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Optimal Feature Selection using Particle Swarm Optimization with Random Forest Classifier for Lymph Diseases Prediction

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Abstract: ***ML-based data classification approaches can be used as a decision making tool in various fields such as healthcare, disease prediction, etc. Presently, most of the data in medical domain comprise nature of high dimensionality Sometimes, FS (FS) methodologies is employed to improvise the classification results especially for high dimensionality issue by extracting the appropriate training instances to more number of determined features. This paper made an attempt to study the application of FS approaches on the classifier performance. For FS, genetic algorithm and particle swarm optimization (PSO) algorithm is used whereas random forest (RF) classifier is used for classification lymph diseases dataset. In the first stage, GA and PSO are used to reduce the feature subset and in the second stage, RF classifier is used. From the experimentation part, it is evident that the PSO based FS increases the classifier results compared to GA based FS. It is also studied that the FS process improvises the classifier results in a significant manner interms of diverse performance measures.***

Keywords: Lymph disease; FS; Classifier; Healthcare.

I. INTRODUCTION

In the past decade, Computer aided diagnosis (CAD) systems has been employed. Medical diagnosis is called as subjective because it depends on physician experience not only over the data available. For physician's analysis [1, 2], it has been recommended that computer transformation might embrace solution parts. To build CAD systems, machine learning (ML) methods are highly employed due to its high capacity in deriving composite relationship in data from biomedical area [3,4]. To aid the data analysis, huge size of medical data needs few useful approaches in classification. It is a significant problem of accuracy in classification method employed in diagnosing diseases that has to be considered. Most of the data in medical domain comprise nature of high dimensionality [5, 6]. In common, high dimensional data needs mining the most discriminative or descriptive characteristics that have to be chosen and therefore the dataset dimension must be diminished [7]. To eliminate the unrelated characteristics out of a data set [8, 9], dimension reduction acts as a significant role in diagnosing systems. The reduction in the complexity of the dataset with the benefit of enhanced classification performance, dimension reduction process is helpful. Eliminating the count of unrelated

characteristics for implementation of model makes it more convenient, screens tests faster and less costly. With a view to enhance the accuracy in diagnosis, the present studies are aimed over the determination of an optimal feature subset for lymphography dataset.

The lymphatic system supports the immune system by eliminating and eradicating ravage, cancer cells, removing waste, pathogens, dead blood cells, and debris. It assimilates fat-soluble and fat vitamins out of the digestive system and gives these to the body cells whether they are employed through the cells. Also, among the interstitial spaces in cells, it eliminates waste things and excess fluid. The lymphatic system comprises of lymph nodes, two collecting ducts [10] and thin-walled lymphatic vessels. With the Lymph vessels, circulatory system vessels are nearly linked. Large lymph vessels are same as veins. Over the body, Lymph capillaries are scattered. Skeletal muscle contraction evokes the lymph fluid movement by valves. Lymph nodes vary in diameter which is of rounder kidney-shaped. Over the body, it is distributed over abdomen, neck, armpit, groin and pelvis. Lymph nodes are posts of T, B and other immune cells. Two third of entire lymphatic tissue and lymph nodes are inside otherwise close to gastro intestinal tract. Prior to returning to the circulatory system, the node's role is to filter the lymph. But, this node might decrease otherwise increase in volume over life, every node that has been destroyed otherwise damaged does not stimulate. Through lymphography medical imaging methods [11], lymphatic system state might be detected. For non-invasive examination of lymph node, Magnetic resonance lymphography is used. While diagnosing malignant lymph nodes [12], the method uses ultra small super paramagnetic elements of iron oxide and found to be extremely specific and sensitive. The present status of lymph nodes with derived data out of lymphography method can determine the examined finding [13] classification. The lymph node swelling can acts as a key to hard situations and extend to highly important situations which threats life [14]. In addition, the lymph node status can recommend the cancer occurrence [9]. Hence, this paper major contribution is to examine the RF efficiency in testing the lymph disease diagnostic issue.

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CAD system depended RF is introduced, focusing at enhancing the effectiveness and efficiency of the accuracy while classifying lymph disease diagnosis. The variation among this research and others is this undertakes the similar issue that a strong classifier system has produced through merging random forest decision tree methods with genetic algorithm (GA) based FS and particle swarm optimization (PSO) based FS that has very significant inclusion of sound classification and dimension reduction to distinguish among abnormal and normal cases. Moreover, these technique additional outcomes compared with the other techniques tested in this research. In the first stage, GA and PSO are used to reduce the feature subset and in the second stage, RF classifier is used. From the experimentation part, it is evident that the PSO based FS increases the classifier results compared to GA based FS. It is also studied that the FS process improvises the classifier results in a significant manner interms of diverse performance measures.

The paper organization is below: Introduction and related research are briefly demonstrated in Sections 1 and 2. Section 3 demonstrates theoretical method of RF and FS techniques. In Section 4, dataset and the experimental outcomes are projected. At the end, in section 5, Conclusion and future directions are discussed.

II. RELATED WORK

In research, Lymph disease Detection is a prevailing thing. A new hybrid classification system is projected by Polat and Gunes [15] depending on C4.5 decision tree (DT) classifier and one-against-all method to classification of multiclass issues involving segmentation of image, lymphography and dermatology dataset derived from UCI ML database. C4.5 DT was primarily run over the entire dataset classes and they gained the classification accuracy of 88.79%, 84.48% and 80.11% to segment images, dermatology and lymph dataset employing 10-fold cross validation, correspondingly. For those datasets, the projected method obtains 96.71%, 95.18%, and 87.95% accuracy. For multiclass classification involving lymph disease set, Iannello et al. [16] projected decomposition technique namely Error-Correcting Output Codes (ECOC), Pair Wise Coupling (PWC) and One-per-Class (OpC). By using three various frameworks for the common classifier such as kernel machine, a statistical classifier Nearest Neighbor (NN), is used. By employing ECOC, PWC and OpC, the MLP experimental outcome attains accuracy of 79.32%, 75.84% and 82.90% correspondingly. Using ECOC, PWC and OpC the performance results are 81.36%, 79.44% and 87.85% correspondingly.

III. FS BASED CLASSIFICATION OF LYMPH DISEASE

A. Genetic algorithm (GA)

Within complex and huge search spaces, GA is a heuristic searching technique for resolving best solutions. It is a well-known kind of evolutionary algorithms (EAs) mainly employed for effective FS. This method depends over a collection of individuals known as population, where every individual encodes the problem's input data that are known as chromosomes. Every chromosome is made of genes and it owns a binary value to denote the existence or absence of the particular elements of a collection. The best solution search is supported through an objective function known as fitness function. The chosen solution of high fitness function has higher capability to create fresh solution compared to the low fitness value when that of weaker fitness function will be removed steadily. The optimal solution selection is managed by Fitness function and gives a standard.

While genetic evolution of solutions, the maximum count of training instances are chosen solution which is classified. The fitness function in its easier outline is formed as [17]

$$Fitness = \frac{correctly\ classified\ samples\ in\ number}{training\ samples\ in\ number} \quad (1)$$

The fitness function might involve other factors like minimization of error rate and maximization of prediction accuracy and so on [18] for classification. In GA terms, each iteration in the searching process is known as generation. The fittest one is chosen out of every generation and shared to produce a support for a fresh population with enhanced features. Genetic algorithm is categorized through attributes like crossover, population size [17], input data encoding, mutation and objective function. To attain highest satisfaction level, the GA has to search a correct multiple parameter combination either maximum or minimum based on the problem requirement [19].

B. Particle Swarm Optimization for FS

Kennedy and Eberhart [20] introduced a population-based heuristic optimization method called PSO. Using a finite-length string, a probable candidate solution is encoded known as particle P_i in the search space. In finding a best solution, each and every particle employs it own knowledge and memory attained through the swarm. In order to two characteristics such as the best experience of its flying companions (g_{best}) and its own best previous experience (p_{best}), every particle change its searching direction with a aim to discover optimal solution. With the objective function $f: S \subseteq \Re^n \rightarrow \Re$, every particle moves over the n-dimensional search space *S*. Every particle owns a position $x_{i,t}$ (t indicates the iteration count), a fitness function $f(x_{i,t})$ and "flies" by the problem space with a velocity $v_{i,t}$. A novel location $z_1 \in S$ is known better when compared to $z_2 \in S$ if $f(z_1) < f(z_2)$ [5]. To find a best solution, particles increases constantly depending on shared knowledge with nearby particles; it utilizes its individual knowledge and memory derived through the swarm on the whole. The best search space position particle *i* has visited in anticipation of iteration *t* is its previous experience p_{best}. To every particle, a particle subset is acquired to its nearest particle. The best earlier experiences of entire neighbors of particle *i* is known as g_{best}. Additionally, every particle contains a fraction of old velocity. With the equation below in continues PSO [21], the particle modifies its position and velocity.

$$v_{pd}^{new} = \omega^* v_{pd}^{old} + C_1 * rand_1(\quad) * (pbest_{pd} - x_{pd}^{old})$$

$$+C_2 * rand_1() * (gbest_{d_d} - x_{pd}^{old}) \quad (2)$$

$$x_{pd}^{new} = x_{pd}^{old} + v_{pd}^{new} \quad (3)$$

The initial section in Eq. (2) demonstrates the particle's preceding flying velocity. The second part demonstrates the "*cognition*" part, that it is a personal thinking of the particle itself, where *C*1 is the individual factor. The next part is a "*social*" part that demonstrates the particle cooperation, where *C*2 is the societal factor. The acceleration coefficients (*C*1) and (*C*2) are constants demonstrate the weighting of the heuristic acceleration means which pull every particle to the p_{best} and g_{best} positions. To a maximum velocity, V_{max}, the particle velocity are restricted. Particles can get stuck into local optima, if V_{max} is very small. On the other hand, if V_{max} is too high particles might fly earlier optimal solutions. In accordance with the Eq. (1), the updated particle's velocity is estimated in order to its past velocity and the distance of its present location out of its personal and collective best experience. In order to Eq. (3), the particle then flies to a fresh position. In order to the pre-fixed fitness function, the performance of every particle is determined.

C. Random forest classifier (RF)

For skewed problems [22] and high-dimensional classification, Random forests classifier (RF) is a significant thriving ensemble learning method that are proven as very powerful and popular methods in ML and in pattern recognition. A disadvantage linked with tree classifiers is its huge variance. It is not unusual for a tiny modification in the training dataset to outcome in a variety of tree in practice. Hierarchical character of the tree classifiers is a reason behind these lies. An error which exists in node near to the tree root passes to the leaves in the entire manner. With a view to formulate tree classification more stable, a decision forest technique has been introduced. [23-25] projected the method in a combined form (as "random forest"). A decision forest is an ensemble of DTs. The main standard of RF constructs binary sub-trees employing the training bootstrap instances upcoming from the learning instance L and arbitrarily choosing at every node a subset of *X*. Over all the trees in forest, the decision forest selects the classification that has the higher votes. The RF method comprises Ho's "random selection features" and Breiman's "bagging" idea. Bagging, that meant for "bootstrap aggregation", is a kind of ensemble learning in invented by Breiman [22] with a view to enhance the accuracy of weak classifier through making a collection of classifier. If count of samples in a dataset is *N*, approximately 2/3 of the actual size is arbitrarily chosen by bootstrapping way for *N* times. The rest of the samples are employed as an out-of-bag group to be examined. The out-of-bag set is those annotations which are not employed to construct the sub-trees. For examining error prediction, they have been employed for evaluation. For building a decision node, at every node, a random FS is called. For *m* as a count of characteristics, the size of feature chosen assumed at every split is usually equivalent to $\sqrt{m}$ *or* $\sqrt{m/2}$ [26]. Hence no pruning procedure is performed, sub-trees are all maximal trees.

For every decision tree, RF training is done. In this way, every classifier's training set is produced through arbitrarily deriving *N* samples, with replacement, with *N* the size of the actual training set. The learning model produces a classifier out of the instance and combines all classifiers produced out of the various trials to produce an end classification model. Each classifier record a vote for the class to that it belong and the sample is named as a class member with the high votes. If new class combined gains the maximum count of votes, then the conqueror is chosen in arbitrary manner. Each tree residing in ensemble is grown over an autonomously derived of input bootstrap replica data. Annotations not involved in the replica are "out-of-bag" for this tree [26]. Over its out-of-bag annotations, the bagged ensemble prediction error is calculated through examining predictions for every tree; for every annotation average the predictions on all ensemble and contrasting the out-of-bag predicted response at this annotation with the true value. Like decision tree, bagging works through minimizing difference of an unbiased base learner. This method lead to enhancement in ensemble predictive power as the random selection of characteristics diminishes the correlation among trees within the ensemble.

IV. PERFORMANCE EVALUATION

A. Datasets

Ljubljana, Yugoslavia [27], from the University Medical Centre, Oncology Institute, lymphography database was derived. There are 148 samples on the whole and there are no missing values. There are four classes with 18 numeric value parameters named as malign lymph, fibrosis, metastases and normal.

B. Performance analysis

Through employing performance metrics like specificity, accuracy, *F*-Measure, precision, and sensitivity, the RF performance was examined. Few of the major expressions are followed.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (4)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (5)$$

$$Specificity = \frac{TP}{FP + TN} \quad (6)$$

In Eqs. (4)–(6), TP is the count of true positives; FN, the count of false negatives; TN, the count of true negatives; and FP, the count of false positives. The Matthews Correlation Coefficient MCC that is identified as below [28]:

$$MCC = \frac{TP.TN - FN.FP}{\sqrt{(TP + FN)(TP + FP)(TN + FN)(TN + FP)}} \quad (7)$$

Noticeably, the MCC scope is in the range of $[-1, 1]$. The better the MCC value, higher the classifier performance.

C. FS and classification Accuracy

In constructing classification systems, FS acts as a significant role. It not only diminishes the data dimension however also it lessen the cost of computation and attain a better classification performance. Prior to loading the dataset to RF, six FS methods are used to choose the characteristics. They are: Relief-F [29], PCA [30], Sequential Forward Floating Search (SFFS) in addition to the Sequential Backward Floating Search (SBFS) [31, 32], Fisher [33] and GA. To choose the feature, threshold rate is chosen as 0.1. In Table 1, the optimal FS of these methods are discussed. The dataset lymph disease dimensionality is diminished and therefore less storage space is needed for the algorithm execution. By employing 10-fold cross-validation, when to derive trustworthy computation for classification accuracy over every classification task, set of experimentation had been performed. Usually, the outcome gained is average of 10-folds. RF has been executed over the entire dataset classes in this work. Random forest models gives higher predictive accuracy when compared to single-tree models, however it comprise of some drawbacks that it does not displayed; decision tree forest models are additional of a “black box”.

Table 1 Selected characteristics of lymph disease dataset

FS methods	No. of chosen attributes	Chosen attributes
PCA	15	{1-15}
Relief-F	7	{1,2,9,14,15,17,18}
Fisher	14	{2,4,5,7,8,9,10,11,13,14,15,16,17,18}
SFFS	4	{2,8,10,13}
SFBS	3	{2,13,15}
GA	6	{13,2,15,14,10,11}
PSO	5	{1,3,8,12,14}

Few studies denote that it is better to grown huge trees, so the greatest levels and the least node size control will constraint the tree size. Hence, at 50 trees, the higher tree levels are adapted. To estimate the link among the main splitter chosen for a node and the other predictors together with predictors not assumed as member for divide and Surrogate splitters were employed to manage missing value. For a row, when the rate of the main predictor member is missed, the software will employ the best surrogate splitter which rate is called for the row.

As demonstrated in Table 2, PCA-RF, Relief-RF and Fisher-RF, SFBS-RF attains classification accuracy of 83.9%, 84.2%, and 75.5%, 77.1% and 83.4% correspondingly. The projected technique depending on GA and RF gains 92.2%, 89.5%, and 88.9% for accuracy, sensitivity and specificity correspondingly.

When comparing the outcomes attained by different FS and using RF classifier, the performance results are exhibited in Fig. 1. In terms of Accuracy, PSO-based FS is used which depicts better classification results for RF. On the whole, Fisher-RF is a FS method which shows poor accuracy of 75.5% when compared to all. For all the performance metrics, Fisher-RF is the one which exhibits worst performance. In terms of Precision, Higher precision value of 89% is attained by PSO-RF which it shows its efficiency over all the datasets. In terms of Cohen’s kappa coefficient otherwise kappa statistic (KS), the classifier performance and therefore the chosen feature quality will be examined to measure the agreement among observed and predicted values of a dataset, when adjusting the agreement which happens by probability [35]. It may result to misleading outcomes, using the missing value percentage as the solo meter for accuracy in classification performance comparisons. When doing such validations, the error cost must be considered. To examine classifications, Kappa statistic in this circumstance is a good index which might happen due to probability. Kappa error is a suggested measure to assume for examining targets and it is estimated through:

$$KS = \frac{P_o - P_c}{1 - P_c} \tag{9}$$

where Po is total agreement probability, in addition to Pc is the hypothetical probability of chance agreement. From the Fig. 1, it is clearly shown maximum classification performance is attained by the PSO-FS under all the performance measures compared to GA-FS. The improved classification performance with the use of FS can be clearly shown in the table and figure values. It is also found that the PSO-FS with the RF classifier is an appropriate classification tool for Lymph disease dataset.

Table 2 Analysis of classification performance

Performance index	No FS	PCA-RF	Relief-F-RF	Fisher-RF	SFFS-RF	SFBS-RF	GA-RF	PSO-RF
Accuracy	81.2	83.9	84.2	75.5	77.1	83.4	92.2	94
Sensitivity	80.4	83.1	83.1	74.3	76.4	81.8	89.5	91
Specificity	81.9	84.5	84.8	76.3	77.5	84.7	88.9	90
Precision	80.7	82.7	83.1	74.3	74.2	80.1	87.4	89
MCC	62.7	67.8	68.8	50.8	54.6	66.0	87.7	89
F-Measure	80.3	82.8	82.9	74.3	75.2	80.8	87.9	89

AUC	90.9	89.9	91.3	84.3	85.1	87.7	95.4	97
KS	62.77	62.77	62.79	51.29	53.81	65.17	87.9	89

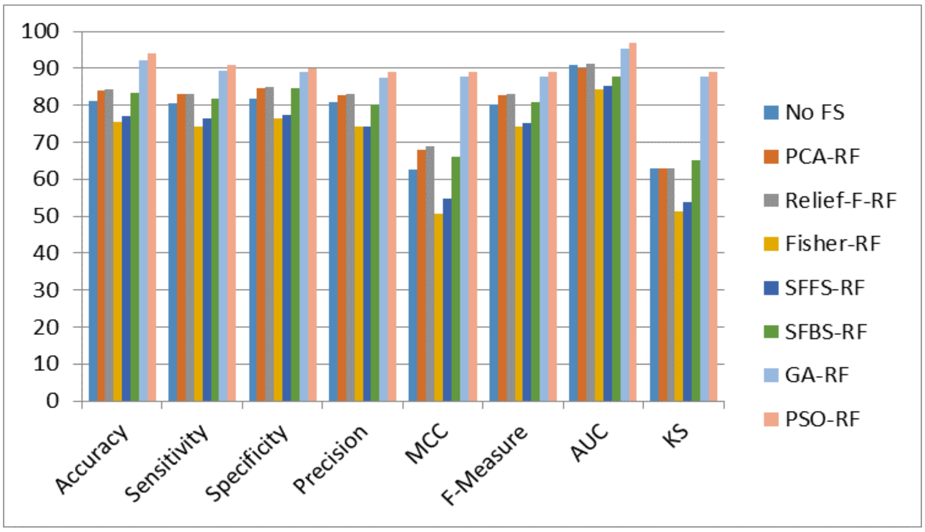

Fig. 1: Comparisons of performance measures for RF classifier with the FS methods

V. CONCLUSION

In this paper, we made an attempt to investigate the usage of FS approaches on the classifier performance. For FS, we have employed GA and PSO algorithms are used whereas RF classifier is used for classification lymph diseases dataset. In the first stage, GA and PSO are used to reduce the feature subset and in the second stage, RF classifier is used. From the experimentation part, it is evident that the PSO based FS increases the classifier results compared to GA based FS. It is also studied that the FS process improvises the classifier results in a significant manner interms of diverse performance measures. From the experimentation part, it is evident that the PSO based FS increases the classifier results compared to GA based FS. It is also studied that the FS process improvises the classifier results in a significant manner interms of diverse performance measures. In future, we extend the classification performance with the use of new EAs.

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