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Development of Convolutional Neural Network-Based Diagnostic System for Detection of Coronavirus Using Magnetic Resonant Imaging (Mri)

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ABSTRACT

This paper presents the development of convolutional neural network-based diagnostic system for detection of coronavirus using Magnetic Resonant Imaging (MRI). The research was embarked upon to address the growing rate of Covid-19 disease, which has increased death rate in the world, of which one of the reasons is due tothe delay in getting test result after a Covid test.The research developed a technique for Covid testing which brings out result in about nine minutes. The work was implemented using image acquisition toolbox, image processing toolbox, machine learning toolbox, deep learning toolbox and Matlab. For this research, a total of 2650 MRI images were collected. The primary sources of data collection were the Colliery hospital and Park-lane hospital, both in Enugu State, Nigeria. The Colliery Hospital provided data for Covid-19 pneumonia patients, being the only authorized hospital to treat Covid-19 patients in Enugu State. The sample size of the data collected from this hospital was 1200 MRI data from confirmed patients with Covid-19 pneumonia. The confirmation tests were done (performing all necessary medical procedures) which revealed that the patients considered were Covid-19 Pneumonia positive before they were referred to the radiology ward for MRI scanning in the hospital. The MRI provided data for each patient and were stored in MySQL software for further processing. The other class of data needed was provided by Park-lane hospital which is the MRI images of normal pneumonia patients without coronavirus. The data collected in this case was1450 images from patients. Before the image processing, the data was first pre-processed and then blurred for morphological operation using Gaussian 3D model. This processed data was then fed into a Deep Learning network which trains and classifies the data with an already developed reference model of convolutional layers using softmax model, and then predicts the Covid-19 status of the image via the classification output layer. This process takes an approximate time of nine minutes to train, detect and predict result, with high prediction accuracy of 99.37%.

KEY WORDS/PHRASES: Coronavirus, Covid-19, Magnetic Resonant Imaging, Deep Learning, Machine Learning.

I. INTRODUCTION

Throughout the history of mankind, nothing has killed more human beings than viruses, parasites and bacteria that cause diseases. Not natural disasters like floods, earth quakes, or volcanoes and not even the first and the Second World War combined. The plasmodium parasite for instance which causes malaria has stalled humanity for thousands of years, and while death toll have reduced significantly over the past 20years, it still snuffs out about half a million people every year globally according to [1].

Over the millennia, epidemics specifically have been mass killers on a scale which one cannot begin to image today, even at this time of coronavirus pandemic. This effect is due to the replicating biological nature of the pathogens. This is to say that when virus like the corona for instance infects a host, the infected individual becomes a cellular factory to manufacture more viruses with common symptoms of communicable diseases which can be easily transmitted from that person to another.Today, Covid-19 according to the world health organization (WHO), is very much the disease of the moment, emanating from Wuhan china and has spread all over the world within few months. It is a colony of virus that causes illness ranging from the common cold to more severe symptoms such as severe acute respiratory syndrome and even death. It is unfortunate that despite the advancement reached in the global medical domain today, our only effective response when the virus arrived was to shutdown the society and the assembly line of global capitalism.

In theory, the properties of coronavirus have been characterized from other diseases [2], however the problem of implementing a system which effectively performs this function without delay remains a case to ponder. This has been a very serious challenge all over the world, thus making the testing process very difficult and time delaying with over seven days before a result is back from test. This problem if not rectified soon, considering the exponential rate of the virus spread increase can lead to severe consequences as already been experienced today in countries like brazil and US with over 1000 deaths daily average as at July 23, 2020.

Various methods like Reverse Transcription Polymerase Chain Reaction (RTPCR), isothermal amplification assays, antigen, radiographic imaging, serology among others, have been employed for the testing and prediction of corona virus.However none provided a feedback result in less than a week. The use of radiographic imaging using image processing techniques have produced promising result in terms of processing speed; however the image processing result for Covid-19 viral pneumonia and influenza pneumonia is always similar after segmentation and therefore has high rate of false prediction. The RTPCR on the other hand has low positive rate in the early stage to predict Covid-19, other techniques already mentioned like serology with more accurate results takes between 7 to 21 days to predict result of the tested sample. To address this global novel pandemic, scientists and clinicians in medical industries are searching for new technology to screen infected patients in various stages, finding best clinical trials, control the spread of this virus, developing a vaccine for curing infected patients, tracing contact of the infected patient and achieving real time testing and result processes.

Over the time, Magnetic Resonance Imaging (MRI) has been used in various medical domains for biomedical image analysis based on magnetic field and radiowave to detect tissues among other abnormalities in medicine. However, MRI is a non invasive vivo imaging approach which employs radio frequency signal to excite target tissues so as to produce internal image view under influence advanced magnetic field and has achieved great success. Due to this huge merit, today, MRI is among the standard techniques used for data collection via radiology machines and analysis by experts using artificial intelligence solutions [3].

Recent studies suggested machine learning (ML) and other artificial intelligence (AI) techniques as promising technologies employed by various Healthcare providers as they result in better prediction accuracy, speedup processing power, system reliability and even outperform humans in specific healthcare tasks.

Machine learning is the study of computer algorithms that improve automatically through experience and by the use of data. It is seen as a part of artificial intelligence. This ML is basically classified into supervised and unsupervised learning. Supervised learning are algorithm used to train data which are labeled while unsupervised learning trains unlabeled data and make classifications themselves. This unsupervised learning was used in this research to train the data which was collected as the study proceeds using Convolutional Neural Network (CNN).

CNN is a type of neural network which provides best result for image classification problem among other machine learning algorithms under artificial neural network.It has been applied in various fields due to the huge successes it recorded competing with human intelligence.

This CNN will be applied in this case for the classification of Covid-19 pneumonia; which till date, is a very big challenge worldwide to differentiate between the normal pneumonia and influenza pneumonia. Even though some authors have applied the technique to solve this same problem, but their accuracy was limited by the number of data used in their dataset and also the design configuration of the CNN. Hence this research will collect reliable data of MRI based Covid-19 pneumonia cases from domain expert, and then design a well structured CNN architecture for training these data and make high level decision for the detection of Covid-19.

Thus, the aim of this research is todevelop a convolutional neural network-based diagnostic system for detection of coronavirus using magnetic resonant imaging.

II. LITERATURE SURVEY

2.1 Review of Related Literature

In [4], Covid-19 detection using Deep Learning models to exploit Social Mimic

Optimization and structured chest X-ray images using fuzzy colour and stacking approaches was presented. The work was able to reconstruct extracted feature vector using fuzzy colour and social mimic optimization technique and then trained using support vector machine. The work recorded an accuracy of 92.27%, however the training dataset was very poorly constructed with few scanned images, hence a more robust dataset is required to justify the training performance and prediction accuracy recorded.

Ali [5] published a research work on "Automated Systems for Detection of Covid-19 Using Chest X-ray Images and lightweight Convolutional Neural Networks" where he explained that the clinic experts made use of the real-time reverse transcription-polymerase chain reaction (RT-PCR) as a gold standard for the detection of the coronavirus to report whether an individual has the virus or not.But the technique takes too long.He proposed and implemented the use of artificial intelligence technique which combines convolutional neural network and softmax classifier for the prediction of the feature vector. He recorded an accuracy of 93%. But despite the success he achieved, the model designed was too complex to understand and will be challenging for improvement.

Akib [6] presented a research work on "Machine Learning-based Approaches for Detecting Covid-19 Using Clinical Text Data", where they made use of classical machine learning algorithms to classify textual clinical reports into four classes. To engineer the features, they used three different techniques like Term Frequency/Inver Document Frequency (TF/IDF), Bag of Words (BOW) and report length. These features were transferred into the traditional machine learning classifiers. Logistic regression and Multinomial Naïve Bayes presented better results more than other machine learning algorithms by getting up to 93.2% accuracy after testing. However, they suggested that the use of neural network algorithms could produce better results.

Yang [7] presented a work on the modified SEIR and A.I prediction of the epidemic trend of the Covid-19 in China. The work was developed using the data collected from the Wuhan hospital under the guidance of the China Public Health Intervention Agency. The work was able to employed the Unsupervised Machine Learning technique (support vector machine) for the training and diagnostic prediction of the Covid-19 patients. They deduced that the use of other A.I techniques like the artificial neural network will produce a better result, superseding theirs with prediction accuracy of 89%.

Yichi [8] presented a research paper on the mathematical modeling and epidemic prediction of Covid-19 and its significance to epidemic prevention and control measures; annals of infectious disease and epidemiology. The work was developed based on time series and kinetic model to design the epidemic transmission control mechanism. The data used for the research was limited to pneumonia as one of the Covid-19 symptoms. The performances were measured using the confusion matrix parameters and based on the results of the sensitivity analysis, the work revealed that enhanced treatment of the bodies of deceased patients can be effective in ensuring that the bodies themselves and the process do not result in additional viral infections, and once the pneumonia patients with the Covid-19 are cured, the antibodies left in their bodies may prevent them from re-infecting Covid-19 for a longer period of time.

Yichi[9] researched on new machine learning method for image based diagnosis of Covid-19. They proposed a machine learning method to classify the chest X-ray images of patients in two classes: Covid-19 person and non-Covid-19 person. The work used fractional multichannel exponent moments (FrMEMs) to extract feature vectors from the chest X-ray images, utilization of multi-core computational framework to speed up the computational process, and then uses the modified manta-ray foraging optimization based on differential evaluation to select the most significant features. They used 2 Covid-19 x-ray datasets to test the accuracy of the proposed method. The accuracy achieved was up to about 96.09% and 98.09% for the first and second datasets respectively. However, the delay time for training and prediction is over nine minutes, but the researcher believed that this time can be improved.

Sethy [10] researched on "Detection of Coronavirus Disease (Covid-19) Based on Deep Features".The work employed deep learning methodology for the detection of coronavirus in patients X-rayed. The deep learning approach was trained using SVM to predict the feature vectors with accuracy of 91.41%. However due to the poor construction of the dataset used, the result when tested with influence scanned image gave a false positive result, hence there is need for improvement and reconstruction of the training dataset.

[11] presented a research on Covid-19 Prediction and Detection Using Deep Learning.

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They used real world datasets on artificial intelligence technique based on deep convolutional neural network (CNN) to detect Covid-19 patients. Their system uses and examines chest X-ray images for the data collection. They feature vectors trained with the CNN model was predicted using Prophet Algorithm (PA), Long short-term Memory Neural Network (LSTM) and Autoregressive Integrated Moving Average (ARIMA) model; and were compared respectively with an average prediction accuracy of 93%. However despite the success achieved, the prediction model was very complicated in the work and needs to be redressed for easy understanding and future improvement.

2.2 The Symptoms of Corona Virus

The severity of Covid-19 symptoms can range from very mild to severe. Some people may have only a few symptoms, and some people may have no symptoms at all. People who are older or who have existing chronic medical conditions, such as heart disease, lung disease, diabetes, severe obesity, chronic kidney or liver disease, or who have compromised immune systems may be at higher risk of serious illness. This is similar to what is seen with other respiratory illnesses, such as influenza. Some people may experience worsened symptoms, such as worsened shortness of breath and pneumonia, about a week after symptoms start. According to the NCDC, these signs and symptoms of Covid-19 may appear two to 14 days after exposure. This time after exposure and before having symptoms is called the incubation period. These symptoms are classified as shown in table 1.

Table 1: Symptoms of Covid-19

Other symptoms	**Common symptoms**	**Severe symptoms**	**Emergency symptoms**
Shortness of breath	Fever	Pneumonia	Trouble breathing
Muscle aches	Cough	Severe Organ failure	Persistent chest pain
Chills, Nausea	Tiredness	Heart problems	Inability to stay awake
Sore throat	Fever	Lung disease, SARS	New confusion
Loss of taste	Headache	Blood clots	Blue lips or face
Vomiting	Chest pain	Kidney failure	
Rash , diarrhea		Bacterial infection	

2.3 Causes of Coronavirus

The Covid-19 virus appears to spread easily among people, and more continues to be discovered over time about how it spreads. Data released by CDC has shown that it spreads from one person to another among those in close contact (within about 6 feet, or 2 meters). The virus spreads by respiratory droplets released when someone with the virus coughs, sneezes or talks. These droplets can be inhaled or land in the mouth or nose of a person nearby. It can also spread if a person touches a surface with the virus on it and then touches his or her mouth, nose or eyes, although this isnot considered to be the main way it spreads.

2.4 COVID-19 Testing

The testing process of Covid-19 involves the analysis of suspected individual samples for the presence of severe acute respiratory syndrome coronavirus. These covid-19 testing is divided into categories which are the viral and antibody test.The viral test detects the presence of virus so as to diagnose individual cases and thus allow public health authorities to contain and control the virus spread. An antibody test on the other hand is performed to reveal the individual once had the virus. This method is not very vital in the diagnoses of new cases due to the fact that the anti bodies may not be developed for weeks after infection; however the technique can predict if one once had the virus or estimate the infection fatality rate.

2.5 Overview of Medical Imaging

Medical Imaging is a process and technique of creating visual representation of the internal part of a body for medical intervention and clinical analysis to visualize vital body parts like tissues in radiology. This process will reveal the internal structure of the body hidden beneath the skin and bones for the purpose of diagnoses. This image data collected is employed for the establishment of an image training dataset of anatomy and physiology for the identification of anomalies within the body structure. This process of medical imaging incorporates biological and radiological paradigms using imaging technology such as x-ray radiography, magnetic resonance imaging, ultrasound, medical photography, nuclear medical functional imaging among others. Overtime, medical imaging is designed for noninvasively produce images of internal sections of the human body using mathematical inverse models. In the case of radiology for instance, the probe employs the x-ray radiation which is absorbed at various rates via the different tissues like the muscles, fat and bones.

2.6 Artificial Intelligence in Health Care

Over time mankind has struggled to combat viral or infectious diseases using various tools, techniques and methods. In the early time, when the world was young, various natural herbs were employed, extracted or heat with water as a form of local medicines from herbalist. This process was more of a trial and error technique of which the dosage cannot be measured; however as time progresses and human became more civilized due to the evolution of western education, science was used to modify these herbal medicines in a more purified manner to become more effective [12].

As a result great success was recorded in the medical industries, with all various forms of medicines produced.But unfortunately, as medicines multiply so also are the rise of all forms of viral infections. This becomes difficult to control as these infectious diseases not only multiply but also grow resistant against some of the drugs manufactured, and this becomes a serious challenge integrated into the ever growing population of the world. Various means have been adopted since then to optimize the medical industries performance like building more hospitals, manpower, and employing other factors of production.However, due to the exponential rate of disease infection, there is need to take a new approach.

In other industries like the manufacturing sector for instance, the use of artificial intelligence have been applied to boast performance and control response. This also is believed to have the capacity to help the health sector. Various researchers have employed machine learning techniques to solve various pattern recognition problems like detection and prediction of cancer, diabetes, heart diseases among others; with high accuracy and fast processing speed. This is therefore believed to also have the capacity to help solve the recent Covid-19 problem of testing performance in precised manner using any machine learning techniques as discussed below.

2.7 Overview of Machine Learning

Machine Learning (ML) is a field of computer engineering and a branch of Artificial Intelligence (AI) that uses statistical technique to develop a computer's ability to learn with data, without being explicitly programmed. This learning can be achieved by progressively improving the system's performance on a particular task through pattern recognition, data mining, making data-driven predictions, decisions, and through building models from sample inputs.

According to Isizoh [13], the mathematical models can be trained to produce useful controlled outputs when fed with input transfer function. These models are providing experiences in form of training data, and are tuned to produce accurate predictions for the training data by an optimization algorithm. The models generalization abilities are typically estimated during training using separate data set, validation set, and used as feedback for further tuning of other models in iterative manner. After several iterations of training and tuning, the final model is evaluated on a test set used to simulate how the model will perform when faced with new unseen data.

2.8 Design of the ANN Security Scheme

Artificial Neural Network is an interconnected massive parallel computational models, units or nodes, whose functionality mimic the animal neural network in order to process information from the input to the output using the connection strength (weight) obtained by adaptation or learning from a set of training patterns. The mathematical description of ANN process is shown in Figure 1.

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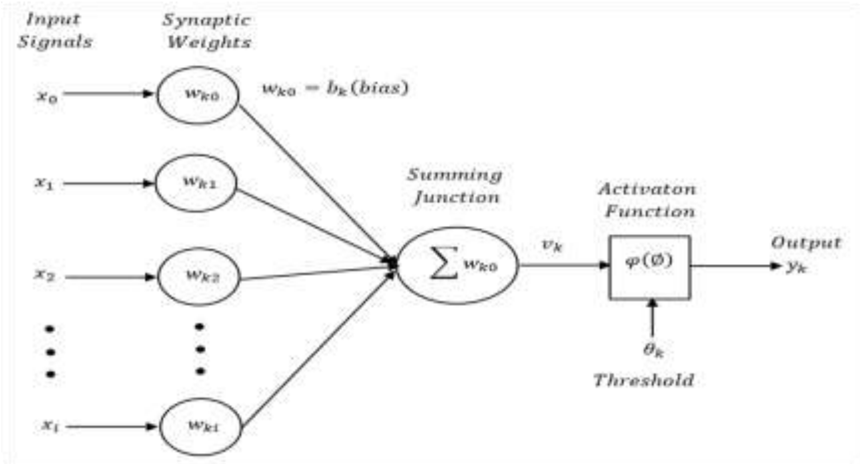

Figure1: Mathematical Model description of an Artificial Neuron

The neuron is a unit of computation that reads the inputs given, processes the input and gives the output in processed form. To get the output of the Artificial Neuron from the activation function, we compute the weighted sum of the inputs as:

$$v_k = \sum_{i=1}^{N} w_{ki} x_i \quad (1)$$

Where
x_i is the neuron's input.
w_{ki} is the corresponding weight to the input x_i.
The neuron's output is obtained by sending the weighted sum v_k as the activation function φinput that resolves the output of the specific neuron. $y_k = \varphi(v_k)$. A step function with threshold t can be used to express a simple activation as;

$$\varphi(x) = \begin{cases} 1 \; if x \geq t \\ 0 \; if x < t \end{cases} \quad (2)$$

However, bias is most time used instead of a threshold in the network to learn optimal threshold by itself by adding $x_o = 1$ to every neuron in the network. The step activation function
for the bias becomes;

$$\varphi(x) = \begin{cases} 1 \; if \; x \geq 0 \\ 0 \; if x < 0 \end{cases} \quad (3)$$

For the learning process to speed up and also adaptive learning capacity, multiple neurons are were used as a multi layered network of neurons formed by feeding the output of one neuron to the input of another neuron as shown in Figure 2.

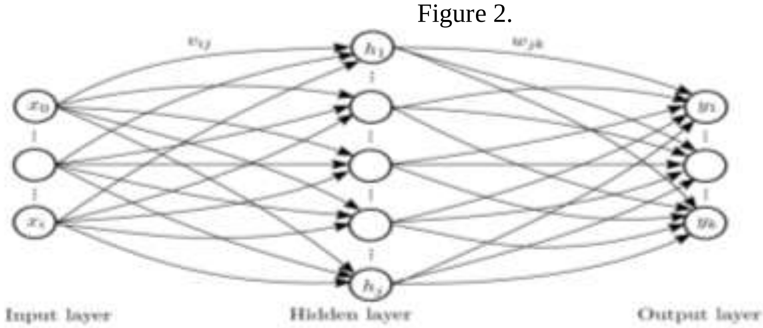

Figure 2: Basic Structure of a Multilayer Artificial Neuron.

The layers between the input and output layers are termed hidden layers. Each layer of the multilayer network is made up of a bunch of neuron nodes with each input feed with the class of the data set.

The neurons are connected by a link that has a weight which represents the connection strength between each interconnected neurons. In Figure 2 the w_{ij}^l denotes the weight for a link between unit j in layer l and unit i in layer $l+1$. Also b_i^lrepresents the bias of the unit i in layer $l+1$. For any neural network, the associated parameters inside it are expressed as a function of the weight and the bias of the neurons as;

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$(w,b) = (w^1 b^1, w^2 b^2, w^3 b^3, \dots)$ (4)

The components of equation 4 can be written in the form of $w^1 \in \mathbb{R}^{3\times 3}$ and $w^1 \in \mathbb{R}^{1\times 3}$. Let the activation of unit i in layer $l$be represented by a_i^l, then the input for the layer labelled as L_1 we have $a_i^1 = x_i$ for the ith input of the whole network. Other layers are given by$a_i^l = f(z_i^l)$, where z_i^l is the total weighted sum of the inputs to unit i in layer l in addition to the bias term. The activation function of a nine-input ANN with bias can be computed as;

$$a_n^2 = f(w_{n1}^1 x_1 + w_{n2}^1 x_2 + w_{n3}^1 x_3 \dots\dots\dots\dots\dots\dots\dots. + b_n^1) \quad (5)$$

Where n is the number of input classes.
The equation can be re-written as below;

$$h_{w,b}(x) = a_1^3 = f(w_{1n}^2 a_n^2 + w_{1n}^2 a_n^2 + w_{1n}^2 a_n^2 + b_n^1) \quad (6)$$

Where $h_{w,b}(x)$ is a real number representing the output of the ANN, n is the number of inputs from the dataset. The activation function f(Zn) can be applied to vectors in element-wise as $f([z_1, z_2, z_3,,,,,,, Zn]) = [f(z_1), f(z_2), f(z_3) (Zn),]$. Therefore equation 6 can be written as;

$$h_{w,b}(x) = a^3 = f(z^3) \quad (7)$$

So, for any given layer l with activationa^l, the activation a^{l+1} of the next layer $l+1$ is obtained as;

$$z^{l+} = w^l a^l + b^l,$$
$$a^{l+1} = f(z^{l+1}) \quad (8)$$

When the computation of the signal moves from the input to the output of the ANN (feed forward network), it is called Forward Propagation. To make the network recurrent, the ANN could have a closed-loop back to itself from a neuron. Also, when an ANN has every neuron in each layer connected to the neurons in the next layer, it is called a fully-connected network.

A nonlinear activation function is used in multilayer networks, which is why it can solve nonlinear issues. A common activation function in ANN is the sigmoid functions which are like the logistic function as in equation

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad (9)$$

Where z is the activation function, and when z is large, then e^{-z} tends to zero (0), so $\sigma(z) = 1$. Conversely, if z is a small or very large or very large negative number, then e^{-z} tends to one (1), so $\sigma(z) = 0$.

2.9 Deep Learning

Traditionally, machine learning models are trained to perform useful tasks based on manually designed features extracted from the raw data, or features learned by other simple machine learning models. In deep learning, the computers learn useful representations and features automatically, directly from the raw data, bypassing this manual and difficult step. By far the most common models in deep learning are various variants of artificial neural networks, but there are others. The main common characteristic of deep learning methods is their focus on feature learning: automatically learning representations of data. This is the primary difference between deep learning approaches and more “classical” machine learning. Discovering features and performing a task is merged into one problem, and therefore both improved during the same training process.

2.10 Deep Learning in Medical Imaging

Deep learning is a form of artificial intelligent technique employed today mainly for radiological image processing and analysis for detection of anomaly in the image structure via CT scan. Today deep learning is applied in medical imaging especially in radiology, magnetic resonance imaging (MRI), theranostics, radiomics, radiooncology, endomicroscopy and other related fields for automated detection of intra-operative images.

Another important application area is advanced deformable image registration, enabling quantitative analysis across different physical imaging modalities and across times. For instance in the registration of a three dimensional MRI and trans-rectal ultrasound for guiding targeted prostate biopsy, deformable registration for brain MRI where a deep regression network learns from a given set of training images the displacement vector associated with a pair of reference subject patches; fast deformable image registration of brain MR image pairs by patch-wise prediction of large deformation using a diffeomorphic metric mapping model, unsupervised Convolutional neural network-based algorithm for deformable image registration of cone beam CT to CT using a deep Convolutional Inverse Graphics networks, deep learning based 2D/3D registration framework for registration of Pre-operative 3D data and intra-operative 2D X-ray images in image-guided therapy, real time prostate segmentation during targeted prostate biopsy, utilizing temporal information in the series of ultrasound images, among other numerous applications.

2.11 Convolutional Neural Network (CNN)

In medical imaging the interest in deep learning is mostly triggered by convolutional neural network (CNN). This tool is a powerful way to learn useful representations of images and other structured data. CNN can be used for efficiency improvement in the practice of radiology through protocol determination based on short-text classification technique. It is a particular kind of artificial neural network aimed at preserving spatial relationships in the data, with very few connections between the layers. The input to a CNN is arranged in a grid structure and then fed through layers that preserve these relationships, each layer operates on a small region of the previous layer and is able to form highly efficient representation of the input data well suited for image oriented tasks. This network structure has multiple layers of convolutions and activations, often interspersed with pooling layers, and trained using back propagation algorithm and gradient descent as for standard artificial neural networks.

2.12 Magnetic Resonance Imaging (MRI) for Health Care

MRI is one of the commonly employed image processing technique in the field of neuroscience and neurosurgery. In medical imaging and segmentation, computerized diagnosis is a vital trend usually researched on. This concept was first proposed in 1980s, with the aim of providing a second opinion for radiographies in the interpretation of scanned biological imagery.

In clinical environments, the MRI is employed for the evaluation of physiological and anatomy of the body system for disorder in the pathological structure of the human tissue. Traditionally, the X ray scanning differs from the MRI as it uses radiation instead of radiofrequency pulse aligns of hydrogen atoms which resides naturally in the body system. This process does not affect the tissue system chemically, the energy captured in the MRI scanner uses the information to design an image of the tissue scanned which can be interpreted by the radiologist. MRI system is used for the differentiation of normal and disorder tissues with other image modalities like the X ray, ultra sound and CT scan.

III. PROPOSED METHODOLOGY AND DISCUSSIONS

3.1 Methodology

The system will be developed using process model guided by geometric approach, self defining equations, object oriented design analysis methodology, and then implemented using necessary Matlab and Deep Learning tools.

In this paper, an Artificial Neural Network-based MRI segmentation algorithm was used which converts images from MRI scans of the lung to digital data using image processing techniques. Using feature selection and extraction techniques, the data is segmented and classified automatically by the algorithm as either normal or abnormal to indicate the health condition of the lung scanned.

3.2 Data Collection

For this research, a total of 2650 MRI images were collected. The primary sources of data collection were the Colliery hospital and Park-lane hospital, both in Enugu State. The Colliery Hospital provided data for Covid-19 pneumonia patients, being the only authorized hospital to treat Covid-19 patients in Enugu. The sample size of the data collected from this hospital was 1200 MRI data from confirmed patients with Covid-19 pneumonia. The confirmation tests were done (performing all necessary medical procedures) which revealed that the patients considered were Covid-19 Pneumonia positive before they were referred to the radiology ward for MRI scanning in the hospital. The MRI provided data for each patient and were stored in MySQL software for further processing. The other class of data needed was provided by Park-lane hospital which is the MRI images of normal pneumonia patients without coronavirus. The data collected in this case was1450 images from patients.

To collect these necessary data used for the research, the domain experts from the various hospitals were consulted, requesting for the data to be used for the purpose of this research only. These data were provided and used as the training dataset for the research. All the data collected were of the same MRI format but varies in sizes due to different hospitals and MRI machine settings.However this was taken care of by the researcher using MySQL software to resize all the images into 600 x 200 pixels and then arranged in various classes. Samples of the MRI data for

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Covid-19 pneumonia class are presented in Figure 3.

Figure 3: Covid-19 Viral Pneumonia Lungs

The sample data presented in Figure 3 shows the lungs of Covid-19 patients with pneumonia while Figure 4 shows the samples of patients with normal pneumonia.

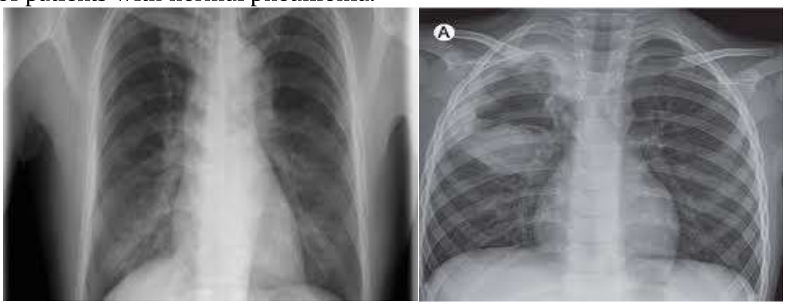

Figure4: Patients with Normal Pneumonia

3.3 Methods

The methods or processes are: image pre-processing, image processing, data extraction, classification and prediction, as shown in Figure 5.

Figure 5: Proposed method for the research

3.3.1 Image Pre-processing

This process involves the elimination of the background noise induced by the MRI machine on the scanned image quality. This noisy effect on the image is usually experienced more on scanners that have exceeded their Mean Time to Failure (MTF) and affects the quality of scanned output. This preliminary filtration process was done using histogram equalization technique which assigns intensity values of pixels on the MRI image to

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ensure uniform histogram without any loss of information.

3.3.2 Image Processing

This process involves various techniques which were adopted to resize, filter, segment and extract features from the MRI scanned images for training. These techniques are image resizing, filtration, morphological operation and data extraction and are discussed below.

3.3.3 Resizing the 3-D Volumetric Image

A chest scanned image is a three dimensional volumetric image with very huge size and variable resolution depending on the MRI machine. Before further processing can be performed on the image, there is need to resize the MRI file to a compatible size. This will be done using the three element vector technique which employs a scale factor to specify as three elements vector of positive values for the row, column and plane dimensions respectively. This was done using the input layer of the convolutional neural network before training.

3.3.4 Filtration

In image processing, the choice of filtration varies from image enhancement, blurring, smoothing, noise removal, dilation, erosion among others depending on the user requirements. However for a 3-D volumetric image of a scanned respiratory system which has already been preprocessed using histogram equalization to reduce background noise reflection from the scanning environment, there is need to further remove noise from the image itself. This was done using image normalization technique which filters the image from noise using a linear 2D Grey Scale filter. The filter design will be presented in the system design section using Gaussian model.

3.3.5 Morphological Operation

In the conventional systems reviewed in the literature (see Section 2.1), edge detection based segmentation was used as the image processing technique; this method partitions an image into segments without revealing the internal structure of the section. In this case, a chest scan that is affected internally by virus or bacteria will not be properly revealed. This is the main reason image processing was criticized by the WHO recently for testing Covid-19. However this research adopted the morphological image processing technique which visualizes and analyzes the internal structure of an image based on shapes by applying a structural element on the image input and creating an output image of the same size. The structuring element is a matrix which identifies the pixel in the MRI image and relates a binary neighborhood of multidimensional with the true pixel included in a morphological computation while the false pixels are not. The center of the pixel is used to identify the image pixel and is called origin as shown in Figure 6.

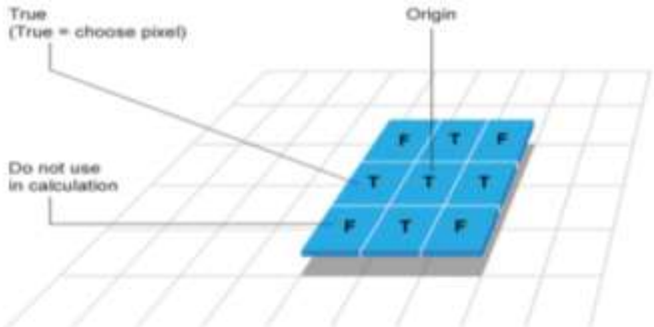

Figure6: Flat Structuring Element Matrix of the MRI image

3.3.6 Data Extraction

This process is the dimensional reduction which represents the interesting part of the image as a compact feature vector. This process is done before feeding the extracted feature vectors to a Learning model for training. The data extraction method used in this work is the statistical method which extracts compact feature vectors of the MRI image into numerous statistical values for training using histogram of oriented gradient descriptor.

3.4 Training

The training process was done using Deep Learning. It is a branch of machine learning which teaches a computer how to perform classification tasks directly from images using artificial neural network combined nonlinear passive layers in parallel convolutional connection. The learning training process was designed using convolutional neural network in the system design section which

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will train the feature vectors extracted for classification and predictions.

3.5 Development of Convolutional Neural Network (CNN)

The CNN was made of the input layer, two convolutional layers, pooling layer, fully connected layer and the output layers. Each of these layers performs certain operations which aid to the learning of the feed forward MRI data. From the training dataset the MRI data are fed to the input layer for processing through scaling and dimensionality reduction, then the feature maps are pooled to the convolutional layers using set of filters which learned the data using various convolutions and pooling function. The number of convolutional layer is the output of each scanning process from the filter and the outputs are the feature maps pooled via the pooling layer to the next convolutional layer. This process continues until the fully connected layer where the data learned are gathered and trained with neural network for classification using the output layer. The architecture of the CNN is presented in Figure 7.

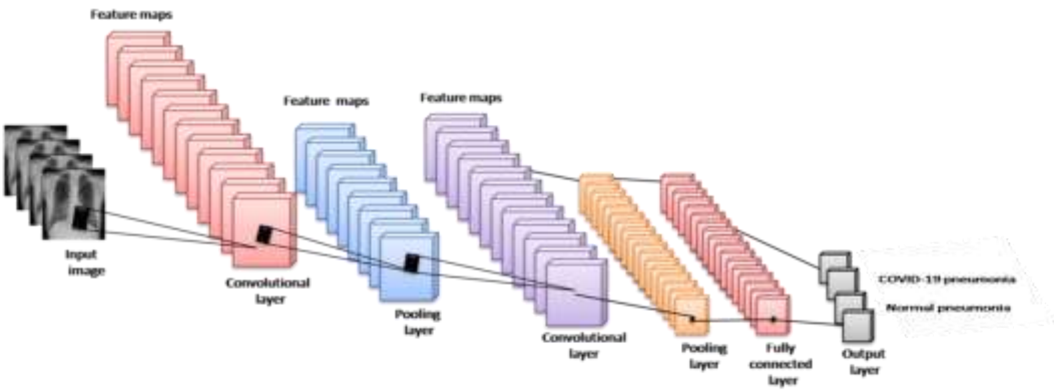

Figure 7: The Convolutional Neural Network Network

3.5.1 Input Image Layer

This image input layer contains the raw pixel values of the radiology images, defining the dimensions and channels in a convolutional neural network. This layer is responsible for the dimensional scaling of the MRI images with a scale factor of length (y) and weight (x) from the origin respectively, then the corresponding channel size which is usually 3 for grey scale image. After the scaling process, the data are fed forward to the convolutional layer.

3.5.2 Convolutional Layer

Now that the images have been scaled, the sub regions are connected via neurons consisting of the convolutional layer which learns the features localized by these regions while scanning through the images. This feature is localized using set of weight called filters which is a function of the input image length (y), weight (x) and channel (=3). The number of weights is the number of the channels in the input, while the number of filters determines the number of output convolutional layers.

As the filter scans the input MRI image, it employs similar weights and bias for the convolution process to form a feature map. The number of feature maps a convolutional layer has equates the number of filters, and hence output channels. Each feature map has a different set of weights and bias function, hence the total parameters in the convolutional layer is presented as:

$$C_l = L * w * c + b\,(N) \quad \ldots \quad (10)$$

Where C_l is the Convolutional layer, L is the length, w is weight, c is channels, b is the bias function and N is the number of filters.

3.5.3 Pooling Layer

This is a down sampling operation which minimizes the spatial size of the feature maps to eliminate redundant spatial information, thereby increasing the filters in deeper convolutional layers with computational delay. The output of this process is a rectangular region of the input specified by the characteristics size of the parameters presented in equation (10), where the bias function and channel size are 3 respectively.

3.5.4 Fully Connected Layer

The fully connected layer is a feed forward neural network layer which the neuron connects to all the activation units in the proceeding layer. This process combines all the features learned by the convolutional layers across the image to identify the larger pattern and form the output layer which presents the feature vectors with vital information.

3.5.5 Output or Prediction Layer

This is the final layer of the network which produces the desired output of the training process. This layer is designed for a classification problem like the case study using a Softmax activation function. This function is a mathematical model which transforms the image feature vectors into probability distributions consisting of various probabilities proportional to the various exponential of the input image as shown below.

$$y_r(x) = \frac{\exp(a_r(x))}{\sum_{j=1}^{k} \exp(a_j(x))}; \qquad (11)$$

Where $0 \leq y_r \leq 1$ and $\sum_{j=1}^{k} y_j = 1$

y_r is the softmax function, x is the image input matrix, a represents input vector, while r and j are the vector features, k and j represent the various distributive probabilities for classification. The computational learning process is presented in Figure 8.

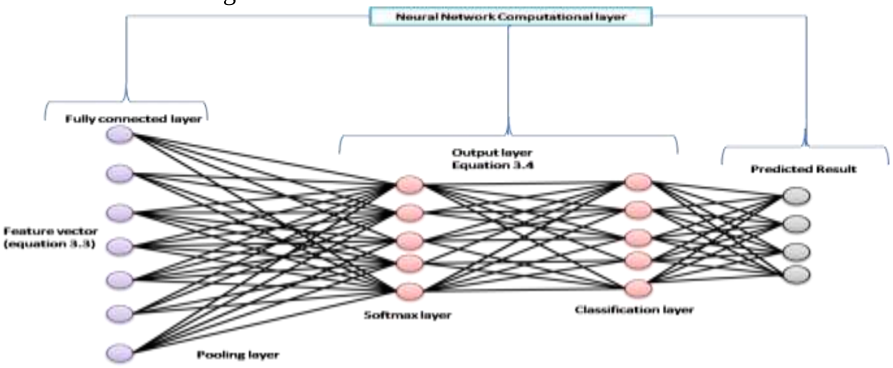

Figure8: Computational Learning model

From the structure presented in Figure 8, the feature vectors identified by the model in equation 10 is feed-forward to a multi convolutional layer which learns the information and feed to a fully connected layer through pooling. The fully connected layer is responsible for integrating all feature vectors learned by the total number of convolutional layers and then channel to the output layer for probability distribution (see Table 2 for setting details). This output layer is composed of the softmax which identifies the feature input vectors and normalizes them into a probability distribution proportional to the exponential function of the input image as shown in the model in equation (11), while the classified probability outcome is predicted by the classification layer as the reference prediction layer. The complete training process is presented using the flowchart of Figure9.

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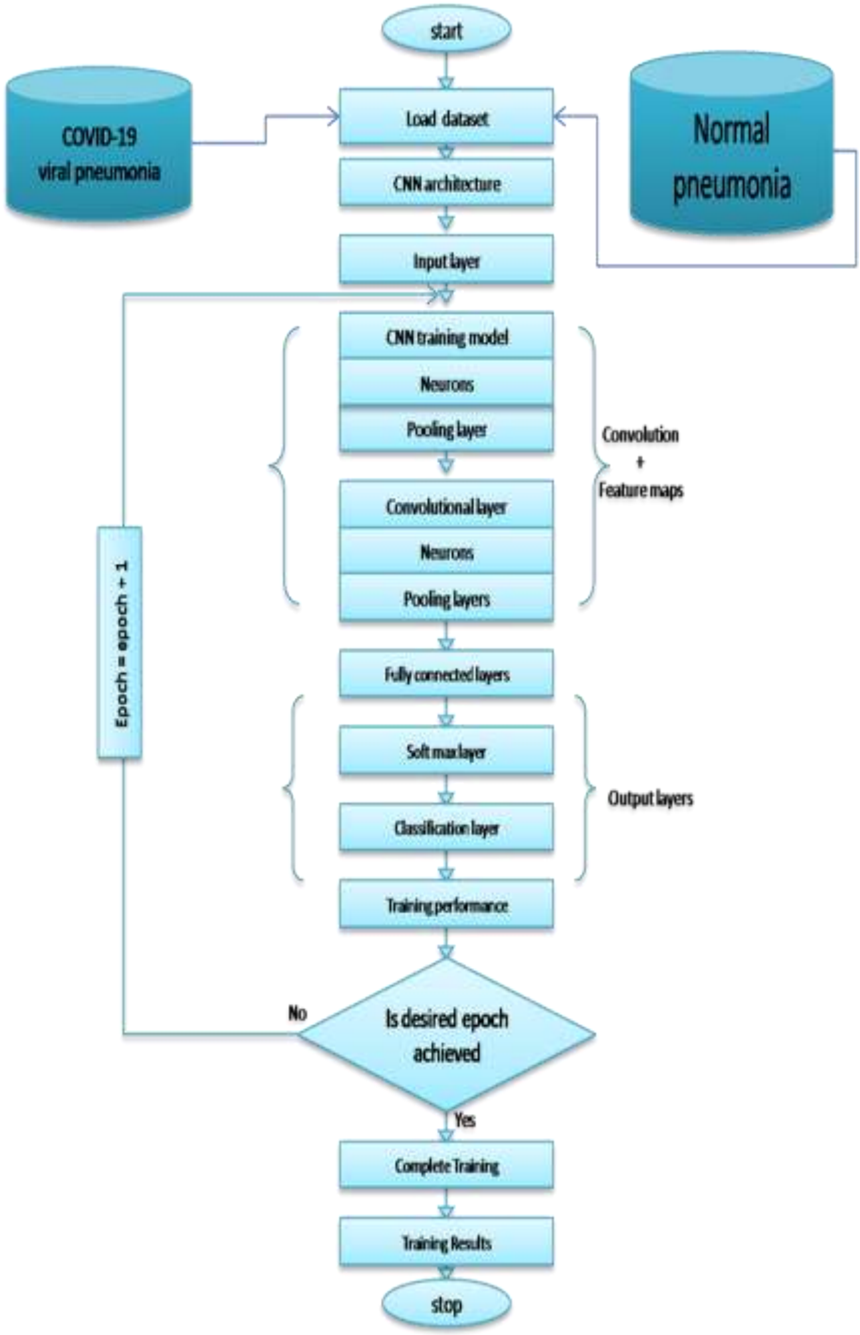

Figure 9: Flowchart of the Developed Convolutional Neural Network

From the flowchart of Figure 9, the training sets are loaded on the deep learning structure using the input layer which identifies the dimensions of the images, channels; and then passed to the convolutional training model via neurons in a spatial feature vector. These features are scanned using filter in convolutional layers whose design is based on the size of the images, filters and weights respectively as presented in Table 2. After this learned process, the outcome is feed to a fully connected layer which computes all the learning functions and feed forward to the output layer for normal distribution using the softmax layer and classification using the classification layer. At this point the training performance is examined to determine if the

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desired epoch value is realized, if not an incremental epoch is triggered and the process retrained until the desired epoch is achieved, then the classified convolutional learning model is saved for training and classification of future input images.

Table 2: Deep Learning Settings

Maximum number of epoch to train	15
Epoch between display	1
Maximum time to train in sec	Infinity
Maximum validation failure	5
Scale factor for length	600
Scale factor for weight	200
Initial step size	0.01
Minimum performance gradient	1e-6
Cost horizon	7
Control horizon	2
Number of bias function	1
Number of Channel	3

3.6 System implementation

The system design will be implemented using the necessary toolboxes which are embedded in Matlab for the realization of the objectives of the mathematical and process models designed in the previous sections. These toolboxes designed for the implementation of each process model was employed and integrated on a high level software development environment in Matlab. The Figure 10 presents the user interface design of the proposed system using image acquisition toolbox, image processing toolbox, signal processing toolbox, mathematics and statistics toolbox and Deep Learning toolbox.

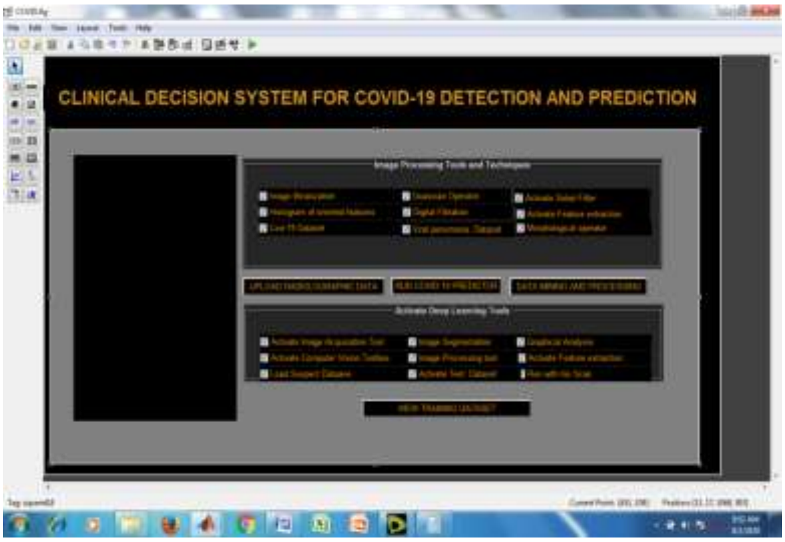

Figure 10: The Implemented Software Design

This implemented structure in Figure 10 was developed using the image acquisition toolbox to capture and decode the MRI image from the testing datasets. These data are processed using the image processing toolbox to ensure that noise reflection due to lightening intensity is eliminated using histogram equalization technique. This toolbox was also used for the image resizing process in a dimension of 600 x 200 as discussed in section 3.3.3 before the overall image filtration. The signal processing toolbox was responsible for the implementation of the filtration effect discussed in section 3.3.4 and was developed using the Gaussian filter model designed in equation 9 to achieve the desired blurring effect as the normalized image ready for morphological process. The image processing toolbox was used to implement the morphological operator discussed in

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section 3.3.5 which reveals the interesting part of the image for better data extraction into the input layer of the Convolutional Neural Network using the statistics and mathematics toolbox for training. The input later identifies the image using a scale factor considering the dimensions and channels to a feature map as shown in equation (10), into a Convolutional layer. This layer learns the feature vectors and then transfer in a feed-forward manner to the output layer which was designed using the Softmax function in equation 11 and then predict with the classification layer. This learning process was implemented using deep Learning toolbox. The complete functionalSystem Flowchart which summarizes the operational data transfer and learning process is presented inFigure 11.

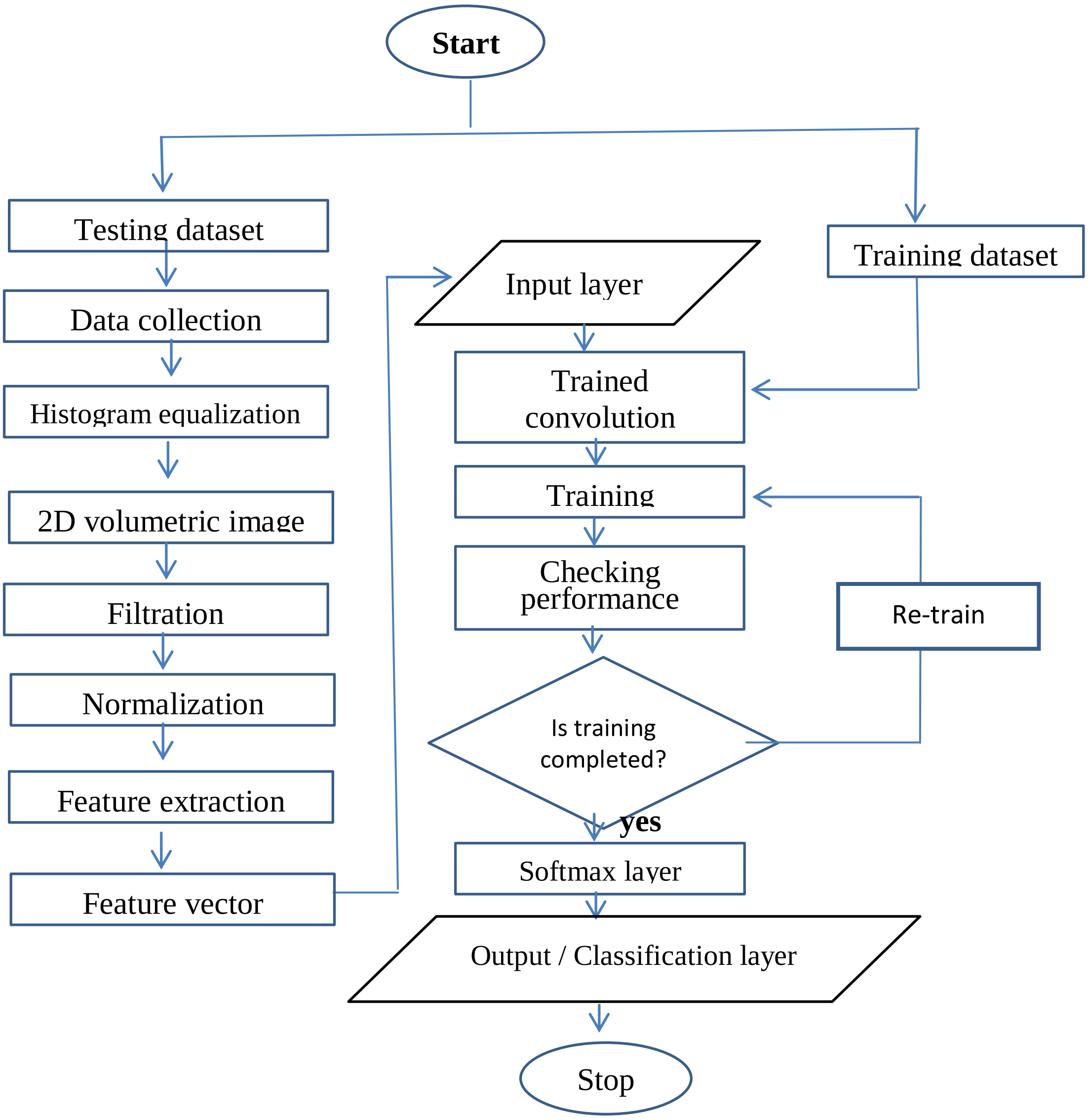

Figure11: System Flowchart

From Figure11, the testing set was used to collected query data for a suspected Covid-19 patient and preprocessed for noise and compatibility. The data was then further processed for elimination of lighting intensity to achieve a blurring effect before data extraction into a compact feature vector which is feed to the convolutional neural network for training using the already trained Convolutional Learning model (see Figure 10). This model was used to classify the input data and then predict for Covid-19. The accuracy of this prediction will be evaluated

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alongside the result of the various image processing techniques and learning used to achieve the prediction response in section 3.7.

3.7 Performance Measures/Validation Accuracy

The accuracy of a classifier on a given test set is the percentage of test set tuples that are correctly classified by the classifier layer and is computed using the model in equation (11).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}. \quad . \quad . \quad .(12)$$

Where: TP is true positive rate, TN is true negative rate, FP is false positive rate and FN is false negative rate.

To minimize the bias associated with the random sampling of the training and the test data samples, k-fold cross validation was adopted. In k-fold cross validation, the initial data are randomly partitioned into k mutually exclusive subsets or 'folds'. G1, G2, Gk each of approximately equal size, the training and testing is performed k times. Accordingly, it is known that the extensive tests on numerous datasets, with different learning techniques, have shown that 10 is about the right number of folds to get the best estimate of error, and there is also some theoretical evidence that backs this up. There has been a continuous debate in Machine Learning and Data Mining circle about what is the best scheme for evaluation, but 10-fold Cross-Validation has remained the standard method in practical terms. Test has also shown that the use of stratification improves results slightly. Thus the standard evaluation technique in situations where only limited data is available is stratified Ten-Fold Validation. The main advantage of 10-fold or any number of folds cross validation is to reduce the bias associated with the random sampling of the training and hold out data samples by repeating the experiment 10 times each using a separate portion of the data as hold out sample.The cross validation estimate of the overall accuracy of a model is calculated by simply averaging 10 individual accuracy measures.

$$CVA = \frac{1}{10}\sum_{1}^{10} Ai \ldots \quad . \quad .(13)$$

Where, CVA stands for Cross Validation Accuracy and A is the accuracy measure of each fold.

IV. EXPERIMENTAL RESULTS

4.1 Deep Learning Training Results

This section discusses the training performance of the Convolutional Learning process in terms of prediction accuracy as shown in the model of equation (3.5). This training performance was achieved creating a multi set of testing, training and validation sets respectively and then specifying the convolutional neural network designed in section 3.5 using the setting in the Table 2 which contain the training parameters. When the Deep Learning training tool was simulated, the training process was monitored and shown in Figure 12.

Figure12: Deep Learning Training Performance

From the result presented in the Deep Learning monitor in figure 12, it was observed that the training process took a total of 9 minutes 5 seconds to reach the final iteration point, with a total number of 465 iterations performed at a learning rate of 0.01 per epoch. From the monitor, it was shown that the validation accuracy of the training process is 99.50%. The implication of this

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result shows that the learning accuracy of the convolutional model developed using the CNN training architecture in Figure 7 is very precised and can now be reliable to test and predict future Covid-19 patients based on their radiological scan. However to confirm this result, another training process was performed and the result presented in Figure 13.

Figure13: Result of Another Training Process

From the result in Figure 13, it was observed that the second training process took a total of 8 minutes 2 seconds to complete the training process with a validation accuracy of 99.30%. However, since there is a variation in the accuracy and training time, the researcher adoptedTen-fold Validation technique to determine the standard accuracy and training response time. To perform this task, the training process was tested for another 10 times with the already presented trained results, as discussed earlier (see Figures12 and 13), and the performances are monitored and presented as shown in Table 3.

Table 3: Ten-Fold Validation Data

Training	Response time	Validation accuracy	Loss
1	9min 5sec	99.50	0.50
2	8min 2sec	99.30	0.70
3	8min 9sec	99.30	0.70
4	7min 3sec	99.30	0.70
5	8min 7sec	99.40	0.60
6	8min 2sec	99.30	0.70
7	7min 5sec	99.30	0.70
8	9min 2sec	99.50	0.50
9	7min 6sec	99.50	0.50
10	8min 3sec	99.30	0.70
Average	8min 2sec	99.37	0.63

From the result presented in table 3, reporting the respective training performance of the deep learning process, the average value generated is computed and taken as the validation accuracy and response time. This is recorded as 99.37% for the average validation accuracy of the training process and at a delay time of 8min 2 secs.The implication of this result showed that the system will correctly detect Covid-19 pneumonia or normal pneumonia with an accuracy of 99.37%.

4.2 Implementation Testing Result

This section discusses the performance of the new system developed. The essence is to critically evaluate the system performance using MRI image samples before it can be recommended or deployed for commercial use. The researcher already prepared two testing sets composed of normal pneumonia and healthy patients scanned images. These will be used to test the system and discuss the prediction performance; starting with the training sets, image processing results, and the

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prediction for the training response. The test started with an normal pneumonia image as shown in figure 14 against the Convolutional Learned model, trained with the Covid-19 Viral pneumonia dataset in figure 15.

Figure 14: MRI Scan of an Normal Pneumonia Patient

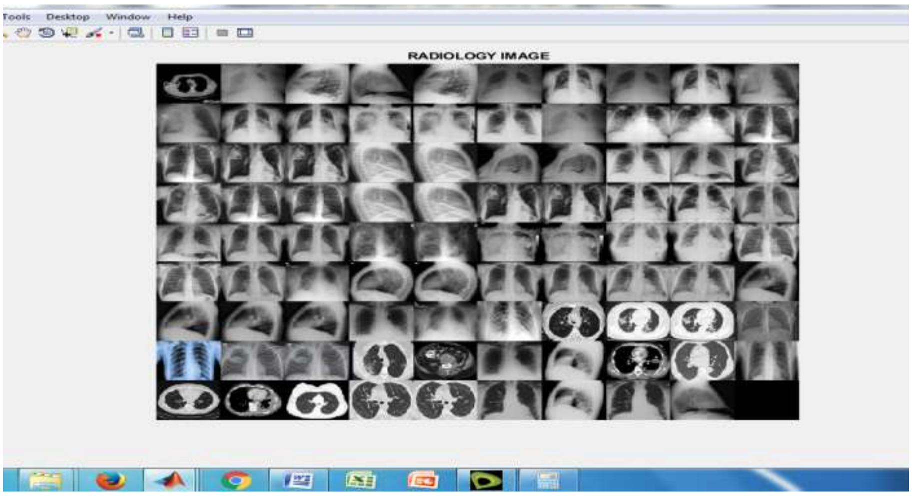

Fig.15: The Loaded Training Dataset of MRI Images

The results presented in Figures14 and 15 respectively present the query MRI scanned images and the training set used to develop the convolutional classification layer which was used to classify and predict the result of the query scanned image input. However, before the training process is used for the testing image, the input data is pre-processed using histogram equalization technique; as discussed in section 3.3.4. The result is presented as shown in Figure 16.

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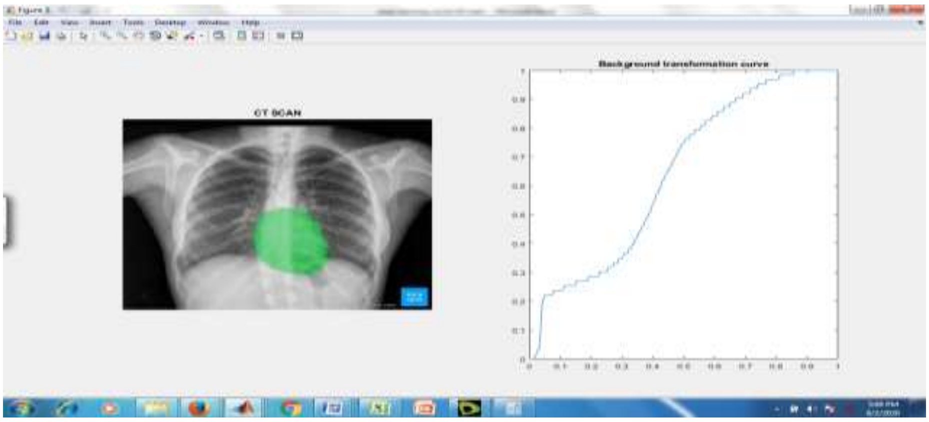

Figure16: Result of the Histogram Equalization Technique

The result of Figure 16 presents the background transformation curve of the image using Histogram Equalization technique. The essence of this process is to eliminate noise effects arising from the scanning machine in the form of shadow or light reflection; and it was implemented using the image processing toolbox. This preliminary filtering process then precedes the main filtration step discussed in section 3.3.4 and designed using the Gaussian model as earlier stated. The model was designed to effect 1D and 2D blurring effects on the image and was implemented using the signal processing toolbox to realize a normalization effect on the image as shown in Figure 17. This process prepares the image dilation and extraction which was implemented using the Source code inAppendix A.

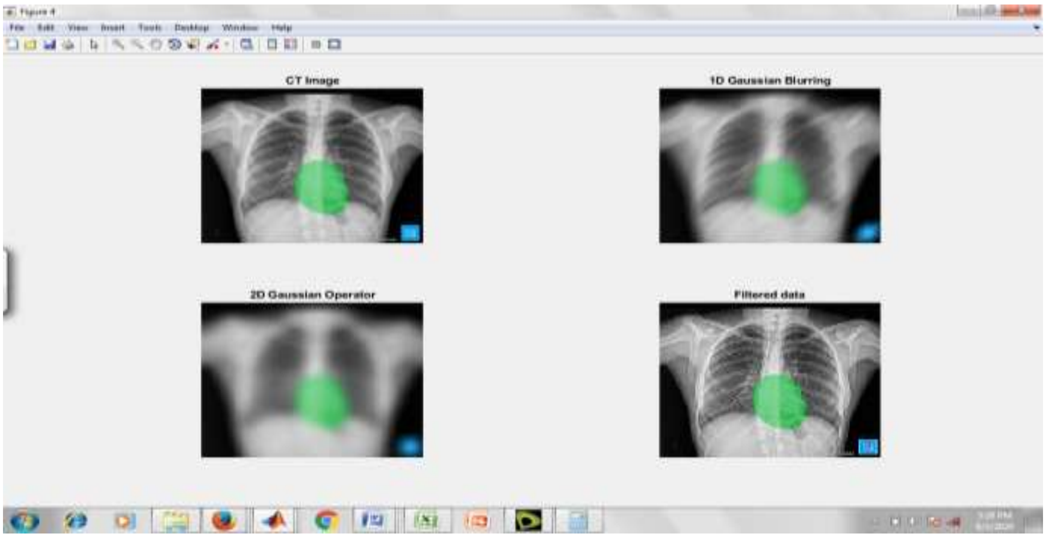

Figure17: Result of the Image Filtration Process

The result of Figure17 presents the performance of the one-dimensional Gaussian function on the image data, which shows a high blurring effect without normalization of the image, however the complete blurring and normalization effect was achieved by applying the Gaussian function to generate the desired filtered data.

This processed data is now extracted and fed into the input layer of the Convolutional Neural Network for classification using the Softmax function designed in equation (11) for prediction of the normal probability using the classification layer. The prediction result is presented as shownin Figure 18.

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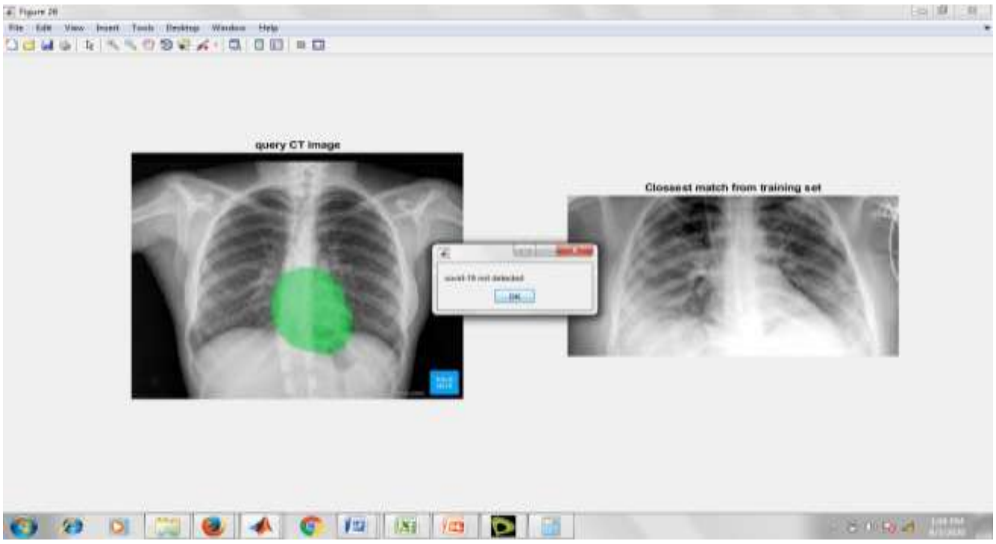

Figure18: Testing Result with NormalMRI Image

From the result presented in Figure 18, the query MRI scan (or CT) image is presented alongside the nearest classified image detected from the training set, then a conclusion is made based on the normal distribution probability value of the training image feature vectors and the distribution value of the testing images vector (images with normal pneumonia) to predict the Covid-19 status stating if the patient has Covid-19 or not.The result showed that COVID-19 pneumonia was not detected, which means that the patient suffers from normal pneumonia.

The next result in Figure 19 presents the system performance when tested with data of COVID-19 pneumonia as shown.

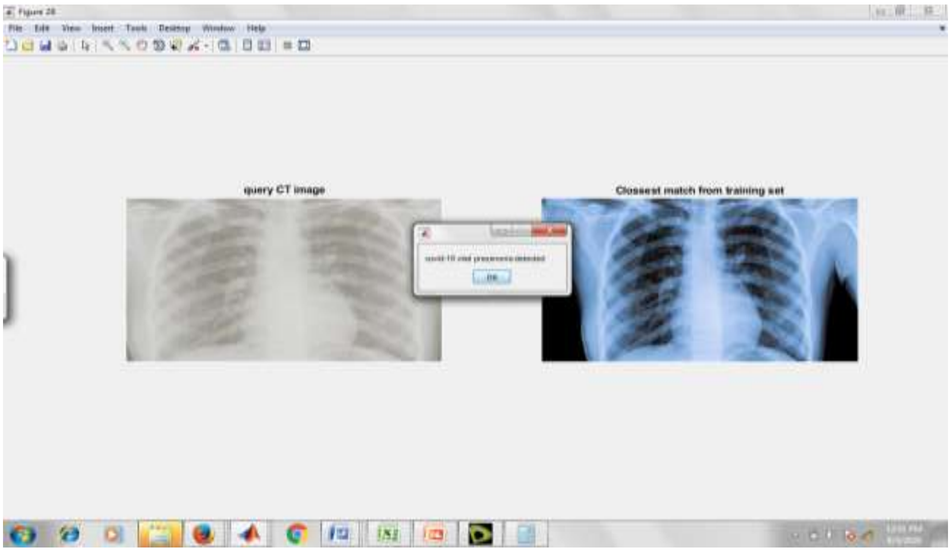

Figure19: Test Result with Covid-19 Viral Pneumonia Image

From the result presented in Figure 19, it was observed that the clinical decision system was able to detect and predict intelligently the COVID-19 status of the patient using the input MRI images trained. The result was able to correctly predict that the first case tested with normal pneumonia image do not have COVID-19 (see Figure 18), the second case tested with COVID-19 viral pneumonia image was correctly predicted to have viral pneumonia (see Figure 19)

4.3 Discussions

The reliability and application of any clinical decision system depends mainly on the

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accuracy of its sensitivity and prediction response. This has been the criterion to measure the performance of the existing expert system designed for medical assistance in the past as pointed out in the literature review. However, the gold standard has always been to develop a system which can function effectively and even outperform humans in some cases, and as a result have become a difficult not to crack, especially in this time of Covid-19. However this gold standard has been achieved in this work by developing an intelligent training process with 99.37% sensitivity for Covid-19 detection. This intelligence was used as a reference convolutional platform for the classification and prediction of future input data from a carefully prepared testing dataset. The work was tested and the result shows that a Covid-19 suspected patient can be examined in approximately 9 minutes using the MRI scan result with accurate prediction.

V. CONCLUSION

In most medical domains, before Covid-19 patient is diagnosed, series of medical tests are performed, ranging from serology, radiology, among others. However in a severe case whereby the patient suffers from respiratory disease which most of the time is pneumonia, it is always a challenge to distinguish viral pneumonia caused by Covid-19 from normal pneumonia. This process takes weeks for a reliable result to be produced and within this delay time, they cannot be treated effectively until the test result is out. This delay time has resulted inhaving majority of the death cases today recorded from Covid-19. Furthermore,it has been revealed statistically that Africa has 1 doctor in 500 individuals compare to developing nations like US where a doctor stands for15 people. The implication of this statistics shows that there are limited number of doctors to attend to patients with Covid-19, and if the rate of increase of new cases is not controlled, then a time will come when the death rate will be devastating. Hence, there is need for a clinical assistance system which can be relied upon to help in the medical diagnosis. This research has therefore presented one of such systems with high prediction accuracy, cheap to adopt and reliable for detection of Covid-19.

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