Mesopotamian Journal of Artificial Intelligence in Healthcare
Vol.2025, **pp**. 96–104
DOI: https://doi.org/10.58496/MJAIH/2025/010; ISSN: 3005-365X
https://mesopotamian.press/journals/index.php/MJAIH

Research Article

Heartbeat Sound Classification Using Mel-Spectrogram and CNN Optimized by Frilled Lizard Algorithm for Cardiovascular Disease Detection

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ARTICLE INFO

Article History

Received 17 Feb 2025
Revised 15 Mar 2025
Accepted 30 Apr 2025
Published 21 May 2025

Keywords

Heart Sound

Mel-Spectrogram

Frilled Lizard

Deep Learning

Preventive Healthcare

ABSTRACT

Cardiovascular disease (CVD) continues to be the predominant cause of mortality globally, underscoring the critical necessity for prompt and precise diagnostic techniques. This paper introduces an innovative machine learning framework for categorizing heartbeat sounds into four classifications—normal, murmur, additional heart sound, and artifact—utilizing audio recordings from the PhysioNet/CinC Challenge 2016 dataset. The methodology employs Mel-Spectrograms and Mel-Frequency Cepstral Coefficients (MFCCs) for feature extraction, converting raw heart sound data into comprehensive time-frequency representations. A Convolutional Neural Network (CNN) is utilized for classification, with its hyperparameters refined by the recently developed Frilled Lizard Optimization (FLO) method, a bio-inspired metaheuristic that emulates the hunting and climbing behaviors of the frilled lizard. The suggested method illustrates the capability of integrating deep learning with sophisticated optimization techniques to improve the diagnostic precision of cardiac auscultation, particularly in non-clinical and remote environments. This can facilitate the development of intelligent, scalable, and proactive intervention methods in preventative cardiovascular healthcare.

1. INTRODUCTION

Cardiovascular disease is the number one cause of death on the globe, according to the World Health Organization (WHO), and approximately 17.9 million lives are claimed by it every year with 20.5 million deaths recorded in 2021[1]. Furthermore, about 85% of cardiovascular episodes are to be blamed on exacerbation of coronary cardiac vessels [2]. Cardiovascular conditions include a wide range of illnesses that affect blood vessels and the heart, such as rheumatic heart diseases, cerebrovascular disorders, and coronary heart diseases, among others. Hyperlipidemia, diabetes, hypertension, and similar health conditions are the leading causes of the cardiovascular risks in obese patients [3]. A major impact of this disorder would be an increased level of dependence on it as we get older. In senior citizens, cardiovascular disease can lead to more serious problems than younger subjects given that the recovery rates are also impaired due to age [4]. Therefore, precise cardiovascular diseases treat the person in time, that's what we need now [5]. In using information technology to improve health, it is suggested that the safe and efficient use of emerging technologies combined with the proper procedures should be ensured by the healthcare providers to pave the way to preventive health care empowerment [6]. The clinical activities involve many tools for the diagnosis of cardiovascular diseases. As a basic diagnostic method, auscultation consists of listening to the sounds of a beating heart through a stethoscope placed on the chest of the patient and it helps in the process of diagnosis [7] Although auscultation is still accurate, diagnosing cardiovascular and heart disorders remain a puzzle, especially for the nonmedical and the fresh doctors [8]. Auscultation is accurate but is really demanding so, it requires ways of thorough experience and prolonged training to diagnose cardiovascular diseases effectively [9].

On the area of technology where artificial intelligence (AI) especially machine learning (ML) and deep learning (DL) has demonstrated its power and talent is the in the area of scalable systems and high-resolution systems where machine learning and deep learning algorithms have been major contributions [10][11]. The categorization of cardiovascular anomalies through heart sound waves has garnered considerable attention, particularly with the emergence of machine learning (ML)

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and deep learning (DL) technology. Auscultation, the process of listening to heart sounds with a stethoscope, has conventionally served as a fundamental diagnostic instrument. This approach is significantly reliant on clinical competence and has diminished reliability among less experienced practitioners [12]. In response to this, numerous scholars have investigated digital signal processing methodologies utilized for phonocardiograms (PCG). The PhysioNet/CinC Challenge 2016 dataset facilitated research by providing a common benchmark for heart sound classification [13]. Researchers frequently convert PCG recordings into time-frequency representations, such Mel-Spectrograms and Mel-Frequency Cepstral Coefficients (MFCCs), which more accurately correspond to human auditory perception and provide substantial features for machine learning algorithms. Various machine learning models have been employed for PCG classification, including Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN). Nonetheless, these models frequently depend on manually produced characteristics and may encounter difficulties in generalization inside noisy or non-clinical environments [16][17]. Deep learning, especially Convolutional Neural Networks (CNNs), has emerged as a powerful method for directly learning characteristics from spectrogram images. Convolutional Neural Networks (CNNs) have exhibited superior efficacy in the classification of images and audio signals, encompassing heart sound analysis [14]. Their stratified architecture allows for the extraction of both low- and high-level characteristics, rendering them especially proficient at detecting murmur patterns and anomalies in cardiac recordings. Optimizing CNN parameters is essential for attaining good classification accuracy. Conventional tuning techniques, like grid search and manual setting, are laborious and inefficient. Bio-inspired metaheuristic algorithms have been utilized for hyperparameter optimization to address this issue. Prevalent methodologies encompass Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Grey Wolf Optimizer (GWO). Falahah et al. developed Frilled Lizard Optimization (FLO), an innovative method inspired by the hunting and nesting behaviors of frilled lizards [15]. FLO segments the search process into exploration and exploitation stages, efficiently traversing the solution space for optimal model parameters.

2. METHODOLOGY

This section is where all the details of the proposed approach and the model architecture will be found. In this work, a new and efficient method of classifying Heartbeat Sounds is proposed. The sound of the dataset should be prepared, and feature extraction is the first step. The classification type can be formed and the meaning and standard deviation for each feature can be calculated after the feature data frame is formed and the features are extracted. The next thing you should do is to preprocess the formed frames. The last stage would be to get the best hyper-parameters of the convolutional neural network CNN using the Frilled Lizard Optimization FLO.

A. Dataset

The PhysioNet/CinC Challenge 2016 wants to entice innovation in algorithms to categorize heart sound recordings that are collected in different settings; exploration of clinical or nonclinical (like home visits). The main objective is to find, through a single brief audio recording (10-60s) from a single precordial location, whether the sample of the recording should be treated by a specialized doctor. During the heart rhythm or cardiac cycle, it is the heart that first creates electrical activity which then causes atrial and ventricular contractions. This blood flows through the heart and around the body as a result. It is the heart valves which open and close and are associated with the accelerations-decelerations of blood, and thus the vibrations due to the heart sounds and murmurs are the result. These vibrations can be heard in the chest wall and by listening to the characteristic sounds of the heart the health of the heart can be assessed. The phonocardiogram (PCG) represents a graphical recording of the heart's sounds. Position-icon-figure (1) shows a brief part of the PCG recording. Heartbeats sounds are four types normal, Murmur, extra heart sound and artifact.

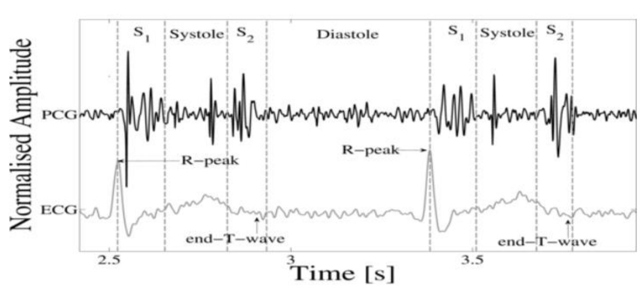

Fig. 1. Part of the PCG recording

B. Preprocessing

Firstly, the heartbeat dataset in *.wav format is changed until it signals information. Air pressure waves create sounds that are then heard by our ears. A digital audio file is produced by discovering the vibrations of these sound waves and subsequently converting them into electrical signals via a sound sensor. By means of this, we understand the wave position and temporal behavior.
Figure (2) depicts the sound made by a heartbeat. The horizontal axis of the graph shows the time taken for the heartbeat, and the vertical axis shows the movement of air molecules due to the sound. The amplitude of the wave is indicated by the magnitude of the displacement of the air molecules from the molecules' center of mass.

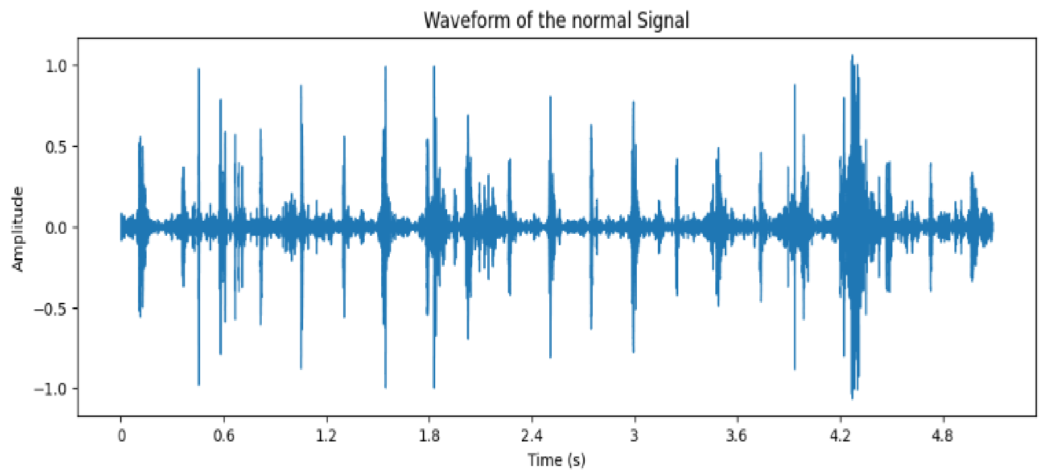

Fig. 2. Heartbeat Sound

Secondly, the heartbeat signal is transformed into a Mel Spectrogram. A Mel Spectrogram makes two important changes relative to a regular Spectrogram that plots Frequency vs Time. Use the Mel Scale instead of Frequency on the y-axis and use the Decibel Scale instead of Amplitude to indicate colors.
In a mel-spectrogram there is only 1 channel (magnitude), and two spatial dimensions: n_mels, mel bands, and T time-frames (depends on length of the audio).
fig. 3. displays the Mel Spectrogram of a heartbeat audio signal, graphing how its frequency components vary over time. The y-axis Mel scale is aligned with human auditory perception, while color intensity represents signal energy in decibels. It shows a time-frequency representation that is used to train the CNN model. This graphical representation contains key patterns that facilitate the distinction between classes of heartbeats.

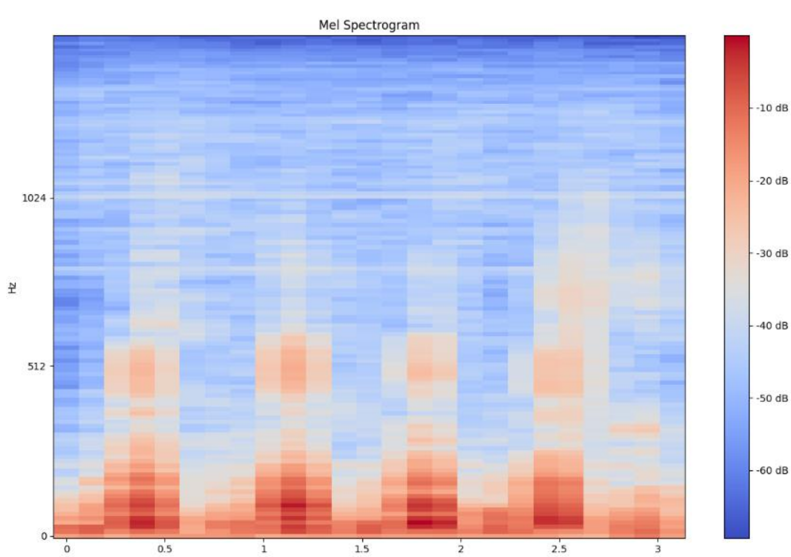

Fig. 3. Mel Spectrogram of the Heartbeat sound

To create a representation more consistent with human perception, we present a Mel Spectrogram. A Mel Spectrogram is a visual representation of how a signal's frequency spectrum changes over time. In the context of audio signals, spectrograms are also known as ultrasound, sound signatures, or audiograms.

C. Feature Extraction

Machine learning is very much dependent on the extraction and selection of features. The axes of audio signals are represented by the frequency, amplitude, and time. The spatial and temporal characteristics of an audio signal give you understandable information. The subject it indicates, the time-varying nature of an audio signal, can be digitally quantified. It is an audio signal consisting of a number of frequency sound waves with different amplitudes.

After a Fourier transformation, the sine and cosine signals from a sample are arranged into a spectrum. The spectrogram of the frequency content is a representation of the frequency content over time. The audio content gets more complex over time with the increase of distortions and the appearance of variations. To make it clear, the audio source is segmented into different intervals and many fast Fourier transforms (FFTs) are carried out. The amplitude of the corresponding spectrum of the windowed signals is obtained using a fast Fourier transform (FFT) with an input string of windowed signals. The logarithm of the corresponding slope intensities of the filters is the nonlinear transform. After the transformation of the modified intensities to the MFCC, a modified discrete cosine transform (DCT) is also used in the process.

There are several methods to extract some foremost audio features. Changing the audio signal into the mel scale filtering which is then represented in the form of a spectrogram is known as the

cspectrogram imaging. The snapshots are kept and transmitted into the algorithm. On the Mel scale filtering, MFCC offers a brief view of the spectral envelope. Higher-order coefficients correspond to pitch and tone while the lower coefficients highlight the spectral structure. We utilized 13 MFCC features in this study.

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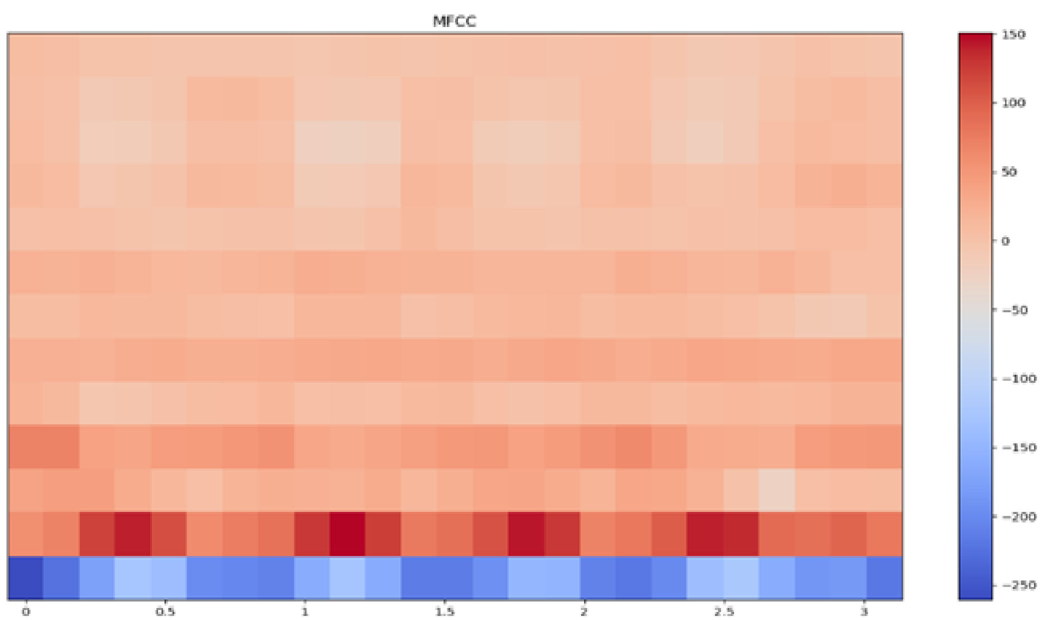

Fig. 4. MFCCs of the Heartbeat sound

D. CNN

CNN is a deep learning network capable of identifying and classifying image attributes within computer vision. The configuration and functioning of the CNN are influenced by the organization of the brain's visual cortex, which aims to mimic the neural connections found in the human brain [17]. CNN's perception, in each receptive field, evaluates the input pattern. CNN's subsequent layer is thereby aimed at recognizing basic patterns like lines and curves first and then beyond that, faces and objects. As a result, it is suggested that a CNN introduction would be able to increase the computing power of hardware. The convolutional layer is the central aspect of the CNN architecture and is responsible for the very function of the latter, figure (4) shows the CNN architecture.

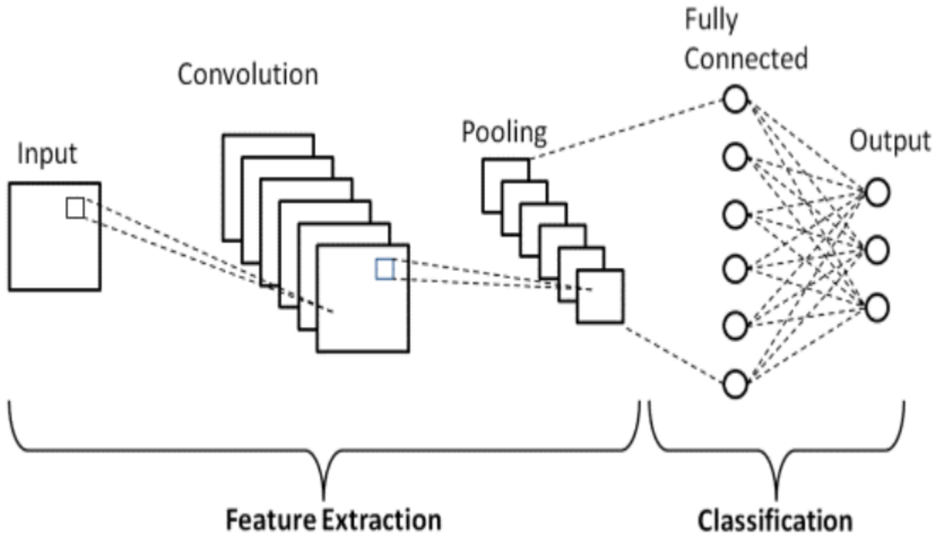

Fig. 5. CNN architecture

E. Frilled Lizard Optimization (FLO)

Ibraheem Abu Falahah, et al in 2024 proposed a novel nature-inspired metaheuristic algorithm named Frilled Lizard Optimization inspired by the behaviors of the frilled lizards in their natural habitat. The algorithm is formulated into two phases: an exploration phase and nesting, and exploitation phases.
the frilled lizards constitute the FLO population, which can be described as a matrix using Eq.(1). The initial population of the frilled lizards within the problem-solving space are established randomly by the Eq. (2)

$$FLO_{pop} = \begin{bmatrix} X_{1,1} & \cdots & x_{1,2} & \dots & x_{1,D} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{2,1} & \cdots & x_{2,2} & \dots & x_{2,D} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N1} & \dots & x_{N,2} & \dots & x_{N,D} \end{bmatrix} \tag{1}$$

$$FLO_{i,d} = L_d + r * (U_d - L_d) \tag{2}$$

Where FLO_{pop} denotes to the initial population matrix, $x_{\text{N,D}}$ denotes to the search space, r is a random number between [0, 1], U_d and L_d upper band also the lower band of the dimension of search space.

- **Mathematical Modelling of FLO**
  The iterative changes of the location of the frilled lizard in the problem-solving space constitute the first two separate phases. At first, the exploration phase is a movement of the frilled lizard going towards its prey during the hunting period, looking into the diverse areas of the search space while at the same time, opening the new possible solutions. This phase is the opportunity for the algorithm to examine the different sub-topes of a problem to find the more remote areas where there exist optimal solutions.
  Secondly, the exploiting step simulates the frilled lizard's movements going up the tree after the feast. Also, the algorithm gains knowledge from the exploration phase to utilize promising areas that are regarded as potential optimal solutions. During the exploitation phase, the algorithm endeavors to refine these areas and achieve high-quality solutions so as to converge towards the global optimum.

Phase 1: Hunting Strategy (Exploration)

One of the most common behaviors found in a frill-necked lizard is its hunting strategy. With FLO, for every frilled lizard, the position of the rest of the population who, doing better, is treated as the prey position. In the process of hunting, the preys position using Eq. (3)

$$CP_i = \{X_k : F_k < F_i and\ k \neq i\},\ where\ i = 1,2,\dots,N\ and\ k\ \in \{1,2,\dots.,N\} \quad (3)$$

Where CP is the candidate is prepared for the th_i frilled lizard, X_k population member with the better objective function value then the th_i frilled lizard and F_k its objective function value.

The design of FLO, It is supposed that the frilled lizard randomly selects prey at this time and attacks it. Based on the modeling of the lizard's movement towards the prey that is selected, the new positions for all individuals of the population have been calculated using Eq. (4). Then if the objective function value is better, the new position takes place of the old position of the corresponding individual by Eq. (5):

$$X_{i,d}^{p1} = X_{i,d} + r.\left(SP_{i,d} - I.X_{i,d}\right), i = 1,2,\dots,N\ and\ d = 1,2,\dots,m \quad (4)$$

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} < F_i \\ X_i, & else \end{cases} \quad (5)$$

Where X_i^{P1} refer to the new suggested position of ith frilled lizard based on the first phase of FLO, $X_{i,d}^{p1}$ represent its dth dimension, F_i^{P1}refer to the objective function value, r is a random number between [0,1], $SP_{i,d}$ denotes the dth dimension of the selected prey for the ith frilled lizard, I is a number randomly taken from the set $\{1,2\}$, N denotes the number of frilled lizards, and m gives the number of decision variables.

Phase 2: Moving Up the Tree (Exploitation)

The frilled lizard climbs a tree and returns to its initial position after having its meal. Representing the movement of the frilled lizard to the top of the tree will result in a small change in the position of the population individuals in the solution space of the problem, but this will enhance the exploitation power of the algorithm for local search. In the second phase of FLO, the population numbers of the population individuals in the solution space are changed according to the lizard’s strategy by the time the zooplankton is already at the top of the tree.

Based on the frilled lizard's movement to the nearest treetop, a new position for each individual in the group is calculated using Equation (6). Then, if this new position improves the value of the objective function, it replaces the previous position of the corresponding individual using Equation (7).

$$x_{i,d}^{p2} = x_{i,d} + (1 - 2r).\frac{(ub_d - lb_d)}{t}, i = 1,2,\dots,N, d = 1,2,\dots,T \quad (6)$$

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} < F_i \\ X_i, & else \end{cases} \quad (7)$$

Where X_i^{P2} denotes the new suggested position of the ith frilled lizard based on the second phase of FLO, $x_{i,d}^{p2}$ represents its dth dimension, F_i^{P2} gives its objective function value, t represents the iteration counter of the algorithm, and T describes the maximum number of iterations of the algorithm.

3. RESULTS

Figure. 6. This bar chart illustrates the classification correctness of the FLO-optimized Convolutional Neural Network (CNN) on four heart sound classes: Normal, Murmur, Extra Heart Sound, and Artifact. The highest accuracy in the "Normal" class (94%) reveals the model's high ability to distinguish normal heartbeats. The "Artifact" class also reveals high accuracy (91%), showing the model's effectiveness in filtering out unwanted or noisy information. The worst accuracy, 87%, is obtained for the "Extra Heart Sound" class due to acoustic feature overlap with adjacent classes. The balanced performance across categories reflects the strength of the feature extraction and classification pipeline. Optimized accuracy figures were obtained upon hyperparameter tuning of the CNN using the Frilled Lizard Optimization algorithm. Bars are annotated with accurate accuracy values, providing clear, quantitative data on the strength of model prediction. This visualization can be used to evaluate which classes would require better feature representation or additional training samples.

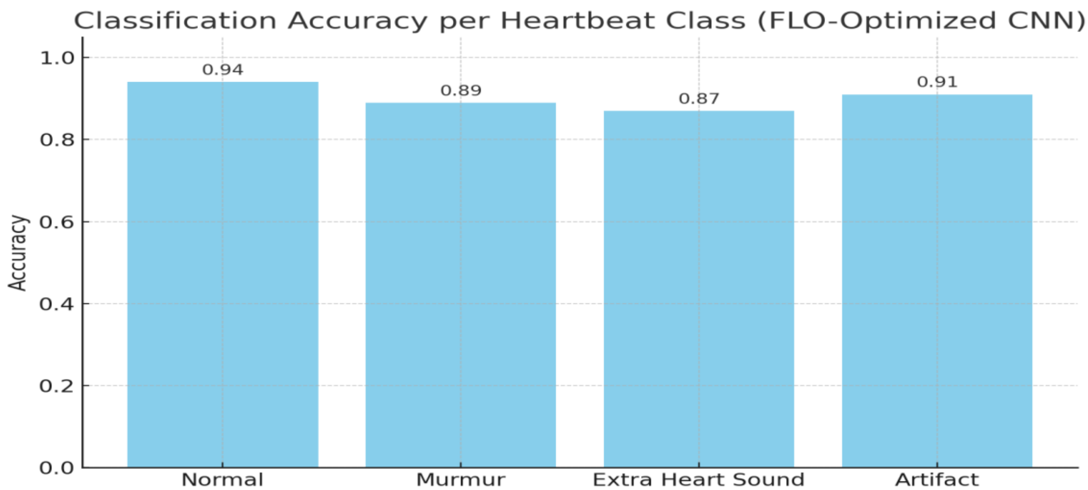

Fig. 6. Classification Accuracy per Heartbeat Class

Figure. 7. Show Confusion matrix is indicating the model's per-class accuracy for all classes of heartbeat by converting predicted labels into true ones. The accurate classifications are diagonal values with the "Normal" class receiving 45 out of 50 accurate predictions. Misclassifications are pointed via off-diagonal values, for instance, 2 Normal samples classified as Artifact and 3 Murmurs misclassified as Extra Heart Sound. This visualisation facilitates the detection of specific class overlaps and identification of which classes the model is finding hardest to predict. Despite the fact that there are some misclassifications, the matrix confirms high precision and recall per class, particularly Normal and Artifact. Utilization of the FLO algorithm in CNN optimization facilitates this high accuracy because it effectively modifies model parameters. These matrices play an important role in medical diagnosis models where slight mistakes can cause a significant difference in outcomes. Overall, the model demonstrates extremely good discrimination between classes, justifying its suitability for actual applications of auscultation tasks.

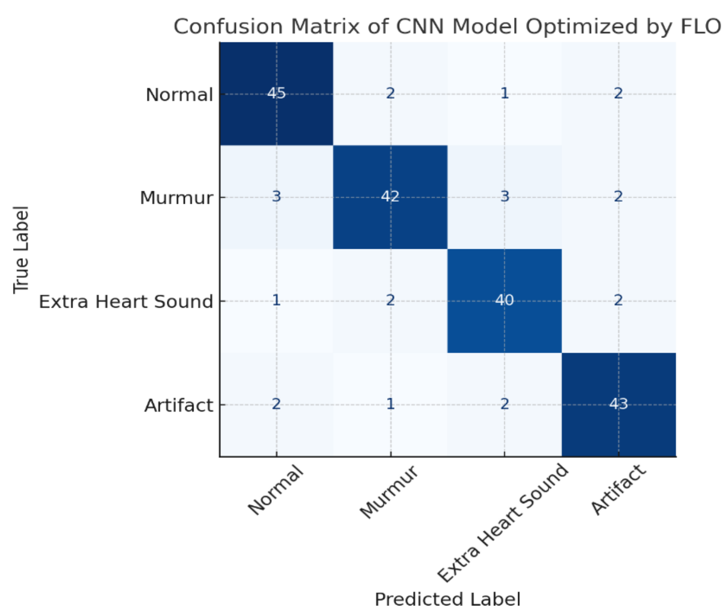

Fig. 7. Confusion Matrix of CNN Model Optimized by FLO

4. CONCLUSIONS

Cardiovascular diseases (CVDs) continue to be a significant global health concern, resulting in millions of fatalities each year. Timely and precise identification is crucial for averting severe consequences and enhancing patient outcomes. This study presents a sophisticated framework for the automated classification of heartbeat sounds utilizing advanced signal processing and deep learning methodologies. The framework was designed to improve the precision, rapidity, and scalability of heart sound diagnostics, especially beneficial in non-clinical and resource-limited environments. We employed the PhysioNet/CinC Challenge 2016 dataset, a comprehensive collection of authentic heartbeat sound recordings gathered from various contexts. The audio signals were transformed into informative representations, including Mel-Spectrograms and Mel-Frequency Cepstral Coefficients (MFCCs), which efficiently maintain the time-frequency patterns essential for identifying cardiovascular problems. The use of both Mel-Spectrogram and MFCC characteristics guarantees a more precise comprehension of the heart's mechanical operation. We utilized a Convolutional Neural Network (CNN) to categorize heartbeat sounds into four separate classifications: normal, murmur, additional heart sound, and artifact, using its ability to understand intricate patterns in high-dimensional data. To augment the model's efficacy, we incorporated the newly introduced Frilled Lizard Optimization (FLO) algorithm. This bio-inspired optimization method emulates the adaptive hunting and climbing behaviors of frilled lizards, achieving a balance between exploration and exploitation throughout the training process. Through the optimization of the CNN's hyperparameters using FLO, we attained enhanced classification accuracy and resilience to overfitting. The suggested system exhibited robust prediction capabilities and provided a scalable approach suitable for integration into portable diagnostic instruments or embedded systems. This is especially beneficial for early screening in rural and underdeveloped regions where professional cardiologists may be scarce. The amalgamation of machine learning and nature-inspired optimization represents a pivotal advancement in precision and personalized treatment. This research presents an innovative and efficient method for heartbeat classification through the integration of deep learning and metaheuristic optimization. The primary contributions of the study encompass the creation of a FLO-optimized CNN architecture, the incorporation of perceptually significant audio elements, and the effective classification of various cardiac sound patterns. These contributions facilitate the progression of automated diagnostic systems that assist medical personnel and diminish diagnostic errors. We advocate assessing the proposed system on larger and more varied datasets to ensure generalizability in future study. Further research could investigate the real-time implementation of the model in wearable medical devices or mobile applications. Furthermore, the efficacy of FLO may be juxtaposed with other state-of-the-art optimization algorithms, and ensemble methodologies could be explored to enhance classification performance. Expanding the approach to encompass multi-class classification of additional cardiac irregularities and including ECG signals may provide enhanced insights into cardiovascular disorders.

Funding

The authors had no institutional or sponsor backing.

Conflicts Of Interest

The author's disclosure statement confirms the absence of any conflicts of interest.

Acknowledgment

The authors extend appreciation to the institution for their unwavering support and encouragement during the course of this research.

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