

Data Analysis in health care using competitive ensemble machine learning technique

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Abstract

Machine learning (ML) has become an important tool in healthcare for disease prediction, diagnosis, and treatment. Ensemble methods have been developed to improve the performance of individual ML algorithms by combining them. However, traditional ensemble methods do not consider the competitiveness of the individual algorithms. Competitive ensemble methods have been developed to address this issue. This review paper provides an overview of the competitive ensemble machine learning technique in healthcare and its applications in various diseases. It also discusses the challenges and future directions for competitive ensemble machine learning in healthcare.

Keywords: machine learning, health, competitive ensemble, ML algorithms

1. INTRODUCTION

The supervised classification function normally uses a sample of historical data gathered from the training samples already available to calculate the forecast outcome. The testing sample is subsequently used to validate the trained classification model, which was developed using the data acquired from the training samples. The training sample is necessary for training the classification algorithm. We call this guided learning. To make the classification process as effective and efficient as possible, one of the main goals in classification is to attain a high accuracy with a little amount of training samples. Although the classifier used for classification has a high accuracy rate, some context-sensitive data mining jobs may not be suitable for it.

In this situation, creating an ensemble of classifiers by merging one or more classifiers is helpful for obtaining the classifier with the highest predicted accuracy. The classification model can perform better by using these ensemble modeling techniques. These classifiers are frequently referred to as ensemble classifiers. AdaBoost and Packing are two of the most famous and

engaging troupe learning calculations that produce more exact forecasts than the by and large acknowledged substitutes. The craft of troupe includes blending various individual models to make do on the working of the model. This could expand consistency, strength, or infrequently even both.

AdaBoost and packing are two instances of notable troupe classifiers that attention on execution. Yoav Freund and Robert Schapire fostered the AI meta-calculation known as AdaBoost [1], which represents Versatile Helping. AdaBoost is viewed as the best out-of-the-crate classifier when utilized with choice trees as the powerless students [2]. A well known technique for summing up the order exactness in light of the information sacks is given by packing [3].

The two techniques mentioned above are employed in the majority of applications, although their generalization to new datasets has not been thoroughly studied. Many evaluation methodologies can be used to investigate and assess the model's overall correctness. In this paper, the k-fold cross-validation method is one such technique.

1.1. Background of the Study

In order to forecast, diagnose, and cure diseases, machine learning (ML) has been widely applied in the medical field. By mixing different ML algorithms, ensemble approaches have been created to enhance the performance of the individual algorithms. Conventional ensemble techniques like bagging and boosting mix distinct algorithms without engaging in competition. Individual algorithms, however, compete with one another in competitive ensemble approaches to make the best forecast. In the field of healthcare, this competitive ensemble machine learning technique has demonstrated promising outcomes.

2. Applications of Competitive Ensemble Machine Learning Technique in Healthcare:

Many healthcare issues, including disease prediction, diagnosis, and treatment, have been addressed using competitive ensemble machine learning techniques. The following are some examples of competitive ensemble machine learning applications in the healthcare industry:

Breast Cancer: The prediction and diagnosis of breast cancer have been accomplished using competitive ensemble machine learning. SVM, ANN, and k-Nearest Neighbors (k-NN) algorithms served as the foundational classifiers [4]. A linear discriminate analysis was the meta-classifier that was employed (LDA). A genetic algorithm was utilized as the selecting method (GA). The accuracy of the competitive ensemble machine learning technique was 96.2%.

Diabetes: The prediction and diagnosis of diabetes have been accomplished using competitive ensemble machine learning techniques. SVM, decision trees, and Naive Bayes algorithms served as the foundational classifiers. Logistic regression was the meta-classifier that was utilized [5].

Particle swarm optimization was the selection method employed (PSO). The accuracy of the competitive ensemble machine learning technique was 91.4%.

Lung Cancer: The prediction and diagnosis of lung cancer have been performed using competitive ensemble machine learning. SVM, ANN, and decision tree algorithms served as the foundational classifiers [6]. AdaBoost was the meta-classifier that was employed. GA was the selecting method employed. The accuracy of the competitive ensemble machine learning technique was 93.2%.

2.1. Machine Learning in Medical Imaging

Research in medical imaging is expanding quickly since it is frequently necessary to diagnose disorders. When examining the machine learning process for producing predictions from a picture, several processes may be distinguished. An image will be broken into many pieces after being provided as input in order to zoom in on the desired location. Features can then be drawn out of those locations using information retrieval techniques. The necessary features are picked out of them, and the noise is eliminated. After classifying the retrieved data, the classifier will next make predictions based on the categorization.

Accurate disease diagnosis using extensive medical data processing is becoming essential in the medical community. Machine learning algorithms are being used for a variety of tasks in the fields of biology and medicine. Among the applications are the distributions of data based on their characteristics, the investigation of clinical information, the preparation of infection conclusion and therapy, the assortment and assessment of information, the amendment of analytic of different illnesses by clinical imaging, and the extraction of highlights from clinical pictures on sicknesses.

As far as life systems and medical procedure, the skull is one of the most confounded pieces of the human body, making careful attention very testing while managing a great many problems. However, as of late, the endonasal endoscopic course has been viewed as a reasonable technique for treating various injuries that start from the skull. One significant advantage is that utilizing an endoscope to do a skull-based a medical procedure through the nose considers the immediate perception of the neurovascular engineering of different areas of the skull base with minimal measure of cerebrum development and control. Moreover, the endoscope offers a more extensive and multi-age close-up view, which is extremely helpful in the careful field [7]. With regards to conditions like rectal malignant growth, X-ray assumes a pivotal part since it can precisely portray the neighborhood degree of the illness and create the relevant information required for guesses, which can straightforwardly influence the choice of the best restorative methodology for every patient, supporting the field of customized medication [8].

2.2. Machine Learning for Drug Repurposing

System biology is used More than 90% of medications that fail during the initial stages of clinical trials do so for reasons including negative reactions, side effects, or ineffectiveness. The idea of repurposing drugs has been suggested as a solution to these problems. Both drug- and disease-based repurposing are possible. Strongly ant correlated medications are most likely candidates for repurposing. The first study to investigate the functional relationship of medications was the connectivity map. It even took into account how diseases and medications function together. By focusing on the interactions of the parts of biological entities, systems biology can be 271ignalin to find and develop medications. Medications are ranked according to how much gene-related disease-specific disruption they induce.

The knowledge about disease-related genes, therapeutic targets, 271ignaling pathways, and gene-gene interactions is combined to create a drug disease network (DDN).

The Kyoto Encyclopaedia of Genes and Genomes (KEGG) 271ignaling pathways are used to define all interactions between medication targets and genes relevant to a specific disease. These interactions are represented by the DDN. The Pearson correlation coefficient between the gene perturbation signatures of the drug-disease pairs is used to determine the repurposing scores, which can range from 1 to 1. A high positive value suggests that the drug and the disease affect the system in ways that are comparable to each other, whereas a high negative value suggests that the drug and the disease have opposite signatures of gene disruption. This value can be used to determine whether a medicine is one that might be used to treat a specific condition [9].

Consequently, it is evident that when a patient seeks assistance from healthcare, decision-making begins with the patient's disease diagnosis and continues through the patient's prescription of the right treatment or drug. Healthcare uses machine learning methods in this process, which is a chain of decisions, to support each choice. Machine learning techniques are being used to support physicians in making prompt and accurate decisions on tasks like disease prediction or diagnosis, hidden disease detection, clinical decision support, and even determining whether a medicine is suitable as a treatment for the specified ailment. Moving forward, even after a patient has been cured of a condition, their EHRs are processed and analysed using machine learning techniques to find any potential future health hazards.

3. METHODS

By increasing the precision and effectiveness of disease prediction and diagnosis, machine learning has the potential to change healthcare. Healthcare has made extensive use of ensemble machine learning approaches, which integrate various machine learning models to increase performance. The assumption made by these methods—which may not be accurate—is that each model in the

ensemble is equally effective. To solve this problem, competitive ensemble machine learning approaches have been presented [14]. These techniques make use of competition to choose the best models for the ensemble.

3.1. Competitive Ensemble Machine Learning Technique:

A competitive way of merging individual machine learning algorithms is known as competitive ensemble machine learning. Individual algorithms compete against one another in this method to deliver the best forecast [10]. The base classifiers, meta-classifier, and selection method are the three essential elements of the competitive ensemble machine learning technique. Individual AI (ML) procedures, for example, choice trees, support vector machines (SVMs), and counterfeit brain organizations, act as the key classifiers (ANNs). The outputs of the base classifiers are combined by the meta-classifier. The best base classifiers are chosen by the selection technique for the meta-classifier to combine.

3.2. Competitive ensemble machine learning techniques have been applied to various healthcare tasks, including:

- Disease diagnosis: Techniques for competitive ensemble machine learning have been applied to increase the precision of illness diagnosis, including Alzheimer's disease and breast cancer.
- Drug development: To anticipate drug toxicity and efficacy, competitive ensemble machine learning approaches have been utilized, which has increased the effectiveness of drug discovery.
- Analysis of electronic health records: To forecast illness risk and outcomes, competitive ensemble machine learning techniques have been used to the analysis of electronic health data.

3.3. Advantages of Competitive Ensemble Machine Learning Techniques:

Comparing competitive ensemble machine learning techniques to classic ensemble techniques, the following benefits are present:

1. Increased accuracy: Competitive ensemble machine learning approaches choose the best models for the ensemble, increasing the precision of the forecasts.
2. Less bias: While competitive ensemble machine learning algorithms can still favour some models over others in the ensemble, this bias is lessened because the models are chosen based on performance.

3. More interpretability: Competitive ensemble machine learning approaches can reveal the significance of several features or models for the prediction, leading to greater model interpretability.

4. Discussion

By enabling more precise and effective diagnosis, individualized therapies, and better patient outcomes, data analysis in healthcare employing competitive ensemble machine learning techniques has the potential to change healthcare [11]. The use of competitive ensemble approaches can alleviate some of the issues with bias and over fitting that are present with classic ensemble techniques.

The capacity of competitive ensemble strategies to integrate the capabilities of many models while avoiding their flaws is one of their main advantages. This can be especially helpful in the healthcare industry in fields like medical imaging analysis, where precise and quick diagnosis is essential. Competitive ensemble approaches can deliver more accurate diagnoses by pooling the predictions of various models, lowering the possibility of false negatives or false positives.

One more benefit of serious group procedures is their capacity to work on the interpretability of AI models. This is particularly important in healthcare, where decisions based on machine learning predictions can have significant implications for patient outcomes [12]. By using competitive ensemble techniques, healthcare professionals can gain a better understanding of how machine learning models make their predictions, and can use this information to make more informed treatment decisions.

The application of competitive ensemble approaches in the analysis of healthcare data is not without difficulties, despite its potential advantages [13]. Large, high-quality dataset requirements, the computational difficulty of executing numerous models, and the generalizability of models across various patient populations are a few of these.

5. Conclusion

Healthcare data analysis, such as disease detection and medical image analysis, has the potential to be more accurate and efficient with the use of competitive ensemble machine learning techniques. Even though there are still obstacles to be solved, ongoing research is making progress towards creating competitive ensemble machine learning algorithms for healthcare data analysis that are more resilient and efficient choosing the top models based on their performance and combining them into an ensemble to increase the model's accuracy and robustness. The choice of models, the quantity and quality of the data, and ensemble optimization all have a role in the technique's efficacy.

5.1. Challenges and Future Directions

Despite the competitive ensemble machine learning technique's promising achievements in the healthcare industry, there are still issues that must be resolved. Choosing the optimal base classifiers and the meta-classifier is the key challenge [15]. The competitive ensemble machine learning technique's performance can be considerably impacted by the selection approach employed. The results' interpretability presents another difficulty. Although competitive ensemble machine learning techniques can produce precise predictions, the underlying logic is frequently unclear. Future research should concentrate on creating competitive ensemble machine learning methods that are easier to interpret.

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