COVID-19 DETECTION FROM CBC USING MACHINE LEARNING TECHNIQUES

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ABSTRACT:

Covid-19 pandemic has seriously affected the mankind with colossal loss of life around the world. There is a critical requirement for timely and reliable detection of Corona virus patients to give better and early treatment to prevent the spread of the infection. With that being said, current researches have revealed some critical benefits of utilizing complete blood count tests for early detection of COVID-19 positive individuals. In this research we employed different machine learning algorithms using full blood count for the prediction of COVID-19. These algorithms include: “K Nearest Neighbor, Radial Basis Function, Naive Bayes, kStar, PART, Random Forest, Decision Tree, OneR, Support Vector Machine and Multi-Layer Perceptron”. Further, “Accuracy, Recall, Precision, and F-Measure” are the performance evaluation measures that are utilized in this study.

Keywords—Machine Learning, Data Mining, COVID-19 Prediction, CBC Test

INTRODUCTION

In the last months of 2019, a new infectious disease, COVID-19, was reported, which quickly spread all over the world. This fatal disease is caused by the virus SARS-CoV-2. In order to contain this disease many efforts have been made everywhere for its initial screening as well as timely treatment. “Reverse Transcription Polymerase Chain Reaction (RT-PCR)” is a test that is developed for the diagnosis of covid-19 disease with DNA sequencing and identification [1, 2]. Despite its popularity, this test has some flaws. It is time consuming, costly, specific laboratory apparatus is needed and it has approximately false-negative rate of 20% [3]. Moreover, a shortage has always been observed of RT-PCR test kits worldwide. Just like RT-PCR, IgM/IgG antibodies tests have their own disadvantages with sensitivity and specificity being as low as 18.8% and 77.8% respectively in initial screening of COVID-19 [4]. Although CT scans and chest X-rays images based on Machine learning [5] have shown positive results, however these tests are not much useful due to high dosage of radiation. Recently some studies [6-11] have been conducted, which revealed that COVID-19 patients' blood features alter immensely so recognizing and working with these parameters can help in early detection of the virus. Machine learning is very resourceful in observing and separating different patterns in the attributes of blood examinations. The machine learning framework designed with blood examinations samples for covid-19 initial screening is speedy, easy to handle and cheap in comparison with high priced and slow tests. A model like this will have a huge influence in countries that cannot afford expensive tests like RT-PCR etc. and lack appropriate equipment and specialized laboratories.

RELATED WORK

Machine learning algorithms are being focused by the many researchers to recognize the hidden patterns as well as to mine the valuable information from raw data. Some of the research fields in which machine learning played a vital role, include: sentiment analysis [12-18], rainfall prediction [19-20], and network intrusion detection [21-22], software defect prediction [23-32], health and medical data mining [33-40]. Moreover, a lot of researchers have focused on the use of machine learning techniques to detect covid-19 patients by exploring the patterns in CBC test results, some of the related studies are discussed here. Researches in [41] developed a machine learning model using the complete blood test samples. This model, named as ER-CoV, and used for early detection of covid-19 infected individuals. In the proposed technique, three algorithms are employed, including: “Support Vector Machine, SMOTE Boost and Ensemble”. This model provided 70.25% sensitivity, 85.98% specificity and 86.78% AUC. For covid-19 detection a LASSO Logistic Regression Model was developed by [42] by using blood test results. The dataset was divided into a ratio of 80:20 and contained 110 samples. 15 important attributes were chosen by implying m RMR algorithm that were further reduced to 7. This framework showed 98% sensitivity and 91% specificity. Researchers in [43] employed the techniques including: “Decision Tree, Extremely Randomized Trees, K Nearest Neighbors, Logistic Regression, Naive Bayes, Random Forest and Support Vector Machine” for the prediction of covid-19 disease using blood samples. Random Forest algorithm was tuned to improve the results. These algorithms accomplished an accuracy of 82%–86% and a sensitivity of 92%–95%. Researchers in [44] developed a framework to diagnose covid-19 patients with the help of machine learning techniques using blood samples from emergency care unit. “Neural Networks, Gradient Boosting Trees, Random Forest, Logistic Regression and Support Vector Machine” were employed for detection of this virus. Support Vector Machine outperformed with 68% sensitivity, 85% specificity and 85% AUC. Researchers of [45] designed a machine learning based model using blood test results to detect covid-19. This framework employed following algorithms: Bayesian Networks, Random Forest, Support Vector Machines, Multilayer Perceptron and Naive Bayes. The dataset contained 5644 test samples which were acquired from Albert Einstein Hospital in Brazil. Class imbalance problem was resolved and feature selection was done. The model showed positive results with 96.8% sensitivity, 93.6% specificity and 95.159% accuracy. Researchers in [46] came up with four frameworks utilizing machine learning algorithms, including Artificial Neural Networks, Random Forest, and Lasso-elastic-net Regularized Generalized Linear Network and Linear Regression. These models were used to predict covid-19 infected patients on the basis of blood samples. These frameworks accomplished an AUC of 80–86%, sensitivity of 43–65%, specificity of 81–91% and accuracy of 81–87% with 14 chosen attributes.

MATERIALS And METHODS

The dataset used in this research was made available publicly by Kaggle. The full dataset contains record of 5644 patients collected from “Albert Einstein Israelita Hospital located in Sao Paulo, Brazil” [47]. We have taken only those records which have values in CBC parameters. These patient records were obtained from March 28, 2020 till April 3, 2020. The attributes that were chosen to work with in this study include: “red blood cells (RBC), lymphocytes, mean corpuscular hemoglobin concentration (MCHC), leukocytes, basophils, hematocrit, hemoglobin, platelets, mean platelet volume (MPV), mean corpuscular hemoglobin (MCH), eosinophils, mean corpuscular volume (MCV), monocytes and red blood cell distribution width (RBCDW)”. Pre-processing activities including cleaning and normalization are performed before classification (Fig 1). The dataset chosen for this research has a dependent attribute which contains either the value of ‘Y’ or ‘N’. ‘Y’ depicts that patient is covid-19 positive and ‘N’ shows that the patient is covid-19 negative. The dependent attribute is targeted attribute which we are going to predict/classify and independent attribute is the one which is utilized to predict the dependent attribute. The data was split into 70% training and 30% test data. For classification following algorithms are used: “K Nearest Neighbor, Radial Basis Function, Naive Bayes, kStar, PART, Random Forest, Decision tree, OneR, Support Vector Machine and Multi-Layer Perceptron”. The tool used for this experimentation is Weka”, which was developed at the University of Waikato, New Zealand for data mining tasks.

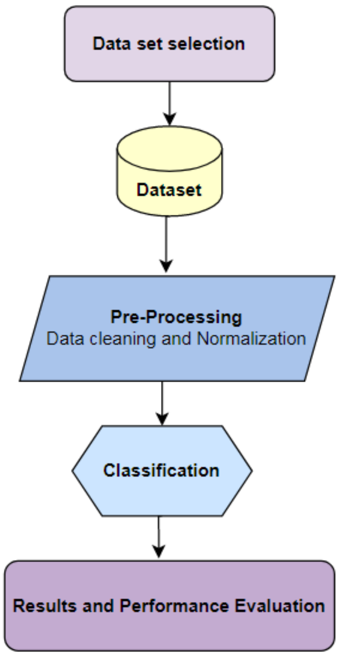

Fig: 1 Prediction of Covid-19 Patients using CBC Results

RESULTS AND DISCUSSIONS

In this section we will see how the selected machine learning algorithms performed in predicting the covid-19 disease. Accuracy evaluation is an important element and an ultimate goal of performance analysis [12-40], [48-50]. The used classification algorithms are analyzed by using the measures, such as: "precision, recall, f measure and accuracy". All of these measures are extracted by the parameters of confusion matrix. The parameters reflected by the confusion matrix are discussed below [21-25]:

"True Positive (TP): Instances which are actually positive and also classified as positive".

"False Positive (FP): Instances which are actually negative but classified as positive".

“False Negative (FN): Instances which are actually positive but classified as negative”.

“True Negative (TN): Instances which are actually negative and also classified as negative”.

The calculation formulas of used performance measures are given below [21-28]:

$$Precision = \frac{TP}{(TP + FP)}$$

“Recall is defined as the ratio of True Positive (TP) instances with respect to the total number of instances that are actually positive” [21-28].

$$Recall = \frac{TP}{(TP + FN)}$$

“F-measure provides the average of Precision & Recall” [21-28].

$$F - measure = \frac{Precision \times Recall \times 2}{(Precision + Recall)}$$

“Accuracy reflects that how much the prediction is accurate” [21-28].

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

All these measures of performance are provided by Weka tool. The training results for each class Y and N are given in Table 1 and testing results for both the classes are provided in Table 2. In case of class imbalance problem, a question mark ‘?’ symbol is displayed as these accuracy measures are sensitive to this issue. Highest accuracy achieved during training is 100 % by three algorithms KNN, kStar, and RF. In testing, the maximum accuracy achieved is 88% by OneR.

Table 1: Training Results

Classifier	Class	Precision	Recall	F-measure	Accuracy
NB	Y	0.447	0.667	0.535	84.2482
	N	0.943	0.870	0.905	
MLP	Y	0.960	0.842	0.897	97.3747
	N	0.976	0.994	0.985	
RBF	Y	0.500	0.018	0.034	86.3962
	N	0.866	0.997	0.927	
SVM	Y	?	0.000	?	86.3962
	N	0.864	1.000	0.927	
KNN	Y	1.000	1.000	1.000	100
	N	1.000	1.000	1.000	
kStar	Y	1.000	1.000	1.000	100
	N	1.000	1.000	1.000	
OneR	Y	0.630	0.298	0.405	88.0668
	N	0.898	0.972	0.934	
PART	Y	0.757	0.930	0.835	94.9881
	N	0.989	0.953	0.970	
DT	Y	0.959	0.825	0.887	97.136
	N	0.973	0.994	0.984	
RF	Y	1.000	1.000	1.000	100
	N	1.000	1.000	1.000	

Table 2: Testing Results

Classifier	Class	Precision	Recall	F-measure	Accuracy
NB	Y	0.410	0.667	0.508	82.6816
	N	0.943	0.852	0.895	
MLP	Y	0.444	0.333	0.381	85.4749
	N	0.901	0.935	0.918	
RBF	Y	0.000	0.000	0.000	82. 1229
	N	0.860	0.948	0.902	
SVM	Y	?	0.000	?	86. 5922
	N	0.866	1.000	0.928	
KNN	Y	0.261	0.250	0.255	80. 4469
	N	0.885	0.890	0.887	
kStar	Y	0.355	0.458	0.400	81. 5642
	N	0.912	0.871	0.891	
OneR	Y	0.636	0.292	0.400	88. 2682
	N	0.899	0.974	0.935	
PART	Y	0.375	0.625	0.469	81. 0056
	N	0.935	0.839	0.884	
DT	Y	0.444	0.500	0.471	84. 9162
	N	0.921	0.903	0.912	
RF	Y	0.538	0.292	0.378	87. 1508
	N	0.898	0.961	0.928	

CONCLUSION:

Initial screening of covid-19 disease is crucial for timely treatment and for preventing the disease from spreading. Blood test samples have proven to be effective for early diagnosis of this disease. In this study we used several machine learning techniques like "K Nearest Neighbor, Radial Basis Function, Naive Bayes, kStar, PART, Random Forest, Decision Tree, OneR, Support Vector Machine and Multi-Layer Perceptron" to predict covid-19 with the help of complete blood count test results. Measures which were used to evaluate the performance, include: "Accuracy, Recall, Precision, F-Measure and ROC".

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