

Development of an Artificial Neural Network Model for Detection of COVID-19

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ABSTRACT

Background: The insurgence and resurgence of waves of the COVID-19 virus pandemic, aside its recorded mortality, has posed a lot of burden on the global health, social and economic systems. Its burden is worsened by the difficulty in its diagnosis due to the level of confusability in its symptoms which overlap with other diseases. **Aim:** The aim of this project was to develop an Artificial Neural Network (ANN) model for diagnosis of COVID-19 based on data acquired from COVID-19 patients. **Materials and Method:** A COVID-19 dataset was obtained from an online repository containing a total of 5434, with 4383 positive (80%) and 1051 negative cases as confirmed by Polymerase Chain Reaction (PCR) based test. The dataset was split into training and testing in the ratio 80:20 respectively. The ANN Covid-19 model (ANNCovid) model was built on the training dataset and tested on the testing dataset. Model performance was assessed using sensitivity analysis and accuracy. **Results:** Twenty features were identified from the dataset. The 20 features were ranked to identify their importance and diagnostic potentials. Ranking was done using Mutual Information Gain and three classification experiments were carried out after feature ranking: using 11, 14 and all 20 features as ranked by their corresponding P-values. The full-feature experiment yielded 98.44% accuracy, 99.31% sensitivity and 94.88% specificity. The 14-feature experiments gave 97.88% accuracy, 98.72% sensitivity and 94.76% specificity. The 11-feature experiment yielded accuracy, sensitivity and specificity of 97.33%, 97.75% and 95.50% respectively. This result shows that 20-feature experiment gave the highest accuracy and the highest sensitivity but the 11-feature experiment gave the highest specificity. **Conclusion:** Results show that the ANNCovid model has a great predictive potential. Results also show that the use of all features offer higher predictive potential than just using a few. These show that the proposed model can help to reduce PCR related cost as patients can be diagnosed easily and accurately by using the proposed ANNCovid model.

Keywords: artificial neural; COVID-19; ANNCovid model

INTRODUCTION

Coronavirus Disease 2019 (COVID-19) is an infectious disease caused by a novel severe acute respiratory syndrome coronavirus (SARS-Cov-2) [1]. Most people infected with SARS-Cov-2 experience mild to moderate respiratory illness and recover without requiring special treatment [2]. Older people, and those with underlying medical conditions like cardiovascular disease, diabetes, chronic respiratory disease, history of organ failure, blood clotting problem and cancer are more likely to develop serious illness [3]. This killer virus that started in December 2019 in Wuhan City, the capital of Hubei province in China has been declared as a pandemic by the World Health Organization (WHO), because its incident is now a threat to global health [4-6]. In fact, as at December, 2021, 326 million infection and 5.4 million deaths have been confirmed globally [7]. It is spreading very rapidly and there are a lot of research efforts to understand its prevention, diagnosis, treatment and vaccination. The dynamics of the pandemic has led to the introduction of social distancing, quarantine

and self-isolation which are now national orders in all countries of the world. Additionally, there has been a partial or complete closure of borders and businesses all over the world.

The detection of COVID-19 and reduction of its spread has been an ongoing high priority research focus [8-10]. Some computational and mathematical models have been proposed towards the early detection and diagnosis of COVID-19 [11, 12]. Real-Time reverse transcriptase Polymerase Chain Reaction (RT-PCR) is one of the most clinically acceptable form of medical diagnosis of COVID-19 virus [13-15]. RT-PCR is a well validated nuclear- derived method for establishing the presence of specific genetic material in any pathogen, including a virus. It has been used in the detection of several diseases such as Ebola virus and Zika virus [16-21] with great accuracy, and hence, many countries have quickly adopted it as one of the best ways of detecting the COVID-19 virus.

RT-PCR testing requires a sample to be collected from the parts of the body where the virus gathers such as the person's nose or throat. The sample is then treated with several chemicals to remove substances such as proteins and fats. Ribonucleic Acid (RNA) is then extracted which is then reverse-transcribed to Deoxyribonucleic Acid (DNA) using specific enzymes. If the virus is present in the collected sample, they attach themselves to target sections of the viral DNA which is then detected by the RT-PCR machine. This method is widely accepted and recommended by the World Health Organization (WHO) because it is highly sensitive, specific, reliable and with relatively desirable turnaround time (three to four hours) [22-25].

Medical imaging, specifically chest radiography and chest Computed Tomography (CT), has been proposed as a useful supplement to RT-PCR testing [26-28]. This method, although not a first-line diagnostic test [29-32], has gained publicity in its effectiveness in the detection of COVID-19. It is noteworthy, however, that chest imaging and radiographs findings on COVID-19 infection are confusable as they mimic other infections such as severe acute respiratory syndrome coronavirus, influenza virus, acute lung injuries from drug reactions, congestive heart failures and connective tissue diseases [33]. Its confusability has limited the specificity and True Negative Rate (TNR) of the method [34-36]. Currently, RT-PCR is the gold standard for diagnosis of COVID-19 but RT-PCR is very expensive. The feasible alternative to a cost-effective solution to diagnosis is the use of mathematical models or dedicated software.

When COVID-19 started, a lot was unknown about it and that made many to fall prey of the deadly disease. Now, there is increasing knowledge about the etymology of COVID-19 although there are a lot of misinformation and fake news as well. The quest for knowledge, prediction, protection and diagnosis of COVID-19 has led to the development of many mathematical models focusing on the characteristics, patterns and dynamisms of its incidence [37-41]. Some of the commonly used parameters are social distancing, quarantine, nose mask effects, restriction of social gatherings and climatic seasons. Some of the existing models are based on ordinary differential equations and epidemiological behavior of the pandemic, e.g. the Susceptible-Exposed-Infectious-Recovered-Death (SEIRD) model [12, 42-47].

In addition to mathematical modeling, soft computing, data mining and machine learning techniques have been explored as promising options for the prediction and diagnosis of COVID-19 infection, severity and recovery [48-50]. Data mining models such as decision tree and linear regression have also been proposed to offer a promising for diagnosis of COVID-19 [47, 48]. The most common machine learning models proposed so far are Support Vector Machine, Random Forest, Logistic Regression, LASSO regression, Exponential Smoothing and image-techniques techniques such as Convolutional Neural Network (CNN) [51-53].

RT-PCR is not cost effective and the existing machine learning techniques for diagnosis of COVID-19 have limited predictive value. The aim of this study is to develop a cost-effective model that will have a good predictive value. In this study, we propose an Artificial Neural Network (ANN) model for detection of COVID-19. The existing models are largely based on symptoms, but the proposed model will use symptoms, medical history, travel history and compliance with COVID-19 protocol. We hypothesized that the proposed model will have a good potential at detecting COVID-19. The proposed model is called Artificial Neural Network for diagnosis of COVID-19 (ANNCOVID).

ANN is a relatively new and widely used prediction model for supervised, semi-supervised and unsupervised tasks. Although it is mostly used for complex pattern recognition tasks, it has also been proven powerful for classification and regression tasks [54-56]. It has the advantage of automatically detecting and modeling complex linear and non-linear relationships between inputs to the network and can consider all possible relationships between the input variables [57, 58].

MATERIALS AND METHODS

a. Data Description

COVID-19 dataset was obtained from an online repository containing a total of 5434, with 4383 positive (80%) and 1051 negative cases as confirmed by PCR based test. Twenty features were identified in the original dataset. These are breathing problems, fever, dry cough, sore throat, running nose, asthma, chronic lung disease, headache, heart disease, diabetes, hypertension, fatigue, gastrointestinal disease, abroad travel, contact with infected patient, attendance of large gatherings, visit to publicly exposed places, family working in publicly exposed places, mask wearing, sanitization from the market and the binary classification label of the PCR outcome as given in the medical laboratory. The features can be grouped into 4 categories, these are symptoms of COVID-19 (fever, sore throat, dry cough, breathing difficulty, running nose, headache and fatigue), medical history (diabetes, heart problem, asthma, hypertension, gastrointestinal and chronic lung disease), contacts (contacts with COVID-19 patients, family working in publicly exposes places, visited publicly exposed places, travelled abroad and attended large gathering) and compliance with COVID-19 protocols (wearing of masks and regular sanitization)

b. Computational Modelling

The proposed ANNCOVID model uses 20 features which fall into 4 categories, COVID-19 symptoms, medical history, travel history and compliance with COVID-19 protocol. ANN model was developed to compute the weights of each of the 20 features [59]. Training was repeated to obtain the lowest level of error by changing the number of neurons and the epoch number. Figure 1 shows the ANN system framework of the proposed COVID-19 prediction model. The testing phase of the modelling requires entering of the testing dataset. Once the testing data were entered into the model, the trained model was applied on them and a value on positivity was computed.

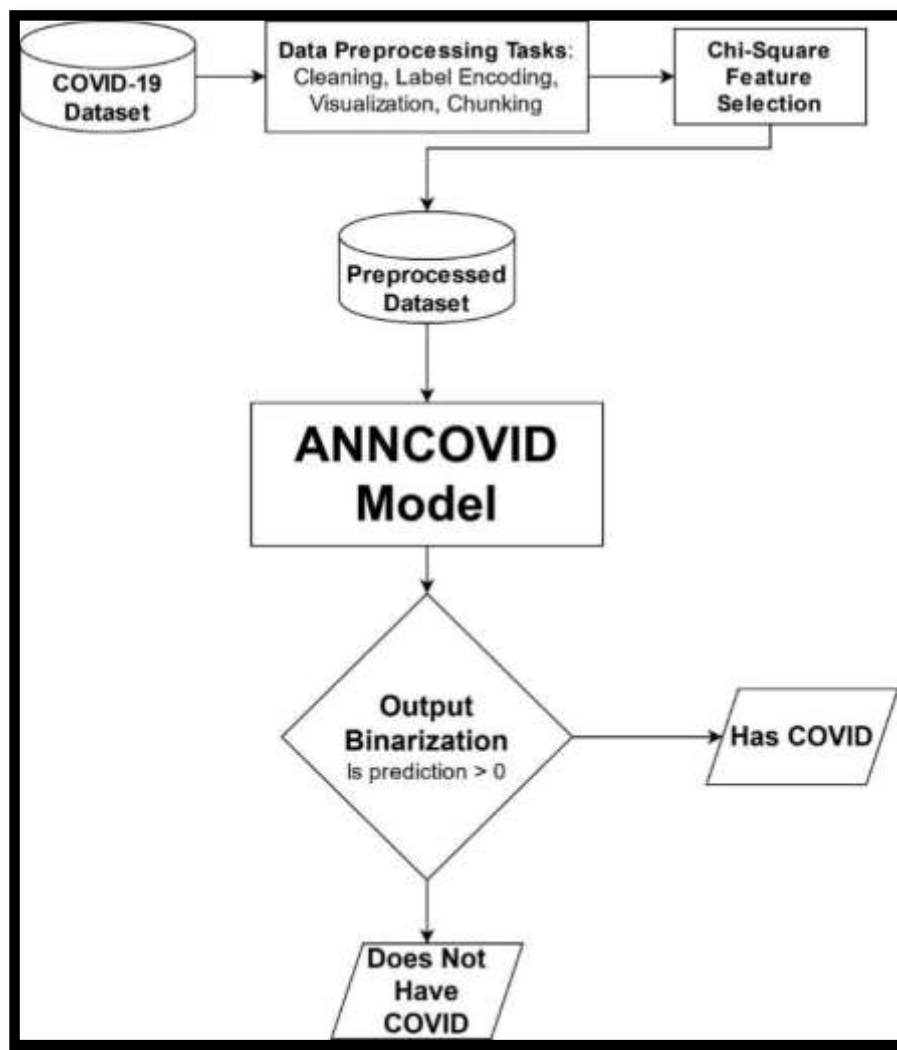


FIGURE 1: System Framework of the Proposed ANNCOVID Model

- i. **Data Preprocessing:** Data collected from subjects primarily or as secondary data normally require preprocessing as a preparatory step for statistical or machine learning models depending on the nature of a given study. The dataset for this study was cleaned and label-encoded visualized and chunked into a training and testing set. Cleaning helped to remove noise and incomplete observations from the dataset. Encoding refers to the steps taken in converting the values of each feature into numerical data for the ANNCOVID model to work on. Data splitting into training and testing was done optimally in the ratio of 80:20. In our study, we also tested for 10-fold cross validation. However, this did not have a significant change in the result of this study. This shows that train-test splitting is also a stable and generalizable method for the dataset we used in this experiment.
- ii. **Feature Selection:** Given that not all features in a dataset may have predictive value, feature importance was performed on the dataset. This led to the ranking of the features based on how each one independently predicted the target variable (i.e. COVID19). Features were selected based on their p-values < 0.05 using Chi-Square technique [60, 61]. Features that did not have any predictive value were eliminated and the rest was passed into the ANNCOVID model.
- iii. **ANNCOVID Model Development and Testing:** Several applicable neural network models were tested and optimized to obtain the best configuration for the prediction of COVID using known symptoms. The modeling technique was based on the principle of backpropagation. This principle breaks the model into three layers: an input layer, one or more hidden layers and an output layer; each of which includes one or more neurons. As shown in Figure 2, nodes from one layer are connected to all nodes in the following layer, however, with no lateral connections within any layer and no feedback edges. This is known as a feedforward neural network model. Although many transfer functions can be used in ANN models, logarithmic and tangential sigmoid transfer functions have been adopted for the input and output hidden layer neurons. This allows the network to learn non-linear and linear relationships between input and output vectors [1, 2]. In training our neural network, we avoided overfitting and underfitting by using a weight regularization technique in the objective function. This model penalty technique has the effect of reducing generalization error and allowing the model to pay less attention to less relevant input variables. The neurons in one layer are connected to other neurons in another layer through connection weights.

Figure 2 shows the system structure of the proposed ANNCOVID model. In the hidden layer, we set batch = 10 and epoch = 100 with the Rectified Linear Unit (relu) as our activation function.

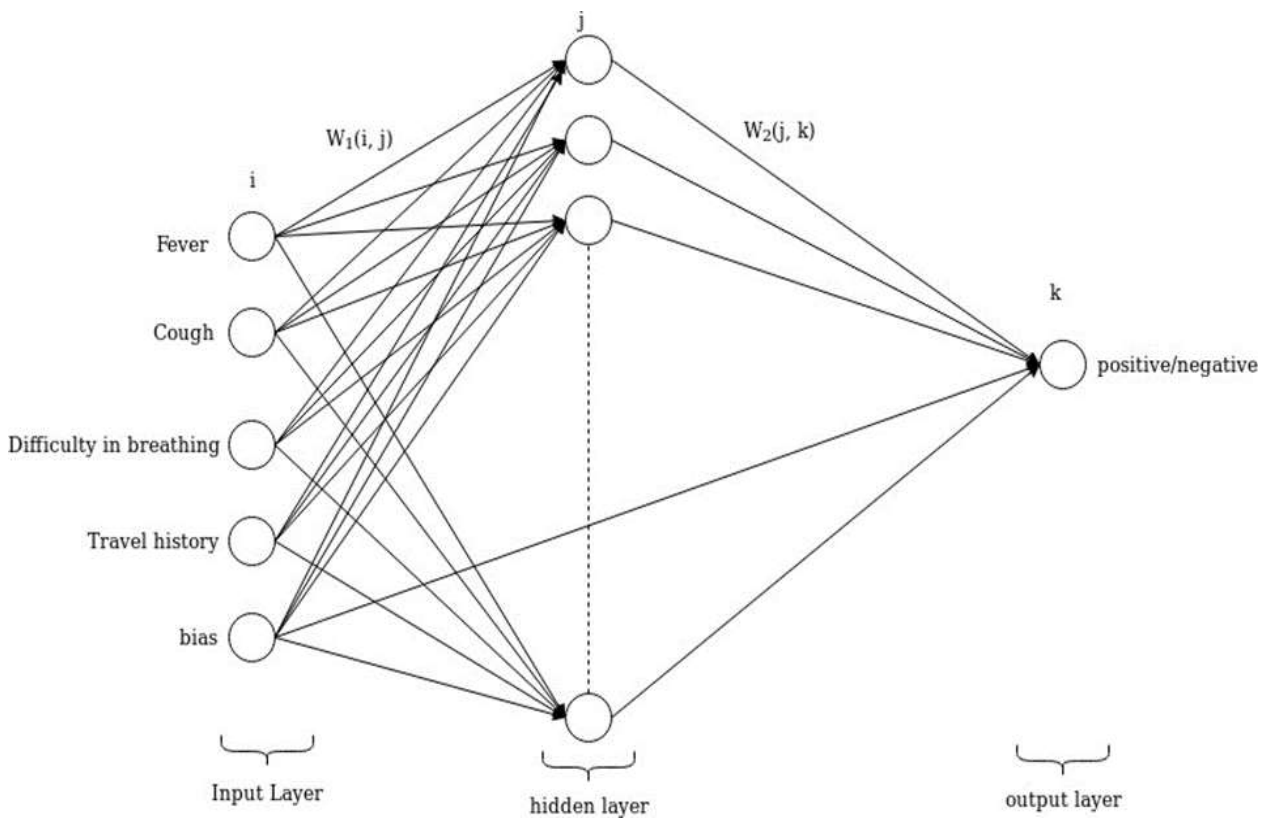


FIGURE 2: Structure of the ANNCOVID model

The input weights link the input layer and hidden layer and the output weights link the hidden layers with the output layer. The activation function used in the input and output layers are given in Equations (1) and (2) respectively.

$$y_i = \frac{1}{1 + e^{-\sum w_{ki} x_k}} \quad (1)$$

$$\hat{y}_i = \frac{2}{(1 + e^{-2\sum w_{ki} x_k})} \quad (2)$$

Where

- x_k = the input value at the input neuron i
- w_{ki} = the weight connecting node k from the input layer with node i from the hidden layer
- y_i = the value of the hidden neuron i
- w_{ij} = the output weight between the hidden neuron i and the output neuron j
- \hat{y}_i = the output value of output neuron j

Output binarization is used to categorize the y_i value to either COVID-positive or COVID-negative using a defined threshold.

RESULTS

Of the of 5434 subjects in the study, 4383 were positive (80%) and 1051 negative individuals confirmed by PCR based test. Of these, 79 had fever and dry cough while 73% had sore throat. 67% had breathing problem while only about 45% had attended large gathering or had travelled abroad (Table 1, Figure 3). About 46% had ongoing medical conditions like Chronic lung disease, asthma, heart disease or diabetes. None of them wore face mask or used hand sanitizers.

TABLE 1: Description of the Features

Feature	Number	%	Feature	Number	%
Fever*	4273	79	Hypertension*	2663	49
Dry Cough*	4307	79	Diabetes*	2588	48
Sore throat*	3953	73	Chronic Lung Disease*	2565	47
Breathing Problem*	3620	67	Gastrointestinal	2551	47
Running Nose	2952	54	Asthma*	2514	46
Fatigue*	2821	52	Heart Disease	2523	46
Visited Public Exposed Places*	2820	52	Attended Large Gathering*	2510	46
Headache	2736	50	Abroad travel*	2451	45
Contact with COVID Patient*	2726	50	Family working in Public Exposed Places*	2262	42

Note. * implies that feature was selected to have good predictive value using Mutual Information Gain

Twenty features were identified from the dataset and 5434 instances with no null values. In the preprocessing stage, feature selection was done using Mutual Information Gain. This ranked the features in the dataset in ascending order of importance using their corresponding p-values. The 14 features selected are Abroad travel, Attended Large Gathering, Sore throat, Breathing Problem, Contact with COVID Patient, Dry Cough, Fever, Family working in Public Exposed Places, Visited Public Exposed Places, Hypertension and Asthma. Three experiments were hence set up after the feature selection process and removal of the two redundant features. These were classification using 11, 14 and 20 features. Table 2 shows the results obtained in the three experiments set up for validation of our proposed ANNCOVID model.

In order to further improve the predictive value of the model, we reduced the p-values and selected only features with p-values <0.0001. This yielded 11 features namely, Abroad travel, Attended Large Gathering, Sore throat, Breathing Problem, Contact with COVID Patient, Dry Cough, Fever, Family working in Public Exposed Places, Visited Public Exposed Places, Hypertension and Asthma. Three experiments were hence set up after the feature selection process and removal of the two redundant features. These were classification using 11, 14 and 20 features. Table 2 shows the results obtained in the three experiments set up for validation of our proposed ANNCOVID model.

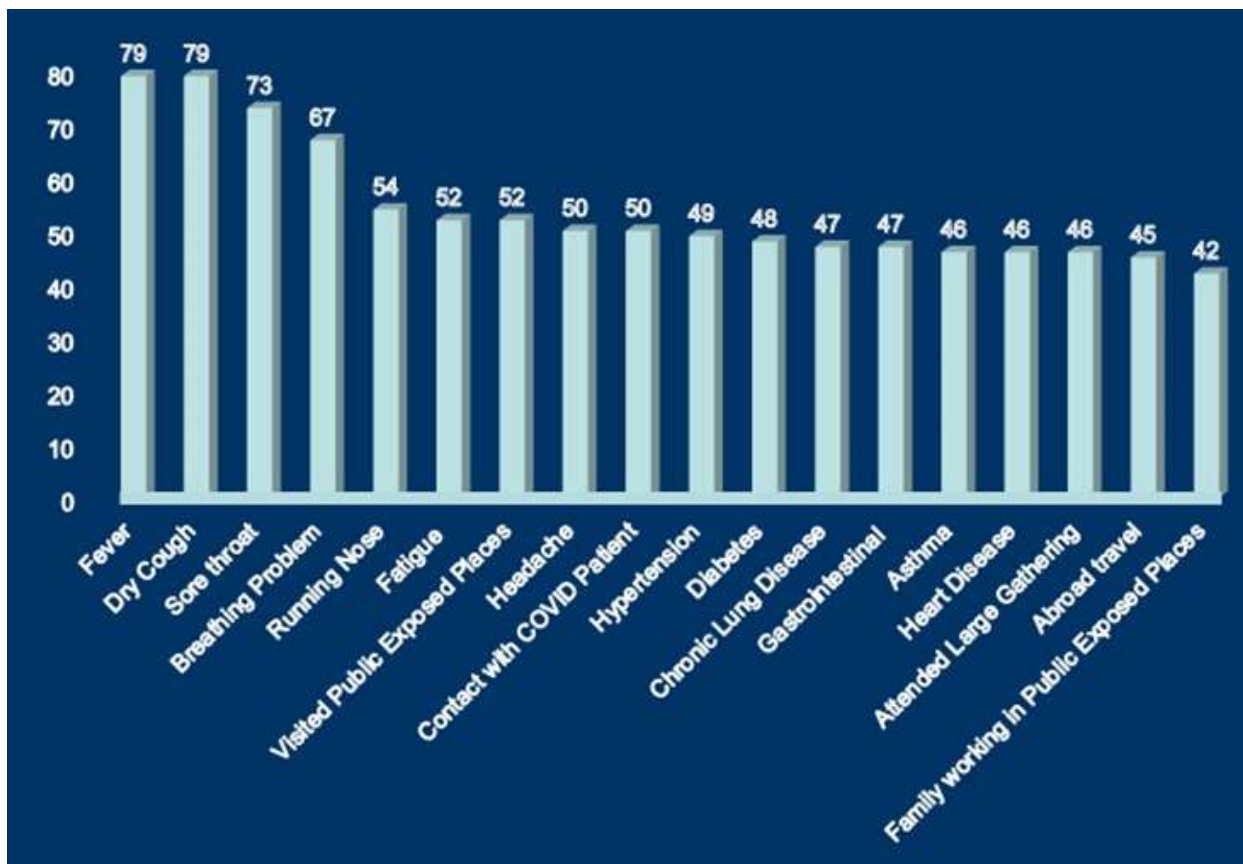


FIGURE 3: Descriptions of the Features

The result shows that the sensitivity, specificity and accuracy for the 11 Most Important Features were 97.75%, 95.50% and 97.33% respectively while the sensitivity, specificity and accuracy for the most 14 Most Important

Features were 98.72%, 94.72% and 97.88% respectively. The sensitivity, specificity and accuracy for all the 20 Features were 99.31%, 94.88% and 98.44% respectively.

TABLE 2: Model’s Experimental Performance

Experiment	Sensitivity (%)	Specificity (%)	Accuracy (%)
11 Most Important Features	97.75	95.50	97.33
14 Most Important Features	98.72	94.72	97.88
20 Most Important Features	99.31	94.88	98.44

DISCUSSION

We developed an ANN based model called ANNCOVID for diagnosis of COVID-19 using 20 features grouped into four categories, namely, symptoms, medical history, travel history and compliance with COVID-19 protocol. The 20 these are symptoms of COVID-19 (fever, sore throat, dry cough, breathing difficulty, running nose and fatigue), medical history (diabetes, heart problem, asthma, hypertension, gastrointestinal and chronic lung disease), contacts (contacts with COVID-19 patients, family working in publicly exposes places, visited publicly exposed places,

travelled abroad and attended large gathering) and compliance with COVID-19 protocols (wearing of masks and regular sanitization)

Feature extraction using Information Gain identified 11 features when p-values was set to 0.0001 and 14 features when p-value was set to 0.05. The 11 features are Abroad travel, Attended Large Gathering, Sore throat, Breathing Problem, Contact with COVID Patient, Dry Cough, Fever, Family working in Public Exposed Places, Visited Public

Exposed Places, Hypertension and Asthma while the 14 features identified when p-value was set to 0.05 are Abroad travel, Attended Large Gathering, Sore throat, Breathing Problem, Contact with COVID Patient, Dry Cough, Fever, Family working in Public Exposed Places, Visited Public Exposed Places, Hypertension, Asthma, Chronic Lung Disease, Fatigue and Diabetes. Based on the outputs of feature extraction, three classification experiments were conducted based, these are the use of 11 features, 14 features and 20 features.

The classification experiments show that the 20-feature experiment gave the highest accuracy and the highest sensitivity but the 11-feature model gave the highest specificity. This result established that the full-feature gave the most reliable result of the three approaches. This shows that all the features investigated in this study are very important. The implication of this is that a robust model, like the ANNCovid model proposed in this study is required for accurate diagnosis of COVID-19. Our results hence confirm that the ANNCovid model has a great predictive potential.

After the model training, which takes about 57 seconds, the model testing takes less than 14 seconds. Additionally, adopting this model implies that self-diagnosis without the use of PCR is possible. These show that COVID-19 can be easily and quickly be diagnosed at no cost if the proposed model is adopted. This is very important because it can reduce the burden on the global health and save cost.

We compared our model with some existing machine learning techniques. Our results show that the proposed model outperforms most of the existing machine learning techniques. For example, we compared our model with gradient boosting machine learning technique [62] and biterm topic model [63]. These models used symptoms only and gave maximum of 87.30% sensitivity and maximum of 79.18% specificity [62] [63]. Some previous empirical studies have confirmed that underlying sicknesses such as chronic obstructive pulmonary disease (COPD), cerebrovascular disease (CEVD), cardiovascular disease (CVD), type 2 diabetes, malignancy, and hypertension, as well as asthma are significant features for classifying those deceased versus those who survived COVID-19[64].

In view of this, some other machine learning models included medical conditions and got improved diagnosis, e.g, XGBoost, Support Vector Machine, k-nearest neighbor and ANN model that combined symptoms with medical condition gave accuracy of 96%, 87.3% sensitivity and 72% specificity [65-69]. Our model gave sensitivity of 99.31%, specificity of 94.88% and accuracy of 98.44%, this clearly shows that our model outperformed most of the existing machine learning models. Some existing studies that used machine learning gave high performance (E.g. Accuracy of 99%) comparable with ours but they were based on the use of x-ray and Mammogram images [50, 68, 70, 71]. However, the use of imaging parameters suggests that adoption of such techniques will be difficult, most especially in the middle- and low-income countries where imaging is very expensive. Our study combined symptoms, medical information and contact history and gave a very high-performance value at predicting COVID-19. This is very novel with high possibility of adoption.

One of the main strengths of our model is the fact that, contrary to the use of symptoms or self-reported history only, our model combined symptoms with medical history, contact history and compliance with covid-19 protocols. This can explain the reason why our model outperformed most of the existing models.

Another strength of our model is the fact that we assessed performance using sensitivity analysis. We paid special attention to the sensitivity and specificity of our model and this helps us to fine tune the modeling parameters empirically to ensure that the best result was produced. This is in contrary to most of the existing models that focused largely on accuracy without investigating the sensitivity and specificity. Sensitivity helps to identify the covid-19 patients who were identified as covid-19 patients while specificity helps to identify the non-covid-19 patients who were identified as non-covid-19 patients. It is very important to pay attention to both sensitivity and specificity because accuracy alone is not an enough metric to trust a machine learning model [72].

CONCLUSION

In this study, we focused on the development of an ANN model for the prediction of COVID-19 using information obtained from patients who were suspected to have been infected with the virus. This model has proven to be effective in predetermination of COVID-19 patients. It can also serve as Decision Support System (DSS) for clinicians in predicting the status of a patient before the popular PCR test outcome. Adoption of this method is fast, reliable and cost-effective. This study also offers a self-screening model and repository, providing at-home safety for the populace and thereby saves lives. Prompt access to the model will lead to early help and hence save lives.

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