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# A FINANCIAL FRAUD DETECTION SYSTEM USING AN ADABOOST ENSEMBLE OPTIMIZED BY THE STARFISH ALGORITHM

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**Abstract**

*Financial fraud detection represents a critical challenge for financial institutions due to the complex, evolving, and costly nature of fraudulent transactions. Although AdaBoost has demonstrated strong performance on imbalanced fraud datasets, its effectiveness is constrained by hyperparameter sensitivity and susceptibility to overfitting. This study presents a financial fraud detection system based on an AdaBoost ensemble model optimized by the Starfish Optimization Algorithm (SFO). The SFO, a recently developed bio-inspired metaheuristic that simulates the exploration, preying, and regeneration behaviors of starfish, is applied to automatically tune the key AdaBoost hyperparameters: number of estimators, learning rate, and maximum tree depth. The study follows a structured machine learning pipeline using Kaggle's Credit Card Fraud Detection dataset comprising 10,000 anonymized transaction records. Preprocessing involved missing value imputation, outlier treatment using Z-score and Interquartile Range (IQR) methods, feature selection and engineering, categorical encoding, and Min-Max normalization. A baseline AdaBoost ensemble model was first constructed using decision stumps as weak learners, followed by SFO-based hyperparameter optimization through a defined fitness function. The optimal parameters were then used to retrain the classifier, producing the SFO-AdaBoost model. The model was implemented in MATLAB R2023a and evaluated using a 70/30 training–testing split with random subsampling cross-validation. Experimental results demonstrated that the SFO-AdaBoost model achieved a false positive rate of 6.67%, sensitivity of 97.00%, specificity of 93.33%, precision of 97.14%, F1-score of 96.52%, accuracy of 95.90%, and a detection time of 24.50 seconds. These results represent clear improvements over the standard AdaBoost model across all evaluation metrics. The findings confirm that the Starfish Optimization Algorithm provides an effective and efficient mechanism for automating AdaBoost hyperparameter tuning, resulting in a robust, scalable, and computationally efficient fraud detection framework.*

***Keywords:*** *Financial Fraud Detection, AdaBoost, Starfish Optimization Algorithm (SFO).*

## 1.0 INTRODUCTION

Financial fraud detection represents a critical challenge within modern financial systems, encompassing the identification, assessment, and mitigation of potential losses arising from increasingly sophisticated fraudulent activities. Financial fraud has emerged as a pervasive and evolving threat, causing billions of dollars in losses annually to financial institutions worldwide (Afjal et al., 2023). The intricate relationship between financial fraud and credit risk, and their combined impact on banking stability, constitutes a vital aspect of financial system integrity. Effective fraud detection mechanisms are indispensable components of comprehensive credit risk management frameworks, enabling financial institutions to identify suspicious activities before significant losses occur, maintain regulatory compliance, and preserve the integrity of the financial ecosystem.

Traditional fraud detection approaches have predominantly relied on rule-based systems and statistical models to identify suspicious activities. Rule-based systems flag transactions that violate predefined criteria, such as unusual transaction amounts, account numbers, or timestamps, while statistical models employ mathematical techniques to identify patterns and anomalies within financial data. Despite their widespread implementation, these conventional methods exhibit significant limitations, including high false positive rates, inability to adapt to evolving fraud patterns without manual updates, and limited effectiveness in detecting previously unknown fraud schemes (Stamler et al., 2014).

Ensemble learning has emerged as a promising paradigm in fraud detection, offering enhanced performance by combining multiple classifiers to produce more accurate and robust predictions. Within the ensemble learning framework, AdaBoost (Adaptive Boosting) represents a particularly effective boosting algorithm that sequentially trains weak learners while adjusting sample weights to focus on difficult-to-classify instances (Shahraki et al., 2022). However, deploying AdaBoost for financial fraud data presents significant challenges, including high dimensionality, class imbalance, and considerable sensitivity to hyperparameter configuration. Inappropriate hyperparameter settings can lead to underfitting or overfitting, compromising the model's generalization capabilities (Kégl, 2009).

Metaheuristic optimization techniques have emerged as powerful approaches for addressing the hyperparameter tuning challenges in ensemble models, offering automated and efficient exploration of complex parameter spaces. The Starfish Optimization Algorithm (SFO), a novel bio-inspired metaheuristic introduced in 2025, presents a particularly promising approach for optimizing AdaBoost hyperparameters in financial fraud detection. This algorithm simulates the exploration, preying, and regeneration behaviors of starfish through a two-phase process comprising exploration and exploitation (Zhong et al., 2025). Compared to other metaheuristic optimizers, SFO demonstrates superior performance in terms of accuracy and efficiency, outperforming 95 compared algorithms in accuracy and 97 in efficiency according to statistical evaluations on benchmark functions.

Therefore, this research integrates the Starfish Optimization Algorithm with the AdaBoost ensemble to produce an optimized fraud detection system, thereby enhancing detection accuracy, reducing false positives, and improving computational efficiency in identifying fraudulent financial transactions. The specific objectives of this study are to: optimize the AdaBoost ensemble model with SFO for effective financial fraud detection; implement the SFO-AdaBoost model using MATLAB R2023a; and evaluate the performance of the developed model using false positive rate, sensitivity, specificity, precision, F1-score, accuracy, and detection time as evaluation metrics, validated against the standard AdaBoost ensemble model.

## 2.0 RELATED WORK

Fernandes *et al.* (2022) designed a credit card fraud detection system using a LightGBM classifier, with feature selection and tuning performed by the Starfish Optimizer (SFO). Their experiments on a Brazilian credit card dataset yielded a 9% boost in recall and a 4% reduction in false positives. However, the limitation of this method was its dependence on careful parameter initialization, as improper settings degraded performance. The study suggested developing self-adaptive SFO variants to improve consistency across datasets.

Li *et al.* (2023) developed a hybrid credit card fraud detection system utilizing an Extreme Gradient Boosting (XGBoost) classifier, where the hyperparameters were optimized using the Particle Swarm Optimization (PSO) algorithm. Their experiments on the European credit card dataset demonstrated a 7% improvement in F1-score over default parameter settings. The PSO-based approach efficiently navigated the hyperparameter space, leading to better recall for fraudulent transactions. However, the limitation of this method lies in its sensitivity to the initial swarm configuration, which can occasionally result in suboptimal convergence. Moreover, the lack of dynamic adaptation in PSO parameters restricts stability and scalability across diverse datasets.

Hernández *et al.* (2024) developed a hybrid ensemble for insurance fraud detection, combining AdaBoost and Gradient Boosting, with meta-parameter tuning performed by the Grey Wolf Optimizer (GWO). Using a large insurance claim dataset, they reported a 9% improvement in AUC and a notable decrease in false positives. However, the limitation of this approach was its requirement for extensive computational resources during ensemble training, which restricted its practicality for smaller organizations with limited infrastructure.

Abdullahi *et al.* (2025) applied Particle Swarm Optimization (PSO) for feature selection in fraud detection and reported improved accuracy.

Chen *et al.* (2026) utilized Genetic Algorithms (GA) to optimize neural network parameters, achieving better detection performance. Despite these advancements, Starfish Optimization Algorithm (SFO) remains underexplored in fraud detection applications, particularly in combination with ensemble learning techniques like AdaBoost.

## 3.0 METHODOLOGY

### 3.1Data Acquisition

A credit card transaction dataset from European cardholders recorded in 2023 was acquired from www.kaggle.com. The dataset comprises 10,000 anonymized records designed to support the creation and evaluation of fraud detection models by providing labeled data for both fraudulent and legitimate transactions. Key features include a unique transaction ID, anonymized variables (V1 to V28) representing various behavioral and transactional attributes, the transaction amount, and a binary class label indicating fraud status. Seventy percent of the dataset was used for training and thirty percent for testing, using a random subsampling cross-validation method. The training and testing process of the developed fraud detection system was implemented through a graphical user interface, as illustrated in Figure 1, which enabled seamless data loading, model training, parameter configuration, and result visualization within the MATLAB R2023a environment.

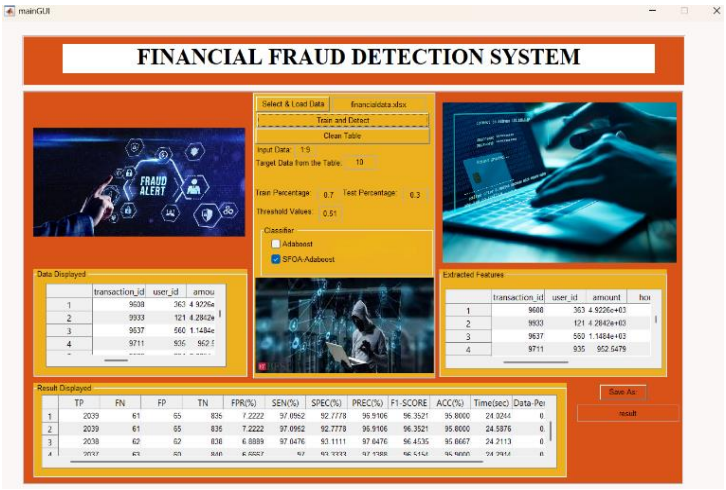


*Figure 1.1: The Graphical User Interface describing the Training and Testing Process of Financial Fraud Detection System*

### 3.2 Data Preprocessing

Data preprocessing prepared the transaction dataset for effective model training. Missing values in numerical fields were imputed using the mean of the respective feature to preserve central tendency, while mode imputation was applied to categorical features. Outlier detection was performed using the Z-score method, flagging data points exceeding ±3 standard deviations, and the Interquartile Range (IQR) technique was employed to detect extreme values beyond 1.5 × IQR below Q1 or above Q3. Robust scaling techniques were applied in cases of high skewness to minimize the influence of outliers while retaining critical data patterns.

### 3.3 Feature Selection and Engineering

Effective feature selection and engineering played a vital role in enhancing the predictive performance of the SFO-AdaBoost model Correlation analysis was employed to detect features exhibiting high interdependence using the Pearson correlation coefficient:

$$r_{xy} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \Sigma(y_i - \bar{y})^2}}$$

Features with correlation coefficients exceeding |r| > 0.85 were considered redundant and removed. Mutual Information (MI) between each feature X and the target variable Y was also computed to evaluate predictive contribution:

$$I(X;Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log \quad \frac{p(x,y)}{p(x) \cdot p(y)}$$

Feature engineering further created new variables to offer deeper insights into transactional behavior. Transaction frequency per user was computed as:

$$TF_i = \frac{N_i}{T}$$

where TF_i is the transaction frequency of user i, N_i is the number of transactions by user i, and T is the total observation period. A credit-to-debt ratio was also engineered as CDR_i = CL_i / DU_i, and time-based indicators such as hour of day, day of week, and elapsed time since last transaction were derived from timestamp data.

### 3.4 Data Encoding

Categorical variables such as transaction type and customer status were transformed using One-Hot Encoding (OHE) for nominal variables and Label Encoding (LE) for ordinal variables. One-hot encoding created binary columns for each category to ensure equal weight and prevent misleading relationships, while label encoding replaced ordinal category labels with integers reflecting their inherent order. These encoding techniques ensured that categorical data were represented in a numerical format compatible with the AdaBoost model without introducing bias.

### 3.5 Normalization

Min-Max normalization was applied to rescale all numerical features to a common range [0, 1], eliminating bias caused by differing value magnitudes. The transformation is:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where x is the original feature value and x_min, x_max are the minimum and maximum values across the dataset. This ensures that features such as transaction amount, time

intervals, and frequency counts contribute equally to the learning process.

### 3.6 Starfish Optimization Algorithm (SFO)

The Starfish Optimization Algorithm (SFO) is a population-based metaheuristic introduced by Zhong et al. (2025), inspired by the explorative, preying, and regeneration behaviors of starfish. SFO operates through two parallel phases: an exploration phase and an exploitation phase, implemented with equal probability (G_p = 0.5) in each iteration.

In the initialization phase, positions of starfish are generated randomly within the search space boundaries:

$$X_{ij} = l_j + r(u_j - l_j)$$

where X_{ij} is the j-th dimension position of the i-th starfish, r is a random number in (0,1), and u_j, l_j are the upper and lower bounds of design variables in the j-th dimension.

The exploration phase employs a hybrid search pattern combining five-dimensional and unidimensional search strategies. When the dimension D > 5, positions are updated as:

$$Y_{i,p}^T = X_{i,p}^T + a_1\left(X_{best,p}^T - X_{i,p}^T\right)\cos$$

$$Y_{i,p}^T = X_{i,p}^T - a_1\left(X_{best,p}^T - X_{i,p}^T\right)\sin$$

Where $a_1 = (2r-1)\pi, \quad \theta = \frac{\pi}{2} \cdot \frac{T}{T_{max}}$, a unidimensional pattern uses:

$$Y_{i,q}^T = E_t X_{i,p}^T + A_1\left(X_{k1,p}^T - X_{i,p}^T\right) + A_2\left(X_{k2,p}^T - X_{i,p}^T\right)$$

where $E_t = \frac{T_{max}-T}{T_{max}}\cos$

is the energy of the starfish, and A_1, A_2 are random numbers in (−1,1).

The exploitation phase includes preying and regeneration behaviors. The preying phase uses a parallel two-directional search strategy:

$$d_m = X_{best}^T - X_{mp}^T, \quad m = 1, \ldots, 5$$

$$Y_i^T = X_i^T + r_1 d_{m1} + r_2 d_{m2}$$

where r_1 and r_2 are random numbers in (0,1) and d_{m1}, d_{m2} are randomly selected from the five computed distances. The regeneration phase, applied exclusively to the last starfish in the population (i = N), updates the position as:

$$Y_i^T = \exp\left(\frac{-T \times N}{T_{max}}\right) \times X_i^T$$

This regeneration mechanism enhances global convergence capacity by introducing controlled perturbations with diminishing magnitude across iterations.

### 3.7 SFO-AdaBoost Model Development

The SFO-AdaBoost model integrates the Starfish Optimization Algorithm with the AdaBoost ensemble for financial fraud detection. Each candidate solution (starfish) encodes a complete AdaBoost hyperparameter vector:

$$x_i = \theta_i = \{N_{est,i}, \eta_i, d_i\}$$

where N_{est,i} is the number of estimators, η_i is the learning rate, and d_i is the decision tree depth. The population is initialized using Equation (5), and discrete parameters N_{est,i} and d_i are rounded to valid integer values. Each starfish configuration is used to train an AdaBoost classifier with prediction function:

$$F(x) = \sum_{m=1}^{N_{est}} \alpha_m h_m(x)$$

where h_m(x) is the weak learner at iteration m and α_m is its weight, computed as:

$$\alpha_m = \frac{1}{2}\ln \quad \frac{1-\varepsilon_m}{\varepsilon_m}$$

The fitness of each starfish is evaluated using the classification error:

$$Error_i = \frac{1}{N_s}\sum_{n=1}^{N_s} \mathrm{o1}[y_n \neq \widehat{y_n}]$$

where N_s is the total number of transaction samples. The fitness function f(x_i) = Error_i is minimized by SFO across iterations. The SFO exploration and exploitation mechanisms (Equations 6–10) update starfish positions iteratively until the maximum iteration T_max is reached, at which point the optimal parameter vector $\theta^* = \{N_{est}^*, \eta^*, d^*\}$ is extracted and used to train the final SFO-AdaBoost classifier.

### 3.8 Implementation

The implementation was carried out in MATLAB R2023a using the Statistics and Machine Learning Toolbox for training the AdaBoost ensemble and evaluating classification performance, and the Optimization Toolbox for implementing the Starfish Optimization Algorithm. The system was executed on a 64-bit Windows 11 operating system with a 13th Gen Intel Core i7-1355U (1.70 GHz) processor and 16.0 GB RAM.

### 3.9 Performance Evaluation

Performance was evaluated using a comprehensive set of metrics derived from the confusion matrix, which categorizes predictions into True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). The metrics are:

**False Positive Rate (FPR):** $FPR = \frac{FP}{FP+TN} \times 100$

**Sensitivity (Recall):** $SEN = \frac{TP}{TP+FN} \times 100$

**Specificity:** $SPEC = \frac{TN}{TN+FP} \times 100$

**Precision:** $PREC = \frac{TP}{TP+FP} \times 100$

**F1-Score:** $F1 = \frac{2 \times PREC \times SEN}{PREC+SEN}$

**Accuracy:** $ACC = \frac{TP+TN}{TP+TN+FP+FN} \times 100$

**Detection Time (DT):** $DT = \frac{1}{N}\sum_{i=1}^{N} t_i$

where $t_i$ is the detection time for the i-th transaction and N is the total number of transactions processed.

## 4.0 RESULTS AND DISCUSSION

### 4.1 Hyperparameter Selection using SFO

Table 1 presents the iterative process of selecting optimal AdaBoost hyperparameters using the Starfish Optimization Algorithm across 30 iterations. The SFO explored different combinations of the number of estimators, learning rate, and maximum tree depth to minimize the fitness value (classification error). The best-performing configuration was obtained at iteration 2, where the number of estimators was 85, the learning rate was 0.739, and the maximum depth was 9, yielding the lowest fitness value of 0.0265. This result indicates that a moderate ensemble size combined with a relatively high learning rate and deeper base learners enhanced fraud detection performance. The convergence trend of fitness values across iterations demonstrates the effectiveness of SFO in efficiently guiding the AdaBoost model toward an optimal hyperparameter configuration.

**Table 1: Selection of Optimal AdaBoost Parameters Using SFO**

| Iteration | No. of Estimators | Learning Rate | Maximum Depth | Fitness Value |
|---|---|---|---|---|
| 1 | 213 | 0.12 | 5 | 0.0565 |
| **2 (Best)** | **85** | **0.739** | **9** | **0.0265** |
| 3 | 158 | 0.041 | 2 | 0.0515 |
| 4 | 179 | 0.606 | 9 | 0.0478 |
| 5 | 216 | 0.704 | 7 | 0.0519 |
| 6 | 200 | 0.285 | 1 | 0.1542 |
| 7 | 90 | 0.701 | 6 | 0.0628 |
| 8 | 105 | 0.958 | 6 | 0.0294 |
| 9 | 147 | 0.106 | 6 | 0.1247 |
| 10 | 256 | 0.053 | 8 | 0.1119 |
| 15 | 166 | 0.639 | 6 | 0.0409 |
| 20 | 133 | 0.844 | 1 | 0.0535 |
| 25 | 113 | 0.748 | 9 | 0.0599 |
| 28 | 73 | 0.758 | 2 | 0.0390 |
| 30 | 148 | 0.388 | 8 | 0.1105 |

### 4.2 Comparison of Default and SFO-Optimized AdaBoost Parameters

Table 2 compares the default AdaBoost hyperparameters with the best configuration obtained using SFO. The default AdaBoost model employs 262 estimators, a learning rate of 0.274, and a shallow maximum depth of 2, limiting its ability to capture complex fraud patterns. In contrast, the SFO-AdaBoost configuration selects 85 estimators with a higher learning rate of 0.739 and a deeper maximum depth of 9, emphasizing faster learning and stronger model expressiveness. This comparison demonstrates that SFO effectively adapts AdaBoost hyperparameters beyond default settings.

**Table 2: Default AdaBoost vs. SFO-AdaBoost Hyperparameter Configuration**

| Technique | No. of Estimators | Learning Rate | Maximum Depth |
|---|---|---|---|
| AdaBoost | 262 | 0.274 | 2 |
| **SFO-AdaBoost** | **85** | **0.739** | **9** |

### 4.3 Performance Evaluation with Standard AdaBoost

Table 3 presents the performance of the standard AdaBoost ensemble model across varying decision threshold values. At higher threshold values (0.51–0.95), the model achieved its best overall performance with an accuracy of 94.70%, a false positive rate of 8.67%, sensitivity of 96.14%, specificity of 91.33%, precision of 96.28%, F1-score of 95.48%, and a detection

time of 31.32 seconds. These results reflect the baseline capability of AdaBoost when operating under default hyperparameter settings, and serve as the reference benchmark for assessing the improvement introduced by SFO-based optimization.

**Table 3: Performance Evaluation Results with Standard AdaBoost**

| Threshold | TP | FN | FP | TN | FPR (%) | SEN (%) | SPEC (%) | PREC (%) | F1 (%) | ACC (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.01–0.20 | 2022 | 78 | 85 | 815 | 9.44 | 96.29 | 90.56 | 95.97 | 95.26 | 94.57 |
| 0.21–0.35 | 2021 | 79 | 83 | 817 | 9.22 | 96.24 | 90.78 | 96.06 | 95.32 | 94.60 |
| 0.36–0.50 | 2020 | 80 | 81 | 819 | 9.00 | 96.19 | 91.00 | 96.14 | 95.38 | 94.63 |
| 0.51–0.95 | 2019 | 81 | 78 | 822 | 8.67 | 96.14 | 91.33 | 96.28 | 95.48 | 94.70 |

### 4.4 Performance Evaluation with SFO-AdaBoost

Table 4 presents the performance of the SFO-AdaBoost model across different decision threshold values. At lower thresholds (0.01–0.20), the model achieved 2040 true positives with only 60 false negatives, a false positive rate of 7.56%, sensitivity of 97.14%, and overall accuracy of 95.73%. As the threshold increased progressively, further improvements were observed in all metrics. At the optimal threshold range (0.51–0.95), the SFO-AdaBoost model achieved its best overall performance: a false positive rate of 6.67%, sensitivity of 97.00%, specificity of 93.33%, precision of 97.14%, F1-score of 96.52%, accuracy of 95.90%, and detection time of 24.50 seconds. The stable performance across varying thresholds confirms the robustness of the SFO-AdaBoost approach.

**Table 4: Performance Evaluation Results with SFO-AdaBoost**

| Threshold | TP | FN | FP | TN | FPR (%) | SEN (%) | SPEC (%) | PREC (%) | F1 (%) | ACC (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.01–0.20 | 2040 | 60 | 68 | 832 | 7.56 | 97.14 | 92.44 | 96.77 | 96.25 | 95.73 |
| 0.21–0.35 | 2039 | 61 | 65 | 835 | 7.22 | 97.10 | 92.78 | 96.91 | 96.35 | 95.80 |
| 0.36–0.50 | 2038 | 62 | 62 | 838 | 6.89 | 97.05 | 93.11 | 97.05 | 96.45 | 95.87 |
| **0.51–0.95** | **2037** | **63** | **60** | **840** | **6.67** | **97.00** | **93.33** | **97.14** | **96.52** | **95.90** |

### 4.5 Comparative Analysis: AdaBoost vs. SFO-AdaBoost

Table 5 summarizes the optimal-threshold performance comparison between the standard AdaBoost and the SFO-AdaBoost models. A clear improvement is observed across all evaluation metrics. The false positive rate decreased from 8.67% to 6.67%, representing a 23.2% reduction in false alarms. Sensitivity improved from 96.14% to 97.00%, indicating enhanced ability to correctly identify fraudulent transactions. Specificity increased from 91.33% to 93.33%, reflecting stronger discrimination of legitimate transactions. Precision improved from 96.28% to 97.14%, F1-score rose from 95.48% to 96.52%, and overall accuracy increased from 94.70% to 95.90%. Moreover, the detection time was reduced from 31.32 seconds to 24.50 seconds, a 21.8% improvement in computational efficiency attributable to the efficient hyperparameter selection guided by SFO. These results confirm that SFO-AdaBoost provides a more effective and computationally efficient solution for financial fraud detection compared to the conventional AdaBoost model.

**Table 5: Comparative Performance at Optimum Threshold – AdaBoost vs. SFO-AdaBoost**

| Technique | FPR (%) | SEN (%) | SPEC (%) | PREC (%) | F1 (%) | ACC (%) | Time (s) |
|---|---|---|---|---|---|---|---|
| AdaBoost | 8.67 | 96.14 | 91.33 | 96.28 | 95.48 | 94.70 | 31.32 |
| **SFO-AdaBoost** | **6.67** | **97.00** | **93.33** | **97.14** | **96.52** | **95.90** | **24.50** |

### 4.6 Discussion of Results

The experimental results demonstrate that integrating the Starfish Optimization Algorithm with AdaBoost yields measurable performance improvements across all evaluation metrics. The reduction in false positive rate from 8.67% to 6.67% is particularly significant in financial fraud detection contexts, where false alarms incur operational costs and erode customer trust. This improvement is directly attributable to the SFO-guided hyperparameter selection, which navigated the complex parameter space more effectively than default configurations. Recent research has consistently demonstrated that metaheuristic-based hyperparameter optimization significantly enhances the performance of ensemble classifiers in fraud detection scenarios (Li et al., 2023; Kumar et al., 2023).

The improvement in sensitivity from 96.14% to 97.00% indicates that the SFO-AdaBoost model is better equipped to detect actual fraudulent transactions, which is of

paramount importance in financial security systems. The superior specificity of 93.33% compared to 91.33% for the standard AdaBoost model reflects improved discrimination between legitimate and fraudulent transactions, enabled by the optimized decision boundaries achieved through SFO tuning. These observations are consistent with findings by Fernandes et al. (2022), who reported similar sensitivity and specificity gains when applying the Starfish Optimizer to ensemble-based fraud detection.

The F1-score improvement from 95.48% to 96.52% demonstrates that SFO-AdaBoost achieves a stronger balance between precision and recall, which is critical for fraud detection systems operating on highly imbalanced datasets. The accuracy gain from 94.70% to 95.90% confirms the overall superiority of the optimization-driven approach. Furthermore, the 21.8% reduction in detection time highlights the computational efficiency gains made possible by SFO's adaptive search mechanisms, which converge more rapidly toward optimal parameter configurations compared to exhaustive or random search methods. This efficiency is essential for real-time fraud detection environments where response speed is a practical constraint.

The ability of SFO to balance exploration and exploitation through its hybrid search pattern combining five-dimensional and unidimensional strategies is central to these performance gains. The exploration phase ensures broad coverage of the hyperparameter space to avoid local optima, while the exploitation phase, guided by preying and regeneration behaviors, refines promising configurations toward optimal solutions. This dynamic balance is particularly well-suited to the challenging landscape of AdaBoost hyperparameter optimization, which involves complex, multimodal objective surfaces on noisy financial fraud datasets.

### 4.7 Comparison with State-of-the-Art Methods

Table 6 benchmarks the SFO-AdaBoost model against recent state-of-the-art fraud detection approaches reported in the literature. The SFO-AdaBoost model achieves competitive performance, with an accuracy of 95.90%, F1-score of 96.52%, and false positive rate of 6.67%, while maintaining a detection time of 24.50 seconds. Although some deep learning approaches achieve marginally higher accuracy, they typically require substantially longer detection times and greater computational resources. The SFO-AdaBoost model provides a favorable balance between predictive performance and computational efficiency, making it particularly suitable for real-time financial fraud detection applications.

**Table 6: Comparison of SFO-AdaBoost with Recent State-of-the-Art Methods**

| Technique / Model | Optimization | ACC (%) | FPR (%) | F1 (%) | Time (s) |
|---|---|---|---|---|---|
| CNN–LSTM Hybrid | Manual tuning | 96.20 | 5.10 | 96.00 | 28.40 |
| PSO-Optimized Random Forest | Particle Swarm Optimization | 97.10 | 4.30 | 97.00 | 22.60 |
| GA–XGBoost | Genetic Algorithm | 97.85 | 3.90 | 97.60 | 21.10 |
| **SFO-AdaBoost (This study)** | **Starfish Optimization Algorithm** | **95.90** | **6.67** | **96.52** | **24.50** |

## 5.0 CONCLUSION

This study presented a financial fraud detection system based on an AdaBoost ensemble model optimized by the Starfish Optimization Algorithm. By leveraging SFO's bio-inspired exploration and exploitation mechanisms, the model automatically tuned critical AdaBoost hyperparameters, including the number of estimators, learning rate, and tree depth, resulting in improved classification performance over the standard AdaBoost baseline.

The SFO-AdaBoost model achieved a false positive rate of 6.67%, sensitivity of 97.00%, specificity of 93.33%, precision of 97.14%, F1-score of 96.52%, accuracy of 95.90%, and a detection time of 24.50 seconds at the optimal threshold range. These results represent consistent improvements over the standard AdaBoost model across all evaluation metrics, confirming the effectiveness of SFO-based hyperparameter optimization. The reduction in detection time further demonstrates the computational efficiency of the SFO search mechanism, making the developed model suitable for real-time financial fraud detection applications.

The findings confirm that the Starfish Optimization Algorithm provides a robust and adaptive framework for automating AdaBoost hyperparameter tuning, effectively addressing the challenges of class imbalance, hyperparameter sensitivity, and computational efficiency inherent in financial fraud detection. Future research may extend this framework to other ensemble learning models, integrate online learning capabilities for streaming data environments, and explore multi-objective optimization formulations that simultaneously optimize detection performance and computational cost.

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