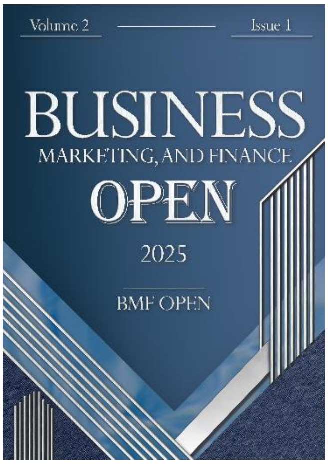
Explanation and Evaluation of the Water Cycle Algorithm Metaheuristic Method in Corporate Bankruptcy Prediction

Kamran Khalili [1], Mehdi Maranjory [2,*] , Razieh Alikhani [3] and Yosef Taghipourian [4]

[1] Department of Accounting, Cha.C., Islamic Azad University, Chalus, Iran;
[2] Department of Accounting, Cha.C., Islamic Azad University, Chalus, Iran;
[3] Department of Accounting, Cha.C., Islamic Azad University, Chalus, Iran;
[4] Department of Accounting, Cha.C., Islamic Azad University, Chalus, Iran;

* Correspondence: Mehdi_maranjory@iauc.ac.ir



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Abstract: This study investigates corporate bankruptcy prediction in a competitive environment influenced by various regulatory frameworks. The statistical population comprised companies listed on the Tehran Stock Exchange. Based on the predefined sample selection criteria, data from 329 listed firms were collected and analyzed for the period 2018–2021. The study examined various financial indicators, including cash holdings, assets, liabilities, and profitability, and employed the Water Cycle Algorithm (WCA) to select the most influential features. The results indicated that the Water Cycle Algorithm (WCA) identified fourteen key financial ratios with an accuracy exceeding 97% and a negative predictive value greater than 99%. These ratios were subsequently used as inputs to the prediction model. Furthermore, the results obtained from the Water Cycle Algorithm were evaluated using a confusion matrix comprising four performance metrics: accuracy, precision, sensitivity, and specificity. In addition, to ensure the reliability of the findings, each of the implemented methods was executed multiple times. The results demonstrated that the Water Cycle Algorithm achieved an accuracy rate of 97.86%, indicating strong predictive performance. The findings also suggest that the Water Cycle Algorithm outperformed other approaches, including AutoML and XGBoost.

Keywords: Bankruptcy, Bankruptcy Prediction, Water Cycle Algorithm.

1. Introduction

Corporate bankruptcy is one of the most consequential forms of organizational failure because it reflects the inability of a firm to maintain financial continuity, meet obligations, preserve stakeholder confidence, and remain competitive within dynamic markets. In management and financial decision-making, bankruptcy is not merely a legal or accounting outcome; rather, it is the final manifestation of accumulated strategic, operational, financial, governance, and institutional weaknesses. The prediction of bankruptcy has therefore become a central issue in accounting, finance, risk management, auditing, banking, credit assessment, and corporate governance. As firms operate in environments characterized by market volatility, regulatory pressure, capital constraints, and increasing competition, early identification of financial distress can support timely corrective action, protect investors and creditors, and improve the allocation of financial resources. Recent studies have emphasized that bankruptcy prediction is particularly important in sectors and economies where firms are exposed to liquidity constraints, inefficient capital structures, weak governance mechanisms, and unstable macroeconomic conditions [1-3].

The significance of bankruptcy prediction has increased as business environments have become more complex and data-intensive. Traditional financial analysis often relied on a limited number of ratios, expert judgment, or classical statistical models to evaluate whether a firm was financially healthy or distressed. Although these approaches have contributed substantially to the development of financial distress research, they may not fully capture nonlinear relationships, interaction effects, and hidden structures within corporate financial data. Bankruptcy is usually not caused by a single factor; rather, it emerges through the interaction of liquidity weakness, profitability decline, excessive leverage, inefficient asset utilization, poor working capital management, and governance deficiencies. Studies in different contexts have shown that liquidity, unprofitability, capital structure, credit risk, and institutional inefficiency are closely related to bankruptcy and default risk [4-6]. Therefore, contemporary bankruptcy prediction requires models that can process multiple financial indicators simultaneously and identify the most informative variables for classification.

Financial distress prediction has traditionally been grounded in the use of accounting-based indicators, such as profitability ratios, liquidity ratios, solvency ratios, leverage ratios, and activity ratios. These indicators provide interpretable information about a firm's capacity to generate income, meet short-term obligations, finance assets, and maintain operational continuity. For example, studies using financial distress scores and bankruptcy models have demonstrated that accounting ratios remain valuable in assessing the probability of corporate failure, especially when the purpose is to provide practical evidence for managers, creditors, regulators, and investors [6, 7]. However, the predictive power of financial ratios depends on the economic environment, industry structure, accounting practices, and institutional setting. A ratio that performs well in one country or sector may not produce the same level of accuracy in another context. This issue is especially relevant in emerging markets, where market inefficiencies, inflationary pressures, regulatory constraints, and differences in financial reporting quality can alter the relationship between accounting indicators and bankruptcy risk.

In recent years, the development of artificial intelligence and machine learning has transformed bankruptcy prediction research. Instead of relying only on linear assumptions, modern models can learn complex patterns from data and produce more accurate classifications. Machine learning methods such as decision trees, support vector machines, neural networks, ensemble learning, deep learning, and data balancing techniques have been increasingly applied to financial distress and bankruptcy prediction. These methods are particularly useful when datasets contain nonlinear relationships, imbalanced classes, or multiple interacting predictors. Comparative evidence indicates that machine learning models can improve predictive performance in bankruptcy classification, although their effectiveness depends on feature selection, model tuning, class imbalance handling, and evaluation criteria [8-10]. Systematic reviews have also shown that artificial intelligence is increasingly used in financial accounting forecasting, highlighting its relevance for improving prediction accuracy, reducing uncertainty, and supporting managerial decision-making [11].

Despite these advances, bankruptcy prediction remains methodologically challenging. One important challenge is the high dimensionality of financial data. When many financial ratios are entered into a predictive model, some variables may be redundant, noisy, weakly informative, or even misleading. Including all available variables can increase computational complexity, reduce model interpretability, and lead to overfitting. Therefore, feature selection is a critical stage in bankruptcy prediction. By selecting only the most relevant financial indicators, researchers can improve model efficiency, strengthen classification performance, and provide more meaningful managerial implications. This is particularly important in financial management research, where the selected ratios must not only improve prediction but also offer interpretable evidence about the mechanisms of distress. Recent optimized deep learning and artificial intelligence studies confirm that prediction quality is strongly affected by the way input features are selected and structured [12, 13].

Another major challenge in bankruptcy prediction is class imbalance. In many datasets, the number of non-bankrupt firms is substantially larger than the number of bankrupt firms. This imbalance can cause models to classify most observations as healthy while failing to correctly identify distressed firms. In management and financial risk assessment, this problem is serious because misclassifying a bankrupt firm as healthy may lead to poor lending decisions, inappropriate investment choices, and delayed managerial intervention. Research on machine learning and data balancing methods has emphasized that bankruptcy prediction models should be evaluated not only through overall accuracy but also through sensitivity, specificity, precision, negative predictive value, and area under the curve [8, 13]. These criteria provide a more complete view of model performance, especially when the cost of false negatives and false positives differs across managerial, auditing, and regulatory contexts.

Bankruptcy prediction is also closely related to governance and strategic decision-making. Corporate governance failures, earnings management, business strategy, and creative accounting can distort financial signals and increase bankruptcy risk. Recent studies have shown that bankruptcy is not solely the result of operational weakness; it may also be associated with governance deficiencies, managerial opportunism, manipulation of accounting information, and poor strategic alignment [14-16]. This implies that bankruptcy prediction should be viewed as an interdisciplinary management problem rather than a purely technical classification task. Predictive models that identify early warning signs can help boards, auditors, investors, and regulators detect financial vulnerability before the firm reaches a legal or operational crisis. In this regard, reliable bankruptcy prediction contributes to corporate sustainability, accountability, and risk governance.

In banking and credit markets, the prediction of insolvency and default is equally important. Financial institutions require accurate models to assess borrowers, allocate credit, manage capital adequacy, and reduce systemic risk. Studies on bank stability and personal bankruptcy prediction have shown that logistic models and multidimensional diagnostic approaches remain useful, but they also reveal the need for more flexible and adaptive methods in complex financial environments [17, 18]. Furthermore, hybrid approaches combining optimization algorithms, neural networks, and partner selection mechanisms have been used to reduce insolvency risk and total costs in the banking sector [19]. These developments suggest that optimization-based and intelligent models can play an important role in financial risk reduction by improving the quality of classification and decision-making.

Within this methodological evolution, metaheuristic optimization algorithms have received increasing attention. Metaheuristic algorithms are designed to search complex solution spaces efficiently and identify near-optimal or optimal solutions where conventional methods may be insufficient. Their value lies in their ability to perform global search, avoid local optima, and handle complex nonlinear optimization problems. In bankruptcy prediction, metaheuristic algorithms can be used for feature selection, parameter tuning, weighting of indicators, or hybridization with machine learning classifiers. Such methods are especially suitable when the research objective is not only to classify firms but also to determine which financial indicators contribute most strongly to predictive performance. The growing use of optimization-based neural networks and ensemble approaches in financial distress prediction confirms the potential of metaheuristic methods for improving bankruptcy prediction accuracy [13, 19].

The Water Cycle Algorithm (WCA) is one of the prominent nature-inspired metaheuristic optimization algorithms. It was originally introduced as a novel method for solving constrained engineering optimization problems and is inspired by the natural water cycle, including the movement of streams and rivers toward the sea [20]. In WCA, the best solution is represented as the sea, good solutions are represented as rivers, and the remaining candidate solutions are represented as streams or raindrops. Through iterative movement toward better solutions, evaporation, raining, and redistribution mechanisms, the algorithm explores the search space and attempts to converge toward an optimal solution. Subsequent developments extended WCA to constrained multi-objective optimization problems and demonstrated its effectiveness in producing high-quality solutions across complex optimization tasks [21]. Further research introduced chaotic mechanisms to enhance the efficiency and exploration capacity of the algorithm, showing that WCA can be adapted for diverse optimization applications [22].

The application range of the Water Cycle Algorithm has expanded considerably since its introduction. A comprehensive review of WCA and its applications indicates that the algorithm has been successfully used across engineering, energy, scheduling, structural optimization, and computational intelligence problems [23]. For example, WCA has been applied to short-term hydrothermal coordination with evaporation rate, demonstrating its usefulness in complex energy optimization problems where multiple constraints and objectives must be considered [24]. These applications confirm that WCA is not limited to its original engineering domain but can be transferred to other fields that require intelligent search and optimization. Given that bankruptcy prediction also involves selecting optimal indicators and improving classification performance, WCA provides a theoretically and methodologically appropriate framework for financial distress modeling.

The relevance of WCA to bankruptcy prediction lies particularly in feature selection. In corporate financial datasets, many financial ratios may appear relevant, but only a subset may have strong discriminatory power between bankrupt and non-bankrupt firms. WCA can search among possible combinations of financial ratios and identify the subset that minimizes classification error while reducing unnecessary dimensionality. This capacity is valuable because it helps address two problems simultaneously: improving predictive accuracy and enhancing interpretability. Compared with purely statistical approaches, WCA-based feature selection can better explore the solution space and detect combinations of ratios that may not be obvious through conventional analysis. This is consistent with the broader shift in bankruptcy prediction research toward optimized, hybrid, and intelligent models that integrate financial theory with computational methods [9, 12, 25].

The need for such models is particularly evident in the context of companies listed on the Tehran Stock Exchange. Listed firms operate under specific institutional, legal, and financial reporting conditions, and bankruptcy classification is influenced by domestic regulations, including legal criteria related to capital loss. Moreover, Iranian capital market firms may differ from firms in other countries in terms of financing structure, inflation exposure, liquidity constraints, and accounting practices. Therefore, bankruptcy prediction models developed in foreign contexts may not be directly transferable to domestic companies without empirical validation. Recent Iranian studies have examined bankruptcy prediction using neural networks, support vector machines, creative accounting indicators, earnings management, and business strategy, indicating growing interest in modern measurement and intelligent modeling methods for corporate failure prediction [15, 16, 25]. However, further research is needed to evaluate the performance of metaheuristic algorithms, especially WCA, in selecting effective financial features and improving prediction accuracy in the Iranian stock market.

In addition, bankruptcy prediction has practical implications for sustainable business growth and institutional efficiency. Early insolvency prediction allows managers to recognize financial weakness, revise financing policies, restructure liabilities, improve asset management, and prevent the escalation of distress. It also supports investors in portfolio risk assessment and helps creditors evaluate repayment capacity. From a policy perspective, effective bankruptcy prediction contributes to market transparency and reduces the social and economic costs of corporate failure. Research on insolvency institutions and sustainable business growth emphasizes that early diagnosis of financial distress is a key requirement for improving firm survival and supporting efficient financial systems [2, 3]. Therefore, developing accurate and context-sensitive prediction models is essential for both corporate management and broader financial stability.

Overall, the literature shows that bankruptcy prediction has evolved from traditional ratio-based and statistical models toward machine learning, artificial intelligence, and optimization-based approaches. While classical models remain useful for interpretability, modern algorithms provide stronger capacity to handle nonlinear relationships, complex interactions, and high-dimensional data. At the same time, the performance of these models depends on selecting meaningful financial features and evaluating results through multiple classification metrics. The Water Cycle Algorithm offers a promising metaheuristic framework for feature selection because of its proven optimization capability and adaptability across complex problem domains. Nevertheless, its application in corporate bankruptcy prediction, particularly in emerging capital markets such as Iran, remains underdeveloped and requires empirical assessment.

The aim of this study is to explain and evaluate the Water Cycle Algorithm as a metaheuristic feature-selection method for predicting the bankruptcy of companies listed on the Tehran Stock Exchange during 2018–2021.

2. Methodology

In terms of the degree of control over the research variables, the present study is descriptive. In terms of its objective, the study is applied in nature. The present research falls within the category of correlational studies and, on the other hand, is also evaluative, because it involves a process of collecting and analyzing information for decision-making. In terms of data collection, the research method is library-based. Methodologically, it is descriptive-correlational, and because historical information of companies is used in this study, it is an ex post facto study. The variables of this study, for testing the hypotheses, are divided into two groups: dependent and independent variables. The dependent variable in this study is corporate bankruptcy, and its diagnostic criterion is Article 141 of the Iranian Commercial Code, according to which a company is considered subject to bankruptcy conditions when, due to incurred losses, at least half of the company's capital is lost. Therefore, if a company is subject to Article 141 of the Commercial Code, the value of this variable is equal to 1; otherwise, it is equal to 0. The independent variables include 24 financial ratios selected based on the results of previous studies conducted in the field of bankruptcy prediction. In selecting the variables, an attempt was made to use variables that had been identified in domestic studies as effective predictors of bankruptcy, because many financial ratios proposed in foreign studies have not been recognized as appropriate predictive factors for domestic companies and are not consistent with the conditions of domestic firms.

In terms of subject scope, this study falls within the field of accounting and finance. In terms of temporal scope, the research covers a four-year period and uses data related to the years 2018 to 2021 for 329 active companies listed on the Tehran Stock Exchange, collected from its official system.

The statistical sample of this study includes all active companies listed on the Tehran Stock Exchange that met the following conditions:

1. To increase comparability and homogenize the conditions of the sample companies, the company's fiscal year had to end in March of each year, and the fiscal year of the relevant companies must not have changed during the period for which information was available.
2. To homogenize the type of items and their classification in the financial statements, the selected company must not belong to exchange-listed industries such as banks, credit institutions and other monetary institutions, other financial intermediaries, financial investment companies, or diversified industrial holding companies. Based on the collected data, a total of 1,316 observations were examined, corresponding to 329 companies over four years. Among these observations, there were 94 bankrupt cases and 1,222 non-bankrupt cases. The data of these companies were organized based on the financial information presented in Table 1.

Table 1. Financial Information Used in the Dataset to Identify Indicators Affecting Bankruptcy

No.	Financial Information	No.	Financial Information
1	Cash holdings	12	Capital
2	Short-term investments	13	Accumulated profit and loss
3	Inventory of materials and goods	14	Shareholders' equity
4	Prepayments	15	Sales revenue
5	Current assets	16	Gross profit
6	Fixed assets	17	Operating profit/loss
7	Non-current assets	18	Financial expense
8	Total assets	19	Profit before tax
9	Current liabilities	20	Tax expense
10	Non-current liabilities	21	Net profit
11	Total liabilities	22	Net cash inflow/outflow

Based on the financial information presented in Table 1, 24 main financial ratios were ultimately selected as features affecting corporate bankruptcy. Table 2 presents the initial features examined in this study.

Table 2. Initial Features Examined in This Study for Bankruptcy Estimation

Variable	Financial Ratio / Feature Affecting Bankruptcy	Variable	Financial Ratio / Feature Affecting Bankruptcy
X1	Current liabilities / Operating profit/loss	X13	Current assets / Non-current liabilities
X2	Total liabilities / Current liabilities	X14	Total assets / Shareholders' equity
X3	Gross profit / Financial expense	X15	Total assets / Total liabilities
X4	Current liabilities / Current assets – Prepayments – Inventory of materials and goods	X16	Total assets / Non-current liabilities – Current assets
X5	Sales revenue / Operating profit/loss	X17	Total assets / Total liabilities
X6	Shareholders' equity / Accumulated profit/loss	X18	Total assets / Cash holdings + Short-term investments
X7	Sales revenue / Current assets	X19	Financial expense / Operating profit/loss
X8	Total assets / Non-current liabilities	X20	Sales revenue / Net profit
X9	Fixed assets / Sales revenue	X21	Sales revenue / Gross profit
X10	Total assets / Sales revenue	X22	Total liabilities / Shareholders' equity
X11	Total assets / Accumulated profit/loss	X23	Total assets / Net profit
X12	ln (Total assets)	X24	Total assets / Profit before tax

It should be noted that the research variables were calculated using Excel software, and then the Water Cycle Algorithm method was implemented using MATLAB software.

The Water Cycle Algorithm is a nature-inspired optimization algorithm that operates based on the natural water cycle, including evaporation, precipitation, and the flow of rivers toward the sea. Its objective is to find the best solution to a problem through an intelligent search among different possible solutions. In other words, it is based on observing the process of the water cycle in nature, and the way rivers and streams flow toward seas forms the basis of the algorithm. In general, there are three main elements in this algorithm: the sea, which represents the current best solution; rivers, which represent good solutions but not as good as the sea; and raindrops, which represent the remaining solutions that are still searching. Rainwater falls from upstream, corresponding to the initial random solutions, and gradually moves through rivers toward the sea. This movement is analogous to the search process in the solution space, with the aim of reaching the best solution. This algorithm is a powerful optimization tool that can determine the best combination or weighting for accurately predicting bankruptcy. This method was first introduced by Eskandar, Sadollah, Bahreininejad, and Hamdi (2012) to solve engineering optimization problems. They showed that the Water Cycle Algorithm has greater capability than the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in finding a range of solutions. Compared with GA and PSO, WCA has achieved remarkable success in providing high-quality solutions for many complex engineering optimization problems. As mentioned in the theoretical foundations section, given the high efficiency of the Water Cycle Algorithm in solving and predicting engineering problems, this algorithm has recently been used in the financial field in three studies:

1. Stock portfolio prediction by Moradi et al. (2017), whose results indicated the superior efficiency and performance of the Water Cycle Algorithm compared with the Genetic Algorithm and the Bird Algorithm.
2. Prediction of auditors' opinions using the Water Cycle Algorithm by Eskandar et al. (2023), whose results showed the better efficiency of this algorithm compared with the logistic algorithm.
3. Prediction of voluntary auditor change using the Water Cycle Algorithm by Eskandar et al. (2024), whose results indicated that this algorithm is more suitable than logistic regression for predicting auditor change.

Similar to other developed models, the Water Cycle Algorithm begins with an initial population, which is referred to as raindrops. First, the best and most qualified indicator, namely the best water droplet, is identified as the sea. Then, a number of good raindrops are considered rivers, and the remaining droplets are considered streams that flow into the rivers and the sea. In this method, a single solution is referred to as a "raindrop."

The main challenge at this stage is determining the fitness function for feature selection. As noted by Çınar (2023), various fitness functions exist to minimize the feature selection error for better classification. The most important of these functions are introduced below:

$$FF_1 = \text{Classification Error Rate}$$

$$FF_2 = 0.2 \times \text{Classification Error Rate} + 0.8 \times \frac{\text{Number of selected features}}{\text{Number of all features}}$$

$$FF_3 = a_{\max} \times \frac{1}{T} \times \frac{\text{Number of selected features}}{\text{Number of all features}} + \left(1 - a_{\max} \times \frac{t}{T}\right) \times \frac{\text{Classification Error Rate}}{\text{All-features error rate}}$$

$$FF_4 = a \times \text{Classification Error Rate} + (1 - a) \times \frac{\text{Number of selected features}}{\text{Number of all features}}$$

$$FF_5 = a \times \text{Classification Error Rate} + (1 - a) \times \frac{\text{Number of all features} - \text{Number of selected features}}{\text{Number of all features}}$$

$$FF_6 = 1 - \left[a \times (1 - \text{Classification Error Rate}) + (1 - a) \times \frac{1}{\text{Number of selected features}}\right]$$

$$FF_7 = 1 - \left[(1 - \text{Classification Error Rate}) + 0.001 \times \left(1 - \frac{\text{Number of selected features}}{\text{Number of all features}}\right)\right]$$

$$FF_8 = 1 - \left[0.8 \times (1 - \text{Classification Error Rate}) + 0.2 \times \left(1 - \frac{\text{Number of selected features}}{\text{Number of all features}}\right)\right]$$

$$FF_9 = 1 - \left[(1 - \text{Classification Error Rate}) + 0.8 \times \left(1 - \frac{\text{Number of selected features}}{\text{Number of all features}}\right)\right]$$

Equation 1 has been used in the studies of Gholami et al. (2020), Tu et al. (2019), Tubishat et al. (2020), and Zhou et al. (2012). Equations 2 and 4 were also used in the studies of Zhou et al. (2012a, 2012b). Because Equation 4 produced desirable results, it has been used in many studies, including Abdel-Basset et al. (2020), El-Battar et al. (2020), El-Kenawy et al. (2020), Ghosh et al. (2020), Emary et al. (2016), and Jia et al. (2019). In these studies, the value of $\alpha$was equal to 0.99. Equation 5 was also used in studies such as Gao et al. (2018), Faris et al. (2018), and Hemeida et al. (2020), in which $\alpha$was equal to 0.90. Emary et al. (2016) also used Equation 6, in which $\alpha$was equal to 0.99. Equation 7 was used in the studies of Gaha et al. (2020) and Anache et al. (2015), in which $\alpha$was equal to 0.90. Sheikh et al. (2020) and Tahir et al. (2020) also used Equation 8. Equation 9 was used in the study of Mohamed et al. (2020).

Accordingly, in the present study, the fitness function presented in Equation 4, namely FF_4, was used to select the optimal features. This equation was applied in the fitness function of the Water Cycle Algorithm to select the optimal features. Accordingly, by setting the population size to 100 and the number of iterations to 100, the optimal features were selected from the dataset. By implementing this algorithm, the convergence plot for feature selection was obtained, as shown in Figure 1.

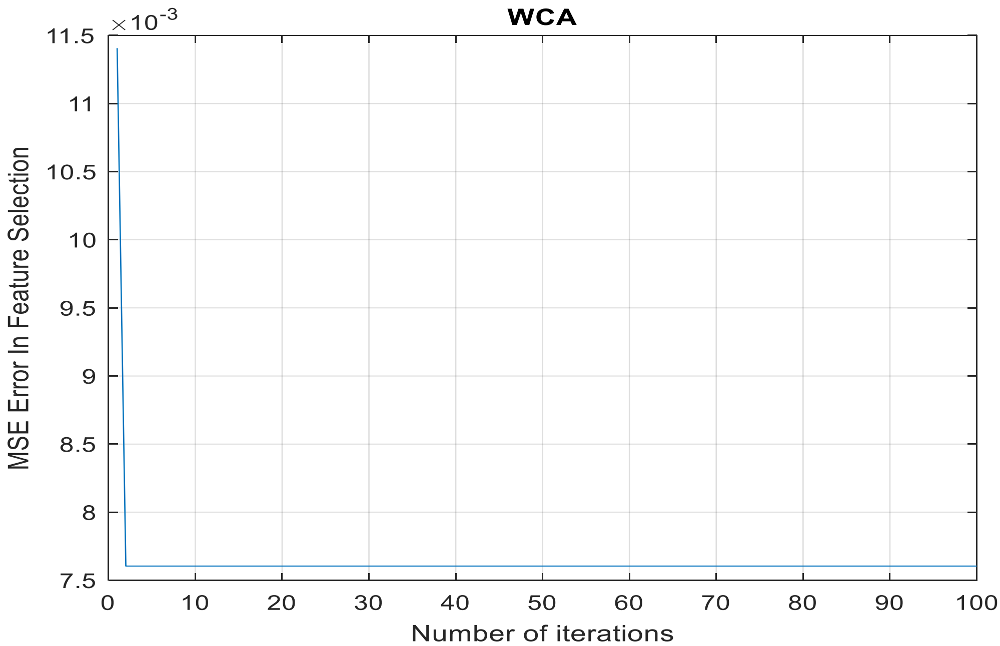

Figure 1. Convergence Plot of the Water Cycle Algorithm in Selecting Optimal Features

The result of feature selection is also presented in Table 3.

Table 3. Feature Selection Result Obtained Using the Water Cycle Algorithm

Number of Main Features	Number of Selected Features	Feature Selection Error Using the Water Cycle Algorithm (WCA)
24	14	0.0076

The features selected by the Water Cycle Algorithm are shown in Table 4.

Table 4. Features Selected by the Water Cycle Algorithm for Estimating Corporate Bankruptcy

Variable	Financial Ratio / Feature Affecting Bankruptcy	Variable	Financial Ratio / Feature Affecting Bankruptcy
X1	Current liabilities / Operating profit/loss	X11	Total assets / Shareholders' equity
X2	Total liabilities / Current liabilities	X14	Total assets / Total liabilities
X5	Sales revenue / Operating profit/loss	X17	Total assets / Cash holdings + Short-term investments
X6	Shareholders' equity / Accumulated profit/loss	X18	Total liabilities / Shareholders' equity
X7	Sales revenue / Current assets	X22	Total assets / Accumulated profit/loss
X9	Fixed assets / Sales revenue	X23	Total assets / Net profit
X10	Total assets / Sales revenue	X24	Total assets / Profit before tax

As shown, the 10 indicators $X3$, $X4$, $X8$, $X12$, $X13$, $X15$, $X16$, $X19$, $X20$, and $X21$had lower influence compared with the other indicators. Accordingly, they were removed from the final dataset and were not entered into the classification and prediction stage.

After constructing a classification model, that is, after identifying an algorithm that must determine the class or group of a new observation, the efficiency of the proposed model was evaluated by comparing the model output with the actual output, as shown in Table 5.

Table 5. Confusion Matrix

Actual Group	Predicted Positive	Predicted Negative	Evaluation Criterion
Positive	True Positive (TP)	False Negative (FN), Type II Error	Sensitivity: $\frac{TP}{TP+FN}$
Negative	False Positive (FP), Type I Error	True Negative (TN)	Specificity: $\frac{TN}{TN+FP}$
Evaluation Criterion	Precision: $\frac{TP}{TP+FP}$	Negative Predictive Value: $\frac{TN}{TN+FN}$	Accuracy: $\frac{TP+TN}{TP+TN+FP+FN}$

When the basis of analysis is the evaluation and efficiency of a model in classification problems, the confusion matrix, as shown in Table 5, functions as a binary classification model, for example healthy or bankrupt, to summarize model performance. It includes the following elements:

TPrepresents a correct positive prediction, or true positive. In fact, it refers to the number of records whose actual class was positive and whose class was correctly identified as positive by the classification algorithm.

FNrepresents an incorrect negative prediction, or false negative/type II error. In fact, it refers to the number of records whose actual class was positive but whose class was incorrectly identified as negative by the classification algorithm.

FPrepresents an incorrect positive prediction, or false positive/type I error. In fact, it refers to the number of records whose actual class was negative but whose class was incorrectly identified as positive by the classification algorithm.

TNrepresents a correct negative prediction, or true negative. In fact, it refers to the number of records whose actual class was negative and whose class was correctly identified as negative by the classification algorithm.

NPVrepresents the negative predictive value and indicates the percentage of samples predicted by the model as negative that are actually negative.

3. Findings and Results

The confusion matrix obtained from applying the Water Cycle Algorithm across 100 implementations is presented in Table 6. Based on the output results, among the companies that were actually bankrupt ($n = 94$), 92 companies were correctly predicted. The number of companies that were actually bankrupt ($n = 94$)but were incorrectly predicted was 2. Among the companies that were actually non-bankrupt ($n = 1{,}222$), 1,104 companies were correctly predicted. The number of companies that were actually healthy ($n = 1{,}222$)but were incorrectly predicted was 118. This indicates that the model tends to be overly cautious. According to Table 7, the model's precision, accuracy, sensitivity, and specificity were 98.77%, 97.86%, 98.16%, and 90.32%, respectively. Furthermore, based on the calculation of the negative predictive value (NPV), the model predicted bankruptcy and non-bankruptcy correctly with approximately 99% probability.

Table 6. Output of the Water Cycle Algorithm Across 100 Implementations

Actual Group	Predicted 1	Predicted 0	Evaluation Criterion
1	$TP = 92$	$FN = 2$	Sensitivity = 98.16%
0	$FP = 118$	$TN = 1104$	Specificity = 90.32%
AUC		$AUC \approx 0.9424$	
Evaluation Criteria	Precision = 98.77%	$NPV \approx 99.82\%$	Accuracy = 97.86%

Table 7. Results of the Water Cycle Algorithm (WCA) in Bankruptcy Prediction

Criterion	Value (%)
Accuracy	97.86
Precision / Positive Predictive Value	98.77
Sensitivity	98.16
Specificity	90.32

Based on the results presented in Table 7, the Water Cycle Algorithm, with an accuracy value of 97.86%, indicates that the model generally has excellent performance and correctly classified nearly 99% of the total samples. Moreover, with a sensitivity value of 98.16%, the model was able to correctly identify actual positive cases. In other words, the false negative error rate was very low. The high percentage of positive precision confirms that the model performed very strongly in predicting positive samples and had only about 1.2% false positive error, meaning that most positive predictions were actually correct. Therefore, the model was able to predict corporate bankruptcy with very high performance.

Based on the negative predictive value (NPV)of approximately 99%, when the model predicts a sample as negative, there is nearly a 99% probability that the sample is actually negative. The final value of $AUC \approx 0.9424$indicates that the model has very good performance, because an AUC value close to 1 represents a very strong model. This value indicates, with approximately 94% probability, the high ability of the model to distinguish between bankrupt and non-bankrupt companies.

4. Discussion and Conclusion

The purpose of this study was to explain and evaluate the performance of the Water Cycle Algorithm (WCA) as a metaheuristic optimization approach for corporate bankruptcy prediction among companies listed on the Tehran Stock Exchange. The findings demonstrated that the Water Cycle Algorithm successfully reduced the initial set of 24 financial ratios to 14 optimal features and achieved an overall prediction accuracy of 97.86%, a precision of 98.77%, a sensitivity of 98.16%, a specificity of 90.32%, a negative predictive value of approximately 99%, and an area under the curve (AUC) of 0.9424. These results indicate that the proposed model was highly effective in distinguishing between bankrupt and non-bankrupt firms and that the selected financial indicators provided substantial discriminatory power for bankruptcy classification.

One of the most important findings of this study was the ability of the Water Cycle Algorithm to identify a relatively small subset of financial ratios while maintaining a very high prediction accuracy. This result confirms the importance of feature selection in bankruptcy prediction models. In many financial distress studies, the inclusion of excessive financial indicators may increase noise, reduce interpretability, and introduce redundancy into predictive models. By selecting only 14 effective indicators from an initial pool of 24 variables, the Water Cycle Algorithm was able to minimize classification error while preserving predictive performance. This finding is consistent with studies emphasizing the critical role of feature selection and optimization in financial distress prediction. For example, machine learning investigations have demonstrated that the quality of selected features significantly influences model performance and predictive reliability [8, 12]. Similarly, systematic reviews of artificial intelligence applications in accounting and forecasting have highlighted that selecting relevant predictors is often more influential than increasing model complexity [11].

The very high classification accuracy obtained in this study further supports the growing body of literature suggesting that optimization-based and artificial intelligence approaches outperform many traditional statistical methods in bankruptcy prediction. The achieved accuracy of 97.86% exceeds the predictive performance commonly reported for conventional financial distress models based solely on accounting ratios or logistic regression. Previous research has shown that machine learning techniques can capture nonlinear relationships among financial variables and therefore generate more accurate bankruptcy predictions than traditional linear methods [9, 18]. Likewise, optimized deep learning frameworks and ensemble-learning approaches have demonstrated superior predictive capabilities when compared with classical classification techniques [12, 13]. The findings of the present study reinforce this conclusion and suggest that WCA-based optimization can substantially improve bankruptcy prediction performance.

Another noteworthy finding concerns the model's sensitivity value of 98.16%. Sensitivity reflects the ability of the model to correctly identify bankrupt firms. In practical terms, this means that only a very small proportion of distressed companies were misclassified as financially healthy. This result is particularly important because false negative errors represent one of the most costly mistakes in bankruptcy prediction. When a distressed company is incorrectly classified as healthy, creditors, investors, auditors, and managers may fail to take preventive action, resulting in significant financial losses. Previous studies have emphasized the importance of maximizing sensitivity in financial distress models because the consequences of failing to detect bankruptcy are generally more severe than the consequences of incorrectly labeling a healthy company as distressed [6, 7]. Therefore, the high sensitivity observed in the present study demonstrates the practical usefulness of the proposed model as an early warning system.

The specificity value of 90.32% also indicates a strong ability to correctly identify non-bankrupt companies. Although specificity was somewhat lower than sensitivity, it remained at a very satisfactory level. This outcome suggests that the model maintained a reasonable balance between detecting distressed firms and avoiding excessive false alarms. In bankruptcy prediction research, achieving high sensitivity often comes at the expense of lower specificity because models become more conservative and classify more firms as potentially distressed. The present findings indicate that the Water Cycle Algorithm successfully balanced these competing objectives and maintained strong classification performance across both categories. This result aligns with studies highlighting the importance of evaluating bankruptcy prediction models through multiple performance indicators rather than relying exclusively on overall accuracy [8, 13].

The precision value of 98.77% and the negative predictive value of approximately 99% further confirm the robustness of the proposed model. Precision reflects the proportion of predicted bankrupt firms that were actually bankrupt, while negative predictive value indicates the probability that firms predicted as healthy were truly healthy. The high values observed for both indicators demonstrate that the model generated reliable classifications across both categories. These findings are consistent with recent studies emphasizing the importance of reducing both false positive and false negative errors in financial risk assessment and insolvency prediction [17, 18]. In practical applications, high precision can improve investor confidence in prediction outputs, while high negative predictive value can help managers and creditors identify financially stable firms with greater certainty.

The obtained AUC value of 0.9424 provides additional evidence regarding the effectiveness of the proposed model. An AUC value exceeding 0.90 is generally considered indicative of excellent discriminatory performance. This means that the model possesses a very strong ability to distinguish between bankrupt and non-bankrupt firms across different classification thresholds. Similar studies employing machine learning and optimized prediction frameworks have reported that AUC is one of the most informative measures for evaluating bankruptcy prediction models because it assesses overall discrimination capability independent of a specific classification threshold [9, 12]. The high AUC value obtained in the present study therefore confirms that the Water Cycle Algorithm provides a reliable basis for bankruptcy classification.

From a financial perspective, the selected features reveal important insights into the determinants of corporate bankruptcy. Most of the retained variables were related to leverage, profitability, liquidity, operational efficiency, and capital structure. This finding is theoretically meaningful because bankruptcy is generally preceded by deterioration in these financial dimensions. Previous studies have consistently reported that leverage ratios, liquidity measures, profitability indicators, and capital structure variables are among the strongest predictors of financial distress and bankruptcy risk [4-6]. The feature selection results of the present study therefore support the broader literature and suggest that the Water Cycle Algorithm successfully identified financially meaningful predictors rather than merely statistical artifacts.

The findings also support recent research emphasizing that bankruptcy is influenced not only by operational performance but also by broader governance and managerial factors. Although the present study focused on financial ratios, the selected indicators may indirectly capture managerial decision quality, financing strategies, and risk management effectiveness. For example, excessive leverage, declining profitability, and inefficient asset utilization often reflect weaknesses in strategic planning and governance structures. Recent evidence suggests that corporate governance failures, earnings management practices, and creative accounting behavior may increase bankruptcy risk and weaken financial stability [14-16]. Consequently, the strong predictive performance observed in this study may partly reflect the ability of financial indicators to capture underlying governance-related vulnerabilities.

A particularly important contribution of this study is the successful application of the Water Cycle Algorithm in a financial context. Although WCA was originally developed for engineering optimization problems, its use in financial prediction remains relatively limited. The current findings provide empirical evidence that WCA can effectively perform feature selection and improve classification accuracy in bankruptcy prediction tasks. This result is consistent with the original studies introducing and extending the algorithm, which demonstrated its capability for solving complex optimization problems and identifying high-quality solutions in multidimensional search spaces [20, 21]. Furthermore, subsequent developments incorporating chaotic mechanisms and enhanced exploration strategies showed that WCA possesses strong optimization capabilities compared with alternative metaheuristic methods [22]. The present study extends this evidence by demonstrating the applicability of WCA within accounting and financial management research.

The findings are also consistent with the broader literature examining the practical effectiveness of the Water Cycle Algorithm. Reviews of WCA applications have reported successful implementation across numerous domains, including structural optimization, scheduling, energy systems, and computational intelligence [23]. Likewise, studies applying WCA to hydrothermal coordination and other optimization problems have reported high-quality solutions and strong convergence characteristics [24]. The ability of WCA to achieve excellent bankruptcy prediction performance in the present study suggests that its optimization mechanisms are sufficiently flexible to address financial classification problems in addition to engineering applications.

Another important implication concerns the growing role of artificial intelligence and optimization in financial management. Contemporary financial environments generate large volumes of data and involve increasingly complex relationships among financial indicators. Traditional statistical approaches may not adequately capture these complexities. Consequently, researchers have increasingly advocated the integration of optimization algorithms, machine learning methods, and hybrid prediction systems into financial risk assessment frameworks [11, 19]. The findings of the present study provide empirical support for this perspective and demonstrate that optimization-driven feature selection can significantly improve bankruptcy prediction performance.

Finally, the results contribute to the ongoing discussion regarding the importance of early bankruptcy detection for sustainable business development. Effective bankruptcy prediction provides opportunities for timely intervention, restructuring, improved risk management, and more informed investment decisions. Research on insolvency institutions and sustainable business growth has consistently emphasized that early detection of financial distress can reduce economic losses and improve organizational resilience [1-3]. The high predictive performance achieved in this study indicates that the Water Cycle Algorithm can serve as a valuable tool for supporting these objectives and enhancing decision-making among managers, investors, creditors, auditors, and regulators.

Despite the promising findings, several limitations should be acknowledged. First, the study focused exclusively on companies listed on the Tehran Stock Exchange, which may limit the generalizability of the findings to firms operating in different institutional and economic environments. Second, only financial ratios were included as predictive variables, whereas governance indicators, macroeconomic variables, market-based measures, and qualitative information were not incorporated into the analysis. Third, the sample contained a substantially smaller number of bankrupt firms compared with non-bankrupt firms, creating a degree of class imbalance despite the strong predictive performance achieved. Finally, the study evaluated only the Water Cycle Algorithm and did not conduct a direct empirical comparison with a broad range of alternative metaheuristic optimization methods under identical conditions.

Future studies should examine the performance of the Water Cycle Algorithm in different industries, countries, and regulatory environments to evaluate its generalizability. Researchers may also integrate financial variables with governance indicators, market-based information, environmental factors, and macroeconomic measures to construct more comprehensive bankruptcy prediction models. Comparative investigations involving alternative optimization algorithms, such as genetic algorithms, particle swarm optimization, ant colony optimization, and newer hybrid metaheuristic methods, could provide additional insights into the relative strengths and weaknesses of different approaches. Furthermore, future studies may explore hybrid frameworks that combine Water Cycle Algorithm-based feature selection with advanced deep learning architectures, ensemble methods, or explainable artificial intelligence techniques.

Managers should employ intelligent bankruptcy prediction systems as part of their strategic risk management processes and regularly monitor key financial indicators associated with liquidity, profitability, leverage, and operational efficiency. Investors and creditors can utilize optimized prediction models to improve portfolio evaluation, credit assessment, and investment decision-making. Auditors may incorporate advanced prediction systems into analytical review procedures to identify early warning signals of financial distress. Regulatory authorities and stock exchange supervisors can also benefit from such models by establishing monitoring mechanisms capable of identifying vulnerable firms before severe financial deterioration occurs. Finally, organizations should invest in analytical infrastructure and data-driven decision-making capabilities to enhance their ability to detect and respond to financial distress at an early stage.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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References

[1] J. Wang, M. Li, M. Skitmore, and J. Chen, "Predicting Construction Company Insolvent Failure: A Scientometric Analysis and Qualitative Review of Research Trends," *Sustainability*, vol. 16, no. 6, p. 2290, 2024, doi: 10.3390/su16062290.

[2] Y. Zhou, Z. Qi, and S. Jiang, "A Survey of Research on Efficiency of Insolvency/Bankruptcy Institutions and Financial Distress," pp. 23-33, 2023, doi: 10.2991/978-94-6463-246-0_4.

[3] D. Kušter, B. Vuković, S. Milutinović, K. Peštović, T. Tica, and D. Jakšić, "Early Insolvency Prediction as a Key for Sustainable Business Growth," *Sustainability*, vol. 15, no. 21, p. 15304, 2023, doi: 10.3390/su152115304.

[4] R. Poliakov and I. Zayukov, "Assessment of the Relationship Between Liquidity and Unprofitability of Companies in Preventing Their Bankruptcy," *Problems and Perspectives in Management*, vol. 21, no. 1, pp. 141-153, 2023, doi: 10.21511/ppm.21(1).2023.13.

[5] R. Baha, A. Lévy, and A. Hasnaoui, "Capital Structure and Default Risk of Small and Medium Enterprises: Evidence From Algeria," *The Journal of Risk Finance*, vol. 24, no. 4, pp. 523-536, 2023, doi: 10.1108/jrf-04-2023-0105.

[6] S. Gyawali, "Exploring Financial Distress Through Altman Z" Score: Example of Selected Private Commercial Banks in Nepal," *Journal of Emerging Management Studies*, vol. 1, no. 1, pp. 94-107, 2023, doi: 10.3126/jems.v1i1.60165.

[7] A. V. Rejimon and M. Usha, "Financial Distress Analysis for the Prediction of Corporate Bankruptcy – A Case Study of a Public Sector Company in India," *Salud Ciencia Y Tecnología - Serie De Conferencias*, vol. 3, p. 904, 2024, doi: 10.56294/sctconf2024904.

[8] O. Liashenko, T. Kravets, and Y. Kostovetskyi, "Machine Learning and Data Balancing Methods for Bankruptcy Prediction," *Ekonomika*, vol. 102, no. 2, pp. 28-46, 2023, doi: 10.15388/ekon.2023.102.2.2.

[9] D. Máté, H. Raza, and I. Ahmad, "Comparative Analysis of Machine Learning Models for Bankruptcy Prediction in the Context of Pakistani Companies," *Risks,* vol. 11, no. 10, p. 176, 2023, doi: 10.3390/risks11100176.

[10] K. Fodor, "Classification of Retail Loans Using Decision Tree," *Multidiszciplináris Tudományok,* vol. 13, no. 3, pp. 212-220, 2023, doi: 10.35925/j.multi.2023.3.21.

[11] M. Kureljusic and E. Karger, "Forecasting in Financial Accounting with Artificial Intelligence – A systematic Literature Review and future Research Agenda," *Journal of Applied Accounting Research,* vol. 25, no. 1, pp. 81-104, 2023, doi: 10.1108/jaar-06-2022-0146.

[12] D. Quinteros-Navarro and C. Rodríguez, "Optimized Deep Learning Model to Predict Business Bankruptcy," *Ingénierie Des Systèmes D Information,* vol. 29, no. 5, pp. 1763-1777, 2024, doi: 10.18280/isi.290510.

[13] S. A. Safi, P. Á. Castillo, and H. Faris, "Cost-Sensitive Metaheuristic Optimization-Based Neural Network With Ensemble Learning for Financial Distress Prediction," *Applied Sciences,* vol. 12, no. 14, p. 6918, 2022, doi: 10.3390/app12146918.

[14] N. M. Tsabita and A. Gunadi, "Corporate governance failures leading to bankruptcy in state-owned enterprises (SOEs)," *Subsidiari,* vol. 10, no. 2, 2025. [Online]. Available: https://acopen.umsida.ac.id/index.php/acopen/article/view/12991.

[15] K. Rabiei and H. Fotouhi Fashtami, "Investigating the Nonlinear Impact of Earnings Management and Business Strategy on Corporate Bankruptcy Risk Using the Generalized Method of Moments (GMM)," *Management Accounting and Auditing Knowledge,* vol. 14, no. 56, pp. 183-192, 2025. [Online]. Available: https://www.jmaak.ir/article_23510.html?lang=en.

[16] J. Pourghaffar and A. Eghbal Mazraeh, "The Relationship between Creative Accounting and Corporate Bankruptcy in Companies Listed on the Tehran Stock Exchange," in *First National Conference on Professional Ethics and Social Responsibility in Management and Financial Sciences with an Islamic Approach*, Urmia, 2025. [Online]. Available: https://civilica.com/doc/2441573.

[17] E. G. Shershneva and M. Z. Hao, "Russian Banks Financial Stability Loss Diagnostic: Multidimensional Logit-Model Approach," *Journal of Applied Economic Research,* vol. 23, no. 2, pp. 476-498, 2024, doi: 10.15826/vestnik.2024.23.2.019.

[18] S. H. S. Nor, S. Ismail, and Y. B. Wah, "Personal Bankruptcy Prediction Using Logistic Regression Model," *Information Management and Business Review,* vol. 16, no. 3S(I)a, pp. 366-378, 2024, doi: 10.22610/imbr.v16i3s(i)a.4139.

[19] M. Azarbad, A. Shojaie, F. Abdi, V. Ghezavati, and K. Khalili-Damghani, "Reduction of Insolvency Risk and Total Costs in Banking Sector Using Partners Selection Approach With Genetic Algorithm and Multilayer Perceptron Neural Network," *International Journal of Engineering,* vol. 37, no. 8, pp. 1667-1690, 2024, doi: 10.5829/ije.2024.37.08b.18.

[20] H. Eskandar, A. Sadollah, A. Bahreininejad, and M. Hamdi, "Water Cycle Algorithm -- A Novel Metaheuristic Optimization Method for Solving Constrained Engineering Optimization Problems," *Computers & Structures,* vol. 110-111, pp. 151-166, 2012.

[21] A. Sadollah, H. Eskandar, and J. H. Kim, "Water Cycle Algorithm for Solving Constrained Multi-Objective Optimization Problems," *Applied Soft Computing,* vol. 27, pp. 279-298, 2015.

[22] A. A. Heidari, R. A. Abbaspour, and A. Rezaee Jordehi, "An Efficient Chaotic Water Cycle Algorithm for Optimization Tasks," *Neural Computing and Applications,* vol. 28, pp. 57-85, 2017.

[23] M. Nasir, A. Sadollah, Y. H. Choi, and J. H. Kim, "A Comprehensive Review on Water Cycle Algorithm and Its Applications," *Neural Computing and Applications,* vol. 32, pp. 17433-17488, 2020.

[24] S. S. Haroon and T. N. Malik, "Short-Term Hydrothermal Coordination Using Water Cycle Algorithm with Evaporation Rate," *International Transactions on Electrical Energy Systems,* vol. 27, no. 8, p. e2349, 2017.

[25] M. N. Nezami, F. M. Nodeh, and S. Khordyar, "Modeling Bankruptcy Prediction with Emphasis on Modern Measurement Methods Using Neural Networks and Support Vector Machines," *Journal of Accounting and Management Auditing,* vol. 55, pp. 265-278, 2025.