DL archetypes, given the current state of affairs. The study also recommends that an educational change concerning those technologies through research papers and international symposiums is required at the academic level.

This paper concludes that financial variables and network topology are critical determinants of systemic risk (SR) [19]. At the multiple levels of initial shocks, we get SR with institutions in the

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interbank market of Brazil by applying the specific DebtRank approach methodology. The FI-specific determinants of SR were evaluated through two machine learning techniques: XGBoost and random forest, which are some of the most popular ensemble methods for making predictions. Shapley values analysis seemed to be one of the best ways to explain the results in people-friendly language. In this regard, the observation further investigates the separate impact of objects on SR with consideration of initial shock level, type of FI, and dimension of risk measured. The systemic impact was found to be mainly determined by topological factors for both types of FIs, and the role of these factors becomes more robust if the size of the initial shock is significant when we are talking about banks. Still, this role weakened if the shock was negligible during the case of credit unions. In the initial period of the shock implementation, the most significant vulnerability was observed when financial features came into the picture. This was determined to be an increased role of the same financial features for both types of financial institutions when the initial level of the shock was elevated.

Financial risk management tends to be a critical factor for many companies as the primary purpose is to minimize the loss and allow the companies to attain as much profit as possible. This process mainly depends on decision-making, which can be driven by information at the end of the day, thereby making machine learning an essential source for new methodologies and technologies. In the last few years, a trend has been witnessed as more machine learning techniques are applied in the decision-making tasks associated with managing risk. However, machine-learning researchers often struggle to navigate the vast and complex domain knowledge and the fast-evolving literature. A giveaway of a comprehensively done systematic study of the enormous literature on machine learning for financial risk management was provided by [20]. The paper's contributions will be the presentation of finances, tackles of the most prominent papers in the past researcher's deification, and the indication of trends are cut, assuming some others will be followed, and the other redirections' able finance is an exciting field in academia; what is shocking, however, is the fragmentation at which science offers its pieces of the puzzle through a subset rather than the whole of sustainable finance. The quilt of this gap is tied to the hands of the big-scale review, which provides the overview of the current state of the performance and organization of sustainable finance provided by [21]. The study carried out a study of sustainable financing research, which involved the analysis of big data and computational learning of scholarly research. The following tasks included a summary of leading journals and authors, sources of contributions, institutions, and countries implicated in green finance research. In addition to methodological choices, the context in which the green (finance) research was played out. Research unveiled sustainability finance intelligences such as socially acceptable investment, climate financing, green finance, impact investing, carbon finance, energy financing, and governance of green supplier-customer relationships. Numerous ideas for the research topics of sustainable finance in the future were also suggested, among which these proposals can be highlighted: building innovative sustainable finance instruments, making sure the profits and returns are managed, designing sustainable finance to be more sustainable, creating the policies and frameworks, eliminating the greenwashing from the corporate sustainability reports, applying the behavioural finance to the sustainable finance, and using the new-age technologies, such as

For decades, intelligent computing in finance has been one of the most famous scientific issues and the world's catalytic worlds. Many studies have generated different models; one of the most obvious is the major shift to the deep learning area, which has resulted in better than classical models. Ample versions with different depth levels of DL are available now, and this is the subject of growing curiosity. One particular area in AI, finance, has gained traction, but many unclosed science questions remain. A comprehensive DT picture of advanced DL models used in financial applications was given by [22]. The works were classified according to their direction of work in finance and studied according to the prevailing models of DL. The presentation included Potential future implementations and the research path for further research work within the alimented literature on empirical assets in the Chinese stock market; it constructed a comprehensive set of factors that used different machine learning algorithms to achieve the performance of return prediction for the listed stocks on the Shanghai and Shenzhen exchanges. The most important term is liquidity. As such, one of the factors that has been studied is the impact of transaction costs. The likely effect of the dominant position of retail investors can be seen in short-term signal forecast ability, especially for smaller stocks. The traceability of shares of the big companies and the state-owned enterprises influences the assets as they are more easily predictable on the Chinese market's short a market's horizons, unlike the US market, where there is a possibility of market unpredictability on more or less timeframes. The out-of-sample performance remained economically significant after financially related expenses were the subject of maths.

The Machine learning trading strategies based on market predictability of the top three major cryptocurrencies—bitcoin, Ethereum, and Litecoin—were investigated by [24]. When the models were being validated, there was a period of instability and obscurity like never before, and we checked their robustness in a bear market period to assess the accuracy of the predictions despite the changes in the market directions. A thorough analysis was carried out by looking at trading and financial network aspects from August 15, 2015, to March 03, 2019, with the test data starting on April 13, 2018. Among the 18 single models, five with success bail degrees below 50% were launched. The model system, specifically Model 5, proved the soundness of machine learning technique among the identified turbulent revile of cryptocurrency, thus providing accurate and profitable trading strategies even in unfavourable conditions.

3. Dataset

To understand the basic principles of cryptocurrency trading, we have been actively using a dataset extracted from Yahoo Finance, an absolute authority and most popular source of financial data. Yahoo Finance provides market coverage of the global financial market, which is the source of a lot of stock price data. We applied the dataset for BBCA: JK is one of the significant domestic institutions listed at the Jakarta exchange. Yahoo Finance is recognized as being painstakingly thorough and accurate throughout, equipping it to be a suitable source from the perspective of acquiring the top-notch financial data needed for analysis and modeling [25].

The range of data begins in January 2019 and continues up to the present time, creating a complete image of the stock's performance over multiple years. This is when various market conditions prevail; the market goes through certain turbulences, unstable states, economic events, or even study areas span its width over a long period, allowing for a high degree of trend and pattern analysis across the sample price movements. This is essential and a source of significant information important for creating predictive solid models because the market history can demonstrate the overall dynamics that contain the entire market behavior. According to the application of the recent data, simulations can stay relevant and respond to current movements in the market.

The dataset consists of several empirical attributes, and the model process includes all of them, contributing utilized and significant information for the analysis. These attributes include:

1. Date: The trading day date corresponds to the period required for a time series analysis. The instruction "date" core is used to arrange the data regarding the time order and perform calculations on trends, seasonality, and forecasting.

2. Open: The exchange price of the stock at which the first trade was transacted on a given trading day. It is an essential attribute which may be used to indicate the initial trend as well as from an observation of the intraday price changes an opening price may also signal the markets of the previous trading, or any news and events which happened between the close of the previous trading session and the beginning of the current one.

3. High: The highest stock price of a particular trading session characterizes the market's profitable entry and exit points and the predicted price ceiling. The moving average indicator is an excellent tool for helping traders establish the high price level and determine the high price and volatility range within a day.

4. Low: The stock price found during the trading day with the lowest price. This particular allows for challenging the market highs and lows. The hopefully low price is, in fact, essential when it comes to evaluating the upside stress and the markets to face the negative aspects of the economy.

5. Close: An amount of money at which a particular stock was determined to be sold on a specific trade day. The closing price is the most significant, showing the sum of the consensual value attributed to the stock that day. Indicators, trend analysis, and technical indicators are popular tools among traders and analysts that they mainly apply to the closing price to determine their tactics.

6. Adj Close: The adjusted closing price, which incorporates the impact of dividends, stock splits, and other adjustments, will also be considered. This characteristic, which reassesses the stock's value and brings it closer to its real value in the long run, is very significant. The specific notion of close is highly important for long-term analysis and adhering to uniform historical price series.

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7. Volume: Without the number of shares traded on a trading day. The magnitude or level of volume is a significant parameter for the market and liquidity, which determines the strength of price movements. Extremely high trading volume intermingles with drastic price movements, leading to better ideas and patterns of trader preferences on how the market works.

Figure 1: Time Series Plot for the Financial Data

Figure 1 is time series plot, a crucial tool in our analysis, illustrates the stock prices for PT Bank Central Asia Tbk's (BBCA. JK) shares from January 2019 to the latest. This graph showcases the cyclic dynamics of stock prices. It provides a glimpse into their historical trend and patterns, revealing how the data behaves over time regarding upward and downward movements. We can decipher the market behaviors and find seasonal or cyclical patterns by emphasizing the stock price changes that display volume and stability. This visualization forms the cornerstone for the subsequent analytical work and modeling, underscoring its importance in our financial analysis.

Figure 2: Correlation Heatmap of the Dataset

The correlation heatmap in Figure 2, a powerful tool in our analysis, shows the primary connections between different attributes in financial data. Each cell in this heatmap webpage represents the correlation value between two variables and values ranging from -1 to 1. The positive association means that these features move in the same direction while, on the other hand, the negatively related ones move in the opposite direction. The heatmap is an effective measure that assists in locating the strengths of the correlations between features, a crucial step in feature selection and understanding the connections of the dataset. By showing these associations, we can be more precise in our modeling process, allowing us to minimize multicollinearity and verify the accuracy of data, highlighting the relevance of this tool in our financial analysis. Altogether, these characteristics make the formation of a deep knowledge of the portfolio style, thus allowing tone o broadly analyze price shifts and trading features. Through combined examination of these facts, researchers can gain valuable information regarding the triggers of stock price changes, among other things, to see trends and irregularities in the market performance and to build models for the prediction that capture the complexity of the market. The comprehensive and contextually rich (historical background) nature of these attributes contributed by the mentioned periderms the use of a dataset that will help to achieve the research objectives and improve the reliability and accuracy of the findings.

4. Proposed Methodology

3.1 Dataset Preprocessing

Data preprocessing is a fundamental stage in pre-analysis and modeling, and every effort must be made to ensure that the dataset is fit for analysis. Data management is required for cleaning, transforming and structuring the raw data to maintain its reliability and suitability for later manipulation. Data preprocessing properly improves the accuracy of machine learning models and ensures that the output and results are justified and appropriate. The critical stages in the data preprocessing pipeline for this research are as follows:

1. Data Cleaning:

- Handling Missing Values: There are some reasons behind the missing values of the dataset. Those include errors in data entry, lack of data during the data collection, or the market being shut down. These important missing values are dealt with if biased analysis is to be averted. In this research, we adopted multiple methods to treat the value gap. The interpolation techniques, including linear and spline interpolation, were the regimes we relied on to estimate the missing values that may belong to the continuous variables, like stock prices, by analyzing the surrounding data points. As opposed to the fact that interpolation was inappropriate in some cases, we proceed according to the fill forward and fill backward techniques to spread the last valid observation. Adopting such methods translates into the consistency of time series data, so there are no gaps.

- Removing Duplicates: Duplicates lead to twisted results and inexact conclusions. To maintain data accuracy, we eliminated the rows that mistakenly appeared twice in our dataset. This step will give authentic and different data from each observation.

2. Data Normalization:

- Scaling Features: Stock data price can go up and down so much that the models perform poorly due to insufficient and extensive value input. To deal with this problem, we used methods including Min-Max scaling and Z-score normalization as our normalization techniques. Min-Max scaling changes the data to a particular segment. g. Feature scaling is an essential normalization process where a range of variability is uniformly transformed from 0 to 1. Feature transformation through z-score normalization occurs by subtracting the mean and dividing by the standard deviation; the features will have a mean of 0 and a standard deviation of 1. Scale indication guarantees that all features are equally influential and avoids feature dominance by those with larger magnitudes.

3. Feature Engineering:

- Creating New Features: Apart from the initial attributes we used as baselines, the new features were added to inform more and provide the models with the required details to perform better. For instance, we built the lagged variables to comprise historical indicators and calculated technical indicators like moving averages, relative strength index (RSI), and Bollinger Bands. This enables models to track same-day occurrences and explores time-based data patterns. The historical context

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presented by the lagging variables broadens the view of the market, while technical indicators grant access to the market pulse and price inversions.

- Transforming Existing Features: We gained an extra edge by transforming original features so that the new features increased their interpretability and applicability. In addition, we first applied logarithmic transformations, which regulated the instability of variance and mitigated the effects of outliers on price values. Logarithmic transformation is an excellent normalizing technique used in building models as it reduces the skewness in data.

4. Feature Selection:

- Applying Feature Selection Models: The feature selection portrays the most appreciated traits from data that predict stock prices. Through featuring this experiment, we utilized numerous algorithms, such as bGGO, bGWO, bGWO_PSO, bPSO, bWAO, bBBO, bMVO, bSBO, bGWO_GA, and bFA. The algorithms were graded on mean error, pop size and fitness criteria. A testing selected the most efficient feature selection model. Besides this, by choosing among the best feature sets, we wanted to mend the model's Evaluating Feature Importance: Dependency on the model-based feature importance methods. Through the importance of permutation, you obtain the effect of having the feature exchange (shuffling) and affecting the model's performance; the model-based importance uses the internal properties of the model to rank the features. These techniques elucidated which of the most relevant details should be conserved and which irrelevant and redundant data were stripped off.

5. Data Splitting:

- Training and Testing Sets: The data set was preprocessed by exacting the training and testing subsets for model evaluation. Typically, a standard split ratio of 70: When 30% or 80% of models were trained with a lower ratio reserved for testing the model's predict model was used for testing the predictive accuracy. This model's nature, model's is evaluated on unbiased, sed data that gives the most realistic performance.

- Validation Set: The other aspect of our approach is establishing validation aside from training and testing sets to retrain the model parameters and avoid overfitting. Among cross-validation techniques, including k-fold cross-validation, I used these to check the model exactly. In the k-fold cross-validation process, the data is divided into k groups, and the model is trained and tested with each of these data groups: k: times, the validation sets for which are different each time and the remaining data sets for training. This method provides a protocol of the performance seam that is calculated across different data splits and looks more completely implementing data and pretreatment; we managed enough to get a precedent state for feature selection and predictive modeling. Through this, with arrayal of methods, we created the models that could maximally use of the data. The complete and accurate nature of the data cleaning improves the final res, dura, and quality so that the following modeling and analysis phases are done accurately and correctly.

3.2 Feature Selection

Feature selection is a fundamental process in the prediction modeling process generally and even more so when dealing with a high dimension to which stock prices belong. The goal is to find the predominant features that provide the most outstanding value regarding prediction ability. This not only enhances the model performance but also reduces computational complexity. This study is based on selecting among different advanced feature selection algorithms and determining which features are the most suitable for predicting stock price. In the lines below, we outline how each algorithm works and what metrics will be used for evaluation [26-28].

1. Binary Greylag Goose Optimization (bGGO):

- Inspiration and Mechanism: The GGO Algorithm is inspired by the patterns of the Greylag goose's migration. This algorithm designs the smile flocking of birds where the goose leads others, and they adjust their positions to find the optimum solution. This algorithm compares lists of features, representing them as 1s and 0s, to show whether a feature is relevant.

- Key Features: bGGO utilizes the leader-follower approach and position-updating operations to explore and exploit the search space maximally. It gives half versus half (search for new features versus refine known good features) to obtain the best combination of final features.

2. Binary Grey Wolf Optimizer (bGWO):

- Inspiration and Mechanism: By studying the respective ways of hunting by wolves, this algorithm includes a hierarchical structure where wolves are categorized into alpha, beta, delta, and omega, having respective roles in searching. An alpha wolf prods the search team, whereas a beta and a delta have their assistance, and an omega wolf follows.

- Key Features: By following the leaders' movement, this algorithm employs a dynamic repositioning mechanism in which wolves change their positions on the fly. Thus, the structure facilitates exploring a wide range of options and converges on the most optimal solution.

3. Binary Grey Wolf Optimizer with Particle Swarm Optimization (bGWO_PSO):

- Inspiration on and Mechanism: The hybrid algorithm based on the Grey Wolf Optimizer combines its exploration capabilities with PSO, which has exploitation advantages. The mechanism applies particle sociality to calculate the leadership structure of wolves and performs feature selection.

- Key Features: Although bGWO_PSO uses PSO velocity and position updates, and GWO leadership hierarchy is the basis of the decision process, the method remains unbalanced. As a result, the algorithm can optimally tune its search for the most helpful feature combinations.

4. Binary Particle Swarm Optimization (bPSO):

- Inspiration and Mechanism: Designed to imitate the social behavior of bird flocks and fish schools, bPSO optimizes feature identification by making particles (the particles may represent the potential solutions) fly through the search space. Every P article's movement is influenced by its own best position and the swarm's best position.

- Key Features: bPSO checks and measures particle velocities and positions to find desirable solutions. The bits in the binary form act as the feature subset carrier, each being one or zero, representing either the feature present or not.

6. Binary Biogeography-Based Optimization (bBBO):

- Inspiration and Mechanism: This algorithm is grounded in the biogeography principle, which describes why different species often occur in very distinct ecosystems. It employs techniques such as migration and mutation to improve and select better features

- Key Features: Notably, subsets of the features are used as habitats, whereas the migration mechanism is implemented by exchanging solutions at each iteration. The mutation leads to new variations and eventually enables the avoidance of disadvantages and the search for unexplored areas.

7. Binary Multiverse Optimization (bMVO):

- Inspiration and Mechanism: It used the multiverse theory to simulate multiple universes with different feature sets, using the same information interchangeably to converge on the best answer.

- Key Features: bMVO utilizes inflation and white/black hole constructions within the space to render feature transfer among multiverses. This way, random forests provide a comprehensive search of the space of features and ultimately settle at optimal subsets of features.

8. Binary Satin Bowerbird Optimizer (bSBO):

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- Inspiration and Mechanism: This algorithm duplicates the mating mechanism of satin bowerbirds, using attraction strategies similar to those of male bowerbirds to maximize feature selection.

- Key Features: bSBO mimics the selection process as it is a mating display where appealing sex features are chosen. The algorithm focuses on finding the optimal feature set with a high degree of exploration and exploitation.

9. Binary Grey Wolf Optimizer with Genetic Algorithm (bGWO_GA):

- Inspiration and Mechanism: This hybridization created the algorithm (wolf grey optimizer with genetic algorithm principles). The crossover and mutation operator allows an improved search of the best function features.

- Key Features: bGWO_GA comprises GWO's hierarchical search sequence and GA's exploration of genetic diversity. Here, crossover and mutation are explored to find new attributes, whereas GWO is used to carefully exploit all the current attributes.

10. Binary Firefly Algorithm (bFA):

- Inspiration and Mechanism: The algorithm grammar is inspired by the flashing activity of fireflies; it estimates the attractiveness of the fireflies as a measure of the direction the search process will take. This firefly movement pattern signals other individuals to join in and search for potential solutions that yield maximum results.

- Key Features: In the case of an artificial bee colony, fireflies are attracted to better solutions, which can attract brighter fireflies. Algorithms based on a fitness model selected observable traits but then modified those features and eliminated the others to promote convergence to optimal feature subsets.

To evaluate the performance of the feature selection models, we used the following criteria:

1. Average Error:

- Definition: For these end goals, the standard error, which represents the mean prediction error for the selected features, is the average error. It does so by comparing the value of what is predicted and what it is.

- Significance: A decline in the mean value shows that the model fits well and determines the more responsive features. This factor guarantees that discovered characteristics are significant to the prediction models.

2. Average Select Size:

- Definition: Consequently, this criterion is meant to quantify the number of features.

- Significance: This criterion quantifies the model ought to keep a low number of features enough to get high predictive accuracy. Having a reduced set of the size of the selected parameters not only simplifies the elimination of unnecessary parameters but also reduces the associated computational cost.

3. Average Fitness:

- Definition: Performance is an indicator that explains how suitable the solution (feature subset) is regarding the objective function.

- Significance: Greater fitness average means that alpha functions are the highly predicting features that output the target variable. Considering the comparison, the highest impact of such is certainly the quality of these subsets.

4. Best Fitness:

- Definition: This criterion documents the most optimal value of fitness achieved throughout the algorithm's search process.

- Significance: Larger fitness values represent prefixes that are superior to other ones.

5. Worst Fitness:

- Definition: The second criterion, the worst fitness measurement, shows the lowest fitness value that the least efficient feature subset provides.

- Significance: The lower worst fitness statistic denotes a more regular algorithm behavior. A good algorithm must be resourceful and efficient. Hence, this algorithm assesses the reliability of avoiding poor solutions.

6. Standard Deviation of Fitness:

- Definition: This measurement of the different fitness values will evaluate the differences between each algorithm run.

- Significance: With a low standard deviation, the feature selection method proves helpful, reliable and consistent. It is designed to be stable so that the results will be accurate.

Applying these assessment criteria, we can critically determine each feature selection algorithm's strength, consider each algorithm's specific characteristics, and find the one that best suits our stock price prediction model. These selected features will feed as ARIMA model inputs and, thus, make the predictive model both exact and economical. With this all-encompassing assessment structure, we can benefit from all the advantages that diverse algorithms will bring, resulting in a solid predictive model of what stock price will be at any given time, thus making an informed decision.

3.3 ARIMA Model

The ARIMA (Auto Regressive Integrated Moving Average) model is a statistical method for large-scale noise removal. It is particularly efficient for foresight and target assignment, in which the single affected variable is proportionately distributed between all previous observations that exhibit a temporal relationship with the observer [29-31]. The ARIMA model is prevalent in financial forecasting, e.g., stock price prediction, because it can deal with a range of data characteristics of time series, which proves the Arguments historically accurate.

The ARIMA model is composed of three components:

1. Auto Regressive (AR) Component: This step interacts with observations at any time of the series with a number of lagged observations, thus making it possible to model the time series data. Besides, "p" is a symbol order for the AR component, which means that a certain number of lagged observations will be contained in the model.

2. Integrated (I) Component: This particular plane deals with deterring the series by imposing statistical properties like mean and variance that do not alter over time. d is the order of differencing and is written in the form that "d" takes.

3. Moving Average (MA) Component: Compliant to this segment is a relation depicting how an observation gives rise to a residual error of the moving average model for lagged observations. The order of the MA component is denoted by, term t" a" stands for forecasting error's value in the model.

The ARIMA model is commonly known as ARIMA (p, d, q), where p, d, and q specify the parameters that must be provided for the model. The model employs these elements to pinpoint the latent patterns and forecast the series, which are usually accurate.

Deciding the suitable value of the ARIMA model's, d, and q) is part of the model fitting process. This process typically includes the following steps:

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1. Identifying the Order of Differencing (d):

- Stationarity Test: The first step is whether random or a pattern is detected in the stationary time series. In econometric terms, stationarity implies that no essential changes occur in the descriptive statistical parameters. Anytime the stationarity of the data is not given, diffusion is applied until stationarity is reached. The augmented Dickey-Fuller (ADF) test is applied to tests for underlying stationarity.
- Differencing: If it is shown that the ADF test is not stabilized, then the series is differenced. The argument 'd' that stand' for order of differencing is calculated from the number of times the data needs to be differenced so that it has the stabilization characteristic.

2. Identifying the Order of AR and MA Components (p and q):

- Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF): With these plots, the ACF with PACF is used to choose the correct 'p' and 'q' values. Plots give information on how terms are defined in the presence of MA while PACF plots do the same for AR terms.

- Model Selection Criteria: Several alternatives to the model selection criterion, such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), compare various ARIMA models and select the one with the lowest criterion value.

After the initial model is selected, the parameter tuning is carried out to the model's best ability to determine. Here, the whole process starts with picking the "3-parameters" model" (p, d, q) "and several ones to get the best-fitted data. The steps for parameter tuning include:

1. Grid Search:

- Definition: Grid search is a systematic process of simulating the range of values as parameters.

- Implementation: The grid search process sweeps all the possible combination of "p", "d", “q", which is "d" fined in the polynomial times. The model is used for each option then trained data is used to assess his/her performance by metrics like AIC, BIC and Mean Squared Error (MSE).

2. Cross-Validation:

- Definition: Cross-validation is a very useful method for assessing models' performance models through empirical splitting of data into multiple subsets and later conducting model evaluation on different subsets. It helps save on optimization time and ensures that the model works well out of the training dataset.

- Implementation: When the problem is set in a time series frame, one can apply the k-fold cross-validation. Splitting the data into k sequential folds is the most common implementation. The k-fold scheme is used for training and testing the model using the rest of the fold as the test dataset. First, the algorithms are executed k times, and the average performance is computed.

3. Evaluating Model Performance:

- Metrics: The quality of the ARIMA model is assessed by implementing diverse evaluation techniques, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R2). These techniques are crucial to evaluating the model's usefulness since they measure the accuracy and reliability of its forecasts.

- Residual Analysis: Examining residuals (the disparities between the predicted and observed values) assumes the role of determining the model fit and its performance. The "residuals" s "could be " whitened no "e," which means" that they should have an average of zero and no autocorrelation in this case. If there are structures in the residuals, and many of them, it is proof that a model must be re-developed.

Through this modeling process, which includes model selection and parameter tuning, we shall be able to confirm that the ARIMA model is well-calibrated and offers precise forecasts for stock prices. Combining feature selection with the application of the ARIMA model is an indispensable instrument that improves the accuracy of the predictions and gives significant intelligence to the financial sector.

5. Results

Feature selection uses different advanced algorithms to determine which features are more critical and can be used to predict stock movements. The linstocks feature classification is summarized in Table 1.

Table 1: Feature Selection Results

	bGGO	bGWO	bGWO_PSO	bPSO	bWAO	bBBO	bMVO	bSBO	bGWO_GA	bFA
Average error	0.36455	0.38175	0.42105	0.41555	0.41535	0.38375	0.39225	0.42385	0.40185	0.41395
Average Select size	0.31735	0.51735	0.65065	0.51735	0.68075	0.68115	0.61385	0.68765	0.44015	0.55185
Average Fitness	0.42775	0.44395	0.45225	0.44235	0.45015	0.44805	0.47205	0.48205	0.45005	0.49425
Best Fitness	0.32955	0.36425	0.40575	0.42265	0.41425	0.43775	0.39725	0.42515	0.42785	0.41295
Worst Fitness	0.42805	0.43115	0.51575	0.49035	0.49035	0.52425	0.51525	0.50485	0.50405	0.51055
Standard deviation Fitness	0.25005	0.25475	0.27295	0.25415	0.25635	0.29905	0.30485	0.31505	0.25535	0.29095

- Average Error: The Binary Greylag Goose Optimization (bGGO) algorithm achieved the lowest average error (0.36455), indicating its superior performance in selecting features contributing to accurate predictions. The Binary Firefly Algorithm (BFA) had a higher average error (0.41395), suggesting its feature selection was less effective.

- Average Select Size: The average select size indicates the number of features each algorithm selects. bGGO selected the smallest number of features on average (0.31735), which suggests that it was able to identify the most relevant features with minimal redundancy. In contrast, bWAO and bBBO selected more features (0.68075 and 0.68115, respectively), indicating a less efficient selection process.

- Average Fitness: Fitness measures how well the selected features predict the target variable. bGGO achieved a high average fitness (0.42775), demonstrating the effectiveness of the selected features. bFA showed the highest average fitness (0.49425) but with higher variability, as indicated by its standard deviation.

- Best and Worst Fitness: The best fitness values show the optimal performance achieved by each algorithm. bGGO had the best fitness value of 0.32955, further validating its superior feature selection capability. The worst fitness values provide insights into the algorithms' consistency. bGWO_PSO had the worst fitness value (0.51575), indicating less consistent performance.

- Standard Deviation of Fitness: The standard deviation of fitness indicates the variability in the performance of the selected features across different runs. bGGO had the lowest standard deviation (0.25005), suggesting more consistent performance. Higher variability was observed in algorithms like bMVO and bSBO, indicating less reliability.

By analyzing, bGGO performed better than their counterpart models in terms of average error, select size, and fitness reliability. This means that bGGO decides which variables are the most useful in its stock market price prediction. Meanwhile, other methods, such as bee-related genetic algorithm (bGWO) and bee-inspired

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evolutionary computing (bBBO), also demonstrated advanced performance but with larger average select size and variance.

Having finished the feature selection procedure there was subsequent ARIMA model use to forecast future share prices using the most important features. Visually, in Table 2, readers may see a summary of the ARIMA model's performance metrics

Table 2: ARIMA Model Performance Metrics

Model	MSE	RMSE	MAE	R	R2	RRMSE	NSE	WI
ARIMA	0.001368	0.036984	0.031865	0.933621	0.871649	4.388123	0.65602	0.681276

- Mean Squared Error (MSE): The ARIMA model achieved a low MSE of 0.001367831, indicating that the model's predictions to the actual stock prices. This low error rate demonstrates the model's high accuracy.

- Root Mean Squared Error (RMSE): The RMSE of 0.0369842 further confirms the model's precision. The RMSE model measures the average magnitude of the errors, taking the square root of the average squared differences between predicted and observed values.

- Mean Absolute Error (MAE): The MAE of 0.031864717 indicates that, on average, the model's predictions determine actual stock prices by a small margin. This metric is less sensitive to outliers compared to MSE and RMSE.

- R-value (Correlation Coefficient): The R-value of 0.933621476 suggests a strong positive correlation between the predicted and actual stock prices, implying that the model effectively captures the underlying trend in the data.

- R-squared (R^2): The R^2 value of 0.87164906 indicates that the model can explain approximately 87.16% of the variance in stock prices. This high R^2 value signifies a good fit of the model to the data.

- Relative Root Mean Squared Error (RRMSE): The RRMSE of 4.388122911 provides a normalized measure of the RMSE relative to the range of the observed values. Although higher than the other metrics, it still indicates reasonable model performance.

- Nash-Sutcliffe Efficiency (NSE): The NSE of 0.656019687 suggests that the model performs well in predicting stock prices, with values closer to 1 indicating better predictive accuracy.

- Willmott Index (WI): The WI of 0.681276457 indicates a good agreement between the predicted and observed values. This index ranges from 0 to 1, with values closer to 1 representing better model performance.

The ARIMA model demonstrated excellent predictive ability, as indicated by the low MSE, RMSE and MAE values and high R and R^2 values. Such indicators mean that the model correctly recognizes these patterns, and there is a minimum risk for the model. These forecasts will be not only affordable but also reliable. The fact that both co-efficient correlation and R^2 value are very high indicates that the model is appropriately calibrated and explains the significant variability in the stock prices.

As shown in Figure 3, The residual plot of the histogram shows the statistics of errors produced from the ARIMA model. Response is the figure obtained by subtracting the predicted values from the observed stock prices. This histogram helps determine how well the model works, marking the residual's alignment (or lack thereof) with zero. Ideally, in best circumstances, the residuals should be normally distributed with a mean of zero, which shows the proportionality of the errors and unbias of the model. Any significant change from this pattern should convey something in which any model is inaccurate, or structures are not established or contained by the model.

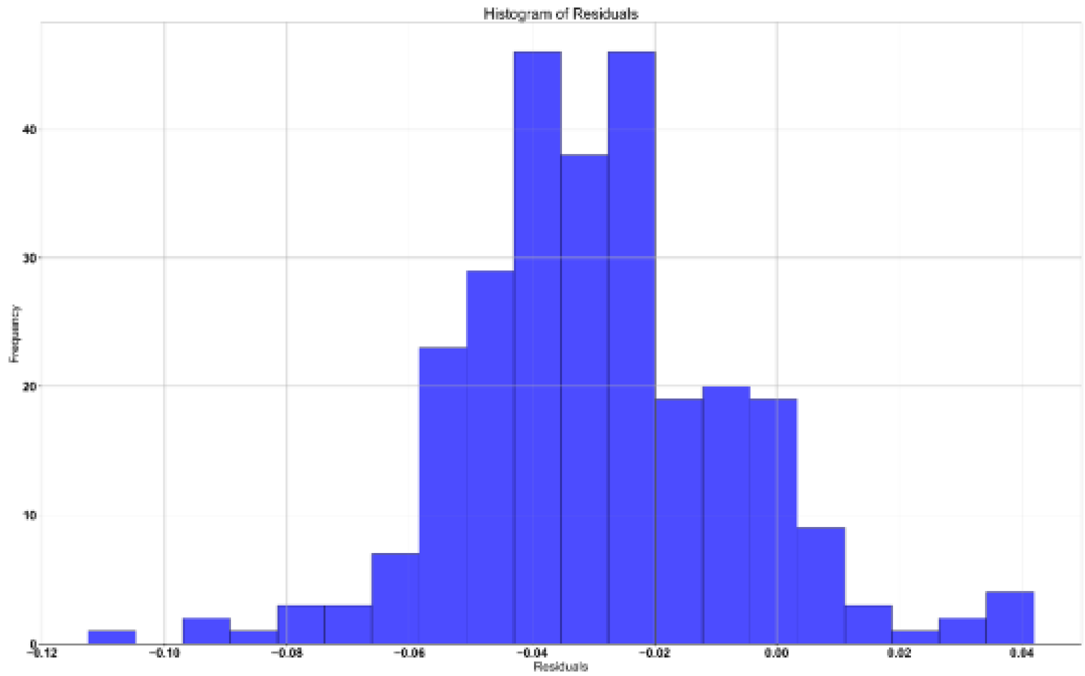

Figure 3: Histogram of Residuals

As shown in Figure 4, The actual vs. predicted plot is used to benchmark the performance of the ARIMA model. The plot compares the stock pricing against predicted values for the forecast period. Now we have the plot that helps us visually evaluate the precision of the model forecasts, and the period where the model applied is far from reality. Ensuring that the predicted data aligns with the actual data is another way of testing how well the model portrays the underlying variations and how accurate the predictions are. Such correlation qualifies the model's reliability and adequacy to be applied as a tool in stock price forecasts in the practical world.

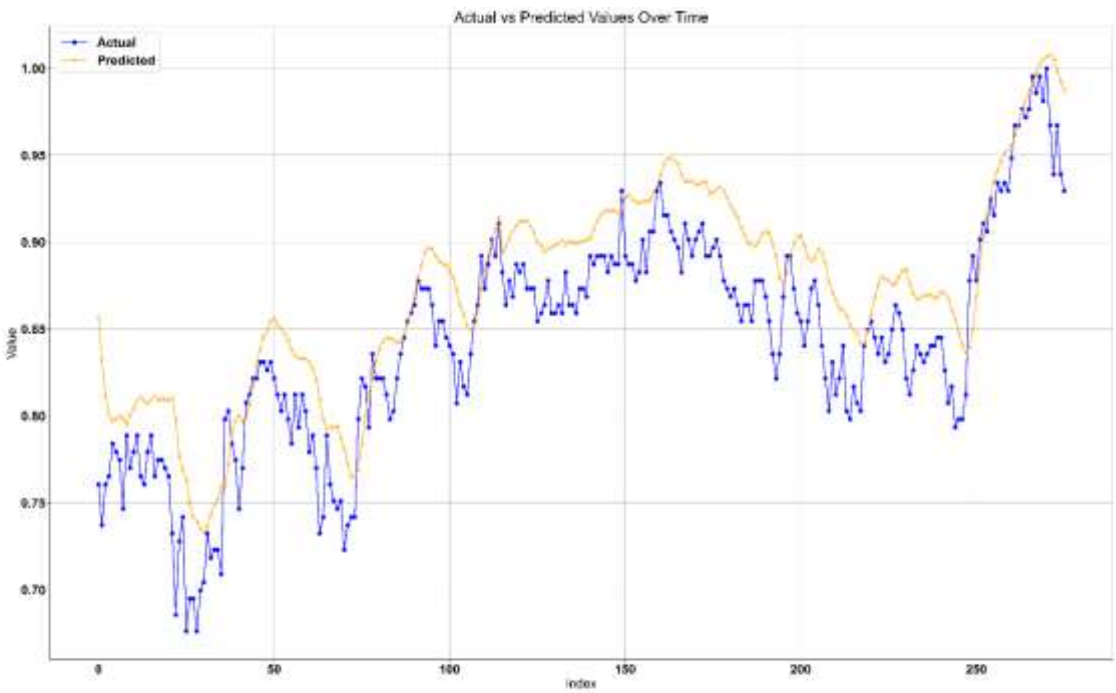

Figure 4: Actual vs Predicted Values Over Time

Combining the intelligent bGGO with the widely used ARIMA model is essential in achieving accurate results in the present study. Indeed, the above results show that choosing a suitable feature is crucial, just like relying on a valid forecasting model to attain a correct stock price prediction. Investors and analysts can use the

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outcomes as they show the great potential of bioinspired optimization algorithms and time series models in short-term financial forecasting.

6. Conclusion

This paper proposed a comprehensive assessment of the predictability of the stocks following the mixed approach of the ARIMA model and a variety of novel feature selection algorithms. The bGGO algorithm showed the maximum accuracy in the model's construction. The ARIMA model applied to bGGO-classified features had powerful bright forecasting qualities with low Mean Squared Error (MSE) and high R-squared (R^2) value, which regressed forecasts. This relates to the recognition that an increase in prediction accuracy also occurs through feature selection, which portrays this process as of utmost importance to investors. However, the research limitations include the dataset's particular range of focus, model parameters that are not dynamic, absence of external factors like indexes for macroeconomic indicators and news dissemination about the company in question. Future research may be designed following the same methodology, yet a more comprehensive range of stocks could be scrutinized; both external factors should be accounted for, and adaptive models should be developed. Models' performance must be compared to other time series forecasting models. Actions directed towards the abovementioned issues will likely improve the knowledge and skills of advanced optimization algorithms and time series models' application in making financial predictions that will undoubtedly provide more accurate and reliable predictions of stock prices.

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