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RESEARCH ARTICLE

A Feature Ensemble Framework for Stock Market Forecasting Using Technical Analysis and Aquila Optimizer

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ABSTRACT Stock market prediction relies heavily on combining different features due to the complex factors affecting stock prices and varying datasets. This study introduces a new method for feature fusion that improves predictions for traders and investors. We focus on three key types of technical analysis: momentum, trend, and volatility, and combine them using four different fusion strategies. These strategies include combinative fusion-based feature set (CFFS), adaptive feature-weighted fusion-based feature set (AWFS), feature-type fusion-based optimized feature set (FTFOFS), and feature-based optimized fusion feature set (FOFFS). The Aquila optimization technique is used to enhance these feature sets, adjusting feature weights to improve accuracy. We tested the performance of these optimized feature sets using forecasting models like decision tree (DT), naive bayes (NB), support vector regression (SVR), and multi-layer perceptron (MLP). The effectiveness of our approach is compared with other optimization methods, such as genetic algorithm (GA) and particle swarm optimization (PSO), over a 10-year period (2012-2022) with data from State Bank of India (SBI) and ICICI Bank Ltd (ICBK). The models predict short-term stock movements (3, 7, and 15 days ahead), and we evaluate their performance using various metrics like mean absolute error (MAE) and correlation coefficient (R^2). Our results show that the FOFFS-Aquila method significantly improves the MLP's predictions compared to other models. We also provide insights into the efficiency of the MLP based on FOFFS-Aquila, including its statistical validity and execution time.

INDEX TERMS Aquila optimizer, feature fusion, momentum indicators, stock market analysis, trend indicators, volatility indicators.

I. INTRODUCTION

Stock market analysis enables the investors and traders to gain an edge in this financial market. The study of this market through past and current data helps with making informed decisions on buying or selling the assets. The stock market analysis is basically comprising of fundamental analysis and technical analysis [1]. The fundamental analysis is based on company's financial statements, balance sheets, income statement and cash flow statements to ascertain the revenue, expenses and the profits made by the company whereas; the technical analysis involves study of past and present price action to forecast the future price movements, volume, demand and supply of the stocks in the market [2], [3].There is a huge need of technical research in the study of past stock prices to forecast the future price and trends which shows the magnitude and direction of the share prices. This portrays a meaningful insight on the sharp rise or falls in the price of the share and shows the stocks which are in high demand and traded in huge volumes. The types of stock market forecasting activities such as forecasting of stock price movement and the values are commonly

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known as classification and regression problems respectively [4], [5].

Financial investors and traders are increasingly using computer-assisted algorithmic trading strategies, leveraging soft computing, machine learning, and deep learning tools to enhance their stock trading processes due to their excellent performance in nonlinear regression [2], [3], [4]. However, when modeling financial time series with soft computing, machine learning, or deep learning strategies, data preprocessing or feature engineering presents a significant challenge [5], [6]. Effective feature engineering, which involves manipulating data at the feature level, has proven crucial for improving model training, accuracy, and predictive ability. Among feature engineering strategies, feature augmentation and feature fusion are prominent methods. Feature augmentation involves increasing the number of features by adding or modifying existing ones to create synthetic features. In contrast, feature fusion focuses on selecting an optimal subset of features from combined feature sets through ranking techniques [7], [8]. This approach aims to enhance the predictive accuracy of forecasting models by integrating and refining features rather than just expanding them.

Feature fusion offers several advantages, including reducing dimensionality and computational complexity by combining relevant features, which can lead to more efficient and effective models. It also improves the robustness and generalizability of predictive models by integrating diverse feature sets, capturing a broader range of information. Additionally, feature fusion can address issues of data redundancy and noise by selecting the most informative features, thus enhancing the overall performance of forecasting models [9], [10]. The scope of feature fusion extends to various applications, including stock market prediction, where it can significantly enhance the accuracy of predictions by integrating different types of technical indicators and market data. Its versatility makes it applicable across various domains where feature-level integration can lead to better model performance and insights.

Additionally, in the financial markets like, stock trading, the traders and investors generally use various technical quantitative tools such as momentum, trend and volatility indicators to forecast the movements, sentiments and psychology of the markets through graph patterns, various signals and oscillator [11], [12]. Traders most often choose the indicators that work best for their trading analysis, and they also combine the technical indicators with more technical analysis tools to provide a better quantitative nature to the automated decision-making systems. The literature suggests that the best use of technical tools in tandem with other technical indicators improves reliability and productivity [11], [12], [13], [14], [15], [16]. The advantages of fusion approaches have also been explored in this financial market to develop more accurate and robust forecasting models in comparison to single forecasting models. The design of optimized feature fusion framework with the help of those technical tools and indicators is the key idea behind this study to design a stock trading framework. The primary objectives that underpin the creation of this feature fusion framework for stock market prediction are as follows:

(a) To delve into the realm of ensemble learning at the feature level, amalgamating predictions from various technical tools and indicators. This approach aims to achieve superior predictive accuracy compared to using individual predictors in isolation.
(b) To leverage a diverse array of independent models capable of handling both linear and non-linear features. This diversity enhances the framework's adaptability to different types of market dynamics.
(c) To harness the power of technical indicators in constructing ensemble sets of features. These sets, when combined, have the potential to significantly enhance prediction accuracy through this feature-level ensemble approach.

The manuscript's contributions and novelty can be summarized as follows:

a) This work presents a feature-level fusion approach that combines a wide range of technical analysis tools, including momentum, trend, and volatility indicators such as momentum, trend, and volatility indicators [11], [12], [13], [14], [15], [16], including fast stock oscillator (FSO), slow stock oscillator (SSO), rate of change (RoC), community channel index (CCI), relative strength index (RSI), simple moving average (SMA), exponential moving average (EMA), displaced moving average (DMA), T3 moving average (T3MA), volatility ratio (VR), average true range (ATR), Bollinger bands (BBs), Keltner channel (KC), etc. aiming to enhance the informativeness and resilience of feature sets for stock market prediction by encompassing three categories of technical analysis tools.
b) The paper introduces four diverse fusion strategies: combinative fusion based feature set (CFFS), adaptive feature weighed fusion based feature set (AWFS), feature type fusion based optimized feature set (FTFOFS), and feature-based optimized fusion feature set (FOFFS), which exploit various approaches to combine features and indicators, synergistically boosting predictive accuracy in the ensemble model.
c) The paper employs the Aquila optimizer [17], [18], [19], [20], [21], a nature-inspired optimization technique, to optimize weights in FTFOFS and FOFFS, mimicking Aquila bird's hunting behavior to enhance feature selection and thereby improving ensemble performance.
d) The effectiveness and robustness of the proposed feature-level ensemble methods are thoroughly demonstrated through rigorous evaluation using four forecasting models and a range of evaluation metrics including mean absolute error (MAE), mean relative

error (MRE), Nash-Sutcliffe coefficient (NSE), scatter index (SI), correlation coefficient (R^2), and Theil's U [22], [23].

e) The practical applicability of the proposed methods is demonstrated through their application to actual financial data from State Bank of India (SBI) [24] and ICICI Bank Ltd (ICBK) [25] spanning a decade, with short-term predictions for 3 days, 7 days, and 15 days ahead, highlighting the real-world effectiveness of the feature-level fusion techniques in stock market prediction.

f) The research notably advances feature engineering in financial time series analysis by emphasizing its pivotal role in data pre-processing and feature manipulation to substantially elevate the precision and predictive capacity of forecasting models.

g) The paper tackles the obstacles encountered by financial traders and investors in implementing algorithmic trading tactics by amalgamating soft computing and machine learning approaches, with the introduced feature-level ensemble methods furnishing a blueprint for automating stock trading procedures.

h) The innovative ensemble technique strives to enhance predictive accuracy beyond individual predictors by harnessing a diverse range of technical indicators and fusion strategies.

i) The study's results hold potential for elevating forecasting accuracy in the financial realm, thereby enriching decision-making for traders and investors through informed insights.

In summary, the manuscript introduces a novel feature ensemble framework that harnesses technical analysis tools and Aquila optimizer for stock market prediction. It combines diverse indicators, innovative fusion strategies, and nature-inspired optimization to improve predictive accuracy and demonstrate practical applicability in real-world financial data. The research offers valuable insights into feature engineering and its impact on financial time series forecasting, making a notable contribution to the field.

The remaining sections of this paper are organized as follows; in Section II we review literatures of feature level fusion or ensemble strategies and the use of technical indicators in the financial market forecasting. The methodologies adopted for this study along with the broad scope of this work are depicted in Section III. The experimentation and result analysis along with the key observations, expected contributions and impact of the study are also discussed in Section IV and finally, the Section V presents the conclusion and future scope of this work.

II. RELATED WORKS

Artificial intelligence and machine learning are crucial for stock market prediction because they analyze large datasets and detect complex patterns that traditional methods might miss. Techniques like decision trees (DT), naive Bayes (NB), support vector regression (SVR), and multi-layer perceptron (MLP) each offer unique strengths for forecasting. DTs are interpretable and visualize decision-making processes, NB uses probability to manage independence assumptions, SVR handles non-linear relationships, and MLPs model complex patterns through multiple layers [1], [2], [3], [4], [5], [6]. Feature engineering [7], [8], [9], [10], especially feature fusion, significantly enhances model performance by integrating various trend indicators like moving averages, relative strength index (RSI), and moving average convergence divergence (MACD). This approach combines multiple data perspectives, improving the model's ability to capture intricate market trends and boost predictive accuracy [11], [12], [13], [14], [15], [16]. This section discusses various feature fusion strategies proposed utilizing various machine learning techniques.

Zhang et al. [26] introduced the collaborative attention transformer fusion model (CoATSMP) for stock movement prediction, which integrates textual and price data through sophisticated fusion techniques, achieving improved accuracy and trading profits. Nejad et al. [27] addressed generative associative networks (GANs') training instability with a novel framework combining DRAGAN and feature matching, which enhances stability and accuracy, outperforming long short-term memory (LSTM) and other GAN variants. Albahliet al. [28] used a deep learning approach with an auto encoder and DenseNet-41, processing ten years of Yahoo Finance data to provide reliable buy, sell, or hold signals. Bareket and Parv [29] focused on a 70-day forecasting horizon using artificial neural network (ANN) and support vector machine (SVM) models with innovative indicators and techniques, enhancing predictability for major indices. Sun et al. [30] proposed a hybrid CEEMDAN-LSTM-Light GBM model optimized with Simulated Annealing, which improved accuracy and fitting compared to single LSTM and other hybrids. Aksehir et al. [31] developed the ICE2DE-MDL model, combining entropy and secondary decomposition with various machine learning techniques to forecast stock prices with notable accuracy and low error metrics. Yan [32] integrated AdaBoost-based feature selection with LSTM to predict stock index futures, showing superior performance over other models. Vanguri et al. [33] introduced a competitive swarm feedback algorithm-based deep LSTM classifier, demonstrating enhanced prediction accuracy through advanced feature fusion. Alotaibi [34] proposed a three-phase model involving feature extraction, selection with RDAWA, and ensemble prediction, showcasing its effectiveness against conventional methods. Chauhan et al. [35] utilized LSTM and gated recurrent units (GRU) models with particle swarm optimization (PSO) for Nifty 50 index prediction, achieving high accuracy and precision through effective ensemble and optimization techniques.

The studies, such as [26] and [31], focused on enhancing model performance through advanced architectures and optimization techniques but often overlook the development of innovative feature engineering methods. While [28] and [33] utilized a variety of features and fusion techniques, they frequently rely on static features or fixed technical indicators. Research by [34] employs hybrid models for feature selection but may not fully address the complexities of adapting features to evolving market conditions. Additionally, studies like [30] and [35] show the benefits of ensemble and hybrid models but do not thoroughly evaluate or compare different feature fusion techniques. Many approaches focus on either temporal or non-temporal features without effectively integrating both. There is an opportunity to advance feature engineering by incorporating dynamic and domain-specific features, combining diverse data types such as textual data and sentiment analysis in real-time, and developing adaptive feature selection methods that can evolve with market conditions. Further research is needed to evaluate how various feature fusion strategies impact model performance and to develop scalable methods that can handle large volumes of real-time data efficiently.

III. METHODOLOGIES AND OVERALL ARCHITECTURE DESCRIPTION

This proposed feature fusion-based ensemble architecture for stock market forecasting goes through five stages of experimentation. The SBI [24] and ICBK [25] stock data has been collected for last 10 years from 2012 to 2022 in the first phase, and thenin the second phase, the momentum, trend and volatility indicators as mentioned in **Section I** are computed based on the data collected during first phase to obtain three categories of feature sets. The third phase depicts four types of proposed ensemble-based strategies to obtain feature sets such as CFFS, AWFS, FTFOFS and FOFFS (as detailed below) which are evaluated based on four predictive networks such as DT, NB, SVRand MLP [1], [2], [3], [4], [5], [6] in the fourth phase of experimentation and finally, the performance of the proposed ensemble strategies are evaluated and validated.The schematic representation of the proposed feature fusion strategies is depicted in **Figure 1**.

The proposed ensemble-based feature fusion strategies are borrowed from the information fusion approach of machine learning to improve the performance of the predictors by fusing the new features constructed based on the three indicators as mentioned above and combining them through various proposed fusion approaches. Here, the CFFS is one of the simplest forms of feature fusion proposed by combining all the computed features based on momentum, trend and volatility indicators named as *combinative fusion* (**Figure 2**) represented as $(Feature\ set_{momentum}, Feature\ set_{trend}, Feature\ set_{volatility})$. The second category of feature set fusion is based upon adaptively assigning weights (w_1, w_2 and w_3) to the features and forming a combined feature set named as AWFS (**Figure 3**) presented as $(w_1 \times Feature\ set_{momentum}, w_2 \times Feature\ set_{trend}, w_3 \times Featureset_{volatility})$. The third and fourth categories of feature set fusion strategies such as; FTFOFS and FOFFS are focused on generation of optimized feature sets based on Aquila optimizer [17], [18], [19], [20], [21] (pseudo code is available in **Section III-B**). The FTFOFS (**Figure 4**) basically forms combined weighted feature set and then tries to optimize the assigned weights to the features and returns optimized weights for each feature type giving rise to generation of feature type fusion-based feature sets and represented as, $\left([w_1]_{1\times1}\ Featureset_{momentum}\right)$, $\left([w_2]_{1\times1}\ Featureset_{trend}\right)$, $\left([w_3]_{1\times1}\ Feature\ set_{volatility}\right)$.

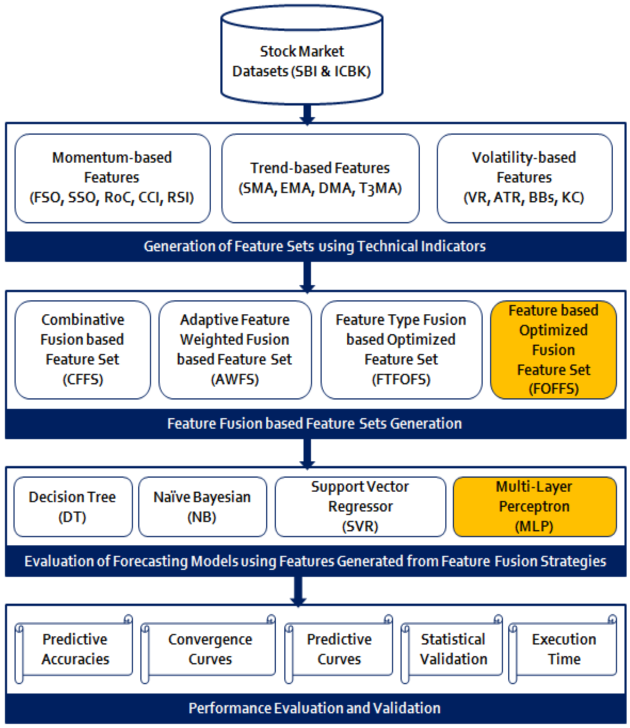


FIGURE 1. Overview of the proposed feature-level fusion strategies.

In contrast to FTFOFS, the FOFFS (**Figure 5**) forms combined weighted feature sets and returns optimized weights based on each feature set to form a fusion-based feature set and mentioned as, $\left([w_1]_{1\times5}\ Featureset_{momentum}\right)$, $\left([w_2]_{1\times4}\ Featureset_{trend}\right)$,$\left([w_3]_{1\times4}\ Featureset_{volatility}\right)$, where $w_1 : [w_{11}w_{12}w_{13}w_{14}w_{15}]_{1\times5}$, $w_2 : [w_{21}w_{22}w_{23}w_{24}]_{1\times4}$, and $w_3 : [w_{31}w_{32}w_{33}w_{34}]_{1\times4}$.

The FTFOFS and FOFFS mainly focus on optimized decision variables (weights of the predictive model) utilizing the Aquila optimization algorithm namely FTFOFS-Aquila and FOFFS-Aquila. In FOFFS-Aquila, optimal weights are adaptively chosen to create a combined weighted feature set, incorporating various technical indicators such as momentum, trend, and volatility. Through this process, FOFFS effectively combines weighted feature sets and returns optimized weights for each set, forming a fusion-based feature set. The FOFFS model offers distinct advantages. Its dynamic weight adaptation permits nuanced adjustments to feature contributions. By considering features from multiple categories of technical indicators and selecting the most influential ones, this approach captures a diverse range of informative features,

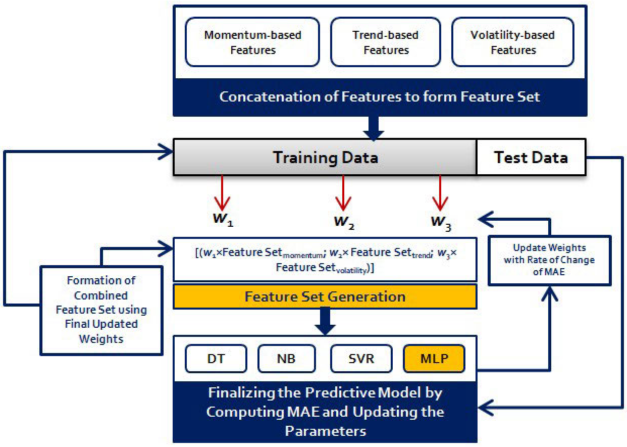


FIGURE 2. **The CFF feature-level fusion strategy.**

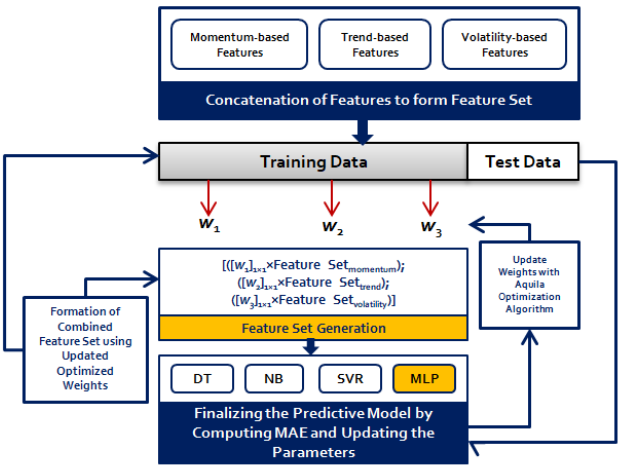


FIGURE 3. **The AWFS feature-level fusion strategy.**

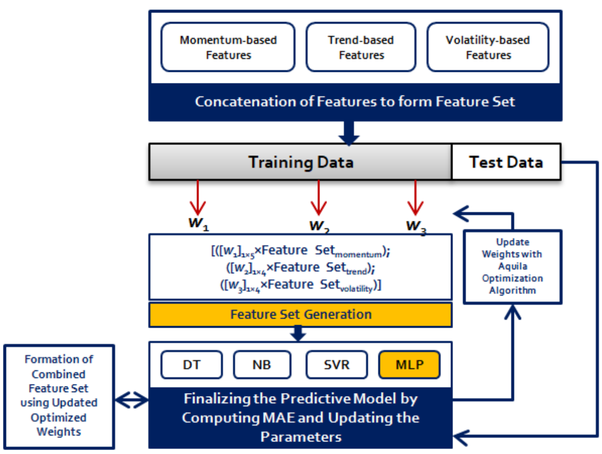


FIGURE 4. **The FTFOFS-Aquila feature-level fusion strategy.**

potentially leading to improved predictive performance. The data-driven selection process and emphasis on optimizing feature sets align seamlessly with the overarching goal of enhancing prediction accuracy. Consequently, this model's superiority is evident due to its adaptiveness, comprehensive technical indicator utilization, and data-driven feature selection, collectively contributing to superior prediction outcomes.

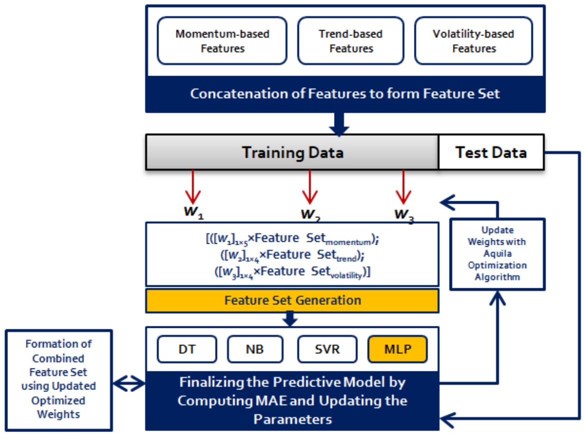


FIGURE 5. **The FOFFS-Aquila feature-level fusion strategy.**

A. PROPOSED OPTIMIZED FEATURE LEVEL FUSIONSTRATEGIES BASED ON AQUILA OPTIMIZATION

The Aquila optimization is a nature-inspired optimization algorithm proposed by Laith Abualigah et al. [17] being inspired by the hunting behaviour of a dark brown colored eagle type bird generally seen in the northern hemisphere. They basically hunt the grounded preys such as; rabbits, hares, squirrels, snakes etc. based upon their talons and speed. The hunting behavior of these birds is based on four natural methodologies are discussed below [17], [18], [19], [20], [21] which are simulated to obtain the optimized values of weights $\boldsymbol{w_1}$, $\boldsymbol{w_2}$ ***and*** $\boldsymbol{w_3}$ which are further used for designing the optimized version of FTFOFS and FOFFS feature fusion strategies.

(a) **High soar and vertical stoop** (hovering in the air at a great height), commonly termed as called as *expanded exploration* and mathematically it is represented in **Equation (1)**.

$$NS_1(CI+1) = NS_{best}(CI) \times \left(1 - \frac{CI}{MI}\right) + \left(NS_{LMV}(CI) - NS_{best}(CI) \times rand\right) \quad (1)$$

where, $NS_{LCV}(CI) = \frac{1}{PS}\sum_{i=1}^{PS} NS_i(CI), \forall j = 1, 2, \ldots, VS$;

NS_1 is the first method representing new solution, CI is the current iteration; MI is the max iteration; NS_{best} is the best solution; $\left(1 - \frac{CI}{MI}\right)$ is used to control the exploration; NS_{LMV} is the location mean value; *rand* is the random value; and *VS* is the variable size.

(b) **Contour flight and short glide attack** (after recognizing the prey area, technique of flying at a constant altitude and to make a circle above the prey), commonly known as *narrowed exploration* and can be represented using **Equation (2)**.

$$NS_2\,(CI+1)=NS_{best}\,(CI)\times Levy(D)+(NS_{RSR}\,(CI) - (s_b - s_a)\times rand) \tag{2}$$

where, $Levy\,(D) = c \times \frac{r_1\times\sigma}{|r_2|^{\beta}}$; $\sigma = \left(\frac{\Gamma(1+\beta)\times sine(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2})\times\beta\times 2^{(\frac{\beta-1}{2})}}\right)$ $c = 0.01$; r_1 and r_2 are random numbers between 0 and 1; $\beta = 1.5$; s_b and s_a represent the spiral shape of the search area where prey isdetected and computed as; $s_b = z \times \cos(\theta)$, $s_a = z \times \sin(\theta)$; z can be computed as $z = z_1 + SV \times SS$; $\theta = -\varphi \times SS + \theta_1$; $\theta_1 = \frac{3\times\pi}{2}$; z_1 represents the number of search cycles between $[1 to 20]$; SV is small fixed value (0.00565); SS is the search space representing the dimension and φ is another small fixed value with 0.005; NS_2 is the second method of representing the new solution; and $NS_{RSR}\,(CI)$ is the random solution range between 1 to n.

(c) **Low flight with slow decent attack** (recognizing the prey and exploring the area with slow landing to attack the prey), known as *expanded exploitation* and is represented using **Equation (3)**.

$$NS_3\,(CI+1) = (NS_{best}\,(CI) - NS_{LMV}\,(CI)) \times \rho - rand + ((U_{bound} - L_{bound}) \times rand + L_{bound}) \times \tau \tag{3}$$

where, NS_3 is the third method of representing the new solution; $NS_{best}\,(CI)$ is the approximate location of the prey until the i^{th} iteration i.e. until the best solution is obtained; $NS_{LMV}\,(CI)$ is the location mean value as given in **Equation (1)** at i^{th} iteration; *rand* is a random value between 0 and 1; the exploitation adjustment parameters ρ and τ (fixed to a small value 0.1);L_{bound} and U_{bound} shows the lower and upper bund of the given problem respectively.

(d) **Walking and Grab the Prey** (walking on the land, getting closer to the prey and attack), known a *narrowed exploitation* and is represented in **Equation (4).**

$$NS_3\,(CI+1) = Q_f \times NS_{best}\,(CI) - (Motion_1 \times NS\,(CI) \times rand) - Motion_2 \times Levy\,(D) + rand \times Motion_1$$
$$Q_f\,(CI) = CI^{\frac{2\times rand-1}{(1-MI)^2}};$$
$$Motion_1 = 2\times rand - 1;\ and$$
$$Motion_2 = 2\times(1-\frac{CI}{MI}) \tag{4}$$

where, NS_3 is the fourth method of representing the next iteration of CI;the quality function Q_f is basically used to equilibrium the search strategies;the various motions of prey during elope is represented as $Motion_1$ and $Motion_2$, where $Motion_2$ represents the decreasing values from 0 *to* 2 representing the flight slope of the Aquila that is used to follow the prey during elope from the first location (1) to last location (CI) i.e. the behaviour of Aquila; and NS (CI) is the current solution at the ith iteration; rand value ranges between $0 to 1$; Levy(D) is the levy flight distribution function computed using **Equation (2)**.

The flowchart (**Figure 6**) and working principle of this Aquila optimizer (for 50 iterations) is be given below as pseudo-code which has been used in the proposed FTFOFS and FOFFS to obtain the optimized version of weights w_1, w_2 *and* w_3 is detailed below;

Pseudocode 1 Working Principle of Aquila Optimizer

Step 1. For fifty iterations initialize w_1, w_2 *and* w_3;
Step 2. For $i = 1 : nPS$ (nPS is the n number of population size)
  Calculate MAE using randomly initialized weighted features;
Step 3. For $j = 1 : i$ iterations
    If $j \leq \frac{2}{3}MI$ (MI is the maximum iteration)
      If *rand* ≤ 0.5
      Apply high soar with vertical stoop (*expanded exploration*) and update w_1, w_2 *and* w_3 using **Equation (1);**
      Else
      Apply contour flight with short glide attack (*narrowed exploration*) and update w_1, w_2 *and* w_3 using **Equation (2);**
      End if
    Else
Step 4. If *rand* ≤ 0.5
  Apply low flight with slow decent attack (*expanded exploitation*) and update w_1, w_2 *and* w_3 using **Equation (3);**
  Else
  Apply walking and grab the prey(*Narrowed Exploitation*) and update w_1, w_2 *and* w_3 using **Equation (4);**
  End if
Step 5. Calculate fitness using the updated weights (w_1, w_2 *and* w_3) and keep the best
  If $fitness\,(CI+1) < fitness\,(CI)$
  Return best weighted features.

B. THE WORKING PRINCIPLES OF CFFS, AWFS, FTFOFS AND FOFFS

The working principles of four proposed strategies are shown below for easy reference to the readers as Pseudocode 2, Pseudocode 3 and Pseudocode 4 and Pseudocode 5 respectively.

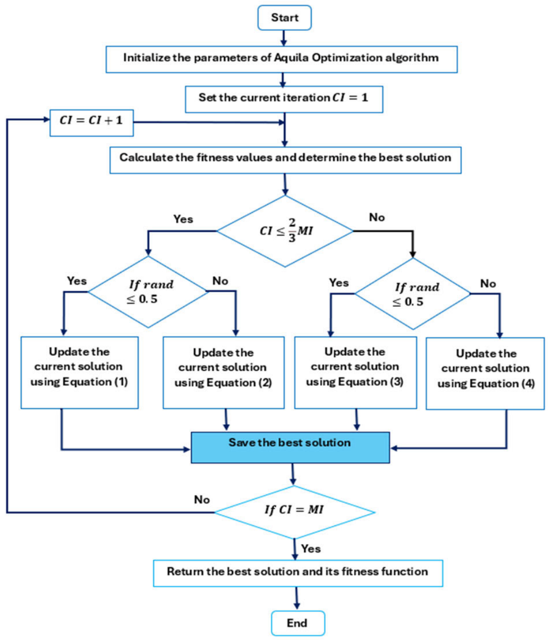


FIGURE 6. Flowchart of Aquila optimization algorithm.

Pseudocode 2 Working Principle of CFFS

Step 1. Input original historical stock data;
Step 2. Compute momentum based features such as; FSO, SSO, RoC, CCI and RSI, then augment with original stock data (five more features);
Step 3. Compute trend based features such as; SMA, EMA, DMA and T3MA, then augment with original stock data (four more features);
Step 4. Compute volatility based features such as; VR, ATR, BBs and KC, then augment with original stock data (four more features);
Step 5. Split the datasets into training and testing sets in 70:30 ratio;
Step 6. Formation of combined feature set of training data
Iterate over number of iterations
Formation of combined weighted feature set such as;

$$Fetaureset_{momentum},$$
$$Fetaureset_{trend} \text{ and}$$
$$Fetaureset_{volatility};$$

Generated feature set is set as input to the predictors;
Compute MAE(based on MLP);
Update weights;
Step 8. Similarly, formation of feature sets for test data;
Step 9. Record performance of the predictive models;

C. TECHNICAL INDICATORS

The design of datasets in this study utilizes a variety of technical analysis indicators, including the FSO, SSO, RoC, CCI, RSI, SMA, EMA, DMA, T3MA, VR, ATR, BBs and KC [11], [12], [13], [14], [15], [16]. These indicators are organized into three categories—momentum, trend, and volatility—and used both individually and in augmented form to facilitate feature-level fusion. Integrating these diverse range of these indicators significantly enhances stock market prediction models. Momentum indicators like FSO and RoC assess the strength and speed of price movements, aiding in the identification of entry and exit points. Trend indicators, such as SMA and EMA, reveal market direction and

Pseudocode 3 Working Principle of AWFS

Step 1 to Step 5 is same as CFFS
Step 6. Initialization of random weights;
Step 7. Formation of combined weighted feature set of training data
Iterate over number of iterations;
Formation of combined weighted feature set such as;

$$w_1 \times Fetaureset_{momentum},$$
$$w_2 \times Fetaureset_{trend} \text{ and}$$
$$w_3 \times Fetaureset_{volatility};$$

Generated feature set is set as input to the predictors;
Compute MAE (based on MLP);
Update the weights;
Step 8. Similarly, formation of feature sets for test data;
Step 9. Record performance of the predictive models;

Pseudocode 4 Working Principle of FTFOFS

Step 1 to Step 6 is same as AWFS
Step 7. Formation of combined weighted feature set for training data with three weights (w_1, w_2 *and* w_3) such as;

$$w_1 \times Fetaureset_{momentum}, w_2 \times$$
$$Fetaureset_{trend} \text{ and } w_3 \times$$
$$Fetaureset_{volatility};$$

Initialization of optimization parameters;
Iterate over number of iterations;
Decision variables (w_1, w_2 *and* w_3) are passed to the predictors;*(Obtained through Aquila optimization algorithm)*
Returned Calculate MAE (based on MLP) is considered as cost of the predictive models;
Returns three optimized weights for each feature type (i.e. momentum based, trend based and volatility based);
Step 8. Formation of combined feature set for test data such as;

$$\begin{bmatrix} \left([w_1]_{1\times1}\, Fetaureset_{momentum}\right), \\ \left([w_2]_{1\times1}\, Fetaureset_{trend}\right), \\ \left([w_3]_{1\times1}\, Fetaureset_{volatility}\right) \end{bmatrix}$$

Step 9. Record performance of the predictive models;

Pseudocode 5 Working Principle of FOFFS

Step 1 to Step 6 is same as AWFS and FTFOFS

Step 7. Formation of combined weighted feature set for training data with thirteen weights (w_1, w_2 *and* w_3) such as;

$$\begin{bmatrix} \left([w_1]_{1\times5}\, Fetaureset_{momentum}\right), \\ \left([w_2]_{1\times4}\, Fetaureset_{trend}\right), \\ \left([w_3]_{1\times4}\, Fetaureset_{volatility}\right) \end{bmatrix}$$

$$w_1 : [w_{11}w_{12}w_{13}w_{14}w_{15}]_{1\times5}$$

$$w_2 : [w_{21}w_{22}w_{23}w_{24}]_{1\times4}$$

$$w_3 : [w_{31}w_{32}w_{33}w_{34}]_{1\times4}$$

Initialization of optimization parameters;
Iterate over number of iterations; Decision variables ($w_{11} \ldots w_{15}, w_{21} \ldots w_{25}, w_{31} \ldots w_{35}$) are passed to the predictors;*(Obtained through Aquila optimization algorithm)*
Returned Calculate MAE (based on MLP) is considered as cost of the predictive models;
Returns thirteen optimized weights based on each feature;

Step 8. Formation of combined feature set for test data;

Step 9. Record performance of the predictive models;

trend persistence, crucial for recognizing long-term patterns. Volatility indicators, including BBs and ATR, measure price fluctuations and market stability, providing insights into market risk. This multi-faceted approach enriches the feature set, capturing a broader spectrum of market behaviors, improving predictive accuracy, and enhancing the model's resilience to varying market conditions for more robust and actionable insights.

IV. EXPERIMENTATION, RESULTS AND DISCUSSIONS

The empirical aspects of the research are comprehensively covered within this section, encompassing details related to the system configuration, utilized packages, stock datasets, technical analysis tools deployed for feature augmentation and fusion, experimentation parameters, and an array of performance evaluation metrics. This section also outlines the experiment procedures, result analysis, model evaluation, and validation processes. The experimental evaluations are conducted within the Google Colab environment, employing a Windows 7 platform equipped with a 64-bit architecture and 4GB of RAM in an Intel i3 configuration. Google Colab provides an effortlessly configurable platform with access to GPUs, enabling seamless Python coding and execution directly in the researcher's web browser. Additionally, it offers facile sharing capabilities and harnesses the capabilities of well-regarded libraries for data analysis and visualization, including Keras, Numpy, Pandas, Sklearn, Datetime, and Stats models. For the experimental study, two prominent financial institutions are chosen as subjects. In this study we have used the SBI and ICBK stocks for experimentation by taking the historical data for the period of 3rd September 2012 to 3rd September 2022 for 10 years with 2496 number of samples and four financial attributes or features such as open price, low price, high price and close price with a 70:30 ratio of training and testing samples. Central to this study, the utilization of three distinct categories of technical quantitative tools—momentum, trend, and volatility—are underscored for feature expansion. The resultant expanded features are then harnessed for both feature augmentation and feature fusion within the ensemble framework.

A. PARAMETERS SETTING

The parameters setting for this experimentation are evaluated under different values and the best values are chosen for experimentation of genetic algorithm (GA) [36], [37], particle swarm optimization (PSO) [35] [38], and Aquila [17], [18], [19], [20], [21] is summarized in **Table 1**.

TABLE 1. Various optimization techniques and prediction strategies and their associated values.

Techniques	Parameters and their associated values
GA	Number of decision variables=3; Maximum number of iterations =50 Population size=10; Selection method=Roulette wheel
PSO	Number of decision variables=3; Maximum number of iterations =50 Number of particles=10; Inertia weight=1 Inertia weight damping ratio =0.99; Personal learning coefficient =1.5 Global learning coefficient=2.0
Aquila	Number of decision variables=3; Maximum number of iterations =50 Number of particles=10; Beta=1.5; U=0.00565; Alpha=0.1; Delta=0.1

B. EXPLANATORY ANALYSIS AND RESULT DISCUSSION

For setting of the experimentation, we choose both technical indicators and ensemble approach to serve as baseline of this experimentation. As discussed in **Section III**, the proposed CFFS, AWFS, FTFOFS-GA, FTFOFS-PSO, FTFOFS-Aquila, FOFFS-GA, FOFFS-PSO and FOFFS-Aquila feature level fusion strategies are evaluated utilizing four standard predictive models such as DT, NB, SVR and MLP for all three short term predictive days such as 3 days, 7 days and 15 days ahead of prediction. The datasets presented in **Table 2** and **Table 3** delves into a comprehensive analysis of predictive accuracies using MAE for the SBI and ICBK datasets respectively. The study intricately explores various predictors and prediction horizons, concurrently calculating percentage improvements achieved by the proposed feature fusion strategies compared to the baseline (CFFS). Within **Table 2**, it becomes evident that the FTFOFS-Aquila consistently

TABLE 2. Predictive accuracies observed by MAE for SBI dataset.

Predictors	Prediction Horizon	Proposed Feature Fusion Strategies							
		CFFS	AWFS	FTFOFS-GA	FTFOFS-PSO	FTFOFS-Aquila	FOFFS-GA	FOFFS-PSO	FOFFS-Aquila
DT	3 Days	0.069	0.059	0.0589	0.0588	0.0576	0.0688	0.0588	**0.0578**
NB		0.0689	0.0589	0.0579	0.0578	0.0572	0.0602	0.0562	**0.0552**
SVR		0.065	0.045	0.0448	0.0442	0.0439	0.0651	0.0451	**0.0431**
MLP		0.0601	0.0401	0.0389	0.0288	0.0388	0.0521	0.0321	**0.0221**
DT	7 Days	0.2110	0.1841	0.2284	**0.1770**	0.2432	0.2553	0.1784	0.1837
NB		**0.1803**	0.1815	0.2490	0.2224	0.1635	0.2565	0.2081	0.2008
SVR		0.2305	0.2272	0.2026	0.1881	0.1807	0.2278	**0.1578**	0.1963
MLP		0.2409	0.2263	0.1937	0.2050	0.1711	0.1802	0.1657	**0.1300**
DT	15 Days	0.4703	0.4130	0.4247	0.4470	0.4479	0.4416	0.3268	**0.2086**
NB		0.4792	0.4111	0.4271	0.4669	0.4145	0.4406	0.3079	**0.1570**
SVR		0.4410	0.3860	0.3929	0.4440	0.4471	0.4267	0.2556	**0.2097**
MLP		0.4545	0.4489	0.4471	0.4448	0.4578	0.4321	0.2383	**0.1548**

TABLE 3. Predictive accuracies observed by MAE for ICBK dataset.

Predictors	Prediction Horizon	Proposed Feature Fusion Strategies							
		CFFS	AWFS	FTFOFS-GA	FTFOFS-PSO	FTFOFS-Aquila	FOFFS-GA	FOFFS-PSO	FOFFS-Aquila
DT	3 Days	0.2110	0.1841	0.2284	**0.1770**	0.2432	0.2553	0.1784	0.1837
NB		0.1803	0.1815	0.2490	0.2224	**0.1635**	0.2565	0.2081	0.2008
SVR		0.2305	0.2272	0.2026	0.1881	0.1807	0.2278	**0.1578**	0.1963
MLP		0.2409	0.2263	0.1937	0.1711	0.2050	0.1802	**0.1300**	0.1757
DT	7 Days	0.4064	0.4536	0.4536	0.4188	0.4213	0.4497	0.2919	**0.2401**
NB		0.4576	0.4267	0.4267	0.4637	0.4813	0.4765	0.3523	**0.2158**
SVR		0.4033	0.4279	0.3932	0.4220	0.3924	0.4322	0.2913	**0.2177**
MLP		0.4466	0.3834	0.3750	0.4021	0.4520	0.4043	0.2972	**0.2154**
DT	15 Days	0.4767	0.5941	0.5443	0.5749	0.5869	0.5061	0.3434	**0.1653**
NB		0.5723	0.5607	0.5979	0.6066	0.5009	0.4678	0.2807	**0.2140**
SVR		0.6015	0.4512	0.5209	0.5823	0.5218	0.5851	0.3086	**0.1833**
MLP		0.5479	0.5636	0.4868	0.5605	0.4989	0.4817	0.2658	**0.1114**

achieves enhancements of about 1% to 2% across multiple predictors during a 3-day prediction interval, affirming its stability. For a 7-day forecast, FTFOFS-Aquila impressively showcases improvements ranging from 13% to 19%, underscoring its efficacy. Remarkably, both FTFOFS-Aquila and FOFFS-PSO strategies demonstrate substantial enhancements of around 25% for a 15-day prediction period, highlighting their robustness for longer-term predictions. **Table3**'s data provides a thorough analysis of predictive accuracies assessed using MAE for the ICBK dataset. Notably, within the 3-day prediction window, both FOFFS-Aquila and FOFFS-PSO consistently exhibit improvements of approximately 2% across diverse predictors, showcasing their effectiveness. For the 7-day prediction horizon, FOFFS-Aquila exhibits enhancements ranging from 10% to 20%, signifying its strong performance. Over a 15-day prediction period, the FTFOFS-Aquila strategy demonstrates substantial improvements, reaching approximately 25% in specific instances, thereby highlighting its potency for longer horizons. These findings underscore the significance of specific fusion strategies, especially FOFFS-Aquila, which significantly enhance predictive accuracy. Furthermore, the MLP consistently emerges as a top performer when compared with all fusion strategies, including CFFS, AWFS, FTFOFS-GA, FTFOFS-PSO, FTFOFS-Aquila, FOFFS-GA, and FOFFS-PSO. The findings emphasize how FOFFS-Aquila effectively enhances predictive accuracy across various horizons and predictive models within the context of both the SBI and ICBK datasets.

From the performance comparisons made above (**Table 2** and **Table 3**), it is now understood that the FOFFS-Aquila and FOFFS-PSO are performing well for both SBI and ICBK stock datasets.

Hence, we further attempt to monitor the performance of the two above well suited proposed optimized feature level fusion strategies through various *learning curves* or *convergence curves* which in turn represents time or experience through various iterations in x-axis and the improvements in learning process (based on MAE) in y-axis. The obtained convergence curves of optimized variants of both FTFOFS and FOFFS are shown in **Figure 7** and **Figure 8** for SBI and ICBK datasets respectively based on MLP forecasting model. From those two figures, it can be summarized that, FOFFS-Aquila is converging very well for 15 days ahead of prediction at around 10^{th} iteration and for 7 days and 3 days ahead of predictions; this fusion approach is converging very well in comparison to rest of the optimized fusion approaches at around 20^{th} and 40^{th} iterations respectively for both SBI and ICBK datasets.

From the convergence curves (**Figure 7** and **Figure 8**) now, it is observed that, the FOFFS fusion approach is really outperforming the rest of the fusion approaches, and then we again tried to observe the predictive accuracies of optimized versions of FOFFS such as; FOFFS-GA, FOFFS-PSO and FOFFS-Aquila for both SBI and ICBK datasets for all three predictive horizons based on actual closing price and predicted price as shown in **Figure 9** and **Figure 10** respectively.

The FOFFS-Aquila demonstrates robust and superior performance across both the SBI and ICBK stock datasets, as evidenced by its strong convergence in learning curves, outperforming other fusion strategies. Notably, in the 15-day prediction horizon, FOFFS-Aquila consistently achieves accurate predictions with remarkable alignment between actual and predicted stock values.

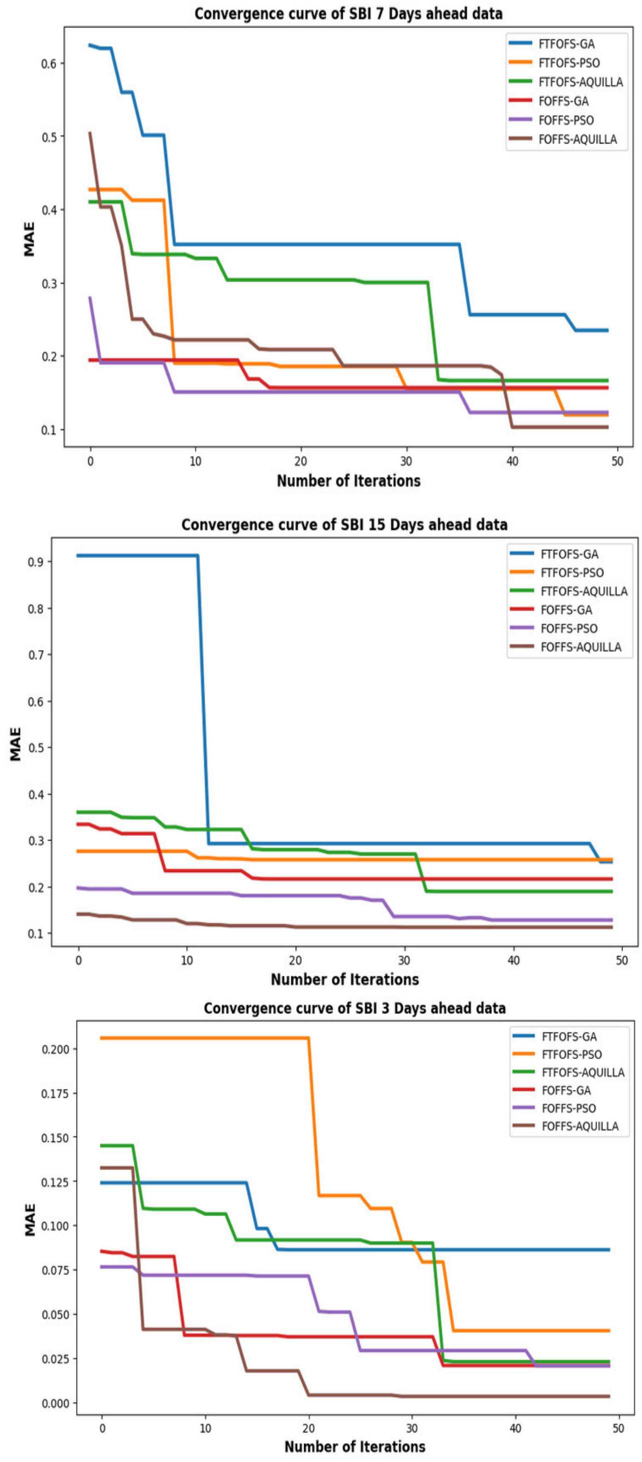


FIGURE 7. Convergence curves of SBI stock dataset for 3 days, 7 days and 15 days ahead of predictions.

C. MODEL COMPARISON, EVALUATION AND VALIDATION

The performance assessment of the experimented forecasting models, aimed at predicting the closing price of stock market data through feature level fusion architecture, involves the

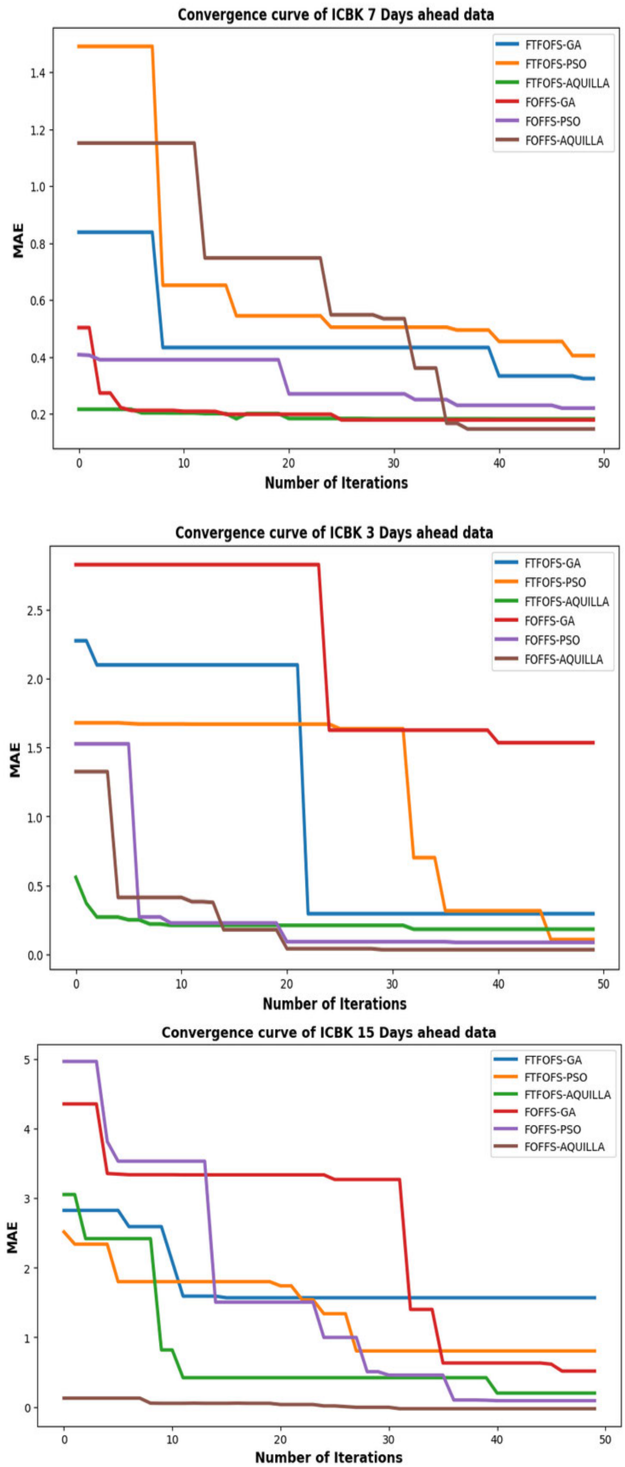


FIGURE 8. Convergence curves of ICBK stock dataset for 3 days, 7 days and 15 days ahead of predictions.

evaluation of seven key metrics: MSE, MAE, MRE, NSE, SI, R^2, and Theil's U [22], [23]. MSE quantifies the average squared difference between predictions and actual values, offering an overall measure of predictive quality. Smaller MSE values indicate closer alignment between predictions and actual data, reflecting improved model fitting. MAE is predominantly utilized to summarize the effectiveness of machine learning-based forecasting models. It aids in formulating learning algorithms towards optimization, providing a measurable indication of prediction errors. A lower MAE signifies heightened forecasting accuracy. MRE, the ratio of absolute error to actual value, gauges the magnitude of relative errors within a range of 0 to 1. NSE, proposed by Nash and Sutcliffe, is a normalized statistic that measures the relative magnitude of residual variance or noise in relation to actual data, with values close to 1 indicating accuracy. SI assesses the suitability of root mean squared error (RMSE) normalized to data mean, with an acceptable SI value being less than 1. R^2 indicates how well a regression line approximates actual data, with a range of 0 to 1 and higher values signifying a better match. Theil's U identifies models with significant errors by measuring relative accuracy and emphasizing deviations for larger errors. The MSE, MAE, MRE, NSE, SI, R^2 and Theil's U are computed using the **Equation (5)**, **Equation (6)**, **Equation (7)**, **Equation (8)**, **Equation (9)**, **Equation (10)** and **Equation (11)** respectively. Where, y_i is the actual value, $\hat{y}_i$ is the predicted value for n sample size and t is the time.

Table4 and **Table 5** provide a comprehensive overview of predictive accuracies achieved through various performance measures for the SBI and ICBK datasets respectively. The analysis focuses on three predictive models: FOFFS-GA, FOFFS-PSO, and FOFFS-Aquila, spanning different prediction horizons (3 days, 7 days, and 15 days).

$$MSE = \frac{1}{n}\sum (y_i - \hat{y}_i)^2 \tag{5}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left|y_i - \hat{y}_i\right| \tag{6}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n} \left(\frac{y_i - \hat{y}_i}{y_i}\right) \tag{7}$$

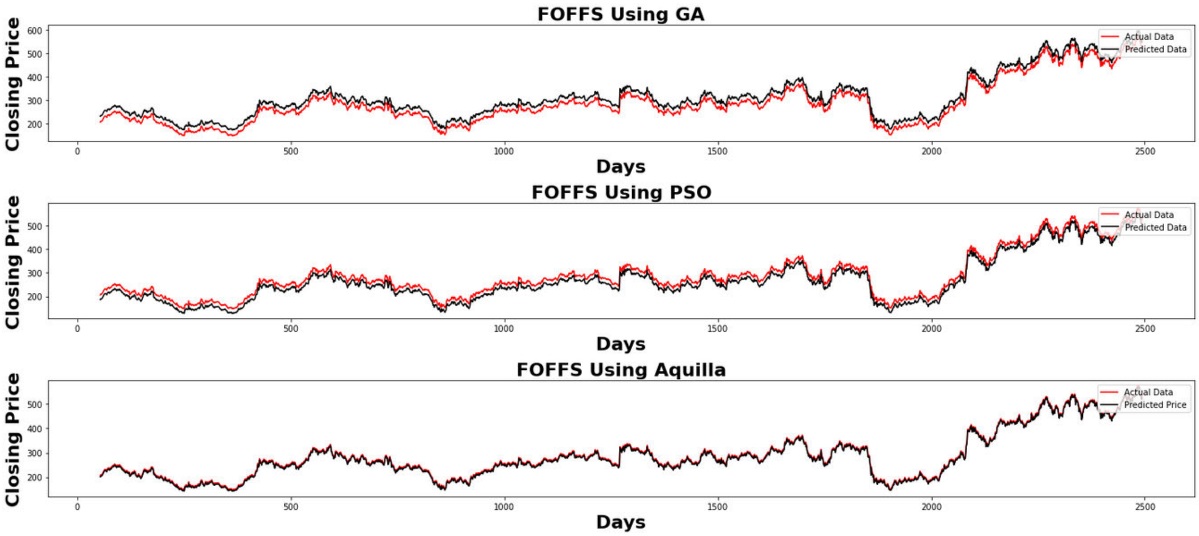
$$NSE = 1 - \left[\frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n} \left(y_i - \bar{\hat{y}}\right)^2}\right] \tag{8}$$

$$SI = \frac{\frac{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y}_i{}^2)}}{n}}{\bar{y}_i} \tag{9}$$

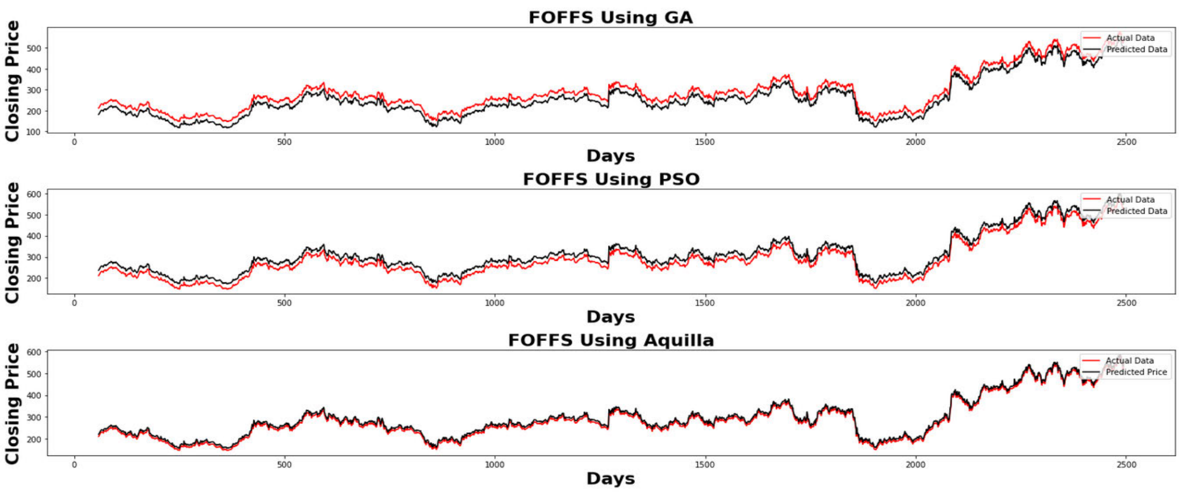
$$R^2 = \left[\frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}}_i)^2}}\right] \tag{10}$$

$$Theil'sU = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{\hat{y}_{i_{t+1}} - y_{i_{t+1}}}{y_{i_t}}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{y_{i_{t+1}} - y_{i_t}}{y_{i_t}}\right)^2}} \tag{11}$$

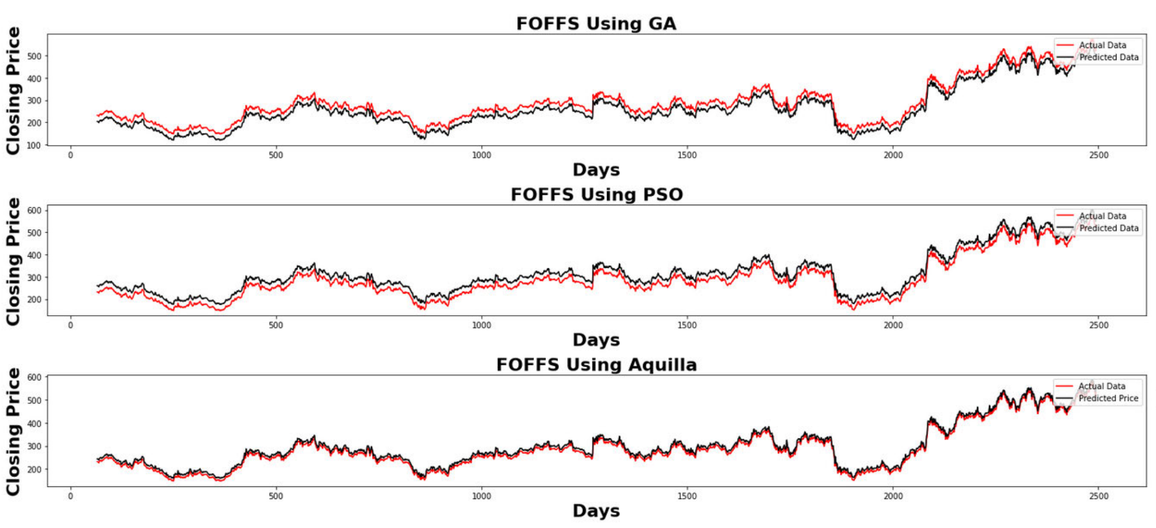
For SBI datasets, **Table 4** summarizes the predictive performance of three models—FOFFS-GA, FOFFS-PSO, and FOFFS-Aquila—across various metrics and prediction horizons for the SBI dataset. The analysis reveals that FOFFS-Aquila consistently delivers superior results compared to the other models. For instance, in terms of MSE,



(a) 3 days ahead of prediction for SBI dataset

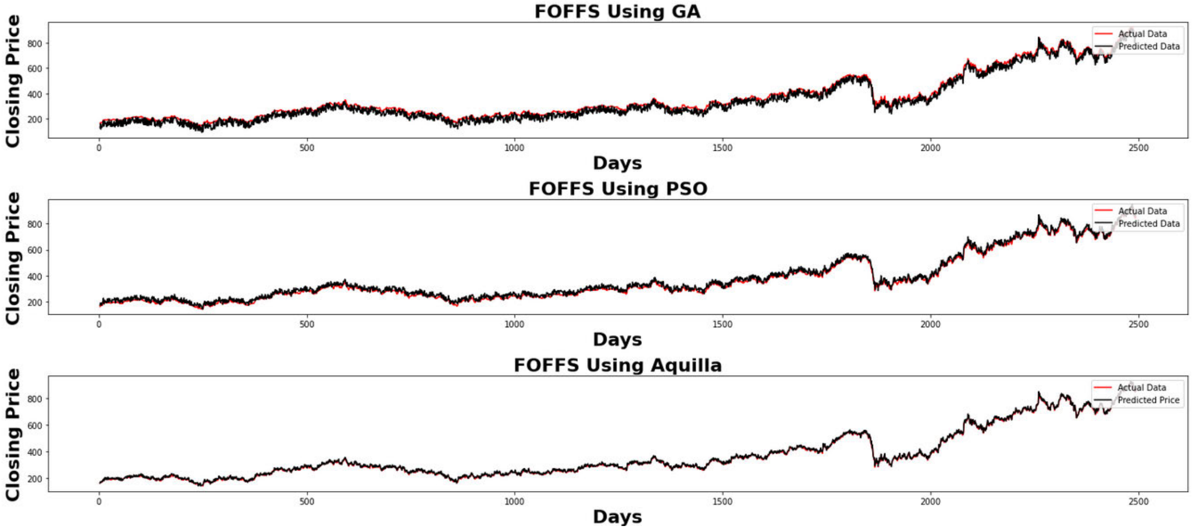


(b) 7 days ahead of prediction for SBI dataset

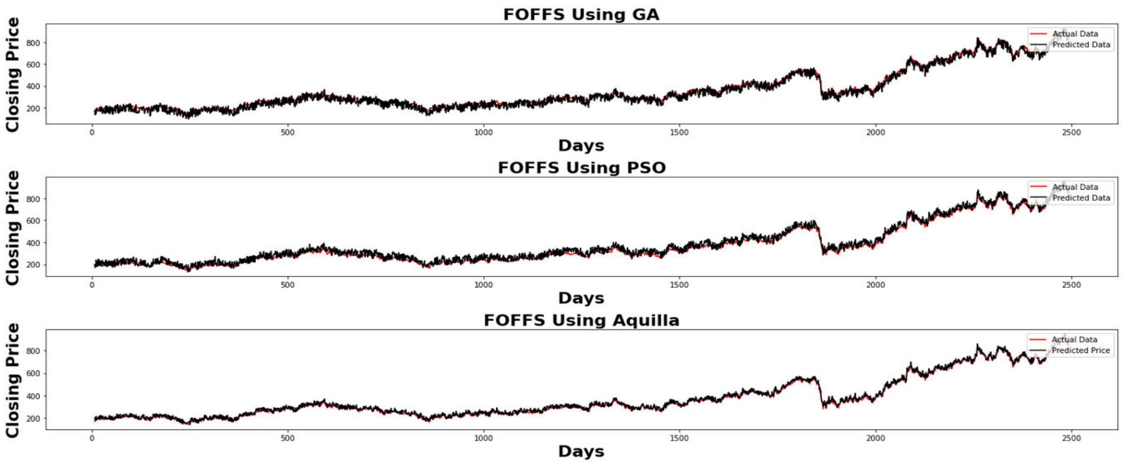


(c) 15 days ahead of prediction for SBI dataset

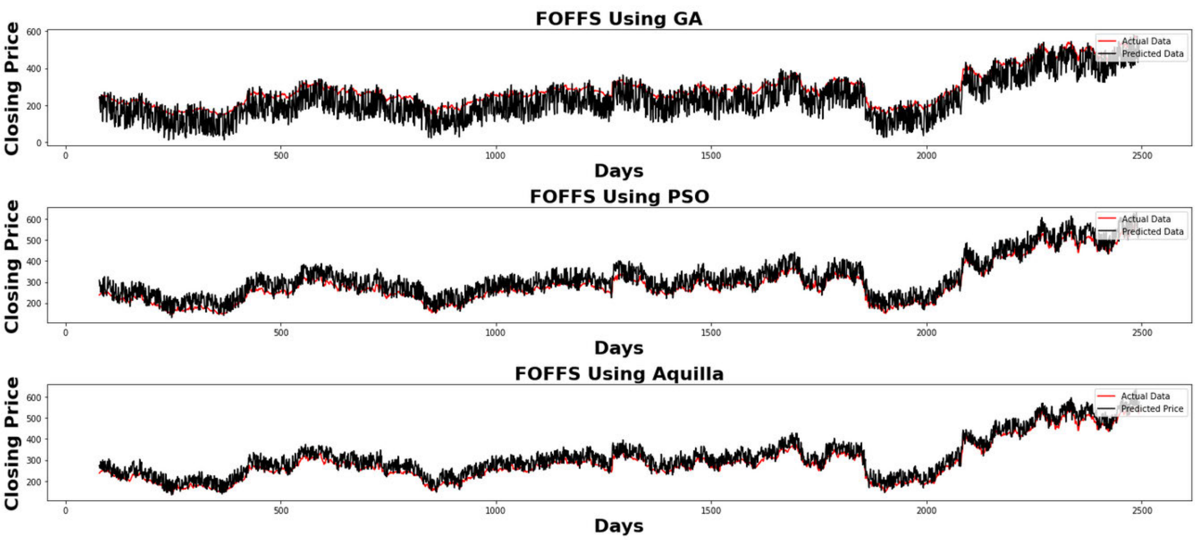
FIGURE 9. **Prediction curves of SBI dataset for (a) 3 days, (b) 7 days and (c) 15 days ahead of predictions.**



(a) 3 days ahead of prediction for ICBK dataset



(b) 7 days ahead of prediction for ICBK dataset



(c) 15 days ahead of prediction for ICBK dataset

FIGURE 10. Prediction curves of ICBK dataset for (a) 3 days, (b) 7 days and (c) 15 days ahead of predictions.

FOFFS-Aquila achieves the lowest values across all time horizons, indicating the most accurate predictions. This trend is also evident in Mean Absolute Error (MAE) and Mean Relative Error (MRE), where FOFFS-Aquila outperforms FOFFS-PSO and FOFFS-GA. In terms of Nash-Sutcliffe Efficiency (NSE), FOFFS-Aquila maintains the highest scores, suggesting the best fit between observed and predicted values. Similarly, FOFFS-Aquila shows the most favorable results for the Smoothing Index (SI) and R-squared (R^2) metrics, highlighting its effectiveness in minimizing errors and capturing data variance. The model also demonstrates the lowest Theil's U Statistic, indicating its superior predictive accuracy and reliability. Across all prediction horizons—3 days, 7 days, and 15 days—FOFFS-Aquila remains the most robust model, with performance generally declining as the prediction horizon lengthens. This suggests that while all models perform well in the short term, FOFFS-Aquila provides the most reliable predictions over varying time frames. The results underscore FOFFS-Aquila's strength in delivering accurate stock price forecasts and its potential as a preferred model for financial predictions.

For ICBK dataset, **Table 5** provides a comparative analysis of the predictive performance of three models—FOFFS-GA, FOFFS-PSO, and FOFFS-Aquila—across different prediction horizons for the ICBK dataset. For the 3-day prediction horizon, FOFFS-PSO achieves the lowest MSE and MAE values, indicating the highest accuracy among the models. FOFFS-Aquila follows closely, offering competitive results in MSE, MAE, and MRE, but slightly trailing FOFFS-PSO in NSE and R^2. FOFFS-GA shows the highest values for MSE and MAE, suggesting it is less effective compared to the other models for short-term predictions. In the 7-day prediction horizon, FOFFS-PSO continues to perform well with lower MSE and MAE compared to FOFFS-GA, though FOFFS-Aquila shows improved accuracy over FOFFS-GA, particularly in MAE and NSE. FOFFS-GA's performance declines notably in this horizon, while FOFFS-PSO and FOFFS-Aquila demonstrate better stability. For the 15-day horizon, FOFFS-Aquila excels with the lowest MSE, MAE, and MRE, showcasing its robustness in longer-term predictions. It also achieves the highest NSE and R^2 values, reflecting its strong model fit and accuracy. FOFFS-PSO performs well but shows higher MSE and MAE compared to FOFFS-Aquila. FOFFS-GA's performance deteriorates further in this longer horizon, with the highest MSE and MAE values. The FOFFS-Aquila consistently delivers strong performance across all prediction horizons, particularly excelling in longer-term predictions. FOFFS-PSO performs well in shorter horizons and shows competitive results but does not match FOFFS-Aquila's long-term accuracy. FOFFS-GA, while effective in some cases, generally lags in performance, especially in longer prediction periods. These results highlight FOFFS-Aquila's effectiveness in providing accurate and reliable predictions across varying time frames.

Furthermore, a straightforward comparison has been made with the existing literature based on stock market forecasting with the proposed method and presented in **Table 6**.

Finally, **Table 7** presents the results of statistical validation for the FOFFS-Aquila predictive model using the SBI and ICBK datasets, with a focus on paired comparisons against FOFFS-GA and FOFFS-PSO models across different predictive horizons. The $p-values$ and $h-values$ are indicative of the significance of the performance differences between FOFFS-Aquila and the other models. In the case of the SBI dataset, for all three predictive horizons (3 days, 7 days, and 15 days), the $p-values$ for FOFFS-Aquila's comparison against FOFFS-GA and FOFFS-PSO are below the typical significance threshold of 0.05. This suggests that FOFFS-Aquila exhibits statistically significant differences in predictive performance compared to FOFFS-GA and FOFFS-PSO on the SBI dataset. Similarly, for the ICBK dataset, FOFFS-Aquila shows significant differences in predictive performance against both FOFFS-GA and FOFFS-PSO across all predictive horizons. The $h-values$ of 1.0 indicate that the null hypothesis cannot be rejected, suggesting that FOFFS-Aquila consistently outperforms both FOFFS-GA and FOFFS-PSO in terms of predictive accuracy for both datasets and across various predictive horizons. Overall, these findings highlight the superiority of FOFFS-Aquila in comparison to the other two models, underscoring its potential as an effective predictive tool for financial analysis using the SBI and ICBK datasets.

The provided **Figure 11** presents the execution times, measured in minutes, for three distinct predictive periods (3 days, 7 days, and 15 days) across two datasets: SBI and ICBK. The data showcases the performance of three feature fusion models—FOFFS-Aquila, FOFFS-PSO, and FOFFS-GA—within this context. Upon analyzing the table, several trends emerge. Notably, FOFFS-Aquila consistently exhibits the shortest execution times across all predictive windows for both datasets. For the SBI dataset, the execution times for FOFFS-Aquila range from 12.1 minutes for a 3-days prediction to 14.45 minutes for a 15-days prediction. Similarly, in the ICBK dataset, the execution times range from 13.14 minutes to 13.52 minutes for the same predictive periods. FOFFS-PSO demonstrates intermediate execution times, with a progression from 12.42 to 15.74 minutes for SBI and from 14.51 to 14.42 minutes for ICBK. Conversely, FOFFS-GA tends to yield the longest execution times, spanning from 17.48 to 17.61 minutes for SBI and from 16.23 to 15.79 minutes for ICBK, as the predictive period increases. The FOFFS-Aquila consistently boasts the fastest execution times across all predictive horizons for both datasets, while FOFFS-PSO and FOFFS-GA showcase comparatively slower performance, with FOFFS-GA often requiring the longest execution times, particularly for longer predictive intervals. This analysis underscores the nuanced relationship

TABLE 4. Predictive accuracies observed through various performance measures for SBI dataset.

Predictive Models	Prediction Horizon	Performance Measures						
		MSE	MAE	MRE	NSE	SI	R^2	Theil's U
FOFFS-GA	3 Days	0.0027	0.0521	-0.0002003	-7.398*10^17	0.00018277	0.9695	0.2012
FOFFS-PSO		0.0010	0.0321	-0.00012344	-2.808*10^17	0.00011261	0.9754	0.1998
FOFFS-Aquila		0.0004	0.0221	-0.00084987	-1.331*10^17	0.00077529	0.9897	0.1854
FOFFS-GA	7 Days	0.0325	0.1802	-0.00069356	-8.871*10^18	0.00011408	0.9588	0.2101
FOFFS-PSO		0.0275	0.1657	-0.00063775	-7.501*10^18	0.00096462	0.9609	0.2011
FOFFS-Aquila		0.0169	0.1300	-0.00050035	-4.617*10^18	0.00059374	0.9705	0.1868
FOFFS-GA	15 Days	0.1867	0.4321	-0.00000017	-1.198*10^20	0.00065807	0.9367	0.2238
FOFFS-PSO		0.0568	0.2383	-0.00091877	-3.646*10^19	0.00020015	0.9532	0.2111
FOFFS-Aquila		0.0240	0.1548	-0.00059684	-1.538*10^19	0.00084459	0.9658	0.2049

TABLE 5. Predictive accuracies observed through various performance measures for ICBK dataset.

Predictive Models	Prediction Horizon	Performance Measures						
		MSE	MAE	MRE	NSE	SI	R^2	Theil's U
FOFFS-GA	3 Days	0.0325	0.1802	-0.00059802	-7.163*10^19	0.00008	0.9701	0.2262
FOFFS-PSO		0.0169	0.1300	-0.00043143	-3.728*10^19	0.00004	0.9714	0.2004
FOFFS-Aquila		0.0309	0.1757	-0.00058309	-6.809*10^19	0.00005	0.9841	0.1989
FOFFS-GA	7 Days	0.1635	0.4043	-0.0013	-6.865*10^22	0.00044	0.9527	0.2238
FOFFS-PSO		0.0883	0.2972	-0.00098734	-3.709*10^22	0.00024	0.9688	0.2185
FOFFS-Aquila		0.0464	0.2154	-0.00071559	-1.948*10^22	0.00012	0.9798	0.2124
FOFFS-GA	15 Days	0.2320	0.4817	-0.0016	-7.335*10^20	0.00064	0.9411	0.2295
FOFFS-PSO		0.0706	0.2658	-0.00088493	-2.233*10^20	0.00019	0.9628	0.2210
FOFFS-Aquila		0.0124	0.1114	-0.00037089	-3.923*10^19	0.00034	0.9742	0.2132

between execution efficiency and the chosen feature fusion model, which plays a pivotal role in time-sensitive predictive applications.

D. DISCUSSIONS,PRINCIPAL CONTRIBUTIONS AND IMPACT

The manuscript introduces an innovative stock market prediction approach blending technical analysis and optimization in an ensemble framework. Notably, it presents a novel feature-level fusion technique that combines momentum, trend, and volatility indicators. This comprehensive fusion generates robust feature sets, enhancing prediction accuracy across diverse horizons. Additionally, the manuscript proposes diverse fusion strategies—CFFS, AFWFS, FTFOFS, and FOFFS—designed to synergize various indicators, thereby elevating ensemble model accuracy. By systematically integrating these strategies, the manuscript establishes a more robust and accurate stock market prediction framework.

Moreover, the study introduces nature-inspired optimization via the Aquila optimizer. This inventive use enhances the ensemble model by selecting refined feature weights. Techniques like expanded exploration (high soar and vertical stoop), narrowed exploration (contour flight and short glide attack), and both expanded and narrowed exploitation (low flight with slow descent attack and walking and grab the prey) are leveraged from the Aquila optimizer to determine optimal feature set weights for FTFOFS and FOFFS strategies. The feature sets for FTFOFS include; $([w_1]_{1\times1} Featureset_{momentum})$, $([w_2]_{1\times1} Featureset_{trend})$,

TABLE 6. Comparison of stock prediction models.

Source	Year	Networks Utilized	Dataset Source	Predictive Horizon	Time Frame	Performance	Key Issues Observed
[34]	2021	SVM, RF1, RF2, NN, and Red Deer Adopted Wolf Algorithm (RDAWA)	Saudi stock market	Short-term	Jan 2012 - Dec 2019	RDAGW model: up to 98.75%	Emphasizes selection; lacks evolving features or real-time integration.
[28]	2023	DenseNet-41 with TI's	Yahoo Finance	Short, medium, long-term	Jan 2011-Dec 2021	MAPE score of 0.32	Focuses on model performance with existing features.
[32]	2023	LSTM, AdaBoost	CSI300	Short-term	Jan 1, 2017 - Dec 31, 2021	MAE score 0.48	Lacks integration of diverse or dynamic feature types.
[35]	2023	RNNs, LSTM, GRU	Nifty 50 index, NSE	Short-term	Jan 4, 2000 - Apr 29, 2021	LSTM & GRU ensemble accuracy 57.72%	Lacks evaluation of feature fusion and temporal/non-temporal integration.
[29]	2024	ANN, SVM	NASDAQ100, Dow Jones, DAX	Medium-term	Jan 1, 2010 - May 15, 2022	NASDAQ100: Accuracy 0.93, AUC 0.82; Dow Jones: Accuracy 0.94, AUC 0.84; DAX: Accuracy 0.65, AUC 0.66	Relies on traditional indicators; lacks evolving features.
[30]	2024	CEEMDAN-LSTM-SA-LightGBM	Salesforce, Alibaba, etc.	Short-term	Jan 2013 - Dec 2022	Accuracy over 67%	Limited evaluation of feature fusion techniques.
[33]	2024	CSFA-based Deep LSTM	Yahoo Finance	Short-term	Jan 2012 - Dec 2022	MAE 0.1418, MSE 0.1119, RMSE 0.2557	Focuses on fusion but not dynamic feature integration.
Proposed	2024	FOFFS-Aquila, DT, NB, SVR, MLP	SBI and ICBK	Short-term	3rd September 2012 to 3rd September 2022	Accuracy improved by 1-25%	-

($[w_3]_{1\times1} Featureset_{volatility}$). while the FOFFS forms the feature sets like; ($[w_1]_{1\times5} Featureset_{momentum}$), ($[w_2]_{1\times4} Featureset_{trend}$), ($[w_3]_{1\times4} Featureset_{volatility}$), where $w_1 : [w_{11}w_{12}w_{13}w_{14}w_{15}]_{1\times5}$, $w_2 : [w_{21}w_{22}w_{23}w_{24}]_{1\times4}$, and $w_3 : [w_{31}w_{32}w_{33}w_{34}]_{1\times4}$.

The proposed fusion strategies (CFFS, AFWFS, FTFOFS, and FOFFS) are rigorously evaluated with diverse predictive models (DT, NB, SVR, MLP) across 3, 7, and 15-day predictions. Remarkably, FOFFS-Aquila consistently enhances accuracy by 1-2%, 13-19%, and 25% for the respective horizons. This is further highlighted by MLP's superior performance, underscoring FOFFS-Aquila's efficacy (Table 3 and Table 4).

The manuscript undertakes extensive experimentation to validate its contributions. It systematically tests all fusion strategies alongside predictive models, enhanced by

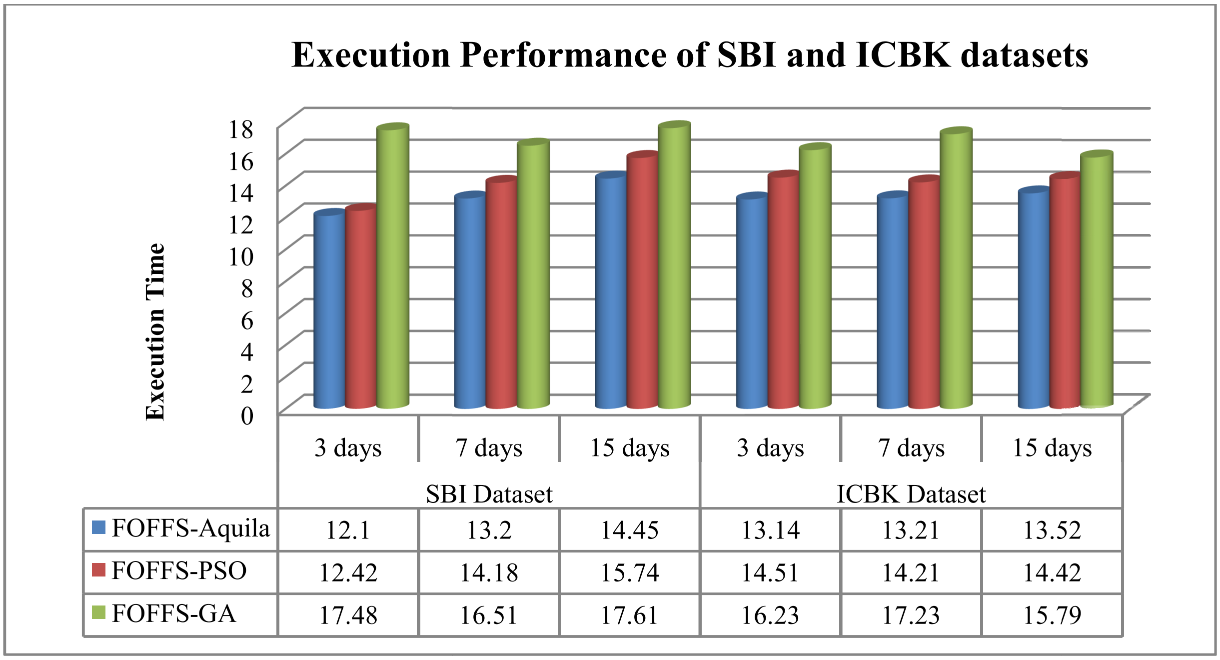


FIGURE 11. Execution time taken (in minutes) for SBI and ICBK datasets by FOFFS-Aquila, FOFFS-PSO and FOFFS-GA for three predictive days.

TABLE 7. Statistical validation of FOFFS-Aquila for SBI and ICBK dataset.

Paired Predictive Models	Predictive Horizons	$p-value$	$h-value$
SBI Dataset			
FOFFS-Aquila / FOFFS-GA	3 days	0.0091	1.0
FOFFS-Aquila / FOFFS-PSO		0.0061	1.0
FOFFS-Aquila / FOFFS-GA	7 days	0.0153	1.0
FOFFS-Aquila / FOFFS-PSO		0.0044	1.0
FOFFS-Aquila / FOFFS-GA	15 days	0.0856	1.0
FOFFS-Aquila / FOFFS-PSO		0.0599	1.0
ICBK Dataset			
FOFFS-Aquila / FOFFS-GA	3 days	0.0007	1.0
FOFFS-Aquila / FOFFS-PSO		0.0078	1.0
FOFFS-Aquila / FOFFS-GA	7 days	0.0296	1.0
FOFFS-Aquila / FOFFS-PSO		0.0147	1.0
FOFFS-Aquila / FOFFS-GA	15 days	0.0586	1.0
FOFFS-Aquila / FOFFS-PSO		0.0342	1.0

optimization techniques. The evaluation is supported by diverse learning and prediction curves, alongside meticulous metric assessments. FOFFS-Aquila and FOFFS-PSO stand out, exhibiting strong convergence and exceptional predictive performance in SBI and ICBK datasets. FOFFS-Aquila excels in datasets, demonstrating robustness and accuracy in learning curves. Particularly, in 15-day predictions, it consistently aligns actual and predicted stock values. Performance evaluations (Tables 5 and 6) substantiate FOFFS-Aquila's superiority across 3, 7, and 15-day predictions in terms of various metrics, underlining its efficacy in enhancing predictive accuracy.

Statistical validation confirms FOFFS-Aquila's significant predictive performance against FOFFS-GA and FOFFS-PSO models, showcasing its efficacy for financial analysis. The Table 7 displays statistical validation for FOFFS-Aquila against FOFFS-GA and FOFFS-PSO models in SBI and ICBK datasets across different horizons. Low p-values (<0.05) confirm FOFFS-Aquila's significant predictive performance. H-values of 1.0 support FOFFS-Aquila's superiority in predictive accuracy for both datasets and horizons, showcasing its efficacy in financial analysis.

Further, execution time analysis underscores FOFFS-Aquila's efficiency, thereby providing a holistic perspective on the model's contributions, impact, and observed limitations. Figure 6 illustrates execution times (in minutes) for FOFFS-Aquila, FOFFS-PSO, and FOFFS-GA in SBI and ICBK datasets across 3, 7, and 15-day predictions. FOFFS-Aquila consistently exhibits the shortest times, while FOFFS-GA tends to be the longest, highlighting the connection between model choice and execution efficiency in time-sensitive predictions.

The integration of CFFS, AFWFS, FTFOFS, and FOFFS in the research serves several vital purposes and contributes to the advancement of stock market prediction methodologies. These fusion strategies address the following key challenges and offer significant contributions to the field:

- The integration of these fusion strategies aims to enhance the accuracy of stock market predictions. By combining multiple technical analysis tools such as momentum, trend, and volatility indicators, these strategies create enriched and robust feature sets. This leads to more accurate and reliable predictions, aiding investors and financial analysts in making informed decisions.
- Each fusion strategy harnesses the synergies among different technical indicators. By integrating various types of indicators, the strategies capture diverse aspects of market behaviour, providing a more comprehensive view of stock trends. This synergy contributes to improved predictive power, as different indicators complement each other's strengths and mitigate weaknesses.
- The combination of different fusion strategies creates an ensemble effect, where the strengths of individual strategies are combined. This ensemble approach tends to improve overall predictive accuracy by minimizing biases and reducing overfitting.
- The integration of these strategies contributes to the development of a comprehensive framework for stock market prediction.
- The introduction of these fusion strategies represents innovation and novelty in the field of financial analysis. These strategies extend beyond traditional methods and explore new avenues for leveraging technical analysis indicators to enhance predictive accuracy.
- By providing more accurate predictions, these strategies aid investors and financial experts in making informed decisions about trading and portfolio management. The improved accuracy can lead to more favourable investment outcomes and reduced losses.

E. LIMITATIONS AND FUTURE RECOMMENDATIONS

The study presents a robust approach to stock market prediction through feature fusion and optimization, yet several limitations and potential improvements can be identified. The current work primarily focuses on intrinsic features derived from technical analysis tools such as momentum, trend, and volatility. To enhance predictive accuracy and robustness, future research could incorporate external factors, including macroeconomic indicators and sentiment analysis. The study's scope is limited to short-term predictions (3, 7, and 15 days); expanding this approach to longer-term forecasts could offer valuable insights into its performance across different market conditions. Although the MLP network has proven effective, exploring alternative architectures like recurrent neural networks (RNNs) or LSTM networks may provide deeper insights into sequential data patterns. Additionally, future work should consider qualitative aspects, aligning predictions with market trends, and evaluating decision-making implications to offer a more comprehensive understanding of the fusion strategies' effectiveness. Further experiments should investigate varying dimensions of feature sets and complexity levels to assess how these strategies adapt and perform under different conditions. By examining these factors, we aim to refine our approach and enhance its applicability.

V. CONCLUSION

Forecasting the time series trends and obtaining an accurate market value over a period is a decision support process is stock market data analysis which is typically a representative of financial time series. The technical analysis of this financial market is regarded as a pattern recognition problem in which, the forecasting models need to train with historical data, technical analysis tools or indicators to predict the future stock price. In this work, before involving the forecasting models to predict the future price of the stocks, an attempt has been made to obtain feature sets which can contribute more accurate prediction through a fusion approach at feature level. The intrinsic features obtained through three technical analysis tools such as momentum, trend and volatility are fused to form feature sets based on CFFS, AWFS, FOFTFS and FOFFS approaches. Then, the hunting behaviors of Aquila optimizer are explored and simulated to obtain optimal values of the weight vectors to generate optimized weighted feature sets for FTFOFS and FOFFS approaches. The study presents a comprehensive approach to predicting stock market trends using feature fusion and predictive models.

DATA AVAILABILITY

Data will be made available on request to the first author.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AI GENERATED TEXT

There is no AI generated text used in preparing this manuscript

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