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MACHINE LEARNING TECHNIQUES FOR MEDICAL DIAGNOSIS: A REVIEW

Josna M Alexander, Reeja Susan Reji, Riya Raju, Abhay P Anish(Students at Kristu Jyothi College of Management and Technology, Changanassery, Kerala, India)

ABSTRACT

Machine learning algorithm can essentially help in taking care of the medical services issues by creating classifier frameworks that can help doctors in diagnosing and anticipating infections in beginning phases. Nonetheless, removing information from clinical information is trying as this information might be heterogeneous, disorderly, and high dimensional and may contain commotion and exceptions. Most fitting strategy can be picked solely after investigating all the accessible AI procedures and approving their exhibitions as far as precision and fathomability. This writing has looked into the utilization of AI calculations like decision tree, support vector machine, random forest, evolutionary algorithms and swarm intelligence for accurate medical diagnosis. The reliance on clinical pictures for diagnosing an illness is on ascent. Since deciphering current clinical pictures is turning out to be progressively intricate, AI calculations in clinical imaging can give critical help with clinical finding. AI strategies could be utilized for huge scope and complex organic information investigation as these methods are effective and modest in taking care of bioinformatics issues.

Keywords: Decision Tree, Evolutionary Algorithms, Machine Learning, Medical Diagnosis, Protein Function Prediction, Random Forest, Medical Imaging, Swarm Intelligence, Support Vector Machine.

1.INTRODUCTION

Machine learning, a sub discipline in the field of Artificial Intelligence, explores the study and design of algorithms that can learn from data [1]. AI gives techniques/calculations that make framework computationally shrewd. Such calculations fabricate models dependent on information and afterward utilize these models to settle on expectations or choices.

AI is basically valuable in situations where algorithmic/deterministic arrangements are not accessible for example there is an absence of formal models or the information about the application space is scant. The calculations have been created in assorted arrangement of disciplines like statistics, computer science, robotics, computer vision, physics, and applied mathematics. Benefits of AI over factual models are precision, mechanization, speed, adaptability and versatility.

As medication assumes an extraordinary part in human existence, robotized information extraction from clinical informational collections has become a colossal issue. Research on knowledge extraction from medical data is growing fast [2]. All exercises in medication can be isolated into six undertakings: screening, analysis, treatment, visualization, checking and the executives. As the medical services industry is turning out to be increasingly more dependent on PC innovation, AI techniques are needed to help the doctors in distinguishing and relieving irregularities at beginning

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phases. Clinical analysis is one of the significant exercises of medication. The precision of the finding contributes in choosing the right treatment and along these lines in fix of sicknesses. Machine Learning is extensively used in diagnosing several diseases such as cancer [3], [4], [5], diabetes [6], heart [7] and skin diseases [8]. Utilization of Machine learning calculations works on the indicative speed, precision and unwavering quality. Among various algorithms in data modelling, decision tree is known as the most popular due to its simplicity and interpretability [8], [9]. Recently, more efficient algorithms such as SVM and artificial neural networks have also become popular [2], [4], [10].

Further, medical imaging has also been one of the most successful techniques to diagnose diseases related to the internal human organs [11], [12], [5], [4], [13], [14]. Albeit the way toward recognizing any anomalies in the caught pictures is totally reliant upon the determination given by the radiologist/doctors, yet the development of the clinical information has made it hard for radiologists or doctors to keep record of all the conceivable finding of different sicknesses. Utilization of AI in clinical imaging can help less just as profoundly experienced radiologists in diagnosing the intricate cases.

It has been observed from literature review that research is also being done in application of machine learning algorithm in areas such as protein function prediction and gene expression [15], [16]. Dissimilar to arrangement and construction based techniques for protein work forecast, AI strategies don't need unequivocal information on homology and homology-determined boundaries with the end goal of capacity expectation. In this way research on creating proper AI methods for forecast of protein work for infection determination is on ascent.

This paper investigates the AI strategies that have been used in building PC supported conclusion. Segment II momentarily presents about the different characterization calculations utilized in clinical area. Segment III audits the writing canvassed in five significant regions: Decision trees, Support vector machine, Random timberland, Evolutionary calculation and Swarm insight. The last segment finishes up and underlines the future work in this area.

2.BACKGROUND DETAILS

Grouping calculations are generally utilized in different clinical applications. Information characterization is a two stage measure in which initial step is the preparation stage where the classifier calculation assembles classifier with the preparation set of tuples and the subsequent stage is arrangement stage where the model is utilized for grouping and its presentation is investigated with the testing set of tuples. Brief about the different order calculations in clinical space are:

2.1 Decision Tree Algorithm

The decision tree is one of the classification algorithms. The learning algorithm applies a divide and conquer strategy to construct the tree [17]. The arrangements of examples are related by a bunch of traits. A choice tree contains hubs and leaves, where hubs address a test on the upsides of a trait and leaves address the class of a case that fulfills the conditions. The result is true or false. The tree pruning must be done to eliminate superfluous preconditions and duplications.

2.2 Support Vector Machine

SVM calculations depend on the learning framework which utilizes the factual learning technique and they are prevalently utilized for arrangement. In SVM procedure, the ideal limit, known as hyperplane, of two sets in a vector space is gotten freely on the probabilistic dissemination of preparing vectors in the set. This hyperplane finds the limit that is generally far off from the vectors closest to the limit in the two sets. The vectors that are put close the hyperplane is called supporting vectors. In the event that the space isn't straight distinct there might be no isolating hyperplane. The portion work is utilized to take care of the issue. The portion work examinations the relationship among the information and it makes an intricate division in the space.

2.3 Random Forests

Arbitrary backwoods calculation is truly outstanding among order calculations and can arrange huge sums of information with high exactness. It is an outfit learning technique building models that develops various choice trees at preparing time and yields the modular class out of the classes anticipated by singular trees. It is a blend of tree indicators where each tree relies upon the upsides of an arbitrary vector tested freely with similar circulation for every one of the trees in the woodland. The essential guideline is that a gathering of "feeble students" can meet up to frame a "solid student".

2.4 Evolutionary Algorithms

A Genetic Algorithm (GA) is a transformative and stochastic technique for discovering ideal arrangements in enormous and complex pursuit spaces. A GA is enlivened by normal development: a populace of encoded applicant arrangements (called "chromosomes") is developed through ages utilizing hereditary like tasks like hybrid and change. At every age, arrangements are probabilistically chosen dependent on their wellness, to produce posterity and make the future. The underlying populace is haphazardly created, and at every age, each up-and-comer arrangement is considered in contrast to a target work to acquire a wellness score. In a learning framework, the target work is normally the proportion of the exactness of an applicant over a preparation set of occasions.

2.5 Swarm Intelligence

Swarm intelligence (SI) is a computational intelligence technique to solve complex real-world problems. It involves the study of collective behaviour of individuals in a population who interact locally with one another and with their environment in a decentralized control system. The inspiration often comes from nature, especially biological systems. The agents follow very simple rules, and although there is no centralized control structure dictating how individual agents should

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behave, local and to a certain degree random interaction between the agents lead to an "intelligent" global behaviour which is unknown to the individual agents. Some of the popular SI algorithms are Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC).

3. REVIEW OF LITERATURE

Classification of medical data is a complex optimization problem. The aim is not just to find optimal solution but to provide an accurate diagnosis. Many researchers are applying different kinds of machine learning algorithms for solving this problem. This section reviews the literature covered in five major areas: Decision trees, Support vector machine, Random forest, Evolutionary algorithm and Swarm intelligence.

3.1 Decision Trees

Research on using decision trees for medical classification or disease diagnosis purpose has caught a lot of attention in recent past [9], [18]– [21]. Among various algorithms in data classification, decision tree is known as one of the most popular due to its simplicity and interpretability [2].It has been utilized in the finding of sicknesses, for example, bosom malignant growth, liver malignant growth, cerebrum tumour and dermatologic infections.

Decision tree has been used as classifier for breast cancer diagnosis [18], [19], [20]-[22].It has been compared with different classification algorithms in each paper such as ANN, logistic regression, Bayesian network, KNN and case based reasoning. Case based fuzzy decision tree outperforms other approaches with an average accuracy rate of 99.5% in breast cancer diagnosis [21]. Azar and ElMetwally [9] proposed a decision support 3waEXzTD45tool for the detection of breast cancer based on three types of classifiers. They are single decision tree SDT, boosted decision tree (BDT) and decision tree forest and reported that BDT performed better than SDT with 98.83% and 97.07% accuracy respectively. Yeh et al. [23] presented decision tree model as the optimum model for cerebrovascular disease with accuracy of 99.59% in comparison to Bayesian classifier and back propagation neural network. Luk et al. [24] proposed classification and regression tree (CART) model that provides discrimination between Hepatocellular Carcinoma (HCC) and non-malignant liver tissue. HCC is known as the riskiest malignancy due to not being analysed until cutting edge tumour stages. Choice tree calculations were effectively applied for building characterization model dependent on secret example in the issue dataset. Further, Fan et al. [21] proposed model case based reasoning and fuzzy decision tree (CBFDT) for liver disease whose accuracy is highest among various other models with accuracy of 81.6%. Significant limits of choice tree in clinical information are imbalanced and cost affectability issue. Further they are touchy to conflicting information.

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3.2 Support Vector Machine

SVM calculations have been proposed as a successful measurable learning strategy for order as a result of their high speculation execution. Naturally, given a bunch of focuses which have a place with both of the two classes, a SVM can discover a hyperplane having the biggest conceivable part of points of a similar class on something similar plane. This hyperplane, called the ideal isolating hyperplane (OSH), can limit the danger of misclassifying instances of a test set.

There has been a lot of research on medical diagnosis of breast cancer using SVM with Wisconsin breast cancer diagnosis (WBCD) data in literature and most of them reported high classification accuracies [25] – [30]. In Polat and Gunes [26], least square SVM was used and an accuracy of 98.53% was obtained. Further, SVM model with grid search and feature selection was proposed [27], [28] for breast cancer diagnosis. When using SVM, two problems are confronted: how to choose the optimal input feature subset for SVM and how to set the best kernel parameters. Feature selection limits the number of input features in a classifier in order to a good predictive and less computationally intensive model. In addition to the function selection, right model parameters putting can improve the SVM category accuracy. The parameters that have to be optimized encompass penalty parameter C and the kernel feature parameters along with the gamma (c) for the radial basis feature (RBF) kernel. F-rating is customized to discover the essential functions, and the grid search approach is used to look the most beneficial SVM parameters. Proposed version showed 99.51% accuracy for eighty-20% training-take a look at partition. Hassanien and Kim [31] identified breast cancer using hybrid technique (ANN + SVM + Fuzzy). The proposed method utilized kind-II fuzzy algorithm for improving the quality of MRI photo. Then, segmentation became achieved using pulse coupled neural networks a good way to extract areas of hobby. Wavelet capabilities were extracted from these areas and finally, SVM became used for the real analysis and discrimination of various regions of interest to decide whether they constitute cancer or no longer. Results showed that the accuracy presented by proposed hybrid version using SVM turned into high in comparison to other system gaining knowledge of algorithms inclusive of selection tree, neural 0

SVM has been largely and efficaciously utilized in hybrid approach for clinical diagnosis of diverse sicknesses which includes Genetic + Fuzzy + SVM for the prognosis of diabetes, liver and coronary heart diseases [10], ANN + SVM for prostate cancer prognosis [32], ANFIS + SVM for ache identification [33] and nonnegative matrix factorization + SVM for Alzheimer's ailment [14]. However, sensible obstacle of the SVM-primarily based category model is its black-field nature. A viable answer for this trouble is the use of SVM rule extraction techniques or using hybrid-SVM model blended with other more interpretable fashions.

3.3 Random Forest

Research has been completed the usage of Random forest as a classifier and feature choice set of rules for clinical diagnosis. Ozcift [34] used nice first seek random forest set of rules to select most reliable features for 4 scientific datasets: colon cancer, leukemia cancer, breast cancer and lung cancer. The proposed model with extracted functions accuracy was in comparison with 15 broadly used classifiers educated with all functions and confirmed stepped forward classification accuracy. Nguyen et al. [35] extensively utilized random wooded area classifier mixed with function choice for breast cancer analysis and stated ninety 99.82% category accuracy. Taking into consideration

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sensitivity, specificity and ordinary classification accuracy, random woodland is ranked first amongst all the classifiers tested in prediction of dementia the use of several neuropsychological assessments [36]. Random forest has been correctly used as a classifier in the analysis of illnesses along with Abdominal lymphadenopathy [37], Alzheimer's sickness and cardiovascular danger.

3.4 Evolutionary Algorithms

Genetic algorithms (GA) are utilized in growing the decision assist machine for the analysis of numerous diseases inclusive of breast most cancers [38], prostate most cancers [39], mind tumour [40], colon cancer [41] and heart illnesses [42]. Evolutionary algorithms (EAs) are commonly mixed with different type algorithms to form hybrid systems to expand pc aided diagnosis for certain organs [41] – [44]. Chaochang et al. [43] built a diagnostic version for high blood pressure by means of a hybrid of GA, apriori and decision tree with excessive accuracy. [41], [42] diagnosed coronary heart sicknesses, colon, lymphoma and leukaemia most cancers by hybrid fuzzy + GA. Asymptomatic carotid stenosis is considered as an important component of stroke. It has several threat elements inclusive of smoking, hypertension, diabetes, cardiac illnesses and physical state of no activity. Bilge et al. [44] discovered regulations for these hazard factors and asymptomatic carotid stenosis through hybrid technique of GA and regression. EAs are usually applied in scientific facts mining as a parameter finder. Evolutionary techniques search for the parameter values of the expertise illustration installation via the designer so that the mined facts are optimally interpreted (presence or absence of sickness). A GA efficiently searches the sizeable boundary functions of the mind tumour vicinity and feed them to ANFIS [40]. A GA searches for most fulfilling shape and training parameters of neural network for a higher prediction of lung sounds and consequently reducing the processing load and time [45]. A system has been developed to analyse digital mammograms the using of novel neuro-genetic algorithm [46]. The device starts first by using extracting capabilities, then the GA selects the maximum sizeable functions and makes use of them as input to a neural network. This machine has completed a completely exceptional overall performance. Genetic programming at the side of other class algorithms are used to broaden version for disease prognosis which includes ANN + GP to diagnose thalassemia [47], choice tree + GP for chest ache diagnosis [48] and GP with photo processing strategies to hit upon lung abnormalities at an early stage [49].

3.5 Swarm Intelligence

Swarm intelligence (SI) algorithms along with PSO, ACO are typically used as perfect pre-processing tools to help optimize function choice in classifier systems for clinical diagnosis. This will increase the classification accuracy and maintains the computational assets needed to a minimal [50]. Improved binary particle swarm optimization (IBPSO) is used to implement a feature (gene) selection, and a Knearest neighbour (K-NN) serves as an evaluator of IBPSO for gene expression information type problems [51]. The category accuracy obtained by the proposed method turned into the very best in 9 out of the 11 gene expression statistics take a look at problems. An ACO has been used to select appropriate wavelet coefficients from mass spectral records as function selection technique for ovarian most cancers analysis and has confirmed high category accuracy [52]. Hybrid class fashions are evolved the usage of PSO/ACO for the prognosis of several diseases. Case based totally reasoning + PSO (CBRPSO) and SVM +PSO hybrid fashions for analysis of breast cancer have additionally been proposed [53], [54]. The CBRPSO has been discovered to outperform the alternative procedures with

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an average accuracy charge of round 97.4% for breast most cancers. The CBRPSO model is likewise used for liver problems with a mean accuracy of 76.8%. Hybrid version using PSO with different type algorithms for prognosis of coronary artery disease [55], leukaemia [56] and MR brain photo classifier [13] had been proposed with excessive category accuracy. Thus, SI algorithms had been used as optimization strategies in many regions consisting of feature optimization, ANN training, fuzzy system manipulate and medical analysis.

4. CONCLUSION

Successful implementation of device mastering algorithms in scientific diagnosis can help the mixing of computer-based systems inside the healthcare environment. Especially in developing and exceedingly populated country like India in which mortality ratio is excessive and there is handiest one health practitioner for each 1700 humans, machine mastering strategies in scientific prognosis can assist physicians to diagnose and remedy illnesses at early level. Technology can no way to update a doctor's experience and knowledge, but it is able to contend with exceptionally sincere but time eating diagnostic tasks and doctors can take in clinically extra disturbing method.

The dependence on scientific pictures for diagnosing a sickness is on rise. Since deciphering current clinical pictures is turning into more and more complicated, device getting to know algorithms in scientific imaging can offer sizeable help in scientific analysis. They can assist interns or much less skilled physicians to reliably evaluate medical pictures and therefore enhance their diagnostic accuracy, sensitivity and specificity.

Protein characteristic prediction is any other vital area wherein device studying techniques have a important role to play. Machine mastering techniques could be used for big scale and complex biological records analysis as those strategies are efficient and less expensive in solving bioinformatics issues. The research in this area will not only be beneficial for physicians in phrases of diagnosing diseases, it could also help fitness planners for diagnosing and stopping sicknesses at a big scale.

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