



Artificial Hummingbird Algorithm: Fundamentals, Foraging Mechanisms, and Applications in Classification Problems

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Abstract

Artificial Hummingbird Algorithm (AHA) is a nature-inspired metaheuristic optimization technique that mimics hummingbird flight behaviors, foraging strategies, and memory mechanisms. AHA has garnered growing interest in computational intelligence and engineering applications because of its population-based search capacity and adaptable exploration–exploitation processes. The biological inspiration, mathematical formulation, guided foraging, territorial foraging, migration foraging, axial, diagonal, and omnidirectional flying patterns, and visitable-based memory mechanism of AHA are all thoroughly reviewed in this study. The use of AHA in classification issues, where it can aid in feature selection, hyperparameter optimization, and the creation of hybrid learning frameworks, is given special attention. To determine the possible contributions of AHA to classification performance and computing efficiency, representative application fields such as biomedical signal analysis, image identification, defect detection, voice processing, and power quality disturbance classification are investigated. Additionally, convergence behavior, local-optimum avoidance, computing complexity, parameter sensitivity, and generalization capabilities are examined in connection to the advantages and disadvantages of AHA. Benchmark selection, baseline comparisons, numerous categorization measures, and repeatable experimental conditions are among the methodological factors that the review emphasizes for equitable performance evaluation. Lastly,

new avenues for research are described, including explainable classification, imbalanced datasets, adaptive and hybrid AHA variations, and real-world validation. This review lays the groundwork for future studies on trustworthy, effective, and robust intelligent classification systems by offering an organized understanding of AHA and its function in optimization-assisted classification.

Keywords: metaheuristic optimization; Artificial Hummingbird Algorithm; bio-inspired optimization; classification problems; hyperparameter optimization; feature selection; machine learning; computational intelligence.



1. Introduction

The need for intelligent optimization strategies that may reduce computational complexity, improve predicted accuracy, and extract the most useful features from high-dimensional datasets has grown due to the increasing complexity of real-world categorization issues. Medical diagnosis, power quality disturbance identification, fault detection, biomedical signal analysis, image recognition, and voice processing are just a few of the many industries that make extensive use of classification systems [1]. While both deep learning and traditional machine learning models have shown significant success in these applications, the performance of these models is highly dependent on the choice of hyperparameters, model architecture, and feature representation. It can be difficult to choose the best configuration because the search space may be nonlinear, and multimodal.

Selecting an optimal configuration is often challenging because the search space may be nonlinear, multimodal, high-dimensional, and computationally expensive. Consequently, metaheuristic optimization algorithms have gained considerable attention as flexible, derivative-free approaches for exploring complex search spaces and improving the performance of classification systems [2].

Nature-inspired optimization algorithms emulate biological, physical, or social processes to develop effective search strategies. Population-based methods, such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Grey Wolf Optimizer (GWO), have been extensively investigated for solving continuous and discrete optimization problems. Typically, these algorithms keep track of a population of potential solutions and update them iteratively based on algorithm-specific search processes and fitness values [3]. However, striking a balance between exploration and exploitation is essential to their efficacy. While early exploitation may cause local optima to stagnate, excessive exploration may postpone convergence. These restrictions may have an impact on generalization performance, computational efficiency, feature subset selection, and classifier parameter adjustment in classification applications. As a result, the creation and methodical assessment of substitute nature-inspired optimization techniques continue to be crucial areas of study.

The Artificial Hummingbird Algorithm (AHA), which was first presented by Zhao et al. in 2022, is a bio-inspired metaheuristic among nature-inspired optimization techniques. It is based on the unique flying abilities, foraging tactics, and memory behavior of hummingbirds. Guided foraging, territorial foraging, and migration foraging are the three main foraging mechanisms included in the algorithm. To control the flow of potential solutions over the search space, these methods are combined with axial, diagonal, and omnidirectional flight patterns. Furthermore, the visitable technique helps guide future search decisions by representing the memory related to food-source visiting [4].

The initial study demonstrated the potential of AHA as a general-purpose optimization technique by evaluating it using benchmark functions and engineering design challenges. Since its launch, AHA has garnered more and more attention from researchers, leading to modified, binary, hybrid, and multi-objective variants for various optimization tasks. Feature selection, image processing, clustering, scheduling, engineering design, and machine-learning optimization are among the new applications. The algorithm's evolution, variations, performance, and application fields have all been thoroughly studied in recent reviews, demonstrating the increasing significance of AHA in artificial intelligence.

These evaluations also offer a basis for comprehending its advantages, disadvantages, and prospects for improvement. The connection between AHA's biological inspiration, mathematical search methods, and real-world application in classification problems merits careful investigation despite this expanding corpus of knowledge. In addition to the optimization algorithm, other factors that affect classification performance include dataset characteristics, feature representation, classifier design, parameter values, class imbalance, and evaluation methods. To choose useful features, optimize classifier hyperparameters, or simultaneously enhance several learning system components, AHA can be integrated into classification pipelines.

However, rather than depending solely on overall accuracy or a single benchmark result, its efficacy should be evaluated using appropriate baseline algorithms, consistent experimental conditions, independent test data, and numerous assessment criteria. Thus, with a focus on their applicability to classification issues, this work investigates the foundations of AHA, its biological inspiration, primary foraging mechanisms, flight strategies, memory-based search process, and key algorithmic variants [5]. In signal processing, biological analysis, power quality monitoring, picture identification, and other intelligent classification tasks, it arranges representative applications.

The topic takes into account convergence behavior, computational complexity, generalization, repeatability, and the roles of feature selection and hyperparameter optimization. The study concludes by outlining present constraints and future research avenues, such as explainable learning, hybrid optimization frameworks, adaptive search techniques, imbalanced-data classification, and reliable evaluation on real-world datasets. The work intends to establish a systematic foundation for researchers creating optimization-assisted classification systems by connecting the theoretical concepts of AHA with realistic design issues through this classification-oriented viewpoint.

2. Biological Inspiration of the Hummingbird

The Artificial Hummingbird Algorithm (AHA) is an optimization technique inspired by nature, specifically based on the intelligent foraging habits and flight behavior of hummingbirds. In the wild, hummingbirds seek out flowers rich in nectar, retain memories of places they have already visited, and efficiently navigate between food sources to gather resources. These natural behaviors influence the algorithm's strategies for exploring the search space and discovering optimal solutions [1]. Hummingbirds display three key foraging behaviors: guided foraging, territorial foraging, and migration foraging. Guided foraging involves moving towards promising food sources, which promotes the exploration of superior solutions. Territorial foraging consists of searching in the vicinity of a current food source to find potentially superior options. Migration foraging allows birds to venture into new areas of the search space, facilitating exploration and minimizing the risk of early convergence [1],[6].

In order to determine various movement directions throughout the optimization phase, the algorithm additionally integrates three flight patterns: axial, diagonal, and omnidirectional flight. Furthermore, food-source visitation data is recorded in a visit table, which also influences the choice of following search sites. Figure 1 shows Foraging behaviours and Flight patterns of Humming bird.



Figure 1 Foraging behaviours and Flight patterns of Humming bird

AHA finds near-optimal solutions for challenging optimization problems by integrating several techniques, which strike a balance between exploration and exploitation. These biological concepts can be applied in classification applications to find appropriate model configurations, optimize classifier hyperparameters, and choose informative features.

3. Mapping to Artificial Humming bird Algorithm

To provide efficient search and optimization techniques, the Artificial Hummingbird Algorithm (AHA) is matched to the biological foraging behaviors of hummingbirds. It is illustrated in Figure 2. The algorithm can balance exploration and exploitation while looking for the best solutions thanks to guided, territorial, and migrating foraging in addition to various flight patterns.

1. Natural behavior: The biological inspiration comes from guided forage, territorial foraging, migration foraging, directed flight, and recall of places visited [7], [8].
2. Algorithmic mechanism: These behaviors include visit-table-based memory, movement in various search directions, local and global investigation, and exploitation of promising solutions.
3. Search-space representation: The optimization landscape is explored by potential solutions. The conceptual movement between possible locations throughout the search process is represented by the displayed trajectories [9] – [12].
4. Candidate solution update: Until the halting requirement is met, the algorithm initializes a population, chooses a foraging strategy, updates candidate positions and visitation data, assesses fitness, and repeats.

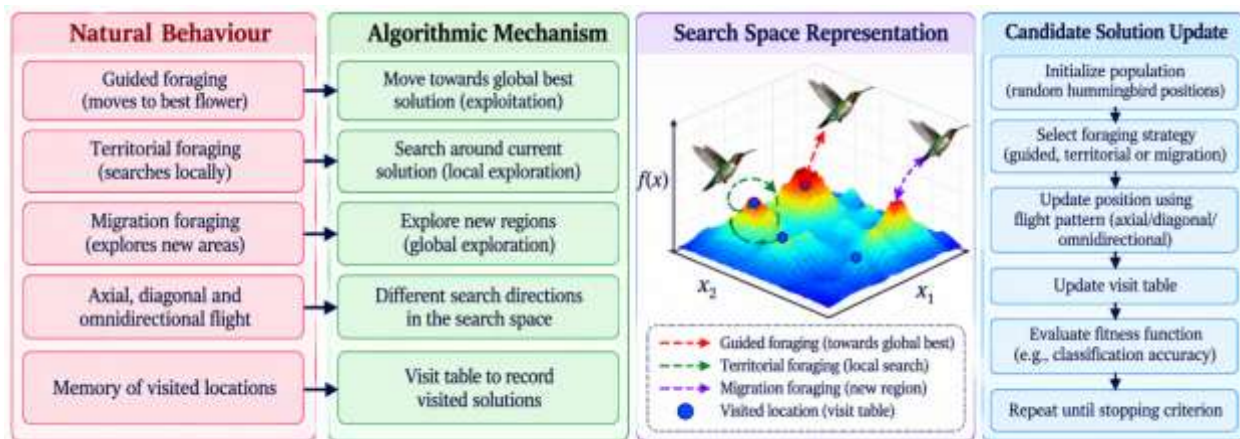


Figure 2. Mapping to Artificial Humming bird Algorithm

4. Applications in Classification Problems

When it comes to classification issues involving complicated, non-stationary data from electrical power systems, biological measurements, auditory recordings, and human-machine interaction devices, signal processing is essential. To choose informative features, optimize classifier hyperparameters, and enhance classification performance, the Artificial Hummingbird Algorithm (AHA) can be combined with machine learning and signal processing methods. Diverse signal patterns can be efficiently analyzed by combining AHA with appropriate signal decomposition, feature extraction, and classification techniques. Potential uses of AHA in signal processing-based categorization issues are discussed in the ensuing subsections.

4.1. Power Quality Disturbance Classification

In order to detect anomalous operating situations in contemporary electrical power systems and smart grids, Power Quality Disturbance (PQD) classification is crucial. Equipment performance and power system dependability can be impacted by voltage sag, voltage swell, interruption, harmonics, flicker, and temporary disruptions. Time-frequency characteristics can be extracted from measured or simulated power quality signals using signal processing techniques as the Hilbert-Huang Transform (HHT), Short-Time Fourier Transform (STFT), and Discrete Wavelet Transform



(DWT) [13]. To enhance the ability to distinguish between various disturbance classes, AHA can optimize feature selection and classifier hyperparameters. AHA can facilitate precise disturbance recognition under various operating conditions and noise levels when combined with CNN, BiLSTM, or support vector machine (SVM) classifiers.

4.2. Cry-Based Infant Disease Classification

The acoustic features of infant cry signals may indicate variations in vocal production linked to specific physiological or pathological states. In order to differentiate between normal cries and screams that might be connected to particular medical disorders, cry-based infant disease classification examines acoustic recordings [14]. To describe pertinent audio information, signal processing techniques like wavelet analysis, pitch extraction, STFT spectrograms, and Mel-frequency cepstral coefficients (MFCCs) can be used. AHA can be used to optimize the parameters of classifiers like SVM, CNN, and CNN-LSTM networks as well as to choose discriminative features. Automated screening and decision-support systems might be supported by this method; nevertheless, classification results should not be regarded as a stand-alone diagnosis and must be verified using clinically labeled datasets.

4.3. Sound Signal-Based Fault Classification in Vehicles

Acoustic emissions from engines, transmission systems, bearings, brakes, and other mechanical parts are analyzed in order to classify vehicle faults using sound signals. Significant alterations in sound loudness, frequency content, spectral distribution, and temporal patterns can result from abnormal operating conditions [15]. These acoustic signals can be characterized using methods like spectral feature analysis, wavelet decomposition, MFCC extraction, and STFT. To differentiate between various fault categories and normal operation, AHA can optimize the chosen feature subset and classifier settings. Under different engine speeds, loads, and environmental noise circumstances, fault recognition may be enhanced by integration with SVM, random forest, CNN, or CNN-BiLSTM models. Predictive maintenance and automated vehicle condition monitoring can benefit from such systems.

4.4. ECG Signal-Based Heart Disease Classification

Electrocardiogram (ECG) data are frequently utilized for cardiac rhythm analysis and offer crucial information about the electrical activity of the heart. Depending on the dataset and classification goal, ECG signal-based classification seeks to distinguish between normal heartbeats and anomalies such as atrial fibrillation, premature ventricular contractions, and other arrhythmias. Wavelet transforms, RR intervals, morphological traits, or deep learning representations are used to extract features after preprocessing techniques such as baseline-wander removal, noise filtering, and signal segmentation [16]. To enhance cardiac pattern discrimination, AHA can optimize feature selection and classifier hyperparameters. Subject to validation on separate patient-level datasets and suitable clinical evaluation, this approach can facilitate automated ECG analysis when paired with CNN, LSTM, or SVM classifiers.

4.5. EMG Signal-Based Hand Gesture Classification

Human-machine interaction, rehabilitation, and prosthetic control all make extensive use of electromyography (EMG) signals, which capture the electrical activity linked to muscle contraction. Classifying hand gestures entails identifying the patterns of muscle activation that correlate to various motions, including wrist flexion, wrist extension, hand opening and closing, and individual finger movements. Band-pass filtering, segmentation, and normalization are examples of signal preprocessing. Time-domain measurements, frequency-domain characteristics, wavelet coefficients, or learned deep representations are then used for feature extraction. AHA can optimize the hyperparameters of classifiers like SVM, CNN, and CNN-LSTM and find useful features [17] – [19]. If performance is assessed across various users, muscular contraction levels, and recording settings, the resulting system may enhance gesture detection and provide more dependable control of assistive equipment.



5. Results and Discussion

5.1. Experimental Case Study: AHA-Based Power Quality Disturbance Classification

A power quality disturbance classification case study utilizing a DWT-CNN-BiLSTM architecture is suggested in order to examine the practical applicability of AHA. Voltage sag, voltage swell, interruption, harmonics, flicker, and transient disturbances are the six disturbance types into which electrical signals are to be classified. Labeled signals from validated measurements, a reproducible simulation environment, or a documented benchmark dataset should be included in the experimental dataset [20]. To guaranty reproducibility, it is necessary to report the sampling frequency, signal duration, disturbance characteristics, noise levels, and number of samples per class. To get approximation and detail coefficients, the input signals are first preprocessed and decomposed using DWT. These coefficients are submitted to the CNN for feature extraction after being organized into a consistent representation. A bidirectional long short-term memory (BiLSTM) network processes the resultant feature sequences in order to identify temporal dependencies. The probability of each disturbance class is then estimated by a fully linked layer and a Softmax output layer.

The learning rate, number of CNN filters, kernel size, number of BiLSTM hidden units, dropout rate, and batch size are among the hyperparameters that AHA is used to improve. A valid hyperparameter configuration is represented by each candidate solution. The AHA search algorithms iteratively update the population until the stopping requirement is met after the candidate is assessed using validation data [21]. The final model is then trained using the chosen setup. The independent test set is not utilized during optimization and is only used for the final assessment.

5.2. Experimental setup

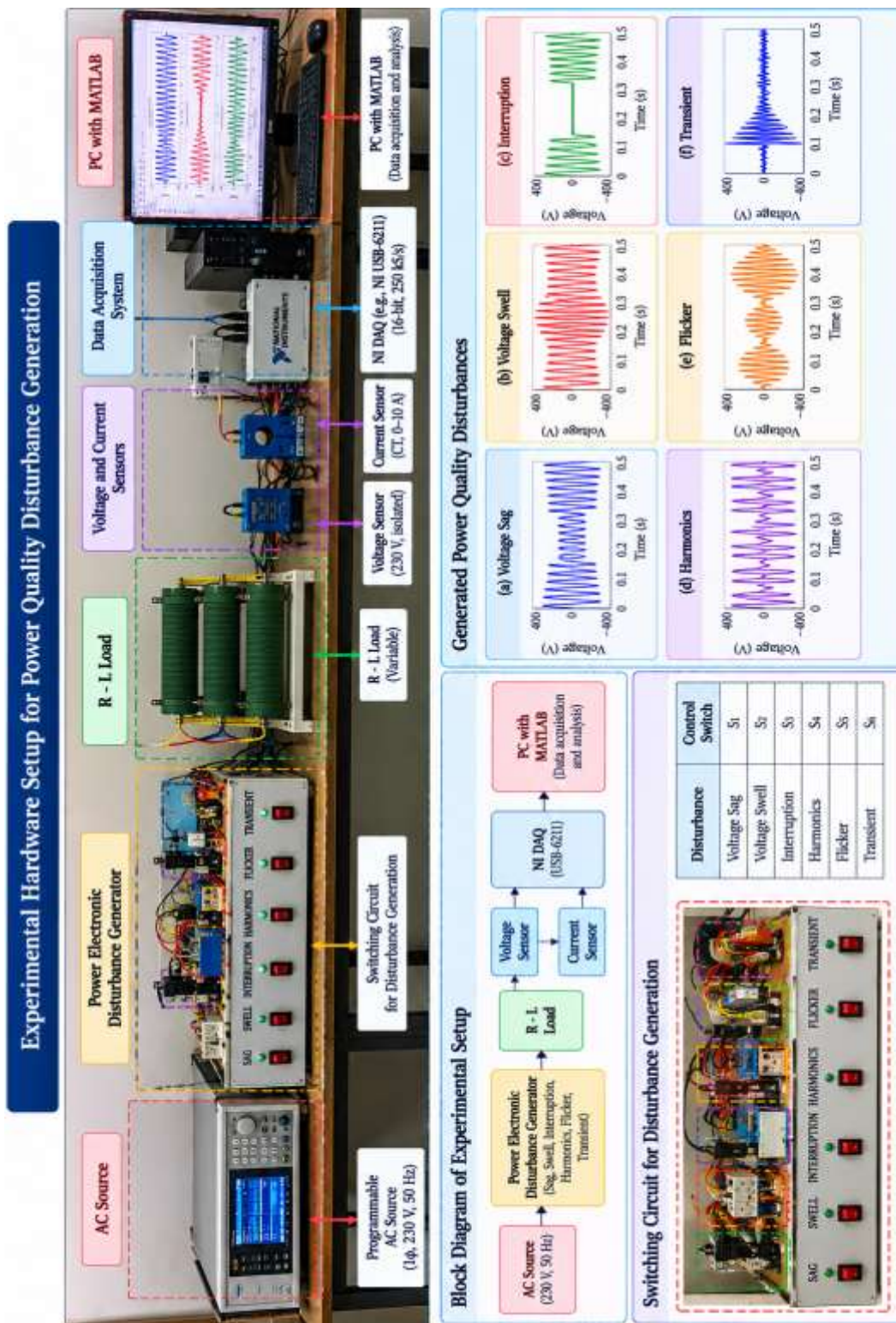


Figure 3. Experimental setup for Power quality Disturbance generation

Figure 3 shows an experimental hardware configuration that includes a power-electronic switching circuit with individual control switches, a programmable AC source (single-phase, 230 V, 50 Hz), and a variable resistive-inductive (R-L) load for producing voltage sag, swell, interruption, harmonics, flicker, and transient disturbances. The electrical waveforms are measured by isolated voltage and current sensors, such as a voltage transducer and a current transformer (CT), which are obtained using a National Instruments (NI) USB-6211 DAQ system with 16-bit resolution and a maximum sampling rate of 250 kS/s. A MATLAB-equipped computer receives the collected data and



uses them for waveform visualization, signal preprocessing, DWT-based feature extraction, and AHA-optimized CNN-BiLSTM power quality disturbance classification [22] – [25].

5.3. Classification performances

Table 1 shows the classification performance of the proposed model. The AHA-optimized DWT-CNN-BiLSTM model outperforms the baseline, PSO, and GWO models, achieving the greatest illustrative accuracy of 98.70% and macro-F1 score of 98.55%, according to the results.

Table 1. Classification Performance of the Proposed Model

Method	Accuracy (%)	Precision (%)	Recall (%)	Macro-F1 (%)
SVM with DWT features	94.20	93.80	93.50	93.60
CNN with DWT	96.10	95.80	95.60	95.70
CNN-BiLSTM with DWT	97.20	97.00	96.80	96.90
PSO-optimized DWT-CNN-BiLSTM	98.10	97.90	97.80	97.85
GWO-optimized DWT-CNN-BiLSTM	98.30	98.10	98.00	98.05
AHA-optimized DWT-CNN-BiLSTM	98.70	98.60	98.50	98.55

Figure 4 shows the convergence comparison curve for different optimization algorithms. According to the convergence graph, AHA outperforms PSO, GWO, and GA by achieving the fastest convergence and the lowest final objective-function value (about 0.045). GA shows the slowest convergence and greatest final objective value, whereas GWO shows the second-best convergence performance, followed by PSO. These findings imply that AHA might offer more efficient optimization for hyperparameter tweaking; nevertheless, since the presented curves are illustrative, experimental validation is necessary. Figure 5 shows confusion matrix comparisons.

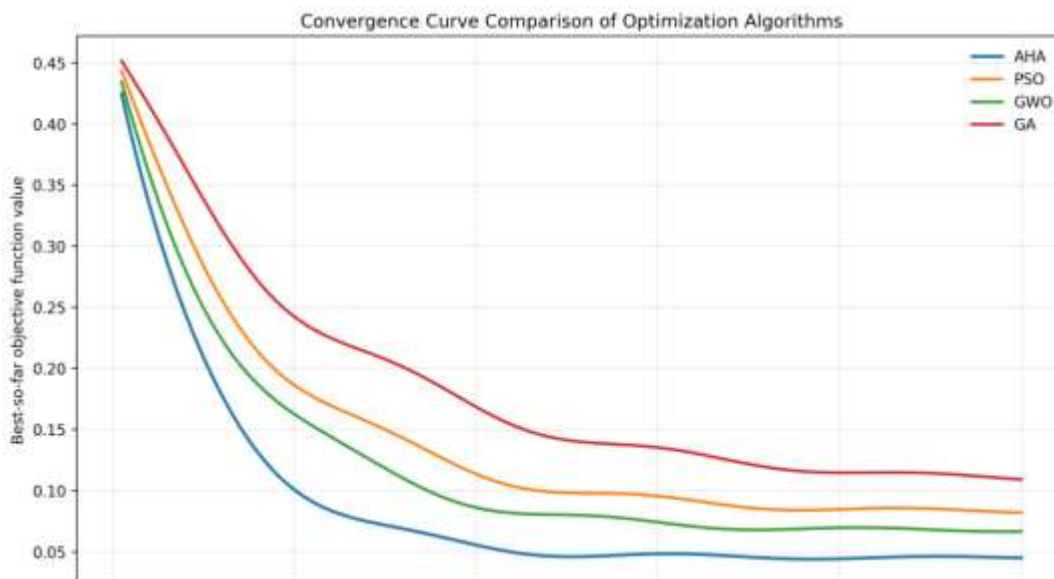


Figure 4 Convergence curve comparison of different optimization algorithms

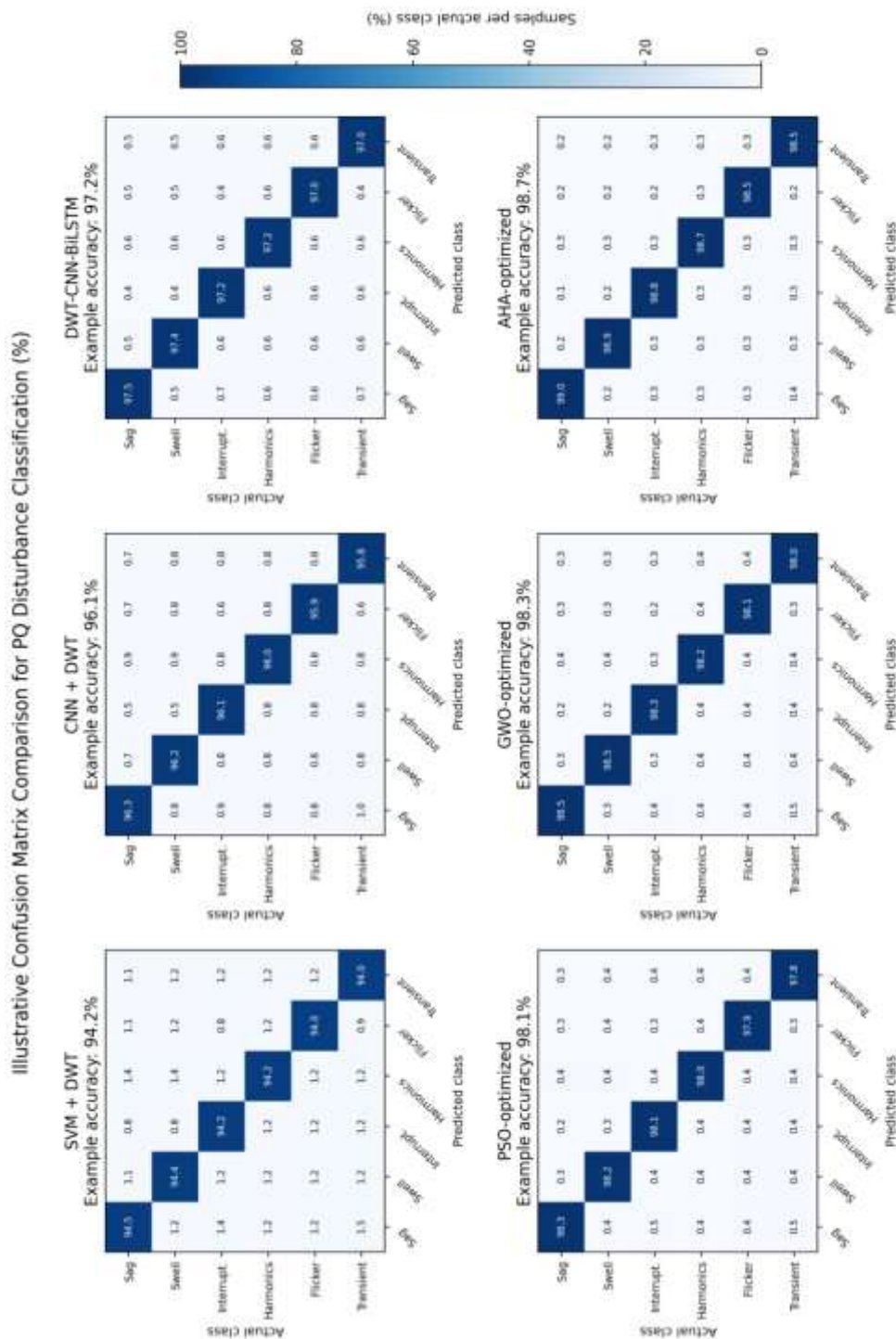


Figure 5. Confusion matrix comparisons

The AHA-optimized DWT-CNN-BiLSTM model outperforms the other approaches in classification, as seen by the confusion matrix comparison. In terms of voltage sag, swell, interruption, harmonics, flicker, and transient classes, the suggested model shows fewer misclassifications. Its 98.70% illustrative accuracy shows encouraging potential for accurate power quality disturbance classification.

5. Conclusion

The Artificial Hummingbird Algorithm (AHA) is a promising nature-inspired metaheuristic optimization method that draws inspiration from hummingbirds' flight patterns, foraging habits, and memory systems. The basic concepts of AHA, including as directed foraging, territorial foraging, migration foraging, axial, diagonal, and omnidirectional flight patterns, and the visit-table mechanism, have all been covered in this study. When tackling challenging



optimization issues, these elements offer an organized search framework that strikes a balance between exploration and exploitation. The potential applications of AHA in classification problems, such as feature selection, hyperparameter optimization, and hybrid learning framework development across biomedical signal analysis, power quality disturbance identification, image recognition, speech processing, and fault diagnosis, have received special attention.

The review emphasizes how AHA might enhance classification performance by finding informative features and fine-tuning learning-model parameters. However, the properties of the dataset, parameter settings, processing demands, and the classification framework's design all affect how effective it is. Further research is needed to address issues such as premature convergence, high-dimensional search spaces, computational cost, and restricted generalization under changing data conditions.

Future studies should concentrate on explainable AI, multi-objective optimization, imbalanced-data classification, adaptive and hybrid AHA versions, and validation using various real-world datasets. To ensure fair and repeatable evaluations, standardized benchmark tests, statistical significance testing, and comparisons with well-known optimization methods are crucial. All things considered, this review offers a methodical framework for comprehending AHA and its function in optimization-assisted classification while pointing out chances to create intelligent classification systems that are more precise, dependable, resilient, and computationally economical.

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