

Evaluating Class-Imbalanced Data Handling for Enhanced Financial Distress Prediction Using an Attention-Based Deep Neural Network and Heuristic Optimization Algorithms

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ABSTRACT

Financial distress prediction remains important for identifying companies at risk, as it reflects both business stability and economic forecasting accuracy. A major challenge in financial distress data is class imbalance. Deep Learning (DL) techniques have gained global acceptance for financial distress prediction due to their powerful nonlinear modeling capabilities, which capture complex patterns in financial data and enhance prediction performance. This paper proposes an Enhanced Financial Distress Prediction method using Attention-based Deep Neural Network and Heuristic Optimization Algorithms (EFDP-ADNNHOA). The method evaluates the effectiveness of data handling in improving the precision and reliability of financial distress prediction models. The EFDP-ADNNHOA framework begins with data pre-processing, including data cleaning and Z-score normalization to standardize inputs. Feature Selection (FS) is performed using the Flying Fox Optimizer Algorithm (FFOA), whereas classification is carried out with the Bidirectional Gated Recurrent Unit with Attention (BiGRU-A). Finally, the Coati Optimization Algorithm (COA) fine-tunes the parameters of the BiGRU-A model. Tested on the Australian Credit dataset, EFDP-ADNNHOA outperformed existing methods, achieving 97.06% accuracy.

Keywords-financial distress prediction; class imbalance; data handling; Coati Optimization Algorithm (COA); attention; deep neural network

I. INTRODUCTION

Business and economic stability largely depend on the accurate prediction of financial distress in today's rapidly evolving economic environment [1]. A key challenge in financial distress data is class imbalance, as distressed cases are far fewer than non-distressed ones. Accurate prediction enables stakeholders to assess bankruptcy risk and implement preventive actions [2]. The dominance of stable firms makes distress detection difficult, yet it remains crucial for lending decisions and the evaluation of financial institutions [3]. Financial reports, particularly cash flow statements, play an essential role in forecasting distress [4]. Previous studies have utilized financial data from different periods to classify companies experiencing prolonged financial difficulties [5], and financial indicators from pre-delisting periods have been shown to help detect distress [6]. Traditional methods, based on rigid assumptions and expert judgment [7], often lack adaptability to real-world conditions [8]. In contrast, Machine learning (ML) models, such as ensemble methods, Deep Learning (DL), Decision Trees (DTs), Long Short-Term Memory (LSTM) and Logistic Regression (LR), demonstrate higher accuracy and stronger recognition capabilities [9, 10].

Authors in [11] presented a detailed and precise prediction tool using ensemble ML and feature optimization models, where the Modified Dandelion Optimizer (MDO) captured complex patterns and the Chaotic Secretary Bird Optimizer (CSBO) reduced data dimensionality. In [12], an Adaptive Whale Optimization Algorithm with a DL model (AWOA-DL) was proposed, where AWOA was applied for tuning and a Multilayer Perceptron (MLP) for prediction. Authors in [13] introduced the Extended Osprey Optimizer Algorithm with a Bayesian Neural Network (BNN) for Predicting Financial Crisis (EOOABNNPFC), combining EOOA-based Feature Selection (FS) with a BNN for optimal FS and prediction. Authors in [14] proposed a Jellyfish Search Algorithm-based FS with an optimum DL model (JSAFS-ODL) for Financial Crisis Prediction (FCP), where JSA and Recurrent Neural Network-Gated Recurrent Unit (RNN-GRU) models were used for FS and prediction, and the Coati Optimizer Algorithm (COA) was applied for tuning.

Authors in [15] addressed financial crisis early warning for Small and Medium-sized Enterprises (SMEs). Authors in [16] introduced Lightspace-SMOTE, combined with the LiFoL ensemble model integrating focal loss and LightGBM. Authors in [17] proposed an Attention-based Fuzzy Neural Network (AFNN) technique for crisis prediction. Authors in [18] developed the White Shark Optimizer with DL-based Bankruptcy Prediction for Financial Crisis Assessment (WSODL-BPFCA), applying min-max scaling and an Attention-based LSTM (ALSTM) model, with hyperparameters optimized by WSO. Authors in [19] combined Convolutional Neural Network (CNN), Bidirectional LSTM (BiLSTM), and Attention Mechanism (AM), optimized with hyperband and SMOTE. Authors in [20] presented a hybrid DL approach that integrates peephole LSTM with a Temporal Attention Layer (TAL) to improve prediction.

This paper proposes an Enhanced Financial Distress Prediction method using Attention-based Deep Neural Network and Heuristic Optimization Algorithms (EFDP-ADNNHOA). The major contributions of the EFDP-ADNNHOA model are as follows:

- Data cleaning and Z-score normalization are applied during pre-processing to standardize input data and improve reliability, contributing to enhanced learning efficiency and reduced noise in classification.
- The Flying Fox Optimizer Algorithm (FFOA) is used for effective FS, mitigating dimensionality and computational cost while retaining critical information, thereby enhancing classification performance and model interpretability.
- The Bidirectional Gated Recurrent Unit with Attention (BiGRU-A) captures temporal and contextual patterns for classification, whereas COA fine-tunes its parameters to improve prediction stability and performance.
- The EFDP-ADNNHOA model introduces a hybrid framework integrating FFOA, BiGRU-A, and COA to improve learning efficiency, capture complex patterns, and ensure robust classification. The novelty lies in the dual-optimizer strategy tailored for high-accuracy financial distress prediction.

II. MATERIALS AND METHODS

In this article, the EFDP-ADNNHOA technique is proposed. The aim is to enhance the accuracy and reliability of financial distress predictions through effective data handling. Figure 1 illustrates the overall workflow of the EFDP-ADNNHOA model.

A. Data Cleaning and Standardization

The EFDP-ADNNHOA model begins with a data pre-processing stage that includes data cleaning and Z-score standardization to transform the data into a suitable format [21]. Data cleaning is performed by checking for null values using the null function, confirming that the dataset contains no missing entries. To prepare the data for ML, any duplicates and nulls are removed, ensuring a clean dataset. Next, Z-score standardization is applied to normalize the data by adjusting the mean to 0 and the standard deviation to 1, improving consistency across features:

$$x' = \frac{x - \mu}{\sigma} \quad (1)$$

where μ denotes mean and σ represents the standard deviation.

After standardization, the data distribution is examined to ensure that the procedure has not introduced bias or removed significant information.

B. Dimensionality Reduction Using Flying Fox Optimizer Algorithm

For the FS process, the FFOA is employed to identify beneficial feature subsets. The FFOA is a nature-inspired meta-heuristic model based on the hunting behavior of the flying fox, which searches for food in swarms [22]. The algorithm replicates this swarm behavior to find optimal solutions by

balancing exploration and exploitation, with agents updating their positions through either random search or convergence:

$$X_i^{t+1} = X_i^t + \alpha \cdot r_1 \cdot (G^t - X_i^t) + \beta \cdot r_2 \cdot (P_i^t - X_i^t) \quad (2)$$

where X_i^t is the position of the i -th fox at iteration t , G^t is the global best solution found so far, P_i^t is the personal best position of the i -th fox, α , β are learning factors balancing exploration and exploitation, and $r_1, r_2 \in [0,1]$ are random

vectors introducing stochasticity. The fitness of candidate solutions is evaluated using a multi-objective function:

$$f(X) = w_1 \cdot T_r^{-1} + w_2 \cdot C_r + w_3 \cdot E_r \quad (3)$$

where T_r is recovery time (to be minimized), C_r is connectivity (to be maximized), E_r is energy efficiency (to be maximized), and w_1, w_2, w_3 are application-dependent weights.

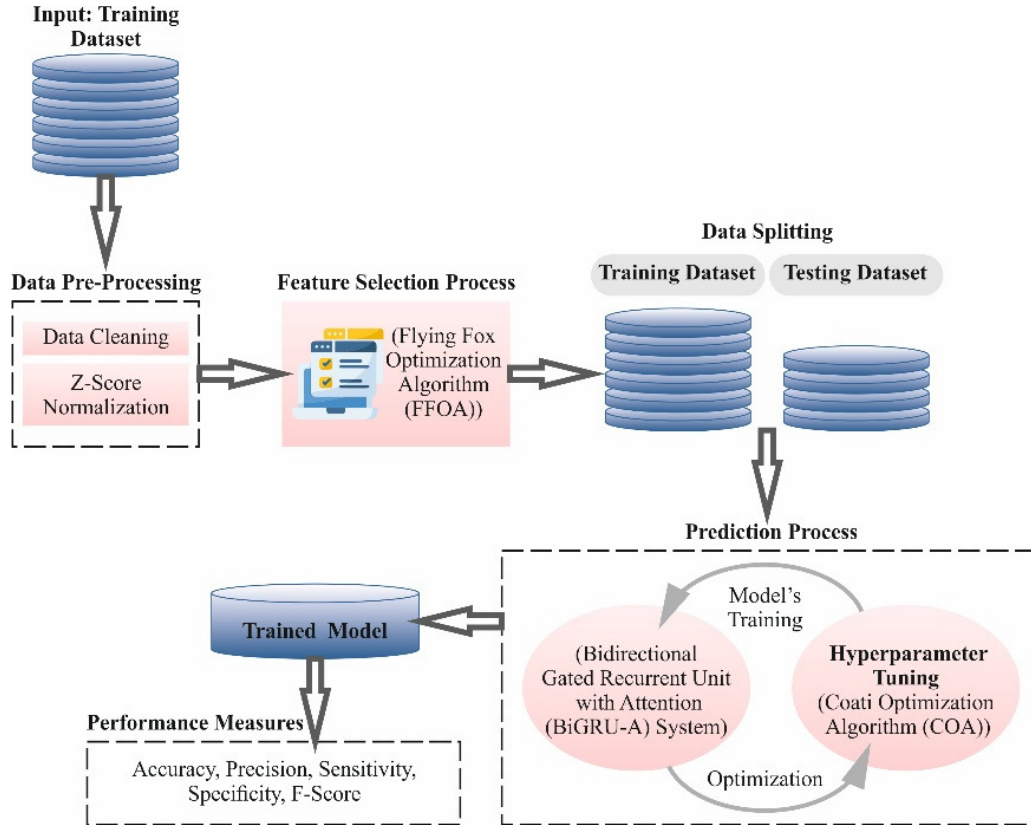


Fig. 1. Overall workflow of the EFDP-ADNNHOA model.

1) Initialization Population

The initial population of flying foxes is randomly distributed within the search space, representing possible routing or recovery strategies. These positions are constrained within feasible solution bounds. The objective function $f(X)$ determines the fitness of each fox, with high fitness assigned to solutions that minimize recovery time while maximizing connectivity and energy efficiency.

2) Exploration and Exploitation Mechanisms

Exploration and exploitation are controlled through the adaptive parameters α and β . Early iterations concentrate on exploration, enabling foxes to cover a wide search space, whereas later iterations focus on exploitation, refining solutions near the global optimum. Exploration includes random perturbations in fox positions to maintain diversity:

$$X_i^{t+1} = X_i^t + \gamma \cdot U \quad (4)$$

where U denotes a uniformly distributed random vector and γ controls the step size. Exploitation uses knowledge of the global best solution, directing foxes toward promising areas:

$$X_i^{t+1} = X_i^t + \delta \cdot (X_{best}^t - X_i^t) \quad (5)$$

where δ dynamically adjusts with the iteration number to accelerate convergence. Equation (4) promotes exploration in early iterations, whereas (5) enhances exploitation in later stages for local refinement.

The final fitness function considers both classifier accuracy and the number of selected features:

$$Fitness = \alpha \cdot ErrorRate + (1 - \alpha) \cdot \frac{\#SF}{\#All_F} \quad (6)$$

Here, $ErrorRate$ represents the classification error rate (ranging from 0 to 1), $\#SF$ denotes the number of selected features, and $\#All_F$ is the total number of features in the dataset. The parameter α balances the trade-off between classification quality and feature subset length.

C. Classification Using Attention-Based Bidirectional Gated Recurrent Unit

The BiGRU-A system is employed as the classification model. Conventional RNNs can encode sequential data [23], but they often struggle with long-term dependencies. To address this limitation, LSTM and GRU networks were introduced, improving prediction outcomes while requiring fewer matrix multiplications. Compared with LSTM, the GRU framework is simpler and contains fewer parameters. GRU combines a reset gate r_t and an update gate z_t to regulate information flow. At the current time step t , the update equations are as follows:

$$z_t = \sigma(U_z f_t + W_z h_{t-1} + b_z) \quad (7)$$

$$r_t = \sigma(U_r f_t + W_r h_{t-1} + b_r) \quad (8)$$

$$c_t = \tanh(U_c f_t + r_t(W_c \odot h_{t-1}) + b_c) \quad (9)$$

$$h_t = (1 - z_t) \odot c_t + z_t \odot h_{t-1} \quad (10)$$

where h_t and f_t denote the output and input at time step t , h_{t-1} is the output from the previous step, c_t is the candidate state, and b_i , U_i , W_i represent the bias, input, and recurrent weight matrices for z_t , r_t , and c_t , respectively.

Although GRU generally outperforms LSTM and RNNs, BiGRU was introduced to capture information in both forward and backward directions. At time step t , with input dimension d , the forward GRU input is $f_t(t = 1, 2, \dots, d)$, and the backward GRU input $f_t(t = d, d - 1, \dots, 1)$. The BiGRU outputs are computed as:

$$\vec{h}_t = \overrightarrow{GRU}(\vec{h}_{t-1}, f_t), \quad t = 1, 2, \dots, d \quad (11)$$

$$\overleftarrow{h}_t = \overleftarrow{GRU}(\overleftarrow{h}_{t+1}, f_t), \quad t = d, d - 1, \dots, 1 \quad (12)$$

$$h_t = [\vec{h}_t, \overleftarrow{h}_t] \quad (13)$$

1) Attention Mechanism

Attention is applied after the BiGRU to emphasize key features using query (Q), key (K), and value (V) matrices, improving model focus and performance. Given an input X , the attention computation is defined as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right) \quad (14)$$

where $Q = W_q X$, $K = W_k X$, $V = W_v X$, and X is the input. The parameter d denotes the dimensionality of Q and K , whereas W_q , W_k , and W_v are the weighted matrices applied to compute Q , K , and V , respectively.

D. Coati Optimization Algorithm for Parameter Optimization

Finally, the COA is used to fine-tune model parameters. The COA is a nature-inspired swarm intelligence optimizer based on the hunting behavior of coatis, which hunt iguanas and avoid predators [24]. This model provides robust global search and fast convergence, although it may suffer from limited initial coverage, local optima, or slower convergence in multi-modal problems. The initial population is generated as follows.

$$X_i: x_{i,j} = lb_j + r \cdot (ub_j - lb_j), \quad i = 1, 2, \dots, N, \quad j = 1, 2, \dots, m \quad (15)$$

where X_i denote the location of the i -th coati in the search space, $x_{i,j}$ is the value of the j -th decision variable, N is the population size, m is the number of decision variables, $r \in [0, 1]$ is a random number, and lb_j and ub_j are the lower and upper bounds of the j -th variable.

1) Exploration Stage

During exploration, the COA simulates coatis attacking iguanas. Half of the coatis climb trees to approach the prey, while the others remain on the ground. The individual with the highest fitness represents the iguana's location.

For tree-climbing coatis:

$$X_i^{P1}: x_{i,j}^{P1} = x_{i,j} + \text{rand}(0,1) \cdot (G_j - I \cdot x_{i,j}), \quad i = 1, 2, \dots, \left\lfloor \frac{N}{2} \right\rfloor, \quad j = 1, 2, \dots, m \quad (16)$$

where X_i^{P1} is the new location of the i -th coati, G_j is the iguana's location in the j -th dimension, and $I \in \{1, 2\}$ is a random factor. If the iguana drops to the ground, it moves to a random location:

$$G^g: G_j^g = ub_j + \text{rand}(0,1)(ub_j - lb_j) \quad (17)$$

For ground-based coatis, the location is updated as:

$$X_i^{P1}: x_{i,j}^{P1} = \begin{cases} x_{i,j} + \text{rand}(0,1) \cdot (G_j^g - I x_{i,j}), & F_{i,j}^g \leq F_i \\ x_{i,j} + \text{rand}(0,1) \cdot (x_{i,j} - G_j^g), & \text{otherwise} \end{cases} \quad (18)$$

where $i = \left\lfloor \frac{N}{2} \right\rfloor + 1, \dots, N$, $j = 1, 2, \dots, m$, G_j^g is the position of the iguana on the ground, and F is the objective function value.

After evaluation, if the new location improves the objective function, it is accepted; otherwise, the coati remains at its original position:

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} \leq F_i \\ X_i, & \text{otherwise} \end{cases} \quad (19)$$

These strategies allow COA to balance local exploitation and global exploration effectively.

2) Exploitation Stage

In the second stage, the COA simulates coatis evading predators by moving to safer nearby locations. The updated position is:

$$X_i^{P2}: x_{i,j}^{P2} = x_{i,j} + (1 - 2r) \cdot (lb_j^{local} + r \cdot (ub_j^{local} - lb_j^{local})) \quad (20)$$

where $i = 1, 2, \dots, N$, $j = 1, 2, \dots, m$, $ub_j^{local} = \frac{ub_i}{t}$ and $lb_j^{local} = \frac{lb_i}{t}$ are the local bounds of the j -th variable, $t = 1, 2, \dots, T$ is the iteration counter, and X_i^{P2} is the new position.

If the new position improves the objective function, it is accepted; otherwise, the coati remains at its previous location:

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} \leq F_i \\ X_i, & \text{otherwise} \end{cases} \quad (21)$$

3) Fitness Evaluation

The fitness function for COA evaluates classifier performance:

$$fitness(x_i) = \frac{ClassifierErrorRate(x_i) = \frac{Misclassified\ instance\ counts}{Total\ instance\ counts} \times 100 \quad (22)$$

This measures classification error as a percentage, guiding COA to optimize parameter settings for improved model performance.

III. PERFORMANCE EVALUATION

The performance of the EFDP-ADNNHOA method is evaluated using the Australian Credit dataset [25]. This dataset contains 690 instances divided into two classes. It includes 14 features, of which only A1, A3, A6, A7, A8, A11, A13, and A14 are selected. These features capture applicant-related data such as credit history, personal demographics, and financial indicators, as shown in Table I.

TABLE I. DETAILS OF THE AUSTRALIAN CREDIT DATASET

Dataset	Total instances	No. of features	Classes	Financial_Crisis/ Non-Financial_Crisis
Australian Credit	690	14	2	383/307

The classifier outcomes of EFDP-ADNNHOA under a 70:30 train-test split are reported in Table II. With 70% training data (TRPHE), the model achieves an accuracy ($Accu_y$) of 95.96%, precision ($prec_n$) of 96.13%, sensitivity ($sens_y$) of 95.96%, specificity ($spec_y$) of 95.96%, and F1-score (F_{score}) of 96.03%. Under 30% testing data (TSPHE), the EFDP-ADNNHOA model attains an average $accu_y$ of 97.06%, $prec_n$ of 98.03%, $sens_y$ of 97.06%, $spec_y$ of 97.06%, and F_{score} of 97.48%.

TABLE II. CLASSIFICATION OUTCOMES OF EFDP-ADNNHOA MODEL (70:30 SPLIT)

Class labels	$Accu_y$ (%)	$Prec_n$ (%)	$Sens_y$ (%)	$Spec_y$ (%)	F_{score} (%)
TRPHE (70%)					
Financial_Crisis	97.32	95.49	97.32	94.59	96.39
Non-Financial_Crisis	94.59	96.77	94.59	97.32	95.67
Average	95.96	96.13	95.96	95.96	96.03
TSPHE (30%)					
Financial_Crisis	100.00	96.06	100.00	94.12	97.99
Non-Financial_Crisis	94.12	100.00	94.12	100.00	96.97
Average	97.06	98.03	97.06	97.06	97.48

A comparative study between EFDP-ADNNHOA and existing approaches is presented in Table III. The results

highlight that EFDP-ADNNHOA achieves the highest performance, surpassing methods such as XGBoost, AdaBoost, Linear Discriminant Analysis (LDA), Random Forest (RF), Support Vector Machine (SVM), MLP, and SMOTE-based models. Specifically, EFDP-ADNNHOA achieves 97.06% $accu_y$, 98.03% $prec_n$, 97.06% $sens_y$, and 97.06% $spec_y$, demonstrating its robustness in handling class imbalance and improving prediction accuracy.

TABLE III. COMPARATIVE OUTCOMES OF EFDP-ADNNHOA WITH EXISTING CLASSIFIERS

Classifier	$Accu_y$ (%)	$Prec_n$ (%)	$Sens_y$ (%)	$Spec_y$ (%)
XGBoost [26]	96.75	89.99	94.03	95.36
AdaBoost [26]	94.85	94.29	89.41	94.06
LDA [26]	91.22	92.03	90.93	93.71
RF [26]	95.10	93.18	89.45	93.75
SVM [27]	91.98	94.99	91.96	94.02
MLP [27]	89.15	89.00	93.34	95.69
SMOTE [27]	93.36	90.02	93.36	91.76
EFDP-ADNNHOA (proposed)	97.06	98.03	97.06	97.06

IV. CONCLUSION

In this paper, an Enhanced Financial Distress Prediction method using Attention-based Deep Neural Network and Heuristic Optimization Algorithms (EFDP-ADNNHOA) is proposed. The objective is to evaluate the effectiveness of data handling techniques for improving the accuracy and reliability of financial distress prediction models. The proposed framework involves data pre-processing, feature subset selection, classification, and parameter tuning. The EFDP-ADNNHOA approach was validated on a benchmark dataset and demonstrated superior performance compared with existing methods across multiple evaluation metrics.

However, several limitations were identified. First, the method depends heavily on historical stock data, which may not adequately capture sudden market shocks or external economic factors. Second, the performance may vary across different markets, limiting generalizability. Finally, the computational complexity of the hybrid model may limit its feasibility in real-time applications.

Future research should address these challenges by improving adaptability to market volatility, reducing computational demands, and enhancing efficiency to support broader practical deployment.

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