

# Design and Implementation of an Online Coronavirus Testing Software

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## Abstract:

The coronavirus disease (COVID-19) has spread across the world and has been classified as a pandemic and a public health emergency of global importance. Researchers have claimed that one of the reasons the coronavirus is deadly is because it attacks the respiratory system, which is like severe acute respiratory syndrome (SARS). The coronavirus causes shortness of breath and reduces the oxygen level in the blood. The coronavirus can also cause fever, taste and smell loss, and other symptoms. Early detection of infected persons and thorough contact tracing helps in reducing and mitigating the transmission of this virus. However, in rural communities where resources for testing are little or are not even available, this aim becomes unachievable. This system focuses on designing and implementing a coronavirus testing software that utilizes a deep neural model to detect the probability of COVID-19 based on user input data. After a one-time registration, users answer a few questions about how they feel, and the input data is then fed into the DNN model. The model is designed to detect if the individual is a suspect of COVID-19, providing a list of COVID-19 test laboratories based on their current location. With early detection of infected individuals and thorough contact tracing, this system aims to reduce and mitigate the transmission of COVID-19, especially in rural communities with limited resources for testing.

**Keywords** — COVID-19; Web application; Deep learning; Coronavirus

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## I. INTRODUCTION

SARS-COV-2, a critical respiratory disease, was first identified as a pulmonary incident of uncertain cause in China's Wuhan province in December 2019 (Ceci et. al, 2021), which subsequently led to the coronavirus disease epidemic (National Center for Biotechnology Information, 2021). Since the first public case, the rest of the world has faced numerous health challenges, including uneven public health policy implementation, a lack of widely available testing, and confusion over reliable diagnostics (Sofra, 2021). The World Health Organization declared COVID-19 a global infectious disease on

March 11, 2020, as it had already infected around 100,000 people in roughly 100 states (Beta South-Ayrshire, 2021). The symptoms of COVID-19 begin with shortness of breath and evolve into a fever, cough, respiratory symptoms, and difficulty breathing. The disease is fatal and can cause bronchitis, pneumonia, acute respiratory suffering, and severe breathing conditions like SARS. The elderly, infants, those with cardiac illnesses, and immune-conceded persons are at higher risk of complications due to their weak immune systems. The global expiry proportion of the disease is estimated to be around 3.41 per cent (Coronavirus CDC, 2019). Experts have warned of the risks of the

virus's spread in Africa due to the region's delicate medical facilities and adjacent marketable relations with Beijing. Although coronavirus germs are expected to have minor existence proportions in hot Africa (SOAS University London, 2020), the continent has still been significantly affected. Nigeria has recorded 323 COVID-19 cases and ten deaths as of April 13, 2022. It is essential to acknowledge that Nigeria, being the most populated country in the region, has a significant role to play in controlling and managing the spread of COVID-19. Research has indicated that early detection and diagnosis of the virus can significantly increase the chances of recovery, particularly if there are no delays between assessment and analysis. A well-improved investigation scheme would encourage more individuals to get tested, leading to a better understanding of the extent of the disease. Viral infections have been a significant concern in human health, and COVID-19 has affected 221 countries and territories with over 230 million confirmed cases and 4.7 million deaths. In Nigeria, there have been over 203,000 confirmed cases and 2,644 deaths, indicating the need for better control measures. Effective contact tracing and timely diagnosis of infected patients is critical for healthcare organizations to manage and alleviate the COVID-19 illness. However, in remote areas where testing facilities are limited, controlling the spread of the virus becomes more challenging. To address this issue, self-testing can help people identify the symptoms before seeking medical attention, preventing false alarms, and wasting time. Therefore, improving the investigation scheme in Nigeria is crucial for controlling and containing the COVID-19 pandemic.

## **II. LITERATURE REVIEW AND THEORETICAL ANALYSIS**

### ***A. Literature Review***

The National Institutes of Health conducted a study on the applicability of smartphone apps in conjunction with the QuidelQuickVue At-Home COVID-19 Test. This was supported by NIH through the RADx initiative. Over 200 participants

enrolled on this study, and it involved a two-week testing period. Then a software called Mydatahelps was developed by CareEvolution LLC, which provided step-by-step instructions for taking the test, but unhappily it was only beneficial to America only. Using the terms "Coronavirus," "respirational condition coronavirus 2," and COVID-19, a previous study that was focused on the analytical and serological analyses for SARS-Cov-2 was disregarded. From their launch to 16 April 2020, the PubMed, Google Scholar, and EMBASE databases were searchable in any language. They were then updated on 15 May 2020. The preprint attendees for both fitness disciplines and genetic records were analyzed for the quickly emerging arena and fast dissemination of systematic responses concerning COVID-19 (Li M, 2020). Using machine learning techniques, some authors created a prediction model to tackle COVID-19 in China and other impacted places worldwide (Li M, 2020). To calculate the number of illnesses and catastrophes that have been reported around the universe, particularly in China, the authors employed a methodology. Between January 20 and March 1, 2020, data that served as the basis for the models were collected. According to their calculations, on the 22nd of February, and 10th of April 2020, in mainland China and globally respectively, the COVID-19 epidemic reached its climax. Additionally, the scientists estimated that global eradication of COVID-19 would be around mid-June 2020 and in China, at the start of April 2020. They estimated that there would be approximately 89,000 COVID-19 patients in 2010. Using the ARIMA model, which is an autoregressive integrated moving average, some authors forecast that COVID-19 would greatly spread in the globe's 15 most contaminated nations. They forecast that conditions will deteriorate in both Europe and Iran. Additionally, they anticipated that South Korea's and China's mainland's severity of illness will stabilize. Additionally, the study predicted that COVID-19 would spread swiftly in the US and that swift, rigorous government intervention would be needed to halt the disease's growth. However, there were expected to be one million COVID-19 cases in

the US between April 8 and April 30, 2020, there were only 677,570 instances on April 17, 2020. Additionally, despite an anticipated 300,000 cases, Italy only reported 168,941 cases. 100 different chest X-ray images, fifty per cent (50%) of Coronavirus victims and fifty per cent (50%) who were not infected were used by some authors to develop a CNN-based framework that could be used to detect COVID-19 sufferers. ResNet-50 demonstrated the greatest detection performance when three (3) CNN versions—Inception-ResNet-v2, Inception-v3, and Inception-v3—were tested utilizing five-fold inter (98 per cent). Also, some authors classified chest X-ray images as healthy or sick using a support vector machine after extracting attributes from the images using a deep-learning method (SVM) (Narin et al, 2021). The authors used AlexNet, Inception-ResNet-v2, ResNet-18, DenseNet-20, Inception-v3, XceptionNet, GoogLeNet, ResNet-50, VGG16, VGG19, and ResNet-101 (Chen et al, 2020), (Sharma et al, 2021). They collected two datasets: one had 133 infected patients (including those with MERS, SARS, and ARDS) and 133 uninfected clients, whereas the other had 25 infected people and 25 uninfected sick people. With ResNet-50 and SVM, they were able to extract independent features from each dataset with 95.38 per cent accuracy (Sethy and Behera, 2020). Additionally, some authors unveiled COVIDX-Net, a method that could aid radiologists in using X-rays to diagnose COVID-19 patients (Hemdan et al, 2020). 50 distinct X-ray images, divided into 25 COVID-19-negative images and 25 COVID-19-positive images, were employed to validate their framework of theirs. The employed photos were reduced to pixels 224x224. The ResNet-v2, Xception, MobileNet, and Inception-v3 deep learning models are employed by the COVIDX-Net framework., modified VGG19, and Inception-ResNet-v2. The VGG19 and DeneNet models fared well, based on their analysis results and equally, having a COVID-19 F-score rate of 91% (Redie et al, 2022). More also, work on tuberculosis regarding patients in rural areas using the E-health solution scheme was carried out by (Shoewu, O.O. et.al,

2019). Additionally, Other machine learning, game theory, and metaheuristic algorithms, including genetic algorithm (GA), particle swarm optimisation (PSO), and others such as game theory, will be used to expand and validate this study in the future (Ekwe,S.O., 2020, Ekwe,S.O., 2021). Numerous engineering issues, including those involving wireless networks, automation, and process control, to name a few, have been successfully solved using these techniques (Oladejo. S.O., et al, 2021) and (Oladejo. S.O., et al, 2021). Also, a deep learning approach has been employed in autonomous robotic car (Shoewu, O.O. et al, 2021) and (Shoewu, O.O. et al., 2023). This scheme can equally be employed in health-related case. There is a wide variety of commercial software on the market that may be evaluated online for the COVID-19 virus. The contribution of this study lies in the strength to predict any pandemic before it occurs to avoid such deadly disease that ravaged the world in 2019. The following is a list of such global COVID software-based tests:

## **B. Theoretical Analysis**

**1. Viral Testing Tool:** The Coronavirus Infectious Toolkit is a collaborating online software aimed to assist both fitness care suppliers and people comprehend COVID-19 testing choices. This software delivers pertinent, actionable data for persons to make knowledgeable conclusions regarding which test they might require. Once you have the assessment outcome, the software would take you to CDC references for that trial outcome. This virtual, mobile-friendly software inquires a sequence of queries and delivers suggested schedules and means based on the consumer's answers (Coronavirus CDC, 2019).

**2. Detection Management Software for Coronavirus:** Due to physical Coronavirus Test supervision methods, clinics, analytical workrooms, portable testing sites, hospitals, and fitness care providers all over the biosphere waste hours of productivity that could be spent on patient care. Xyblion provides COVAPP which is a thorough

point-to-point Coronavirus Check Supervision app, in rebuttal to the Coronavirus pandemic and the requirement to quickly educate infected persons of the outcomes of their testing. COVAPP eradicates physiological processes with full regulatory requirements and fully automated test result notices.

**3. Cloud COVID-19 LIMS:** To evaluate, identify, and enhance coronavirus disease vaccines, medical testing and investigation workshops around the world are working nonstop. By using FDA permission and well-organized work streams, CloudLIMS has already helped several workshops get up and running in a week. The following are some of the common situations that COVID-19 testing labs deal with:

- Fast confirmation of FDA-permitted COVID-19 test work movements.
- Growth, regulation, and authentication of innovative approaches for detecting Coronavirus.
- Recording detection consequences according to CDC and FDA strategies.
- Ensuring global supervisory rules, like ISO 15189:2012, HIPAA, and CLIA.

Perfectly timed analysis of Coronavirus presumed cases plays a key role in effective isolation and medication handling. To combat the SARS-CoV-2 epidemic, for automatic COVID-19 identification on chest CT, a deep learning-focused prototype is being created. A poorly managed deep learning-built system was designed to comprehend COVID-19 utilizing 3D CT dimensions. The chest region of each victim was divided using an effective UNet, and a 3D deep neural network was then given the segmented 3D chest region to forecast the likelihood of Coronavirus infection. 499 CT dimensions were collected between 13 December 2019 and 23 January 2020 for teaching, whereas 131 CT sections were obtained between 24 January and 6 February 2020 for learning (Zheng et al, 2020). The deep learning system achieved a 0.976 PR AUC and a 0.959 ROC AUC. In the ROC curvature, there was an effective terminal with a sensitivity of 0.907 and 0.911. By classifying COVID-negative and COVID-positive utilizing a probability margin of 0.5, the method was

able to attain an efficiency of (90.1%), a positive prefiguring rate of (84.0%), with a large negative prefiguring rate of (98.2%) (Zheng et al, 2020). Running a single client's CT data through a special GPU only took 1.93 seconds. Without the need to interpret the cuts for learning, the shakily implemented deep learning prototype could accurately anticipate the likelihood of COVID-19 infection in chest CT collections. A casual method of classifying COVID-19 sufferers is made possible by the simple-to-use yet very successful deep learning approach, which is useful for preventing the spread of SARS-CoV-2 (Zheng et al, 2020).

### III. METHODOLOGY

This section discusses the methodology employed in this study. The Figure 1 depicts the block diagram used for this study using the deep neural network model for the COVID case.

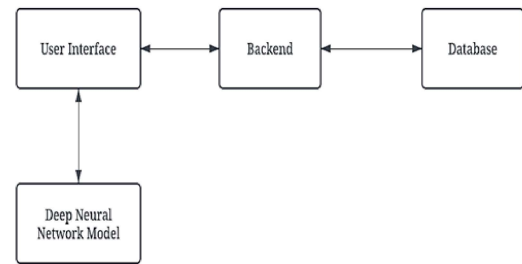


Fig 1: Block diagram of the system

#### A. Literature Review

**1. User Interface:** This is the graphical user interface of the application that allows communication between the system and the user. This component is a web application to be used on a web browser and it was built with modern web technologies such as HTML, CSS, and VueJS (JavaScript). This system's user interface was created as a Single Page Application (SPA), which implies that data is passed from one page to the next without the need to download new HTML content from the server.

**2. Backend:** The backend was built using Laravel, a PHP framework that enables developers to create

server-side applications and web services. Employing the REST Application Programming Interface, the backend delivered endpoints to enable the communication between the interface and the database. It serves as an intermediary between the user interface and the database.

**3. Deep neural network model:** The proposed system incorporates a deep neural network (DNN) model as the backbone of the COVID-19 testing software. The DNN model serves as the decision-making component, where it receives an input tensor from the user interface and returns a probability that the user has COVID-19 based on the provided input. The model was designed and trained in a Colab notebook using the Python programming language and several libraries such as Pandas, Numpy, PyTorch, and sklearn. These libraries enabled the creation of a high-performing and efficient model that accurately classifies the user's input as positive or negative for COVID-19. The DNN model's ability to learn and generalize from large datasets makes it an ideal choice for COVID-19 diagnosis, allowing for efficient and reliable testing even in areas with limited resources. Overall, the deep neural network model represents a critical component of the COVID-19 testing software, providing accurate and reliable predictions to aid in the fight against this global pandemic.

**4. Database:** The database stores the data sent from the Frontend through the Backend service. It is the source of data for the whole system. The database technology that was used in this system is MySQL.

**B. System Design**

In the deep neural network model, the classification was handled by a feed-forward neural network that used deep learning. Multi-layer perceptron (or MLPs) is another name for feedforward topologies. The outputs from units in each layer are transmitted to units in the next higher layer, with no outputs being passed back to lower levels in a feedforward arrangement. An artificial neural network (ANN) having multiple levels between both the layer of input and output is known

as a deep neural network (DNN). Both neural networks employ the same modules: neurons, weights, biases, and functions. The neural network algorithm resembles how the human brain works. Any neural network needs input and output layers. The objective parameter is present in the layer of the output, whereas the layer of the input includes system parameters. An input layer, hidden layers nodes, and an output layer make up the model (Tawadrou and Katsabani, 2005). The layer of the input of the model has 18 nodes, the initial unknown level of the process has 11 nodes, the second hidden layer of the model has 3 nodes, and the output layer has just a single node (Geoffrey, 2002).

In this study, Figures 2 and 3 depict the flowchart of the deep neural network model and architectural structure of the deep neural network, respectively. The flowchart indicates every step taken from the feeding the input data to output using the dataset to train the developed model.

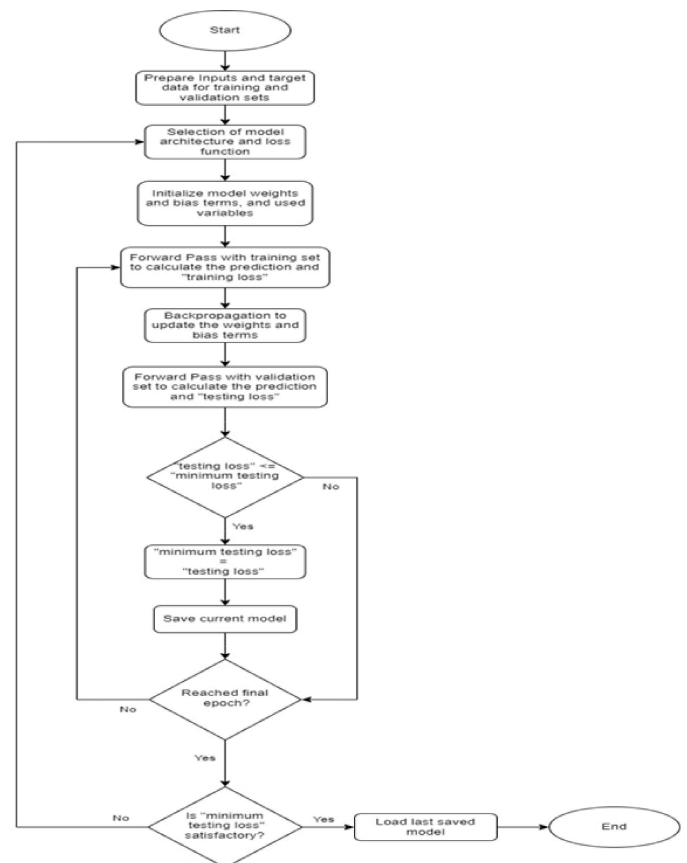


Fig 2: Flowchart of the deep neural network model.

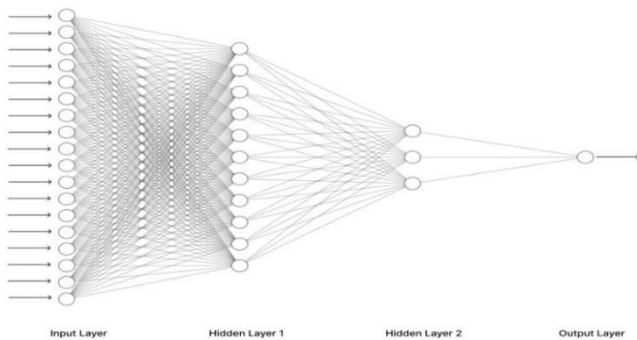


Fig 3: Architectural structure of the deep neural network.

The dataset is prepared by converting all the parameters from “Yes” and “No” to 1s and 0s (1 representing “Yes” and 0 representing “No”) and then dividing the data into training and testing data. The deep neural network architecture of linear layers and a binary cross-loss function is chosen. The model weights and bias terms, epoch, minimum testing loss, and all other required variables are initialized.

To derive the prediction and training loss, forward propagation is used with the training data from the input layer to the output layer. After the training loss has been obtained, a backward propagation is then carried out to update the weight and bias terms and then increase the accuracy (en.wikipedia.org, 2020).

The forward pass is now repeated with the validation sets in other to obtain the testing loss (Kumar, 2020). If the testing loss is less than or equal to the minimum testing loss, the minimum testing loss is updated with the value of the current testing loss and the model's current state is saved. The process is repeated for the selected number of iterations. If the minimum testing loss is not satisfactory, the architecture is changed a little and the process repeats. After the iteration has been completed, and the minimum testing loss satisfied, the last saved state of the model is loaded. The activation function of the last layer is a sigmoid function which converts the single node output into probability.

### A. Results

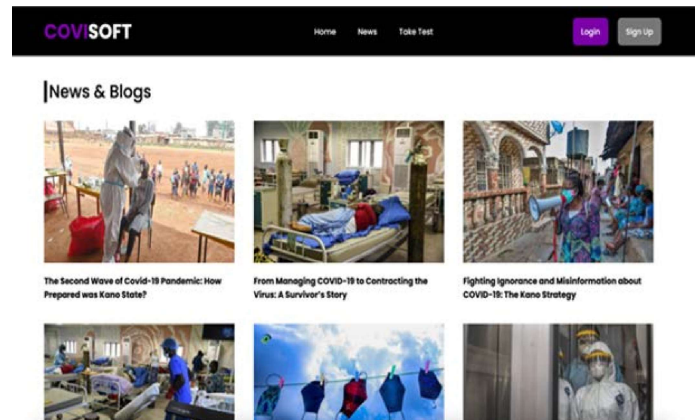


Fig 5: COVID-19 news page.

Figure 4 is a snapshot of the Covisoft news page which is the online page for publishing the latest news on the damages caused by the pandemic. In Figure 5, a patient is captured trying to do covid self-assessment after login into his dashboard on the Covisoft app by answering some questions which are automatically used in determining the status of the patient. A total of about 13 different questions are programmed on the app.

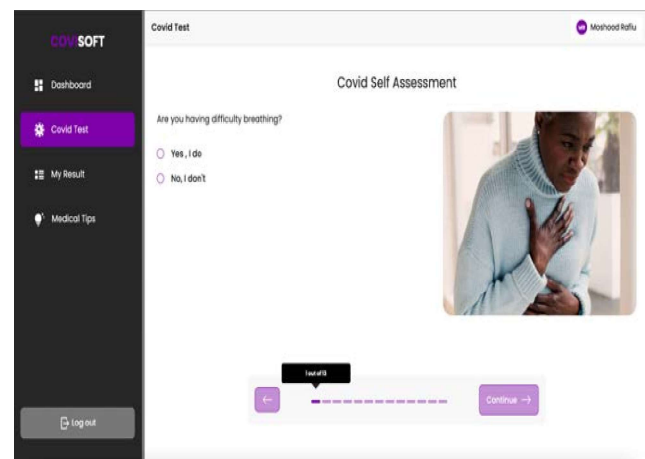


Fig 4: COVID-19 assessment start page.

Figure 6 captures the last stage of the self-assessment page which queries the suspected patient

if they contacted anyone who has directly or indirectly contacted a covid patient or medical personnel.

review button. The risk levels are in 3 categories namely: pass, risky, and warning.

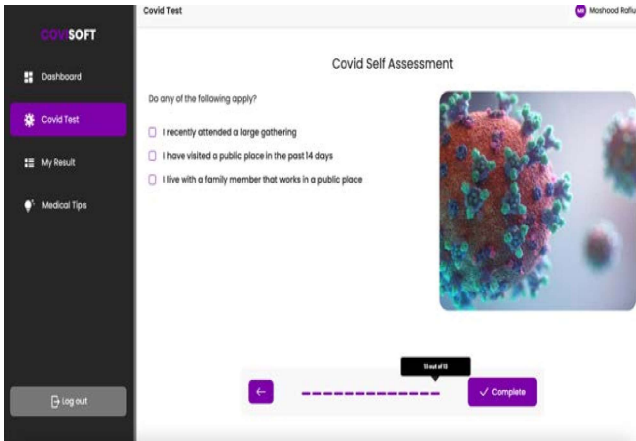


Fig 6: COVID-19 assessment complete page.

The result of the self-assessment session is displayed in Figure 7 based on the analysis of the answers provided and a recommendation is made available for the patient. In addition, it suggests a possible and close-by hospital for easy access to treatment.

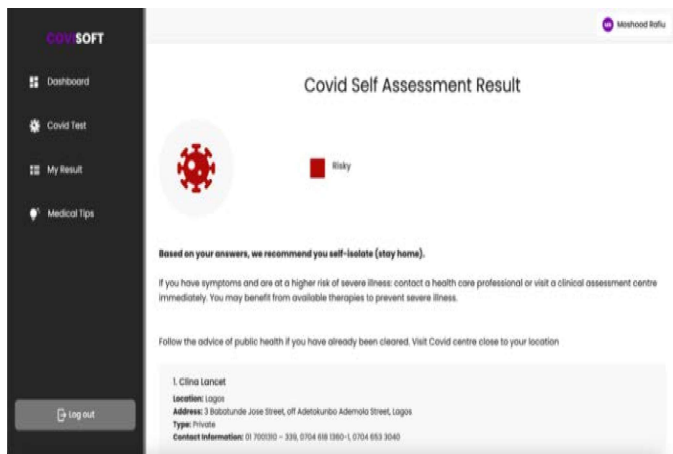


Fig 7: COVID-19 assessment result page.

Figure 8 shows the summary list of previous results generated on the online testing software. The results table shows four distinct parameters which are result ID, risk level, date of the test, and the

S/N	Result ID	Risk Level	Date	View
1	CVSF10000	Pass	Jun 13, 2022 at 07:58 AM	View Report
2	CVSF10009	Risky	Jun 12, 2022 at 16:16 PM	View Report
3	CVSF10008	Risky	Jun 11, 2022 at 22:00 PM	View Report
4	CVSF10007	Pass	Jun 11, 2022 at 21:54 PM	View Report
5	CVSF10006	Warning	Jun 11, 2022 at 21:54 PM	View Report
6	CVSF10005	Warning	Jun 11, 2022 at 21:38 PM	View Report
7	CVSF10004	Warning	Jun 11, 2022 at 16:12 PM	View Report
8	CVSF10003	Risky	Jun 11, 2022 at 14:15 PM	View Report
9	CVSF10002	Pass	Jun 11, 2022 at 14:12 PM	View Report

Fig 8: List of assessment results on the page.

In Figure 9, medical tips on curbing the spread of covid are itemized, which is the last icon on the dashboard.

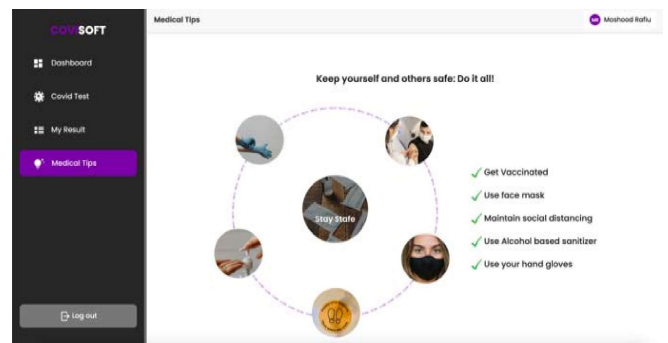


Fig 9: Medical tips page.

Figure 10 shows the graph of binary cross-entropy against the epochs or iterations to reveal the neural network training convergence from a global dataset. A steady state was achieved from about 20000 iterations against about 1.5 binary.

In Figure 11, the rise was constant up until the 20000 epoch and remained steady until it ultimately converged at around 0.94. After the 150000 epochs, a final accuracy of roughly 94% was attained (iterations). After 20000 epochs (iterations), the model converged, yielding an average training rate of 95%.

Available at [www.ndu.edu.ng/journalofengineering](http://www.ndu.edu.ng/journalofengineering) (iterations), the model converged, with an average training rate of 86%.

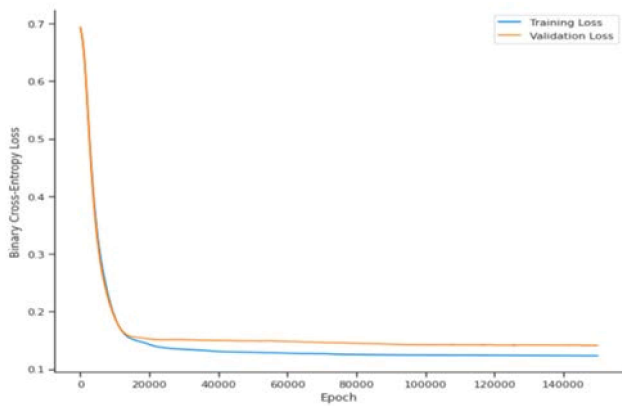


Fig 11: Neural network training convergence from a global dataset.

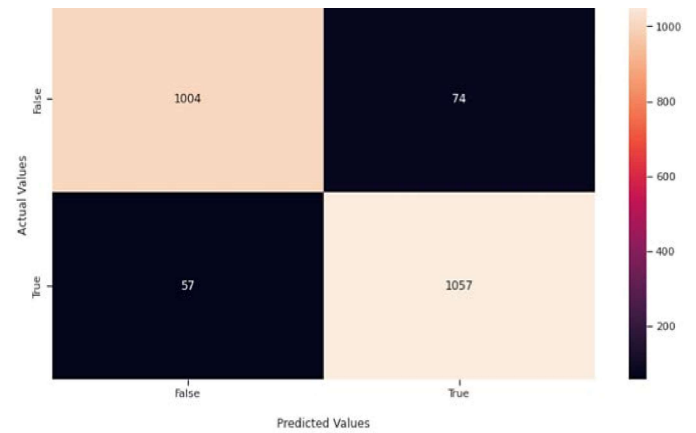


Fig 13: Confusion matrix for testing the global data model.

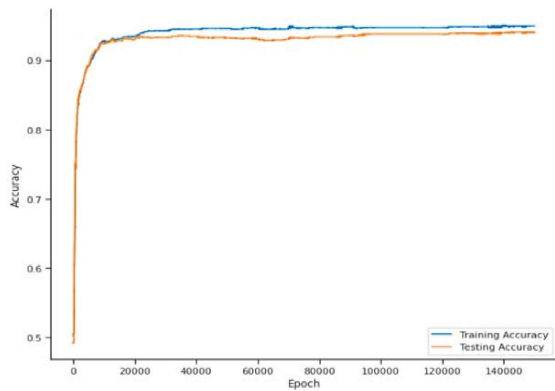


Fig 12: Accuracy neural network model from a global dataset.

Figure 12 is the confusion matrix for testing the global dataset and matrices [2, 2] show the highest prediction of 1057. Meanwhile,

Figure 13 is the neural network training convergence from the synthetic local dataset. The convergence diminished from about 20000 epochs. However, the convergence rate between the training and the testing dataset increases as compared to that of the global dataset.

Also, Figure 14 shows a steady rise up to the 17000th epoch before remaining steadily rising until it ultimately converged at around 0.86. After 150000 epochs, a final accuracy of roughly 86% was attained (iterations). After roughly 100000 epochs

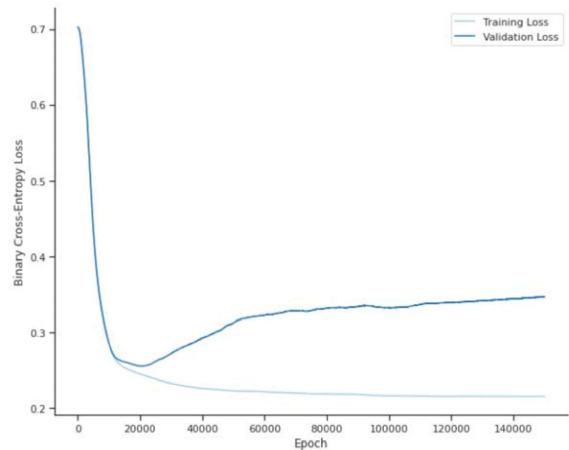


Fig 10: Neural network training convergence from the synthetic local dataset.

The confusion matrix of Figure 15 shows that matrices [1, 1] have the highest prediction of 449 which is lower than that of the global dataset.

Figure 16 are depicting the histograms to represent the effect of each symptom on the patient's result, while Figure 17 are the histograms to represent the effect of each symptom on the patient's result.

Figure 18 are the doughnut charts representing the COVID and non-COVID patients based on symptoms for local data while Figure 19 are the doughnut charts representing the COVID and non-COVID patients based on symptoms for global data.



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the lack of dataset locally or globally and more importantly paucity of time. To extend this study in the future, other machine learning algorithms and metaheuristic algorithms such as genetic algorithm (GA), particle swarm optimization (PSO) and so on will be employed to validate this study. These schemes have been extensively employed to solve engineering problems such as wireless networks, automation and process control to mention a few

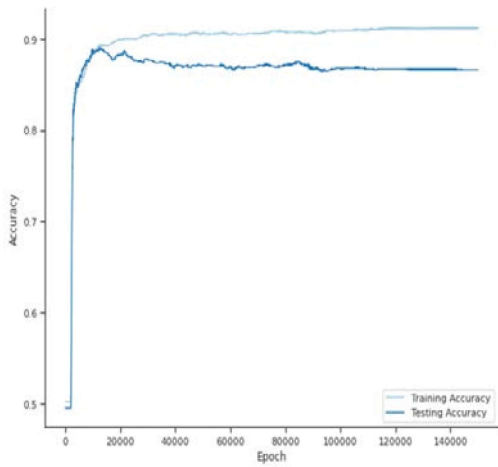


Fig 14: Accuracy neural network model from the local dataset.

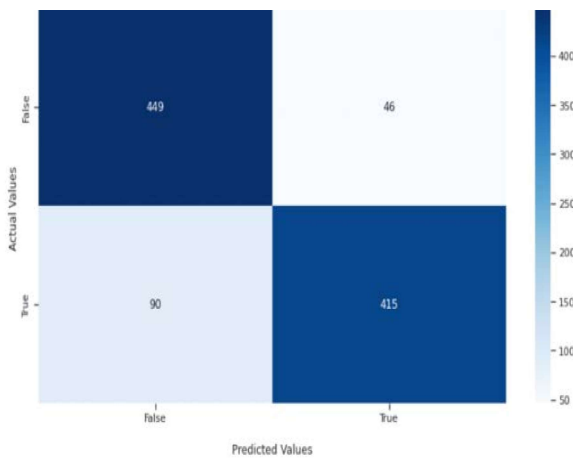


Fig 15: Confusion matrix for testing the local data model.

## B. Discussions

### 1. Statistical Analysis from Dataset

The feature parameters from the global and local datasets were visualized using histograms and doughnut charts and pie charts to show how each feature parameter contributes to the goal parameter. It should be noted that the obtained numerical results could not be compared with other machine learning algorithms or metaheuristic algorithms because of

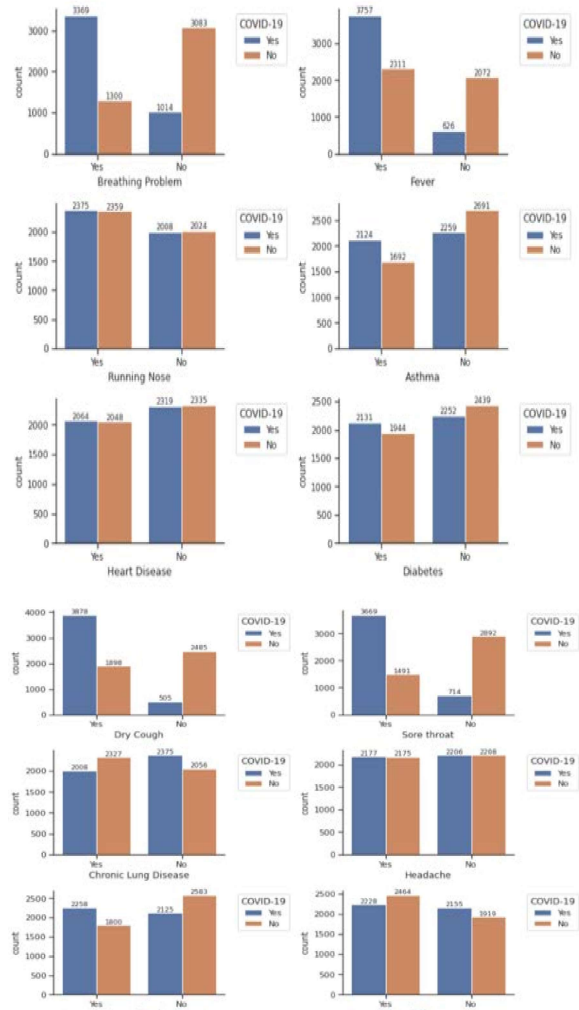


Fig 16: Histograms for global data

## V. CONCLUSION

In conclusion, the proposed system of designing and implementing a coronavirus testing software that utilizes a deep neural model to detect the probability

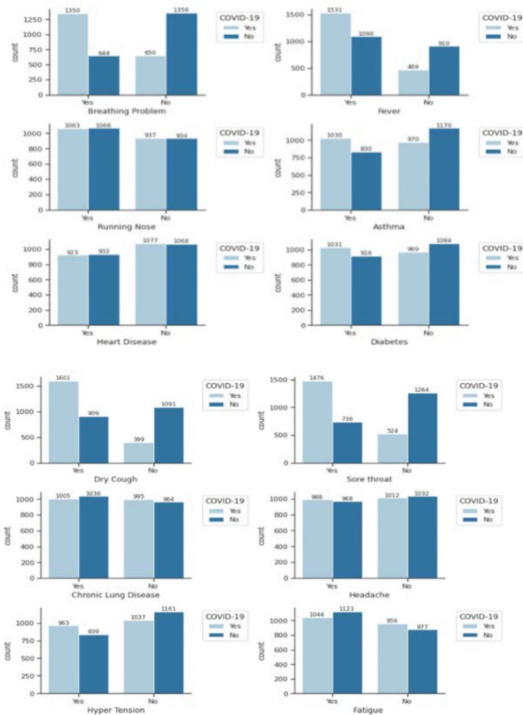


Fig 18: Histograms for local data



Fig 17: Doughnut charts for global data.



Fig 18: Doughnut charts for local data.

of COVID-19 based on user input data offers a solution to this challenge. After a one-time registration, users answer a few questions about how they feel, and the input data is then fed into the DNN model, which provides a list of COVID-19 test laboratories based on their current location. With early detection of infected individuals and thorough contact

tracing, this system aims to reduce and mitigate the transmission of COVID-19, especially in rural communities with limited resources for testing. The system offers a practical solution to enhance the fight against the spread of COVID-19, particularly in resource-limited settings, and it highlights the critical role of technology in global public health

emergencies. After accurate examination and analysis of the software created it could be resolved that the software is an effective, practical, and consistent online COVID-19 testing software system. It is functioning appropriately and sufficiently fulfils the least prospects from the task. The innovative software is anticipated to assist the user concerning efficacy in the practice of the COVID-19 testing system. Therefore, this study has demonstrated that DNN is a perfect candidate to predict and classify any form of the pandemic in the near future.

## RECOMMENDATION

To get the maximum benefits, the web-based COVID-19 testing software should be able to have the following features as well.

- If someone is found to be at a high risk of contracting COVID-19 infection, the web-based COVID-19 testing software should schedule them for physical tests.
- The web-based COVID-19 testing software should be able to book appointments and contact doctors directly or other paramedical staff.

## REFERENCES

- Absar N, Mamur B, Mahmud A, Talha B.E et al. (2022). Development of a computer-aided tool for detection of COVID-19 pneumonia from CXR images using machine learning algorithm, *Journal of Radiation Research and Applied Sciences*.
- Ceci A, Muñoz-B.C, Tegge A, Brown K. et al. (2021). Development and implementation of a scalable and versatile test for COVID-19 diagnostics in rural communities, Cold Spring Harbor Laboratory.
- Chen Y, Jiang G, Li Y, Tang Y, Xu Y, Ding S, Xin Y, Lu Y. (2020). A Survey on Artificial Intelligence in Chest Imaging of COVID-19, *BIO Integration.en.wikipedia.org*
- Ekwe, S.O, Akinyemi, L.A, Oladejo, S.O, and Neco Ventura (2021) "Social-Aware Joint Uplink and Downlink Resource Allocation Scheme Using Genetic Algorithm" *IEEE AFRICON*
- Ekwe, S.O, Oladejo, S.O, Akinyemi, L.A, and Neco Ventura (2020). A Socially-Inspired Efficient Resource Allocation for Future Wireless Network" *IEEE 16<sup>th</sup> International Computer Engineering Conference (ICENCO)*
- Hassan H, Ren Z, Zhao H, Huang S, Li D, Xiang S, Kang Y, Chen S, Huang B. (2022). Review and classification of AI-enabled COVID-19 CT imaging models based on computer vision tasks', *Computers in Biology and Medicine*.
- Hemdan E.E., Shouman M., and Karar M. (2020). COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-Ray Images, *ArXiv*.
- Kumar P. (2020). Forecasting the dynamics of the COVID-19 Pandemic in Top 15 Countries', *ARIMA Model with Machine Learning Approach*. medRxiv, p. 2020.03.30.20046227, Apr. 05,
- Li M. (2020). Predicting the epidemic trend of COVID-19 in China and across the world using the machine learning approach, medRxiv; 03 (18) 2003-8117
- Narin A, Kaya C, and Pamuk Z. (2021). Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks, *Pattern Anal Applic*, Aug.; 24 (3) 1207–1220
- Okigbo P.O. (2021). Nigeria must not forget its poor in the Covid-19 world, *ORF*. <https://www.orfonline.org/expert-speak/nigeria-must-not-forget-its-poor-in-the-covid-19-world-64389/>
- Oladejo, S.O, Ekwe, S.O, and Akinyemi, L.A (2021). Multi-tier multi-tenant network slicing: A multi-domain games approach *ITU Journal on Future and Evolving Technologies, Wireless Communication systems in beyond 5G era*, pp. 57-82, vol. 2, Issue 6,
- Oladejo, S.O, Ekwe, S.O, and Akinyemi, L.A (2021). Multi-Tier Multi-Domain Network Slicing: A Resource Allocation Perspective" *IEEE AFRICON*.
- Peters D.J. (2020). Community Susceptibility and Resiliency to COVID-19 across the Rural-Urban Continuum in the United States, *J Rural Health*, Jun.; 36 (3) 446–456
- Redie D.K, Sirko A.H.E, Demissie TM, Teferi SS et al. (2022). Diagnosis of COVID-19 using chest X-ray images based on modified DarkCovidNet model, *Evolutionary Intelligence*,
- Sethy PK. and Behera S.K. (2020). Detection of Coronavirus Disease (COVID-19) Based on Deep Features, Mar.
- Sharma N, Sharma R, Jindal N. (2021). Machine Learning and Deep Learning Applications-A Vision, *Global Transitions Proceedings*.
- Shoewu, O.O., Akinyemi, L.A., Folorunso, C.O. (2019). An E-Health Solution Provider for Tuberculosis Patient in Rural Areas, *The Fourteenth*

(14th) Annual **Research Conference** and **Fair** of the University at the Jelili Adebisi Omotola Halls, **UNILAG**, Akoka, on August 21 – 23.

- Shoewu, O.O., Adebayo, S.O, Ayangbekun, J.O,  
Akinyemi, L.A (2021) Application of Deep Learning to Autonomous Robotic Car” International Journal of Computer Applications
- Shoewu, O.O., Akinyemi, L.A., and Edozie, R. (2023) UAV Cellular Communication in 5G New Radio Wireless Standards” Under Processing for Publication by Springer
- Sofra X. (2021). Vaccines’ Safety and Effectiveness amid Covid-19 Mutations, *Health*; 13(03):283–298
- Tawadrou A.S, Katsabani P.D. (2002). Prediction of surface blast patterns in limestone quarries using artificial neural networks, *Fragblast*, 2005 Geoffrey EH. Training Products of Experts by Minimizing Contrastive Divergence, *Neural Computation*,
- Yvonne M and Yap B. (2020). Coronavirus: Amid the global pandemic, lessons for Africa, *Brookings*, <https://www.brookings.edu/blog/africa-in-focus/2020/03/20/coronavirus-amid-the-global-pandemic-lessons-for-africa/>
- Zheng C, Deng X, Fu Q, Zhou Q, Feng J, Ma H, Liu W, Wang X. (2020). Deep Learning-based Detection for COVID-19 from Chest CT using Weak Label, Cold Spring Harbor Laboratory.