AI in Financial Management in Saudi Arabia

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Abstract—Financial management is vital for organizational stability and strategic decisions, especially in Saudi Arabia's dynamic, data-driven economic environment. Conventional financial prediction models are limited by market volatility, data inconsistency, and complex interdependencies among financial indicators, resulting in lower accuracy. This research overcomes these challenges using an artificial intelligence (AI)-driven framework that integrates optimization techniques, attention-based feature learning, and deep neural modeling. The financial management datasets were collected from Saudi Arabian financial systems. Then, Min–Max normalization and missing-value handling were applied to standardize data and improve learning stability. Discrete Wavelet Transform (DWT) was utilized to extract meaningful time-frequency financial features, enhancing signal representation and reducing noise. Mayfly Optimized–Driven Attention Deep Neural Network (MFO-Att-DNeuroNet) was proposed to enhance financial prediction accuracy and model robustness in financial management applications. The Att-DNeuroNet selectively emphasized the most informative financial features while modeling complex nonlinear relationships within the data. MFO was employed to optimally tune model parameters, ensuring faster convergence and improved predictive performance. Experimental evaluations demonstrated that the MFO-Att-DNeuroNet achieved superior prediction accuracy (0.97) when using Python 3.10. The MFO-Att-DNeuroNet provided an effective and scalable solution for intelligent financial management, offering significant potential to support accurate forecasting and strategic decision-making in Saudi Arabian organizations.

Index Terms—Financial Management, Artificial Intelligence (AI), Decision-Making, Dynamic Economic

I. INTRODUCTION

The financial management is very important in facilitating proper planning, control and analysis of financial resources to aid the strategic decision making, profitability, sustainability and long-term organizational growth (Liu and Fu, 2024). Over the past few years, the field of artificial intelligence (AI) has evolved financial management in a remarkable way. With simple tools of automation, it has given place to the usage of predictive and prescriptive analytics, which are more complex to set up (Najem et al., 2025; George, 2024). Due to the development of machine learning (ML), natural language processing, and big data analytics, AI systems have become able to analyze complex and high-dimensional financial data and detect the underlying patterns and predict market fluctuations with greater precision (Nofel et al., 2024). This development helps organizations make proactive and data-driven decisions, enhance planning of investments, and perform a full risk assessment.

Financial management is also a critical component of strategic decisions made by AI. This helps make timely decisions and improve the quality and reliability of financial decisions (Rane et al., 2024). AI applications assist the optimization of investments, management of portfolios, detection of fraud, and assessment of risk by processing high volumes of data in real-time. The capabilities enable the financial managers to foresee the changes in the market, optimize resource allocation and enhance competitive positioning in the volatile financial markets (Oyedokun et al., 2024).

Conversely, traditional financial management approaches are based on manuality and model rigidity and hence inability to react to changing conditions of the market. Conservative methods tend to be sluggish, prone to errors and unable to process increasing volume and complexity of financial data (Oko-Odion, 2025). Furthermore, they make inflexible assumptions and limited processing capacity, which limits their capacity to integrate new factors like market volatility, economic changes, and new risks (Patil, 2024). Therefore, such innovative AI-driven financial decision-support systems are thus necessary. AI systems have been shown to be better than traditional ones in market forecasting, risk assessment, and anomaly detection by incorporating real-time data, adaptive learning, and predictive modeling (Ojeda et al., 2025). These systems improve the budgeting process, strategic plans, and scenario analysis by means of constant learning and through the use of automatic insights.

Nevertheless, there are issues, such as the quality of data requirement, explainability of the model, ethical issues, and the cost of implementation. The question of transparency, accountability, and bias should also be considered to ensure trust and fairness on AI-based financial decision-making (Li and Xu, 2025). Figure 1 describes how an effective allocation of funds leads to profitability, risk management, liquidity, sustainability and operational effectiveness.

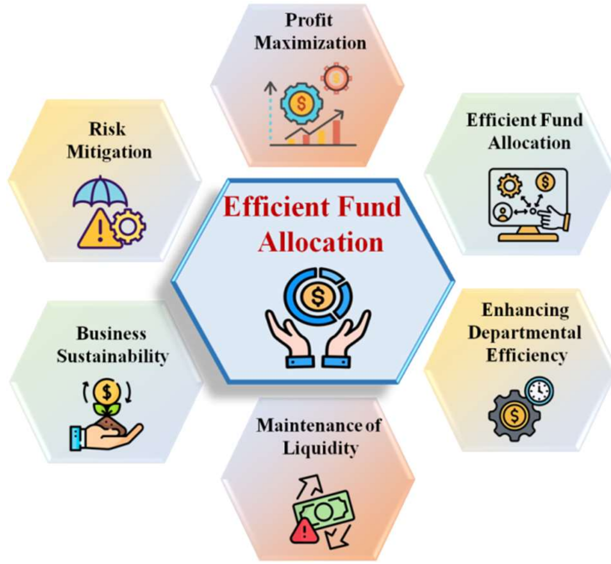


Figure 1 Key benefits and outcomes of efficient fund allocation in financial management systems

A. Research objective

The research focuses on improving financial management and forecasting in Saudi Arabian firms by tackling market volatility, data inconsistency, and the intricate interplay of financial indicators. It suggests creating a robust AI-hybrid framework to enable precise predictions and informed, data-driven strategic decisions amid changing financial conditions. The key contributions are listed as follows:

- MFO-Att-DNeuroNet is a hybrid of attention-based DL and MFO, enhancing the quality of predictions and their resilience.
- It applies WT and attention algorithms to compute significant time-frequency financial features, minimizing noise and emphasizing significant features
- The proposed approach enables real-time decision-making and strategic planning that offers a scalable, Python-based solution that can process large amounts of Saudi Arabian data.

B. Research frameworks

The research framework is assigned as given; Section I demonstrates the introduction of AI engagement in financial management, Section II emphasizes the literature review's prediction of financial management in different methods, Section III includes the methodology from data collection to novelty contribution in financial management, Section IV presents the results and discussion, and Section V details the conclusion of the research findings.

II. LITERATURE REVIEW

A study by Alsaadi et al. (2024) evaluated deep learning (DL) as a predictor of financial risk using a dataset of 490 engineered financial ratios. It found that the Convolutional Neural Network (CNN) model outperformed the Neural Network (NN) with 94.5% accuracy and a 0.97 Area Under the Curve (AUC), compared to 91.2% and 0.92 for NN. Noted limitations lied in the dataset size and generalizability. Mozumder et al. (2024) analysed how the Inception Version 3 CNN (InceptionV3 (CNN)) could influence decision-making in banking and business intelligence with high-quality organizational data. The results indicated an accuracy of 90%. This percentage is regarded as higher than the conventional result. Constraints included high infrastructure costs, privacy concerns, ethics, and data dependency.

The methods ML, NN, and big data analytics are effective methods to improve financial forecasting and risk prediction as they allow detecting the patterns in real time, assess credit risk, and optimize investments (Faheem et al., 2024). Such methodologies enhance predictive accuracy and response to changes, but there are still some issues with data security, interpretability, and ethical use. CNN-Long Short-Term Memory (CNN-LSTM) model that used social media sentiment of 33k comments on Reddit and 9.9k tweets had a good performance in predicting the cryptocurrency markets (Tiwari et al., 2025). The model performed at 98.7% and an F1-score of 0.987 with feature extraction, attention mechanism, and grid search optimization, and further outperformed variants of GRU. However, there is a problem with data quality and market volatility.

To enhance risk forecasting in fractional commercial real estate using an LSTM -Extended Model (LSTM-X model) which uses extra external market variables (Wali, 2024). The results indicate that it is more accurate to predict the change in property values, rental revenue and the investment risks. The restriction are the sensitivity of market volatility and data sets quality dependence and the reliance on the generalizability of the region. Yao et al. (2025) concentrated on the improvement of predictive quality and understandability using such techniques as data augmentation, feature extraction, and Generative Adversarial Explanation (GAX). This methodology produced more precise and comprehensible findings than conventional models. However, issues of data quality, cost and regulation must be carefully considered and further researched.

The Bidirectional LSTM-Based Financial Risk Prediction (BiLSTM-FRP) uses an attention mechanism (AM) as an enhancement to the financial risk prediction of an enterprise (Chen, 2025). BiLSTM-FRP utilizes forward and backward tendencies along with influential features used for temporal financial data. Findings indicate that it has an accuracy (0.93) better than baselines.

A study by Nallakaruppan et al. (2024) noted that as interpretable AI advanced in credit risk management, it improved transparency and trust in financial applications. The researchers used interpretable models, such as decision trees and random forests, to provide local and global explanations for the outcomes. The results showed that the models achieved accuracies between 0.89 and 0.93 and demonstrated robustness even with large datasets. However, this study focused on binary classification, which limited its broad application to the financial sector.

Big data enhances financial decision-making by addressing information asymmetry, principal–agent issues, and risk management, thereby improving forecasting accuracy, decision relevance, and competitive advantage in integrated business–finance systems (Ren, 2022). Advanced information systems support efficient management, budget control, and investment decisions, although firm-specific data limits wider applicability. Digital financial access also influences individual financial well-being. Mobile and internet banking improve resilience and informed decision-making, while features such as mobile bill payments may encourage impulsive spending (Carton et al., 2022). IT-enabled finance shows mixed impacts, and broader, multidisciplinary research is needed to better inform policy and consumer behavior.

The research gap of the present study was inferred from neglected issues found in previous studies. One of the previous studies was done by Mozumder et al. (2024) as they did not explore cost-effective deployment strategies, adaptability to low-resource environments, or methods to ensure real-time scalability and ethical compliance, leaving practical implementation in diverse banking contexts unaddressed. Though Chen (2025) proposed a high-metric model named BiLSTM-FRP in predicting financial risks, the model is not adaptable to small-scale enterprises and is not robust to noisy data. Nallakaruppan et al. (2024) developed an XAI-based credit risk management model that is fairly precise, however it did not cover multi-class prediction and dynamic market integration gaps. Additionally, it is limited by the quality of the data used, and operates in binary classification.

It is clear that the existing models have scaled noisy data, sensitive, and uninterruptible. On the other hand, the proposed MFO-Att-DNeuroNet addresses these issues by combining attention-dependent feature learning, WT to reduce noise, and MFO to tune the parameters efficiently. This is a hybrid AI solution that supports high-accuracy and robust financial forecasting, scalability, and better decision-making by Saudi Arabian organizations operating in dynamic and information-driven markets.

III. METHODOLOGY

Financial management data from Saudi Arabian systems was preprocessed using missing-value handling and Min–Max normalization. Figure 2 demonstrates that DWT was applied to extract robust time–frequency features and reduce noise. An Att-DNeuroNet modeled complex financial patterns, while MFO optimally tuned model parameters to enhance prediction accuracy and convergence.

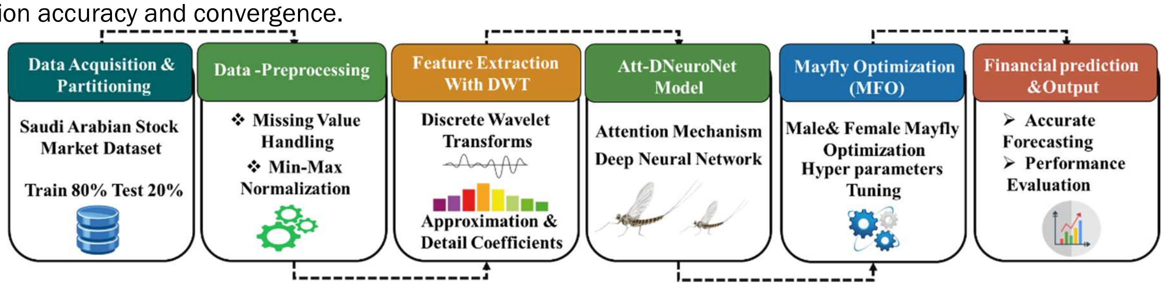


Figure 2 Working flow of MFO-Att-DNeuroNet in AI engagement of financial management

A. Dataset

The research collected the Saudi Arabian Stock Market Dataset from Kaggle website: https://www.kaggle.com/datasets/abdelrahmanalimo/saudi-arabian-stock-market-data. It contains key trading information such as date, open, high, low, close prices, traded volume, and ticker symbol. This dataset provides a detailed view of stock performance for financial analysis and model training, and the dataset was split 80% training and 20% of testing.

B. Data Preprocessing

Min–Max normalization scales financial features to a common range, improving learning stability and reducing bias in neural networks. Missing-value handling replaces absent data using suitable imputation methods, ensuring data continuity, robustness, and accurate financial predictions. Min–Max normalization is a data scaling approach used to transform financial variables into a common numerical range, usually between 0 and 1. It is mathematically expressed as in Equation 1.

$$X' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where X is the original value, and x_{min} and x_{max} are the minimum and maximum values of the feature. Normalization of financial datasets is crucial as differing scales of indicators such as profits, cash flow, and liabilities can distort the learning process in deep neural networks, leading to biased weight updates.

Missing-Value Handling: The missing values are a common problem in the field of financial management because of incomplete records, delays in reporting, or errors in the acquisition of data. It can distort statistical distributions and poor model performance in case they are not treated. Missing-value handling is a technique of recognizing such missing values, and filling them in with an appropriate imputation method, as mean or median imputation in the case of numerical variables, forward or backward filling in time-series data or interpolating. These strategies ensure continuity of data, minimization of information loss, and reduction of learning bias. The reasonable management of missing values enhances robustness of the model, pattern extraction and accurate financial forecasting.

C. Feature extraction using the Discrete Wavelet transform (DWT)

To derive viable information in the financial time-series data, DWT decomposes the signal into a number of frequency sub-bands. DWT provides time-frequency representation in contrast to existing time-domain analysis with providing a possibility to capture both short- and long-term trends in financial data. This financial signal is broken down into approximation coefficients reflecting the general trends, and detail coefficients reflecting volatility and sharp changes. The resulting wavelet coefficients are concise and informative attributes that better signal representation and increase the learning capacity of the deep neural network. The process helps in increasing the accuracy of prediction, generalization, and robustness of financial management applications.

D. MFO-Att-DNeuroNet for Accurate AI-Based Financial Prediction Systems

MFO-Att-DNeuroNet is designed to enhance the performance and feature learning of the model used to predict financial markets with the focus on the highlighting of important financial characteristics and non-linear interaction, and MFO optimizes the network parameters. This is a more effective, robust and accurate way of making financial decisions.

- MFO is utilized to maximize the parameters of the network, increase the rate of convergence and the overall predictive accuracy.
- Att-DNeuroNet is applied to overfit complicated non-linear relationships and underline the most informative financial characteristics in order to be able to make accurate predictions.

(a). Att-DNeuroNet model for Selective Financial Feature Representation Learning

The Att-DNeuroNet also focuses on the impactful financial characteristics that are selectively highlighted, which enhances the representation of features and predictive accuracy. The attention process gives greater weights to the most informative input features and inhibits irrelevant information. It facilitates the model to concentrate on the important patterns and dependencies in high-dimensional and complicated data. This selective focus enhances effectiveness in learning, interpretability and general predictive quality. Equation 2 represents the collection of input feature vectors, such that W_1, W_2, and W C represent individual feature of S samples.

$$X_{feature} = [\{W_1\}, \{W_2\}, \dots, \{W_C\}]^S \quad (2)$$

$X_{feature}$ denotes the input feature matrix. $W_1, W_2, \dots, W_C$represent the individual feature components, where $C$is the total number of features, and Sindicates the number of samples over which these features are observed. Equation 3 shows the computation of attention weights by applying the Softmax function to dense-layer encoded feature representations.

$$X_{Wei} \quad = Softmax(E_{dense}(\{Z\},\{W_1\},\ldots,\{W_C\})) \tag{3}$$

Here, X_{Weigh} denotes the attention weight vector, $E_{dense}(\cdot)$represents the dense encoding function, $Z$is the input feature representation, $W_1 \ldots W_C$are feature weights, and Softmax normalizes them into probability scores. Equation 4 represents feature reweighting using the attention mechanism, where important features are emphasized.

$$X_{DAM} = X_{feature} \odot X_{Weights} \tag{4}$$

Here, $X_{DAM}$is the attention-modulated feature matrix, $X_{feature}$is the original feature matrix, X_{Weigh} denotes attention weights, and $\odot$ indicates element-wise multiplication. Finally, Att-DNeuroNet produces an attention-weighted feature matrix, where informative features are strengthened, and irrelevant features are reduced for improved learning and prediction in financial management.

(b). MFO Algorithm for Optimal Hyperparameter and Model Weight Tuning

The MFO algorithm optimally tunes hyperparameters and network weights in deep models, enhancing convergence and preventing overfitting and local optima entrapment, thus significantly improving the prediction stability and accuracy of financial models. Equation 5 shows the position update of a mayfly based on its current position and updated velocity.

$$o_j(s+1) = O_j(s) + u_j(s+1) \tag{5}$$

Here, $O_j$represents the position of the j^{th}mayfly, $u_j$denotes velocity, and $s$represents the iteration number.

Male Mayfly Velocity Update Strategy: In this mechanism, male mayflies vary their velocities according to the personal and global best solutions. It is a type of exploration and exploitation balance, which assists the model to escape local optima. It is used in the context of financial prediction to refer to the efficient tuning of network weights to converge quickly and achieve better accuracy. Equation 6 is an update of male velocity that uses inertia, personal best and global best attraction.

$$v_j(s+1) = h.v_j(s) + b_1 f^{-\beta q_o^2}\left[w_{g_j} - w_j(s)\right] + b_2 f^{-\beta_h^2}\left[w_h - w_j(s)\right] \tag{6}$$

Here, $h$denotes inertia weight, b_1, b_2 represent attraction constants, $v_j$shows current solution, $w_{g_j}$and $w_h$denote personal and global best, and βrepresents decay factor. Equation 7 shows the Euclidean distance between two candidate solutions.

$$\left|\left|w_j - w_i\right|\right| = \sqrt{\sum_{l=1}^{m}\left(w_{jl} - w_{il}\right)^2} \tag{7}$$

Here, w_j, w_irepresent solution vectors, w_{jl}, w_{il}denote the l^{th}dimension values, $l$represents dimension index, and $m$denotes total dimensions.

Equation 8 $v_j(s+1)$ represents the updated velocity of the j^{th}mayfly at iteration $s+1$, $v_j(s)$denotes the current velocity, $h$represents the inertia weight controlling momentum, $c$denotes the random scaling coefficient,h presents controls the influence of previous velocity.c determines the movement acceleration.$q_1$represents a uniformly distributed random number, j denotes the Mayfly index, and $s$represents the iteration number.

$$v_j(s) + 1 = h.v_j(s) + c.q_1 \tag{8}$$

Female Mayfly Guided Motion: This process demonstrates the way that female mayflies are guided to the global best solution but with randomness as an exploration measure. It is adaptive advice on the best hyperparameters. In financial modeling, it is used to refer to both fined weight and parameter adjustment to improve the stability of the prediction. In Equation 9 the update of the velocity of a female mayfly seeking a global best solution is presented.

$$v_j(s+1) = h.v_j(s) + b_3 f^{-\beta s_{ne}^2}\left[w_h - w_j(s)\right] \tag{9}$$

Here, $v_j(s+1)$ represents the updated velocity of the j^{th}female mayfly, $v_j(s)$denotes the current velocity, $h$represents the inertia weight, b_3 denotes the attraction coefficient, $f$represents the attractiveness function, βdenotes the decay parameter, s_{ne}represents the distance to the nearest elite solution, $w_j(s)$denotes the current solution position, $w_h$represents the global best solution, $j$denotes the mayfly index, and $s$represents the iteration number. Equation 10 shows the random exploratory velocity update of a female mayfly.

$v_j(s) = h.v_j(s) + ek.q_2$ (10)

Here, $v_j(s)$represents the velocity of the j^{th}female mayfly at iteration s, $h$denotes the inertia weight, $e_k$represents the random scaling factor, $q_2$denotes a uniformly distributed random number, $j$represents the mayfly index, and $s$represents the iteration number.

Mayfly Offspring Generation: This mechanism shows the creation of new candidate solutions by combining male and female positions. It represents the exploration of new hyperparameter and weight combinations. In financial prediction, it denotes improved diversity of solutions, preventing premature convergence and boosting model robustness. Equation 11 shows the generation of the first offspring by combining male and female solutions.

$offspring1 = K * male + (1 - K) * feamle$ (11)

Here, $offspring$ 1 represents the first new candidate solution, Kdenotes the mating coefficient, $male$ represents the male parent solution, and $female$represents the female parent solution.

Equation 12 shows the generation of the second offspring by combining male and female solutions. Here, Equation 12 $offspring2$ represents the second new candidate solution, Kdenotes the mating coefficient, $male$ represents the male parent solution, and $female$ represents the female parent solution. MFO-Att-DNeuroNet framework effectively optimizes hyperparameters and network weights.

$offspring2 = K * male + (1 - K) * feamle$ (12)

The MFO-Att-DNeuroNet framework (see Figure 3) shows how input financial information is represented by dense encoding and attention-based weighting achieved through Mayfly Optimization to produce correct and credible financial prediction. Algorithm 1 was used to preprocess financial data using normalization and DWT to extract features. It employs an attention-based DNeuroNet to emphasize essential financial indicators, and the MFO algorithm to optimize the weights and hyperparameters of the network, which increases the convergence rate, prediction performance, and stability in financial forecasting.

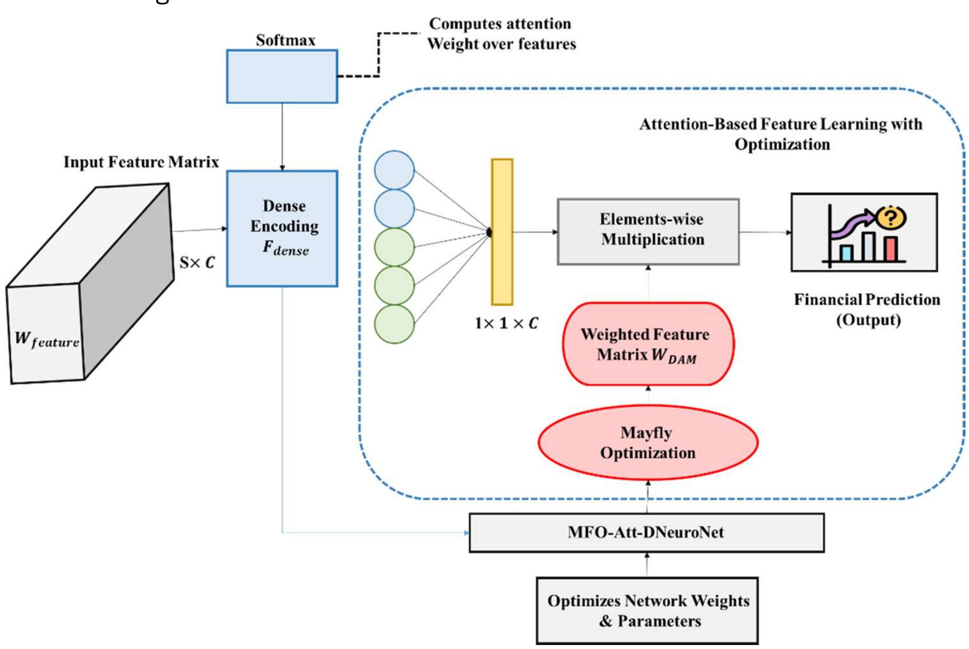


Figure 3 MFO-Att-DNeuroNet with attention-based feature weighting

Pseudocode 1: MFO-Att-DNeuroNet

1: $Initialize\ Att - DNeuroNet\ and\ male\ mayfly\ population\ MMM\ and\ female\ mayfly\ population\ FFF$
2: $Randomly\ initialize\ positions\ (weights\ \&\ hyperparameters)\ and\ velocities$
3: $Preprocess\ financial\ data\ using\ normalization\ and\ DWT$
4: $Initialize\ Att - DNeuroNet\ architecture$

5: $Evaluate\ fitness\ of\ all\ mayflies\ using\ prediction\ error\ (e.g., RMSE\ /\ MAE)$
6: $For\ iteration\ s = 1s\ =\ 1s = 1\ to\ TTT\ do$
7: $Update\ attention - based\ feature\ weights\ using\ Att - DNeuroNet$
$Compute\ dense\ encoding\ and\ attention\ weights$
$Generate\ attention - modulated\ features$
8: $For\ each\ \boldsymbol{male\ mayfly}\ do$
9: $Update\ velocity\ using\ personal\ and\ global\ best\ (Eq. 6)$
10: $Update\ position\ using\ (Eq. 5)$
11: $End\ for$
12: $For\ each\ \boldsymbol{female\ mayfly}\ do$
13: $If\ distance\ to\ nearest\ elite\ is\ small\ then$
14: $Update\ velocity\ toward\ global\ best\ (Eq. 9)$
15: $Else$
16: $Apply\ random\ exploratory\ velocity\ (Eq. 10)$
17: $End\ if$
18: $Update\ position\ using\ (Eq. 5)$
19: $End\ for$
20: $Compute\ Euclidean\ distance\ between\ candidate\ solutions\ (Eq. 7)$
21: $Generate\ offspring\ solutions\ using\ mating\ operator$
$$offspring1 =\ K \times male + (1 - K) \times femaleK\ \backslash times\ male\ +\ (1 - K)\ \backslash times\ femaleK \times male + (1 - K) \times female$$
$$offspring2 =\ (1 - K) \times male + K \times female(1 - K)\ \backslash times\ male\ +\ K\ \backslash times\ female(1 - K) \times male + K \times female$$
22: $Evaluate\ fitness\ of\ offspring\ solutions$
23: $Perform\ selection\ and\ replacement\ based\ on\ fitness$
24: $Update\ global\ best\ solution$
25: $End\ for$
26: $Return\ optimized\ Att - DNeuroNet\ weights\ and\ final\ financial\ prediction$

The MFO-Att-DNeuroNet is an intelligent framework that merges attention-based DL with the MFO algorithm for precise financial predictions. Its Att identifies key financial features, while MFO optimizes network weights and hyperparameters, leading to improved accuracy, stability, and decision support in complex financial management systems.

IV. RESULT

The research was carried out with Python (v3.11) with the help of TensorFlow (v2.14) and Keras (v2.14) to develop and test the models and optimize. The research proposed MFO-Att-DNeuroNet and considered existing methods such as (fuzzy support vector machine (FSVM), back propagation neural network (BPNN), Factor-Logistic Fusion Approach (FLFA), BiLSTM-FRP (Chen, 2025)), (Extreme Gradient Boosting (XGBoost), CNN (Visual Geometry Group 16), CNN (VGG16), CNN (Residual Network 50), CNN (ResNet50), and CNN (InceptionV3) (Mozumder et al., 2024)) to examine the AI in financial management in decision making.

A. Exploratory Data Analysis and Statistical Characterization of Financial Indicators

The full closing-price time series with strong volatility and frequent trend reversals, reflecting the non-stationary and nonlinear nature of financial markets, as in Figure 4(a) and Figure 4(b), focuses on a shorter interval, revealing localized trends, rapid price changes, and cyclic behavior. Together, these plots highlight the complexity of financial time-series data and motivate the use of advanced feature extraction and deep learning models to capture both global and local temporal dynamics.

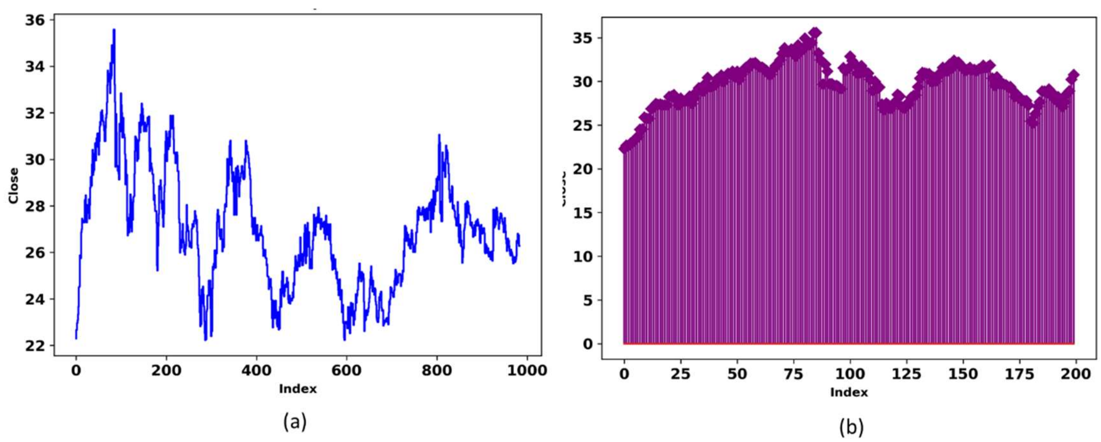


Figure 4 Visualization of financial closing price time series: (a) full-length closing price trend and (b) localized segment highlighting short-term price dynamics

The statistical properties of the financial data are summarized in Figure 5(a–c). Figure 5(a) reveals that the trading volume and closing price have a nonlinear relationship, Figure 5(b) reveals a significant positive correlation between opening and closing prices, and Figure 5(c) reveals the presence of stable price distributions with a few outliers. In general, these trends demonstrate the application of advanced feature extraction and attention-based deep learning frameworks in order to record sophisticated market behavior.

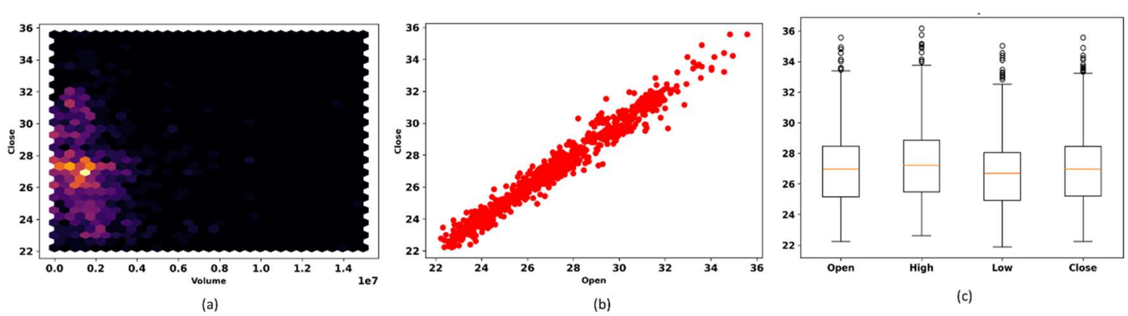


Figure 5 Exploratory data analysis of financial indicators: (a) volume versus closing price, (b) the relationship between opening and closing prices, and (c) distributions of open, high, low, and closing prices

B. Comprehensive Performance and Convergence Analysis of the Proposed MFO-Att-DNeuroNet

The suggested MFO-Att-DNeuroNet is based on a confusion chart, ROC, and PR curve in Figure 6(a-c). The confusion matrix reveals the presence of a good classification with high true positives and negatives and a low number of errors. Both ROC curve and PR curve show a high level of precision at several levels of recall and have an AUC of 0.994 and 0.994, respectively. Altogether, the findings indicate that the model is reliable, accurate, and robust to perform intelligent financial management in Saudi Arabian organizations.

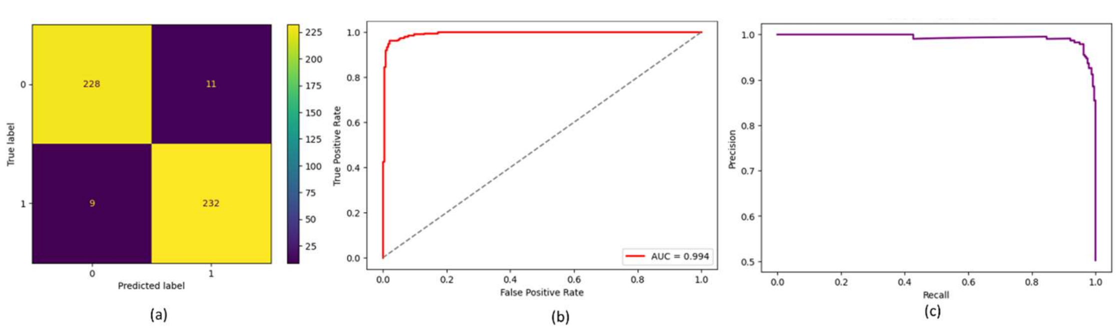
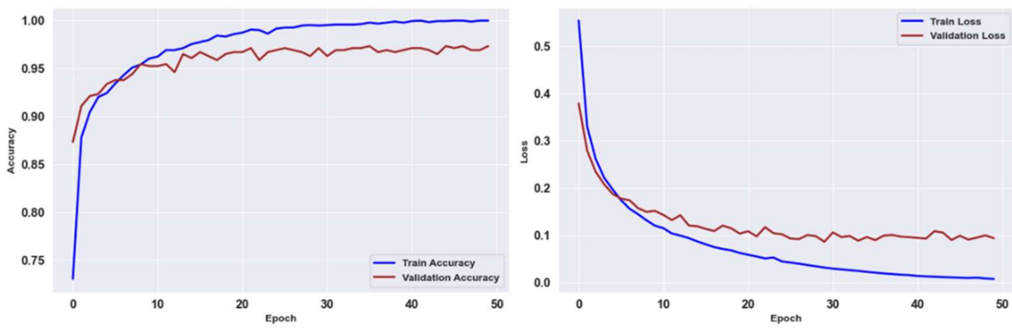


Figure 6 Performance evaluation of the proposed MFO-Att-DNeuroNet model: (a) confusion matrix, (b) ROC curve with AUC = 0.994, and (c) precision–recall curve

The training and validation accuracy and loss of the proposed MFO-Att-DNeuroNet over 50 epochs are shown in Figure 7(a,b). The accuracy curves show rapid convergence with closely aligned training and validation performance, indicating effective learning and minimal overfitting. Correspondingly, training loss drops sharply, while validation loss stabilizes around 0.09–0.10, reflecting efficient optimization and a good bias–variance trade-off. Overall, these trends confirm the model's stability and suitability for reliable financial prediction.



(a) (b)

Figure7 Training and validation performance of the proposed MFO-Att-DNeuroNet model: (a) accuracy versus epochs and (b) loss versus epochs

C. Role of metrics in financial management

- *Accuracy:* Assesses the general accuracy of predictions, assists financial managers in having confidence in AI models to make reliable predictions of risks, investment returns, or credit decisions.
- *Precision:* The percentage of correct prediction of a positive result, and is used to reduce the false alarms when estimating risks and make more focused decisions.
- *Recall:* Reflects the model's capability to detect all real positive events that play an important role in early detection of financial risks and avoidance of unnoticed critical problems.
- *Early Detection:* Measures the speed of alerting about the possible risks to take the necessary proactive measures to minimize losses and increase financial sustainability.
- *Financial Resilience:* Evaluates the system in terms of its capacity to continue performing well in the market during periods of market volatility, informs long-term strategic planning, and risk reduction.
- *AUC-ROC:* Refers to the capability of the model to differentiate the positive and the negative cases and assist managers to make balanced decisions in the uncertain environment.

D. Evaluating the efficiency of MFO-Att-DNeuroNet in financial management against existing methods

The comparison analysis reveals that the traditional models, such as XGBoost, CNN (VGG16, InceptionV3, ResNet50), FSVM, BPNN, FLFA, and BiLSTM-FRP reach the accuracy of 0.82-0.93 and the recall of 0.78-0.91. BiLSTM-FRP is effective (0.93 accuracy, 0.91 recall), but it is unable to deal with complicated financial processes. The proposed MFO-Att-DNeuroNet is superior to all with 0.97 accuracy and 0.95 recall, and it proves that it is a robust financial predictor with the combination of MFO and attention mechanisms and DNeuroNet, as shown in Table 1 and Figure 8.

TABLE 1
COMPARATIVE PERFORMANCE OF ACCURACY AND RECALL

Models	Accuracy	Recall
XGBoost (Mozumder et al., 2024)	0.91	0.90
CNN (VGG16) (Mozumder et al., 2024)	0.90	0.88
CNN (ResNet50) (Mozumder et al., 2024)	0.85	0.85
CNN (InceptionV3) (Mozumder et al., 2024)	0.86	0.87
FSVM (Chen, 2025)	0.82	0.78
BPNN (Chen, 2025)	0.84	0.80
FLFA (Chen, 2025)	0.86	0.83
BiLSTM-FRP (Chen, 2025)	0.93	0.91

MFO-Att-DNeuroNet (Proposed)	0.97	0.95

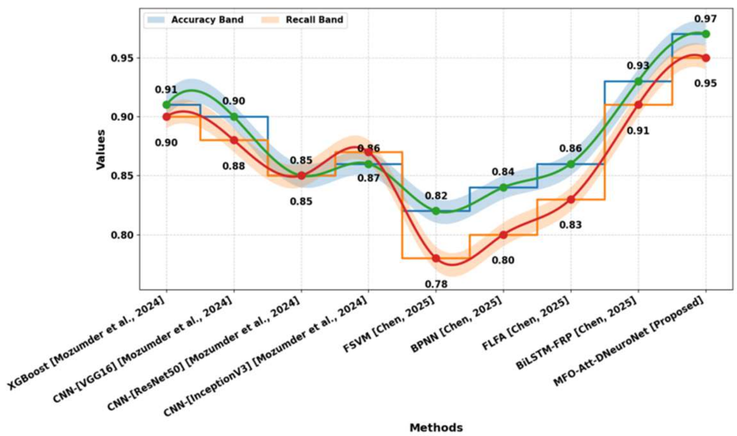


Figure 8 Graphical representation of accuracy and recall outcomes

As per the experiment, the XGBoost has the highest precision and recall, 0.90 and 0.90 respectively, whereas CNN (VGG16) has 0.88 and 0.88 accordingly. CNN (ResNet50) and CNN (InceptionV3) have a precision and recall of 0.86 and 0.87 respectively, which means that they have a moderate level of predictability. MFO-Att-DNeuroNet achieves the best performance; 0.94 precision and 0.93 recall, which indicates that it has a better learning efficiency as indicated in Table 2 and Figure 9.

TABLE 2
QUANTITATIVE VALUES OF ACCURACY AND RECALL

Models	Precision	Recall
XGBoost (Mozumder et al., 2024)	0.90	0.90
CNN (VGG16) (Mozumder et al., 2024)	0.88	0.88
CNN (ResNet50) (Mozumder et al., 2024)	0.86	0.85
CNN (InceptionV3) (Mozumder et al., 2024)	0.86	0.87
MFO-Att-DNeuroNet (Proposed)	0.94	0.93

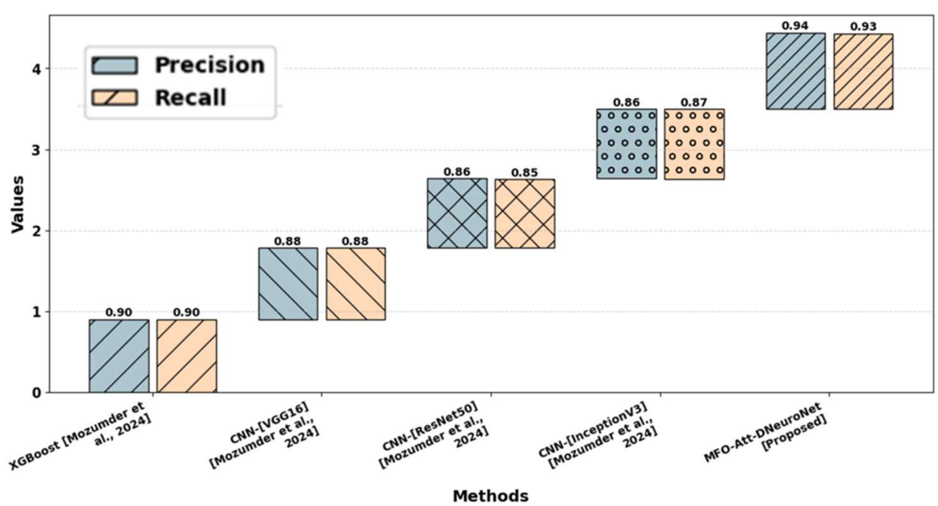


Figure 9 Graphical representation of precision and recall outcomes

The performance analysis shows that the FSVM, BPNN and FLFA have moderate scores of early detection (0.75-0.80) and financial resilience (0.70-0.76) and BiLSTM-FRP shows higher results (0.90 early detection, 0.88 resilience). Table 3 and Figure 10 indicate that the proposed MFO-Att-DNeuroNet is the best with 0.94 in early detection and 0.92 in financial resilience, indicating the process of better risk anticipation and economic stability. These findings prove that the proposed model is effective to improve timely risk detection and promote financial stability in general.

TABLE 3
COMPARATIVE VALUES OF EARLY DETECTION AND FINANCIAL RESILIENCE

Models	Early Detection	Financial Resilience
FSVM (Chen, 2025)	0.75	0.70
BPNN (Chen, 2025)	0.77	0.73
FLFA (Chen, 2025)	0.80	0.76
BiLSTM-FRP (Chen, 2025)	0.90	0.88
MFO-Att-DNeuroNet (Proposed)	0.94	0.92

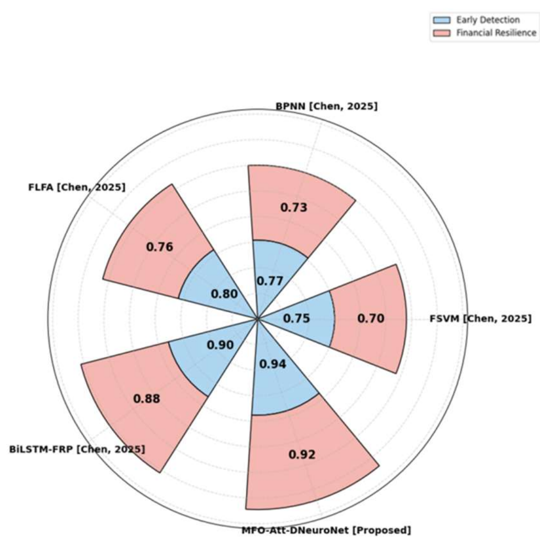


Figure 10 Graphical representation of early Detection and financial resilience outcomes

According to Table 4 and Figure 11, the AUC-ROC analysis indicates that FSVM has 0.79, BPNN yields 0.86 and FLFA yields 0.89 hence moderate discriminative ability. BiLSTM-FRP shows good results with a score of 0.94 on the AUC-ROC value, which is evidence of higher prediction accuracy. Contrary to this, the proposed MFO-Att-DNeuroNet provides the highest value of AUC-ROC of 0.95 that proves higher classification separability and robustness.

TABLE 4
VALUES OF AUC-ROC IN FINANCIAL MANAGEMENT

Models	AUC-ROC
FSVM (Chen, 2025)	0.79
BPNN (Chen, 2025)	0.86
FLFA (Chen, 2025)	0.89
BiLSTM-FRP (Chen, 2025)	0.94
MFO-Att-DNeuroNet (Proposed)	0.95

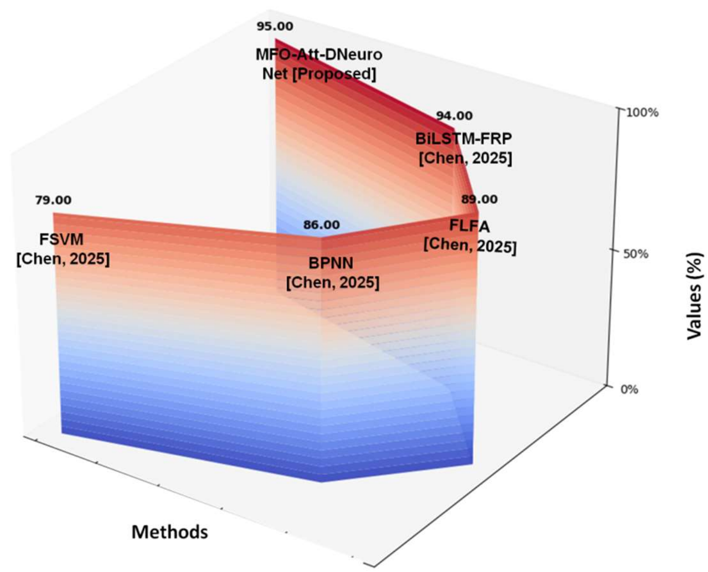


Figure 11 Graphical representation of AUC and ROC outcomes

V. DISCUSSION

Current solutions such as (FSVM, BPNN, FLFA (Chen, 2025)), (CNN variants, XGBoost (Mozumder et al., 2024)) and BiLSTM-FRP have issues with non-linear and complex financial trends, dirty and incomplete data, and do not have dynamic flexibility. In feature extraction, useful information is usually lost compromising predictive accuracy and early risk identification. The proposed MFO-Att-DNeuroNet model effectively addresses the aforementioned issues through a multifaceted approach. It is adaptive and dynamically adjusts model parameters using the Mayfly Optimization algorithm to achieve optimal performance. Moreover, Attention Mechanism prioritizes the most influential financial metrics and increases the importance of the attribute. Wavelets-based multi-resolution feature processing is also used to identify both broad trends and detailed financial models. The processed features are then fed into a Deep Neural Network to model complex nonlinear relationships in the data. These components work synergistically to improve model prediction accuracy, enable early detection of financial risks, and contribute to overall financial stability.

As the practical implication concerns, the suggested model assists the financial managers in Saudi Arabia by allowing them to make correct predictions, anticipate risks, and make wise strategic decisions. It improves reliability in decision making in budgeting, investment analysis and allocation of resources. This is a factor in enhanced financial health and sustainable organizational performance.

VI. CONCLUSION

The research proposed an AI-based hybrid model, MFO-Att-DNeuroNet, to improve financial forecasting within the Saudi Arabian management systems. The model combines data preprocessing, DWT-based feature extraction, attention-driven deep neural networks, and MFO in dealing with the data volatility, noise, and complex non-linear relationships. Experiments demonstrated that the attention mechanism enhances the feature relevance, and MFO provides the optimal parameter tuning and accelerates the convergence. MFO-Att-DNeuroNet is better than the existing models with 0.97 accuracy, 0.94 precision 0.95 recall, 0.94 early detection, 0.92 financial resilience, and 0.95 AUC-ROC. Real-time data, macroeconomic indicators, explainable AI, and similarity with other metaheuristic optimizers can be included in future work to make it more adaptable and interpretable.

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