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A Hybrid Artificial Neural Network and Particle Swarm Optimization algorithm for Detecting COVID-19 Patients

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ABSTRACT

COVID-19, one of the most dangerous pandemics, is currently affecting humanity. COVID-19 is spreading rapidly due to its high reliability transmissibility. Patients who test positive more often have mild to severe symptoms such as a cough, fever, raw throat, and muscle aches. Diseased people experience severe symptoms in more severe cases. such as shortness of breath, which can lead to respiratory failure and death. Machine learning techniques for detection and classification are commonly used in current medical diagnoses. However, for treatment using neural networks based on improved Particle Swarm Optimization (PSO), known as PSONN, the accuracy and performance of current models must be improved. This hybridization implements Particle Swarm Optimization and a neural network to improve results while slowing convergence and improving efficiency. The purpose of this study is to contribute to resolving this issue by presenting the implementation and assessment of Machine Learning models. Using Neural Networks and Particle Swarm Optimization to help in the detection of COVID-19 in its early stages. To begin, we preprocessed data from a Brazilian dataset consisted primarily of early-stage symptoms. Following that, we implemented Neural Network and Particle Swarm Optimization algorithms. We used precision, accuracy score, recall, and F-Measure tests to evaluate the Neural Network with Particle Swarm Optimization algorithms. Based on the comparison, this paper grouped the top seven ML models such as Neural Networks, Logistic Regression, Nave Bayes Classifier, Multilayer Perceptron, Support Vector Machine, BF Tree, Bayesian Networks algorithms and measured feature importance, and other, to justify the differences between classification models. Particle Swarm Optimization with Neural

Network is being deployed to improve the efficiency of the detection method by more accurately predicting COVID-19 detection. Preprocessed datasets with important features are then fed into the testing and training phases as inputs. Particle Swarm Optimization was used for the training phase of a neural net to identify the best weights and biases. On training data, the highest rate of accuracy gained is 0.98.738 and on testing data, it is 98.689.

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1. INTRODUCTION

Severe respiratory infection in December 2019, Wuhan, China, identified a highly infectious ailment known as Coronavirus type 2 (SARS-CoV-2) or Corona Virus disease (COVID-19). Since it has spread so quickly, it has drawn a lot of attention. Because of how quickly it has spread over the world, it has gotten people's attention. As a result of touch, breath, and mouth droplets, they have spread swiftly over the globe. It may cause harm to both people and animals because of its ease of transmission. SARS or severe acute respiratory syndrome is a viral infection that causes fever, shortness of breath, and coughing. COVID-19 or Corona Virus 2 It is important to know how many individuals have been exposed to the virus so that people may be separated and the viral illness chain can be broken, since research [1] shows that the virus is disseminated mostly by personal contact or oral secretions. COVID-19 (the coronavirus pandemic of 2019) is a regular occurrence [2] There have been 76,710,234 cases and 1,693,700 fatalities globally since December 20, 2020 [3]. Efforts are being made to find new vaccinations and medicinal techniques via international alliances and competitions. People with COVID-19 who were unable to breathe on their own were shown to benefit by steroids in the Healing research [4]. Many early therapies for the lethal virus, such as hydroxychloroquine and lopinavir/ritonavir, did not substantially reduce mortality rates in hospitalized patients and were often removed from the trial [4]. Both remdesivir [5] and these studies were flawed scientifically and conducted before scientists had a thorough understanding of illness development [6]. For COVID-19 treatment, three drugs are expected to be available by the end of the year. While remdesivir is often used in the United States as well as Japan and Australia, dexamethasone and failover are more commonly used in the United Kingdom and Japan. Vast progress has been achieved in vaccine manufacturing despite widespread misconception regarding the benefits of drugs in patients with pre-existing illnesses such as type 2 diabetes and loss of consciousness [7–8], underlying malignancy and immunodeficiency. More than 60 vaccines are now in human clinical trials, with 18 moving to the final step [9]. It has now been approved for use in the United States, Canada and a number of other countries for both vaccines, mRNA-1273 from Moderna and BNT162b2 from Pfizer. To avert a worldwide COVID-19 outbreak, at least 60% to 70% of the world's population must be protected, according to a Center for Disease Research study [10]. The worldwide pandemic is expected to continue for at least another 18–24 months, with heat waves occurring on a regular basis in a variety of locations, assuming various degrees of mitigation [10]. In light of this, it is clear that thorough public health measures, such as screening persons with appropriate symptoms and determining those who need testing and quarantine or hospitalization, are critical. COVID-19 symptoms may be diagnosed and treated using these parameters. From the ordinary cold to life-threatening disease, COVID-19 has been associated to a range of symptoms [11]. Concerns about one's health having an understanding of these symptom patterns may help hospitals and healthcare providers make better treatment decisions. It has been linked to unproductive coughing, exhaustion, and fever by the World Health Organization (WHO). Breathlessness, fever, and exhaustion may occur in certain high-risk situations [12]. In addition to shortness of breath or trouble breathing, COVID-19 participants reported a wide range of symptoms including muscular pains, chills, a raw throat, nosebleeds, headache, chest discomfort, and eye irritation. Patients with diabetes, asthma, and heart problems are more likely to get the virus [13]. On average, COVID-19 has a short incubation period of five to six days in people who have been exposed to the virus and are exhibiting symptoms. A surge in infectious illnesses occurs as a consequence of people who are infected with COVID-19 sharing their germs with others. As a result, diagnosing, monitoring, and managing the illness becomes more difficult since many infected people are symptomless. COVID-19's propagation has been aided by the features listed above. The symptoms of this viral illness are clearly visible. It might range from no symptoms at all to a full recovery with no negative health effects. As a consequence, patients, visitors, and medical professionals are exposed to the 2019-nCoV virus due to a lack of timely diagnosis and the limitations of diagnostic devices. As a result, the health insurance and financial services industries are placed in grave danger. COVID-19 is a global pandemic that requires the use of non-clinical technologies such as data mining, machine learning, intelligent machines, and other machine learning methodologies. Healthcare organizations may save a lot of money and time if they used non-therapeutic methods to diagnose and treat 2019-nCoV infections.

2. RELATED WORK

The first case of COVID-19 was observed less than two years ago. Since then, and over 190 countries have experienced COVID-19 cases. Mostly everyone nowadays is fearful of that kind of virus. The biggest reason for this consideration is that COVID-19 disease is becoming more widespread by the day. Many essential steps are being taken to assist slow or stop the spread of the disease. Many countries have declared a state of emergency. People are taking all precautions, such as social distancing, hand sanitization of soap or hand sanitizer, and so on. In this section, we highlight research that used artificial intelligence to obtain disease solutions, with a focus on classification to recognize positive COVID-19 and negative cases, as this is the aim of our work. Based on the intelligent systems and symptoms used to detect COVID-19, the relevant works could be classified into two major groups: describes the literature that proposed various artificial intelligence techniques for COVID-19 detection, such as Neural Networks and Particle Swarm Optimization Algorithms, and also symptoms-based techniques for COVID-19 detection.

2.1. Detection of COVID-19 Using Artificial Intelligence Methods

Learning, interpretation, and problem solving are all examples of human-like mental functions that may be performed by a computer via the use of artificial intelligence. There are several techniques and methods that we will use often in our work that are covered in this part. It was in 2012 when Hong and Zhou and et al. [14] attempted to build an accurate forecasting model using GRNNs, back propagation neural networks (BPNNs), and RBFNNs. According to the statistics, PNN is more popular than artificial neural networks. An individual cell dataset from Pap Smears was analyzed using the PSO approach in 2017 by a number of specialists, including Arifin [15]. Data training and testing were created using the PSO strategy, and the data set was then tested using the categorizing data mining technique to verify that the training had been successful. Besides Arifin, Zhang, Gong and Cheng used PSO in 2017 as well. Using the PSO technique and the Hybrid Phenotype methodology, this study looked at a massive amount of data. According to the study's findings, the Metric Hyper Volume of five data sets can be improved by more than 0.8 by integrating two separate methodologies (HV) [16]. Based on the Lee-Carter model, Richman and Wüthrich [17] used neural networks to provide a variety of rate estimates in 2018. The kernel analysis is done using a "Probabilistic Neural Network (PNN)." PNN helps to speed up the training process [18]. To create a dynamic classification system with decreased statistical parameters, PNN utilizes statistics and neural networks. PNN was also used to characterize and evaluate the capacity of bacteria to flourish in areas with and without bacteria. Working conditions affect evolution [19]. Using previously published chest X-ray pictures, Woniak et al. [20] developed a unique method for identifying respiratory system malignancies. It was suggested that neural networks based on momentum and probabilistic information may be employed instead (PNN). The velocity of the fragmented nodule curves was discovered to be a feature after bulk fragmentation in chest X-ray images. Nodules may be categorized using PNN with 92% accuracy, according to the trials. Hand-foot-mouth disease outbreaks in 2019 might be predicted using a neural network, according to Jia et al. [21]. Machine learning was used by Hamer et al. [22] to forecast the spatial and temporal distribution of hazardous disorders. Aside from predicting epidemics of cardiovascular disease [23,24], influenza [25], and epidemic diarrhea [26], strategies based on artificial intelligence have been proposed. Neural networks are studied by Ke et al. [27] by merging visual features with heuristic techniques. For the procedure to work, there are a number of steps: Probability models for the detection of respiratory illnesses are first developed using essential characteristics and an artificial neural network (ANN). Using heuristic methods, these damaged lung cells may then be identified directly, emphasizing the value of early diagnosis. An artificial intelligence strategy to identifying COVID 19 patients in CT scans was announced by China in 2020 [28]. Over 40,000 CT scan images from 106 individuals were used to train the model on coronavirus identification using the UNet++ [29] architecture framework. Radiologists' time-consuming efforts may be considerably reduced if this strategy is used. [30] In the words of Wong and Wang, Artificial intelligence system COVID-Net was published by researchers who used an imbalanced dataset that included a small number of COVID-19 images from healthy and other non-COVID respiratory tract infection patients, as well as nearly 16,000 images from healthy and other non-COVID respiratory tract infection patients. The researchers trained and tested their method using this imbalanced dataset. Finally, as well as in a prior study soon et al. [31] including nine COVID-19 positive people, the link between chest x-rays and CT pictures was found. Deep Learning (DL) model types specific to neural networks have been developed by others, such as COVID-Net [30] and ResNet50 [32]. In 31 occurrences, COVID-Net identified COVID19 as positive, but ResNet50 identified 25 instances of COVID19 positivity. A seasonal autoregressive integrated moving average (SARIMA) and a neural network non-linear auto regression were used by Wang et al. [33] to analyze tuberculosis incidence data in China (NNNAR). They are employing a broad bacterial illness, COVID-19-induced lung infection, and a developing neural network to search for COVID-19 auto. This is not the first time that a transfer learning approach has been used. A broad variety of anomalies in big sets of basic medical data may be identified with surprising accuracy using transfer learning [34]. [35] Chouhan et al. used numerous neural network models in datasets to extract test features. A network's classification performance is based on the characteristics listed above. In order to ensure that the diagnosis is allocated to the most popular categorization, the data from each network is aggregated using the results of the popular vote. In order to extract COVID characteristics from routine computed tomography testing, Li et al. [36] built a COVNet neural network. As the most often used encoder-decoder networks for feature extraction, the U-net and its variations collect low- and high-level characteristics through the encoder and conceptual features via the decoder. UNet++ was used by Chen et al. [28] to detect the existence of a COVID-like disorder. A capsule network was utilized by Afshar et al. [37] to detect COVID patients in X-ray images. Mei et al. [38] used computed Tomographic observations of symptoms, prior visibility, and laboratory tests to quickly identify COVID-19 positive people.

Table 1: Summary of the modality and method of each author explained in the above section.

Author	Modality (Dataset)	Method
Hong and Zhou et al.	Textual	BPNN, GRNN, and RBFNN
Arifin et al.	Data image	PSO, CFS
Zhang et al., Gong et al. and Cheng et al.	Data image	PSO combined Hybrid Mutation method
Richman et al., Wüthrich et al.	Textual	Probabilistic Neural Network (PNN)
Woźniak et al.	chest X-ray images	Probabilistic Neural Network (PNN)
Jia et al.	Textual	neural network
Hamer et al.	Textual	ML algorithms
Ke et al.	Data image	neural network , heuristic algorithms
China et al.	CT images	AI model (UNet++)
Wang and Wong et al.	chest X-ray image	AI system (COVID-Net)
Soon et al.	CXRs and CT images	neural network-tailored Deep Learning
Wang et al.	Textual	SARIMA, NNNAR
Apostolopoulos et al. and Bessiana et al.	Data image	neural network
Chouhan et al.	Data image	different neural network
Li et al.	CT images	neural network (COVNet)
Chen et al.	CT images	UNet++
Afshar et al.	X-ray images	capsule network
Mei, et al.	CT images, textual	AI algorithms

2.2. COVID-19 detection based on symptoms

A Chinese dataset was used by Ahamad et al. [39] to help with the COVID-19 diagnosis in 2020. Information on the subject's sex (male or female), age (in years), travel history (if applicable), and separation was also included in the dataset. In addition to the XGBoost and SVM models examined by the reviewers, they also considered the DT, RF, and GBM models. If you want to know your age, XGBoost will have the greatest accuracy, with more than 85%. It is also more expensive, and it may result in a drop in viral test findings if you rely on chest imaging to diagnosis respiratory diseases." CT imaging data was examined in combination with many symptoms, visibility, laboratory tests (white cells, neutrophils, proportion neutrophils, immune cells, and percentage immune cells), age, sex, and temperature in order to boost the confidence in COVID-19 test findings [38, 39]. Researchers that examined picture data using a deep CNN and compared the effectiveness of SVM, RF, and MLP designs determined that MLP was the most accurate design in general. The researchers then integrated the photos and clinical data. Similarly, increased demand for images raises prices and may restrict access to COVID-19 test findings in low- and middle-income nations. Thus, based on their symptoms and other demographic data, Zoabi et al. [40] predicted the number of infected individuals in 2021. A gradient boosting machine learning model was constructed to detect the instances. Sex, being over 60 years old, having had prior contact with an infected person, and five early symptoms were all examined in the study: cough, fever, sore throat, dyspnea, and headache. Those who did point out a flaw in the user data did so since it seemed to include flaws and biases as well. When this bias is eliminated, the AUC of the proposed system drops to 0.862 [41]. Banik et al. [42] set out to evaluate the chance of a person developing a COVID-19 viral infection. Numerous techniques are now being researched, including Linear SVM, LR, MNB, and DT, in order to develop an adequate model for predicting the chance of infection based on clinical symptoms. The aforementioned technique has a proportion of criteria that are equally important. Several characteristics, on the other hand, are significantly more essential when it comes to constructing COVID-19 instances. Finally, Zoabi et al. [40] categorized COVID-19 cases as positive or negative based on their gender, age, and symptoms (sore throat, cough, headache, fever, and dyspnea), as well as their association with a well-known example. The authors developed a GBM strategy using data from Israel's Ministry of Health. While using both a reduction set and the original set of features, the GBM technique must have an AUROC of 86 percent and 90 percent, respectively. The experts perceived gender to be more significant throughout the categorization process, which is consistent with previous findings. Additionally, we enhanced by comparing the use of several methodologies to classification. Apart from a cough, a fever, a sore throat, breathlessness, and a headache, to improve performance, we took advantage of symptoms linked with olfaction abnormalities, rhinorrhea, and taste disorders.

Table 2: summarizes the modality and method of each author explained in the above section.

Author	Modality (Dataset)	Method
Ahamad et al.	Textual	XGBoost, SVM, DT, RF, and GBM models
Mei et al.	CT images, Textual	DCNN, SVM, RF, and MLP models
Zoabi et al.	Textual	machine learning model
Banik et al.	Textual	machine learning algorithm(LR, MNB, L SVM, DT)
Zoabi et al.	Textual	GBM model

The effectiveness of NN and PSO in the field of medical diagnosis is demonstrated in this work. Early detection of this disease may help doctors, clinics, and patients in controlling or reducing the effects of COVID-19.

3. METHODS AND MATERIALS

3.1 System Overview

The research approach includes the preparation of data, the description of new data sets, the collection of data, the extraction of features, the classification of data, and the comparison of data (Figure 1). Preprocessing the data from 55,676 patients from Brazil resulted in the creation of several datasets including information about patients who underwent COVID-19 testing utilizing these balanced and unbalanced techniques. The methodological stages involve preparing data, describing new data sets, extracting features, and performing comparisons.

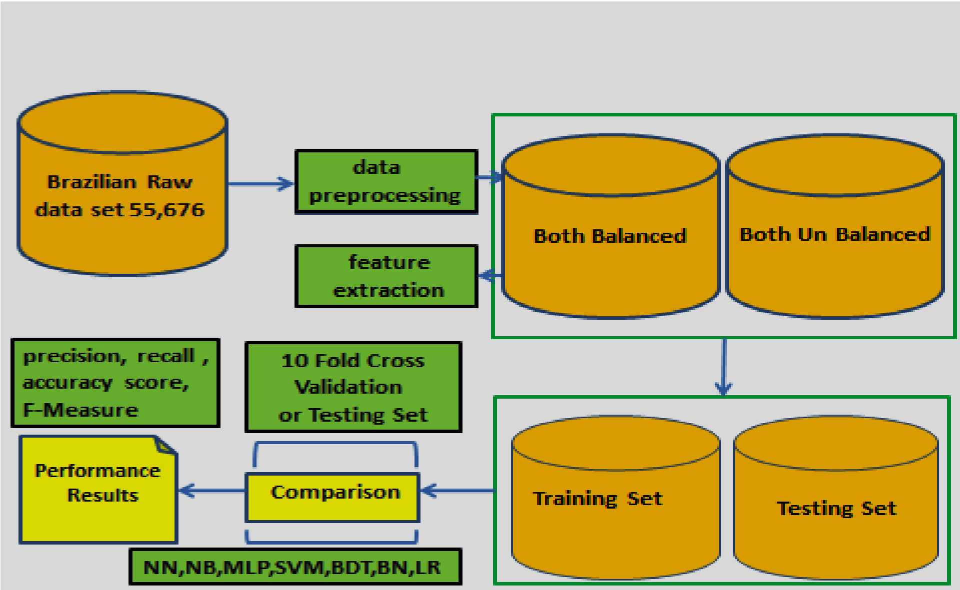

Figure 1: A summary of the original study methodological approach.

We used both balanced and unbalanced data sets to apply the PSO with NN (PSONN) classification models. To compare classification models, we used Logistic Regression, Nave Bayes Classifier, multilayer Perceptron, Support Vector Machine, BF Tree, Bayesian Networks, and other techniques. The following classification metrics were calculated as well: precision, recall, accuracy score, and F-Measure [43].

3.2 System Preparation

3.2.1 Proposed method

This paper employs the proposed Automatic covid-19 detection system based on PSO with NN (PSONN). PSO is used in the training program of the PSONN system, which is an improvement of a dataset method. Figure 2 presents a step by step process of PSONN's main procedures. The software is implemented in java language. Since all of the datasets are received training with PSONN, the process is optimized in the source code. The network will also be studied and the results would be assessed in the following step. One of most complex process is the PSONN, that merges the PSO optimization algorithm with BPNN activities. PSO is being used to evaluate input weights, that are then use for BPNN to check whether the system. Lastly, the results will be presented and compared.

3.2.2 Methods:

Manual first pre-processing is performed to convert the data collected, that is in physical copy file format and excel spreadsheets, to a format suitable for analysis, and therefore we can refer to the final list of the beginning pre-processed data. Following that, samples are divided into 2 parts known as training and testing sets. The following step is preprocessing, which involves balancing data in each class sample. When all of the data sets are used together, feature selection is performed. The final set is then fed into PSONN.

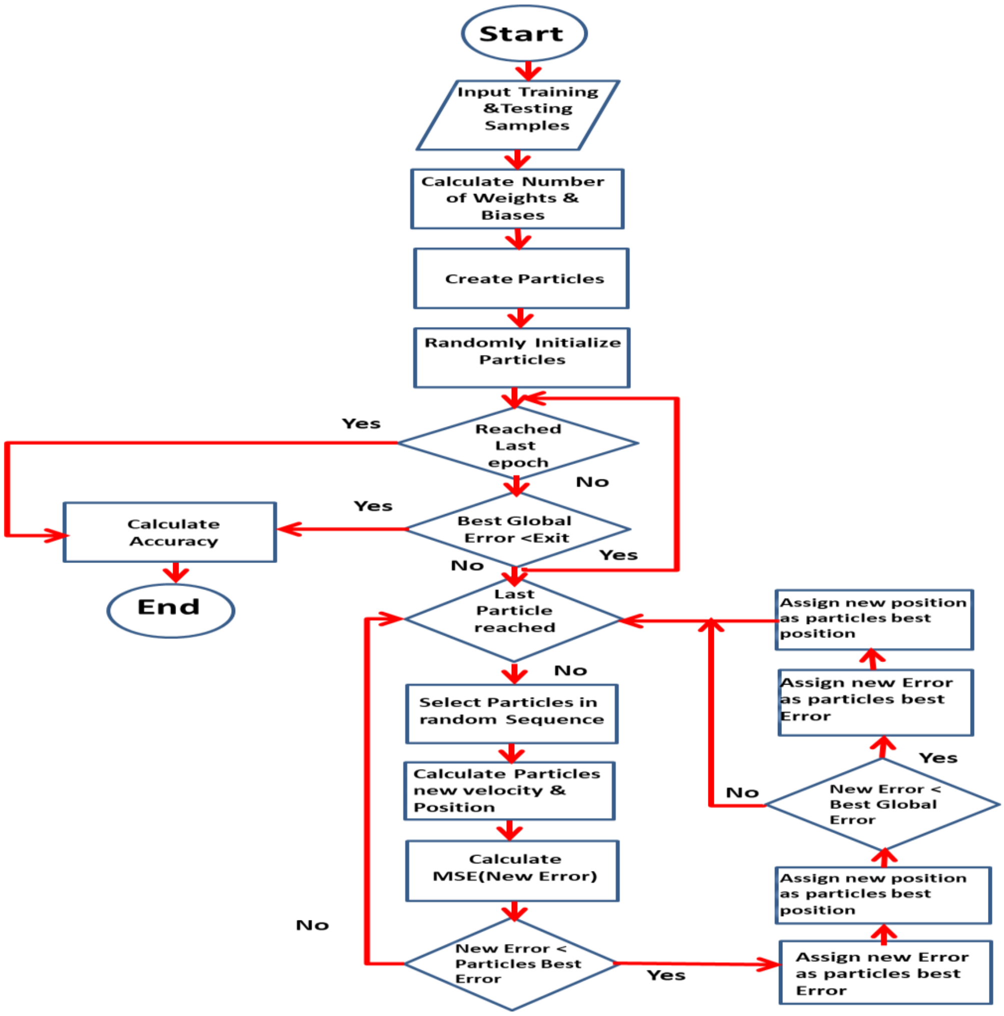

Figure 2: The proposed flowchart of the PSONN Automatic covid-19 detection system.

3.3 Data Set:
3.3.1 Data Description

The original Brazilian COVID-19 real data (from the 26 Brazilian states and the Federal District) contained information about tested patients, including early-stage symptoms, comorbidities, demographic data, and symptom descriptions. Virus and antibody tests were used on the patients. We preprocessed the dataset by removing rows with duplicated instances and asymptomatic patients, selecting only completed tests that were marked as positive or negative, using string matching algorithms to correct some inconsistencies, and removing rows with duplicated instances and asymptomatic patients. To select features, we also focused on the most common and relevant demographic information and reported early-stage symptoms, and we balanced the data by random under sampling using the Near Miss algorithm, taking into account positive and negative cases. The preprocessing produced a dataset containing 2,674 patients. The decrease in the number of patients from 55,676 to 2,674 was caused by asymptomatic patients, duplicated data, few reported symptoms by some patients, and the need for information about the dates of symptom onset and testing. We built and tested supervised machine learning models for COVID-19 detection in Brazil using this dataset, which was based on early-stage symptoms and basic personal information. This dataset is associated with the study "Machine Learning Models for COVID-19 Detection in Brazil Using Symptoms."

3.3.2 Data Collection:

The initial data set consisted of 55,676 patients. On the other hand, data collecting is not a significant addition to this research. The original data were obtained by the Campina Grande public health agency in Paraiba State, Northeast Brazil. This governmental agency receives reports on all COVID-19 tests conducted in Campina Grande. Local health department personnel removed patient identifiers; however, the captured data was re-used to facilitate this research. Healthcare providers, security experts, nationality, test type, pyrexia, raw throat, shortness of breath, sense of smell diseases, cough, chills, strange taste, headache, extra symptomatology, lab results, chronicity, test status, and symptomatology definition are all categorical features included in the raw given dataset.

3.4 Feature extraction:

Identifying the significant features helps to improve the accuracy and reliability because it ignores features that have little relevance to the system.

3.5 Data Preprocessing

We preprocessed the data using the Java programming language. Pattern matching algorithms are used to pre-process the initial data gathering in order to eliminate discrepancies. The existence of empty columns of symptoms established inconsistency; moreover, the same symptoms appeared in a column dedicated to a full review of symptoms. Additionally, the following occurrences were excluded from the 55,676-person sample as a result of our differential diagnosis: Patients with missing tests or ambiguous final classifications (n=12,929), instances of redundancy (n=251), outliers due to user error (n=10,408), tests of various types that are not RT-PCR or rapid (n=771), patients with an unknown gender, and patients without symptoms (n=11,269). Patients without symptoms were excluded from the study because demographic and symptomatologic information were used as inputs to the algorithms. By removing components associated with symptom definitions, the dimensionality of the derived features from the original data set is decreased. For example, fatigue was eliminated after it was reported by 228 of the 55,676 patients. Due to the increasing focus on symptoms, the data sets do not cover chronic illnesses or residual characteristics (e.g., nationality). The following criteria were created based on the most often seen symptoms (fever, raw throat, shortness of breath, olfactory abnormalities, cough, and chills, for example).

Table 3: Data sets containing demographic and symptom information from patients who are symptomatic including both types of tests.

Properties	**20,021: Unbalanced**	**3128: Balanced**
Demographic properties		
Gender	8919: Male (%44.55)	1639: Femlate (%52.40)
Healthcare provider	2485	475
Symptoms		
Fever	9169	1856
Raw throat	5976	848
Shortness of breath	3704	1082
Olfaction diseases	1967	522
Cough	11,641	1944
Chills	1159	266
Strange taste	1596	387
Headache	4034	577

During preprocessing, categorical data are turned into binary characterizations. A score of zero indicates that the patient is female, while a number of one indicates that the patient is male. The number 0 represented a good response to the following characteristics of healthcare providers: fever, raw throat, shortness of breath, olfactory illnesses, cough, chills, taste abnormalities, and headache, while the number 1 indicated a negative response. The near-miss approach was used to undertake under sampling [44], which included both positive and negative COVID-19 cases. To prevent the use of simulated data in the training and testing sets, under sampling was employed rather than over sampling. Additionally, as previously stated, imbalanced data were assumed without under sampling in order to boost the test's representativeness and imitate a real-world scenario in which the percentage of negative COVID-19 instances is greater than the proportion of positive COVID-19 cases. We identified significant demographic factors (gender and healthcare providers) in unbalanced and balanced data sets, as well as taste abnormalities and headaches (Table 3). Healthcare professionals were considered important due to the high frequency of SARS-CoV-2 infection. Additionally, there seems to be no agreement on whether the proportions of men and women exposed to the virus who develop severe acute respiratory syndrome vary (which, in general, is a 50/50 split) [45, 46].

Additionally, the imbalanced data set contains 20,021 individuals who had RT-PCR and rapid assay examinations. Patient numbers were reduced as a result of missed tests, redundancy, outliers due to user error, test type, and asymptomatic patients. Both imbalance data sets have 1564 positive and 18,457 negative COVID-19 cases (7.81 percent and 92.19 percent, respectively), while the balanced data set has 1564 occurrences of each class. 496 female patients (2.48%) tested positive, whereas 10,606 male patients (52.97%) tested negative. Male patients had 1068 positive findings (5.33%), whereas female patients received 7851 negative findings (39.21 percent). The most commonly reported symptom (n=11,641, 58.1 percent) was coughing. The second most often reported symptom was fever (n=9169, 45.8%). At least 5976 (29.9 percent) of persons with symptomatic conditions had persistent symptoms (Figure (3)). 3128 patients were assessed in the balanced data set using RT-PCR and rapid tests. The near-miss method produced a similar number of positive and negative cases; 496 (15.86%) of female patients tested positive, while 993 (31.75%) tested negative. Males had 1068 positive cases and 571 negative cases (34.14 percent) (18.25 percent). Cough and fever, the two most often reported symptoms, remained top and second, respectively. The other symptoms were reported by 1082 (34.6 percent) of patients (Figure (4).

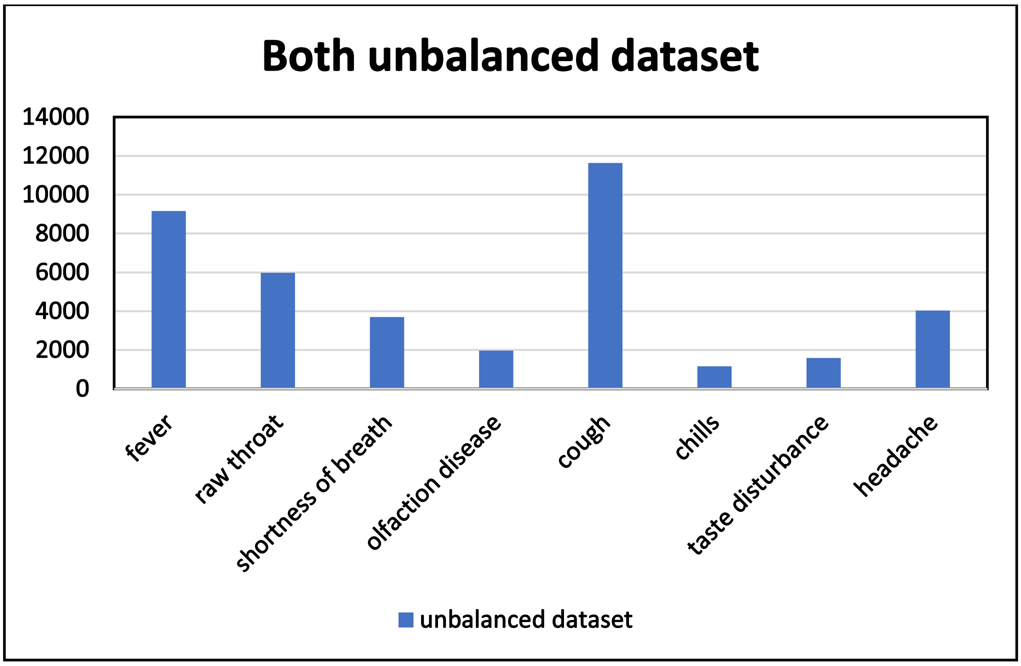

Figure 3: The incidence of symptoms for the 20,021 participants in both imbalance data sets who were symptomatic

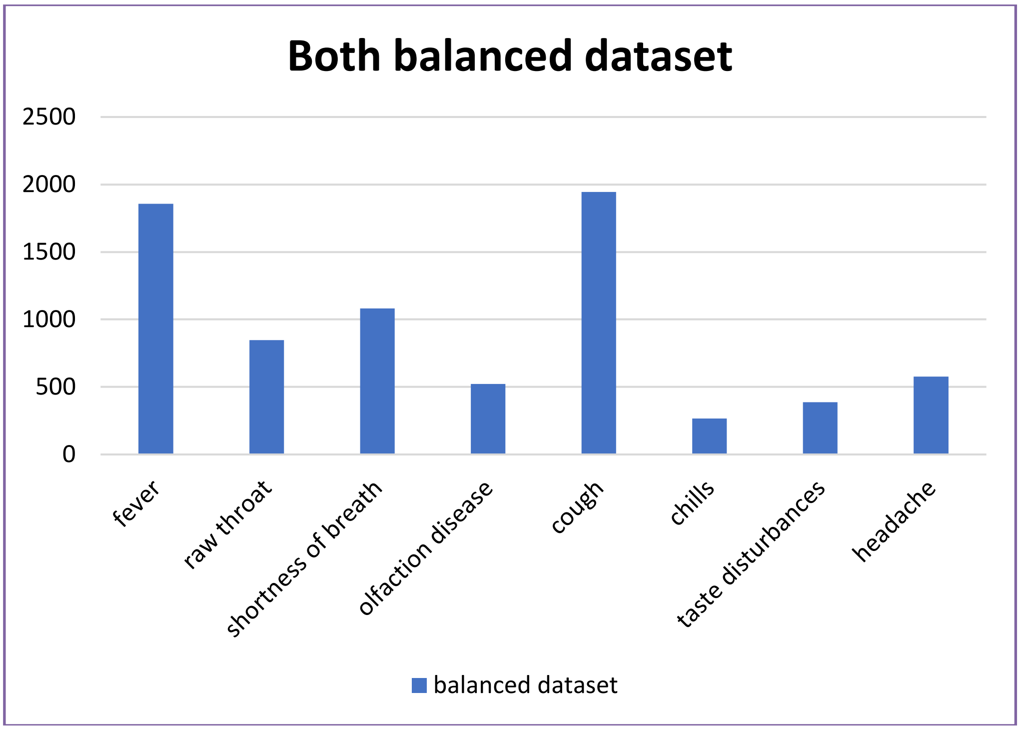

Figure 4: The rate of symptoms for the 3128 patients in both balanced data sets who may have been symptomatic.

Finally, the unbalanced RT-PCR data set has 916 cases of COVID-19 (32.96 percent positive) and 1863 cases of COVID-19 (67.04 percent negative), whereas the balanced data set contains 916 cases of each class. The imbalance data set had 648 instances of positive COVID-19 and 16,594 instances of negative COVID-19 (3.76 percent and 96.24 percent, respectively), whereas the balanced data set contained 648 occurrences of each class. The six models are presented based on a comparison of the results of the categorization models from various types of testing. As a result, there is no need to utilize several approaches or to choose an individual patient's profile in order to acquire the testing results and outcomes discussed in this study.

3.6 Implementation Components

This section explains and clarifies the findings of the experiment. The system is implemented using the Java programming language. Performance analysis is used to evaluate the proposed strategy's precision, F-measure, accuracy, and recall. 90% of the dataset is used for training, whereas 10% is used for testing. Among the operating systems that can assist with distribution are Windows 7, Windows 8, and Windows 10.

4. RESULTS AND DISCUSSIONS

4.1 Introduction

This section explains data collection and the methods in each test before and after applying research contribution. The design analysis of the obtained results, as observed in section three, is also displayed.

4.2 Experimental Result Analysis

This section included the maximum accuracy of the proposed covid-19 identification into a particle Swarm Optimization with Neural Network (PSONN) model through an experimental research. The PSO is used to determine the BPNN training session's ideal weights and biases, which may subsequently be used to assess the BPNN. The proposed model is validated and analyzed using well-established methods. The purpose of this paper is to demonstrate that the proposed particle Swarm Optimization Neural Network (PSONN) outperforms traditional neural networks. As a result, performance evaluation parameters such as accuracy, recall, and f1-measure are considered. Additionally, the datasets are divided into training and testing portions, with 90% of the datasets used for training and 10% for testing. Java is used to implement the preferred particle swarm optimization technique based on neural networks (PSONN).

4.3 The Proposed Model

In the introduced model, the dataset is employed as the system's input features. The pre-processed data is normalized. This PSONN model is used in conjunction with PSO as a classification model to create weights and biases. The model employs two hidden layers (12 neurons in the first and 8 neurons in the second) and 14 input neurons, but only one output neuron is employed. As seen in table (4) the model classifier's parameters Both the training and testing phases use the same set of parameters. The matrix displays the degree to which the misclassifications are equivalent. This indicates that the bulk of misclassifications occur one class above or below the correct categorization. This is mostly because the labeling function is same. Confusion matrix for the model's validation phase, which includes extensive results (See Table (8)). The model's testing phase exhibits the same confusion matrix as the training phase, with almost all sample mis-classifications occurring one class above or below the actual class label.

Table 4: The initial parameters of the Model

Input data	Classifier	W	Hidden	C2	C1	Epoch	Particles
fever, throat pain, dyspnea,cough,coryza, headache, olfactory disorders,taste disorders, gender, are you professional	1	0.729	6	1.4944	1.4944	500	24

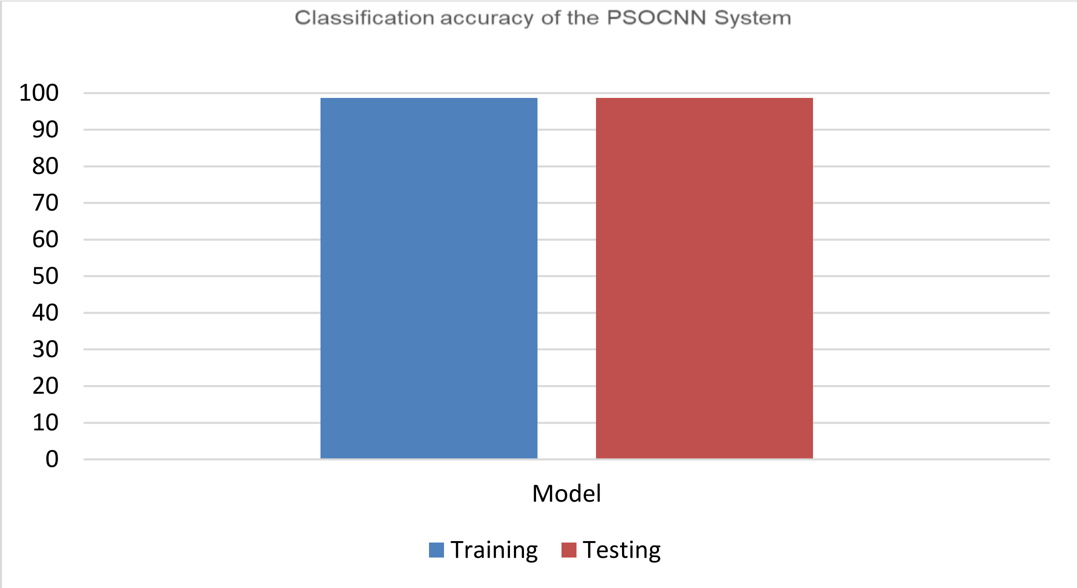

Figure 5: Classification accuracy of the PSONN System

4.4 Performance Evaluation

Numerous statistical measures, such as true positive (TP), true negative (TN), False positive (FP), and false Negative (FN), may be used to approximate the suggested approach (FP). The following table summarizes these values (5).

Table 5: Description of statistical values

Description	**Output**	
	Perfect	Defected
Perfect	TP	FP
Defected	FN	TN

These statistical parameter values are evaluated using the following equations, which are formulated below.

1. Accuracy: It is the ratio of true patterns to the sum of all patterns. It can be explained as

Accuracy = (TN+TP)/(TN+TP+FN+FP)

As a result, the proposed particle Swarm Optimization with Neural Network (PSONN) model has an accuracy on training data of 0.98.73 and an accuracy on testing data of 98.689.

Table 6: Model—Results of Training Accuracy on training data=98.73.

Positive	**Negative**	
TP=1093	FP=0	1093
FN=27	TN=1020	1047

Table 7: Model - Results of Testing Accuracy on testing data=98.689

Positive	Negative	
TP=244	FP=0	244
FN=7	TN=283	290

The results demonstrate the model's efficacy throughout both the testing and training phases (See Figure 5). The fundamental reason for this is that the PSO approach calculates the network's optimum weights, resulting in the network being generalized. The change is advantageous solely for classification; it has no effect on the outcome when the system is used for prediction. Thus, this text has been categorized; this type of modification is highly advantageous. The system's model obtains an accuracy of 98.73 percent throughout the testing phase, outperforming basic BPNN models without PSO.

2. Precision: It is the ratio of true positive patterns to the sum of all positive patterns. It can be explained as

Precision = TP/(TP+FP)

As a result, the precision for the proposed PSO with NN (PSONN) model is 1.0000.

3. F-measure: Both precision and recall values are required to calculate the value of the F-measure. It can be explained as

F-measure= 2 × (Recall X Precision) /(Recall + Precision)

The proposed approach has an F-measure value of =0.98.7.

4.5 Comparative Analysis

The comparison study for the suggested method and existing algorithms, such as Nave Bayes Classifier, Bayesian Networks, Logistic Regression, multilayer Perceptron, Support Vector Machine, BF Tree, and others is described in this section. PSONN methods suggested in this paper can be detected using the weka3.9.4 explorer [43]. Precision, recall, F-Measure, and Accuracy score classification models' mean values were among the best achieved using a 10-fold cross-validation and testing set (8,9). Similar findings were obtained when unbalanced and balanced data sets were used. The Table contains the values for the proposed and present approaches (8,9).

Table 8: The classification models' results of a tenfold cross-validation (unbalanced and balanced)

Datasets and models	precision	Recall	F-Measure	Accuracy score
Naïve Bayes	0.891	0.868	0.880	0.878
Bayesian Networks	0.891	0.868	0.880	0.878
Logistic Regression	0.847	0.897	0.871	0.875
Multilayer Perceptron	0.988	0.962	0.975	0.974
Support Vector	0.869	0.889	0.879	0.880
BF Tree	0.972	0.968	0.970	0.970
Proposed PSOCNN	1.0000	0.975	0.987	0.987

Table 9: The results of the testing set for classification models utilizing both unbalanced and balanced classification models.

Datasets and models	precision	Recall	F-Measure	Accuracy score
Naïve Bayes	0.890	0.866	0.878	0.876
Bayesian Networks	0.890	0.866	0.878	0.876
Logistic Regression	0.848	0.897	0.872	0.975
Multilayer Perceptron	0.994	0.958	0.975	0.974
Support Vector	0.881	0.885	0.883	0.883
BF Tree	0.985	0.982	0.983	0.983
Proposed PSOCNN	1.0000	0.975	0.987	0.987

The results of the existing and presented approach are seen in the tables above. The accuracy achieved for the COVID-19 detection, The presented approach, which obtained 98.73 on training data and 98.68 on testing data, was compared to existing approaches such as Nave Bayes Classifier, Bayesian Networks, Logistic Regression, Multilayer Perceptron, Support Vector Machine, BF Tree, and the proposed particle Swarm Optimization with Neural Network (PSONN).

The accuracy of the existing approaches Naïve Bayes Classifier, Bayesian Networks, Logistic Regression, multilayer Perceptron, Support Vector Machine, BF Tree algorithms using Both unbalanced/balanced 10-fold cross-validation and Testing set are 0.878, 0.878, 0.875, 0.974, 0.880 ,0.970 respectively for 10-fold cross-validation and 0.876, 0.876, 0.975, 0.883 ,0.983 respectively for Testing set.

The precision level for the presented approach is 1.0000, whereas the precision levels for the existing techniques, Naïve Bayes Classifier, Bayesian Networks, Logistic Regression, Multilayer Perceptron, Support Vector Machine, BF Tree algorithms using Both unbalanced/ balanced 10-fold cross-validation and Testing set are 0.891, 0.891, 0.847, 0.988, 0.869, 0.972 respectively for cross-validation and 0.890, 0.890, 0.848, 0.994, 0.881, 0.985 respectively for Testing set. This demonstrates that the precision level for the presented approach was high and that it performed well, giving an effective result.

The recall value for the proposed method is 0.97.5, whereas the recall values for the existing algorithms, Nave Bayes Classifier, Bayesian Networks, Logistic Regression, Multilayer Perceptron, Support Vector Machine, BF Tree algorithms using Both unbalanced/balanced cross-validation of 10-fold and testing set are 0.868, 0.868, 0.897, 0.962, 0.889 ,0.968 respectively for 10-fold cross-validation and 0.866, 0.866, 0.897, 0.958, 0.885,0.982 respectively for Testing set. Finally, the F-measure value for the presented method is 98.7, whereas the F-measure values for the existing approaches, Nave Bayes Classifier, Bayesian Networks, Logistic Regression, Multilayer Perceptron, Support Vector Machine, BF Tree algorithms using Both unbalanced/balanced 10-fold cross-validation and Testing set are 0.880, 0.880, 0.871, 0.975, 0.879, 0.970 respectively for cross-validation and 0.878, 0.878, 0.872, 0.975, 0.883, 0.983 respectively for Testing set.

As a result of this comparative analysis, the presented approach outperforms the existing approaches in recall, precision, accuracy, and F-measure. Figures (6), (7),(8) and (9) show the comparative analysis graph in bar and line diagrams using both unbalanced/balanced dataset 10-fold cross-validation and Testing set .

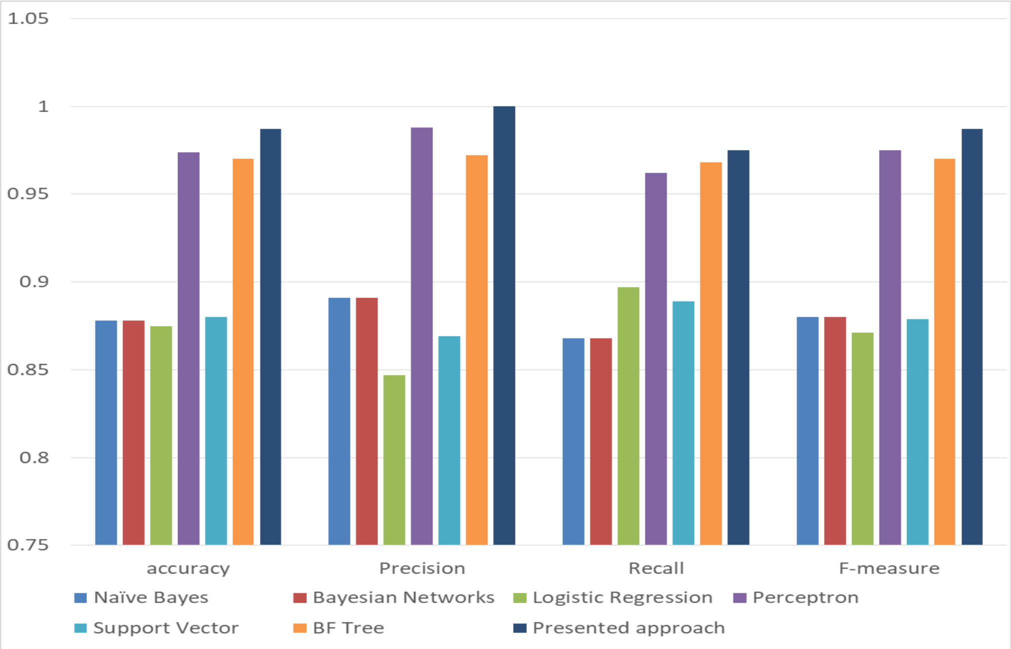

Figure 6: Bar diagram for the comparative analysis using 10-fold cross-validation Both unbalanced/balanced dataset.

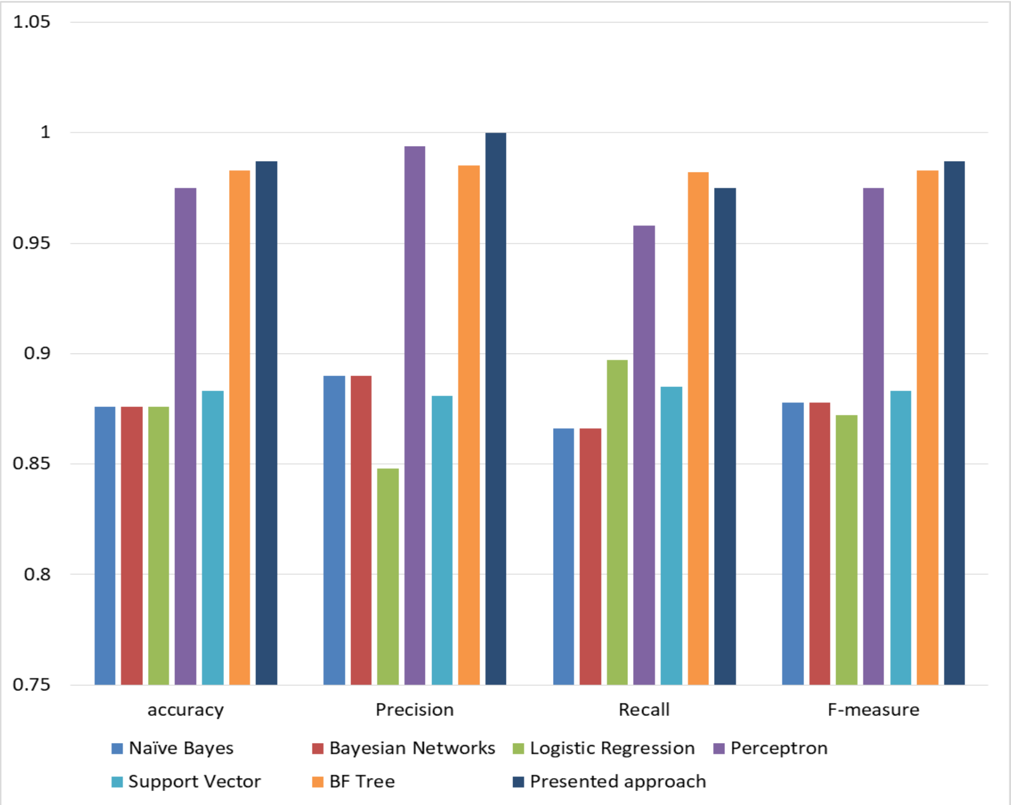

Figure 7: Bar diagram for the comparative analysis using Testing set Both unbalanced/balanced dataset.

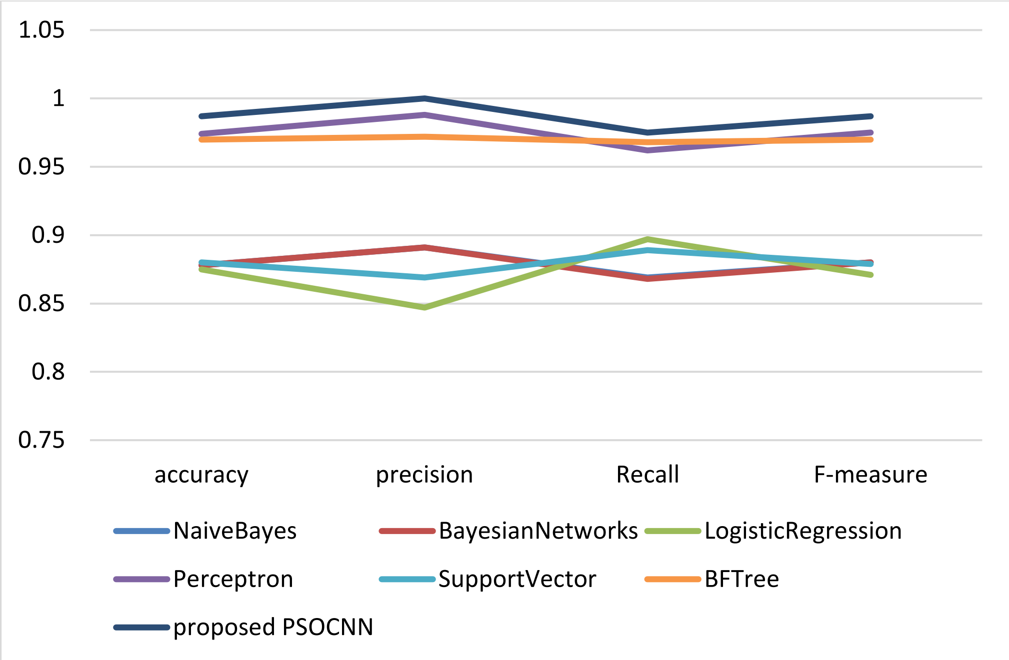

Figure 8: Line diagram for the comparative analysis using 10-fold cross-validation Both unbalanced/balanced dataset.

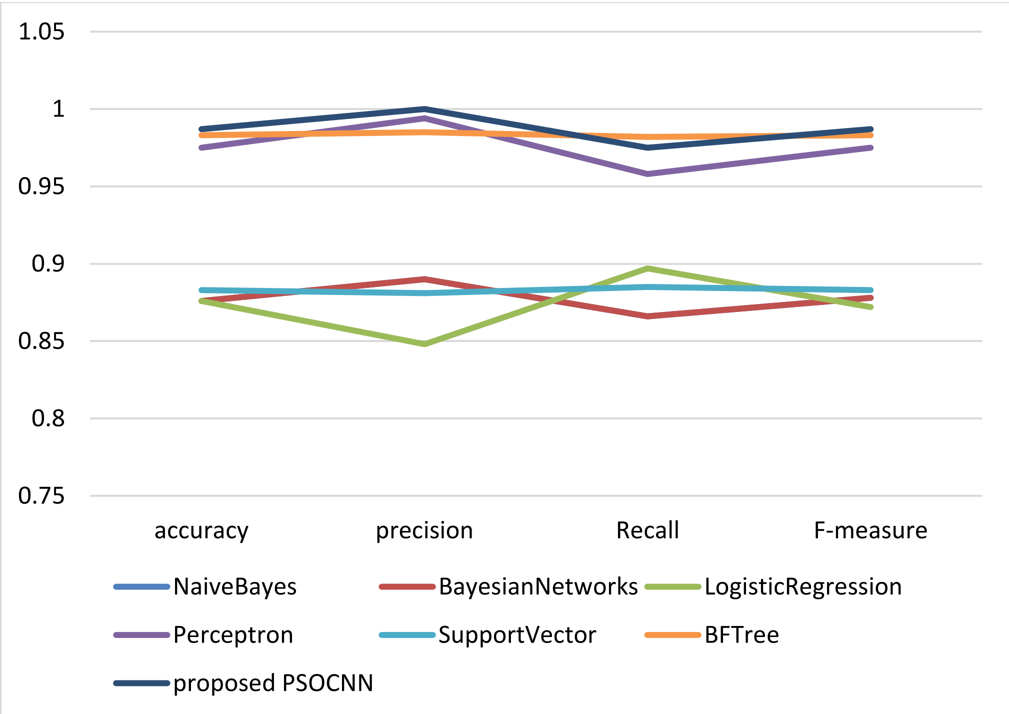

Figure 9: Line diagram for the comparative analysis using Testing set Both unbalanced/balanced dataset.

The x-axis in Figures (6), (7), (8), and (9) depicts COVID-19 detection performance measures such as accuracy, recall, precision, and F-measure. The y-axis displays the parameter values.

The proposed strategy is marked by a grey background color. Bayesian Networks, Logistic Regression, Multilayer Perceptron, Support Vector Machine, and BF Tree are represented by blue, red, green, purple, sky blue, and orange, respectively. This analysis demonstrates unequivocally that the provided technique surpasses current algorithms in terms of accuracy, precision, recall, and f-measure when compared to the Nave Bayes Classifier, Bayesian Networks, Logistic Regression, Multilayer Perceptron, Support Vector Machine, and BF Tree. As a result, the approach provided here is favored for identifying COVID-19.

5. CONCLUSION

Recent results validated the use of adopting COVID-19 categorization methods in Brazil, which are mostly based on non-invasive symptoms. To compare the classifier model, we utilized actual data from 55,676 patients, as well as the cross-validation technique of 10-fold, classification, and the NN with PSO. The Neural Network with Particle Swarm Optimization was widely acknowledged as the best classification strategy for reliably and rapidly classifying symptomatic patients for testing. Comprehensive documentation of the following characteristics in symptomatic individuals aids in the diagnosis of COVID-19: sex, health care professional, sore throat, fever, shortness of breath, olfactory difficulties, cough, rhinorrhea, taste abnormalities, and headache. For instance, patients who live in impoverished but also very difficult environments benefit from the use of non-invasive symptoms.

The following points are actually mainly concluded in this paper:

(1) Adding an extra hidden layer to the presented model's cases and scenarios helps improve a state's accuracy.

(2) Trying to improve accuracy is greatly aided by changing an accuracy method of calculation that included walls and floors rounding functions.

(3) PSO achieves the highest accuracy rate in the PSONN system. Because of the use of PSO for weight optimization as well as a start changing in the accuracy calculation, this model outperformed each other.

We have noticed that in recent years, machine learning and optimization algorithms are still considered one of the most promising algorithms in terms of being integrated with other technologies. This means that the changes and developments in it are continuing to come up with new methods that can be more effective and capable of yielding more satisfying results. For future works, the authors advise the readers to hybridize and evaluate the current proposed algorithm with the following research works: [47-63].

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