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ENHANCED GREY WOLF OPTIMIZER FOR MEDICAL DATASET

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ABSTRACT

High dimensional data classification becomes challenging task because data are large, complex to handle, heterogeneous and hierarchical. In order to reduce the data set without affecting the classifier accuracy. The feature selection plays a vital role in large datasets and which increases the efficiency of classification to choose the important features for high dimensional classification, when those features are irrelevant or correlated. Therefore feature selection is considered to use in preprocessing before applying classifier to a data set. Thus this good choice of feature selection leads to the high classification accuracy and minimize computational cost. Though different kinds of feature selection methods are investigate for selecting and fitting features, the best algorithm should be preferred to maximize the accuracy of the classification. The proposed Hybrid kernel Improved Support Vector Machine (HISVM) classifier is used to train the parameters and optimized using Enhanced Grey wolf Optimization (EGWO). The Novel approach aimed to select minimum number of features and providing high classification accuracy.

INTRODUCTION

This technique was proposed by Mirjalili et al. in 2014 [1]. It imitates the hunting behavior of grey wolves Cheng et al. [2] proposed an innovative approach that combines a student concept model and the change mining mechanism for analyzing the learning problems of students from their historical assessment data. The experimental results showed that those analysis results provided by the innovative approach were helpful to the teacher's in providing appropriate instructional assistance and remedial learning materials for improving the learning achievements of the students. The grey wolf optimizer is a meta-heuristic technique [3]. Meta-heuristic techniques are used to find solutions for optimization problems. These techniques find the best solution to a problem with the constraints of the time required and the amount of information known. Swarm intelligence is the group of natural met heuristics inspired by the "collective intelligence" of swarms. The collective intelligence is built up through a population of homogeneous agents interacting with each other and with their environment. Example of such intelligence is found among colonies of ants, flocks of birds, schools of fish, and so forth. Particle Swarm Optimization [4] is developed based on the swarm behavior of birds. The firefly algorithm [5] is formulated based on the flashing behavior of fireflies. Bat Algorithm (BA) [6] is based on the echolocation behavior of bats. Ant Colony Optimization (ACO) [7] is inspired by the pheromone trail laying behavior of real ant colonies [8]. A new evolutionary optimization algorithm, Cuckoo Search (CS) Algorithm [9], is inspired by lifestyle of cuckoo birds. The major algorithms include Ant Colony Optimization (ACO) , Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) Algorithm [10], Fish Swarm Algorithm (FSA) [11], Glowworm Swarm Optimization (GSO) [12], Grey Wolf Optimizer (GWO) [13], Fruit Fly Optimization Algorithm (FFOA), Bat Algorithm (BA), Novel Bat Algorithm (NBA) [14], Dragonfly Algorithm (DA) [15], Cat Swarm Optimization (CSO) [16], Cuckoo Search (CS) Algorithm [17], Cuckoo Optimization Algorithm (COA) [18], and Spider Monkey Optimization (SMO) Algorithm [19].

The biologically inspired algorithms comprise natural metaheuristics derived from living phenomena and behavior of biological organisms. The intelligence derived with bioinspired algorithms is decentralized, distributed, self-organizing, and adaptive in nature under uncertain environments. The major algorithms in this field include Artificial Immune Systems (AIS) [20], Bacterial Foraging Optimization (BFO) [21], and Krill Herd Algorithm [22].Because of their inherent advantages, such algorithms can be applied to various applications including power systems operations and control, job scheduling problems, clustering and routing problems, batch process

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scheduling, image processing, and pattern recognition problems.GWO is recently developed heuristics inspired from the leadership hierarchy and hunting mechanism of grey wolves in nature and has been successfully applied for solving economic dispatch problems [23], feature subset selection [24], optimal design of double later grids [25], time forecasting [26], flow shop scheduling problem [27], optimal power flow problem [28], and optimizing key values in the cryptography algorithms [29]. A number of variants are also proposed to improve the performance of basic GWO that include binary GWO [30], a hybrid version of GWO with PSO [31], integration of DE with GWO [32], and parallelized GWO [33, 34].Every optimization algorithm stated above needs to address the exploration and exploitation of a search space. In order to be successful, an optimization algorithm needs to establish a good ratio between exploration and exploitation. In this paper, a enhanced GWO (EGWO) is proposed to balance the exploration and exploitation trade-off in original GWO algorithm

PROPOSED METHODOLOGY

This paper proposed a new computational framework shown in fig.1. HISVM-EGWO for medical diagnosis purpose. The proposed Architecture preprocessing the medical datasets, then efficient feature selection based on Modified fuzzy c means clustering with Rough set theory is exposed. Once the feature reduction is formed the classification process gets start by Hybrid kernel improved SVM. After that the optimal kernel is identified by using EGWO the evaluation metrics are analyzed for the dataset, by which can observe the efficiency of proposed feature subset selection system. The results of the measures Sensitivity, Specificity, Accuracy, FPR, and FNR are tabulated. There are two very important phases in the HISVM procedure such as the preparation phase and the testing stage.
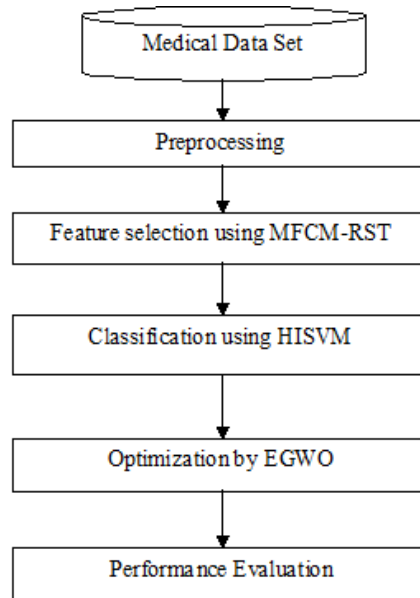
A.HISVM

1. Training phase: Currently, the output of attribute choice is provided as the input of the preparation stage. The input utility supplies the group of values which cannot be alienated. Approximately each and every one of the probable isolation of the position places are comprehend by a hectic plane. In the Lagrange pattern, it is probable to put the partition of the hectic plane standard vector during the divergent kernel task. In this association, a kernel symbolizes a few tasks, which communicate to a dot product for definite kind of attribute recording. The frequent edition of the kernel task is provided as follows.

$$K(U,V) = \varphi(U)^T \varphi(V) \qquad\qquad (1)$$

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In this view, the majority broadly engaged kernel tasks contain the linear kernel, Polynomial kernel, Quadratic kernel, Sigmoid and the Radial Basis task. Specified beneath are the terms for the different kernel task.

$$\text{For Linear Kernel: } linear_k(U,V) = u^T v + c \tag{2}$$

Where u, v represents the inner products in linear kernel and c is a constant.

$$\text{For Quadratic Kernel } quad_k(U,V) = 1 - \frac{\|u-v\|^2}{\|u-v\|^2 + c} \tag{3}$$

Where, u, v - are the vectors of the polynomial kernel function in the input space

$$\text{For Polynomial Kernel: } poly_k(U,V) = \left(\lambda u^T v + c\right)^e, \lambda > 0 \tag{4}$$

$$\text{For Sigmoid Kernel: } sig_k(U,V) = \tanh\left(\lambda u^T v + c\right), \lambda > 0 \tag{5}$$

The uniting Equations 6 and 7 the standard is predictable as recommended in the original technique. The mutual kernel task is successfully engaged in the KSVM and the standard of the kernel task, $avg_k(U,V)$ is delivered beneath.

$$avg_k(U,V) = \frac{1}{2}\left(lin_k(U,V) + quad_k(U,V)\right) \tag{6}$$

$$avg_k(U,V) = \frac{1}{2}\left(\left(u^T v + c\right) + \left(1 - \frac{\|u-v\|^2}{\|u-v\|^2 + c}\right)\right) \tag{7}$$

In the kernel Support Vector Machine, two kernels such as the linear and quadratic are used into description for the principle of classify the search links. The merging of two outcomes, the standard of the outcome is accomplished and developed to classification.

2. Testing phase**:** In the training phases productivity from the classification choice is provided as to the experiment stage and the productivity specifies the subsistence or else the absence.

B. Enhanced Grey Wolf Optimizer
The dim wolves adequately encase a Canidae's segment predecessors and are esteemed as the head predators seeing their course of action at the sustenance's nourishment grouping. They typically delineate a prejudice to detail appropriate as a get together The pioneer speak to a male and a female, set apart as alpha, which are for the larger part division in allegation of captivating legitimate assortment screening differing highlights, for instance, the chasing, resting area, time to wake, et cetera. The determinations arranged by the alpha are acknowledged on to the gathering. The Beta locations to the second grade in the pecking exhibit of the dark wolves.

In our technique, the alpha (α) is esteemed as the most suitable accumulation by a standpoint to recreating judiciously the group pecking arrange of wolves though imagining the GWO arrangement are beta (β) and delta (δ) freely. The left over cheerful arrangement are seen to be the omega (ω). In the GWO strategy the chasing (improvement) is directed by then α, β, δ and ω.

The step by step procedure of gray wolf optimization algorithm is provided as follow,
1. Initialization process

Here we start the pre-processed output data as well $a, A, and\ C$ as coefficient vectors
2. Fitness evaluation
Assess the fitness utility based on the equation (1) and furthermore choose the best result.

d_α, the second finest fitness results d_β and the third finest fitness results d_δ.

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3. Encircling prey

The tracking is aimed at by α , β , δ and ω tag the length of these three contenders.

$$d(t+1) = d(t) + \vec{A}.\vec{K} \qquad (8)$$

4. Hunting

1. Tracking prey, chasing prey, approaching the prey
2. Pursuing the prey, encircling the prey and harassing the prey till it stops moving positions.
3. Attacking prey for prey exploitation
4. Attacking prey for prey exploration

For replication, the novel result is $d(t+1)$ unsurprising by the formulae expressed underneath.

$$\vec{K}^{\alpha} = |\vec{C}_1.d_{\alpha} - d|, \quad \vec{K}^{\beta} = |\vec{C}_2.d_{\beta} - d|, \quad \vec{K}^{\delta} = |\vec{C}_3.d_{\delta} - d| \qquad (9)$$

$$d_1 = d_{\alpha} - \vec{A}_1.(\vec{K}^{\alpha}), d_2 = d_{\beta} - \vec{A}_2.(\vec{K}^{\beta}), d_3 = d_{\delta} - \vec{A}_3.(\vec{K}^{\delta}) \qquad (10)$$

$$d(t+1) = \frac{d_1 + d_2 + d_3}{3} \qquad (11)$$

It can be trial that the closing area would be in an easygoing position encompassed by a circle which is particular by the area of alpha, beta, and delta in the investigate hole. By means alpha, beta, and delta figure the area of the casualty, and further wolves' modernize their area unpredictably in the district of the casualty.

Algorithm.1. Enhanced Grey Wolf Optimizer
Intialize the population of grey wolf search agent
X_i where (i=1,2,3..n)
Initialize co efficient vector As a,A, and c
Calculate each search agent fitness value
X_{α} first dominating search Agent
X_{β} The second best search Agent
X_{δ} The third best search Agent
While (t< Maximum Iterations)
Where, t depicts the iteration number, d (t) corresponds to the prey position
For updation of current search agent by equation

$$d(t+1) = \frac{d_1 + d_2 + d_3}{3}$$

End for
Update coefficient a by
$$a = 2\left(1 - \frac{t^2}{T^2}\right)$$
Update coefficient A and C by
$$\vec{A} = 2\vec{a}r_1 - \vec{a} \text{ And } \vec{C} = 2r_2$$

$\vec{a}$ is linearly lessen from 2 to 0.

$r_1 \, and \, r_2$ Corresponds to the random vector [0, 1].

Calculate all the search agent fitness value

Update X_α , X_β , X_δ

t=t+1

end while

Return X_α

5. Attacking prey (exploitation) and Search for prey (exploration)

In EGWO, the transition between exploration and exploitation is generated by the adaptive values of a and A vectors.. In this, half of the iterations are devoted to exploration By declining A, half of the cycles are consistent to examination ($|A| \geq 1$) and the further half are focused on use ($|A| < 1$).The EGWO contains just two premier restrictions to be acclimated (a and C). However, include the GWO calculation as easy as achievable through the littlest number of agent to be acclimated the technique will be tenacious anticipating the best precision is procured. Finally the finest characteristic is chosen and supply to the extra system.

COMPUTATIONAL RESULTS

The proposed EGWO based HISVM classifier is experimented with the dataset namely Cleveland, Hungarian, Switzerland, Breast cancer, Leukemia, Lung. These datasets are taken from the UCI machine learning repository. Table1.shows the Dataset Description. The experiments were conducted in the MATLAB platform, which ran on Windows 7 ultimate operating system with Intel Core 3-3217U CPU (1.80GHz) and 8GB of RAM. The performance of the proposed feature subset selection and classification method was evaluated by the metrics Accur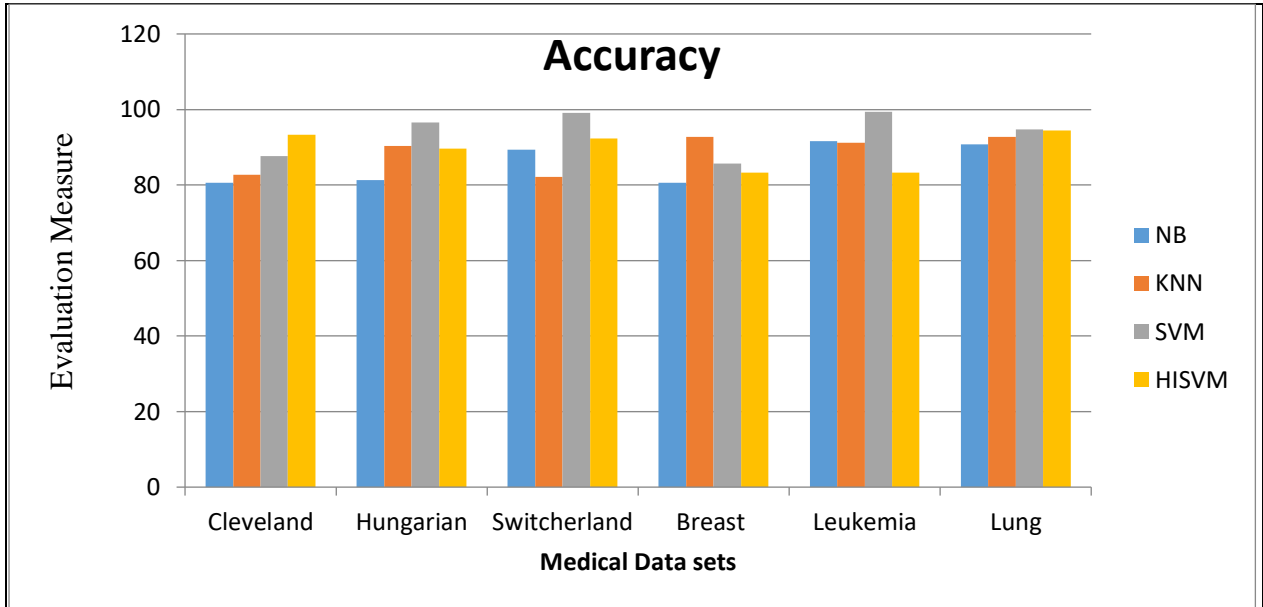acy, Sensitivity, Specificity, FPR, FNR. Accuracy of Different Classification Methods shown in fig.2. Fig.3.shows Accuracy of HISVM classifier with different optimizer, Sensitivity analysis results shows in Fig.4. The results of proposed work help to analyze the efficiency of the process. The subsequent table tabulates the results.

Table.1 Data set Description

Data sets	Number of instances	Number of attributes	Class
Cleveland	303	14	2
Hungarian	294	14	2
Switzerland	123	14	2
Breast	60	7130	2
Leukemia	62	2001	2
Lung	72	2002	2

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Fig.2.Accuracy of Different Classification Methods

Fig.3.Accuracy of HISVM classifier with different optimizer

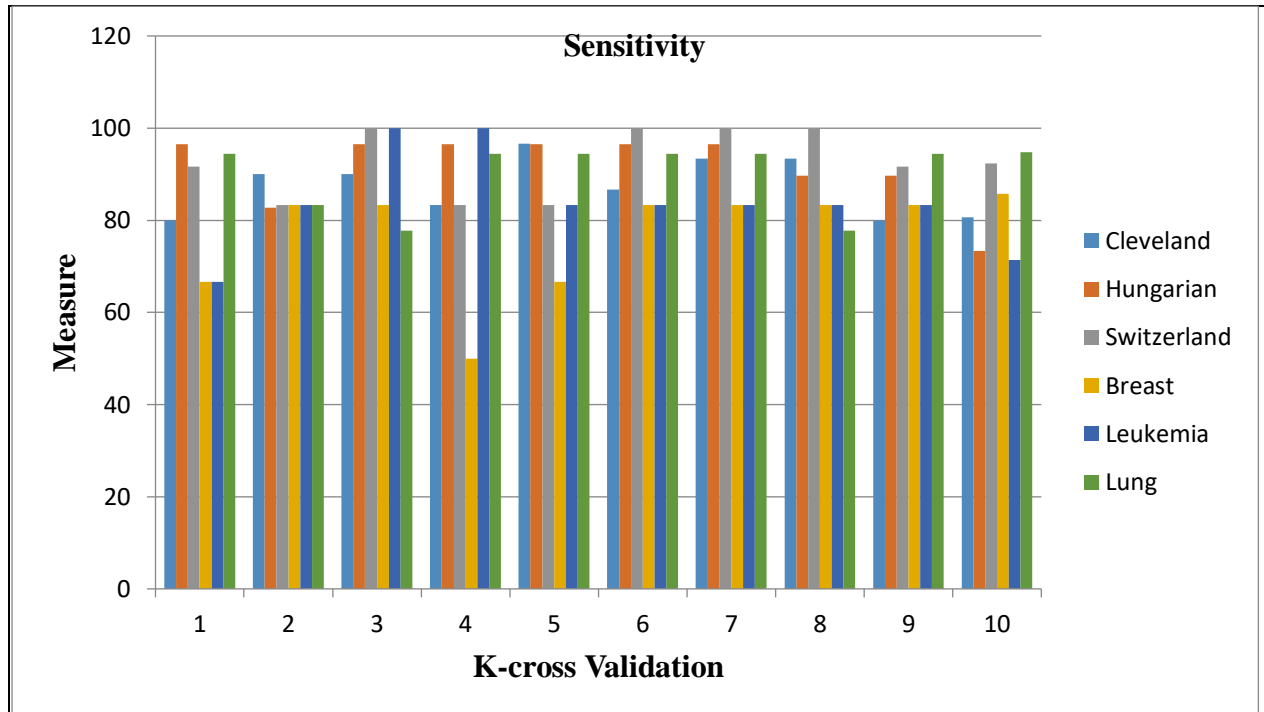Global Journal of Engineering Science and Research Management
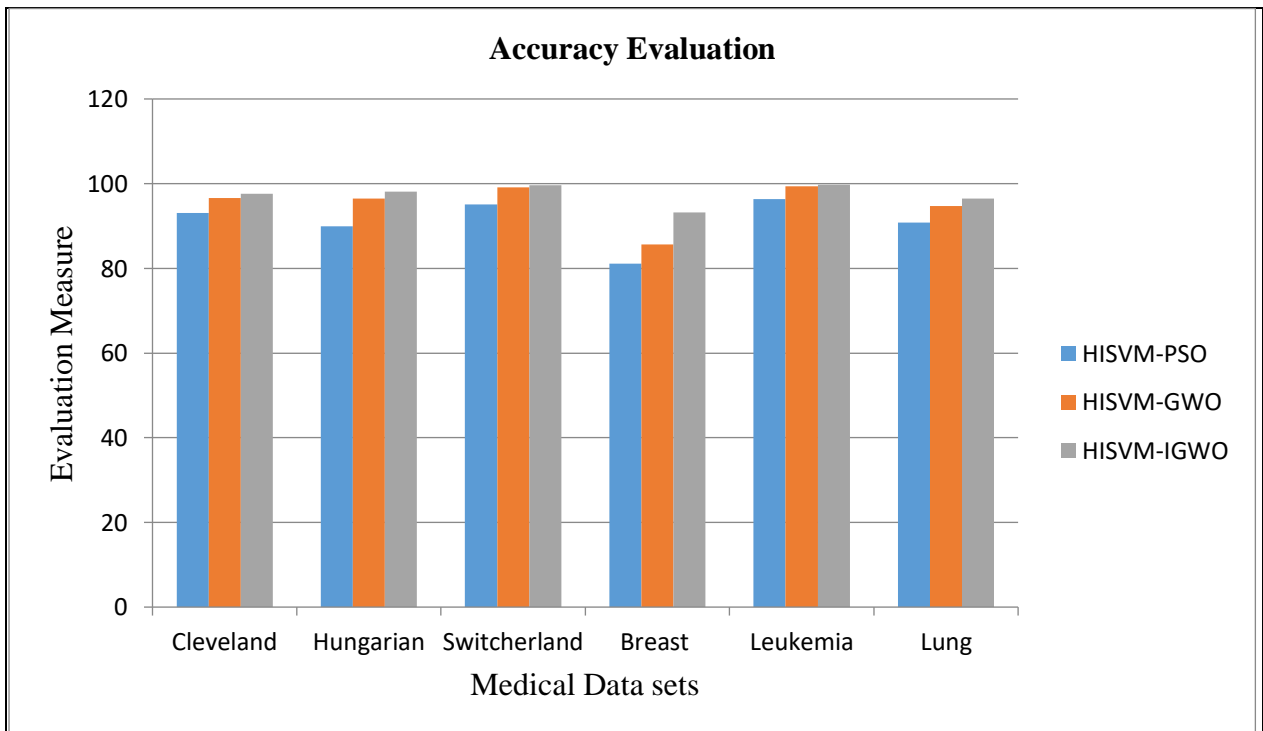
Fig.4.Sensitivity Analysis

CONCLUSION
In this paper, the potential of HISVM was explored by using EGWO strategy. It proposed to identify the most discriminative features for medical datasets. In this proposed optimization approach EGWO was used to update the positions of populations in the discrete searching space, thus getting the better classification based on the HISVM classifier. The HISVM-EGWO is scrupulously examined on the medical data. This includes a rigorous of factors that influence the patient's health status. To the validation of proposed method, other metaheuristic methods including HISVM-GWO, HISVM-PSO were used for comparison of classification accuracy, sensitivity, specificity. The experimental results demonstrate the proposed HISVM-EGWO approach can be regarded as excellent classification accuracy comparative to the other approach.

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