A Systematic Review on Metaheuristic Optimization Techniques for Feature Selections in Disease Diagnosis: Open Issues and Challenges

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Abstract
There is a need for some techniques to solve various problems in today’s computing world. Metaheuristic algorithms are one of the techniques which are capable of providing practical solutions to such issues. Due to their efficiency, metaheuristic algorithms are now used in healthcare data to diagnose diseases practically and with better results than traditional methods. In this study, an efficient search has been performed where 173 papers from different research databases such as Scopus, Web of Science, PubMed, PsycINFO, and others have been considered impactful in diagnosing the diseases using metaheuristic techniques. Ten metaheuristic techniques have been studied, which include spider monkey, shuffled frog leaping algorithm, cuckoo search algorithm, ant lion technique of optimization, lion optimization technique, moth flame technique, bat-inspired algorithm, grey wolf algorithm, whale optimization, and dragonfly technique of optimization for selecting and optimizing the features to predict heart disease, Alzheimer’s disease, brain disorder, diabetes, chronic disease features, liver disease, covid-19, etc. Besides, the framework has also been shown to provide information on various phases behind the execution of metaheuristic techniques to predict diseases. The study’s primary goal is to present the contribution of the researchers by demonstrating their methodology to predict diseases using the metaheuristic techniques mentioned above. Later, their work has also been compared and evaluated using accuracy, precision, F1 score, error rate, sensitivity, specificity, an area under a curve, etc., to help the researchers to choose the right field and methods for predicting the diseases in the future.

1 Introduction

The current era of medicine has a huge contribution to computing facilities and the latest technologies that can, in turn, help humans in different applications. The various applications include assisting in surgery, testing, and composition of multiple medicines and using various tools in training and teaching at other medical universities [1]. All types of body examinations done in the medical area use different computing tools in one way or another. All the evaluation processes used for diagnosing other diseases, if done using computer-aided automated processes, will lead to higher performance and better treatment [2].

As we know, the data extracted and generated in the healthcare domain is huge amounts, and the pace of storing all different healthcare data in the databases related to clinics is growing at a much faster rate. So, there is a strong need to access this data from a large amount of data so that the extracted data should be helpful in diagnosing and treating various diseases of patients [3]. In this era, many researchers are working on automating the diagnosis and prediction of
various diseases using multiple machine learning algorithms so that it, in turn, can be beneficial in effectively treating all diseases [4]. There are several algorithms under the category of machine learning and data mining that researchers are currently using for the diagnosis of diseases [5]. It is possible to develop an automated and intelligent system for detecting diseases using various algorithms of Data Mining, Artificial Intelligence, and Meta-Heuristics [6].

The research community is now working on including various types of sensors for data collection, but this acquisition technique has complications regarding forecasting, decoding, and recognition. Different algorithms of metaheuristics are also used for analyzing the data in terms of validity for data mining algorithms, which helps increase the performance of various algorithms on healthcare data [7]. There is also great diversity in the applications of metaheuristics in areas of medical services, which includes improved classification systems, effective detection systems, and an increase in the detection rate of various diseases [8]. The treatments were also improved using these techniques, decreasing the complications with the patient with prolonged diseases. Some diseases have the disadvantage that if the patient is undiagnosed for a long time, they can unknowingly transmit that disease to many others. This outbreak can be prevented if the disease is diagnosed early. The metaheuristics techniques can be broadly classified into two categories: single solution and population solution-based algorithms [9]. Both categories can be differentiated based on the method used for finding a solution. In single solution-based algorithms, all the solutions are generated randomly until the final and optimal solution is generated. On the other hand, in the case of population-based algorithms number of solutions is generated randomly, and the values of all solutions are updated iteratively. The best solution is developed using various iterations [10].

Different novel metaheuristics algorithms such as Artificial Immune Systems, Cat Swarm optimization, Bat-inspired, Firefly Algorithm, Genetic algorithm, Flower pollination algorithm, Grey Wolf optimization, Flower pollination, Glow worm Swarm Optimization, Whale Optimization, Chicken Swarm Optimization, Lion Optimization, Grasshopper Optimization, Crow Search, Moth Flame Optimization, Elephant Search, Social Spider optimization, Tabu search, Ant colony optimization, Bees algorithm, Chimp Optimization Algorithm and many more are highly useful for feature extraction and selection for different types of disease diagnosis and early detection [11].

1.1 Contribution

In this article, we presented the importance of metaheuristic algorithms for different types of disease detection. The approach is novel as it uses metaheuristic algorithms for its applications in Decision Support Systems (DSS) for detecting various diseases solely alone or as a part of a large and hybrid system. The article covers the novel metaheuristic algorithms and their applicability in disease diagnosis and prediction. The presented article covers the published papers between the year 2011 to 2022 for different types of diseases in which metaheuristic algorithms have been used. There are four main research questions (RQs) that are addressed in this contribution: RQ1. Which state-of-the-art research techniques under the metaheuristics techniques are used in the disease diagnosis? RQ2. Which different types of diseases have applied metaheuristics techniques? RQ3. What are the limitations and challenges for each research area? RQ4. In which other areas of healthcare can metaheuristics techniques be used in the future?

The paper’s road map, as shown in Fig. 1, is organized into various sections. Initially brief about metaheuristics techniques and their applicability in the healthcare system is defined in section 1, which is the introduction. It includes Fig. 2, representing the year-wise distribution of the used papers for metaheuristics techniques. Section 2 gives the methodology section, which covers the article selection criteria. Section 3 discusses the framework for disease diagnosis using metaheuristics techniques. The detailed literature works and a comparative study covering
the disease diagnosis and detection procedure using different metaheuristic algorithms are presented in section 4. In the end, section 5 has the conclusion, which will help the research community find the best applications for these approaches.

2 Methodology

The study deals with the reader’s extensive study of the works in the field of metaheuristic algorithms in the healthcare sector [12]. The wide-ranging survey also illustrates different gaps in knowledge and finds various research paths for the future [13]. The present study renewed the structure which shaped extensive article assessment criteria from published articles. The structure of this survey article consists of three main steps: preparation of the action plan, implementation of that action plan, and finally, reporting and structuring of the research paper, as shown in Fig. 3.

To address various research questions already defined as RQ1, RQ2, RQ3 and RQ4, this review article included many articles that used many metaheuristics techniques for the diagnosis of diseases. The articles were searched from different databases that included Scopus, Web of Science, PubMed, PsycINFO (Psychological Information database) etc. After that the articles were selected having effective information related to selected meta-heuristic techniques. Various combinations used for the searching of articles for the databases are—“Metaheuristic algorithms in healthcare”, “<specific optimization technique> in healthcare”, “<specific optimization technique> in disease diagnosis”, “Review/State-of-art of <specific optimization technique>”. The articles having review and state-of-art techniques were segregated from the articles that used metaheuristic techniques for the diagnosis of various diseases.

3 Framework of Disease Detection Using Metaheuristic

Disease detection is the process of diagnosing various diseases after checking the symptoms and signs of the patients. Different diagnostic tests are used for acquiring symptoms and signs for the diagnosis of multiple diseases [14]. This process becomes more challenging in the case of asymptotic cases where the symptoms are not seen. In all such cases, different tests are required to diagnose several diseases as the patients do not have any symptoms [15]. Also, there is a need to extract information and patterns for diagnosis. In addition, the different ways must be differentiated promptly [16].

As shown in Fig. 4, medical images (different disease images) are taken from the medical dataset repositories and then pre-processed [17]. The desired metaheuristic algorithm is applied for the feature extraction and selection process to reduce the feature set by optimizing the selected features. After selecting the important features, the classification of features into different classes must be performed to evaluate the type of disease [18].

As a result, various metaheuristics approaches has widely used for different types of disease diagnosis. In contrast, the novel metaheuristic algorithms (MAs) can identify the symptoms of Parkinson’s disease at an early stage using the selection of optimal features for disease diagnosis [19]. Using MAs, it is also possible to diagnose Alzheimer’s disease early on using computers to prevent brain disorders [20]. Metaheuristic algorithms also play an essential role in the early diagnosis of diabetes by optimizing the disease symptoms during the training phase [21] by extracting the ECG features for heart disease. Using metaheuristic algorithms can give significant results during classification time [22].
Fig. 3 Article selection criteria for different disease diagnosis using MAs

Fig. 4 Framework for disease detection using metaheuristic algorithms
Similarly, by applying metaheuristic algorithms in HIV-1 infection, the number of infected cells is decreased about the stochastic parameters of HIV. Different characteristics in the area of biology can be controlled by metaheuristic approaches using drug dosage management [23]. At the same time, Metaheuristic approaches are also helpful for detecting and extracting cancer cells from medical images for early cancer prediction. Metaheuristics, in combination with machine learning, can be used for liver disease detection using the best feature selection and classification approach [24]. The different types of symptoms can also be extracted and selected for epidemic diseases using metaheuristic algorithms. Various types of fever can also be detected using metaheuristics and AI techniques by extracting the symptoms of medical illness [25]. Metaheuristic algorithms can be applied for feature selection of Systemic Lupus Erythematosus disease, affecting the joints, skin, kidneys, and other body organs [26]. Metaheuristic algorithms can also extract the different types of allergic features and further optimize the diagnosis of asthma immune-mediated diseases [27]. Metaheuristic algorithms are also suitable for feature extraction and selection for highly contagious viral infections to detect different types of flu or influenza [28].

4 Related Work

In the related work, the metaheuristic algorithms such as spider monkey optimization, dragonfly optimization, shuffled frog leaping algorithm, cuckoo search optimization, bat inspired algorithm, grey wolf optimization, ant lion algorithm, lion optimization algorithm, moth flame optimization, whale optimization algorithm and dragonfly optimization model used by the researchers for various disease detection like cancer, COVID, diabetes, heart disease, genetic disease, retinal disorder, lung disease, Alzheimer’s disease etc. have been shown along with the some other techniques.

4.1 Spider Monkey Optimization

It is an optimization technique in which the societal behavior of the spider monkeys is used to find the optimal solutions. The behavior of the spider monkeys is termed fusion-fission, in which they split or merge themselves. They change their behavior as per the availability of the food. When the availability of food is high, then the cluster is bigger. When the food is scarce, the cluster is divided into further clusters [29]. The implementation of spider monkey optimization includes various steps, which at the first step comprises the initialization of the population with a random distribution process, as shown in Eq. (1)

\[
SM_{ij} = SM_{\text{min}_j} + R(0,1) \times \left( SM_{\text{max}_j} - SM_{\text{min}_j} \right)
\]  

(1)

In which \( SM_i \) referred to the ith spider monkey. \( SM_{\text{min}_j} \) refers to the minimum range and \( SM_{\text{max}_j} \) refers to the maximum range and \( R(0,1) \) refers to the numbers that are generated randomly between the values of 0 and 1. The probability function is used for finding the fitness function value which in turn gives the value of position of the spider monkey as shown in Eq. (2)

\[
P_i = 0.9 \times \frac{\text{fitness}_i}{\max \text{fitness}} + 0.1
\]

(2)

where, \( \max \text{fitness} \) gives the maximum fitness value of the population and \( \text{fitness}_i \) gives the fitness value of the ith spider [30]. Figure 5 shows how Spider Monkey can predict diseases by optimizing the dataset with disease features. During the first step, the parameters were initialized. Then the fitness function was evaluated. The local and global values were calculated, which were used to find the best solution based on a fitness function. Once the values were finalized, the prominent features were selected. In the end, the diseases were predicted based on the selected features.

Fig. 5 Spider Monkey optimization for disease diagnosis [31]
In [31], the authors developed a model for detecting COVID-19 from time series data using a Jaya Spider Monkey Optimization Algorithm. This proposed algorithm used a classifier based on convolutional long short-term memory. It was capable of predicting confirmed, death, and recovered cases. A gene-detection process had been proposed in [32] that were better than the existing tests. The algorithm allowed the user to enter the actual gene results. Features were picked and tuned using spider monkey optimization. Finally, the function was terminated using a support vector machine, classifying the input genes as stable or cancerous. In [33], the authors used SM modeling, which involved spider monkey optimization for the classification of various types of diabetes. This dataset was used for this algorithm. They were examined for both potential advantages and disadvantages. The highest score was found after finding the values of True Positives, Negatives, and Negatives. Accuracy, sensitivity, as well as specificity were measured on the dataset. In addition, an algorithm was used to classify dengue fever, and the greedy forward selection approach was used to preprocess the input genes. The proposed system was trained using a Probabilistic Neural Network, and this performance was compared with the value of the global optima in each cycle. Spider monkey optimization was used to optimize the performance value to close to the optimal value [34]. The authors identified a tool for detecting retinal defects. Photographs of retinal structures were going into the preprocessing system and, subsequently, the post-processing system. Spider monkey optimization was used to determine the value of Shannon suggested for entropy for the tri-based thresholding. Before reaching its highest fitness, the spider monkey optimization was used. Active Contour analysis allowed it to be found post-processing [35].

In [36], it was checked and introduced all of the details concerning Spider Monkey Optimization. The variants, implementations, and analysis performed in all of the spider monkey optimization applications were included in the article. The article included a study of spider monkey optimization and other current optimization strategies in terf applications. The authors in [37] also defined the current state of spider monkey optimization along with all existing techniques. The author’s primary goal was to specifically identify all aspects of spider monkey optimization, including its variants and implementations. The article also described the various spider-monkey optimization solutions in multiple fields. It encouraged researchers to use spider monkey optimization in their problems to find the most successful solutions.

4.2 Shuffled Frog Leaping Algorithm

This algorithm diagnoses various diseases using the behavior of frogs during their food search. This meta-heuristic algorithm is based on memetic criteria that help optimize after considering local and global search spaces and after performing a simulation of the communication amongst frogs [38]. The basic steps in SFLA (Shuffled Frog Leaping Algorithm) optimization are initialization, evaluation, and shuffling of frogs between different sub-populations. The number of key parameters is the basis of implementing the shuffled frog leaping algorithm. It includes the count of the frog population, the count of frogs in each group, the number of groups, and several iterations [39]. These parameters directly affect the values of the fitness function. Figure 6 demonstrates how a shuffled frog leaping algorithm can be used to identify diseases optimally. This algorithm’s disease prediction begins with initializing the frog population and announcing its initial setup. After defining the fitness function, the setup is iteratively refined until the fitness function’s best values are discovered. The solution is finally optimized using the final values. Local searches are performed using various algorithms, and then subpopulations are determined again by jumping the frog from one subpopulation to the next based on fitness values. The fitness functions are rejoined and evaluated before the total number of iterations is reached. The significance of optimal global outcomes is determined [40].

In [41], an algorithm was used to classify brain MRIs (magnetic resonance imaging) based on an Extreme Learning Machine using the Shuffled Frog Leaping algorithm. Likewise, the authors in [42] worked on an algorithm for brain disease detection. The diagnosis of various diseases of the brain was made in a very effective manner using these fused images. The algorithm diagnosed the brain disease using the hybrid Pulse coupled neural network and the SFLA that combined the high-frequency and low-frequency sub-bands. The algorithm proved to be the best in healthcare in detecting glioma disease and Alzheimer’s disease of the brain, as both subjective and objective evaluation was done to check the algorithm’s accuracy. The researchers in [43] also implemented an algorithm that selected the genes optimally from the large data set. While implementing the algorithm, the large datasets were first reduced using some statistical features. Then the features were selected using the shuffled frog leaping algorithm and K nearest neighbor classifier. The algorithm was implemented on CNS (central nervous system), ADCALung, Leukemia, AllAml, and Prostate dataset, which are high-dimensional datasets. The researchers in [44] used a shuffled frog leaping algorithm to develop a method for detecting multiple lesions in retinal fundus images. In this proposed algorithm, Convolutional Neural Network (CNN) was used for creating a hybrid with the Shuffled frog leaping algorithm known spherical fractal convolution neural network (CNN). Spherical fractal convolution neural network achieved effective outcomes by using the shuffled frog leaping algorithm.
A technique to scan food along with CNN’s backpropagation strategy. The algorithm was first used on a single population by optimizing the weights and correcting the values in the backpropagation algorithm.

A technique had been proposed that was able to segment the 3D MRI images for diagnosing brain tumors. The author developed a hybrid SFLA and Tabu Search (TS) technique to elicit the input brain images more effectively. The labeling of the image map was done by Tuberous sclerosis. The method proved very effective for detecting tumors in MRI images [45]. The authors have mentioned in [46] the working of a technique that proved very useful in detecting breast cancer from mammogram images. The proposed method began by clustering the area of interest using k-means clustering. The image’s special and significant characteristics were chosen for further processing. The neuro-fuzzy inference method was used in the classification process, and the results were optimized using the shuffled frog leaping algorithm. A technique had been developed in [47] for the segmentation and classification of prominent features and identification of the biomedical data subsets that could help achieve higher accuracies. This was done with the help of the k-nearest neighbor with a shuffled leaping frog algorithm, which increased the efficiency of disease diagnosis. In [48], the researchers developed a novel method for diagnosing breast cancer in the images of mammograms. The prominent features were extracted using techniques, including Pseudo Zernike Moments and Gaussian Markov Random Field (GMRF) features. As the features extracted were of larger dimensions, the hybrid technique of the shuffled frog leaping algorithm and particle swarm optimization was used to reduce the dimensions and select the prominent features.

The authors reviewed and analyzed the shuffled frog leaping algorithm’s effectiveness compared to existing metaheuristic techniques. The authors included various variations and hybridization done using the shuffled frog leaping algorithm in different applications [49]. In [50], the authors also reviewed the shuffled frog leaping algorithm’s various limitations and future avenues. The authors’ paper contained the frog leaping algorithm’s mathematical model and its research status. The authors discussed and compared all the different variants of the shuffled frog leaping algorithm using running time and success ratio parameters. The fitness value was calculated for each frog using a shuffled frog leaping algorithm after the initialization of the population. Then, the frogs were arranged according to the descending values of the fitness function [51].

4.3 Cuckoo Search Optimization

Cuckoo optimization is simulating the behavior of the bird “Cuckoo”. The behavior of cuckoo birds is their habit of laying eggs in some birds’ nests rather than in their own
nest. They find the best place for laying their eggs that is safer for their eggs. There is a probability that the host birds can find out that the eggs do not belong to them. In that case, they will either throw the eggs or choose a new place for their nest. The best place for laying eggs is chosen by checking the similarity between the eggs of the host bird as well as the availability of the food [52]. In [53], a technique was developed to check the lung status of patients suffering from COVID-19. The features needed for detection were taken from input X-ray images. The proposed method proved effective as it worked accurately on all normal patients and on patients suffering from COVID-19 and pneumonia.

In [54], the researchers proposed an algorithm to help diagnose lung tumors from CT (computed tomography) images of the lungs. The algorithm also detected the stages of lung cancer and lung nodules. Naïve Bayes classifier classified images using a neuro-fuzzy classifier and Cuckoo Search optimization. In [55], an algorithm was proposed using which the images of breast histopathology were segmented. The optimization was done using Cuckoo Search optimization, and classification was done using k-means clustering. A novel method has been applied for diagnosing breast cancer in the images of mammograms. The optimized features were extracted using the Gabor filter bank with Cuckoo search. The features were selected using the Bayesian Regression method. The method was implemented on the publicly available Digital Database for Screening Mammography (DDSM) [56]. In [57], the researchers also developed a method for diagnosing lung cancer. The proposed method used Fuzzy C-Means (FCM) for image segmentation, and also the region of interest was found using the region growing method. After that, the optimized values of the accuracy of the segmented region were evaluated using the Cuckoo Optimization method by selecting more appropriate features in terms of geometry, texture, and statistics. Afterward, the selected features were classified using a Support Vector Machine (SVM).

An algorithm was used in which Cuckoo Search Optimization, was used for training the neural network. The value of the root mean square error was reduced on priority to increase the accuracy values. The feed-forward neural network was used for the training purpose [58]. Likewise, an algorithm was applied in [59] for detecting heart diseases and predicting diabetes. The features were extracted and selected using Rough Sets and the Cuckoo Search Optimization method. The method proved to be better than the existing techniques as the number of attributes was reduced using Rough Sets. It was implemented on the databases given by Cleveland, Hungarian, and Switzerland for heart diseases and real-time data for diabetes prediction.

The researchers in [60] developed a novel technique for detecting brain tumors from MRI images after effective segmentation. The image pixels were labeled using the Markov Random field. The optimization to calculate the optimum value of the threshold was performed with the help of the cuckoo search algorithm. The researchers in [61] used an algorithm for the enhancement of CT images which would enhance the images using log transform. The parameter settings for the log transform were done using the Cuckoo Search algorithm. The researchers in [62] developed a technique for diagnosing many different heart diseases and breast cancer. The initial parameters of the support vector machine were optimized using the Cuckoo Search algorithm. Afterward, particle swarm optimization was used to continue training using the support vector machine. The method helped to diagnose various diseases very early so that treatment could be started. A technique to detect diabetes was developed in [63] using Cuckoo Search optimization, Support Vector Machine (SVM), and Principal Component Analysis (PCA). This algorithm also helped in speeding up by using convergence. The principal component analysis was used to discard irrelevant features, and the support vector machine was used for the optimal classification of features. The authors of [64] reviewed and analyzed the Cuckoo Search optimization algorithm. The authors clearly defined this algorithm’s mechanism of working and its various real-time applications. In [65], the authors also reviewed the development done so far in the Cuckoo Search Optimization algorithm. The researchers also discussed the real-time applications of these algorithms [66] and critically analyzed them. The researcher first introduced the cuckoo search method, followed by its optimization process, and at the end, all the applications of the cuckoo search method were defined clearly.

4.4 Bat Inspired Algorithm

A bat-inspired algorithm is based on the ability of bats to locate their prey using echos. The bats have the unique characteristic of releasing a loud sound, and that sound’s echo helps them find their prey [67]. The values of velocity, frequency, and position of the bat are updated using the importance of local and global minima and maxima, which helped locate nearby prey. The values of frequency (f) position (x) and velocity (v) at any iteration (t) is calculated with the help of following equations (3,4,5)

\[ f = f_{\text{min}} + (f_{\text{max}} - f_{\text{min}}) \beta \]  

(3)

where f is the value of frequency \( f_{\text{min}} \) and \( f_{\text{max}} \) are the minimum and maximum values of the frequency and it is dependent on the domain size of the problem, \( \beta \) is the random vector having values between [0,1].

\[ v^{t+1} = v^t + (x^t - x) \cdot \text{fi} \]  

(4)
where \( x \) is the recent global best location. The biggest advantage of bat inspired metaheuristic algorithm is that it is able to provide solutions at a very fast speed [68]. The applications of the bat algorithm are in-continuous optimization, scheduling, data mining, parameter estimation, etc. Figure 7 clearly defines the working of the bat algorithm, where the system is first trained using manually segmented images from experts. After that, it is used and checked on the testing images. In the first step, the acquired images are enhanced using different pre-processing techniques, and then the next stage of extraction of prominent features is performed. Features were optimized using BAT Algorithm, and then using the trained images and classifier, the images were classified into abnormal and normal images.

In [69], an algorithm was developed for the detection of lung cancer. The process of diagnosing and detection was performed using techniques of segmentation using fuzzy c-means, and Discrete Wavelet Transform (DWT) did the classification process. The Bat optimizer performed the optimization of the extracted features [70]. developed a method to predict drug-target interactions using the Recurrent Neural Network model. The parameter values were optimized using a Bat optimizer, and the work was developed using four different phases: data preparation, parameters optimization phase, learning phase, and tuning phase. In [71], a technique was proposed to detect dengue fever using the Bat and backpropagation algorithms. Initially, the parameters were estimated using the Bat algorithm. After processing parameters, identification and prediction were made using an artificial neural network. The combination of the Bat algorithm with the neural network worked effectively in detecting dengue fever. In [10] neural network based on the firefly optimization algorithm was used to predict and diagnose chronic kidney disease. As per the authors, the main of the research was to diagnose the disease at the earliest stage. Through their implementation, it was analyzed that their algorithm obtained the highest accuracy compared to the other algorithms. In [72], the researchers used an algorithm to classify Retinal arteries and veins. The algorithm proved to be effective enough in the detection of various eye diseases like Diabetic Retinopathy. The novel feature of the algorithm is that it also includes additive color space and a luminous chromaticity model. BAT algorithm helped reduce the dimensionality and select the prominent features for increasing classification accuracy. In [73], the authors gave a technique to classify the White blood cells. The algorithm used the echolocation technique used by bats. The bats, to locate their prey, used the echolocation technique. BAT algorithm also helped in reducing the dimensionality of the extracted features as well as the selection of optimum features. In [74] BAT inspired algorithm was used to detect genes and β-hill climbing based on modified Minimum Redundancy Maximum Relevancy (MRMR). In the first step, filtering was done using various ensemble methods like Chi-Square and Relief. After aggregating the genes, the ranking was done using Minimum Redundancy and Maximum Relevancy. In the second step of wrapping, the bat algorithm and beta hill climbing method helped select optimal genes for cancer detection from the genes. [75] presented a technique after hybridizing Firefly and Bat algorithms for diagnosing diabetes. The algorithm worked in two stages in which the rules were generated optimally using Firefly and Bat algorithms, and the features were classified using ANN and Fuzzy classifier. The patients’ various

\[
x_{t+1} = x_t + v_t
\]  

(5)
features included age, sex, blood pressure, body mass index, cholesterol level, blood sugar level, etc. The features were selected and reduced using the Locality Preserving Projection (LPP) algorithm that helped effectively in the prediction of diabetes. In [76], the Bat algorithm and Extreme Learning Machines (ELM) hybrid were used to predict breast cancer. In the first step of the algorithm, the parameters were selected using Pearson Correlation Coefficient. They were later optimized using the Bat algorithm, and Extreme Learning Machines made error reduction. Two different case studies were performed in which the first one was able to predict whether the breast cancer was recurrent or not, and the second one was able to predict the time of recurrence. In [77], a technique was presented to predict heart diseases using two steps of feature reduction and feature classification, one after the other. The feature reduction method was performed by a linear programming problem that helped reduce the number of features. Only the features or attributes, which had some intense information, were selected. After that, the features were classified using a bat-inspired fuzzy inference system. The proposed technique was also known as Rule based Fuzzy Logic classifier (RBFL). In [78], a technique using the Bat algorithm was developed to detect diabetes mellitus. The technique had the special feature of avoiding the solution being trapped in the local optimum instead of searching for optimum global values. It provided the solutions using randomization. In [79], the authors reviewed the literature related to the Bat algorithm. All the variants of the Bat algorithm, along with the diverse applications of the bat algorithm, were mentioned. All the case studies related to the Bat algorithm were also summarized. The authors in [80] also abridged the Bat-inspired algorithm and its variants. The paper also included the practical engineering problems in which this optimization technique was used and its future avenues.

4.5 Grey Wolf Optimization

This optimization technique is based on the behavior of grey wolves when they search for prey for hunting. The wolves generally perform different roles, and according to that, they are divided into alpha, beta, gamma, and omega groups. Amongst these four groups, the alpha group provides the best solution [81]. This algorithm also works in the same manner as other meta-heuristic algorithms by initializing the population and then searching for the optimum solutions in local and global areas [82]. After finding the optimum solution, it will update the distance value with all other wolves in the group. These are the optimum values given by the alpha, beta, and gamma groups [83]. The process to detect disease using grey wolf optimization has been shown in Fig. 8, where the input dataset after pre-processing has been divided into two subsets as training and testing sets. In the training phase, the assigned weights are adjusted in the number of iterations and optimized using the grey wolf optimization technique, which, in turn, is helpful in the correct classification of the input dataset. The final weights are found after the multiple iterations until the maximum value of the fitness function is found. Later the testing dataset is taken as input, where the model classifies it using the GWO technique to organize the class the data belongs to, i.e., normal or abnormal images.

The researchers in [84] proposed a technique to detect Alzheimer’s disease in which the memory of the patient, if

![Fig. 8 Grey Wolf Optimization in diagnosis of diseases [83]](image)
once lost, is not cured or treated for a long time. The algorithm was implemented on the ADNI dataset. The proposed method pre-processed and segmented the input images using k-means clustering. The features from the images were extracted using the Histogram of oriented gradients (HOG) algorithm. The features were selected using Grey Wolf Optimizer and classified using Mild cognitive impairment (MCI) or Cognitive Normal CN. In [85], the researchers also proposed a model for detecting Alzheimer’s disease after analyzing the images of images. The extracted features included texture, histogram, and scale-invariant transform from the MRI Images of the brain. In [86] algorithm was used to classify Coronary Artery diseases accurately. The fitness function for the selection of features was calculated with the help of Support Vector Machines. The algorithm was tested on the Cleveland dataset. In [87], the researcher initially extracted the features from the pre-processed and segmented images of the lungs. The extracted features can be categorized as Haralick texture, Zernike’s moments, Gabor features, and Tamura features. The optimal features were selected using Grey Wolf optimization methods which further helped classify the images using different classifiers given by the k-nearest neighbor, support vector machine, Random Forest classifier, and decision tree. In [88], an algorithm was implemented for detecting brain tumors from the input brain images. The first pre-processing step was performed using Contrast enhancement and the skull stripping method. Gray Level Co-occurrence Matrix (GLCM) and Gray-level Run Length Matrix effectively did the second step of feature extraction. The last step of classification was done by Deep Belief Network using Grey Wolf Optimization, which helped detect brain tumor images. [89] presented a technique for predicting diabetes in patients. This algorithm used fuzzy logic with Grey Wolf Optimization (GWO) for optimized results. The fuzzy rules were defined using those features, and these rules were optimized. The optimized rules helped to detect diabetes with more accurate values than the existing techniques for diabetes detection. In [90], the researchers also used an algorithm to detect several medical diseases. The features were selected using grey wolf optimization, and the diseases were classified using a recurrent neural network. The algorithm was tested on various datasets like Cleveland, Hungarian, Switzerland, PID, and Mammographic masses. In [91], the researchers performed the first step of pre-processing using different techniques of image smoothening, segmentation of the region of interest, rotation and cropping, and removal of unwanted regions. Grey Level Co-occurrence Matrix did effectively well in the extraction of features and PPCA (Probabilistic Principal Component Analysis) in selecting optimum features. The classification was performed by integrating the Feed Forward Back Propagation method feature and grey wolf optimization, which resulted in the classification of the input kidney images into healthy images, images with cysts, functional parenchyma, stones, and tumors in kidneys with more accuracy than the existing methods. In [92], an algorithm was implemented to detect heart diseases using Naïve Bayes classifier and grey wolf optimization. The input data set used was Cleveland which had various attributes like age, sex, chest pain type, cholesterol level, fasting blood sugar level, etc. The weights of different extracted attributes by the Naïve Bayes classifier were optimized using grey wolf optimization, increasing the algorithm’s accuracy. In [93], the integration of grey wolf optimization and kernel extreme learning machine was used to detect Parkinson’s disease and breast cancer. The technique proved to be more accurate than the existing method. The authors in [94] reviewed and summarized Grey Wolf Optimizer’s applications. In the survey paper, the foundation of the Grey wolf optimizer and all the applications where this optimization technique was used were clearly defined. The future research that can be done was also clearly defined. In [95], the researchers determined the Grey Wolf optimizer and its implementation details. It was also compared with many existing meta-heuristic techniques like Particle Swarm Optimization, Genetic Algorithm, and Fast Evolutionary Algorithm. The authors in [96] summarized the work published in 83 research papers between the years 2014 to 2017. The properties of GWO were given along with its implementation in solving single and multi-objective problems.

4.6 Ant Lion Optimization

This optimization algorithm uses the hunting tricks of ant lions and is also known as doodlebugs. Ant lion optimization has the unique feature of trapping and hunting their prey [97]. Ant lion optimization made a cone or a trap by moving in a circular motion. When the prey is caught in the trap, they start throwing sand on the prey to bury it. Finally, they eat their prey using their jaws, and the remains of the prey are thrown out from the trap [98]. The ant lions hunt their prey when they are in the larva stage; on the other hand, when they are in the adult stage, they reproduce [99]. The optimization process based on the behavior of the ant lions first searches for a suitable place for traps using the technique of random walking. The value of the fitness function will decide the size and depth of the cone or trap. The size and depth will also increase the probability of catching prey by the doodlebugs. After every prey hunting, the value of the Ant lions’ position gets updated in Eq. (6)

\[
\text{Antlion}_t = \text{Ant}_t \text{ if } f(\text{Ant}_t) > f(\text{Antlion}_t)
\]  

where \( t \) represents current iteration and Antlion and Ant gives the position of ants at the specific iteration [100]. The authors in [101] mentioned detecting thyroid diseases using...
Ant Lion Optimizer. This technique selected only the optimal features, which directly affected the values of accuracy as well as computational time and cost. Elitism was used, which ensured that the optimizer should give the best possible solution. The researchers of [102] performed the prediction of Leukemia disease with the help of microarray gene data. The method was a hybrid of Ant Colony Optimization (ACO) and Ant Lion Optimizer (ALO). Integrating both techniques helped reduce the problem of local optima and early convergence. A method was designed to minimize the medical data's dimensionality using the combination of ant lion optimizer and ensemble classifier. The features were selected using an optimizer, and the ensemble classifier helped in achieving higher accuracies by reducing the medical data [103]. The researchers in [163] applied various metaheuristic techniques such as firefly, cuckoo, Bat, and Lion optimizers. The hybridization of Lion and Bat optimization obtained the highest accuracy among others. Classification techniques such as Naïve Bayes and Recurrent neural networks were used to classify the dataset. The authors also designed a smartphone application where the end users can predict the presence or absence of tumors inside the brain. The researchers in [104] used an algorithm to classify breast cancer. A Computer Aided diagnosis system was used for Feature weighting. The weights were finalized with the help of the Ant Lion optimizer, and parametric values were predicted with the value of a multilayer neural network. In [105], an algorithm was implemented to detect Parkinson's disease. In the existing techniques, the possibility of detecting Parkinson's disease at a prior stage was negligible. But the ant lion optimization algorithm helped in the detection of diseases at early stages as well as in less computational time. In [106], the researchers worked on detecting lung cancer using a Probabilistic Neural Network and ant lion optimization. Their proposed technique could predict lung cancer at the preliminary stages and the time of reoccurrence of cancer even after treating it. The features were selected using a chaotic crow search algorithm. They were optimized using ant lion optimization, which included the evaluation of values of different parameters and weights of the probabilistic neural network that helped predict lung cancer from the input images. In [107], a technique was developed for predicting electroencephalogram time series using an artificial neural network and ant lion optimizer. The researchers in [108] developed a method for detecting Chronic Kidney diseases using ant lion optimization and deep learning. Initially, the noise was removed from the input images using different pre-processing techniques. The extracted features were optimized in the next step using ant lion optimization. The features were classified using the Deep Belief Network.

In [109], the researchers detected Chinese Influenza disease with the combination of Ant Lion optimizer and Back Propagation Neural Network. The algorithm was trained and tested on 23 benchmark functions to examine the convergence behavior of ant lions. In [110], the researchers proposed a technique for reducing the noise from electrocardiogram signals so that electrocardiogram signals could help in detecting heart disorders. The Ant Lion optimizer in the last step optimized the signals and helped normalize the cut-off frequency, which helped reduce the noise from the input images. The value of the parameter Signal-to-Noise ratio was enhanced. The authors in [111, 112] presented a comprehensive literature survey of Ant Lion Optimization techniques using the latest papers from 2015 to 2019. The convergence encoding scheme was presented along with the objective formulae and reviewed and analyzed the Ant Lion optimization technique, its various hybrids and variants, and its different applications, respectively.

4.7 Lion Optimization Algorithm

Lion optimizer is a type of meta-heuristic that uses the action of lions for optimization. A lion is either a nomad or a native. This pride includes five to six females and their offspring, two of whom are cubs, along with two adult males the results of teamwork can be seen when they are hunting. The pride members strike the prey from various angles and movements [113]. While applying the lion algorithm mathematically, the population is first specified and then divided into residents and nomads. The researchers of [114] worked on detecting Alzheimer’s disease in MRI Images. The input images were pre-processed using the Otsu thresholding and histogram equalization methods. Different optimization methods performed the segmentation process, and the lion optimization algorithm optimally segmented the Hippocampus (HC) area.

A method for cancer detection was used in [115] using microarray gene selection. The algorithm used in the technique was implemented on five different datasets given by the Prostate, Lung, Leukemia, and Central Nervous system (CNS), Prostate, and Lymphoma dataset. Microarray technology has a vital and significant role in diagnosing cancer by measuring genes’ expression levels. The Lion Optimization Algorithm (LOA) helped select the genes that would eventually help diagnose cancer. In [116], the researchers detected heart diseases using the hybridization of Particle Swarm Optimization (PSO) and lion optimization algorithm. The statistical and higher-order dimensional features were extracted, and these dimensions were reduced using Principal Component Analysis (PCA). The neural network performed prediction, and the weights were optimized using particle swarm optimization and lion optimization algorithms. The researchers in [117] also proposed a technique for the detection of classification of CT images of the liver. After the segmented images were prepared using various
methods of region growing. The watershed algorithm was used to divide the segmented computed tomography image of a liver into different areas. The lion optimization algorithm selected the features, and finally, the liver images were classified by Support Vector Machine (SVM). In [118], a method should be developed to detect diabetic retinopathy in patients who have diabetes. The RGB images from the STARE and CHASE databases were taken as input, from which the green component of the image was taken and pre-processed. The edges of the input images were segmented using the Canny edge operator, and features were extracted using principal component analysis. The features were optimized and selected using the lion optimization algorithm, and finally, the images were classified as normal and abnormal with the help of the Naïve Bayes classifier.

The authors reviewed and published the details of the Lion Optimization Algorithm and proved that the lion optimization algorithm is best in case of fast convergence and global optima [119]. The authors of [120] also reviewed the lion pride algorithm based on lions’ behavior. The lion Pride algorithm is best when implemented in unimodal functions. An algorithm was implemented in [121] to compress biomedical images. The lion optimization algorithm was used to construct the codebook, and Lempel–Ziv–Markov chain algorithm was used to compress the images. The authors in [122] also reviewed the optimization process based on the pride of lions and summarized it very well.

4.8 Moth Flame Optimization

This algorithm is a nature-inspired algorithm based on the moths’ simulation behavior, especially on their navigation behavior at night [123]. This algorithm considers the behavior of moths as they fly at night, and they maintain a fixed angle with respect to the moon. Their navigation also depends on artificial lights and candles [124]. According to the lights, the moths form spiral and straight paths [125]. The moths are flying in all-dimensional space, and their positions of the moths are the solutions to the problems. Analytically, the Moth Flame Optimization Algorithm consists of three parts given by Eq. (7)

\[
MFO = (I, P, T)
\]

where I represent the randomly defined population of the moths along with their fitness values, P represents the update function of moths and their fitness values, and T represents the termination function with values True and False.

In [126], the researchers implemented an algorithm for increasing the accuracy of various classification processes in medical diagnosis. The algorithm was able to perform in variants of datasets. The system proposed by the authors also supported exploring the search space. A technique was used to detect brain tumors from clinical MRI images. Generally, brain tumors were detected from CT images. Still, the method proposed by the authors used Flair and T2 modalities to segment brain tumor images using modified moth fly optimization [127]. The researchers in [128] proposed a technique for selecting genes and classifying microarray data for the detection of different types of cancer using the Moth Flame Optimization (MFO) method. The redundancy and relevancy problems of genes were handled by the Mutual Information Maximization Process, which was further selected with the help of moth flame optimization. The classification process was effectively done using a Support Vector Machine (SVM) classifier.

Similarly, the researchers of [129] used an algorithm to detect pulmonary emphysema disease. If there is an enlargement of the lungs or permanent destruction of the alveoli, that leads to pulmonary emphysema. The features were selected from the extracted features using moth flame optimization. The selected features were finally trained using an Extreme Learning Machine classifier using cross validation technique. The algorithm was tested on the publicly available dataset and the real-time dataset from the hospital using quantitative and qualitative measures. The algorithm proved to be accurate in the detection of disease in comparison to all existing techniques. The researchers [130] also developed a novel method to classify and predict diabetes disease. The technique initially started the work with the help of Feed Forward Neural Networks (FFNN), in which weights were adjusted using moth flame optimization. The method was implemented and experimented on the real-time dataset given by the Wisconsin Hospital dataset, which proved the accuracy as well as the effectiveness of the technique. An algorithm for the detection of somatization disorder by hybridization of kernel extreme learning machine and moth flame optimization had been implemented in [131]. The initial parameters of moth flame optimization were optimized using Grey Wolf Optimization, which helped increase the disorder’s prediction accuracy.

The researchers in [132] used the median filter that effectively performed the pre-processing step. The features were extracted using a grey local co-occurrence matrix. The optimal features were selected using the Moth Flame optimizer. Finally, the images were classified using the selected features with the help of an SVM classifier. The images were diagnosed using two different views, that was Arial as well as the Coronal view. Due to the diagnosis of the image from different views, the method had done effectively well in the detection of Alzheimer’s Disease. The authors in [133] reviewed and summarized the Moth Flame optimization algorithm and its variants and applications. The authors concluded that the moth flame optimization algorithm could be implemented with lesser complexity, and it was fast and did not care about non-linearity.
Various literature on moth flame optimization, its variants and hybrids, its multiple applications, and theoretical analysis have been mentioned in [134]. The authors of [135] also summarized and implemented moth flame optimization along with other meta-heuristic algorithms on 29 benchmarks and eight real-time problems and found that moth flame optimization gave quite promising solutions. The researchers of [136] used an algorithm to detect breast cancer from mammographic images based on an extreme learning machine. The parameters of the extreme learning machine were optimized using moth flame optimization. The proposed algorithm proved more accurate compared to other meta-heuristic techniques.

4.9 Whale Optimization Algorithm (WOA)

This algorithm is based on the behavior of whales when they search for prey. The whales use two mechanisms to search for the best prey and their location. One method encircles the prey, and the other is bubble nets [137]. The whale Optimization Algorithm works on exploration and exploitation behavior in which exploration is used for looking for prey, and exploitation is used for attacks. In that way, they search for appropriate solutions.

The researchers in [138] developed an algorithm for detecting Parkinson’s disease using WOA. The useful features were extracted using the algorithms given by ICA (independent component analysis), PCA (principal component analysis), and Relief. The dimensionality of the features was reduced using WOA. The optimized and selected features were used to classify input data into healthy and abnormal data. Using input MRI images, an algorithm has also been proposed to classify pathological brain images from healthy brain images. The input MRI images were enhanced using a pre-processing technique named Contrast Limited Adaptive Histogram Equalization algorithm (CLAHE) followed by the Fast Discrete Curvelet Transform via Wrapping (FDCT-WR) strategy. The technique was able to perform well in comparison to the existing techniques in the classification of healthy and pathological images of MRI brain images [139]. Likewise, an algorithm had also been created to diagnose brain tumors in images. The input images from datasets given by FLAIR, T1, and T2 images were pre-processed using median filtering methods. The segmentation of the region of interest was done by Otsu’s method. The process of feature extraction and feature selection was performed using the wolf optimization algorithm and Artificial Neural Networks (ANN). The weights were initialized and optimized using WOA, and then perform the process of classification. The final quantitative results of the proposed algorithm proved the performance of the proposed algorithm [140]. In [141], the researchers used an algorithm to detect chronic liver disease, leading to total liver dysfunction. A total of 73 features were extracted from all datasets, including images of normal liver, fatter liver, cancerous liver, etc. The final step of classification was performed with the help of the Ensemble classifier, which classified the images of the healthy and pathological liver with higher accuracy. In [142], the classification of gastric cancer was performed using image pre-processing, segmenting the specific region of interest, extraction of features, selection, and classification. The useful features were selected using the wolf optimization algorithm. The classification was done using a Relevance Vector Machine classifier. The accuracy value was increased from the state-of-art techniques, and the error rate decreased. A technique was proposed for detecting heart diseases on the Cleveland heart dataset. The features were selected using the hybridization of the wolf optimization algorithm and dragonfly optimization method while a Support Vector Machine (SVM) performed the feature classification. The developed method could predict heart diseases more accurately [143]. In [144], a method was suggested to identify cysts and tumors, and the approach was made in three distinct sections, called “conversion of input images to blocks”. The feature was extracted from the grey-level co-occurrence matrix, and finally, the segmentation was performed using a Fuzzy C-means clustering-based wolf optimization algorithm. Compared to all previous techniques, various features extracted were in Entropy, correlation, contrast, etc. In [145], the researchers used a technique for reducing the features of medical datasets. The technique was evaluated on hepatitis, PID, and breast cancer datasets and reduced the extracted features’ dimensionality by optimizing it with a whale optimization algorithm. Only the prominent features were selected and used for diagnosing different medical disorders. In [146], the authors studied the whale optimization algorithm for the segmentation of fundus images. There were two main phases of the proposed algorithm: image pre-processing and image segmentation. The input image was processed using different pre-processing methods, which further refined the image’s quality. A new way to predict COVID-19 was suggested in [147] with computed tomography scan input using a diagnosis module and prediction module. The diagnosis module effectively differentiated between COVID and viral scans using Neural Networks and deep learning. This scanning technique will work on a lot of scans at once. The second factor was based on the class of patients. It included considerations such as age, level of illness, and organ dysfunction. The method worked with real-time data and a huge number of patients. Likewise, an algorithm was used in [148] to diagnose lungs until pre-processing, feature extraction, feature collection, and classification. The pre-processing step was performed by median filtering and global thresholding method that enhanced the input CT image of the lungs. The characteristics were extracted from the texture and statistics co-occurrence.
matrix. The popular features were picked and then categorized by the support vector machine. It worked exceptionally well at locating the tumor in the lungs. In [149], the authors gave an overview of the Whale Optimization Algorithm and its various applications in engineering, classification, clustering, task scheduling, etc. The researchers proposed a variant of the wolf optimization algorithm-based technique named as Chaotic wolf optimization algorithm. The algorithm was tested on 28 cases and proved useful in several applications [150]. The authors in [151] used the wolf optimization algorithm to summarize the work. It also discussed the wolf optimization algorithm’s strengths, weaknesses, and future avenues. In [152], the authors also surveyed the wolf optimization algorithm. Also, they published the comparison of the wolf optimization algorithm with many other metaheuristic techniques after testing it on different benchmarks.

4.10 Dragon Fly Optimization

Dragon Fly meta-heuristic algorithm is based on the behavior of artificial dragonflies. Dragonflies are types of predatory insects as they eat small insects. The algorithm is based on dragonflies’ dynamic and static behavior, which helped in exploitation and exploration behavior. The dragonflies can either fly in large groups in one direction for longer distances to distract enemies, or they can fly in smaller groups in search of prey for smaller spaces [153]. The swarm behavior of dragonflies can be implemented using the following five principles: separation, alignment, cohesion, attraction, and distraction [154]. The researchers worked on a method to select various features of the COVID-19 dataset. The novel feature of the technique was to escape from local optima using the hyper-learning strategy, which increased the searching behavior. The algorithm used was known as Hyper Learning Binary Dragon Fly Algorithm [155].

In [156], the authors identified a test for diabetes type II used Pima Indians with diabetes data input. It contains at least 728 people’s records. The features were extracted, streamlined, and vetted using Dragonfly Algorithm. An example of the synthesis of machine learning methods includes k-nearest neighbor (k-NN), which consists of the Support Vector Machine (SVM), and Adaptive Neural Network Inference Systems (ANIS). The researchers in [157] had put forward a strategy for skin disease identification using the dragonfly optimization approach filtering segmenting the enhanced input image produced an improved image grey level co-occurrence matrix that retrieved the categories such as energy, comparison, correlation, and so on. The features were carefully optimized, selected, and categorized using deep learning techniques. The researchers in [158] implemented an algorithm for classifying brain images. The features were pre-processed before extraction. Statistical features were calculated, including mean, variance, skewness, and kurtosis. Following the dragonfly optimization, all functions were categorized using the Support Vector Machine. As opposed to other classifiers, the algorithm could differentiate between the images more accurately. In [159], the authors mentioned dragonfly optimization to predict heart diseases. The technique worked on the parameters for classifying heart diseases and helped the doctors make appropriate decisions well in time. The authors also used an algorithm for the classification of infant cries. It was based on the cry signals that helped extract many features about infants and the reasons for their crying. The input cry signals were extracted and classified into normal and abnormal cries based on wavelet packet transform based on energy. The non-linear entropies were extracted to evaluate the characteristics of cry signals. The Binary Dragon Fly optimization method was used to select prominent features that accurately helped the cry signals’ classification [160]. The authors in [161] proposed a method to detect Epilepsy, a disorder of the Central Nervous System. The algorithm was implemented on the EEG signals pre-processed by the Kalman Filter (KF) to reduce the impulse noise. The features were extracted using Modified Principal Component Analysis (M-PCA) and were optimized using the Hybrid dragonfly optimization method. The results obtained proved that the proposed algorithm was very effective in detecting epilepsy disease. The authors also worked on detecting cancer using kernel-based learning and feature selection techniques. The features were pre-filtered using support vector machines and recursive feature elimination. The output after pre-filtering was enhanced using Dragonfly optimization, which helped diagnose cancer with a higher classification accuracy rate [162].

5 Comparative Analysis

In the comparative analysis part, the work performed by the researchers has been displayed in tabular form to highlight the findings and limitations using various evaluative criteria. Table 1 depicts the comparison based on the outcome of 10 metaheuristic algorithms such as spider monkey optimization, grey wolf optimization, antlion optimization, dragonfly algorithm, cuckoo search, moth flame optimization, lion optimization, bat-inspired algorithm, whale optimization algorithm, and shuffled frog leaping algorithm that had been applied on other health-based diseases for detection, classification, and prediction by various researchers.

On assaying, it can be seen in Fig. 9 that the whale optimization algorithm has shown the best accuracy in predicting COVID-19 disease by 97.14%, moth flame optimization has achieved the highest rate in microarray gene cancer detection by 99.83%, the dragonfly algorithm has efficiently detected diabetes and heart disease than other techniques by
Table 1. Analysis of different metaheuristic algorithms based on various diseases

| References | Metaheuristic algorithms          | Disease type                                      | Outcomes                                           | Advantages                                                                 | Limitations/Remarks                                                                 |
|------------|----------------------------------|---------------------------------------------------|----------------------------------------------------|-----------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| [31]       | Spider monkey optimization       | Prediction of COVID 19 death, confirmed and rejected cases | Confirmed cases MSE—1.791, RMSE—1.338 Recovered cases MSE—1.945, RMSE—1.394 Death cases MSE—1.609, RMSE—1.268 | The proposed achieved less MSE value and outperformed the other techniques. | Some important parameters like distribution of age, population density, and level of healthcare facilities available in the time series data were not considered. |
| [33]       | Spider monkey optimization       | Diabetes classification                           | Average accuracy—89.87%, Average sensitivity—94.60%, Average specificity—80.11% | SMRule Miner performed well with a minimum number of concise rules.         | Limited dataset.                                                                  |
| [42]       | SFLA                             | Detection of brain diseases—Glioma disease and Alzheimer’s disease | Standard deviation—58:3122, Mean gradient—5:5678, Spatial frequency—16:4776, Information entropy—4:1788 | The model showed satisfactory fusion results.                               | A negative correlation is found between the real time processing speed and medical image fusion. |
| [27]       | SMO                              | Examination of the retinal anatomical structures  | Precision—97%, Recall—95%, F-measure—98%, Specificity—97%, Accuracy—99% | The performance of the heuristic algorithms worked quite well on the dataset. | The model failed to properly classify the dataset.                                |
| [72]       | Bat optimization algorithm       | Retinal artery vein classification                | For DRIVE database Accuracy—91.73%, Precision—77%, Recall—74%, F1-Score—75% For IOSTAR database Accuracy—93.18%, Precision—75%, Recall—76%, F1-Score—75% | The models performed better in cross training.                               | The classification model needed to be improved.                                  |
| [44]       | SFLA with CNN                    | Multiple lesions in retinal fundus images         | Accuracy—96.7%, Sensitivity—96.9%                  | The proposed algorithm optimized the loss value and corrected the parameter value to improve the recognition rate. | Higher time consumption, Limited computing resources.                           |
| References | Metaheuristic algorithms | Disease type | Outcomes | Advantages | Limitations/Remarks |
|------------|--------------------------|--------------|----------|------------|--------------------|
| [59]       | Cuckoo search optimization | Heart diseases and diabetes prediction | Accuracy—91% Sensitivity—94% Specificity—90% | The model had been tested on various datasets such as Cleveland, Hungarian, Switzerland heart disease data sets and it showed great performance | More processing time consumed |
| [62]       | Cuckoo search optimization with PSO and SVM | Heart diseases and breast cancer | Forecasting accuracy—85% Precision—81.82% Recall—90.00% F-measure—85.71% For breast cancer dataset Forecasting accuracy—91.4% Precision—92.08% Recall—64.00% F-measure—75.29% | The proposed algorithm should better performance than the existing ones mentioned in their paper | The accuracy of the model for both the dataset should be improved |
| [77]       | Bat inspired algorithm using fuzzy rules | Prediction of heart diseases | Accuracy—76.51% | The model had been tested on various datasets such as Cleveland, Hungarian, Switzerland heart disease data sets and it showed great performance | The model computed the least accuracy value |
| [54]       | Cuckoo search optimization with neuro fuzzy classifier | Detection of lung nodules in CT images | Accuracy—82.49% Precision—80.60% Computational Sec—3.16 s | The proposed system gave better assistance to the physicians to provide therapeutical decisions | The model needed to improve the size, rate, and location of the nodule |
| [45]       | SFLA with Tabu search | Segmentation of 3D MRI images for detection of brain tumor | Average total correct fraction—0.9574 Average dice coefficient—0.95162 Average volume error—11.698 Average sensitivity—97.39% Average specificity—96.44% | The SFLA algorithm showed the lower average volume error | The model had been trained with small size of 3D image dataset |
| [106]      | Ant Lion optimization using PNN | Detection of lung cancer | Accuracy—86.8% Sensitivity—80.8% Specificity—81.6% | PNN algorithm improved the classification accuracy | The overall performance of the model needed to be improved |
| References | Metaheuristic algorithms | Disease type | Outcomes | Advantages | Limitations/Remarks |
|------------|-------------------------|--------------|----------|------------|--------------------|
| [60]       | Cuckoo Search optimization | Brain tumor segmentation in MRI images | Accuracy—98%  
Sensitivity—98.8%  
Specificity—93.3%  
JSI (Jaccard Similarity Index)—97.67%  
DSS (Dice similarity score)—98.82% | Cuckoo search optimizer performed well for identifying the optimum label during image segmentation | - |
| [69]       | Bat optimizer with CNN    | CAD-based lung cancer prediction | Sensitivity—99.37%  
Specificity—95.5%  
Precision—95.84%  
Recall—99.37%  
F-mean—97.52%  
G-mean—97.38%  
Accuracy—97.43% | The method diagnosed the lung cancer efficiently | Consumed more processing time |
| [87]       | Grey wolf optimization    | Feature selection and identification of Lung Diseases | Accuracy  
With k-NN—99.4%  
With random forest—99.2%  
With SVM(Linear)—99.0%  
With decision tree—98.4% | The proposed performed well with the classification and consumed less computation cost as well as computed high accuracy | The work should include more datasets as well as deep learning techniques to optimize the performance |
| [78]       | Bat algorithm             | Diabetes mellitus detection | Accuracy—98.65% | The proposed algorithm showed their superiority in terms of their performance | The algorithm should be tested on other chronic diseases |
| [70]       | Recurrent neural network using Bat optimizer | Anti viral cure drug of SARS CoV-2 | Accuracy—96.08% | The proposed model showed the best performance of prediction | The model should be incorporated in clinical settings |
| [88]       | Grey wolf optimization    | Brain tumor | Accuracy—94.1%  
Sensitivity—88.9%  
Specificity—100%  
Precision—100% | The performance of the proposed model was better than the existing ones as mentioned in their paper | The model was trained with smaller size of dataset |
| [89]       | Grey wolf optimization using fuzzy logic | Diabetes prediction | Accuracy—81%  
Precision—76.1%  
Recall—82% | The proposed algorithm showed a great potential in long term outcomes | The system worked on few parameters to predict the diabetes |
| [92]       | Grey wolf optimization using naive bayes classifier | Heart diseases | Acc—87.45%  
Sens—89.70%  
F-measure—88.59%  
G mean—87.09% | The proposed model showed the superior efficiency | More learning models should be applied in order to increase the performance accuracy of the system |
### Table 1 (continued)

| References | Metaheuristic algorithms | Disease type                  | Outcomes                        | Advantages                                                                                                           | Limitations/Remarks                                      |
|------------|--------------------------|-------------------------------|---------------------------------|---------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------|
| [86]       | Grey wolf optimization   | Coronary artery disease classification | Accuracy—89.83%                 | The model worked well as compared to the other techniques in terms of their performances                           | More datasets can be applied to enhance the performance of the system |
| [85]       | Grey wolf optimization with convolutional classifier | Alzheimer detection | Accuracy—98.2%                  | Combination of morphometric features and texture features performed better than the existing techniques mentioned in their paper | Consumed more processing time                             |
| [108]      | Ant lion optimization using deep learning | Chronic Kidney Diseases | Acc—96.63%                      | The model worked well with CKD dataset by classifying it with optimal features                                       | Data mining could be used to enhance the execution of classifiers |
| [107]      | Ant lion optimization    | Electroencephalogram (EEG) prediction | MAE—19.4211                     | The technique could be easily used by the physicians to early diagnose the disorder                                | Hybrid techniques could be used to enhance the performance |
| [28]       | Ant lion optimizer using ANN | Prediction of Chinese influenza disease | MAE—0.3254%                     | The model could be used as a powerful tool to deal with benchmark functions                                         | ALO can be merged with swarm intelligence algorithm         |
| [103]      | Ant lion optimizer       | Medical big data processing   | Accuracy—96.12%                 | The proposed work achieved great accuracy and also consumed less processing time                                   | —                                                         |
| [114]      | Lion Optimization Algorithm (LOA) | Alzheimer disease in MR brain images | Accuracy—95.0%                  | The model could help the clinicians to analyze the prognosis of Alzheimer disease                                 | More efficient algorithms could be used to track the development of intellectual impairment |
| [115]      | Lion Optimization Algorithm (LOA) | Microarray data for cancer detection | Classification Accuracy—99%     | The model worked well with the gene selection for classifying cancer                                              | More dataset could be used to train the model for classifying the various cancer issues |
|            |                          |                               | Lymphoma dataset Classification Accuracy—99.19% |                                                                         |                                                                                     |
|            |                          |                               |                                |                                                                         |                                                                                     |
|            |                          |                               |                                |                                                                         |                                                                                     |
| References | Metaheuristic algorithms | Disease type | Outcomes | Advantages | Limitations/Remarks |
|------------|-------------------------|--------------|----------|------------|-------------------|
| [116]      | Lion Optimization Algorithm (LOA) | Prediction of heart diseases | Accuracy—87.09% Sensitivity—73.33% Specificity—100% Precision—100% FPR—0 FNR—26.67% NPV—100% FDR—0 F1-Score—84.6% MCC—76.59% | The models worked well with dimensionality reduction and feature selection | Hybridization of meta-heuristic approaches could be done to improve the performance of model |
| [117]      | Lion Optimization Algorithm (LOA) | CT liver classification | Accuracy—98.00% Sensitivity—96% Specificity—99% F—Measure—94% Precision—97% | LOA and SVM classifier efficiently classified the liver disease using CT scan dataset | Hybrid multilayer perceptron and bio inspired optimization could be used to improve the performance |
| [118]      | Lion Optimization Algorithm (LOA) | Retinal vessel segmentation for eye disorders | Accuracy—95.76% Sensitivity—96% Specificity—99% | The method efficiently detected the location of pathology during treatment | The experiment had been conducted with limited dataset |
| [116]      | Lion Optimization Algorithm (LOA) with PSO and neural network | Heart disease prediction | Accuracy—83.87% Sensitivity—80% Specificity—87.5% Precision—85.71% FPR—0.125 FNR—0.2 NPV—0.875 FDR—0.142 F1-Score—0.8279 MCC—0.677 | The proposed model obtained the best values as compared to the other techniques mentioned in their paper | Hybridized algorithms along with the hybrid classifiers should be used to improve the performance of prediction |
| References | Metaheuristic algorithms | Disease type          | Outcomes                                                                 | Advantages                                                                                                                                   | Limitations/Remarks                                                                 |
|------------|--------------------------|-----------------------|---------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| [132]      | Moth flame optimization algorithm | Alzheimer’s disease | Axial view Accuracy—78.33% Precision—78.32% Recall—78.33% F-score—78.33% | The results showed that SVM polynomial kernel function gave the highest results                                                             | Limited dataset                                                                  |
|            |                          |                       | Coronal View Accuracy—59.48% Precision—62.7% Recall—59.49% F-score—61.05%  |                                                                                                                                             |                                                                                  |
|            |                          |                       | Coronal and Axial View Accuracy—61.36% Precision—54.82% Recall—50.12% F-score—52.38% |                                                                                                                                             |                                                                                  |
| [128]      | Quantum Moth Flame Optimization Algorithm (QMFOA) | Gene selection and classification of Microarray data | Leukemia Dataset Classification Accuracy—100% DLBCL dataset Classification Accuracy—100% CNS dataset Classification Accuracy—99.83% Colon dataset Classification Accuracy—100% Ovarian dataset Classification Accuracy—98.18% Breast dataset Classification Accuracy—86.80% Prostate Tumor dataset Classification Accuracy—100% | The results showed that QMFOA obtained the highest accuracy | QMFOA only worked for gene classification which needed to be improved by adding more issues |
| References | Metaheuristic algorithms | Disease type | Outcomes | Advantages | Limitations/Remarks |
|------------|-------------------------|--------------|----------|------------|-------------------|
| [130]      | Moth flame optimization algorithm | Diabetes data classification and detection | Accuracy—80.68%  
Error Rate—19.61%  
Specificity—75.25%  
Prevalence—52.08%  
Sensitivity—81.79% | The model did well as compared to the algorithms as mentioned in their paper | The model showed least performances in terms of accuracy, specificity and high error rate |
| [129]      | Moth flame and firefly optimization algorithm | Pulmonary emphysema detection | Accuracy—89.02%  
Specificity—79.56%  
Recall—95.5%  
Precision—87.21% | The MFO worked well for real time dataset and FFO performed well for public dataset | CAD framework can be incorporated to improve the performance |
| [126]      | Moth flame optimization algorithm | Medical diagnosis | Average accuracy—77.46% | The model showed superior efficiency in terms of various diseases | Limited dataset |
| [127]      | Modified moth flame optimization | Evaluation of brain tumor | Accuracy—98%  
Precision—85%  
Sensitivity—92%  
Specificity—98% | The novel technique enhanced the threshold outcome and achieved a great mean accuracy of 99% | IoT based remote procedure assessment could be used to improvise the treatment facilities |
| [131]      | Moth flame optimization | Somatization disorder | Accuracy—95.46%  
MCC—89.96%  
Sensitivity—97.86%  
Specificity—90.71% | The model provided consistently better results as compared to the other algorithms mentioned in the paper | The optimization technique needed to be improved by applying new mechanisms such as mutation strategy |
| [139]      | Whale optimization algorithm | Pathological Brain detection from MRI Images | For Data Set—1  
Accuracy—100%  
For Data Set—II  
Accuracy—100% | The technique optimized the input weights and efficiently classified the pathological brains from healthy brains | Metaheuristic techniques could be hybridized to improve the performance |
| [140]      | Whale optimization algorithm | Brain tumor diagnosis | Correct Detection Rate (CDR)—88%  
False Acceptance Rate (FAR)—10%  
False Rejection Rate (FRR)—2%  
Mathew Correlation Coefficient MCC—76.83%  
Computational Time—3.15 secs | The proposed algorithm could be used to classify various types of cancer using medical image dataset | Improvisation in optimization technique is required |
| References | Metaheuristic algorithms | Disease type | Outcomes | Advantages | Limitations/Remarks |
|------------|--------------------------|--------------|----------|------------|--------------------|
| [141]      | Whale optimization algorithm | Chronic liver classification | Error Rate—1.90%<br>Accuracy—98%<br>Sensitivity—96%<br>Specificity—93% | The model efficiently classified the disease by optimally selecting the features for classifiers | Small dataset had been used to conduct the research work |
| [142]      | Whale optimization algorithm | Gastric cancer classification | Accuracy—99.02%<br>Hit Rate—98.9%<br>Elapsed Time—64 s | The proposed classification technique along with WOA performed well to classify the disease | Limited dataset |
| [143]      | Whale optimization algorithm | Heart disease detection | Accuracy—88.89% | The model efficiently detected and diagnosed the heart issue | The model needed to be improved to enhance the performance accuracy by incorporating the best learning models |
| [144]      | Whale optimization algorithm | Detection of kidney cysts and tumors | Accuracy—98.4%<br>Sensitivity—91.13%<br>Specificity—98.6%<br>PPV- 71.82%<br>NPV- 99.69% | The propose technique had been optimally choosing the centroids to segment the image | Other techniques such as feature related K means clustering, intensity related fuzzy c means clustering used in the research obtained less accuracy |
| [146]      | Whale optimization algorithm | Retinal vessel segmentation for detection of eye diseases | Accuracy—97.93%<br>Sensitivity—89.81%<br>Specificity—98.93%<br>AUC—98.2% | The model achieved the highest accuracy and proved to be robust against noise and disease diagnosis | – |
| [147]      | Whale optimization algorithm | COVID 19 | Accuracy—97.14%<br>Sensitivity—96.93%<br>Precision—96.75%<br>F-score—96.84%<br>G-mean—96.93%<br>AUC—99.57% | The experiment work showed the promising results for predicting covid19 | – |
| [148]      | Whale optimization algorithm | Lung tumor | Accuracy—95%<br>Sensitivity—100%<br>Specificity—92% | The radial basis support provided an efficient performance | Different metaheuristic techniques should be used to classify various lung modalities |
| References | Metaheuristic algorithms | Disease type | Outcomes | Advantages | Limitations/Remarks |
|------------|-------------------------|--------------|----------|------------|--------------------|
| [145]      | Whale optimization algorithm | Feature selection for medical datasets | For Hepatitis: Accuracy—87.10%, Sensitivity—100.0%, Specificity—94.12%; For Breast Cancer: Accuracy—97.86%, Sensitivity—98.90%, Specificity—100% | The method reduced the dimensions of medical datasets in diseases and achieved good accuracy | For some diseases, the same technique showed less accuracy which needed to be improved |
| [157]      | Dragon fly algorithm | Skin diseases | Accuracy—98.53%, Sensitivity—84.6%, Specificity—99.56% | The model provided the highest segmentation accuracy | The models only classified the presence or absence of skin diseases which needed to be further extended by classifying types of skin diseases |
| [158]      | Dragon fly algorithm using SVM classifier (DA-SVM) | Classification of MRI images of brain | Accuracy—81.08%, Sensitivity—83.33%, Specificity—80.00%, Error Rate—18.92%, False Positive Rate—20.00%, Precision—66.67% | The model efficiently classified the dementia issue | Parameters of SVM needed to be optimized as wrong selection of features will cause a high penalty |
| [156]      | Natural Exponential Inertia Weight Based Dragonfly Algorithm (NEIWDA) | Diagnosis of diabetes Type—II | Accuracy—99.01%, F-measure—94.58%, Recall—96.12%, Precision—97.43% | The NEIWDA technique had been used along with the machine learning classifiers which provided the best system performance results | |
| [160]      | Dragon fly optimization | Infant cry classification | Accuracy—97.6%, G-Mean—96.07% | The results indicated that the model could be used to detect the subtle changes in the cry | Hybridization of meta-heuristic approaches could be done to improve the performance of model |
| [161]      | Dragon fly optimization | Recognition of Epilepsy—disorder of central nervous system | PPV—95.45%, NPV—100%, Sensitivity—100%, Accuracy—96.6%, False discovery rate—4.5%, False omission rate—0% | The neural network based model provided promising results as compared to other classifiers | Some advanced algorithms are required for dimensionality reduction and classification |
99.01% and 96.39% respectively, spider monkey optimization has very well performed the retinal examination and dengue classification by 98%, grey wolf optimization has stood best in detecting Alzheimer by 98.2%, lung cancer by 99.4%, and Parkinson’s disease by 96.97%, while as cuckoo search optimization showed best results in brain tumor and chronic kidney disease detection by 98% and 99.2%.

### 6 Future Directions

The healthcare sector has significantly benefitted from technological innovation [12]. In addition to the advancement of modern medical treatments, the maintenance and handling of patient data and information, and the therapeutics of chronic diseases, metaheuristic algorithms play a critical role in many health-related fields. In today’s technologically advanced world, metaheuristic algorithms are commonly used to create rationalized administrative processes in medical institutes to map and cure infectious diseases [17] successfully. In addition, there are several other potential future study developments.

#### 6.1 Information Fusion

AS we are now in the big data age, even if we can extract data from various sources (e.g., sensors, computers, machines, or systems), integrating these data remains a difficult issue. Unifying different data formats is not the only concern; how to consistently represent data for the same thing but taking from different outlets of a healthcare system is another critical consideration when building a healthcare system for big data analytics [10]. More specifically, whether the camera signals identifying human status are modified, or whether or not there is a body collapse can need to be checked by other signals from other sensors.

#### 6.2 Knowledge Interpretation

Knowledge interpretation and display have often been essential topics in the healthcare community. Physicians need to consider the system’s research findings, caregivers need to know what a handicap’s condition is, and patients generally want to know their health status. An intuitive approach is providing the customer with an interface that allows them to quickly locate the information they need, such as a dashboard representing the knowledge. One potential strategy is to use metaheuristics for summarising the facts or knowledge from data analytics as key points so that the user of such a method can easily understand them [15].

| References | Metaheuristic algorithms | Disease type | Outcomes | Advantages | Limitations/Remarks |
|------------|-------------------------|--------------|----------|------------|--------------------|
| [155]      | hyper learning binary dragon fly optimization | COVID—19     | Accuracy = 96.39% | The technique could be applied to various clinical applications and it achieved highest accuracy as compared to other techniques. | More novel techniques need to be included to improve feature selection and data classification. |
| [159]      | Dragon fly optimization | Heart disease prediction system | Accuracy = 96.21%, Precision = 95.83%, Recall = 95.83% | The approach generated a higher classification rate. | The experiment was conducted on a limited dataset. |
| [162]      | Dragon fly optimization | Cancer diagnosis | Accuracy = 96.87% | The method performed better and could help the specialists to detect the heart failure in the patient. | Limited dataset, unable to label different types of brain tumors. |
| [163]      | Lion and bat optimization | Brain tumor detection | Accuracy = 98.61% | Smartphone application had been designed to help end users in indentifying the tumor in the brain. | Standard Deviation = 5.30 |
| [10]       | Firefly CKD dataset | CKD dataset | Accuracy = 98.89%, Sensitivity = 98.56%, Specificity = 93.32% | Their algorithm achieved high accuracy rate as compared to other techniques. | Standard Deviation = 5.30 |

- **Table 1 (continued)**
6.3 Medical Imaging

Analyzing images and recognizing the patterns of diseases play an essential role in the medical or healthcare system field. In the medical field, image-guided decision support is the foremost method for diagnosing any disease accurately. But on the other hand, achieving high performance in classifying the disease with the best accuracy is still a demanding task. Hence, metaheuristics algorithms can be used to optimize the model's performance, thereby providing us with the best results in terms of correct prediction of the disease [165–170].

6.4 Security and Privacy

Since most healthcare data are now clustered in a single framework to allow the system to interpret these data from a broader perspective, how to secure these data has been a much more pressing research question than ever before. Most people dislike having cameras in their homes, even though they can increase the accuracy of research results for the healthcare system, because they believe cameras intrude on their privacy [6]. One of the study developments in the near future will be how to use metaheuristics to secure healthcare records. Another healthcare study theme would...
be how to use metaheuristics to increase the identification and prediction rates of sensors without cameras in the home.

### 6.5 E-Health and Tele Medicine

We all know that the healthcare industry yields massive and critical amounts of data in medical records, patient examination results, biomedical research, etc. Handling such data requires an emerging technology like cognitive computing, which allows humans to get interlinked and communicate with the machine to gain insights\[171–173\]. But to, implementing big cognitive data, especially for healthcare, is a bit complex because it does not show any performance efficiency. Hence, metaheuristic algorithms can be used as they enable any technology to self-improvise its performance [164].

### 7 Conclusion

Artifice Intelligence is increasingly encroaching on all aspects of our lives, especially healthcare. According to the paper, researchers are rapidly developing a deeper understanding of the problems and opportunities posed by AI as an intelligent device in the field of health-related disease detection using metaheuristic algorithms. The use of metaheuristic algorithms is a research subject that, if done correctly, would offer a wonderful opportunity for models to diagnose diseases, which would help both doctors and patients.

To detect and classify various health-related diseases based on their optimized results, different metaheuristic algorithms have been used, including spider monkey optimization (SMO), shuffled frog leaping algorithm (SFLA), cuckoo search optimization (CSO), antlion optimization (ALO), lion optimization technique (LO), moth flame optimization (MFO), bat-inspired algorithm (BA), grey wolf optimization (GWO), whale optimization algorithm (WOA), and dragonfly algorithm (DA).

We know that healthcare costs are increasing, and consumers must keep track of their drug expenses. Since metaheuristic algorithms are less computationally expensive than other methods, they can be used in important medical fields such as brain tumor recognition, human retinal images, COVID, diabetes diagnosis, lung cancer screening, and so on. However, it has pitfalls, such as process complexity, a lack of information about a person in a given sense, and the likelihood that these methods will involve an erroneous diagnosis. Consequently, if physicians lack the experience to detect the error, they are more likely to provide inadequate treatment, necessitating the use of a large dataset to train the algorithm and achieve an accurate prediction score.

Overall, metaheuristic-based approaches direct the search process, effectively navigate the search space to find the best answers, offer approximations, and are not problem-specific.

### Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

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