

## RESEARCH ARTICLE

# An Enhanced Binary Multiobjective Hybrid Filter-Wrapper Chimp Optimization Based Feature Selection Method for COVID-19 Patient Health Prediction

JAYASHREE PIRI<sup>1</sup>, PUSPANJALI MOHAPATRA<sup>1</sup>, (Member, IEEE),  
HARPRITH KAUR RAJINDER SINGH<sup>2</sup>, BISWARANJAN ACHARYA<sup>3</sup>, (Senior Member, IEEE),  
AND TAPAS KUMAR PATRA<sup>4</sup>, (Member, IEEE)

<sup>1</sup>Department of CSE, International Institute of Information Technology Bhubaneswar, Bhubaneswar 751029, India

<sup>2</sup>Department of Data Science and Information Technology, INTI International University, Nilai 71800, Malaysia

<sup>3</sup>Department of Computer Engineering-AI, Marwadi University, Rajkot, Gujarat 360003, India

<sup>4</sup>Department of Electronics and Instrumentation Engineering, Odisha University of Technology and Research, Bhubaneswar 751029, India

Corresponding author: Tapas Kumar Patra (tapas.patra.in@ieee.org)

**ABSTRACT** This work aims to discover the relevant factors to predict the health condition of COVID-19 patients by employing a fresh and enhanced binary multi-objective hybrid filter-wrapper chimp optimization (EBMOChOA-FW) based feature selection (FS) approach. FS is a preprocessing approach that has been highly fruitful in medical applications, as it not only reduces dimensionality but also allows us to understand the origins of an illness. Wrappers are computationally expensive but have excellent classification performance, whereas filters are recognized as quick techniques, although they are less accurate. This study presents an advanced binary multi-objective chimp optimization method based on the hybridization of filter and wrapper for the FS task using two archives. In exceptional instances, the initial ChOA version becomes stuck at the local optima. As a result, a novel ChOA termed EBMOChOA is developed here by integrating the Harris Hawk Optimization (HHO) into the original ChOA to improve the optimizer's search capabilities and broaden the usage sectors. The location change step in the ChOA optimizer is separated into three parts: modifying the population using HHO to produce an HHO-based population; creating hybrid entities according to HHO-based and ChOA-based individuals; and altering the search agent in the light of greedy technique and ChOA's tools. The effectiveness of the EBMOChOA-FW is proven by comparing it to five other well-known algorithms on nine different benchmark datasets. Then its strengths are applied to three real-world COVID-19 datasets to predict the health condition of COVID-19 patients.

**INDEX TERMS** COVID-19, feature selection, medical data mining, multi-objective optimization, chimp optimizer, Harris Hawk optimizer.

## I. INTRODUCTION

COVID-19 is a respiratory illness that affects the lungs as well as the upper respiratory tract. Because of its rapid diffusion over the globe, the World Health Organization (WHO) has labelled it a worldwide outbreak. As a result of COVID-19's

expeditious global outbreak and the involvement of health-care centres throughout the world, researchers have access to a vast amount of publicly available data. This virus's activity may be studied in new ways because of this "big data". Despite these advantages, the enormous amount of data makes it difficult to analyse on smaller systems. Scalability is a difficulty on one hand, whereas high dimensionality is a problem on the other. New and more advanced approaches

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are needed to extract relevant information from this large dataset because it was previously unavailable to the scholarly community at this size and ease of accessibility.

One of the best answers to this challenge is the use of FS techniques [1]. In original datasets, an FS approach seeks to determine the best combinations of variables. Due to its prohibitively high computing cost, exhaustive search is not practicable, particularly for huge datasets. Although population-based approaches cannot ensure optimum findings, they can obtain a satisfactory set of features in a fair amount of time. The FS strategies can be divided into two categories based on how they evaluate feature sets in the FS phase: filters and wrappers. To evaluate a subset of attributes, they rely on data traits and specialised machine learning (ML) algorithms, respectively. Filters are quicker than wrappers, but they skip attribute associations and can't handle duplicate features. Wrappers are more expensive than filters, but because they incorporate learning strategies into the assessment process, they can achieve better outcomes than filters [2].

Population-based strategies, also known as wrapper approaches, have shown their worth in addressing FS problems in recent years. To handle the FS issues, a variety of population-based techniques, along with some modern techniques, have been used [3], [4], [5], [6]. Few studies have attempted to integrate filter and wrapper models using evolutionary computing (EC) techniques, as the most extant EC algorithms follow one of these two models: filter or wrapper. The majority also treats FS as a one-objective task.

The probabilistic nature of population-based systems, in general, causes their sluggish convergence to a local optimal. As a result, numerous studies have been conducted in order to improve them.

- 1) One or more tactics are introduced into the algorithms. Chaos [7], Levy flight distribution [8], opposition-based learning [9], mutation and crossover, and other enhanced methods are included. This is the most typical method of advancement.
- 2) Including weighted components. In the revised approaches, weighted factors are introduced to the operators [10].
- 3) Algorithms that can be combined with one another [11]. In the optimization domain, techniques following this design have gained wide acceptance.

In this research, we focused on the third way, i.e., the hybridization of optimizers to handle the FS work. The fact that no single FS strategy can solve all types of FS challenges explains why there are so many of them. As a result, we'll need a lot of opportunities to come up with more advanced designs for FS scenarios. Numerous discrete variants of meta-heuristic approaches have currently been created for the FS task. On the other hand, every meta-heuristic technique's high quality is concentrated and confined. When creating meta-heuristics, it's important to keep both exploration and exploitation in mind. Because meta-heuristic methods work well in certain circumstances but badly in others, striking a

good balance between exploration and exploitation is crucial to improving the methods' efficacy. Each nature-inspired approach has its own unique set of upsides and downsides, making it impossible to predict which method is best for a given task. Particular optimization algorithms cannot discover the best solution for each type of function [12]. Scientists are now faced with the task of implementing and proposing current meta-heuristics with great precision for practical applications [13]. Thus, the hybridization of evolutionary approaches has attracted a large number of researchers to work on FS issues. The goal of hybridization is to find compatible options so that optimization procedures can produce the best results possible. This is done by merging and synchronising the exploration and exploitation stages [14]. Hybridization of evolutionary algorithms is a popular way of addressing such flaws by combining the power of independent systems [13].

The chimp optimization algorithm (ChOA) [15] is a modern evolutionary algorithm motivated by chimps' particular intellect and sexual desire in collective hunting. Among many other familiar meta-heuristic methods, ChOA has been certified for its operational excellence. This technique was developed to overcome two typical flaws in evolutionary techniques: delayed convergence and becoming locked into a local optimal solution. Whenever the search area is large and there are a lot of local extremes, ChOA has been shown to be effective. Continuous issues are resolved with the base variant of ChOA. As a result, this work offers a binary representation of ChOA that has been built. According to previous studies, this approach has a low feature rating rate, a fast processing rate, and great global and local finding [15], [16], [17]. To the best of our knowledge, the power of this system for managing the FS mission has yet to be studied. Although this approach is an effective optimization technique, it does have several difficulties in terms of improving exploration capability, speeding up convergence, and coping with computationally intensive tasks. In most cases, ChOA has a satisfactory convergence rate and a straightforward design. ChOA, on the other hand, may attempt to keep the balance between exploration and exploitation in certain computationally intensive situations and slip into a locally optimal state. The drawbacks of ChOA become more apparent when dealing with high-dimensional functions and multimodal situations. The basic ChOA's optimization power is determined by the best solution. In this study, we present two techniques (multi-objective and HHO) for improving the basic ChOA's efficiency. To make this algorithm more valuable, the application fields of ChOA must be expanded. The hybrid design is used in this research to show a novel advancement in ChOA and its usage in FS.

HHO [18] is a recently released population-based algorithm with excellent continuous challenge optimization capabilities. The dynamically interacting activity of Harris' hawks when seeking prey was a major inspiration for the invention of HHO. Because different pursuit strategies are based on adaptive prey fleeing tactics and natural circumstances,

HHO is divided into two stages: exploration and exploitation. In HHO, the six steps are followed at random to find the best option. The achievement of the classical HHO has been shown to outshine numerous popular approaches, such as PSO, GWO, FOA, ALO, ABC, BA, and WOA. The balance between exploration and exploitation, as well as quick completion, are the key advantages of this optimization method. HHO, in particular, demonstrates excellent exploitative capacity in later phases. For these outstanding benefits, HHO or its revised counterpart has been studied as an optimization method in a variety of studies [19], [20], [21], [22], [23]. Some customised varieties of HHO have also been designed to address certain optimization challenges [24], [25], [26], [27]. Due to the superior performance of HHO, it has been mixed with other optimizers such as HHO-CS [28], HHO-SSA [2], HHO-GWO [29], and HHO-SCA [30] etc., in literature to enhance their performance.

Our approach to the feature selection problem here is a multi-objective variant of discrete ChOA coupled with HHO with hybridization of both filter and wrapper conditions. The ChOA's ability to find encouraging zones in the feature area is used in the suggested algorithm. Also, HHO is included in the classical ChOA to increase the optimizer's search capabilities and expand the diverse applications. For improved performance, the filter and wrapper models are combined. During the optimization process, two fitness criteria are considered. The first fitness function is formulated by taking both the number of features and the classification error rate into account. However, the second fitness function captures the relevance or inter-dependency between the features and the class attribute by considering mutual information (MI) and correlation coefficient. In order to classify COVID-19 patients, we have developed this effective model employing an optimised FS approach and ML methods. Our strategy enables doctors to allocate limited medical resources to the most vulnerable groups, especially during situations of medical scarcity, and deliver urgent care. Clinicians may use the risk prediction method to determine which of their patients most at risk of death is, and they can then implement a tailored preventative strategy. A generic clinical decision support system based on our findings might benefit not just COVID-19 but also other possible pandemics in the future. Biologists may be able to use the patterns shown by this data to develop more effective vaccines and vaccination tactics.

This study makes the following major contributions:

- 1) There is a suggestion for a more efficient ChOA variation.
- 2) The suggested method incorporates HHO processes to improve ChOA's quality in terms of boosting population variety.
- 3) To present an EBMOChOA-FW with two repositories to find Pareto optimal options for the FS job by optimising filter and wrapper conditions at the same time.
- 4) To offer a comparison documentation on the efficiency of the EBMOChOA-FW in the FS challenge by applying healthcare information and the tent chaotic map.

- 5) To compare the presented method against five popular multi-criteria approaches and determine whether it outperforms conventional procedures for shrinking feature subset size and enhancing accuracy rate.
- 6) **To verify the provided method's reliability using three real-world COVID-19 datasets.**

The following is the paper's structure. The background material is discussed in Section II. The introduced FS approach is presented in Section III, and the experimental setups and findings are presented in Section IV. Application of the suggested approach in real world COVID-19 data is presented in the Section V. Finally, Section VI brings the paper to a close.

## II. BACKGROUND

### A. BINARY CHIMP OPTIMIZATION ALGORITHM (BChOA)

ChOA [15] is a novel meta-heuristic method suggested by Khishe and Mosavi in 2020. ChOA is based on the chimpanzee's collective trapping and mating impulses. Prey seeking is used in the ChOA technique to find the best solution to an optimization model. Driving, obstructing, chasing, and hitting are the four main phases in this method's hunting process. At the beginning, the community of chimpanzees is generated at arbitrary. It is then possible to classify the four types of chimpanzees as follows: attacker, barrier, chaser, and driver. Continuous ChOA allows chimpanzees to shift their location at any time and in any direction. There are just two possible outcomes in discrete optimization: 0 or 1. This results in a binary form of the ChOA (BChOA). A discrete meta-heuristic technique has a search area that is identical to a hypercube in shape. Using meta-heuristic strategies, its operators can only move from one corner of the hypercube to the other by flipping from 0 to 1 and back again. Since the BChOA's design relies heavily on the positional change cycle, a number of fundamental principles have to be changed.

In BChOA, the primary location change formula is based on the equation 1 [31].

$$P_j^{t+1} = \text{Discrete\_Comb}(P1, P2, P3, P4) \quad (1)$$

$\text{Discrete\_Comb}(P1, P2, P3, P4)$  is an appropriate combination that is formed in accordance with equation 18. Chimps move in four directions: P1 indicates that they are moving toward the attacker, P2 shows that they are moving towards the barrier, P3 shows that they are moving towards the chaser, and P4 shows that they are moving towards the driver chimp:

$$P_1^d = \begin{cases} 1 & \text{if } (P_{Attacker}^d + E_{Attacker}^d) \geq 1 \\ 0 & \text{Otherwise} \end{cases} \quad (2)$$

$$E_{Attacker}^d = \begin{cases} 1 & \text{if } SF_{Attacker}^d \geq r \\ 0 & \text{Otherwise} \end{cases} \quad (3)$$

$$SF_{Attacker}^d = \frac{1}{1 + e^{-12(a_1^d g_{Attacker}^d - 0.6)}} \quad (4)$$

where,  $P_{Attacker}$  is the first best individual.

$$P_2^d = \begin{cases} 1 & \text{if } (P_{Barrier}^d + E_{Barrier}^d) \geq 1 \\ 0 & \text{Otherwise} \end{cases} \quad (5)$$

$$E_{Barrier}^d = \begin{cases} 1 & \text{if } SF_{Barrier}^d \geq r \\ 0 & \text{Otherwise} \end{cases} \quad (6)$$

$$SF_{Barrier}^d = \frac{1}{1 + e^{-12(a_2^d g_{Barrier}^d - 0.6)}} \quad (7)$$

where,  $P_{Barrier}$  is the 2nd best individual.

$$P_3^d = \begin{cases} 1 & \text{if } (P_{Chaser}^d + E_{Chaser}^d) \geq 1 \\ 0 & \text{Otherwise} \end{cases} \quad (8)$$

$$E_{Chaser}^d = \begin{cases} 1 & \text{if } SF_{Chaser}^d \geq r \\ 0 & \text{Otherwise} \end{cases} \quad (9)$$

$$SF_{Chaser}^d = \frac{1}{1 + e^{-12(a_3^d g_{Chaser}^d - 0.6)}} \quad (10)$$

where,  $P_{Chaser}$  is the 3rd best individual.

$$P_4^d = \begin{cases} 1 & \text{if } (P_{Driver}^d + E_{Driver}^d) \geq 1 \\ 0 & \text{Otherwise} \end{cases} \quad (11)$$

$$E_{Driver}^d = \begin{cases} 1 & \text{if } SF_{Driver}^d \geq r \\ 0 & \text{Otherwise} \end{cases} \quad (12)$$

$$SF_{Driver}^d = \frac{1}{1 + e^{-12(a_4^d g_{Driver}^d - 0.6)}} \quad (13)$$

where,  $P_{Driver}$  is the 4th best individual.  $SF_{Attacker}^d$ ,  $SF_{Barrier}^d$ ,  $SF_{Chaser}^d$ , and  $SF_{Driver}^d$  are sigmoid transfer functions.  $a_1$ ,  $a_2$ ,  $a_3$ , and  $a_4$  are calculated by applying equation 14 and  $g_{Attacker}$ ,  $g_{Barrier}$ ,  $g_{Chaser}$ , and  $g_{Driver}$  are computed by utilizing equation 15.

$$a = 2 * f * rn1 - f \quad (14)$$

Here,  $f$  is the dynamic vector  $\in [0, 2.5]$  [15].

$$\begin{aligned} g_{Attacker} &= |b.P_{Attacker} - cm.P| \\ g_{Barrier} &= |b.P_{Barrier} - cm.P| \\ g_{Chaser} &= |b.P_{Chaser} - cm.P| \\ g_{Driver} &= |b.P_{Driver} - cm.P| \end{aligned} \quad (15)$$

$$b = 2.rn2 \quad (16)$$

$$cm = chaotic\_map(Tent) \quad (17)$$

$$\begin{aligned} &Discrete\_Comb(u_d, v_d, w_d, x_d) \\ &= \begin{cases} u_d & \text{if } r < 1/4 \\ v_d & \text{if } 1/4 \leq r < 2/4 \\ w_d & \text{if } 2/4 \leq r < 3/4 \\ x_d & \text{Otherwise} \end{cases} \end{aligned} \quad (18)$$

Here,  $r$ ,  $rn1$ , and  $rn2$  are the random numbers between 0 and 1.

### B. BINARY HARRIS HAWK OPTIMIZATION (BHHO)

HHO is a swarm-based optimization technique inspired by Harris hawks' ability to trap prey that has evaded capture [32]. In HHO, searching entities are referred to as "Harris hawks", and the targeted rabbit is the best option or near-optimal option that has thus far been found. During the exploration phase, Harris hawks are initially placed arbitrarily in areas where they can be used to identify rabbits. This procedure is divided into two stages based on the hawks' roosting locations. During the exploitation phase, when hawks investigate the desired rabbit, they employ a variety of hunting methods to deal with the rabbit's numerous evasion behaviours. Thus, there are four stages in this operation, each depending on a different seeking strategy. Harris hawks seek a variety of regions in pursuit of prey during their exploration. During each phase, two protocols must be executed with equal probability. Equation (19), as shown at the bottom of the page.

Where,  $P$ : place of Hawk;  $P_m$ : place of the arbitrary hawk;  $P_{best}$ : place of prey;  $Max$ : highest limit of the searching area;  $Min$ : lowest limit of the searching area;  $rn1$ ,  $rn2$ ,  $rn3$ ,  $rn4$ , and  $a$ : random values  $\in [0, 1]$ ;  $P_{mean}$ : average location of hawks in the current population

It is dependent on the prey's power that HHO switches between two different operations. Escaping energy (EE) is characterised as a time-varying probabilistic variable because of how much energy the prey loses while fleeing.

$$EE = 2E_I(1 - \frac{t}{M}) \quad (20)$$

$$E_I = 2rn - 1 \quad (21)$$

where,  $t$ : ongoing iteration;  $M$ : total iterations to complete;  $E_I$ : initial energy in the range  $[-1, 1]$ ;  $rn$ : Random figure  $\in [0, 1]$

In exploitation, searching agents are able to take advantage of alternatives that are close to the optimal solution that has already been found. HHO models the exploitation step using four processes based on the varying pursuing techniques of hawks and the evasive behaviour of rabbits. Whether or not the prey effectively flees, the hawks will determine the method of besieging the target dependent on the strength of the victim. Here, EE is used to govern the switch between soft and hard besiege.

1) Searching agents seek to enclose the fittest one in **soft besiege** ( $rn > 0.5$  and  $|EE| > 0.5$ ). The current sites are as follows:

$$P(t + 1) = \Delta P(t) - EE|JSP_{best}(t) - P(t)| \quad (22)$$

$$P(t + 1) = \begin{cases} P_{rn}(CI) - rn1|P_{rn}(t) - 2rn2P(t)| & \text{if } a \geq 0.5 \\ (P_{best}(t) - P_{mean}(t)) - rn3(Min + rn4(Max - Min)) & \text{if } a < 0.5 \end{cases} \quad (19)$$

where,

$$\Delta P(t) = P_{best}(t) - P(t) \quad (23)$$

$$JS = \text{Jumping strength} = 2(1 - rn5) \quad (24)$$

- 2) In **hard besiege**,  $rn$  is  $\geq 0.5$  and  $|EE| < 0.5$ , the current place is altered using equation 25.

$$P(t + 1) = P_{best}(t) - EE|\Delta P(t)| \quad (25)$$

As previously stated, the two methods happen whenever the prey attempts but fails to flee ( $rn \geq 0.5$ ). Soft besiege and strong besiege are both carried out in the exploitation phase by means of fast dives for successful escapes ( $rn < 0.5$ ). With the use of the Levy flight pattern, these two stages are much smarter than the prior two methods.

- 3) In the 3rd process “**Soft besiege with rapid dives**”, assuming  $rn < 0.5$  and  $|EE| \geq 0.5$ , the search agents might choose their subsequent motions as per the following principle:

$$G = P_{best}(t) - EE|JSP_{best}(t) - P(t)| \quad (26)$$

$$H = G + \alpha \times LF(L) \quad (27)$$

where, G and H: two different brand-new hawks; L: actual #features;  $\alpha$ : an array of L dimensions produced at arbitrary; LF: levy flight function [19]. Then, the older location is modified by using equation 28.

$$P(t + 1) = \begin{cases} G, & \text{if } G \text{ is fitter than } H \\ H, & \text{if } H \text{ is fitter than } G \end{cases} \quad (28)$$

- 4) In the 4th technique “**Hard besiege with rapid dives**”, assuming  $rn < 0.5$  and  $|EE| < 0.5$ , the hawks might choose their subsequent motions as per the following way:

$$G' = P_{best}(t) - EE|JSP_{best}(t) - P_{mean}(t)| \quad (29)$$

$$H' = G' + \alpha \times LF(L) \quad (30)$$

where,  $G'$  and  $H'$ : two different fresh hawks; L: actual #features;  $\alpha$ : an array of L dimensions produced at arbitrary; LF: levy flight function [19]. Then, the older location is modified by using equation 31.

$$P(t + 1) = \begin{cases} G', & \text{if } G' \text{ is fitter than } H' \\ H', & \text{if } H' \text{ is fitter than } G' \end{cases} \quad (31)$$

We treat the FS task as a binary optimization technique because the options are represented as a string of bits whose dimension is equivalent to the number of characteristics in the given dataset. Therefore, in a binary string, 0 indicates that the associated property is not chosen, and 1 indicates the opposite. As a result, the HHO approach applied to tackle the FS challenge should be transformed to a binary variant, denoted as BHHO. Furthermore, the hawk’s continuous point in HHO must be converted to a binary format. The transfer function (TF) is used to turn the continuous location into a binary without affecting the design of HHO. In this research,

the S-shaped TF is applied as follows to squish the continuous values for each aspect:

$$STF = \frac{1}{1 + e^{(-p_j/3)}} \quad (32)$$

where,  $p_j$ : continuous location of the hawk for  $j^{th}$  variable.

$$P_j(t + 1) = \begin{cases} \neg P_j(t), & \text{if } rn < STF \\ P_j(t), & \text{otherwise} \end{cases} \quad (33)$$

where,  $rn$ : random number  $\in [0, 1]$

### C. MULTI-OBJECTIVE OPTIMIZATION (MOP)

Single-objective optimization’s (SOP) main purpose is to identify the “optimal” solution, which refers to the lowest or maximum value of a single objective function that combines all multiple objectives into one. This type of optimization is useful as a tool for providing planners with information about the problem at hand, but it rarely provides a set of potential solutions that trade off distinct objectives.

In a multi-objective optimization (MOP) with competing objectives, on the other hand, there is no single best solution. The interplay of several objectives results in a collection of compromised solutions, which are sometimes referred to as trade-offs, non-dominated, non-inferior, or Pareto-optimal options. A fitness comparison is used to establish a candidate’s superiority over other alternatives in a SOP. Despite this, the idea of dominance is used in MOP to assess the merit of a potential solution. If the following two requirements are true, an alternative A1 in the feasible region of a C-objective problem dominates an alternative A2.

- 1) For all  $C$ : A1 is not inferior than A2
- 2) There is a  $c$ : A1c is surely superior than A2c

### D. RELATED WORKS

#### 1) HYBRID FILTER-WRAPPER APPROACHES FOR FS

The authors in [33] developed a wrapper technique based on genetic algorithms (GAs) that uses NSGAI and the K-Nearest Neighbours (KNN) method to reduce misclassification as well as feature counts. In [34], NSGAI looked at developing two filter techniques, NSGAIIMI and NSGAIIE, using MI and entropy as the assessment criteria, respectively. Recently, a text feature selection technique based on a filter-based multi-objective algorithm was proposed by Labani et al. [35]. A text feature’s significance is determined by using the Relative Discriminative Criterion (RDC), whereas redundancy is determined by using the correlation measure. Cervante et al. [36] employed rough set theory and MOBPSO to do filter-based FS. There were two multi-objective filter FS methods proposed by Xue et al. [37], both of which employed BPSO, modified MI, and entropy to perform superior classification. Three multi-objective ABC techniques (MOABC) were developed by Hancer et al. [38] focused on information theory and incorporating three filter objectives. Studies in the last few years have shown that merging filter with wrapper technique

can produce outstanding results, as in [39], where two filter and one wrapper criteria are handled by multi-objective GA. With mutual information as filter fitness, a new multi-objective GWO for FS is proposed in the article [40], and the generated solutions are enhanced towards higher classification results by the use of wrapper fitness. The authors of the research [41] provides two new filter FS approaches for classification issues based on binary PSO and information theory. The first approach utilises BPSO and the MI between each pair of attributes to assess the subset's significance and duplication. The second approach examines the relevance and duplication of the chosen feature subset using BPSO and the entropy of each feature group. Taha *et al.* [42] presented BAMI, a hybrid Bat Algorithm (BA) based on MI and Naive Bayes. A strategy based on Filter-GA, known as the GAFFS technique, has been presented by the researchers in the publication [43] for FS. Information gain, gain ratio, ReliefF, Chi-square, and correlation feature selector were chosen for picking the most promising attributes from real-world datasets. To pick the most relevant features, GA is then applied, with chromosomal fitness measured using the KNN classifier's classification accuracy. To control duplicate and undesired aspects in a dataset, Nayak *et al.* [44] presented a filter technique employing an elitism-based Multi-objective Differential Evolution algorithm for FS (FAEMODE). The uniqueness lies in this algorithm's objective preparation, which takes into account linear as well as non-linear interdependence among feature sets. Usman *et al.* [45] have proposed two alternative multi-objective filter-based FS architectures built on the boolean cuckoo optimization technique, utilizing the concept of non-dominated sorting GAs, NSGAIII (BCNSG3) and NSGAII (BCNSG2). To this end, four different multi-objective filter-based FS techniques were developed, each using MI and gain ratio based entropy as filter assessment measurements. Using the whale optimization technique (WOA), Got *et al.* [46] suggested a new hybrid filter-wrapper FS solution in 2021. It is a multi-objective technique suggested that optimises both filter and wrapper fitness concurrently. The effectiveness of their approach is proved on twelve standard datasets by a thorough evaluation with seven popular algorithms.

## 2) HYBRIDIZATION OF DIFFERENT EVOLUTIONARY ALGORITHMS FOR FS

Bindu *et al.* [47] have aimed to look into the possibility of enhancing the Artificial Bee Colony algorithm (ABC) by hybridising it with GA. Experimental studies on different datasets showed that the presented hybrid solution outperformed the current ABC strategy. The goal of this research [48] is to improve chaotic dynamic weight particle swarm optimization (CHPSO) by attempting a CHPSODE fusion of DE and CHPSO. The simulation results revealed that CHPSO-DE outperformed other strategies in finding a practical solution to the FS problem. The authors of the study [49] have introduced a FS approach named MA-HS, which is built on Mayfly Optimization and

Harmony Search. The suggested MA-HS technique was tested on 18 UCI data sets and contrasted with 12 other cutting-edge meta-heuristic FS approaches as well as 3 high-dimensional microarray datasets. In contrast to others, test findings show that MA-HS is capable of reaching the required high classification efficiency and lower number of attributes. In the article [50], a hybrid PSO-GE is suggested to improve performance, minimize query processing time, and shorten the processing load of PSO. The findings of the tests demonstrate that the hybrid PSO-GE approach is more efficient than current approaches. The authors of the study [51] have presented a new Salp Swarm Optimizer (SSA) form, known as ISSAFD, for FS. Using sinusoidal mathematical functions inspired by the Sine Cosine optimizer, ISSAFD adjusts follower (F) location in SSA. Al-Tashi *et al.* [52] have proposed a PSO and a hybrid grey wolf optimization (GWO) known as BGWOPSO to find the best attribute subset and to solve FS problems. The research findings showed that the BGWOPSO approach is more effective in terms of quality, including computational time, accuracy, and selecting the best optimal features. The authors of the article [53] have provided 3 hybrid architectures for the FS task based on thermal exchange optimizer (TEO) and seagull optimisation (SOA). The findings from the experiments have shown that the proposed hybrid algorithm improves classification performance, ensures the ability to choose hybrid SOA-algorithms, reduces the time for the CPU and picks the informative variable. In the article [9], in order to improve the capability of the MFO algorithm to exploit and explore and provide another way to create an optimum feature vector that, in particular, represents the complete characteristic, an alternative swarm approach known as OMFODE is presented, in which the OBL technique is linked with the DE and an MFO. In solving the FS tasks, the document [54] suggests a novel hybrid approach called the Hybrid Binary Bat Boosted Particle Swarm Optimization Algorithm (HBBEPSO). The findings of this study show the potential of finding the optimum variable fusion in the suggested HBBEPSO method. The authors of the paper [55] aimed to solve the problem of the Sine Cosine Algorithm (SCA) by using the differential evolution operators as local search methods. The findings of the tests showed that, in terms of success metrics and predictive analysis, the suggested approach will provide better performance than the other approaches. The work suggested by Houssein *et al.* [28] merged the Harris Hawk optimizer (HHO) and Cuckoo Search (CS) and chaotic maps, to improve the efficiency of the initial HHO with the hybrid evolutionary approach called CHHO-CS. In addition, the suggested approach for the collection of chemical descriptors and chemical composites was paired with the help of an SVM classifier. A hybrid optimising approach is suggested in the article [2], which incorporates SCA into HHO. SCA integration aims to address inefficient HHO discovery and also improves exploitation with the complex adjustment of nominee solutions to prevent solution stagnation in HHO. A discrete hybrid GWO and HHO approach called

HBGWOHHO is offered in the article [29]. The sigmoid function translates the continuous region of interest into a discrete area to satisfy the requirements for FS.

Though many researchers assumed their approach to be multi-objective, this implies that the optimization procedure is simultaneously taking place, but the FS is still limited to one objective task as they optimize the objective functions sequentially during the filter and wrapper stages, respectively. In brief, the FS domain has used a number of multi-objective evolutionary strategies. Nevertheless, the vast majority of them use filtering or wrapping. Filter and wrapper models have not been integrated into a single system in significant numbers of studies in the literature to deal with feature selection as a MOP. Furthermore, there is no work in the literature that uses the benefits of both HHO and ChOA in a single architecture to handle FS tasks. Hence, our efforts to create a novel multi-objective hybrid filter-wrapper technique based on the integration of ChOA and the HHO algorithm were prompted by this need. From a literature survey, we found that there are very few evolutionary algorithms for feature selection in COVID-19 data. In exceptional instances, the initial ChOA version becomes stuck at the local optima. A novel ChOA can be developed by integrating the HHO into the original ChOA to improve the optimizer's search capabilities and broaden the usage sectors, including real-world applications such as in COVID-19 data.

### III. PROPOSED TECHNIQUE

The intention of this section is to describe the detailed architecture of the proposed enhanced Multi-Objective binary ChOA (EBMOChOA-FW) to resolve the FS issue in the medical sector. FIGURE 1 depicts the architectural vision of the introduced EBMOChOA-FW-based FS work. The descriptions of the different steps shown in FIGURE 1 are given below:

- 1) **Initialize the Population:** The pictorial representation of the structure of each member's location and the criteria for selection and rejection of a particular characteristic is shown in FIGURE 2.
- 2) **Compute the Fitness and Rank the Options:** This work treats FS as a two-objective hybrid filter wrapper optimization problem. The sole aim of FS is to limit the number of characteristics along with the classification error. Thus, the first objective function is formulated by using the equation 34 [32].

$$Fitness1 = \alpha * classification\_error + (1 - \alpha) * \frac{LS}{L} \quad (34)$$

where,

$$classification\_error = \frac{\#Wrongly\ predicted\ samples}{\#Total\ samples} \quad (35)$$

and  $LS$  = Length of the feature substring,  $L$  = Total feature\_count,  $\alpha$  = controlling parameter.

In order to pick characteristics, one must look for a group of features that collectively have the greatest relevance to the target class and the least amount of redundancy among them all. Therefore, the maximum of the correlation between the feature substring and the class attribute and the reduction of the dependency between the characteristics in an attribute substring are normally emphasised for FS purposes. MI and the Pearson correlation coefficient (PCC) are typical characteristics of relevance or interdependency. This motivated us to formulate the second objective function by using equation 36 [44].

$$Fitness2 = \frac{1}{LS} \sum MI(f_i, class) \times \frac{1}{LS} \sum PCC(f_i, class) \quad (36)$$

where,  $f_i$ : discrete characteristics present in the feature subgroup and  $class$ : class attribute. Then, rank the solutions according to their dominance count. It means rank 1 (the best one) is assigned to that option which is having lowest domination count.

- 3) **Update the Archive1 and Archive2:** Because the EBMOChOA-FW produces a set of Pareto optimal options after every generation, the Archive1 should be reformatted to reflect succeeding evaluations of each population member. Relying on the cases described in FIGURE 3, a newly non-dominated option  $NP_{new}$  of the present population may be added into the Archive1. We assume an option to be best after every repetition if its ranking is 1. So the proposed EBMOChOA updates the Archive1 at the end of each loop so that after completing all the iterations it can output the overall Pareto solutions of the FS task. Simulating the behaviour of chimpanzees requires four optimal answers (" $P_{Attacker} : -P_A$ ", " $P_{Barrier} : -P_B$ ", " $P_{Chaser} : -P_C$ ", " $P_{Driver} : -P_D$ ") in each cycle. However, it is possible that throughout the running of each cycle, there are no four optimal alternatives. As a result, the chimps were sorted in ranking in each repetition, and the four leading options were chosen as  $P_A$ ,  $P_B$ ,  $P_C$ , and  $P_D$ . Thus, we might acquire a new batch of  $P_A$ ,  $P_B$ ,  $P_C$ , and  $P_D$  that is superior to the older ones after every cycle. Therefore, we must remember their values. There needs a supplementary archive (Archive2) here to save each cycle's  $P_A$ ,  $P_B$ ,  $P_C$ , and  $P_D$ . Through applying dominance approach, the newer  $P_A$ ,  $P_B$ ,  $P_C$ , and  $P_D$  team is matched to the prior group, and if it is better, it will occupy the seat of existing gang. Finally, the chimp's positioning is changed with the recent  $P_A$ ,  $P_B$ ,  $P_C$ , and  $P_D$ .
- 4) **Obtain HHO-Based Population:** In this phase, the position update mechanism of BHHO is executed on the current population to produce an HHO-based population. First, for each individual, the escaping energy of the prey is calculated by applying the equation 20.

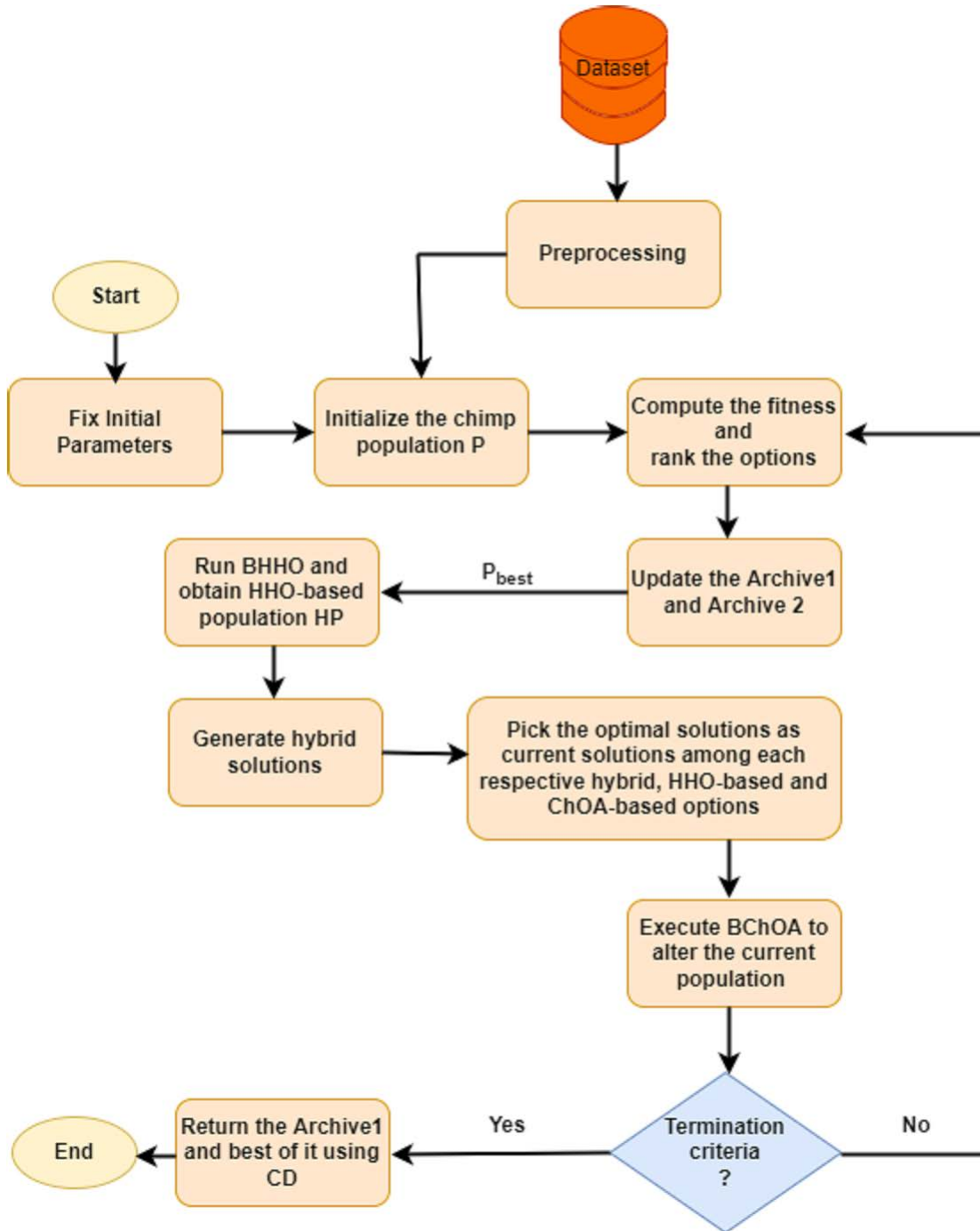


FIGURE 1. Proposed hybrid framework for feature selection.

If  $|EE| \geq 1$ , equations 19 and 33 are used to alter the position of the corresponding member (exploration). When  $|EE| < 1$  (exploitation), equations 22, 25, 28, and 31 are responsible for twisting the location of the population member in continuous domain depending on the conditions of the four cases described in section II-B. Then, equation 33 is used to obtain the place of each individual in the discrete form. During

exploration and exploitation operations of the BHHO, the best solutions stored in Archive1 are used in the location update process (as  $P_{best}$ ) using the crowding distance (CD) measure. In most cases, Archive1 contains more than one optimum option as we are using multiple objectives to evaluate the individuals. Therefore, here, CD value is used to pick one best option (having the highest CD value) from the set of best



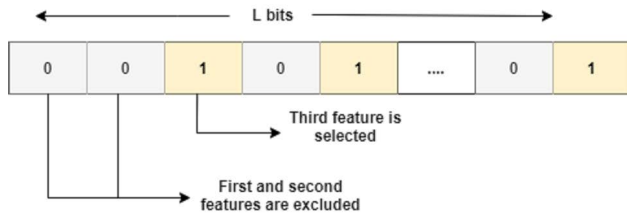


FIGURE 2. Initialization of chimp location as binary string.

ones for updating the position. At this stage, the BHHO process relies on the population’s reaction to individual chimpanzees’ behaviour changes. The enhanced exploratory capability of BHHO, on the other hand, can bridge the exploring gap left by traditional BChOA. As a result of this activity, not only does the diversification of the chimp group increase, but the equilibrium between exploration and exploitation is improved.

- 5) **Create Hybrid Solutions:** Here, a hybrid individual is created by combining a ChOA-based chimp with the corresponding solution from the HHO-based population. Here’s how the novel hybrid solution is derived:

$$P_{hybrid} = \alpha P_j + (1 - \alpha)HP_j \quad (37)$$

where  $\alpha$  is the basic ChOA option’s weight, and its value is between 0 and 1.  $HP_j$  is the location string of the  $j^{th}$  element in the above-mentioned HHO-based population.

- 6) **Choose the Current Solution:** In this phase, a “greedy” technique is used to pick the non-dominated (ND) feasible member as the current solution from the newly generated hybrid option, the initial chimp, and the equivalent HHO-based hawk. If more than one out of three is found to be ND solutions, any one of them can be taken as the current searching individual arbitrarily. In this scenario, it has the potential to increase the reliability of the solutions as well as the robustness of the presented technique. The resultant current entity is then handled via the basic BChOA approach.
- 7) **Position Update Based on BChOA:** The population formed by integrating all the entities elected as the current searching element in the previous step is subjected to the BChOA architecture for update. The place value of each member is altered using the equation 1. The details regarding the step-by-step procedure to calculate equation 1 is given in section II-A. Here, we have used the “Tent” chaotic map to be used in the location change procedure of BChOA.
- 8) **Returning the best of Primary archive:** After the specified number of moves, any outcomes that are not mutually dominated are stored in Archive 1. The CD score is used as a filtering tool to discover the appropriate combination of traits from a collection of non-dominant ones [56], [57]. The detailed algorithm

of the proposed hybrid feature selection approach is given by Algorithm 1.

**Algorithm 1** EBMOChOA-FW for Feature Selection

- 1: Fix population size (PS), Archive1 size (AS), and number of iterations to be carried out (M).
- 2: Generate initial chimp’s position arbitrarily.
- 3: **for**  $t \leftarrow 1$  to  $M$  **do**
- 4:     **for**  $j \leftarrow 1$  to  $PS$  **do**
- 5:         Compute the fitness of  $chimp_j$
- 6:     **end for**
- 7:     Rank the chimps
- 8:     Update the Archive 1 and Archive 2
- 9:     **for**  $j \leftarrow 1$  to  $PS$  **do**     ▷ Generate HHO-based population
- 10:         Use BHHO principle to get HHO-based chimp
- 11:     **end for**
- 12:     **for**  $j \leftarrow 1$  to  $PS$  **do**
- 13:         Create hybrid solutions based on  $P_j$  and  $HP_j$  using equation 37.
- 14:         Obtain the fitness of  $P_{hybrid}$ ,  $P_j$ , and  $HP_j$ .
- 15:         Pick the best one as current member for further processing.
- 16:     **end for**
- 17:     **for**  $j \leftarrow 1$  to  $PS$  **do**     ▷ Treat the current search members as chimp population
- 18:         Compute the fitness of  $chimp_j$
- 19:     **end for**
- 20:     Rank the chimps
- 21:     Update the Archive 1 and Archive 2
- 22:     Obtain recent  $P_A$ ,  $P_B$ ,  $P_C$ , and  $P_D$  from Archive 2
- 23:     **for**  $j \leftarrow 1$  to  $PS$  **do**
- 24:         Update the  $chimp_j$  using equation 1
- 25:     **end for**
- 26: **end for**
- 27: Return Archive1 and the best of it using CD measure.

- 9) **Estimation of Time Complexity** The steps for estimating the time complexity of the proposed feature selection approach are given below:
  - a) The complexity of initialization procedure (step 2) requires:  $O(PS*L)$ .
  - b) The fitness function computation of all the chimp (step 4-6) requires [17]:  $O(PS*[O(L) + O(Q*L)])$ .
  - c) Ranking the chimps (step 7) based on domination count requires [17]:  $O(PS \log PS)$ .
  - d) Getting Pareto solutions for Archive1 (step 8) after each run using dominance tree requires: [58]:  $O(CPS \log PS)$ , where C is the number of fitness criteria.
  - e) Selecting best of Archive1 (required for step 10) for updating location based on CD requires:  $O(CAS \log AS)$ .
  - f) Position update based on BHHO (step 9-11) requires:  $O(PS*L)$ .

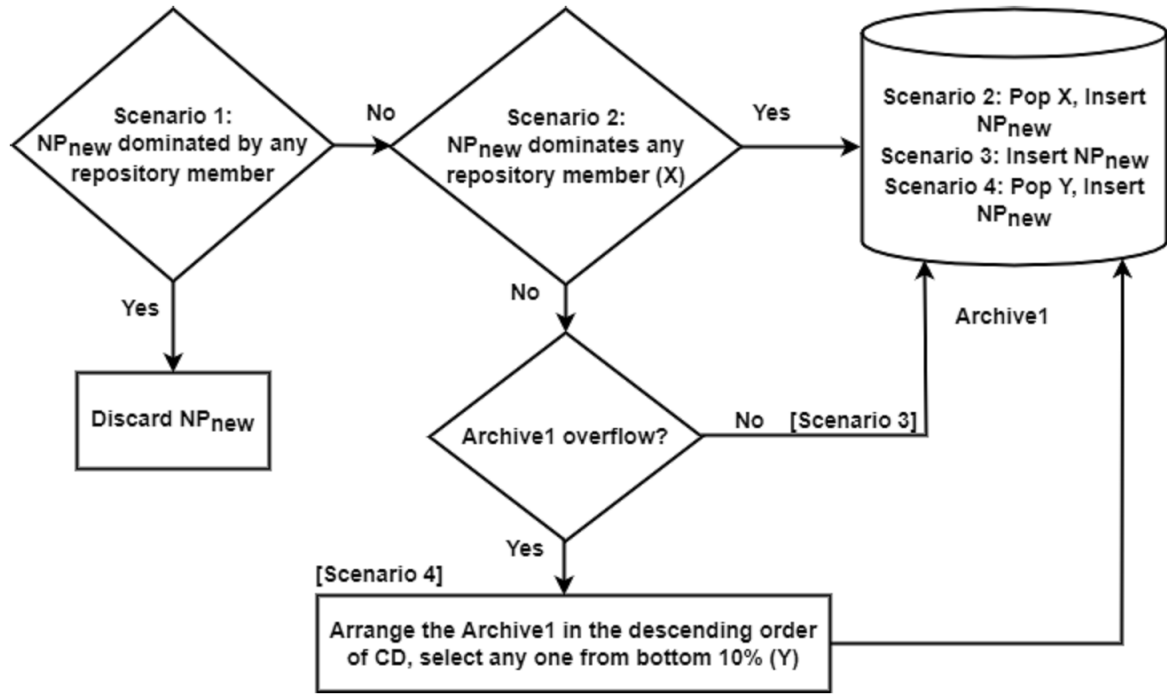


FIGURE 3. Archive1 update mechanism.

- g) Finding hybrid searching member (step 13) requires:  $O(L)$
- h) The fitness assessment of  $P_{hybrid}$ ,  $P_j$ , and  $HP_j$  (step 14) requires:  $O(3*[O(L) + O(Q*L)])$ .
- i) Picking the non-dominated one out of three (step 15) requires:  $O(C*3\log 3)$ .
- j) Step 17-22 requires:  $O(PS*[O(L) + O(Q*L)]) + O(PS\log PS) + O(CPS\log PS) + O(CAS\log AS)$ .
- k) Updating all the current chimp based on BChOA requires:  $O(PS*L)$ .
- l) Selecting best of Archive1 according to the CD value requires:  $O(CAS\log AS)$ .

Finally, the complexity of EBMChOA-FW is:

$$\begin{aligned}
 &O(\text{EBMChOA} - \text{FW}) \\
 &= O(PS * L) + M[O(PS * [O(L) + O(Q * L)]) \\
 &\quad + O(PS\log PS) + O(CPS\log PS) \\
 &\quad + O(CAS\log AS) + O(PS * L) \\
 &\quad + PS * [O(L) + O(3 * [O(L) + O(Q * L)]) \\
 &\quad + O(C * 3\log 3)] \\
 &\quad + O(PS * [O(L) + O(Q * L)]) \\
 &\quad + O(PS\log PS) + O(CPS\log PS) + O(CAS\log AS) \\
 &\quad + O(PS * L)] + O(CAS\log AS) \\
 &\approx O(PS\log PS) \tag{38}
 \end{aligned}$$

#### IV. EXPERIMENTAL SETUPS AND RESULT DISCUSSION

This section details the comparison between the acquired findings and the bench-marking datasets used, as well as

TABLE 1. Datasets in details.

| SID | Name             | #Samples | #Characteristics | #Classes |
|-----|------------------|----------|------------------|----------|
| D1  | Lymphography     | 148      | 18               | 3        |
| D2  | Diabetic         | 1151     | 19               | 2        |
| D3  | Cardiotocography | 2126     | 21               | 3        |
| D4  | Cervical Cancer  | 858      | 35               | 2        |
| D5  | Lung Cancer      | 32       | 56               | 3        |
| D6  | Arrhythmia       | 452      | 279              | 16       |
| D7  | Parkinsons       | 756      | 754              | 2        |
| D8  | Colon tumor      | 62       | 2000             | 2        |
| D9  | Leukemia         | 72       | 7129             | 2        |

the chosen state-of-the-art techniques and their parameter settings.

#### A. DATASETS

The utilisation of seven standard datasets with varying numbers of features from UCI and two microarray cancer datasets [59] confirms the success of EBMChOA-FW. TABLE 1 shows the schematic of each dataset, such as the number of attributes, observations, and classes. In TABLE 2, the URLs for accessing these datasets are given for more details. Each dataset is normalised to solve the numerical challenge. In this study, a KNN classifier with a k value of 5 and 10-fold cross validation is used to determine the classification accuracy.

#### B. METHODS FOR COMPARISON AND PARAMETER SETTINGS

At first, the proposed EBMChOA-FW approach is compared with the existing multi-objective FS methods:

**TABLE 2.** URLs for accessing the datasets.

| Datasets         | URL   |
|------------------|---|
| Lymphography     | <a href="https://archive.ics.uci.edu/ml/datasets/Lymphography">https://archive.ics.uci.edu/ml/datasets/Lymphography</a>   |
| Diabetic         | <a href="https://archive.ics.uci.edu/ml/datasets/diabetes">https://archive.ics.uci.edu/ml/datasets/diabetes</a>   |
| Cardiotocography | <a href="https://archive.ics.uci.edu/ml/datasets/cardiocography">https://archive.ics.uci.edu/ml/datasets/cardiocography</a>   |
| Cervical Cancer  | <a href="https://archive.ics.uci.edu/ml/datasets/Cervical+cancer+%28Risk+Factors%29">https://archive.ics.uci.edu/ml/datasets/Cervical+cancer+%28Risk+Factors%29</a> |
| Lung Cancer      | <a href="https://archive.ics.uci.edu/ml/datasets/lung+cancer">https://archive.ics.uci.edu/ml/datasets/lung+cancer</a>   |
| Arrhythmia       | <a href="https://archive.ics.uci.edu/ml/datasets/arrhythmia">https://archive.ics.uci.edu/ml/datasets/arrhythmia</a>   |
| Parkinsons       | <a href="https://archive.ics.uci.edu/ml/datasets/parkinsons">https://archive.ics.uci.edu/ml/datasets/parkinsons</a>   |
| Colon tumor      | <a href="https://csse.szu.edu.cn/staff/zhuzx/Datasets.html">https://csse.szu.edu.cn/staff/zhuzx/Datasets.html</a>   |
| Leukemia         | <a href="https://csse.szu.edu.cn/staff/zhuzx/Datasets.html">https://csse.szu.edu.cn/staff/zhuzx/Datasets.html</a>   |

MOQBHHO [19] and BMOChOA [17] based on HHO and ChOA, respectively. MOQBHHO is a multi-objective wrapper-based FS technique that uses quadratic transfer functions to solve the FS challenge in the medical domain. Similarly, BMOChOA is also a multi-objective wrapper attempt to find the major aspects causing a particular disease. It has used “tent” chaotic map and CD measure in its architecture.

In the second phase of our experiment, three multi-objective strategies, MOPSO [60], BMOGWO-S [61], and FW-GPAWOA [46], are employed as benchmark approaches in the comparative analysis to confirm the efficiency of the suggested EBMOChOA-FW approach. The MOPSO method is a multi-objective PSO-based technique where a supplementary archive is integrated to save non-dominated options, and an archive controller with an adaptive grid technique is utilised to boost the convergence and variation of the population. BMOGWO-S, a sigmoid transfer function-based binary variant of MOGWO, was designed to optimise FS issues. Here, the Artificial Neural Network (ANN) is utilised to evaluate the classification efficiency of a group of chosen attributes. To begin with, both MOPSO and BMOGWO-S use the number of features as their primary criterion, while the classification error rate serves as their second fitness function. FW-GPAWOA is a hybrid filter-wrapper FS approach based on the whale optimizer. It is a multi-objective approach where MI (filter) and classification accuracy (wrapper) are taken into account to formulate the objectives.

A population size of 100 and 50 iterations are set in all algorithms to have a fair assessment. Each dataset was subjected to a total of 20 separate runs of each method, and they were built and tested in Python 3.7 on an Intel Core i3-7020U CPU @ 2.30 GHz and a 4.00 GB RAM machine.

### C. COMPARISON BETWEEN MOQBHHO, BMOChOA, AND EBMOChOA-FW

Here, the proposed EBMOChOA-FW is executed for 20 separate runs. TABLE 3 is for listing the IGD of the finest Pareto curve attained by MOQBHHO, BMOChOA, and EBMOChOA-FW for 9 different healthcare datasets. For equality in comparison, we have calculated the IGD values of EBMOChOA-FW by taking the number of features and classification accuracy of the generated ND solutions in the horizontal and vertical axis of the objective space,

**TABLE 3.** IGD values of CPFs of MOQBHHO, BMOChOA, and EBMOChOA-FW.

| Datasets         | MOQBHHO | BMOChOA | EBMOChOA-FW |
|------------------|---------|---------|-------------|
| Lymphography     | 0.05    | 0       | 0           |
| Diabetic         | 0.0005  | 0.001   | 0.001       |
| Cardiotocography | 0.02    | 0.02    | 0.002       |
| Cervical Cancer  | 0       | 0       | 0           |
| Lung Cancer      | 0       | 0       | 0           |
| Arrhythmia       | 0.09    | 0.015   | 0.013       |
| Parkinsons       | 0.0001  | 0       | 0           |
| Colon tumor      | 0.02    | 0.06    | 0.02        |
| Leukemia         | 0.031   | 0.048   | 0.025       |

respectively. TABLE 3 shows that, when compared to BMOChOA, the IGD of the calculated Pareto fronts (CPF) produced by EBMOChOA-FW are lower or equivalent for all 9 datasets. Higher convergence speeds are indicated by a smaller IGD value, which signifies the closeness between the true Pareto front (TPF) and the CPF. This shows that the EBMOChOA-FW improves the exploiting and exploratory potential of dimension reduction and addresses the disadvantages of the classic ChOA, which are attributable to the inclusion of the HHO-based strategy. For every chimp’s positional adjustments, EBMOChOA-FW employed a tent map. This is a piece-wise non-smooth map. It spans the complete phase area, and the area is chaotic. The capacity of this map to explore non-repeatedly all states inside a given range may be the explanation for EBMOChOA-FW producing superior non-dominated solutions. This empowers the EBMOChOA-FW to escape local optima and attain the globally optimum more quickly. Furthermore, the Wilcoxon signed rank test was employed to see if the EBMOChOA-FW is markedly fitter than the other methods. The outputs of the Wilcoxon signed rank test are given in TABLE 4. The symbols (++, ==, --) indicate that EBMOChOA-FW is significantly better, equivalent to, or worse than the above two methods. After inspecting the TABLE 4, we observed that EBMOChOA-FW is outstandingly superior to the above two approaches.

### D. PERFORMANCE COMPARISON BETWEEN EBMOChOA-FW, MOPSO, BMOGWO-S, AND FW-GPAWOA

To present an equitable comparison between the best results of all the four multi-objective approaches, we have taken the

TABLE 4. Outcomes of Wilcoxon rank test.

| Datasets         | EBMOChOA-FW vs MOQBHHO | EBMOChOA-FW vs BMOChOA |
|------------------|------------------------|------------------------|
| Lymphography     | ++                     | ++                     |
| Diabetic         | ==                     | ++                     |
| Cardiotocography | ++                     | ++                     |
| Cervical Cancer  | ==                     | ++                     |
| LungCancer       | ++                     | ++                     |
| Arrhythmia       | ++                     | ++                     |
| Parkinsons       | ++                     | ++                     |
| Colon tumor      | ==                     | ++                     |
| Leukemia         | ++                     | ++                     |

TABLE 5. Experimental outcomes of the MOPSO, BMOGWO-S, FW-GPAWOA, and EBMOChOA-FW.

| Datasets         |                   | MOPSO  | BMOGWO-S | FW-GPAWOA | EBMOChOA-FW |
|------------------|-------------------|--------|----------|-----------|-------------|
| Lymphography     | avg_size          | 6.6    | 5.5      | 7.1       | 4           |
|                  | avg_acc           | 0.813  | 0.81     | 0.824     | 0.825       |
|                  | avg_runtime(mins) | 3.52   | 4.11     | 4.65      | 4.02        |
| Diabetic         | avg_size          | 4.6    | 4.25     | 3.75      | 3.5         |
|                  | avg_acc           | 0.629  | 0.691    | 0.659     | 0.7         |
|                  | avg_runtime(mins) | 9.01   | 8.87     | 8.45      | 7.78        |
| Cardiotocography | avg_size          | 7.6    | 6.77     | 5.8       | 4.6         |
|                  | avg_acc           | 0.864  | 0.847    | 0.87      | 0.87        |
|                  | avg_runtime(mins) | 13.23  | 13.11    | 12.96     | 12.56       |
| Cervical Cancer  | avg_size          | 4      | 10.4     | 3         | 4.6         |
|                  | avg_acc           | 0.95   | 0.95     | 0.96      | 0.97        |
|                  | avg_runtime(mins) | 5.16   | 5.67     | 4.08      | 3.97        |
| Lung Cancer      | avg_size          | 19.5   | 18.6     | 10        | 2           |
|                  | avg_acc           | 0.47   | 0.46     | 0.59      | 0.675       |
|                  | avg_runtime(mins) | 7.21   | 5.38     | 5.87      | 7.01        |
| Arrhythmia       | avg_size          | 126.5  | 122.33   | 84        | 3           |
|                  | avg_acc           | 0.63   | 0.61     | 0.66      | 0.63        |
|                  | avg_runtime(mins) | 13.43  | 14.21    | 13.02     | 14.86       |
| Parkinson        | avg_size          | 346.4  | 109.8    | 300.3     | 5           |
|                  | avg_acc           | 0.81   | 0.8      | 0.83      | 0.85        |
|                  | avg_runtime(mins) | 23.03  | 20.87    | 19.98     | 22.67       |
| Colon Tumor      | avg_size          | 966    | 886.33   | 956.85    | 236.25      |
|                  | avg_acc           | 0.83   | 0.84     | 0.81      | 0.8         |
|                  | avg_runtime(mins) | 6.18   | 5.68     | 5.07      | 5.78        |
| Leukemia         | avg_size          | 174.25 | 475.5    | 1371.71   | 941.2       |
|                  | avg_acc           | 0.81   | 0.83     | 0.81      | 0.84        |
|                  | avg_runtime(mins) | 22.76  | 21.84    | 21.04     | 22.01       |

number of features and the corresponding classification accuracy values shown in FIGURE 4 irrespective of the objective functions taken by them. FIGURE 4 shows that for datasets like Lymphography, Diabetic, Cervical cancer, LungCancer, Arrhythmia, Parkinson, Colon tumor, and Leukemia, the curves obtained by the proposed method lie above others, indicating their closeness towards the true Pareto front. For cardiotocography samples, the performances of both the hybrid FW approaches, FW-GPAWOA and EBMOChOA-FW, are very close to each other. In the case of LungCancer data, the proposed EBMOChOA-FW method produced only one solution in its Pareto front with 46% more accuracy by taking only 2 out of 56 features.

TABLE 5 displays the outcomes of the MOPSO, BMOGWO-S, FW-GPAWOA, and EBMOChOA-FW experiments over 20 separate runs of each. The average number of features selected is “avg\_size”, the average classification accuracy attained by the methods is “avg\_acc”, and the average running time is “avg\_runtime”. For datasets like Lymphography, Diabetic, Cardiotocography, LungCancer, and Parkinson, our introduced approach is able to produce higher

classification accuracy with fewer features in less time. However, in some cases, the proposed hybrid method took a little more time to complete the 50 iterations, and this may be due to the maintenance of two archives and the integration of BHHO and BChOA. Furthermore, the Wilcoxon test is used to compare the IGD values statistically to see if there is a substantial variation among the efficiency of methods, and the test results along with the P-values are shown in TABLE 6. TABLE 6 shows that the IGD-measure achieved by EBMOChOA-FW was considerably less than those acquired by MOPSO and BMOGWO-S for seven datasets, equivalent for one dataset, and noticeably worse for one dataset, while the outstanding outcomes of the suggested approach are very apparent in comparison to the FW-GPAWOA method.

Overall, the results reveal that our approach outperforms the comparative techniques in the vast majority of situations. When tested, it was shown that the proposed method was capable of locating and resolving two of the most difficult issues associated with FS: the curse of dimensionality and improving classification efficiency.

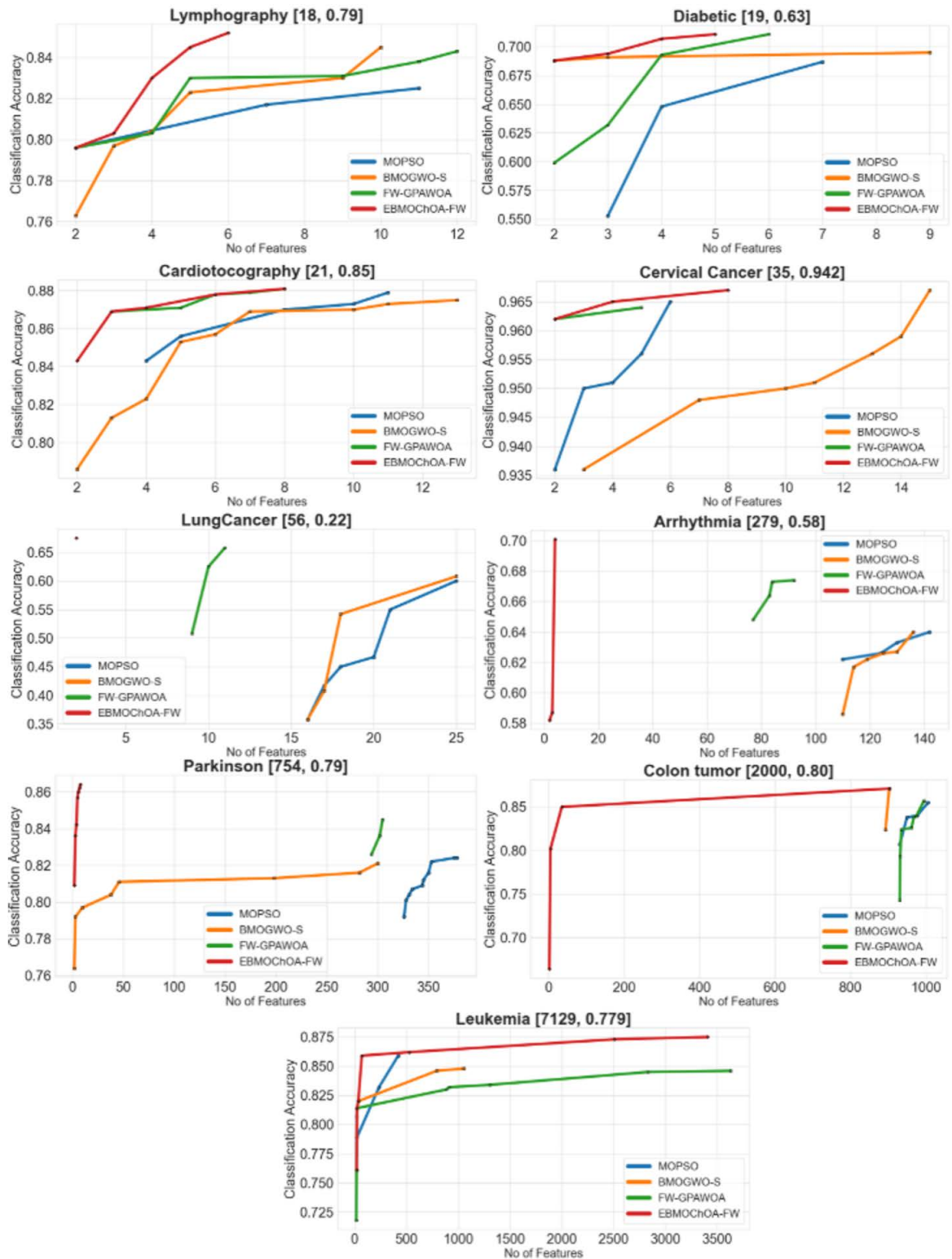


FIGURE 4. Number of features vs classification accuracy.

**V. COVID-19 PATIENT HEALTH PREDICTION USING THE EBMOChOA-FW**

The World Health Organization (WHO) stated in 2020 that the severe acute respiratory syndrome coronavirus 2

(SARS-CoV-2) had begun to target China and had spread fast around the globe. Since August 2020, the SARS-CoV-2 virus, called COVID-19, has killed more than 600,000 people all over the world [62]. Machine learning and deep learning

TABLE 6. Wilcoxon test results on IGD metric.

| EBMOChOA-FW vs | MOPSO    | Sig_diff | BMOGWO-S | Sig_diff | FW-GPAWOA | Sig_diff |
|----------------|----------|----------|----------|----------|-----------|----------|
| D1             | 0.000    | ++       | 1.452E-3 | ++       | 1.000     | ==       |
| D2             | 1.234E-4 | ++       | 0.000    | ++       | 1.113E-5  | ++       |
| D3             | 2.217E-3 | ++       | 0.000    | ++       | 0.000     | ++       |
| D4             | 1.416E-5 | ++       | 0.000    | ++       | 1.005E-2  | ++       |
| D5             | 0.058    | ==       | 3.216E-5 | ++       | 0.000     | ++       |
| D6             | 5.291E-2 | ++       | 2.137E-2 | ++       | 0.061     | ==       |
| D7             | 1.094E-3 | ++       | 1.486E-4 | ++       | 0.000     | ++       |
| D8             | 1.947E-4 | ++       | 3.163E-2 | --       | 1.290E-2  | ++       |
| D9             | 6.234E-2 | --       | 0.073    | ==       | 3.437E-4  | ++       |

TABLE 7. Details of COVID-19 Dataset1.

| SNo | Attributes | Explanation                    | SNo | Attributes | Explanation             |
|-----|------------|--------------------------------|-----|------------|-------------------------|
| 1   | id         | Patients's ID                  | 8   | vis_wuhan  | Patients visited wuhan? |
| 2   | location   | Patients's location            | 9   | from_wuhan | Patients from wuhan?    |
| 3   | country    | Patients' s country            | 10  | symptom1   | Patients's symptoms     |
| 4   | gender     | Patients's gender              | 11  | symptom2   | Patients's symptoms     |
| 5   | age        | Patients's age                 | 12  | symptom3   | Patients's symptoms     |
| 6   | sym_on     | Patients's symptoms date       | 13  | symptom4   | Patients's symptoms     |
| 7   | hosp_vis   | Patients's hospital visit date | 14  | symptom5   | Patients's symptoms     |
|     |            |                                | 15  | symptom6   | Patients's symptoms     |



FIGURE 5. Number of features vs classification accuracy on COVID-19 Dataset1.

have recently emerged as a technical revolution that can be used to battle COVID-19 through diagnosing, treatment, and identification [63], [64]. Classification and clustering have both been shown to benefit from ML-based techniques. When it comes to constructing scalable ML models, we focus on the features that are most relevant to each dataset. It is difficult to build feature vectors that preserve as much information as possible since ML models require a feature string as

input. Because of this, even scalability becomes a problem when the data sets are so enormous [65]. Genomic data from COVID-19 patients has been extensively studied [66], [67]. An important issue in this scenario is converting genomic sequences into a fixed-length feature space so that they may be used as inputs for ML classifiers when making predictions. Recently, Ali *et al.* [68] have designed a COVID-19 virus prediction model using two very popular FS techniques:

TABLE 8. Classification results of COVID-19 Dataset1 before and after feature selection.

| Classifiers | Datasets         | Accuracy    | Sensitivity | Specificity | Precision | FPR   | Error |       |
|-------------|------------------|-------------|-------------|-------------|-----------|-------|-------|-------|
| KNN         | Original         | 0.896       | 0.988       | 0.285       | 0.902     | 0.715 | 0.104 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.946       | 0.984       | 0.617     | 0.956 | 0.383 | 0.054 |
|             |                  | MOPSO       | 0.91        | 0.943       | 0.589     | 0.921 | 0.401 | 0.09  |
|             |                  | BMOGWO-S    | 0.92        | 0.951       | 0.607     | 0.938 | 0.390 | 0.08  |
|             | FW-GPAWOA        | 0.935       | 0.972       | 0.611       | 0.945     | 0.389 | 0.065 |       |
| LR          | Original         | 0.894       | 0.989       | 0.25        | 0.901     | 0.75  | 0.106 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.9         | 1           | 0.198     | 0.897 | 0.802 | 0.1   |
|             |                  | MOPSO       | 0.898       | 0.99        | 0.21      | 0.90  | 0.785 | 0.102 |
|             |                  | BMOGWO-S    | 0.9         | 1           | 0.198     | 0.897 | 0.802 | 0.1   |
|             | FW-GPAWOA        | 0.896       | 0.988       | 0.285       | 0.902     | 0.715 | 0.104 |       |
| SVM         | Original         | 0.875       | 1           | 0           | 0.875     | 1     | 0.125 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.877       | 1           | 0.016     | 0.877 | 0.984 | 0.123 |
|             |                  | MOPSO       | 0.876       | 1           | 0.014     | 0.876 | 0.989 | 0.124 |
|             |                  | BMOGWO-S    | 0.877       | 1           | 0.016     | 0.877 | 0.984 | 0.123 |
|             | FW-GPAWOA        | 0.877       | 1           | 0.016       | 0.877     | 0.984 | 0.123 |       |
| RF          | Original         | 0.947       | 0.988       | 0.628       | 0.954     | 0.371 | 0.053 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.952       | 0.981       | 0.669     | 0.967 | 0.331 | 0.048 |
|             |                  | MOPSO       | 0.949       | 0.98        | 0.642     | 0.958 | 0.356 | 0.051 |
|             |                  | BMOGWO-S    | 0.947       | 0.988       | 0.628     | 0.954 | 0.371 | 0.053 |
|             | FW-GPAWOA        | 0.95        | 0.979       | 0.667       | 0.965     | 0.335 | 0.05  |       |
| DT          | Original         | 0.936       | 0.952       | 0.811       | 0.975     | 0.189 | 0.064 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.934       | 0.958       | 0.714     | 0.969 | 0.286 | 0.066 |
|             |                  | MOPSO       | 0.921       | 0.941       | 0.699     | 0.923 | 0.398 | 0.079 |
|             |                  | BMOGWO-S    | 0.931       | 0.95        | 0.701     | 0.958 | 0.301 | 0.069 |
|             | FW-GPAWOA        | 0.934       | 0.958       | 0.714       | 0.969     | 0.286 | 0.066 |       |

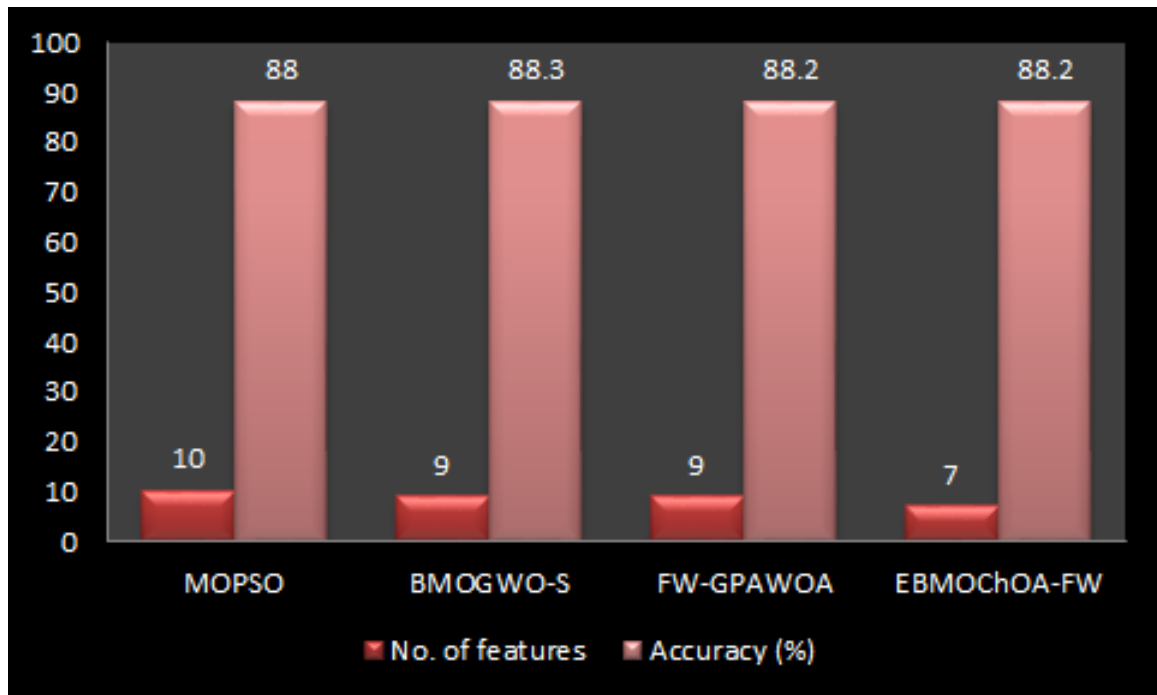


FIGURE 6. Number of features vs classification accuracy on COVID-19 Dataset2.

recursive feature elimination (RFE) and extra tree classifier (ETC). They worked on a data set having 8571 observations and 40 characteristics. Laatifi et al. [69] have developed an ML-based model with a new feature engineering approach known as Uniform Manifold Approximation and Projection (UMAP) to predict COVID-19 severity. The framework proposed by Shi et al. [70] have integrated evolutionary brain storm algorithm with an SVM model for quick identification

of COVID-19 severity. However, the application of evolutionary and, more specifically, multi-objective evolutionary FS techniques for predicting COVID-19 patient health is still an unexplored domain of research. Therefore, we are providing a method for accurately predicting patient death based on a wide range of variables. Doctors can use this problem to prescribe drugs and devise tactics in advance that will assist in saving the most lives. The suggested MOBChOA-FW is used

TABLE 9. Classification results of COVID-19 Dataset2 before and after feature selection.

| Classifiers | Datasets         | Accuracy    | Sensitivity | Specificity | Precision | FPR   | Error |       |
|-------------|------------------|-------------|-------------|-------------|-----------|-------|-------|-------|
| KNN         | Original         | 0.857       | 0.965       | 0           | 0.88      | 0     | 0.143 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.882       | 0.973       |           | 0.894 |       | 0.118 |
|             |                  | MOPSO       | 0.88        | 0.969       | 0         | 0.883 | 0     | 0.12  |
|             |                  | BMOGWO-S    | 0.883       | 0.974       |           | 0.885 | 0     | 0.117 |
|             |                  | FW-GPAWOA   | 0.882       | 0.973       |           | 0.894 |       | 0.118 |
| LR          | Original         | 0.863       | 0.996       | 0           | 0.852     | 1     | 0.137 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.867       | 1           | 0         | 0.852 | 1     | 0.133 |
|             |                  | MOPSO       | 0.865       | 1           | 0         | 0.852 | 1     | 0.135 |
|             |                  | BMOGWO-S    | 0.867       | 1           | 0         | 0.852 | 1     | 0.133 |
|             |                  | FW-GPAWOA   | 0.867       | 1           | 0         | 0.852 | 1     | 0.133 |
| SVM         | Original         | 0.867       | 1           | 0           | 0.852     | 1     | 0.148 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.867       | 1           | 0         | 0.852 | 1     | 0.148 |
|             |                  | MOPSO       | 0.867       | 1           | 0         | 0.852 | 1     | 0.148 |
|             |                  | BMOGWO-S    | 0.867       | 1           | 0         | 0.852 | 1     | 0.148 |
|             |                  | FW-GPAWOA   | 0.867       | 1           | 0         | 0.852 | 1     | 0.148 |
| RF          | Original         | 0.867       | 0.982       | 0           | 0.879     | 0     | 0.133 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.862       | 0.97        | 0         | 0.881 | 0     | 0.138 |
|             |                  | MOPSO       | 0.86        | 0.967       | 0         | 0.88  | 0     | 0.14  |
|             |                  | BMOGWO-S    | 0.862       | 0.97        | 0         | 0.881 | 0     | 0.138 |
|             |                  | FW-GPAWOA   | 0.861       | 0.969       | 0         | 0.881 | 0     | 0.139 |
| DT          | Original         | 0.81        | 0.881       | 0           | 0.893     | 0     | 0.19  |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.828       | 0.902       | 0         | 0.898 | 0     | 0.172 |
|             |                  | MOPSO       | 0.80        | 0.874       | 0         | 0.883 | 0     | 0.2   |
|             |                  | BMOGWO-S    | 0.81        | 0.881       | 0         | 0.893 | 0     | 0.19  |
|             |                  | FW-GPAWOA   | 0.828       | 0.902       | 0         | 0.898 | 0     | 0.172 |



FIGURE 7. Number of features vs classification accuracy on COVID-19 Dataset3.

to predict COVID-19 patient health in this study by taking three COVID-19 datasets from different sources and five well-known classification models [65]: KNN, LR, SVM, RF, and DT.

A. DATASET1

TABLE 7 shows the fifteen factors that make up the referenced COVID-19 sample dataset1 [71]. This research aims

to forecast death and recovery situations based on the given variables. For the validation process, we divided the samples evenly into training and testing sets. All of the characteristics are turned into numerals.

On the COVID-19 dataset1, FIGURE 5 shows the accuracy and feature size of the suggested EBMOChOA-FW and the other 3 multi-objective techniques. It can be shown that EBMOChOA-FW attained a maximum classification



TABLE 10. Details of COVID-19 Dataset3.

| SNO | Name                            | Details   | Values  |
|-----|---------------------------------|---|---|
| 1   | case_month                      | Date received by CDC  | 2020-03, 2020-04, . . . , 2021-08   |
| 2   | res_state                       | State name of USA   | AK,CO,FL,. . . .UT,VT   |
| 3   | state_fips_code                 | Federal Information Processing Standards (FIPS) code for states   |   |
| 4   | res_county                      | Country name  |   |
| 5   | county_fips_code                | FIPS code foe countries   |   |
| 6   | age_group                       | Patients's age group  | 0-17, 18-49, 50-64, and 65+ years   |
| 7   | Sex                             | Gender of patient   | M, F, other, unknown  |
| 8   | Race                            | Race of patient   | American Indian/Alaska Native, Asian, Black, Multiple/Other, Native Hawaiian/Other Pacific Islander, White, Unknown |
| 9   | Ethnicity                       |   | Hispanic, Non-Hispanic, Unknown.  |
| 10  | case_positive_specimen_interval | Weeks between the initial positive specimen collection and the earliest date of collection.   |   |
| 11  | case_onset_interval             | Weeks between earliest date and date of symptom onset.  |   |
| 12  | Process                         | Under what process was the case first recognised  | Clinical evaluation,routine surveillance, multiple. . .   |
| 13  | exposure_yn                     | Any of the following known exposures, such as local or international travel, incarceration, a community event, or contact with a previously reported case of COVID-19, did the patient have in the 14 days before becoming ill? | Yes, unknown  |
| 14  | current_status                  | Current status of the patient   | Laboratory-confirmed case, Probable case.   |
| 15  | symptom_status                  | symptom status of the patient   | Asymptomatic, Symptomatic, Unknown  |
| 16  | hosp_yn                         | Was the patient hospitalized?   | Yes, no, unknown  |
| 17  | icu_yn                          | Was the patient admitted to an ICU?   | Yes, no, unknown  |
| 18  | underlying_conditions_yn        | Weather the patient is having diabetes, hypertension, cardiovascular disease. . . ?   | Yes, no   |
| 19  | death_yn                        | whether the patient die as a result of this illness   | Yes, no, unknown  |

accuracy of 94.6% using only six factors: location, age, vis\_wuhan, symptom5, symptom6, and hos\_vis. The values of the various performance metrics before FS and after FS by the proposed method and the three benchmark methods are listed in TABLE 8. It is observed that, in most cases the highest accuracy is achieved from the reduced datasets by our proposed FS technique. The highest classification accuracy of 95.2% is achieved by RF in predicting the COVID-19 patients' health condition. We discovered that location, age, vis\_wuhan, sym\_on, symptom5, hos\_vis, and symptom6 are the most critical elements in locating death and recovery scenarios after combining the results of all four approaches. However, additional clinical symptoms should be gathered in the near future for a more precise patient health assessment.

## B. DATASET2

The Israelita Albert Einstein Hospital in Sao Paulo, Brazil, maintains a COVID-19 laboratory dataset for patients in the city. The samples were taken from patients in order to identify

those who had been infected with COVID-19 at the start of 2020 [72]. Laboratory results are available for 608 individuals in the collection, which includes information on 18 discoveries. In this dataset, there were 520 cases of no findings and 80 cases of COVID-19 in the population. The characteristics are: patient ID, patient age quantile, hemocrit, haemoglobin, platelets, red blood cells, lymphocytes, leukocytes, basophils, eosinophils, monocytes, serum glucose, neutrophils, urea, proteina C reactiva mg/dL, creatinine, potassium, sodium, alanine transaminase, aspartate transaminase, and result.

On the COVID-19 dataset2, FIGURE 6 shows the accuracy of the wrapper and feature size of the suggested EBMOChOA-FW and the other 3 multi-objective techniques. It can be shown that EBMOChOA-FW attained a classification accuracy of 88.2% considering only seven factors: patient age quantile, haemoglobin, platelets, red blood cells, leukocytes, basophils, and Alanine transaminase. The classification results of before and after FS by the presented EBMOChOA-FW method and the other three benchmark

TABLE 11. Classification results of COVID-19 Dataset3 before and after feature selection.

| Classifiers | Datasets         | Accuracy    | Sensitivity | Specificity | Precision | FPR   | Error |       |
|-------------|------------------|-------------|-------------|-------------|-----------|-------|-------|-------|
| KNN         | Original         | 0.93        | 0.978       | 0.385       | 0.967     | 0.615 | 0.051 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.94        | 0.977       | 0.482     | 0.973 | 0.518 | 0.046 |
|             |                  | MOPSO       | 0.93        | 0.978       | 0.385     | 0.967 | 0.615 | 0.051 |
|             |                  | BMOGWO-S    | 0.92        | 0.978       | 0.379     | 0.951 | 0.631 | 0.08  |
|             |                  | FW-GPAWOA   | 0.94        | 0.977       | 0.482     | 0.973 | 0.518 | 0.046 |
| LR          | Original         | 0.934       | 1           | 0.004       | 0.947     | 0.996 | 0.053 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.934       | 1           | 0         | 0.947 | 1     | 0.053 |
|             |                  | MOPSO       | 0.928       | 0.97        | 0.002     | 0.924 | 0.997 | 0.072 |
|             |                  | BMOGWO-S    | 0.934       | 1           | 0         | 0.947 | 1     | 0.053 |
|             |                  | FW-GPAWOA   | 0.934       | 1           | 0         | 0.947 | 1     | 0.053 |
| SVM         | Original         | 0.934       | 1           | 0           | 0.947     | 0.5   | 0.041 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.934       | 1           | 0         | 0.947 | 1     | 0.053 |
|             |                  | MOPSO       | 0.934       | 1           | 0         | 0.947 | 0.5   | 0.041 |
|             |                  | BMOGWO-S    | 0.934       | 1           | 0         | 0.947 | 1     | 0.053 |
|             |                  | FW-GPAWOA   | 0.934       | 1           | 0         | 0.947 | 1     | 0.053 |
| RF          | Original         | 0.946       | 0.982       | 0.5         | 0.974     | 0.5   | 0.041 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.95        | 0.981       | 0.459     | 0.972 | 0.541 | 0.041 |
|             |                  | MOPSO       | 0.942       | 0.98        | 0.5       | 0.97  | 0.546 | 0.058 |
|             |                  | BMOGWO-S    | 0.946       | 0.982       | 0.5       | 0.974 | 0.5   | 0.041 |
|             |                  | FW-GPAWOA   | 0.947       | 0.982       | 0.5       | 0.973 | 0.543 | 0.053 |
| DT          | Original         | 0.935       | 0.976       | 0.472       | 0.972     | 0.528 | 0.048 |       |
|             | Reduced Datasets | EBMOChOA-FW | 0.942       | 0.982       | 0.442     | 0.971 | 0.558 | 0.044 |
|             |                  | MOPSO       | 0.936       | 0.978       | 0.461     | 0.971 | 0.552 | 0.064 |
|             |                  | BMOGWO-S    | 0.92        | 0.957       | 0.46      | 0.967 | 0.572 | 0.08  |
|             |                  | FW-GPAWOA   | 0.94        | 0.98        | 0.44      | 0.968 | 0.561 | 0.047 |

methods are mentioned in TABLE 9. The classification performance results obtained from the reduced dataset by our suggested approach are quite satisfactory as compared to the other three methods. Here the KNN model outperforms others by producing 88.2% classification accuracy with only seven out of 20 features.

C. DATASET3

This dataset is known as the COVID-19 Case Surveillance dataset, and it may be found on the website of the Centers for Disease Control and Prevention in the United States.<sup>1</sup> There are a total of 32,806,678 records. However, we are left with 10,1017 patient records after deleting the missing and blank entries. The attributes are listed in TABLE 10.

On the COVID-19 dataset3, FIGURE 7 shows the accuracy and feature size of the suggested EBMOChOA-FW and the other 3 multi-objective techniques. It can be shown that EBMOChOA-FW attained an excellent classification accuracy of 94% using only seven factors: sex, case\_onset\_interval, exposure\_yn, res\_county, process, underlying\_conditions\_yn, and age\_group. The classification results of before and after FS by the presented EBMOChOA-FW method and the other three standard approaches are listed in TABLE 11. In most cases, both the hybrid filter-wrapper approaches, EBMOChOA-FW and FW-GPAWOA, performed well as compared to others. Here too, the RF model outperforms others with an excellent 95% classification accuracy, considering only seven out of 18 features.

<sup>1</sup><https://data.cdc.gov/Case-Surveillance/COVID-19-Case-Surveillance-Public-Use-Data-with-Ge/n8mc-b4w4/data>

VI. CONCLUSION AND FUTURE RESEARCH

In order to classify COVID-19 patients, we have developed an effective model employing an optimised FS approach and ML methods. Simple classification algorithms like random forest and KNN were able to accurately forecast the health of COVID-19 patients with our FS approach. A fresh and enhanced hybrid multi-objective optimizer to tackle FS problems is introduced in this article. The suggested technique builds on the latest ChOA approach integrated with BHHO by combining a filter and wrapper model into a single system in the hope of maximising the advantages of each type. During the training phase, a combination of MI and PCC and the performance of the KNN model are employed as filter and wrapper assessment conditions, respectively. Furthermore, the sigmoid transfer function is used to enable EBMOChOA-FW to handle binary situations. A comparative analysis with five well-known algorithms was conducted on nine benchmark datasets and three real-world COVID-19 datasets. The suggested algorithm exceeds the selected alternatives in terms of both the number of features and classification performance, according to the results.

Furthermore, we have noticed that EBMOChOA-FW takes longer to execute in some circumstances due to the presence and administration of two archives as well as the filter function employed. As a result, we intend to examine additional fitness functions in the future in order to maintain higher performance without increasing the running duration. The mutual information and correlation between features and class attributes are only taken into account here. However, the mutual information and correlation between the traits must be considered. This study uses the crowding distance measure to choose the best alternative in the Pareto front that gives

the most unique solution. However, the knee point concept gives the most interesting solution, because a knee point is a point where a small improvement in any objective would lead to a large decrease in at least one other objective. We are also enthusiastic about combining various evolutionary algorithms with other classification algorithms like random forest and ANN. Also, various advanced initialization procedures can also be applied to EBMOChOA-FW to boost efficiency.

## A. CONFLICT OF INTEREST

Authors declare there is no conflict of interest for this research work.

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**JAYASHREE PIRI** received the B.Tech. degree in information technology from BPUT, India, in 2007, and the M.E. degree in information technology from Jadavpur University, Kolkata, India, in 2012. She is currently pursuing the Ph.D. degree with the Department of Computer Science, IIT Bhubaneswar, India. She has more than ten years of teaching experience. She has published more than 15 research articles in peer reviewed journals, such as *Computers in Biology and Medicine*, *IEEE*

*ACCESS*, *MDPI*, *IJIT*, and presented various papers in international conferences. Her research interests include the areas of multi-objective optimization, evolutionary computing, medical data mining, and machine learning.



**PUSPAJALI MOHAPATRA** (Member, IEEE) received the B.E. degree in electrical engineering from IGIT Sarang, Odisha, in 1999, the M.Tech. degree in computer science from Utkal University, Bhubaneswar, in 2002, the Ph.D. degree in CSE from Siksha 'O' Anusandhan University, India, and the M.B.A. degree in systems, IT & HR from BPUT Rourkela, India, in 2009. She is currently an Assistant Professor at the International Institute of Information Technology Bhubaneswar, Bhubaneswar. She has more than 18 years of teaching experience. More than 35 papers in reputed journals, conferences, and book chapters are to her credit. She is also associated with various educational and research societies, such as IEEE, ACM, IAENG, and OITS. She is currently working on research areas biomedical data mining, time series data analysis, and different fields, such as machine learning, deep learning, and evolutionary computing.



**HARPRITH KAUR RAJINDER SINGH** received the B.Sc. degree (Hons) in IT with business information systems from Middlesex University, London, in 1997, and the master's degree in computer science from Universiti Putra Malaysia, in 2002.

She is currently a Senior Lecturer at INTI International University, Malaysia. She has more than 15 years of teaching experience. Her research interests include the areas of data mining, data analytics, and teaching and learning.



**BISWARANJAN ACHARYA** (Senior Member, IEEE) received the M.C.A. degree from IGNOU, New Delhi, India, in 2009, and the M.Tech. degree in computer science and engineering from the Biju Pattanaik University of Technology (BPUT), Rourkela, Odisha, India, in 2012. He is currently pursuing the Ph.D. degree in computer application with the Veer Surendra Sai University of Technology (VSSUT), Burla, Odisha, India. He is currently working as an Assistant Professor with the Department of Computer Engineering-AI, Marwadi University, Rajkot, Gujarat, India. He has a total of ten years of experience in both academia at some reputed universities, such as Ravenshaw University and the software development field. He has published many research articles in international reputed journals and serving as a reviewer for many peer-reviewed journals. He has more than 50 patents on his credit. His research interests include multiprocessor scheduling along with different fields, such as data analytics, computer vision, machine learning, and the IoT. He is also associated with various educational and research societies, such as IACSIT, CSI, IAENG, and ISC.



**TAPAS KUMAR PATRA** (Member, IEEE) received the Master of Engineering degree from the National Institute of Technology, Rourkela, and the Ph.D. degree from the Indian Institute of Science, Bengaluru. He is currently working as a Professor at the Odisha University of Technology and Research, Bhubaneswar. He has more than 25 years of teaching, academic administration, and research experience. He is also a Microsoft Certified Professional (MCP) and Microsoft Certified System Engineer (MCSE). He has received the Best Paper Award in IEEE COMSWARE-2007. In addition, he was awarded a gold medal in the Intel India Embedded Challenge, in 2011, as a Finalist. Furthermore, he has guided many award-winning projects at the national and international levels. He has published many papers in reputed journals and conferences. His research interests include electronic systems, communication, wireless networking, the IoT, artificial intelligence, machine learning, computer vision, VLSI, and embedded systems. He is an Active Member of various societies, such as IEEE, COMSOC, ACM, LMISTE, and LMISOI.

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