

A Classification Model using improved Hybrid Genetic Particle Swarm Optimization Algorithm based on Separability-Correlation Measure

¹B Renuka Devi, ²N.Sharmili, ³K.Vijaya Kumar, ⁴G. Jose Moses, ⁵Dr.E.Laxmi Lydia

¹Professor, Department of CSE, Vignan's Nirula Institute of Technology & Science for Women, Guntur, A. P. India.
Mail id: brdcse@gmail.com

²Associate professor, Computer science and engineering Department, Gayatri Vidya Parishad college of engineering for women, visakhapatnam, Andhra pradesh, India

³Associate Professor, Computer Science and Engineering, Vignan's Institute of Engineering For Women, India.

⁴Professor, Computer Science and Engineering, Raghu Engineering College (Autonomous), Viskahpatnam (Andhra Pradesh), India.

⁵Professor & Big Data Consultant, Computer Science and Engineering, Vignan's Institute of Information Technology, India.

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Abstract

The unpredictable growth in information and data samples has engendered a crucial requirement for novel methodologies and mechanisms which can intellectually and spontaneously transform the processed information into valuable data and knowledge. Thus, it is very essential to carefully obtain the relevant information from the huge databases. Numerous techniques are already available in literature for mining of data. However, the Evolutionary Algorithm and Swarm Intelligent Approaches are playing a vital role in the form of extracting the relevant features from the database and supporting in constructing the classification Models. So as to further highlight the importance of both the approaches, in this paper, a methodology is presented that hybridized the Genetic Algorithm and Particle Swarm optimization for feature Selection by means of Separability-Correlation Measure. The experiment results shows that the proposed novel Feature Selection approach has a high global convergence possibility and a scarce average convergence iterations

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I. INTRODUCTION

The growth in database applications and storage capabilities have enabled large amount of data to be accumulated over years. With the expansion of multimedia devices, Internet technologies, Storage capacities of computers, application of computers and day-to-day problems, the size of databases has increased voluminously. With large amount of available data it becomes a common and essential requirement to analyse databases frequently. Data mining is the procedure of determining expressive novel associations, designs and tendencies by moving through enormous amounts of information stored in data warehouses, employing pattern recognition procedures along with statistical and scientific approaches. It is an interdisciplinary area fetching together the

methodologies from machine learning, pattern recognition, statistics, data samples and visualization, to state the subject of data mining tasks from enormous sized databases[4].

Classification is an important stage of data mining which is possibly the most general data mining approach. Classification has become the emphasis of extensive investigation in the domain of application for which data samples with hundreds or thousands of attributes are accessible. The classification is required for an extensive variety of human action. At the widest, the time period can shield any perspective where certain judgment or prediction are performed on the source of presently accessible data and a classification procedure for recurrently constructing such decisions in novel circumstances [2] Classification is an important process

in many of the real time applications and provided an easy reducibility in size, time and complexity. Classification of data is a major step in data mining, rule extraction, knowledge discovery, decision-making and so on [23-32].

Minimizing the dimensionality of the information via choosing a group of unique features are beneficial for maximum classification approaches comprising the expenditure of constructing, packing and handling measurements. The better performance is often achieved by performing the pre-processing steps prior to the classification to obtain relevant attributes resulting from the unique input. Constructing an attribute illustration is a pre-processing technique which provides a prospect to integrate domain knowledge into the information and is very application oriented.

Genetic algorithm is one of the utmost conventional desired optimization technique that is employed by nearly all kinds of scholars. Owing to the manageable constraints such as population size, mutation rate and crossover rate, GA specifies in close proximity to optimum outcomes for a multifaceted issues considering massive number of variables and parameters. PSO similarly employs certain simple inherent constraints such as inertia weight, optimum position, speed and other social constraints. Thus, the efforts are specified in this paper by hybridizing both the PSO and GA to obtain certain near optimum results.

This paper presented a novel methodology depending on Hybrid of Genetic Algorithm and Particle Swarm Optimization Algorithm to construct a novel classification approach. It proposed hybrid methodology which is the combination of genetic algorithm and particle swarm optimization that reduces the limitations of genetic algorithm and particleswarm optimization and improves searching ability when compared to algorithm. Therefore, employed the correlation and also separability measures amongst the features as the fitness evaluation to Hybrid Genetic Particle Swarm Optimization Algorithm (HGPSOA). The experimental outcomes represented that the novel proposed algorithm obtained an efficient results when compared to classical algorithms like average convergence iteration, the worldwide convergence possibility etc.

Organization of the paper:

particle swarm optimization and genetic algorithm. The proposed Improved Hybrid Genetic Particle Swarm Optimization Algorithm for an Efficient Classification Model is given in details in section 3. The section 4 gives the detailed analysis of the proposed novel

methodology using the medical datasets and also specify the classification accuracy and error attained by the proposed methodology followed by conclusions and references given in section 5 and section 6 respectively.

II. LITERATURE SURVEY

Huge Investigation is done on the hybrid approaches of Evolutionary Algorithms and Swarm Intelligent Approaches through amalgamating the merits and demerits of the approaches successfully. Among which, the new feature selection approach with the incorporation of a genetic approach and particle swarm optimization are suggested [6] proposed a hybrid approach that associations PSO and GA known as Genetical Swarm Optimization (GSO), to design a planar that reflect array antenna, so as to enhance the geometrical attributes of its entities. It is proved that GSO is reliable and effective technique for wider application in electromagnetic. Davide Caputo et al. presents GSO to enhance the interacting energy consumption in a wireless network by choosing the optimum multi hop routing strategies [33-38]. Karnan et al. used hybrid of GA and PSO to detect the nipple position in digital mammogram[15].

[8] suggested a two-phase hybrid evolutionary categorization approaches to discover classification rules that could be employed in clinical practice for well understanding and avoiding undesirable medical actions. A hybrid evolutionary learning strategy was suggested [16] for manufacturing multiclass pattern recognition structures. A substantial work is consumed for establishing complicated attributes that functioned as inputs to a basic classifier.

A hybrid PSO evolutionary approach is suggested by [7]. This hybrid technique implements two structures instantaneously and picks P individuals from every system for substitution after nominating N generations. Another hybrid algorithm for the similar issue was given by [10] where GA is joined with Tabu Search. A hybrid technique using genetic algorithm (GA) and a simulation method was recommended [14]. The GA is employed for enhancements of schedules, and the replication is employed to diminish the higher termination period for the final task with static schedules attained from the GA prototype.

[3] proposed a hybrid method (PSO Ada Boost), which amalgamated PSO with an AdaBoost outline for faceA brief in detection. The proposed algorithm aimed to examine for the optimum feature subset and defined the decision thresholds of AdaBoost concurrently. [1] suggested turbulence in the particle swarm optimization (TPSO) approach to overwhelm issue of stagnation. The

methodology employed a reduced velocity threshold to regulate the velocity of individuals. Certain hybrid varieties of DE and PSO entails Hendtlass technique [19] where the population developed by DE is enhanced by means of PSO, Kannan technique [17] where DE is performed on every individual for a fixed number of generations to specify the finest individual. Methodologies of [20] and Talbi and Batauche employed DE to the optimum individual attained by PSO. [5] introduced a hybrid version comprising of Barebones PSO and DE. In [11] suggested a hybrid version where the candidate outcomes are produced either by DE or by PSO rendering to certain static probability dissemination. A hybrid approach is proposed by [12] that efforts to consider benefits of both the methodologies by exploiting their diverse evaluation standards in diverse exploration phases.

A Classification Model Using Improved Hybrid Genetic Particle Swarm Optimization Algorithm

Applications of evolutionary algorithms, with their inherent hybrid architecture, has been discovered to be potentially helpful for automatic functioning of huge amounts of rare noisy information for optimum bound setting and to determine important and expressive data. In this paper, a novel methodology is suggested to obtain the finest optimum attributes from the enormous data samples. The Hybrid Genetic Particle Swarm Optimization Algorithm (HGPSOA) is employed as arbitrary selection process to proficiently discover a massive search domain that is often mandatory in the event of attribute selection and choose attributes to increase the possibility of desired classification. The suggested approach is generally proposed in two stages given in figure 1. They are:

Phase 1: Feature Selection by means of Hybrid Genetic Particle Swarm Optimization Algorithm (HGPSOA) and Separability Correlation Measure (SCM)

Phase 2: Classification of selected attributes by means of Decision Tree (DT) techniques

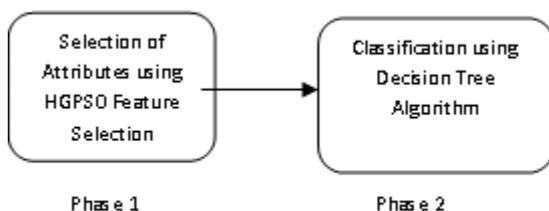


Fig.1: Phases of Improved Hybrid Genetic Particle Swarm Optimization Methodology

Improved Hybrid Genetic Particle Swarm Optimization Algorithm (HGPSOA) for Feature Selection: Scientists have presented various feature selection approaches

along with diverse selection criteria to retrieve the relevant information from the large datasets. To minimize the data measurements, all merged attributes are given to hybrid PSO-GA that eradicates inappropriate attributes and consequences in optimum attributes. Hybridization of evolutionary approaches is becoming widespread owing to its abilities in controlling numerous practical issues comprising complication, noisy surroundings, roughness, ambiguity, and imprecision.

The traditional optimization approach suffer from the local optimality issues, hence, it is difficult to resolve the global optimization issues. The Genetic Algorithm frequently has issues like premature convergence and local convergence. In order to overcome the convergence problem in Genetic Algorithm, in this approach the swarm intelligence operations are applied on the chromosomes prior to genetic crossover and mutation operations. The Particle Swarm Optimization Algorithms and Genetic Algorithms are employed sequentially one after the other. That is the obtained attributes from Particle Swarm Optimization are given as input to the Genetic Algorithm to obtain the final retrieved features. This Hybrid algorithm is designed so as to preserve the strengths of both the algorithms. PSO shares various resemblances with evolutionary computation methods [9]. The methodology is initialized with a populace of arbitrary outcomes and explores for optimum by updating iterations. In GA, evolutionary operations like crossover and mutation are employed to obtain the selected features, which in turn are given as particles to the PSO.

Decision Tree Induction for Classification

Decision Tree classifier categorizes the entire data samples into classes based on the optimized features such as class labels. Decision Tree Induction is one amongst the dominant classification approach that is specified in certain research domains [13] [18]. It is a characteristic inductive technique to acquire knowledge on classification. Decision tree has its benefits like it can generate a system which might signify interpretable rules or logic statement and is further appropriate for predicting categorical results. Decision tree is a classifier in the form of a tree structure, where every node is either a leaf node that specifies the value of the target feature, or a decision node that determines certain trial to be approved out on a single attribute-value by means of single branch and sub-tree for every conceivable result of the trail. The traditional Decision Tree classification technique is applied on the retrieved optimized features of every data sample that produces decision tree rules for the features of training data samples.

In the proposed methodology, the features of the training data samples are the initial populace that is encrypted to numerical string chromosomes as to employ in genetic algorithm. The fitness function applied in this methodology is the Separability Correlation Coefficient Measure. The chromosomes are given to particle swarm optimization operation i.e. the updating of pbest and gbest values and moving the particle or attribute in the direction of the velocity of best attributes so as to obtain the best particle and global values. Then resulted solutions are given as input to the genetic operations i.e. crossover and mutation are executed by selecting a group of appropriate features, and the novel features are substituted with the selected features. The stopping criteria for both the algorithm will accomplish if maximum no of iterations has been attained or if there is no alteration in the populace best fitness. Algorithm 1 and Figure 2 describes the hybrid genetic particle swarm optimization algorithm for feature selection using Separability Correlation Measure is implemented. Solitary those operators will be appropriate to execute genetic and swarm intelligence that are pursuing lower correlation coefficient. That is lesser the correlation coefficient the greater is the fitness value.

Algorithm 1

Consider M no of instances and N no of features in every data samples.

1. The N no of features of every sample are encrypted into numerical particles that are consistently disseminated.
2. The initial population is generated and given to Particle Swarm Optimization Algorithm obtained by selecting the parental individuals from the data sample.
 - i. The fitness value to update particles location estimated by means of the Separability Correlation measure and specified by

$$R_k = \chi S_k + (1 - \chi) C_k$$
 And fitness value = $1 - R_k$
 - ii. If a particle's present location is altered than its preceding location, replace with the new location.
 - iii. Specify the best particle conferring to the particle's preceding best positions.
 - iv. Update particles' velocities using

$$v_{id} = w * v_{id} + c1 * rand * (p_{id} - x_{id}) + c2 * Rand * (p_{id} - x_{id})$$

- v. Update the particles to its new location by means of

$$x_{id} = x_{id} + v_{id}$$

3. Then the achieved final individuals are given as input to the genetic algorithmic operations as initial populace.
 - i. The fitness value for every individual is estimated by means of Separability Correlation measure specified by

$$R_k = \chi S_k + (1 - \chi) C_k$$
 And fitness value = $1 - R_k$
 - ii. The selection operation on chromosomes applied to select the pair of fittest attributes.
 - iii. Then the genetic operations that are crossover and mutation are performed on the group of selected attributes.
4. Now substitute the earlier selected features with the new features calculated and then go to step 3 to accomplish swarm operations on retrieved genetic attributes.
5. Grade the entire selected and fittest attributes of every sample obtained from genetic operations.
6. Select top K number of optimized attributes of each instance from the ranked ones and give this as input to the decision tree classifier algorithm.
7. Decision Tree classifier categorizes entire samples into classes based on the optimized attributes as targets.

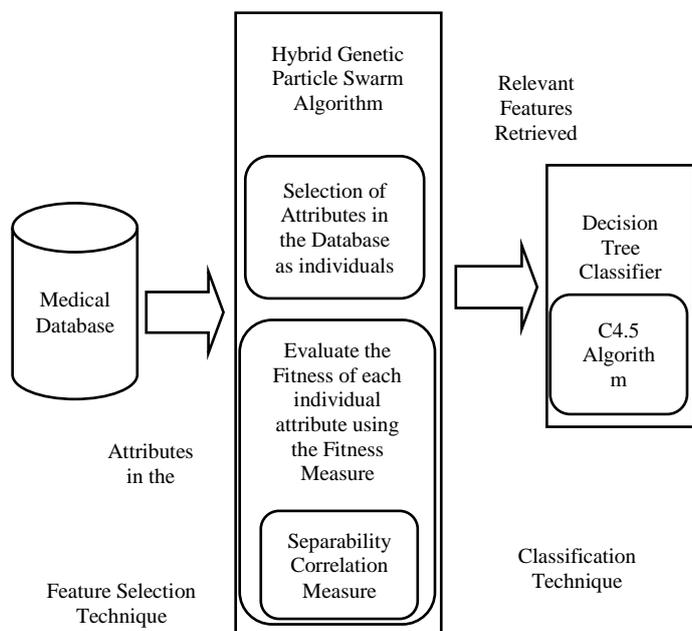


Fig. 2: Block Diagram of the Improved Hybrid Genetic Particle Swarm Optimization Methodology

III. EXPERIMENTAL RESULT AND ANALYSIS

Description of the Data Samples: The efficiency of Improved Hybrid Genetic Algorithm Particle Swarm Optimization based classification model proposed in this paper has been experimented on different medical datasets of Dengue disease that has been collected from the surrounding hospital under the supervision of general physicians and also on the medical database obtained from the medical government website <http://www.ncbi.nlm.nih.gov/gds>. The datasets collected are classified into the class labels (Effected, Not-effected and Severe). Considering the Confidentiality and Authentication issues of the different medical databases collected from the hospital, the datasets and its Experimental results are not revealed in this thesis.

constructing the model and the last attribute that is 17th one is taken as the class label with the values Effected, Not-Effected and Severe. The Data Samples employed in the proposed approach is represented in Figure 3 and the encoding of the complete data samples for the purpose of executing the Improved Particle Swarm Optimization is given in Figure 4.

Fig. 3: Data Samples Used for the Improved Hybrid Genetic Particle Swarm Optimization Approach

Let us consider the Standard Government Dengue Dataset for the illustration of the proposed classification model. The complete dataset is considered for the experimentation which has 2,124 records with 17 attributes in each sample. Most of the patient’s evolution status is also mentioned in that data set whether that particular patient is recovered from dengue fever or died. Here 16 attributes are considered for

Fig 4: Encoded Data Samples in the Improved Hybrid Genetic Particle Swarm Optimization Approach

Performance Evaluation

The performance of the Classification Model Using Improved Hybrid Genetic Algorithm Particle Swarm Optimization Algorithm Based on Separability-Correlation Measure Proposed in this paper are computed in terms of its classification accuracy and error rate. The Accuracy, and Error rate is given as:

$$\text{Accuracy} = (TP+TN) / (TP + FP + TN + FN)$$

$$\text{Error rate} = (FP+FN) / (TP + FP + TN + FN)$$

Where

- TP is the number of True Positives
- TN is the number of True Negatives
- FP is the number of False Positives
- FN is the number of False Negatives

Table 1: Classification Accuracy of the Improved Hybrid Genetic Particle Swarm Optimization Classification Model

S. No.	No. of Attributes Selected	Accuracy	
		Decision Tree Classifier	Proposed Approach
1.	2	90.27	95.10
2.	5	91.57	97.55

3.	10	93.23	97.96
4.	15	94.29	99.17

Table 2: Classification Error Rate of the Improved Hybrid Genetic Particle Swarm Optimization Classification Model

S. No.	No. of Attributes Selected	Error Rate	
		Decision Tree Classifier	Proposed Approach
1	2	9.63	4.9
2	5	8.43	2.45
3	10	6.77	2.04
4	15	5.81	0.83

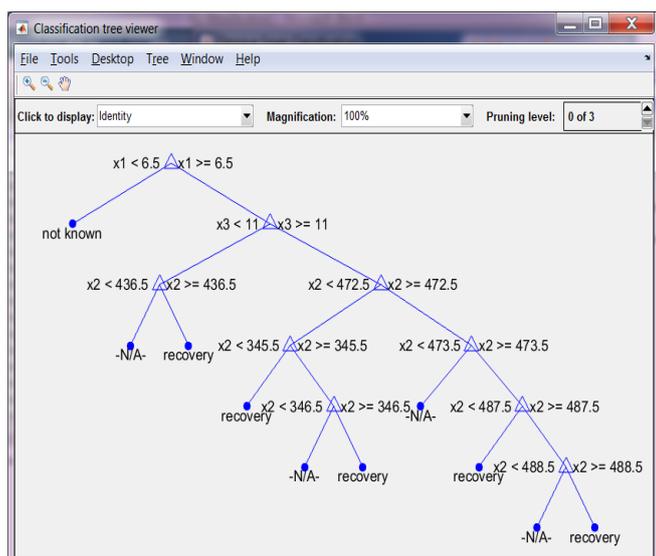


Fig.5: Decision Tree for the Traditional Classification Model

The obtained results have shown that there is an improvement in the accuracy of the proposed model and decreased the error rate of the classification model. The efficiency of the proposed Classification is compared with the existing traditional Classification algorithm that is Decision tree classifier (C4.5). The complete dengue database is pre-processed before applying the classification model.

The database is encoded using the Particle Swarm Optimization as given before. For this reasons, the dataset with categorical, numerical and binary values is transformed to complete numerical form as to run the PSO process. These numerical values are known as chromosomes or individuals in this case. The relevancy and redundancy of every attribute is computed using Separability Correlation Measure and most relevant attributes are retrieved to form the classification model.

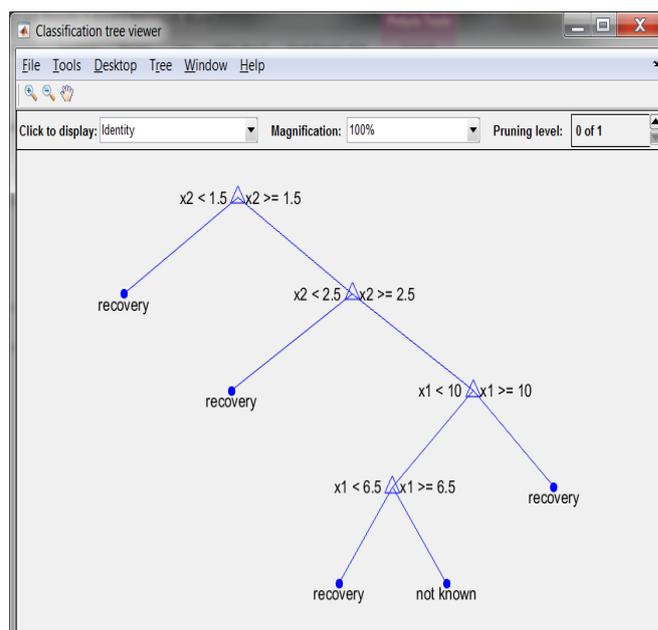


Fig. 6: Decision Tree For the Improved Hybrid Genetic Particle Swarm Optimization

Classification Approach with 4 Attributes

In Table 1 and Table 2, it is shown that the Classification Accuracy and the Error Rate for the Proposed Approach that is the improved Hybrid Genetic Algorithm Particle Swarm Optimization Algorithm based Classification Accuracy is compared with existing Decision Tree Classifier respectively. From the Table 1, it is observed that there is an increase in the Classification Accuracy of the Proposed Approach compared to the existing Decision tree even for the increased number of selected attributes. From the Table 2, it is clearly observed that there is a decrease in the Error Rate of the Proposed Approach compared to the existing decision tree even for the increased number of selected attributes.

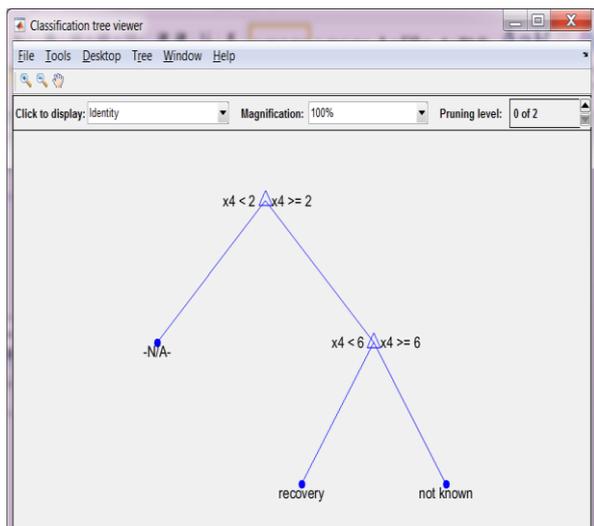


Fig. 7: Decision Tree For the Improved Hybrid Genetic Particle Swarm Optimization

Classification Approach with 2 Attributes

Figure 5 represents the traditional decision tree classification model with 8 attributes in the tree. Figure 6 and Figure 7 represents the tree construction of the proposed Classification Model Using Improved Genetic Particle Swarm Optimization Algorithm Based on Separability-Correlation Measure Approach for 5 and 2 selected attributes. Figure 8 shows the relationship between the Fitness Evaluation function and the number of generations of the proposed approach.

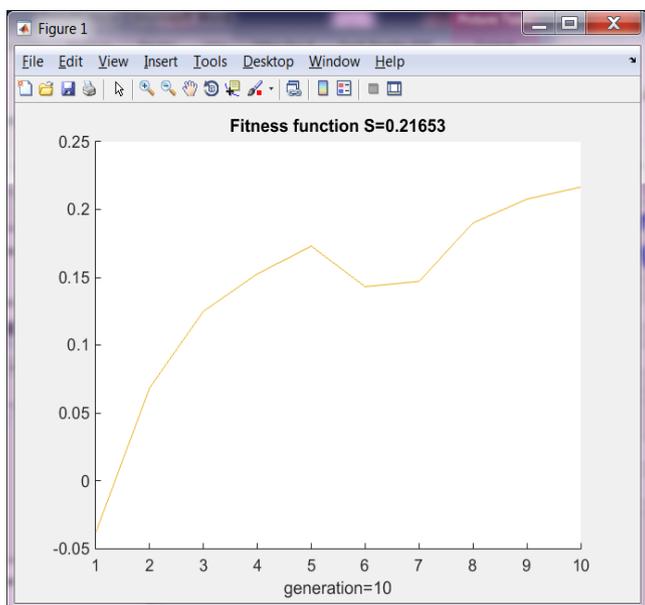


Fig.8: Plotting of Fitness Function Vs No. of Generations

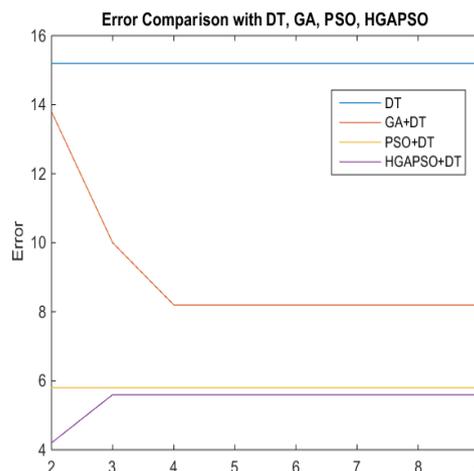


Fig.9: Overall Performance Comparison of Improved Hybrid Genetic Particle Swarm Optimization Approach over Traditional Model Decision tree, GA based Approach, PSO based Approach

This shows that the Fitness Evaluation and number of generations are directly proportion to each other for the fitness value $s = 0.21$. The Figure 9 shows the overall performance of the Proposed Classification Model compared to the Traditional Decision Tree Classification Model, Genetic Algorithm based Classification Model [21], Particle Swarm Optimization Based Classification Model [22].

IV. CONCLUSION

The intention of the paper is to suggest a hybrid algorithm on large data samples for classifying the essential feature which is capable of producing accurate class labels. The classification of the Patients data is accomplished by means of this proposed classification model that uses the Separability Correlation Coefficient measure for correlating the attributes. The experimental results of this paper represents a better classification accuracy matched with the prevailing procedures and similarly presented that there is a substantial reduction in the error rate compared to the prevailing classification models. The experiment results shows that the proposed novel Feature Selection approach has a high global convergence possibility and a scarce average convergence iterations. From the experimental analysis, it is also inferred that this approach is effective and competent pertaining to the number of appropriately classified patterns.

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