Applications of Soft Computing Techniques for Pulmonary Tuberculosis Diagnosis

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Abstract*: Recently, several interesting research studies have been reported on soft computing approaches. Soft computing approaches are solving several kinds of problems and provide alternative solutions. Different Soft computing techniques or approaches have been applied in medical care data for effective diagnosis prediction. Those approaches implemented on diseases diagnosing of pulmonary tuberculosis and obtaining better results in comparison to traditional approaches. This approach is an aggregation of methodologies that were combined various model and provide solutions to those problems that are difficult to handle in real-world situations. Researchers keep developing of an accurate and reliable intelligent decision-making method for the construction of pulmonary tuberculosis diagnosis system. The existing diagnostic testing system procedures are not only tedious, they also take a long time to analyze. Therefore, the diagnosis of tuberculosis still requires further improvements to new rapid and accurate diagnostic model and techniques that enable higher sensitivity and specificity to be achieved, thus promoting disease control and Prevention. State of the art makes approaches to soft computing more powerful, more reliable and more efficient. The importance of this review paper is to distinguish the different soft computing approaches used to support pulmonary tuberculosis disease diagnosis, identification, prediction and intelligent classification. In the field, researchers and medical practitioners look forward to using approaches to soft computing. Some of these are an artificial neural network, genetic algorithm, and support vector machine, fuzzy logic etc. latest methods in the diagnostic field uses artificial neural network. Some of the other benefits of Artificial neural network is an easy - to - optimize, resources and adoptable non - linear modeling of expansive data sets and predictive inference accuracy demonstrating that artificial neural network could serve as a valuable decision support tool in various fields, including medicine.

***Index Terms*: Artificial Neural Network, Fuzzy and Fuzzy Logic, Genetic Algorithm, Pulmonary Tuberculosis, Support Vector Machine.**

I. INTRODUCTION

Tuberculosis is a bacterial infection causing more death than any other infectious disease in the world [1]. Overall, the World Health Organization reported that there were 10.4 Million new tuberculosis cases with related deaths in 1.4 million in 2015 such as India, Indonesia and China having the largest number of cases: 23%, 10% and 10% of total global deaths, respectively [1], [2], [3] and [4], [5].

India is one of the 22 countries with a high burden. High-burden means that by 100,000 populations or more there are about 400 cases. In India, the World Health Organization estimated one million new TB cases per year and Every year 2,2 million individuals contracted tuberculosis and approximately 220,000 died of the disease [1][3]. Unfortunately, it detects only one-third of new cases of TB. The number shows a severe delay in treatment and diagnosis of TB. Long - term lung damage is associated with delayed treatment of PTB, often clinically mistaken for non - tuberculosis pneumonia due to symptom similarities and presentation of chest X - ray (CXR) [6]. They reported that a delay in treatment of more than twelve weeks would result in a greater extent of patients with serious TB, a higher mortality rate, and a more prominent disappointment in treatment [7][8]. For some reasons [9] and [10], diagnosis of tuberculosis is difficult. For pediatric patients with a small number of germs, the first reason [11], [12]. For some reasons [9] and [10], diagnosis of tuberculosis is difficult. The first reason is for pediatric patients with a few germs [10]. The second is for extra - pulmonary tuberculosis [12], [13] and the third for smear - negative pulmonary tuberculosis (SNPT) [14], [15]. Cough, hemoptysis, night sweats, fever, and weight loss are the suggestive symptoms of TB [16]. These symptoms are not only common to lung cancer [8], but also to other diseases [17], [18]. It leads to delays in proper diagnosis and exposure to inappropriate medication [8] as well as misdiagnosis and death [16]. A longer delay in pulmonary tuberculosis diagnosis avoids quick treatment, and the person remains confined. Furthermore, people receiving inadequate treatment are more vulnerable to multidrug-resistant tuberculosis [19], [20]. To overcome these problems, some studies have been done. Studies related to TB diagnosis were conducted as input parameters using sound, images, blood microRNA profiles, and variables. Some studies that use coughing sound detection algorithm to accelerate the process of TB diagnosis with a high degree of accuracy [21] and [6] and using lung sound waves as specificity. The image of the tissue of tuberculosis was used in many studies as an input to help pathologists [3], [8].

A Recent study was conducted using blood miRNA profiles, and the model was also tested using urine and saliva miRNA [6]. Furthermore, soft computing methods to analyze tuberculosis utilizing clinical indications as input have been broadly utilized in numerous studies [22].

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The objective of artificial intelligence (AI) is to imitate cognitive functions of humans. It brings a paradigm shift to healthcare, driven by increased healthcare data availability and rapid progress in analytical techniques [23], [24] and support to minimize complex subjective medical decisions. traditional quantitative analytical approaches inappropriate. Diagnostic tools and knowledge base based on computers certainly help to diagnose diseases early. The Smart systems also can handle inappropriate decision [25].

In the diagnosis of disease, these methods have been shown to be significant, facilitating the improvement of the quality of medical services. Soft computing techniques have attracted many medical diagnostic researchers for days now, and these techniques need to be characterized by high performance and ability to handle missing values and noisy data. Diagnostic systems handle a large quantity of biomedical data. Such a system's accuracy is an important aspect. In order to achieve accuracy, the classifier idea was adopted as different classifiers provide different views and their results are combined to achieve accuracy [25], [24].

To overcome these problems, some studies have been done. TB diagnostic studies were conducted using sound, images, and variables as parameters of input. In [6] and [3], some studies that use sound as an input are conducted. They used coughing sound detection algorithm [15] which uses lung sound waves to speed up the TB diagnosis process with high accuracy and specificity. However, nearly all feature extraction methods in previous works for cough detection are derived from the domain of speech recognition [3], [26]. Using the gamma tone filter bank and an audio feature extraction, the method used was sub-band features. Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Random Forest (RF) are trained and assembled with the relevant sub-band features [9].

However, datasets in health domain are highly imbalanced, voluminous, conflicting and complex in nature, and these can lead to erroneous diagnosis of diseases. It is therefore a challenging task in soft computing to design accurate and robust clinical diagnostic models for such datasets. Numerous standard intelligent models have been proposed for this purpose in literature, but they usually suffer from several disadvantages such as incomprehensibility, incapacity to operate rare cases, inefficiency to make quick and correct decisions, etc. [10], [27]. In fact, specific health application using standard intelligent methods may not satisfy multiple criteria [10], [24].

Recent research, however, indicates that intelligent methods can achieve better performance for health applications by integrating several standard ones [28]. Intelligent modeling is a growing need for data, as the amount of data stored in databases is increasing rapidly and the number of human data analysts is growing at a much lower rate than the amount of data stored and Machine learning is an excellent process to design these models [10]

Furthermore, doctor's intuition and experience are not always sufficient to achieve medical results of high quality. Therefore, medical errors and unwanted results are reasons for the need for state-of-the-art computer-based diagnostic systems that in turn reduce fatal medical errors, increase patient safety and save lives.

II. SOFT COMPUTING METHODS FOR TUBERCULOSIS DIAGNOSIS

The purpose of this study is to outline the relationship between different soft computing techniques and, in particular, the application of soft computing techniques to diagnosis and prediction of pulmonary tuberculosis diseases. This review therefore includes studies based on diagnosis of diseases and predictions using soft computing techniques.

Soft computing is an aggregation of methodologies for modeling and solving the problems that are onerous to deal with in real - world situations [29], [30]. To provide robustness and low - cost solutions, soft computing technique is introduced. The basic principle is to develop computational methods that lead to a satisfactory low-priced solution by exploring an indefinite or definite problem for the comparative solution [15], [24], [20], and [22]. Some soft computer techniques used to predict diseases are Fuzzy Logic, Artificial Neural Network and Genetic Algorithm [27].

Utilizations of delicate registering procedures in respiratory medicine are progressively suitable as they can deal with issues like nonlinearity, multidimensionality, and ambiguity contrasted with hard figuring, for example, probabilistic methodologies. Be that as it may, the number of research endeavors is lower because of the absence of accessibility of the joined area mastery. Information system researchers think that it is difficult to comprehend and demonstrating the infection, its portrayal and assessment. Then again, it is troublesome for respiratory prescriptions to understand the benefits of calculations, their coding and the important execution. Be that as it may, regardless of these obstructions, specialists have been making endeavors to screen and analyze respiratory illnesses utilizing delicate processing methods for a considerable length of time. In the accompanying segment, some ongoing examinations have been portrayed [6]. Medicinal basic leadership all in all is an intricate procedure with higher-dimensional, crude, and emotional clinical information being taken care of. Right choice requires an arrangement of the abnormal state observations and instincts of clinicians so as to comprehend a procedure of illness. Right determination relies upon the quantity of side effects coordinated with the reference sickness agents [6]. Manual conclusion is regularly individualized thus as the introduction of a disease. In this manner, the suitability of the term traditional ends up relative in clinical prescription. Uses of higher delicate figuring technique(s) and ideas of computational knowledge have huge research scopes in demonstrating the procedure of clinical finding because of its operational similarity. It likewise welcomes an open door for the cross-disciplinary research [31].

In addition, medical challenges are increasing gradually in developing countries such as India, [16].

Anyway right analysis of any illness depends on different, and typically ambiguous, information (highlights): for instance, laboratory pathologic assessment, lab and instrumental information, emotional anamnesis of the patient, and contemplations of the clinician. Clinicians are prepared to separate the significant data from each sort of information to distinguish conceivable analyses.

In conventional neural system application such information are designated "highlights". Highlights can be side effects, biochemical investigation information or potentially whichever other significant data helping in conclusion. Thusly, the experience of the expert is firmly identified with the last finding [10], [33].

Highlights that bring deficient, repetitive, non-explicit, or boisterous data about the examined issue ought to be kept away from. The determination/extraction of reasonable highlights among every accessible one is generally completed utilizing different methodologies. The most vital and best-known manipulating tools for variable determination are powerful scientific methods for data processing, for example, key parts principal of component analysis [9], [13] and [33].

A. Fuzzy logic

Fuzzy Logic (FL) used intelligence procedures that manages vulnerability in information and reproduces human thinking in an incomplete or fuzzy information [14]. It is an appropriate and pertinent reason for creating learning based system in differing parts of life, for example, wellbeing. It has been connected to translate sets of restorative discoveries and rule saves the structure of the justification and avoids escapes the logical inconsistency of component [14].

B. Artificial Neural Network

Artificial neural systems bio-driven intelligent framework, broadly connected to forecast, learning extraction of tasks and classification [10], [34].It trying to understand the intricacy of biological sensory system in order to concentrate on what may theoretically matter most from a data preparing perspective.

Medication has dependably profited in different territories of prescription, for example, biomedical examination, and medication advancement however widely utilized in determination to identify sicknesses, for example, disease and heart issues in human [34].

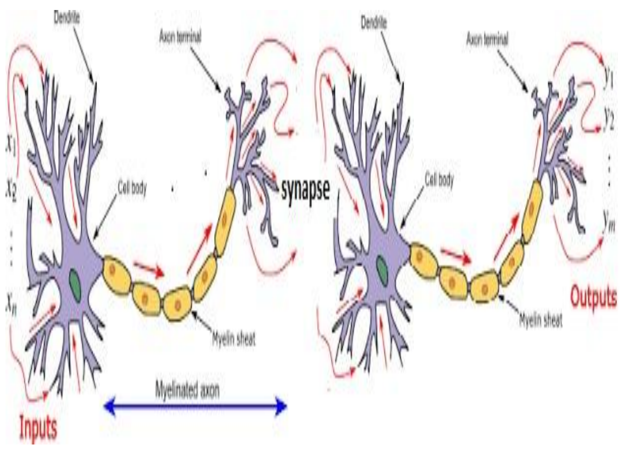


Fig. 1. Neural network Signal transmission between neuron

C. Multilayer perception

Multilayer Perceptron (MLP) Neural network to classify active and inactive pulmonary tuberculosis of the patient. Several studies have proposed useful architecture to predict the outcome of disease and stratify patients [34]. Automatically extracts cases used to characteristic parameters and produces a decision based on the existing parameter and rule such as classification, based on supervised training process learner algorithms how to predict dataset labels. The model used to classified one hidden and output layer [33], [36] and [37].

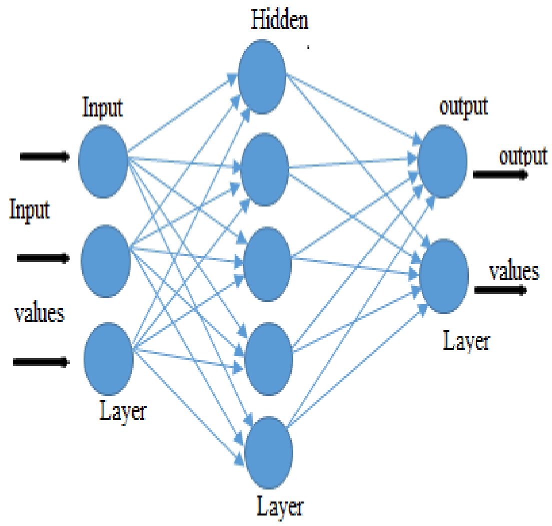


Fig. 2. Multilayer perceptron (MLP) neural network

The artificial neural network utilized in this work had an information layer made out of seven units, every one for every factor, and one yield layer made simply out of one neuron. Estimations of +1 and - 1 were utilized to speak to whenever input information relates to a patient with or without tuberculosis, individually. The hidden layer neuron was built up an exploratory way, testing from 2 to 10 neurons. All neurons had a hyperbolic digression work as enactment work. Between various learn to prepare the artificial neural network, [6], and [21] a cross-validation strategy was also considered in training. Training was conducted with two sets in each case (see Table IV) and validation results were calculated with the maximum classification rate between tuberculosis or not. An early stopping procedure has been implemented to avoid overfitting. The performance of the models obtained was evaluated using sensitivity, specificity, rates of classification, positive prediction and negative prediction measures as shown in Table III [37].

D. Genetic algorithms

A genetic algorithm is a technique for soft computing. It was used in the recognition of patterns, bioinformatics. In order to increase the chance of prosperous treatment, early detection of disease is very important. Soft computing techniques are used to identify a medical issue.

Such as genetic algorithm starts with a population of arbitrarily generated chromosomes. The current problem is solved by each chromosome [38], [39]. Improved chromosomes are achieved by applying genetic operators based on genetic processes that occur in nature. Because of its robust nature, the genetic algorithm had a good measurement performance finding and optimizing problems. It is developed specifically for large complex search spaces where [10], [27] and [39] are not well understood.

III. CURRENTLY USED METHODS FOR PULMONARY TUBERCULOSIS DIAGNOSIS

The most well-known attempts are intelligent classification systems. As neural models, conventional MLP and a variation were used and comparing their performance with two different data sets. The conventional MLP is better classification accuracy. [16], [17] and [40] some researchers compared several methods in order to study which method obtained the highest accuracy in diagnosing tuberculosis. [16], [17].

All these tests however have one of the main disadvantages because they are useless in distinguishing drug Resistance TB. It also takes time to evaluate outcomes and include invasive methods that are tedious to carry out some of the significant TB diagnostic tests. There have been several studies reported focusing on using different neural network models to diagnosis pulmonary tuberculosis disease achieved high classification accuracies using their various dataset [16], [21], [27], [33], [34] and [36].

In addition the intelligent methods such as artificial neural network have been intensively used for classification tasks and also both multilayer neural network and neural network structure successful disease diagnosis techniques [16],[27],[33],[34],[36].

Furthermore [41] the techniques used to analyze pulmonary tuberculosis (TB) disease using the neuro - fuzzy inference system are used as inputs for decision - making based on a predefined rule based on the patient's symptoms and the corresponding risk quotient for tuberculosis is evaluated as output and [41]. The result of crisp has also shown that we can diagnose the patient's low or high risk of disease [41]. Recently several neuro-fuzzy techniques have been reported in the literature [7], [9], [10] and [20] for classification of patterns.

Modern non-measurable pattern classifiers are mostly either expert rules-based systems or classifiers of artificial neural networks. Some attempts are made to integrate the two paradigms where neural networks are used to extract knowledge from raw data and to use approximate reasoning and fuzzy logic to perform inferencing. The most effective solution seems to be extracting knowledge from the raw data through artificial neural network and expressing it in a rule form to design the knowledge base of an expert system with a blurred inferencing method. But there are still many issues [20], [36] and [41] at various levels of designing such an intelligent classification system for real-world issues open to research.

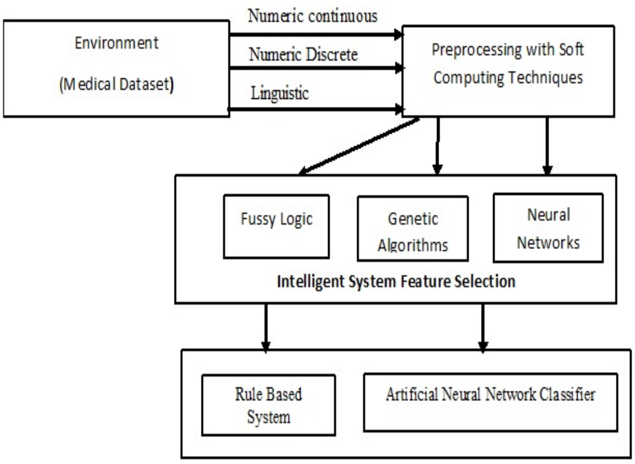


Fig.3. Modern Intelligent pattern Classification System

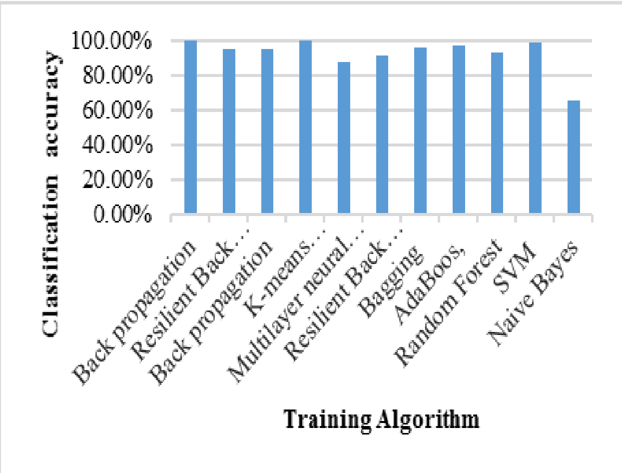
The datasets, methods & techniques, attribute or indicator, assessment measures & classification accuracies of pervious are shown in each column, respectively.

TABLE I. LISTOF ATTRIBUTE AND SIZE OF DATASET

Ref.	Database (Source)	Size of dataset	Attribute
Ibrahim *et al.*,2018	General hospital Mubi	270	11
Orjuela *et al.*, 2018	Hospital Santa Clara(HSC) Colombia 2008-2011	107	6
Joao *at al.*,2018	Policlínica Augusto Amaral Peixoto (PAAP) health center	1114	11
Rusdah *et al.*2017	Jakarta respiratory center perkumpulan pemberantasan tuberculosis Indonesia	1117	17
Joao *et al.*, 2016	General hospital of federal University of Rio de Janeiro 2010-2011	136	12
Omisore *et al.*, 2015	St. Francis Catholic Hospital Okpara-In-Land (Delta State, Nigeria),		24
Évora *et al.*,2015	Diyarbakir Chest Diseases Hospital from southeast of Turkey	357	38
Évora *et al.*, 2015	Do Rio de Janeiro (IETAPSES-RJ), De Referência Oswaldo Cruz – Rio de Janeiro (CRPHFFiocruz-RJ). 2011-2013	280	25

Winarko *et al.*, 2015	Jakarta respiratory center of tuberculosis from 2010-2014	1170	17
Évora *et al.*, 2015	KIMS Hospital, Bangalore	700	11
Errison *et al.*, 2013	IDT/HUCFF/UFRJ, 2001- 2008	972	19
Uçar *et al.*, 2013	Private Health Clinic in Istanbul 2000-2009	503	20
Asha *et al.*, 2010	A state hospital	250	12

Table I. summarized all the experiments' result. It showed that the comparison of accuracy, trained algorithms which classifiers could provide better performance. Besides, according to this fact, the aim of this review by comparing different method and techniques, which trained algorithm more accurate on different dataset. A graph showing in detail the comparison of accuracy, trained algorithms has been shown in fig 4.



A. Fig .4. Soft Computing Techniques Accuracy

A. Comparison of Different Classification Classifiers' Accuracy

There have been a few studies reported concentrating on pulmonary tuberculosis disease detection problem using artificial neural network system structures with respect to other clinical determination issues. These examinations have connected distinctive neural systems structures to the different chest diseases determination problem applying their different dataset [14], [16], [36]. In view of the different dataset used by the researcher, the immediate correlation of the outcomes was unimaginable. In this way, these neural systems were thought about utilizing the equivalent dataset which comprises of various highlights. So we can easily say that MLNN, Levenberg– Marquardt training as shown in Table III [16], [26], and [36].

Researchers compared several methods in order to study which method obtained the highest accuracy in diagnosing tuberculosis. The results showed that various intelligent system methods used for diagnosing tuberculosis are summarized in Table II.

TABLE II. LIST OF METHODS, TECHNIQUES, TRAINED ALGORITHM AND CLASSIFICATION ACCURACY

Ref.	**Methods & Techniques**	**Training Algorithm**	**Classification accuracy (%)**
Ibrahim *et al.*,2018	Adaptive neuro-fuzzy,	back propagation	99.6
Orjuela *et al* ,2018	Artificial neural networks	Back propagation	95
Joao *et al* ,2018	Artificial neural networks	Resilient Back propagation	95
Rusdah *et al*.2017	Discretization, Rough set	SVM – C5.0	97.59
Joao *et al*., 2016	ANN ,Multilayer perceptron	support vector machine	88
Zakhmi , 2016	Genetic algorithm and Neural network backwash	K-means Clustering, Support Vector Machine	99.73
Omisore *et al*., 2015	Genetic-Neuro-Fuzzy Inferential	Back-propagation algorithm	70
Évora *et al*.,2015	Artificial neural networks	multilayer neural network (MLNN)	91
Évora *et al*., 2015	Feed forward Multilayer Perceptron (MLP)	Resilient Back propagation	91.3
Winarko *et al*., 2015	Ensemble	SVM, C4.5, Naive Bayes and Back propagation	70.67, 66,93, 65.58, 63.73
Évora *et al*., 2015	K-Means Clustering	SVM,	98.7
Uçar *et al*., 2013	ANFIS and rough sets	ANFIS Rough sets	97 92
Asha *et al*., 2010	Supervised Machine Learning (ML)	Bagging and AdaBoos, Random Fores	96.00, 97.00, 93

TABLE III. COMPARISON OF METHODS & TECHNIQUES' WITH ACCURACY ON TRAINING DATASETS

Methods & Techniques	**Usage of training dataset (%)**	**Accuracy on percentage (%)**	**Ref.**
Rough Set, discretization function	70.00	97.59	Rusdah *et al*.2017
ANFIS	66.70	99.60	Ibrahim *et al*.,2018

MLP	75.00	95.00	Joao *at al.*,2018
k-means algorithm	50.90	91.30	Errison *et al.*, 2013
MLP ,Support Vector Machine(SVM)	75.00	88.00	Joao *et al.*, 2016
Artificial Immune Recognition Algorithm	80.00	99.14	Shamshirb and *et al.*, 2014

The researcher has attempted to show that an instance selection procedure is assumed [12], [34]. Therefore the primary goal of splitting the data set was to share the most common similar characteristics and differentiate a cluster algorithm.

Early diagnosis of pulmonary tuberculosis was used in their 2017 TB diagnosis study using ensemble method [12].They used 1170 samples with seventy features classified by incorporating a C5.0 & SVM. This modified Moran's approach resulted in the highest learning rate classification accuracy (a) with a value of 0.8[12]. As shown in Table II, the method was (84.54 %) accurate, (84.24 %) sensitive and (85.54 %) specificity [14]. By applying artificial neural network model support to easily detect active pulmonary tuberculosis disease. [14] was the focus of their 2018 finding. The newly developed Multilayer Perceptron (MLP) is viewed for various diagnostic purposes as a potential algorithm and they got viable TB screening performance of 95% as shown in fig 5. The two methods like artificial neural network and genetic algorithms are certainly proved as a very successful diagnostic model [27].

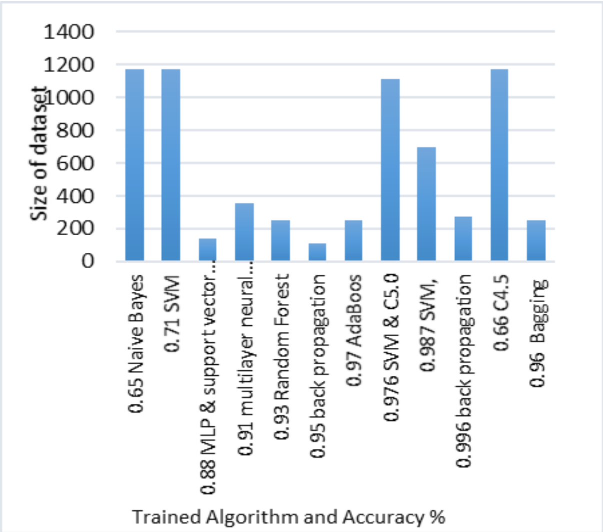


FIG 5. COMPARISON THE SIZE OF DATASET WITH CLASSIFICATION ACCURACY (%)

B. Performance of analysis of testing phase result on different models using cross- validation

There are few studies related to intelligent system for diagnosis of tuberculosis using different soft computing techniques. Most of these studies have high classification accuracy rates. These studies used cross- validation to evaluate the performance of the trained and test dataset.

Cross-validation is a measurable approach utilized in this analysis to assess the execution of learning algorithms and performance of on an unknown dataset of a predictive model. Consequently, the informational collections utilized in research are isolated into a few sub-sets of equivalent size applying cross-validation. On certain subsets known as training sets, the learning model is then learned. 16], [17], [34]. Depending on the number of partitioned subsets. For 10-fold cross validation, the researcher tests K-fold cross-validation and have got 10 results as shown in Table III of various researcher experiments, for training models, different 10 tests are considered for 10-fold cross validation [16], [17], [18], [34], and [36].

Describes the performance achieved as prognostic models for pulmonary tuberculosis (PTB) using alternative computational intelligence methods. Between smear negative PTB cases, the world health organization algorithms, the standard reported of clinical work and chest analysis shows sensitivity values ranged from (58.8 %) to (95 %) and between (79.4 %) and (98 %). Thus, the current model achieves similarly to other scores that include CXR only by using signs and symptoms. With regard to MLP-based PTB screening models, the current clinical score using [14]. Twelve variables are similar in accuracy (88 %) to those reported by [42]. (19 variables and 93.3% accuracy), [14] (11 variables and 95% accuracy).

Approximate probability of active pulmonary tuberculosis was provided by the output of the Rough set, SVM. To train the neural networks, the study used a 10-fold cross-validation procedure and accuracy of the diagnosis result report approximately (84.54) [12] the study performing the classification procedure for artificial immune system structure for chest diseases, 10- Fold cross validation method was used to estimate the performance of the Artificial Intelligence System used and MLNN was accurate with a single-hidden layer (90.48%), while the precision was hidden (93.84%) with two layers., hidden layers are therefore the best result of the accuracy of the classification.

Because there are 257 patient data and 100 healthy data in the entire dataset, there were 36 samples in each fold. Of these 36 samples, 26 were taken from records of patients, while the other 10 were healthy individuals. The classification algorithm was trained and tested 10 times. In each case, one of the folds is taken as test data and the remaining folds are for the training data as shown in Table IV [18]

Table iv. Comparison of classifier using cross-validation, accuracies, sensitivity& specificity.

Study Author	Classifier	Testing performance		
		Accuracy (%)	Sensitivity (%)	Specificity (%)
Joao *at al.*,2018	Multiple layer perception	95.00	92.00	58.00
Orjuela *et al.*, 2018	MLP, SOM	95.00	97.00	71.00
Badnjevic *et al.*,2017	fuzzy logic	97.00	97.26	70.74
Rusdah *et al.*2017	C4.5, Naive Bayes, SVM	84.54	85.24	85.24
		83.31	84.46	84.46
Joao *et al.* 2016	MLP	88.00	95.00	80.00
	support vector machine		86.00	60.00
Omisore *et al.*, 2015	Back-propagation algorithm	70.00	60.00	
Evora *et al.*,2015	forward-propagation algorithm	91.3	95.15	85.47
Shamshirb and *et al.*, 2014	fuzzy logic	99.14	87.00	86.12
Asha *et al.*, 2010	Random Forest	93.00	97.00	96.00

Summarization of the above table IV. The result showed to evaluate the performance of the pulmonary tuberculosis diagnosis predictive models using 10-fold cross validation. The intelligent system's performance, classification accuracy, sensitivity, specificity and usefulness were examined using real medical data for the experiments.

Another researcher used the patterns of inputs to form 14 distinct parameters divided into two group's major demographic variables and findings of constitutional symptoms as shown in Table I. The table above showed that using 10 fold cross validation such intelligent system techniques will help medical experts to improve the quality of healthcare services they provide.

IV. CONCLUSION

This study's main objective is to identify, categorize and evaluate the importance of various soft computing techniques for diagnosing and predicting diseases. This review's main findings are summarized as follows:

Several literatures gathered from many sources that are classified through the size of dataset used for training and testing algorithm, attributes (variables), data preprocessing techniques and methods, comparison of classification accuracy used for tuberculosis diagnosis analysis. From those selected literatures that have been reviewed. We presume that, utilization of soft computing method in medicinal finding have been revealed for PTB diagnosis and prediction. Besides that several researcher observed artificial neural network and genetic algorithm are connected to acquire the upgraded estimation of SVM and artificial neural network (ANN). Fuzzy logic and neuro fuzzy approach support rules to design expert system. The tenets are depicted as on the off chance that, at that point k-nearest Neighbor clustering techniques are embraced to locate the significant parameters of the diseases. Further, it is expressed that the improvement in pulmonary tuberculosis detection with clinical practice is laid in the structuring of insightful system arranged to maladies side effects. Subsequently likewise, insight intelligent system tools can be seen as a potential detection mechanism and for tuberculosis as well as for many life - threatening diseases. This review work can be extended using other soft computing techniques and also for other diseases & finally for a complete medical expert system.

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