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Article

A Quantum based Chaotic Evolutionary Strategy for Multimodal Feature Selection in Biomedical Data

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Abstract: Medical datasets are inherently complex, often exhibiting high dimensionality, multimodal characteristics, and intricate interdependencies among features. These attributes pose significant challenges for traditional feature selection methods, which often struggle with overfitting, computational inefficiency, and difficulty in identifying multiple equally effective feature subsets (multimodal solutions). Most existing evolutionary algorithms tend to converge prematurely or fail to maintain diverse solutions, limiting their applicability to complex medical data. To address these limitations, this paper proposes a Quantum-Inspired Chaotic Evolutionary Feature Selection (QCEFS) approach, which integrates quantum-inspired operators, chaotic initialization, and a hybrid Particle Swarm Optimization (PSO)–Harris Hawk Optimization (HHO) framework. Chaotic initialization ensures wide and diverse exploration of the solution space from the outset, helping to avoid local optima. Quantum-inspired operators enable probabilistic representation and superposition of candidate solutions, promoting a dynamic and efficient search strategy. The hybrid PSO-HHO mechanism further enhances convergence reliability by balancing exploration and exploitation. Moreover, to effectively handle multimodal feature selection—where multiple feature subsets of same cardinality and similar classification accuracy exist—a speciation-based niching technique is employed. This encourages the algorithm to discover and preserve diverse, high-performing multiple feature subsets. Experiments on 21 real-world medical datasets demonstrate the superiority of the proposed method over eight state-of-the-art evolutionary feature selection algorithms. The results indicate notable improvements in classification accuracy, subset compactness, and convergence robustness. Statistical tests further confirm the significant performance of the proposed QCEFS algorithm.
Keywords: Medical data; multimodality; chaotic; particle swarm optimization;quantum based approach; evolutionary algorithm

1. Introduction

The rapid advancement in medical data acquisition technologies has led to an exponential increase in the volume and complexity of medical datasets. These datasets often exhibit high dimensionality, multimodality, and intricate interdependencies among features, posing significant challenges for data analysis. In the present age, data mining and knowledge exposure play a noteworthy role in several applications. For better analysis of the data, the selection of the most useful features is essential. Feature Selection is vastly applied as preprocessing tasks in many areas like pattern recognition, data mining, etc. . Efficient feature selection reduces dimensionality, and enhances the performance of classification models, which are vital for accurate diagnosis, prognosis, and treatment planning in medical applications. Feature selection approaches are divided into three categories based on the relationships between different characteristics and the participation of classifiers: classifier-independent Filter method, classifier-dependent Wrapper method, and embedded method. Filter methods use the intrinsic property of the individual features to include or remove the feature from the selected feature subset. Wrapper-based methods use a classification model to evaluate the performance of randomly selected features. A hybrid approach between filter and wrapper methods is called an embedded method. It makes use of classification methods that have feature selection integrated into them. Also, traditional feature selection methods are effective to some extent but often struggle with the complexities of multimodal datasets and the risk of overfitting, particularly in high-dimensional spaces. These limitations call for innovative approaches that can handle the diverse and challenging characteristics of medical data. Therefore, an efficient algorithm is required which is less expensive and yields efficient global results. These are meta-heuristic algorithms.

The metaheuristic algorithms are the higher-level heuristic algorithms used for solving optimization problems. These algorithms are inspired by natural phenomena. Some of the Nature-inspired algorithms are Particle Swarm Optimization(PSO) algorithm, Harris Hawk Optimization (HHO) algorithm , Whale Optimization algorithm (WOA), etc. Through a process of iterative exploration and exploitation, these algorithms steer the results in the direction of the best solution. To tackle Feature Selection issues, hybrid meta-heuristic algorithms has grown popularity in recent years . Some examples of such algorithms are the Leader Harris Hawk Optimization algorithm (LHHO). In LHHO, adaptive perching during the exploration phase is combined with leader-based mutation selection during the generation of Harris hawks and results in better exploration. In Sine Cosine Harris Hawk optimization algorithm (SCHHO), Sine-Cosine algorithm is integrated with Harris Hawk Optimization algorithm.

With the rapid growth of multimodal medical data—comprising images, genomic sequences, clinical data, and electronic health records—effective identification of relevant features becomes essential. Researchers have focused increasingly on meta-heuristic feature selection for medical applications in recent years because of its capacity to enhance machine learning model performance and deal with the problem of curse of dimensionality . Metaheuristic algorithms are proven to give global best and less computationally expensive results. Numerous studies focus on different optimization techniques to address the feature selection problem. Chuang et. al. proposed improved Binary Particle Swarm Optimization (IBPSO) algorithm to study feature selection problem using gene expression data.

Feature selection problems can be unimodal or multimodal optimization problems. An unimodal optimization problem deals with finding a unique solution to the optimization problem. Multimodal optimization problem deals with finding multiple global solutions. In addition to basic multimodal techniques, some additional work is done to find multiple global solutions. Some techniques are Fitness sharing, dynamic fitness sharing, and niching techniques.Niching techniques deal with dividing the population into subpopulations based on some criteria to generate a variety of global solutions and prevent the solutions from being converged into local optima. In the last decade, researchers have used niching techniques to find multiple global solutions to optimization problems. Xiao-Min Hu et al used speciation and crowding-based niching techniques with Particle swarm optimization algorithm (PSO) to achieve a solution of a multimodal optimization algorithm. Cholmin Rim et al. proposed a niching Chaos Optimization algorithm. The circle map is employed for implementing chaos theory.

The intricacies of multimodal datasets and the possibility of overfitting are challenges for current metaheuristic-based feature selection methods. The researchers have applied quantum theory to their work in order to solve this issue. In order to turn classical feature selection into quantum feature selection, Zhimin He et al. suggested a quantum variant of the classical wrapper-based feature selection approach which uses backward elimination and transformed forward selection. To decrease the dimensionality of the data, Qing Wu et al. suggested a quantum version of the particle swarm optimization algorithm that combines an enhanced quantum behavior with a filtering technique. For feature selection, Abdulhussien et al. presented a quantum-inspired genetic algorithm using Arabic signature verification technique. The algorithm produces the good results in terms of convergence and global search capabilities because quantum theory allows for higher population diversity. Recent studies such as have explored quantum-inspired evolutionary feature selection and enhanced slime mould optimization for biomedical prediction and optimization tasks. Other application on feature selection is described in .

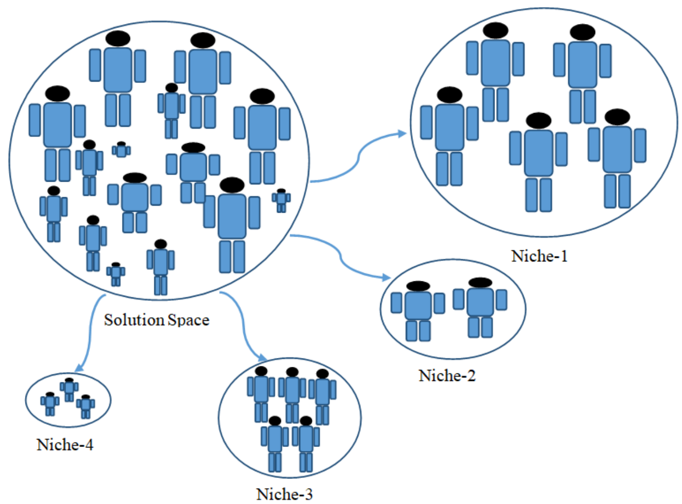


Figure 1: Division of a population among several niches

The intricacies of multimodal datasets and the possibility of overfitting are challenges for current metaheuristic-based feature selection methods. The researchers have applied quantum theory to their work in order to solve this issue. In order to turn classical feature selection into quantum feature selection, Zhimin He et al. suggested a quantum variant of the classical wrapper-based feature selection approach which uses backward elimination and transformed forward selection. To decrease the dimensionality of the data, Qing Wu et al. suggested a quantum version of the particle swarm optimization algorithm that combines an enhanced quantum behavior with a filtering technique. Abdulhussien et al. presented a quantum-inspired genetic algorithm using Arabic signature verification technique. The algorithm produces the good results in terms of convergence and global search capabilities because quantum theory allows for higher population diversity. Recent studies such as have explored quantum-inspired evolutionary feature selection and enhanced slime mould optimization for biomedical prediction and optimization tasks. Other application on feature selection is described in .

This paper introduces a quantum-based chaotic Particle Swarm Harris Hawk Optimization Algorithm for feature selection tailored to medical applications. The proposed framework integrates principles of quantum computing, chaotic theory, and evolutionary optimization to address the limitations of existing methods. Quantum computing concepts provide enhanced search capabilities, enabling efficient exploration of large solution spaces. Chaotic mapping ensures diversity in the initial population and prevents premature convergence, while evolutionary strategies strike a balance between exploration and exploitation, improving convergence speed and solution quality. PSO is used for the exploration phase in the suggested algorithm, which modifies the HHO technique. In the algorithm's exploitation phase, spiral shrinking behavior from the Whale Optimization Algorithm (WOA)[16] is used during the hard besiege phase. The usage of a chaotic tent map improves randomization. Q-bit representation and a quantum rotation gate are utilized to improve population diversification in the generated population. Improved evolutionary operators such as crossover and mutation are also used to boost the algorithm's speed. Eight well-known state-of-the-art algorithms, including Speciation based Particle Swarm Optimization algorithm (SPSO), Crowding based Particle Swarm Optimization algorithm(CPSO), Harris Hawk Optimization algorithm (HHO), Leader Harris hawk Optimization algorithm (LHHO), Sine Cosine Harris Hawk Optimization algorithm (SCHHO), Speciation crowding particle harris hawk optimization algorithm (SCPHHO), Quantum Whale Optimization Algorithm(QWOA), Quantum Harris Hawk Optimization algorithm (QHHO), are compared to QCEFS performance. The algorithms are evaluated according to three criteria: multimodality (measured by the number of solutions found for a given fitness value), fitness function (based on classification error and number of selected features), and algorithm execution time. Twenty one challenging medical datasets are used to test the efficacy of proposed approach. These datasets, which comprise features ranging from tens to thousands, are extracted from from the UCI machine learning repository [32].

The following are the main contributions of the work:

1. A novel hybrid evolutionary algorithm is proposed that combines the strength of particle swarm optimization and harris hawk optimization.

2. The quantum-inspired operators enable efficient exploration of large and complex search spaces, improving the identification of optimal feature subsets in high-dimensional medical datasets.

3. Chaotic initialization is integrated into the framework to ensure diverse population generation, enhancing the algorithm's ability to escape local optima and avoid premature convergence.

4. A speciation-based niching technique promotes the contribution of multimodal solutions in population.

5. The performance of proposed approach is evaluated on 21 challenging medical datasets and compared with 8 state-of-the-art algorithms.

6. Ablation study and statistical tests including Wilcoxon and Freidman test further affirm the performance of proposed algorithm.

The rest of the paper is organized as follows: Section 2 presents a overview of the Quantum-Based Chaotic Particle Swarm Harris Hawk Optimization Algorithm (QCEFS). In Section 3 provides the experimental set along with dataset and parameter description. Section 4 details the experimental results and analysis. Conclusion along with future work is shown in section 5.

2. Proposed Multimodal Multi-objective Feature Selection Algorithm

This section presents a new multimodal feature selection algorithm (QCEFS) that combines powerful exploration part of PSO and exploitation quality of HHO. For improved multimodality a speciation based niching strategy is used. For achieving better randomness in the population, a chaotic map is also used. To foster more diversity and prevent local optima from being stuck, a quantum method is used for generation of population in next phase. For improvement of the result, an improved mutation and crossover method is used. The QCEFS employs following concepts:

2.1. Random Value generation using Chaotic Map

The majority of the metaheuristic algorithms lack a proper balance between exploration and exploitation. The convergence behavior of the metaheuristic algorithms depends on the random sequence passed to various parameters during the execution of the algorithm. Chaos theory is used for generating mathematical randomness which uses simple deterministic system. Chaotic behavior is used in various domains including engineering, medicine, ecology, etc. In recent years chaotic maps have become very popular for generating random numbers. There are various chaotic maps available for generating random numbers like Chebyshev map, Singer map, Sinusoidal map, Piecewise map, Logistic map, Gauss map, iterative map, Sine map, Circle map and tent map. Performance of several maps were tested through experiments and it was found that tent map gives the most promising results. Tent map is represented by the Equation 1.

$$x_{t+1} = \begin{cases} \mu x_t & if \quad x_t < 0.5 \\ \mu(1 - x_t) & if \quad x_t \geq 0.5 \end{cases} \tag{1}$$

Where $x_t \in (0,1)$represents the chaotic variable at iteration t, μ is the control parameter. For fully developed chaotic behavior, $\mu = 2$ is used in this study.

Initialization (Seeding): The initial value x_0 is randomly generated from a uniform distribution in the interval (0,1), excluding boundary values to prevent fixed points. The chaotic sequence $\{x_t\}$ is then iteratively generated and used to replace conventional random number generators in population initialization, and parameter updates. This improves randomness quality and enhances global search capability.

2.2. Quantum-inspired Solution Representation

The base of quantum computing is quantum representation of the data called quantum bits (Q-Bits). It takes the advantage of superposition of basic states. Q-Bit is the elementary unit of the 2 state quantum computer. These two states $|0\rangle$ and $|1\rangle$ are represented as:

$$|0\rangle = \begin{bmatrix}0\\1\end{bmatrix} \text{ and } |1\rangle = \begin{bmatrix}1\\0\end{bmatrix} \quad (2)$$

which are known as ground state and excited state. The quantum state can be represented by the superposition of these two states as given by Equation 3.

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (3)$$

Where α and β are termed as the probability amplitude and are complex numbers weight of the quantum particle in the $|0\rangle$ and $|1\rangle$ locations respectively. Variables α and β are the probability of the Q-bit to be in the states $|0\rangle$ and $|1\rangle$ respectively. Following criteria has to be satisfied for α and β .

$$|\alpha|^2 + |\beta|^2=1 \quad (4)$$

For a feature selection problem with d features, each individual is represented as a vector of Q-bits as Q={(*α1,* β*1*),(*α2,* β*2*),(*α3,* β*3*),…(*αd,* β*d*)}.

a. **Quantum Rotation Gate Update**

To maintain the balance between exploration and exploitation and to get the best solution in a shorter period, quantum rotation gate operators are used in each quantum bit. The most commonly used quantum gates are Hadamard gate, not gate, controlled not gate, and rotation gate. To generate the quantum bits, quantum rotation gate is used in the proposed algorithm:

$$\begin{pmatrix}\alpha_i^{t+1}\\ \beta_i^{t+1}\end{pmatrix} = \begin{pmatrix}\cos\theta_i & -\sin\theta_i\\ \sin\theta_i & \cos\theta_i\end{pmatrix}\begin{pmatrix}\alpha_i^{t}\\ \beta_i^{t}\end{pmatrix} \quad (5)$$

where θ_i represents a rotation angle i^{th} Q-bit. The value of the rotation angle may vary according to the problems. The angle is adaptively determined based on the comparison between the current solution and the global best solution. The rotation mechanism guides the probability amplitudes toward promising regions of the search space while maintaining diversity.

b. **Binarization**

The Q-bit representation must be converted into a binary feature subset for the purpose of evaluating a solution. This is achieved through a probabilistic measurement process: This is achieved through a probabilistic measurement process:The Q-bit can be represented using the following Equation:

$$x_i = \begin{cases}1 & |a_i^2| < threshold\\ 0 & Otherwise\end{cases} \quad (6)$$

Where x_i is the corresponding binary quantum bit which indicates whether the i^{th} feature is selected or not.

2.3. Proposed QCEFS Algorithm

This section presents a new multimodal feature selection algorithm (QCEFS) that combines powerful exploration part of PSO and exploitation quality of HHO. For improved multimodality a speciation based niching strategy is used. For achieving better randomness in the population, a chaotic map is also used. To foster more diversity and prevent local optima from being stuck, a quantum method is used for generation of population in next phase. For improvement of the result, an improved mutation and crossover method is used. Compared with classical binary representation, quantum-inspired probabilistic representation can maintain higher population diversity and improve the exploration ability through probabilistic Q-bit encoding. It enhances the convergence stability and mitigates the premature convergence in high-dimensional feature selection problems. The moderate computational overhead is compensated by the improved optimization performance.

An encircling behavior is incorporated in the proposed QCEFS algorithm when the hawks perform hard besiege on the prey. This behavior is inspired from Whale Optimization algorithm and is modelled as:

$$distance = \lfloor Pos_{best} - Pos_{curr}^{i} \rfloor \quad (7)$$

$$Pos_{curr}^{i} = distance * e^{b*Energy_{ini}} * \cos(2 * PI * Energy_{ini}) + Pos_{best} \quad (8)$$

To identify multimodal feature sets, a speciation-based niching technique is used to divide the population among several niches in our proposed algorithm. For each niche, PSO is used for exploration. For exploitation phase, Harris Hawk optimization algorithm is used. For hard besige with incremental dives, shrinking method of Whale Optimization algorithm is used. To collapse individual Q-bit, its binary equaivalent is employed. In every generation, the rotation gate is used to perform the quantum update of every Q-bit for every quantum hawk in the population.

2.3.1. Speciation Clustering Niching Technique

This method finds the optimal particle in the solution space. The particle with the lowest fitness value is considered the best particle. The particles of niche-1 are those that are closest to this particle, as determined by calculating the hamming distance between all of the particles and the best particle. The particles that are closest to those in niche-1 have now been located, and their positions have been changed to niche-2, and so on. Particles with a hamming distance of less than 50% are considered to be the nearest particles. Algorithm 1 shows the speciation clustering technique's algorithm.

Algorithm-1 Speciation Based Clustering Niching Technique

Input: Particles in the population, Size of population
Output: Particles in the population with niche number
1. Find the best particle $\mathrm{Pos_{best}}$ in the solution space by finding the smallest fitness value.
2. for i=1 to N
3 find the particles closest to Pos_{best}
4 Update the particle niche position to $niche - 1$
5 Find the particles closest to the particles of $niche - 1$, update their position to $niche - 2$ and so on.

2.3.2 Selection of the Solution

The primary goal of proposed algorithm that addresses multimodal optimization problems is to identify several global or local optimal solutions and to preserve these optimal solutions throughout the search iterations . An external archive that verifies the existence of several solutions to a particular problem in the solution space is used in this paper. We contrasted the recently investigated particles in this archive with pre-existing solutions. The solution in the archive is replaced with the new solution if the new particle is superior to the current particle (solution). The hamming distance between the new particle and the existing particle is calculated if the solution is equivalent to the one that already exists. This individuals are added if the hamming distance is larger than zero. Algorithm 2 explains the process of updation of the external archive.

Algorithm-2 Archive updating strategy

Input: Set of particles$Particle_1, Particle_2, Particle_3, \dots \dots \dots$, and associated fitness values $fit_1, fit_2, fit_3, \dots \dots \dots$

$Archive_{out}$: Set of the solutions already present in the archive

$Archive_{best}$: The best solution present in the archive

Pos_{best}: The best solution for the population

φ: Accuracy Level

τ: Threshold value for hamming distance

Output: The solutions present in the archive $Archive_{out}$

if $Pos_{best} < Archive_{Best}$
  Empty the archive. $Archive_{out} \longleftarrow \emptyset$
$Archive_{best} \longleftarrow Pos_{best}$
end if
for i=1 to N
  if $Archive_{Best} < fit$(i)
    $flag = true$
  Else
    $flag = false$
  end if
 if $|fit(i) - Archive_{Best}| \leq \varphi$
  for each solution $Archive_{particle}$ present in the archive
    if $hamming_{dist}(Particle_i, Archive_{particle}) > \tau$ and $Num_{sel_{features}} = Num_{sel_{features}}(archive)$
      $flag = false$
    Else
      $flag = true$
      Break
    end if
end for
end if
 if $flag = false$
    add $Particle_i$ to $Archive_{out}$
end if
end for

The next generation population is generated by considering the best particles of the first generation. The individuals found in the archive is contrasted with the best solution that was found. The archive is emptied and replaced with the best solution if this is the best option. The solution of the archive is the end outcome if the best solution discovered is not superior to the archive current solution. Depending on the accuracy level , the multimodal algorithms identify several solutions to a given problem. Variable ρ has been set to zero. We use the hamming distance between two populations to determine whether there are distinct solutions to a given problem. A particle is added to the archive if the hamming distance between the feature that is available in the archive and the particle in the population that has the similar fitness value and is larger than zero. The value of τ, which represents the different degrees of the chosen features, is assumed to be zero.

The detailed algorithm of QCEFS is given in Algorithm 3.

Algorithm 3: Quantum speciation based chaotic Harris Hawk-Particle Swarm Optimization

Input: Parameters involved in the algorithm
Output: $Archive_{out}$
Initialize the particles$Particle = (Particle_1, Particle_2, Particle_3, Particle_4, \dots \dots \dots \dots \dots \dots .. Particle_N)$
For $i = 1$ to N do
  $fit(i) \leftarrow F(Particle_i)$
  $P_{best} \leftarrow Particle_i$
end for
$Archive_{out} \leftarrow \emptyset$
$Pos_{best} \leftarrow \min(fit_1, fit_2, fit_3, \dots \dots fit_N)$
$Archive_{best} \leftarrow \infty$
Use algorithm 3 to update $Archive_{best}$ and solutions in $Archive_{out}$

$iter \leftarrow 1$
while ($iter \leq iter_{max}$)
Divide the particles into niching using algorithm 1
Find the best particle in each niche
For $i = 1\ to\ niche_{size}$
Compute a=2-t×((2)/max_Iter);
Compute zeta=2×a×random value-a;
Take a random variable test
if test<threshold
if abs(zeta)>=1
Population_rand = tournamentSelection(Best index particle);
Population_rand=Mutation(Population_rand);
P(i,:)=CrossOver(P(i,:),Population_rand);
else if abs(zeta)<1
P(i,:)=CrossOverU($Population_{best}$,$Population_{best}$);
end if
Determine the escape energy $Energy_{escape}$ of the prey
if $|Energy_{escape}| \geq 1$
Choose a random variable q using tent map
if $q \geq 0.5$
Update the velocity of the particles adding levy flight with P_{best}
Else
Update the velocity of the particles using PSO update equation
end if
Update the position of the particles using current and best position of particle
Else
Take a random variable $Chance_{escape}$ using tent map
If ($Chance_{escape} < 0.5\ and |Energy_{escape}| \geq 0.5$)
Update the position of particles using Harris hawk equation
else if $Energy_{escape} < 0.5$
Take a random variable p using tent map
If $p < 0.5$
Update the position using eq. 8
Else
Update the position using eq. 8 using levy flight
end if
else if ($Chance_{escape} < 0.5\ and |Energy_{escape}| < 0.5$)
Update the position of the particle
For $i = 1\ to\ niche_{size}$
$fit(i) \leftarrow F(Particle_i)$
$P_{best} \leftarrow Particle_i$
End for
Update the population using the rotation gate
$Population_{best} \leftarrow \min(fit_1, fit_2, fit_3, \ldots \ldots fit_N)$
Use algorithm 3 to update $Archive_{best}$ and solutions in $Archive_{out}$
$iter \leftarrow iter + 1$
end while

3. Experimental Setup

The performance of the proposed algorithm is compared with eight well known state-of-art meta heuristic algorithms on feature selection. These are Speciation based Particle Swarm Optimization algorithm(SPSO), Crowding based Particle Swarm Optimization algorithm(CPSO), Harris Hawk Optimization algorithm (HHO), Leader Harris hawk Optimization algorithm (LHHO), Sine Cosine Harris Hawk Optimization algorithm (SCHHO), Speciation crowding particle harris hawk optimization algorithm (SCPHHO), Quantum Whale Optimization Algorithm (QWOA) , Quantum Harris Hawk Optimization algorithm (QHHO).

Experiments are performed on 21 datasets of varying dimensions [49]. The aim of this comparison to validate the efficacy of the proposed algorithms over contemporary state-of-the-art algorithms based on fitness function. This function is a combination of error rate and number of selected features. Along with this, multimodality is counted with number of sets having different combinations of same number of features giving same performance. Two feature subsets are considered equivalent if:

$$| Acc_i - Acc_j | \leq \epsilon_{acc} \quad (9)$$

and

$$|| S_i | - | S_j || \leq \epsilon_{feat} \quad (10)$$

where:

- $\epsilon_{acc} = 0.01$
- $\epsilon_{feat} = 2$

This criterion prevents redundant storage of nearly identical solutions in the archive. Additionally, archive threshold parameters were empirically analyzed to avoid artificial inflation of multimodal solution counts.

Along with this, multimodality is counted with number of sets having different combinations of same number of features giving similar performance. In case for small dimension dataset, features can be selected directly through meta-heuristic algorithm. However, in case of high dimension datasets (more than 200 features), feature selection is performed in two steps. In first step, a filter-based feature selection method i.e. the Pearson Correlation Coefficient is used to choose 100 features before applying metaheuristic algorithm on dataset. In second step, metaheuristic algorithm is used to select the relevant features same as implemented for small dimensional datasets. This helped us to deal with the inherent complexity inhigh-dimension datasets. The K-Nearest Neighbor classifier is employed to verify the algorithm's classification accuracy. In our experiments, five-fold cross-validation is used to assess the classification performance and accuracy using both the original and chosen feature sets. For datasets with high dimensionality, the preliminary filtering was performed using only the training partition within each run. The test partition remained completely unseen during feature filtering and feature selection to avoid data leakage.

To improve reproducibility, all experiments were conducted using fixed random seed initialization and repeated over 20 independent runs for each dataset. The parameter bounds, stopping criteria, binarization strategy, and population settings used in QCEFS are explicitly specified. The pseudo-code has also been revised for improved clarity and implementation consistency.

3.1 Dataset Description

Twenty one data sets from medical domains are used to assess the proposed approach. All the datasets are taken from the medical domain and are downloaded from UCI Machine Learning Repository. Description of the data sets including number of instances, features, and classesused in this study is shown in Table 1. Since UCI data sets include a diverse range of features and classes, they are frequently used in literature to assess data categorization.

Table 1: Dataset Details

S. No	Dataset name	Number of instances	Number of features	Number of classes
1	Lung	203	12600	7

2	11-Tumor	174	12533	11
3	Lukemia-2	72	11225	3
4	Brain-2	50	10367	4
5	Prostate	102	5966	2
6	Brain-1	90	5920	5
7	9-Tumor	60	5726	9
8	DLBCL	77	5469	2
9	Lukemia-1	72	5327	3
10	14 tumor	308	5000	26
11	Colon Cancer	62	2000	2
12	Toxicity	171	1203	2
13	Parkinsons	756	754	2
14	Alzheimer	174	451	2
15	LSVT VOICE REHABILITATION	126	310	2
16	Skardi	70	206	8
17	Replicated Acoustic Features	240	48	2
18	Dermetology	366	34	6
19	Breast Cancer Wisconsin (Diagnostic)	569	30	2
20	Lymphography	148	18	4
21	Heart Failure	299	12	2

3.2 Fitness Function

Every hawk position is assessed using a predetermined fitness function F at each iteration. This function is the evaluation criteria that has two objectives- classification error and number of features selected in dataset. Using single fitness function in this work, the two objectives are merged into a single equation with certain weight factor. Error is the classification error determined by dividing the correct predicted value by number of testing data and subtracting the result from 1. The number of features selected and the significance of classification accuracy are managed by weight factor. Here is the sensitivity analysis of weight factors.

3.2.1 Sensitivity Analysis of Fitness Scalarization

The fitness function used in this work combines two objectives:

1. Minimization of classification error
2. Minimization of the number of selected features

The scalarized fitness function is defined as:

$$\mathrm{F} = \alpha \times \mathrm{error} + (1-\alpha) \times \left(\frac{\text{Number of selected features}}{\text{Total Number of Features}}\right) \quad (11)$$

In the original implementation, $\alpha = 0.95$ was selected to prioritize classification accuracy while still penalizing larger feature subsets. However, fixed scalarization weights may introduce bias toward one objective.

Therefore, a sensitivity analysis is conducted to evaluate the robustness of the proposed QSCPHHO under different weight settings.

Table 2: Sensitivity Analysis of Fitness Weights

Weight Setting	**Accuracy (%)**	**Avg. Features**	**Fitness**	**Runtime (s)**
(0.95, 0.05)	**94.27**	31.8	**0.109**	27.9
(0.90, 0.10)	93.91	28.6	0.114	27.5
(0.80, 0.20)	92.84	24.1	0.126	26.9
(0.70, 0.30)	91.72	**20.5**	0.139	26.2

The results in Table 2 indicate that the scalarization parameter significantly affects the balance between classification accuracy and feature subset size.

- Higher values of α prioritize classification performance and generally produce higher predictive accuracy.
- Lower values encourage stronger feature reduction, resulting in smaller feature subsets at the expense of slight reductions in classification performance.

The setting $\alpha = 0.95$ achieves the best overall trade-off between predictive accuracy and sparsity, which justifies its use in the proposed framework. Importantly, the proposed QCEFS demonstrates stable performance across all tested configurations, indicating that the framework is not overly sensitive to a narrow parameter setting.

3.3 Parameter Initialization

QCEFS begins by initialising the hawks positions (solution) in the search space at random and setting customisable parameters. A feature subset with varying lengths and numbers of features is represented by each position. Table 3 shows the parameter configurations of algorithms presented in this work.

Table 3: Parameter configuration

Algorithm	Parameter	Value
Common Parameters	Population size	50
	Number of nearest neighbors	3
	lower bound	0
	upper bound	1
	Maximum iterations	250
	number of runs	20
SPSO	Maximum Velocity, Vmax	6
	Inertia weight, iwt	0.729843788
	Acceleration coefficients cc1&cc2	2
HHO, SCHHO, and LHHO	Beta	1.5
WOA	B	1
SCPHHO and QCEFS	Maximum Velocity, Vmax	6
	Inertia weight, iwt	0.729843788
	Acceleration coefficients cc1&cc2	2

	Beta	1.5
	Theta	0
	Delta	0
	hamming distance	0.50

To further evaluate the robustness of the proposed QCEFS framework, additional experiments were conducted under varying optimization parameter settings, including population size and iteration limits. The observed performance trends remained consistent across different configurations, indicating stable convergence behavior and robustness of the proposed method.

4. Experimental Results and Analysis

4.1 Based on Fitness Value

The fitness value is computed from error values and number of features chosen and is one of the important parameter to evaluate the performance of the proposed algorithm QCEFS. Based on the mean and standard deviation of fitness values from 20 independent runs on 21 benchmark datasets, Table 4 compares QCEFS with other competing metaheuristic algorithms. The bold numerical values indicates the minimal (best) fitness value. Also, a pairwise non-parametric Wilcoxon Signed Rank test [38] [39] is performed which is used to statistically validate the superiority of proposed QCEFS algorithm over other algorithms. Significance level is assumed as 0.05 in our comparison. The QCEFS is either better (+), worse (-), or has no discernible difference (≈) with the compared algorithms.

Table 4:Fitness value of various meta-heuristic algorithms on 21 datasets

S. No.	Dataset	SPSO	CPSO	JBHHO	LHHO	SINE_COSINE_HHO	SCPHHO	QWOA	QHHO	QCEFS
1	Lung Cancer	6.45E-02±0.003(+)	6.23E-02±0.003(+)	5.52E-02±0.006(+)	4.05E-02±0.006(≈)	5.81E-02±0.008(≈)	**1.56E-02±0.010(-)**	4.61E-02±0.005(+)	5.51E-02±0.003(+)	4.04E-02±0.008
2	11-Tumor	2.34E-01±0.008(+)	2.32E-01±0.009(+)	2.51E-01±0.006(+)	2.24E-01±0.010(+)	2.79E-01±0.003(+)	2.22E-01±0.012(+)	2.28E-01±0.008(≈)	2.50E-01±0.005(≈)	**2.12E-01±0.016**
3	Lukemia-2	3.98E-02±0.012(≈)	3.98E-02±0.012(≈)	6.93E-02±0.004(+)	4.11E-02±0.009(≈)	6.51E-02±0.008(+)	5.56E-02±0.008(+)	4.69E-02±0.008(≈)	6.76E-02±0.005(+)	**3.91E-02±0.013**
4	Brain-2	1.44E-01±0.019(≈)	1.32E-01±0.024(≈)	2.14E-01±0.007(+)	1.31E-01±0.020(≈)	1.81E-01±0.012(+)	1.69E-01±0.020(+)	1.53E-01±0.018(+)	1.94E-01±0.009(+)	**1.29E-01±0.027**
5	Prostate Cancer	2.67E-02±0.009(≈)	2.38E-02±0.010(≈)	5.40E-02±0.003(+)	3.47E-02±0.004(+)	4.66E-02±0.003(+)	4.20E-02±0.005(+)	3.42E-02±0.006(+)	5.23E-02±0.003(+)	**2.34E-02±0.010**
6	Brain-1	1.01E-01±0.008(≈)	9.55E-02±0.008(≈)	1.22E-01±0.004(+)	9.94E-02±0.006(≈)	1.19E-01±0.005(+)	1.10E-01±0.007(+)	9.88E-02±0.010(≈)	1.19E-01±0.005(+)	**9.47E-02±0.012**

7	09 Tumor	3.96E-01±0.016(+)	3.97E-01±0.014(+)	3.59E-01±0.018(≈)	3.62E-01±0.019(+)	2.92E-01±0.043(≈)	3.11E-01±0.037(≈)	3.68E-01±0.021(≈)	4.10E-01±0.011(≈)	**2.91E-01±0.034**
8	DLBCL	9.94E-02±0.006(+)	**1.08E-02±0.008(-)**	2.75E-02±0.005(≈)	1.24E-02±0.005(≈)	3.27E-02±0.003(+)	2.21E-02±0.007(+)	2.07E-02±0.005(≈)	3.03E-02±0.003(+)	1.84E-02±0.006
9	Lukemia-1	1.60E-02±0.007(≈)	1.18E-02±0.008(≈)	3.00E-02±0.004(+)	1.46E-02±0.005(≈)	3.23E-02±0.005(+)	2.89E-02±0.005(+)	1.87E-02±0.007(+)	3.41E-02±0.004(+)	**1.09E-02±0.009**
10	14 tumor	5.36E-01±0.003(+)	5.36E-01±0.003(+)	5.34E-01±0.004(+)	5.00E-01±0.012(+)	5.55E-01±0.002(+)	**4.98E-01±0.012(-)**	5.23E-01±0.007(≈)	5.38E-01±0.004(≈)	5.14E-01±0.013
11	Colon Cancer	8.38E-02±0.002(+)	8.14E-02±0.003(+)	6.67E-02±0.004(+)	4.78E-02±0.008(≈)	7.96E-02±0.006(+)	**4.51E-02±0.008(-)**	5.75E-02±0.004(≈)	7.22E-02±0.003(+)	4.93E-02±0.009
12	Toxicity	2.97E-01±0.005(+)	3.00E-01±0.005(+)	2.58E-01±0.010(+)	2.50E-01±0.012(≈)	2.59E-01±0.018(+)	2.43E-01±0.014(≈)	2.79E-01±0.007(≈)	2.79E-01±0.008(≈)	**2.39E-01±0.022**
13	Parkinsons	2.53E-01±0.003(+)	2.49E-01±0.003(+)	1.92E-01±0.006(≈)	**1.65E-01±0.009(-)**	1.98E-01±0.012(+)	1.68E-01±0.010(+)	1.97E-01±0.015(≈)	2.09E-01±0.009(+)	1.81E-01±0.024
14	Alzheimer	1.21E-01±0.004(+)	1.26E-01±0.003(+)	1.16E-01±0.005(+)	5.68E-02±0.011(≈)	4.98E-02±0.032(≈)	**2.06E-02±0.020(-)**	9.89E-02±0.008(+)	1.15E-01±0.005(+)	9.19E-02±0.012
15	LSVT VOICE REHABILITATION	1.95E-01±0.021(≈)	1.91E-01±0.025(≈)	1.80E-01±0.024(≈)	**1.26E-01±0.024(-)**	1.70E-01±0.018(≈)	2.56E-01±0.014(≈)	1.86E-01±0.025(≈)	1.71E-01±0.025(+)	1.96E-01±0.031
16	SKARDI	9.94E-02±0.006(≈)	9.60E-02±0.008(≈)	1.21E-01±0.003(+)	9.79E-02±0.005(≈)	1.24E-01±0.003(+)	1.04E-01±0.010(≈)	9.40E-02±0.010(≈)	1.31E-01±0.002(+)	**9.30E-02±0.012**
17	Replicated Acoustic Features	2.34E-04±0.001(≈)	**2.13E-04±0.001(≈)**	5.32E-04±0.000(≈)	**2.13E-04±0.000(≈)**	**2.13E-04±0.000(≈)**	2.55E-04±0.001(≈)	**2.13E-04±0.000(≈)**	2.77E-04±0.000(≈)	**2.13E-04±0.001**
18	Dermetology	3.35E-02±0.003(+)	3.40E-02±0.002(+)	4.00E-02±0.001(+)	3.05E-02±0.003(+)	4.73E-02±0.001(+)	2.78E-02±0.005(+)	1.34E-02±0.002(≈)	2.04E-02±0.001(+)	**1.31E-02±0.003**
19	Breast Cancer Wisconsin (Diagnostic)	5.60E-02±0.002(+)	5.60E-02±0.002(+)	5.90E-02±0.001(+)	4.89E-02±0.002(+)	6.47E-02±0.003(+)	4.66E-02±0.003(+)	4.57E-02±0.002(≈)	4.87E-02±0.002(≈)	**4.47E-02±0.002**

20	Lymphography	1.19E-01±0.008(+)	1.15E-01±0.009(≈)	1.36E-01±0.005(+)	1.05E-01±0.009(≈)	1.46E-01±0.007(+)	1.13E-01±0.011(≈)	1.08E-01±0.009(≈)	1.41E-01±0.005(+)	**1.05E-01±0.014**
21	Heart Failure	1.36E-01±0.002(+)	1.35E-01±0.003(+)	1.35E-01±0.002(+)	1.33E-01±0.002(≈)	1.43E-01±0.005(+)	1.34E-01±0.003(+)	1.32E-01±0.002(≈)	1.37E-01±0.003(+)	**1.32E-01±0.003**

It can be observed from Table 4 that QCEFS gives better results than other algorithms on 14 datasets out of 21 datasets. On dataset named Replicated Acoustic Features, the performance of proposed algorithm QCEFS is same as that of CPSO, LHHO, SCHHO and QWOA. Out of seven remaining datasets, the proposed algorithm is second best results on two datasets and third best on three datasets. In terms of statistical test, out of 168 pair wise comparisons (21 datasets × 8 algorithms), QCEFS gives statistically better performance on 91 comparisons.

4.2 Based on Convergence Graphs

The convergence behavior of the algorithms on all datasets are represented in Figure 2.1 to 2.21.

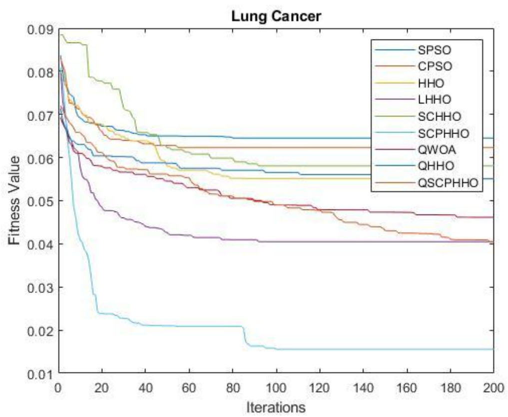


Figure 2.1: Convergence behavior on Lung Cancer

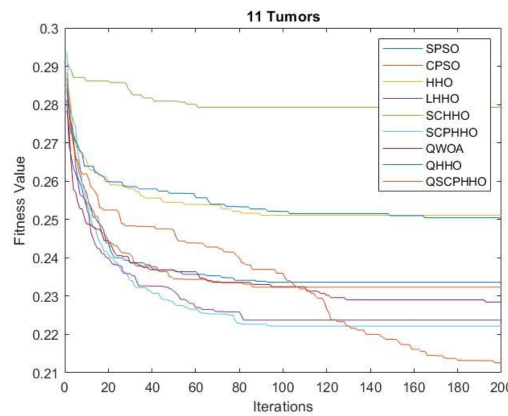
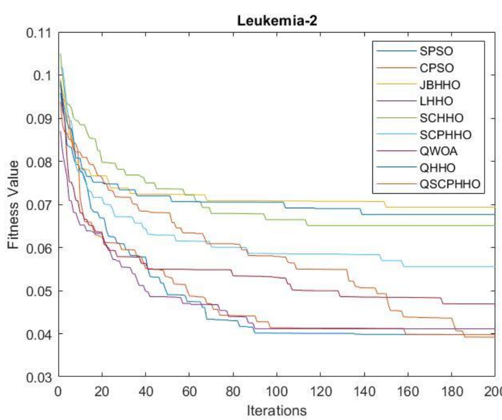


Figure 2.2: Convergence behavior on 11 Tumor



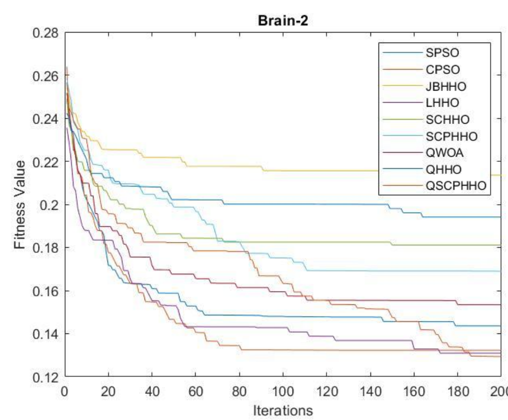
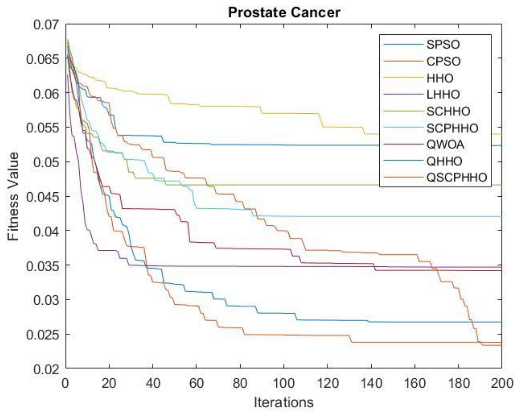


Figure 2.3: Convergence behavior on Leukemia-2 Figure 2.4: Convergence behavior on Brain-2



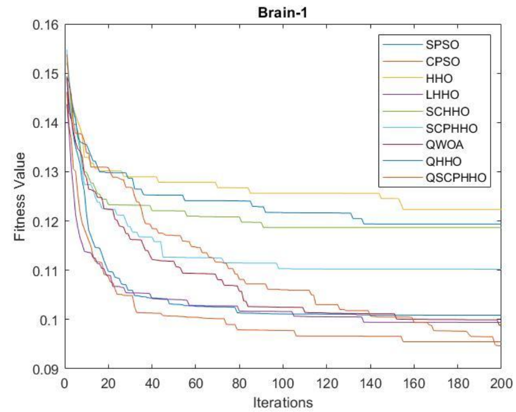
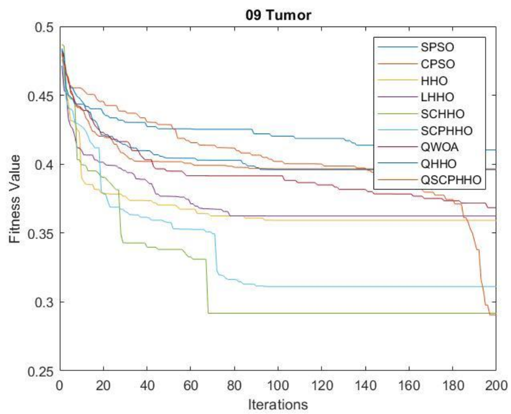


Figure 2.5: Convergence behavior on Prostate Cancer Figure 2.6: Convergence behavior on Brain-1



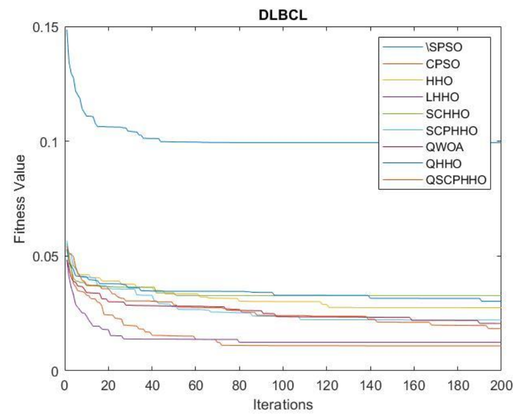
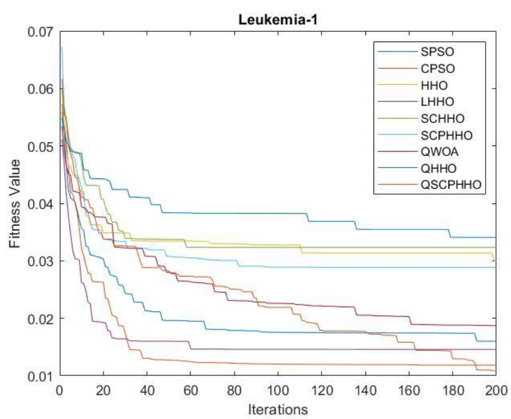


Figure 2.7: Convergence behavior on 09 Tumor Figure 2.8: Convergence behavior on DLBCL



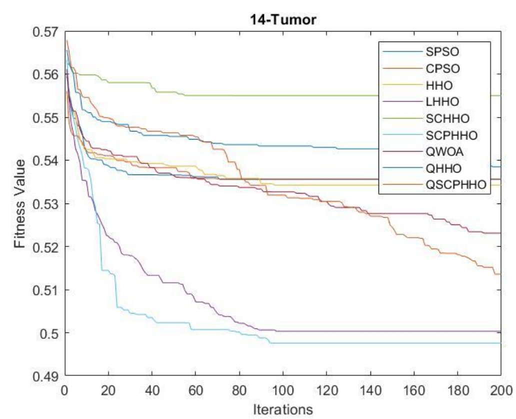
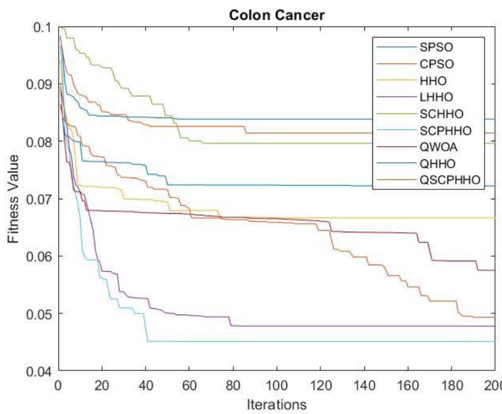


Figure 2.9: Convergence behavior on Leukemia-1 Figure 2.10: Convergence behavior on 14 Tumor



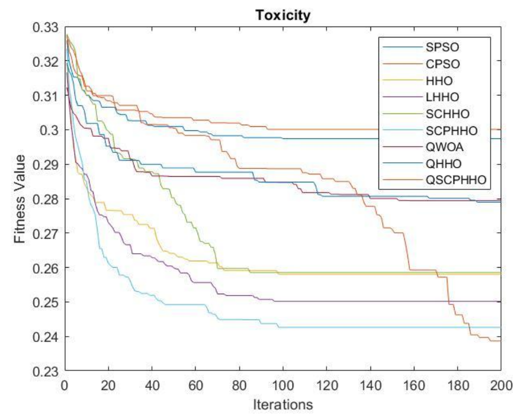
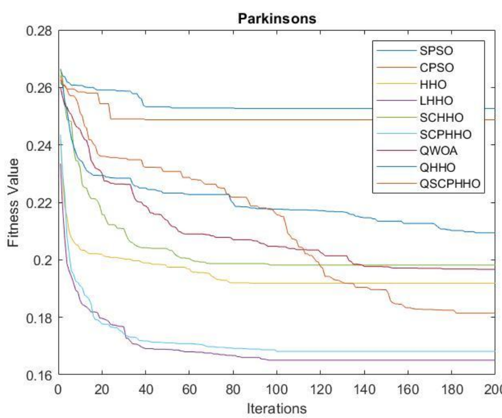


Figure 2.11: Convergence behavior on Colon Cancer Figure 2.12: Convergence behavior on Toxicity



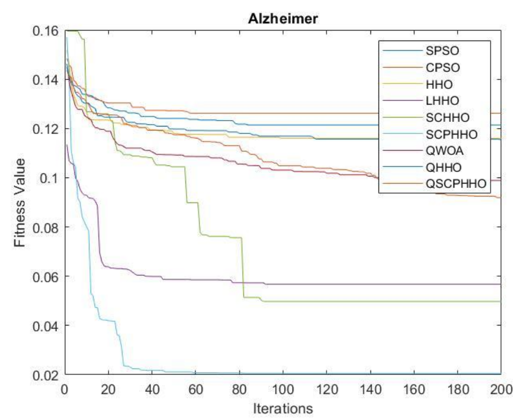
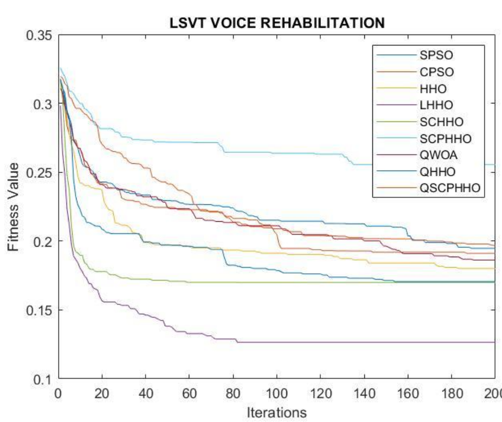


Figure 2.13: Convergence behavior on Parkinsons Figure 2.14: Convergence behavior on Alzheimer



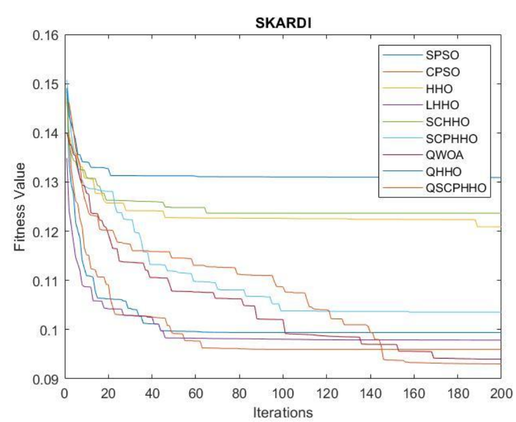


Figure 2.15: Convergence behavior on LSVT Voice Rehabilation Figure 2.16: Convergence behavior on Skardi

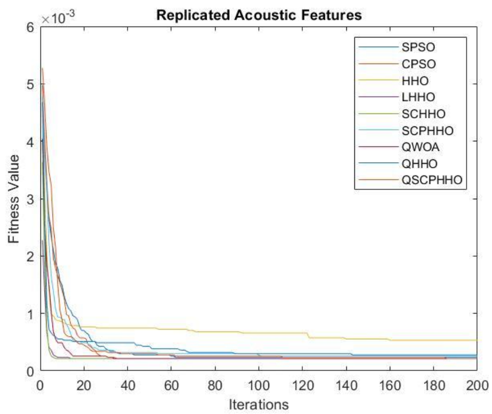


Figure 2.17: Convergence behavior on Replicated Acoustic Features

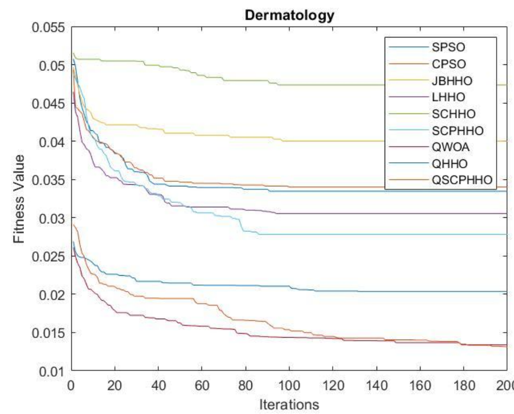


Figure 2.18: Convergence behavior on Dermetology

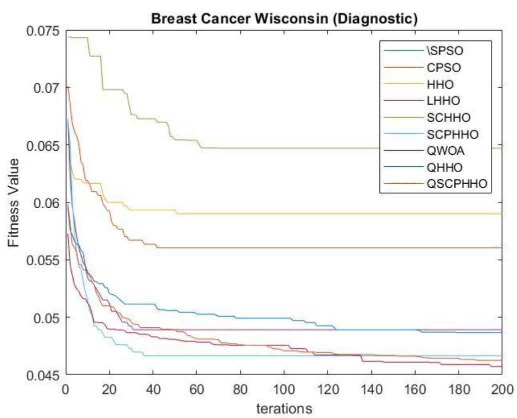


Figure 2.19: Convergence behavior on Breast Cancer Wisconsin

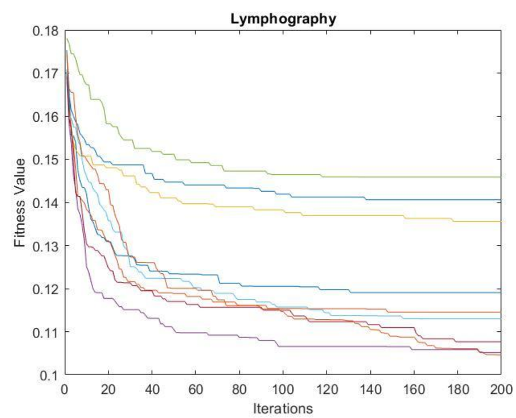


Figure 2.20: Convergence behavior on Lymphography

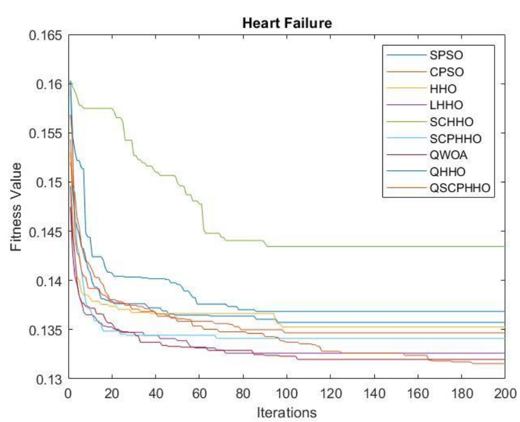


Figure 2.21: Convergence behavior on Heart Failure

It can be seen that SCPHHO produces the best results for the Lung Cancer Dataset, followed by QCEFS and QWOA, respectively. In terms of convergence behaviour, SCPHHO converges at around 85 iterations, while QCPHHO converses at 90 iterations. QWOA is converging after 180 iterations. LHHO converges at 190 iterations. The rest of the algorithms converge before 60 iterations.In the case of 11 tumours, QCEFS delivers the best outcome at 195 iterations, SCPHHO converges at 90 iterations and gives the second best result, and QWOA converges at 85 iterations, giving the third best result. For Leukemia-2, the suggested approach QCEFS converges in 184 iterations and produces the best result. SPSO and CPSO provide the next best results for this dataset. Algorithms SPSO and CPSO converge in 90 and 80 iterations, respectively. For the Brain-2 dataset, QCEFS produces the best results, as the algorithm converges after approximately 185 iterations, while LHHO and CPSO produce second and third best results, respectively. LHHO converges about 170 iterations, while CPSO converges at approximately 80 iterations. In the case of prostate cancer, QCEFS produces the best results followed by CPSO and SPSO. QCEFS converges at approximately 190 iterations, whereas SPSO and CPSO converge at 130 and 110 iterations, respectively. For the Brain-1 dataset, QCEFS produces the best results, followed by CPSO and QWOA. In terms of convergence behaviour, QCEFS converges at 190 iterations, CPSO at 165 iterations, and QWOA at approximately 140 iterations.

4.3 Based on Multimodality

Multimodality in feature selection refers to different sets of features with same cardinality giving similar classification performance. For demonstrating the effectiveness of proposed algorithm on multimodality, the number of multimodal solutions are counted and tabulated in Table 5. This table represents the number of feature sets that give same number of features and same error rate. It can be observed that proposed QCEFS gives highest multimodal solution on 19 out of 21 datasets. The second highest modality is depicted by SCPHHO algorithm.

Table 5: Number of solutions obtained by different algorithms

S. No.	Dataset	SPSO	CPSO	HHO	LHHO	SINE_COSINE_HHO	SCPHHO	QWOA	QHHO	QCEFS
1	Lung Cancer	2	2	1	2	1	3	2	2	**4**
2	11-Tumor	2	2	1	2	2	3	2	2	**5**
3	Lukemia-2	2	1	2	4	2	3	2	2	**4**
4	Brain-2	2	2	1	1	2	3	2	2	**3**
5	Prostate Cancer	1	1	1	1	1	3	2	2	**3**
6	Brain-1	2	2	1	1	2	2	2	2	**2**
7	09 Tumor	1	1	1	1	1	2	1	1	**3**
8	DLBCL	2	2	2	2	2	3	2	2	**3**
9	Lukemia-1	2	2	2	3	2	3	2	2	**3**
10	14 tumor	1	1	1	1	1	2	1	1	**4**
11	Colon Cancer	2	2	2	3	3	3	2	2	**4**
12	Toxicity	1	1	1	1	1	6	1	1	**3**
13	Parkinsons	1	1	1	2	1	3	1	1	**4**
14	Alzheimer	1	3	1	2	1	2	2	1	**3**
15	LSVT VOICE REHABILITATION	2	2	1	2	1	2	2	2	**4**
16	SKARDI	1	1	1	1	1	2	1	1	**3**
17	Replicated Acoustic Features	2	2	1	1	1	2	1	1	**3**

18	Dermetology	3	4	1	3	2	1	2	1	**4**
19	Breast Cancer Wisconsin (Diagnostic)	3	1	1	1	1	2	1	1	**3**
20	Lymphography	1	1	1	1	1	2	1	1	**2**
21	Heart Failure	**2**	1	1	1	1	**2**	1	1	**2**

Table 6 presents representative multimodal feature subsets identified by the proposed QCEFS algorithm. For the Heart Failure dataset, two distinct 8-feature subsets achieve the same classification error of 0.134. Similarly, for the Leukemia-2 dataset, three different 7-feature subsets yield an identical error of 0.149. These results indicate that the proposed method is capable of discovering multiple equally competitive feature combinations, thereby preserving diversity and providing alternative biomarker candidates for subsequent analysis.

Table 6: Sample multimodality on representative datasets

Dataset	No. of Features	Error	Selected Features
Heart Failure	8	0.134	[1,2,3,4,6,7,8,10]
			[1,2,3,7,8,10,11,12]
Leukemia-2	7	0.149	[6,13,23,30,34,44,51]
			[1,13,17,21,30,32,51]
			[6,13,17,21,30,44,55]

4.4 Ranking of Algorithms and Friedman Test

To provide a comprehensive comparison of the competing feature selection algorithms across multiple benchmark datasets, a ranking-based analysis is performed. Since the performance of an algorithm may vary from one dataset to another, relying solely on average fitness values may not adequately reflect its overall effectiveness. Therefore, the Friedman test, a widely used non-parametric statistical test for multiple algorithm comparison, is employed to rank the algorithms based on their performance. For each dataset, algorithms are assigned ranks according to their average fitness values obtained from multiple independent runs, where a lower rank indicates better performance. The average rank across all datasets is then computed to evaluate the overall performance of each algorithm. Table 7 depicts the ranks of different competing algorithms based on mean fitness value. The rank is computed based on the average fitness value obtained from independent runs on each dataset. Considering mean rank on all datasets, proposed algorithm QCEFS takes first position. The second position is acquired by LHHO followed by SCPHHO, then QWOA, CPSO, and SPSO. These results indicate that the proposed algorithm consistently discovers higher-quality feature subsets than the existing approaches across diverse datasets.

Table 7: Rank of algorithms based on fitness value

S. No.	Dataset	SPSO	CPSO	HHO	LHHO	SINE_COSINE_HHO	SCPHHO	QWOA	QHHO	QCEFS
1	Lung Cancer	9	8	6	3	7	1	4	5	2
2	11-Tumor	6	5	8	3	9	2	4	7	1
3	Lukemia-2	3	2	9	4	7	6	5	8	1
4	Brain-2	4	3	9	2	7	6	5	8	1
5	Prostate Cancer	3	2	9	5	7	6	4	8	1

6	Brain-1	5	2	9	4	7	6	3	8	1
7	09 Tumor	7	8	4	5	2	3	6	9	1
8	DLBCL	9	1	6	2	8	5	4	7	3
9	Lukemia-1	4	2	7	3	8	6	5	9	1
10	14 tumor	6	7	5	2	9	1	4	8	3
11	Colon Cancer	9	8	5	2	7	1	4	6	3
12	Toxicity	8	9	4	3	5	2	7	6	1
13	Parkinsons	9	8	4	1	6	2	5	7	3
14	Alzheimer	8	9	7	3	2	1	5	6	4
15	LSVT VOICE REHABILITATION	7	6	4	1	2	9	5	3	8
16	SKARDI	5	3	7	4	8	6	2	9	1
17	Replicated Acoustic Features	6	1	9	1	1	7	1	8	1
18	Dermetology	6	7	8	5	9	4	2	3	1
19	Breast Cancer Wisconsin (Diagnostic)	6	6	8	5	9	3	2	4	1
20	Lymphography	6	5	7	2	9	4	3	8	1
21	Heart Failure	7	5	6	3	9	4	2	8	1

Statistical Analysis

To analyze the statistical significance of obtained results and validate whether the proposed QCEFS algorithm is statistically significant or not, Friedman tests is carried out on 21 datasets. Friedman test is a nonparametric statistical test that tests the significance of multiple competing algorithms instead of pairwise testing.We assumed the Null hypothesis(H_0) as there is no statistical significant difference among the competing algorithms, and alternate hypothesis (H_1) states that at least one algorithm performs significantly differently from the others. The test statistics are given by equation 12.

$$F = \frac{12}{b*k*(k+1)} \sum_{j=1}^{k} {R_j}^2 - 3*b*(k+1) \qquad (12)$$

Where b is the number of datasets and k is the number of competing algorithms. R_j is the rank of the jth algorithm. Its value is 1 if this is the best algorithm. In the case of a tie, the average of ranks is computed. For the present study, the calculated Friedman statistic is 103.77, whereas the critical value at a significance level of α=0.05 with 8 degrees of freedom (k−1) is 14.067. Since the computed test statistic is substantially greater than the critical value (103.77 > 14.067), the null hypothesis is rejected. This result confirms that the performance differences among the competing algorithms are statistically significant.

4.5 Computational Time Complexity Analysis

In addition to fitness evaluation, the computational efficiency of QCEFS is also analyzed as shown in Table 8. Due to the integration of quantum-inspired updates and archive maintenance, the proposed framework introduces moderate computational overhead compared with conventional wrapper-based methods. However, the improved convergence behavior and reduced feature subset size compensate for the additional runtime cost. All methods were executed under identical experimental settings using the same stopping criteria, population size, and cross-validation protocol to ensure fair comparison.

Table 8: Computational Cost Analysis of Compared Methods

Method	Avg. Fitness	Avg. Runtime (s)
SPSO	1.42E-01	14.8
CPSO	1.39E-01	15.6
HHO	1.63E-01	18.9
LHHO	1.08E-01	20.4
SINE_COSINE_HHO	1.51E-01	22.7
SCPHHO	1.02E-01	23.5
QWOA	1.17E-01	21.6
QHHO	1.49E-01	24.2
QCEFS	**9.84E-02**	**26.1**

The complexity of proposed QCEFS algorithm mainly involves three components: a) complexity of fitness function computation b) the complexity of archive updation (given in Algorithm 3) c) complexity of crowding clustering/speciation clustering niching technique (given in Algorithm 1&2). Let N represents population size, D represents number of features present in the dataset and T is the number of maximum iterations. The time complexity of fitness function computation and archive updation is O(N×D). Time Complexity of crowding clustering and speciation clustering is O(N×D). The overall time complexity of SCPHHO is O(N×D×T). Same complexity is shared by CCPHHO. However, the complexity of whale optimization algorithm is O(N×D×T). Hence, the complexity of QCEFS, SCPHHO, and WOA are all nearly same.

4.6 Ablation Study

To evaluate the individual contribution of each component in the proposed QCEFS framework, a component-wise ablation study is conducted as shown in Table 9. The study begins with a baseline hybrid PSO-HHO model and incrementally integrates the following components:

1. Chaotic initialization
2. Quantum-inspired operators
3. Speciation-based niching
4. External archive mechanism

Each variant is evaluated using the same experimental setup described in Section 3. Performance is assessed in terms of Fitness value, Classification accuracy (%), Number of selected features, Computational runtime (seconds). All results are averaged over 20 independent runs.

Table 8: Component-wise Ablation Results (Average over 21 datasets)

Method Variant	Fitness	Accuracy (%)	Features	Runtime (s)
PSO-HHO (Baseline) (PHHO)	0.162 ± 0.012	89.21	42	18.5
PHHO + Chaotic Initialization (CPHHO)	0.148 ± 0.010	90.34	40	19.8
CPHHO + Speciation Niching (SCPHHO)	0.121 ± 0.008	93.08	34	25.4

SCPHHO + Quantum Operators (QSCPHHO)	0.132 ± 0.009	92.15	36	22.6
(QSCPHHO) + Archive (QCEFS)	0.109 ± 0.007	94.27	32	27.9

Analysis and Discussion

The results clearly demonstrate the incremental gains of each component:

- Baseline PSO-HHO has a good balance between exploration and exploitation but suffers from premature convergence and limited diversity issues.
- Chaotic initialization increases the population diversity, thus the exploration, with a remarkable decrease of the fitness value and feature subset size.
- Niching based on speciation enables to identify several promising areas in the search space, which improves the multimodal optimization capability and stabilizes the convergence.
- Quantum-inspired operators improve solution quality in a significant manner by preserving probabilistic diversity in the population which leads to bigger classification accuracy and extra feature reduction.
- Archive mechanism (full QCEFS) preserves the quality and diversity of solutions through the iterations and achieves the best overall performance in fitness, accuracy and feature reduction, with a moderate increase in computational cost.

In summary, the ablation study indicates that all the components contribute positively to the performance of the proposed framework and their integration results in a robust and efficient feature selection method.

5. Conclusion

This study presents a novel Quantum-Inspired Chaotic Evolutionary Feature Selection (QCEFS) approach specifically designed to address the unique challenges posed by high-dimensional, multimodal medical datasets. By integrating quantum-inspired operators, chaotic initialization, and a hybrid PSO–HHO framework, QCEFS effectively enhances exploration, maintains population diversity, and avoids premature convergence—common limitations in traditional feature selection methods. The incorporation of a speciation-based niching technique further enables the discovery of multiple equally effective feature subsets, which is particularly valuable in medical diagnostics where interpretability and reliability are critical. Experimental results across 21 real-world medical datasets validate the proposed method's superiority in terms of classification accuracy, compactness of selected features, and algorithmic robustness. These advancements hold significant promise for improving diagnostic precision, reducing computational overhead, and supporting reliable clinical decision-making. The proposed QCEFS method thus provides a powerful and adaptive tool for advancing data-driven healthcare and personalized medicine.

Future work on feature selection will focus on multi-objective optimization and refining the quantum based algorithm. The research can be extended to real time clinical applications leading to new possibilities for intelligent and efficient feature selection in healthcare.

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Availability of data and materials The datasets analyzed during the current study are available in: https://archive-beta.ics.uci.edu/

https://dataverse.asu.edu/

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics approval and consent to participate Not applicable.

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