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COVID-X: Novel Health-Fog Framework Based on Neutrosophic Classifier for Confrontation Covid-19

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Abstract: The newly identified Coronavirus pneumonia, subsequently termed COVID-19, is highly transmittable and pathogenic with no clinically approved antiviral drug or vaccine available for treatment. Technological developments like edge computing, fog computing, Internet of Things (IoT), and Big Data have gained importance due to their robustness and ability to provide diverse response characteristics based on target application. In this paper, we present a novel Health-Fog framework universal system to automatically assist the early diagnosis, treatment, and preventive of people with COVID-19 in an efficient manner. Achieving an empirical of the proposed framework which mix between deep learning and Neutrosophic classifiers in the task of classifying COVID-19. There are some proposed applications based on the proposed COVID-X framework such as smart mask, smart medical suit, safe spacer, and Medical Mobile Learning (MML) will be presented. Computer-aided diagnosis systems could assist in the early detection of COVID-19 abnormalities and help to monitor the progression of the disease, potentially reduce mortality rates.

Keywords: Coronavirus Pneumonia; COVID-19; Intelligent Medical System; Fog Computing; Health-Fog; Neutrosophic; Deep Learning; Computer-Aided Diagnosis.

1. Introduction

The Coronavirus disease 2019-2020 pandemic (COVID-19) poses unprecedented challenges for governments and societies around the world. In addition to medical measures, non-pharmaceutical measures have proven to be critical for delaying and containing the spread of the virus. This includes (aggressive) testing and tracing, bans on large gatherings, school and university closures, international and domestic mobility restrictions and physical isolation, up to total lockdowns of regions and countries. However, effective and rapid decision-making during all stages of the pandemic requires reliable and timely data not only about infections, but also about human behavior, especially on mobility and physical co-presence of people [1]. There are growing privacy concerns about the ways governments use data to respond to the COVID-19 crisis. As new technologies emerge that aim to collect, disseminate and use data in order to support the fight against COVID-19, we need to ensure they respect ethical best practices. Even in times of crisis, we need to comply with data privacy regulations and ensure that the data is used ethically. One way to do that is to establish independent ethical committees or data trusts. Their role will be to create data governance mechanisms to find the balance between competing public interests, while protecting individual privacy. Examples of such rules include setting up clear guidelines on the purpose and timeline for the use of the data, defining clear processes for the access, processing and termination of use of personal data at the end of the crisis. Tracking a patient from symptoms, lab results and treatments can help a hospital understand how a disease is progressing through a community, how effective treatments are and what isn't working [2].

Technological developments like edge computing, fog computing, Internet of Things (IoT), and Big Data have gained importance due to their robustness and ability to provide diverse response characteristics based on target application. These emerging technologies provide storage, computation, and communication to edge devices, which facilitate and enhance mobility, privacy, security, low latency, and network bandwidth so that fog computing can perfectly match latency-sensitive or real-time applications [3]. Healthcare is one of the prominent application areas that requires accurate and real-time results, and people have introduced Fog Computing in this field which leads to a positive progress. With Fog computing, we bring the resources closer to the users thus decreasing the latency and thereby increasing the safety measure. Getting quicker results implies fast actions for critical COVID- 19 patients. But faster delivery of results is not enough as with such delicate data we cannot compromise with the accuracy of the result [4]. One way to obtain high accuracies is by using state-of-the-art analysis software typically those that employ deep learning and their variants trained on a large dataset. Deep learning techniques showed in the last years promising results to accomplish radiological tasks by automatic analyzing multimodal medical images [5]. Deep convolutional neural networks (DCNNs) are one of the powerful deep learning architectures and have been widely applied in many practical applications such as pattern recognition and image classification in an intuitive way [6]. DCNNs are able to handle four manners as follow [7]: 1) training the neural network weights on very large available datasets; 2) fine-tuning the network weights of a pre-trained DCNN based on small datasets; 3) Applying unsupervised pre-training to initialize the network weights before putting DCNN models in an application; and 4) using pre-trained DCNN is also called an off-the-shelf CNN being used as a feature extractor. Convolutional neural networks are sensitive to unknown noisy condition in the test phase and so their performance degrades for the noisy data classification task including noisy recognition. In this research, a convolutional neural network (CNN) model with data uncertainty handling; referred as NCNN (Neutrosophic Convolutional Neural Network); is proposed for classification task. The Neutrosophic is a new view of Modeling , designed to effectively deal underlying doubts in the real world, as it came to replace binary logic that recognized right and wrong by introducing a third neutral case which could be interpreted as non-specific or uncertain. Founded by Florentin Smarandache [8], he presented it in 1999 as a generalization of fuzzy logic. As an extension of this, A. A. Salama introduced the Neutrosophic crisp sets Theory as a generalization of crisp sets theory [9] and developed, inserted and formulated new concepts in the fields of mathematics, statistics, and computer science and information systems through Neutrosophic [10-12]. Neutrosophic has grown significantly in recent years through its application in measurement, sets and graphs and in many scientific and practical fields [13- 17].

In this work, a proposed novel COVID- X framework was developed as universal Health-Fog system for automatic diagnosis, treatment, and preventive of people with COVID-19 in an efficient manner using deep learning, Neutrosophic and IoT. Health-Fog provides healthcare as a fog service and efficiently manages the data of COVID-19 patients which is coming from different IoT devices. Health-Fog provides this service by using the proposed framework and demonstrates application enablement and engineering simplicity for leveraging fog resources to achieve the same.

In the following, the contributions of this paper are summarized:

- Building altogether a novel framework universal system to automatically assist the early diagnosis, treatment, and preventive of people with COVID-19 in an efficient manner.
- Proposed a generic system architecture for development of ensemble NCNN on fog computing
- Achieving an empirical of the proposed framework which mix between deep learning and Neutrosophic classifiers in the task of classifying COVID-19.
- The proposed COVID-X framework supports interdisciplinary researchers to continue developing advanced artificial intelligence techniques to fight the COVID-19 outbreak.
- This study demonstrated the useful applications of deep learning models to classify COVID-19 based on the proposed COVID-X framework such as smart mask, smart medical suit, safe spacer, and Medical Mobile Learning (MML). These applications are the next milestone of this research work.

The rest of this paper is structured as follows. Section 2 presents the related works. Section 3 gives a review on the state-of-the-art deep convolutional neural network models as image classifiers. Also, a detailed description of the COVIDX-Net framework is presented. Experimental results and comparative performance of the proposed deep learning classifiers are investigated and discussed in section 4. Finally, limitations and this study is concluded with the main prospects in sections 4, 5.

2. Related Work

Some studies have shown the use of imaging techniques such as X-rays or Computed Tomography (CT-scans) for finding characteristic symptoms of the novel corona virus in these imaging techniques. Hemdan et al. [18] developed a deep learning framework, COVIDX-Net, to diagnose COVID- 19 in X-Ray Images. A comparative study of different deep learning architectures including VGG19, DenseNet201, ResNetV2, InceptionV3, InceptionResNetV2, Xception and MobileNetV2 is provided by authors. Barstugan et al. [19] proposed a machine learning approach for COVID-19 classification from CT images. Kassani et al. [20] presented a feature extractor-based deep learning and machine learning classifier approach for computer-aided diagnosis (CAD) of COVID-19 pneumonia. Loey et al. [21] presented a detection model based on GAN network with deep transfer learning for COVID-19 detection in limited chest X-ray images. Table 1 compares the proposed model (HealthFog) with existing models. Recent studies suggest the use of chest radiography in the epidemic areas for the initial screening of COVID-19 [22]. Therefore, the screening of radiography images can be used as an alternate to the PCR method, which exhibit higher sensitivity in some cases [23]. Nevertheless, the main bottleneck that the radiologists experience in analyzing radiography images is the visual scanning of the subtle insights. This entails the use of intelligent approaches that can automatically extract useful insights from the chest X-rays those are characteristics of COVID-19.

Table 1: Comparison of existing models

Work	Fog Computing	IoT	Neutrosophic	Deep Learning	Dataset	Diagnosis	Healthcare applications
Hemdan et al. [18]				✓	✓	✓	
Barstugan et al. [19]				✓	✓	✓	
Kassani et al. [20]				✓	✓	✓	
Loey et al. [21]			✓	✓	✓	✓	
Proposed work	✓	✓	✓	✓	✓	✓	✓

3. Proposed COVID_X Description framework

Fog and Cloud computing paradigms have emerged as a backbone of modern economy and utilize Internet to provide on-demand services to users [24]. Both of these domains have captured significant attention of industries and academia. In this section will proposed a new deep learning framework for automatically identifying the status of COVID-19 extend support to emerging application paradigms such as IoT, Fog computing, Edge, and Big Data through service and infrastructure. The data generated from Things layer can vary in size, for instance, the data sent from sensors. The diversity in data packages size influence the behavior of Fog node during the processing event, thus, data packages will require more time to process than light data packages. Therefore, in the proposed model, there is a distinction processing tasks. In addition, the fog nodes were adopted collaboration framework to achieve the minimal request processing time for heavy data packages. In Figure 1 the collaboration concept was elaborated and the distinction different processing tasks received from Things layer. In addition, in this framework the advance approach was adopted to identify the suitable treatment process, such as, Fog reputation to process specific type of data (e.g., health data).

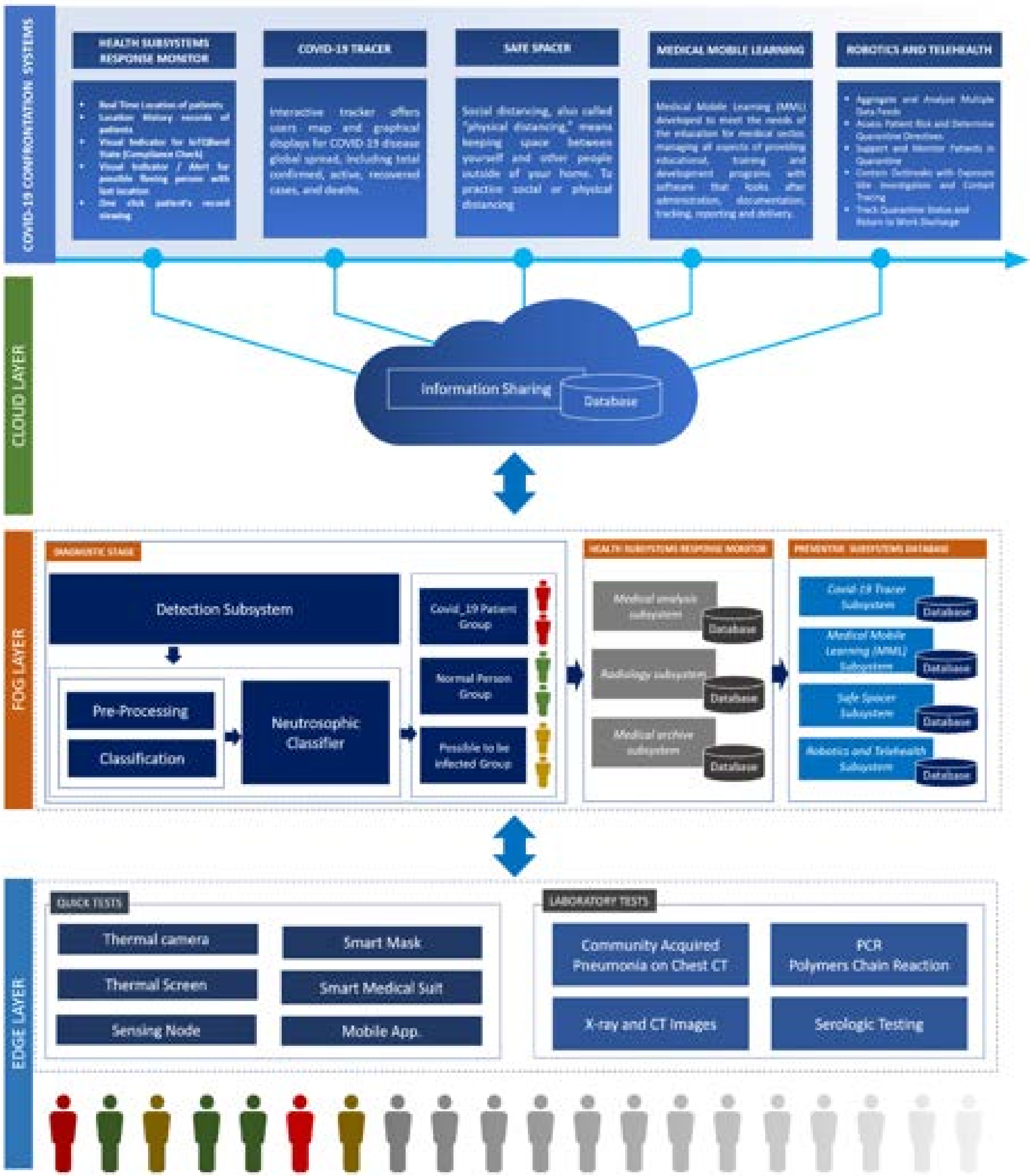

Figure 1. Proposed framework universal system for confrontation covid-19

3.1 Edge Layer:

The edge layer (perception layer), is the starting point of the IoT structure where data is been generated. This layer contains the networked Things (i.e., wireless sensors) such as heart-rate, blood-oxygen and etc., which operate to feed the system with patient symptoms data. Each Thing device/object in this layer is facilitated with communication protocol (such as IEEE 802.15.4, WiFi, Bluetooth, MQTT, and etc.) in which permit the Thing node to transmit the generated data to Fog nodes over the IoT network. In our proposed architecture, A TN denoted by T, is defined as a six-tuple: $T = \langle T_{id}, T_{st}, \tau_i , \mathcal{L}, \mathcal{H}, \mathcal{I}[q] \rangle$ where, T_{id} is an integer representing the unique ID of the TN, $T_{st} = \{0,1\}$, defines whether the node is in active state or not, (τ_i) indicates the type of event that a node senses. $(\mathcal{L})$ is refer to the geo-spatial location of a TN. $(\mathcal{H})$ is represented the specifications of an edge device. $\mathcal{I}[q]$ is a linear data structure, such as a 1-D array (with q elements) that stores the instance IDs of the application instances running on the device. These tuples are essential to represent the Thing node over the IoT network.

3.1.1 Thermal Screen

The smart helmet can also detect high body's temperature in the crowds and send the measured data to be displayed on a phone application. Smart Helmet system work is presented in Figure 2. As the high body temperature of people is one of the very common symptoms, a real time monitoring system of the screening process that automatically appearing the thermal image of temperature of people is needed. So, the diagnosis of the screening process will be less time consuming and less human interactions that might cause the spreading of the coronavirus faster. It can be concluded that the remote sensing procedures, which provide an assortment of ways to identify, sense, and monitoring of coronavirus, give an awesome promise and potential in order to fulfil the demands from the healthcare system [25].

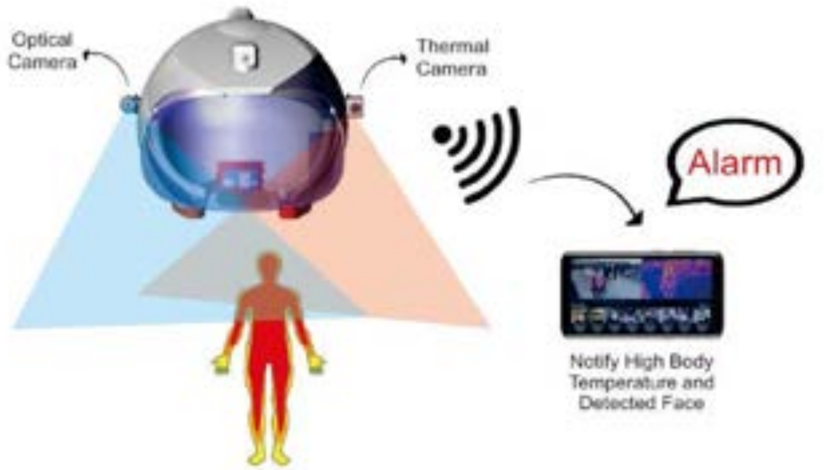

Figure 2. Smart Helmet system work

3.1.2 Sensing Node

Smart City and Intelligent Transportation System (ITS) as shown in Figure 3 offer a futuristic vision of smart, secure and safe experience to the end user, and at the same time efficiently manage the sparse resources and optimize the efficiency of city operations. However, outbreaks and pandemics like COVID-19 have revealed limitations of the existing deployments, therefore, architecture, applications and technology systems need to be developed for swift and timely enforcement of guidelines, rules and government orders to contain such future outbreaks. The proposed architecture and AI assisted applications discussed in the article can be used to effectively and timely enforce social distancing community measures, and optimize the use of resources in critical situations. It offers a conceptual overview and serves as a steppingstone to extensive research and deployment of automated data driven technologies in smart city and intelligent transportation systems [26].

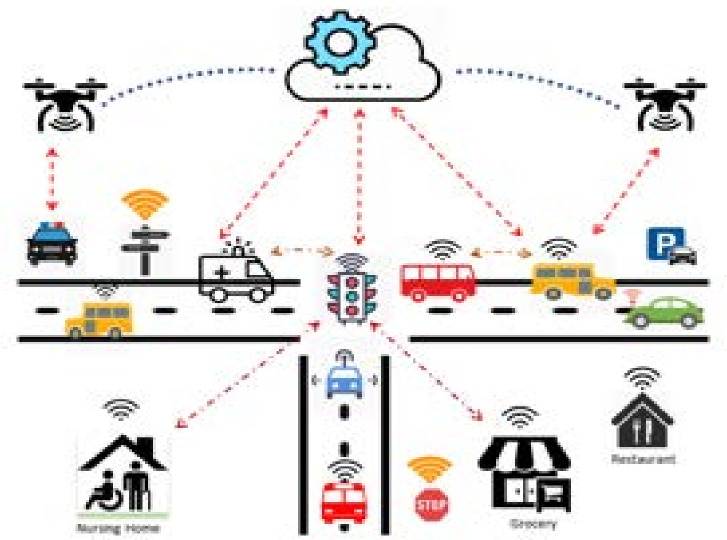

Figure 3. Smart City and ITS Architecture.

3.1.3 Smart Mask

Smart mask can be developed that can record air quality among other features. The Smart Mask is more than your average face mask, as its name suggests. Figure 4 shows the proposed Smart Mask, can record air quality information thanks to various sensors and electronics. Additionally, it can inform wearers of possible changes in lung capacity. While this may prove useful in areas of poor air quality,

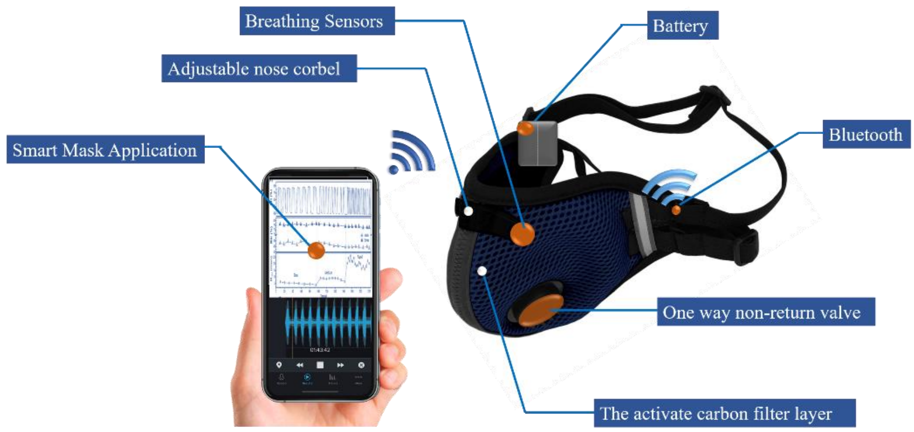

Figure 4. The proposed Smart Mask

Specifications; Type: Head-mounted, rated voltage: DC 5V, rated power: 0.4W, Charging time: 2 hours Standby time: 5~8 hours, Filtering effect: 95%, Protection level: KN95, Function: Dustproof, anti-haze, anti-pollen, anti-tail gas, etc. Feature; Unique ventilation design, a plurality of holes, excellent permeability, Exhale, the valve is opened without resistance, air breathing valve, air resistance is smaller, smooth breathing, uses efficient and low-resistance filter material, combined with the smart electric air supply module to provide fresh air into the mask. The edge is protected by 3D sponge for effective sealing. best protection: The allergy mask separation of 98% of the dust, chemicals, smoke and particles, it can be used for dust, anti-vehicle exhaust, anti-pollen allergy, PM2.5, for cycling, hiking, skiing and other outdoor activities. High-performance breathing valve that reduces heat and moisture build-up for smoother breathing. Built-in adjustable nose clip for a good fit and comfort with the face. Charge once for 5~8-hour endurance to ensure commuting. KN95 industrial safety protection level. Low noise.one mask can be used for 5-8 days. Can be reused and Comfortable ear band made of soft cotton, easy to wear and remove ear loop design.

3.1.4 Smart Medical Suit

The nature of Health care workers job puts them health care at an increased risk of catching any communicable disease, including COVID-19. Where they spend a lot of time up close with the patient doing high risk activities, those high-risk activities include things like placing patients on ventilators or collecting samples of sputum from their lungs. That's why it's so important that they achieve the highest level of protective equipment. The proposed smart medical suits is showed in Figure 5.

Figure 5. The proposed Smart Medical Suit.

3.1.5 Mobile App.

The new MobileDetect COVID-19 test kit in Figure 6 was planned to launch in April 2020. The currently available free MobileDetect App for Apple and Android smartphone and tablet platforms will be updated with the additional COVID-19 testing capability upon launch. Due to the novel design incorporating simplistic operation along with credible field-testing capability, the COVID-19 test kits can be used by federal, state, local response, medical agencies and are also planned to be available to the general public [27].

Figure 6. MobileDetect Application.

3.1.6 X-ray and CT Images

Medical imaging is also playing a critical in monitoring the progression of the disease and patient care. Extracting features from radiology modalities is an essential step in training machine learning models since the model performance directly depends on the quality of extracted features. Figure 7. Illustrates the visual features extracted by VGGNet architecture from an X-ray image of a COVID-19 positive patient. Motivated by the success of deep learning models in computer vision, the focus of this research is to provide an extensive comprehensive study on the classification of COVID-19 pneumonia in chest X-ray and CT imaging using features extracted by the state-of-the-art deep CNN architectures and trained on machine learning algorithms [20].

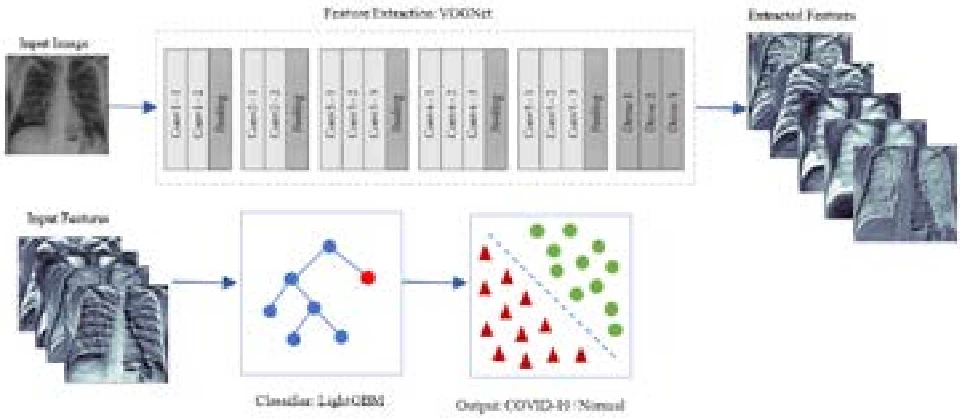

Figure 7. Framework of the method with VGGNet as feature extractor.

3.1.7 Community Acquired Pneumonia on Chest CT

In this study, a 3D deep learning framework was proposed for the detection of COVID-19 as shown in Figure 8. This framework is able to extract both 2D local and 3D global representative features. Deep learning has achieved superior performance in the field of radiology. RT-PCR is considered as the reference standard; however, it has been reported that chest CT could be used as a reliable and rapid approach for screening of COVID-19 [28]

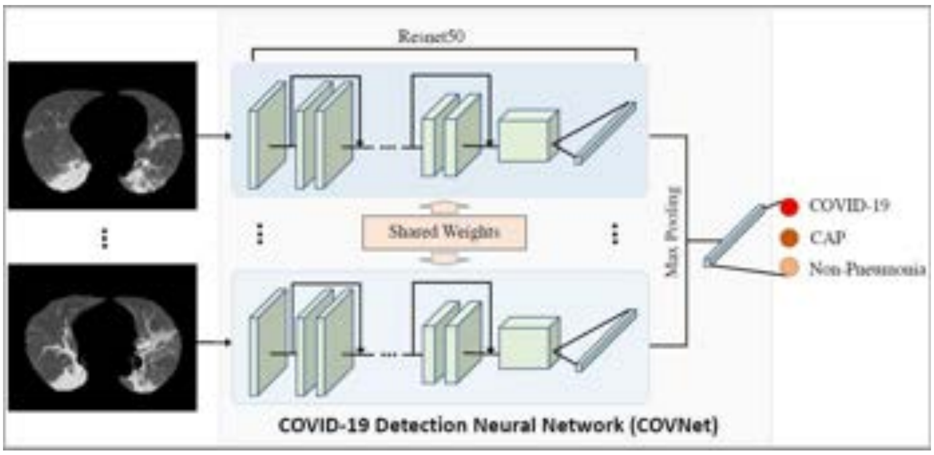

Figure 8. COVID-19 detection neural network (COVNet) architecture.

3.2 Fog Layer:

The Fog layer contains number of decentralized nodes in each given location. This layer handles the primary refining, compute, and processing of data generated in the Things layer. Fog nodes aim to improve efficiency of IoT applications, thus, Fog has the potential to reduce the amount of data transmitted to the Cloud layer and minimizing the requests-response time for IoT applications. This is often required to enhance the Quality of Service (QoS), such as reducing latency and improve network bandwidth. For example, in reference to our scenario the Fog will receive patient's data from their wearable, analyze the data according to predetermined artificial intelligent training, and make outcome available to caregiver over the dashboard and notify cloud with outcome for complex analysis.

3.2.1 Data pre-processing

Covid-19 tested data e.g. the images within the dataset were collected from multiple imaging clinics with different equipment and image acquisition parameters; therefore, considerable variations exist in images' intensity. The proposed method in this study avoids extensive pre-processing steps to improve the generalization ability of the convolution neural network (CNN) architecture. This helps to make the model more robust to noise, artifacts and variations in input images during feature extraction phase. Hence, we only employed two standard pre-processing steps in training deep learning models to optimize the training process [29].

3.2.2 Neutrosophic Classifier

Neutrosophic classifier: a classifier that would use Neutrosophic logic principles and Neutrosophic sets for the classification. Neutrosophic classifier incorporates a simple, Neutrosophic rule based approach like: IF X and Y THEN Z, for solving problem rather than attempting to model a system mathematically similar to fuzzy classifier [30]. Designing of Neutrosophic classification inference system using fuzzy methodology is based on the principles of Mamdani fuzzy inference method [25]. Figure 9 gives the block diagram representation of a Neutrosophic classification system using fuzzy logic toolbox of Matlab. Values of T, I and F Neutrosophic components are independent of each other. So using fuzzy logic toolbox of Matlab, three FIS have been designed: one for Neutrosophic truth component, second for Neutrosophic indeterminacy component and third for Neutrosophic falsity component. Though the working of these components are independent of each other but a correlation is drawn between membership functions of Neutrosophic T, I and F components so as to capture the truthness, indeterminacy and falsity of the input as well as the output.

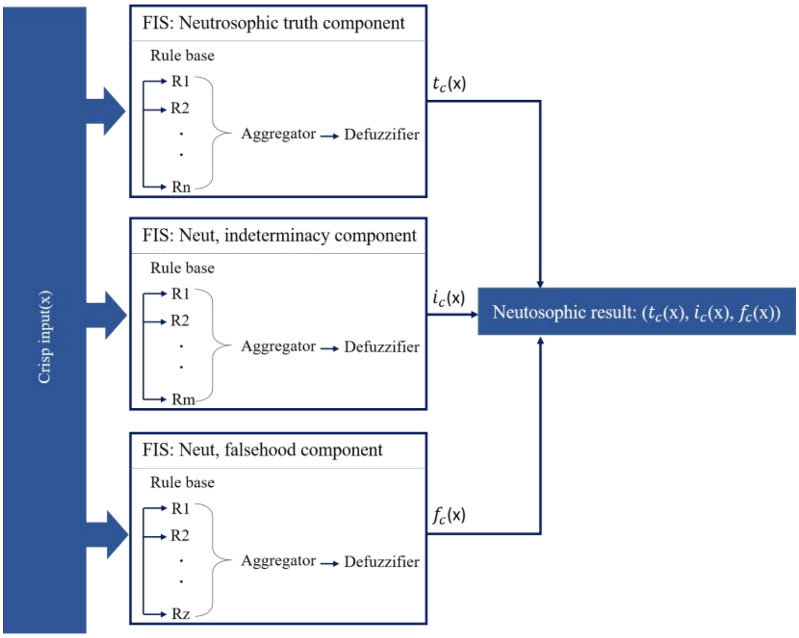

Figure 9. Block diagram for a Neutrosophic components

Neutrosophic Rule-based Classification System (NRCS) which is a rule based system where Neutrosophic logic is used as a tool for representing different forms of knowledge about the problem at hand, as well as for modeling the interactions and relationships that exist between its variables [23]. The generic structure of a NRCSs shown in Figure 10.

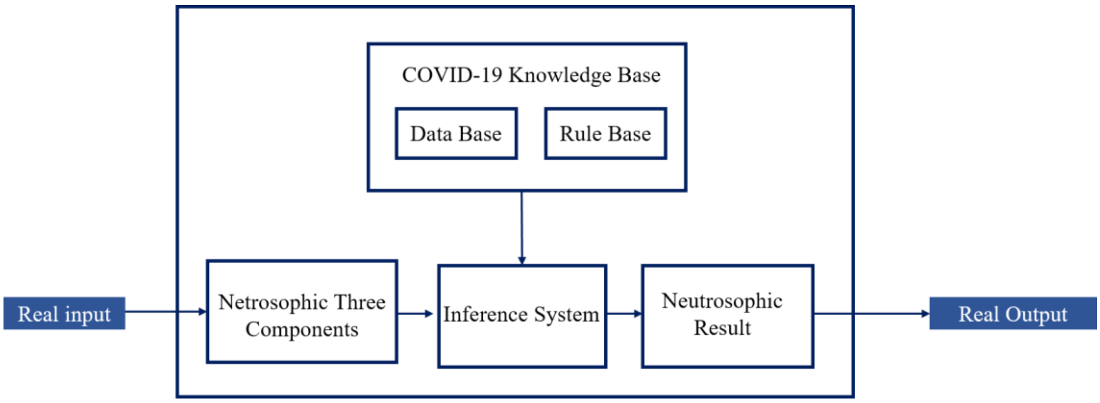

Figure 10. Basic structure of a Neutrosophic Rule-Based Classification System

Let U be a universe of discourse and W is a set in U which composed of bright pixels. A Neutrosophic images P_{NS} is characterized by three sub sets T, I, and F. that can be defined as T is the degree of membership, I is the degree of indeterminacy, and F is the degree of non-membership. In the image, a pixel P in the image is described as P(T,I,F) that belongs to W by its t% is true in the bright pixel, i% is the indeterminate and f% is false where t varies in T, i varies in I, and f varies in F.

The pixelp(i,j)in the image domain, is transformed to

$$NDP_{NS}(i,j) = \{T(i,j), I(i,j), F(i,j)\} \tag{1}$$

Where belongs to white set, belongs to indeterminate set and belongs to non-white set. Which can be defined as [31]:

$$P_{NS}(i,j) = \{T(i,j), I(i,j), F(i,j)\} \tag{2}$$

$$T(i,j) = \frac{\overline{g(\iota,\jmath)} - \bar{g}_{min}}{\bar{g}_{max} - \bar{g}_{min}} \tag{3}$$

$$I(i,j) = 1 - \frac{H_o(i,j) - H_o}{H_{o_{max}} - H_{o_{min}}} \tag{4}$$

$$F(i,j) = 1 - T(i,j) \tag{5}$$

$$H_o(i,j) = abs(g(i,j) - \overline{g(\iota,\jmath)} \tag{6}$$

Where $\overline{g(\iota,\jmath)}$ represents the local mean value of the pixels of window size, and $H_o(i,j)$ which can be defined as the homogeneity value of T at (i,j), that described by the absolute value of difference between intensity $g(i,j)$ and its local mean value $\overline{g(\iota,\jmath)}$.

The Content Based Image Retrieval (CBIR) goal is to retrieve images relevant to a query images which selected by a user. The image in CBIR is described by extracted low-level visual features, such as color, texture and shape. Retrieval System for images embedded in the Neutrosophic domain. In this first phase, extract a set of features to represent the content of each image in the training database. In the second phase, a similarity measurement is used to determine the distance between the image under consideration (query image), and each image in the training database, using their feature vectors constructed in the first phase. Hence, the N most similar images are retrieved. Several distance metrics were suggested for both content and texture image retrieval, respectively. In this paper, we are using a Neutrosophic version of the Euclidean distance, which was presented in [31]. For any two Neutrosophic Sets, the Content Based Image Retrieval (CBIR) goal is to retrieve images relevant to a query images which selected by a user. The image in CBIR is described by extracted low-level visual features, such as color, texture and shape. Retrieval System for images embedded in the Neutrosophic domain. In this first phase, extract a set of features to represent the content of each image in the training database. In the second phase, a similarity measurement is used to determine the distance between the image under consideration (query image), and each image in the training database, using their feature vectors constructed in the first phase. Hence, the N most similar images are retrieved. Several distance metrics were suggested for both content and texture image retrieval, respectively. In this paper, we are using a Neutrosophic version of the Euclidean distance, which was presented in [31]. For any two Neutrosophic Sets,

$$A = \{T_A(x), I_A(x), F_A(x)), x \in U\} \; and \tag{7}$$

$$B = \{T_B(x), I_B(x), F_B(x)), x \in U\} \; in \tag{8}$$

$$U = \{u_1, u_2, u_3, \dots, u_n\} \; then \tag{9}$$

The Neutrosophic Euclidean distance is equal to

$$d(A,B) = \sqrt{\sum_{i=1}^{n} ((T_A(x_i) - T_B(x_i))^2 + ((I_A(x_i) - I_B(x_i))^2 + ((F_A(x_i) - F_B(x_i))^2} \quad (10)$$

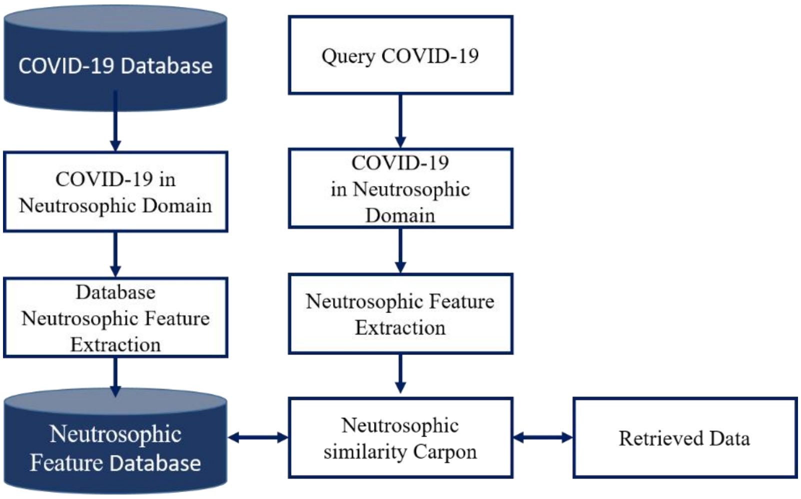

Figure 11. Neutrosophic COVID-19 image classifier Architecture

The algorithm for the proposed system is given below which presented in Figure 11:

1. Convert each image in the database from spatial domain to Neutrosophic domain.
2. Create a database containing various COVID-19.
3. Extract Texture feature of COVID-19 in the database.
4. Construct a combined feature vector for T, I, F and Stored in another database called Featured Database.
5. Find the distance between feature vectors of query COVID-19 and that of featured databases.
6. Sort the distance and Retrieve the N-top most similar.

The RNN structure replaces the traditional neuron by two neurons (lower neuron, upper neuron) to represent lower and upper approximations of each attribute in the CTG data set, its structure formed from 4 layers input, 2 hidden and output layers. The hidden layers have rough neurons, which overlap and exchange information between each other, While the input and output layers consists of traditional neurons as in Figure 12 [32].

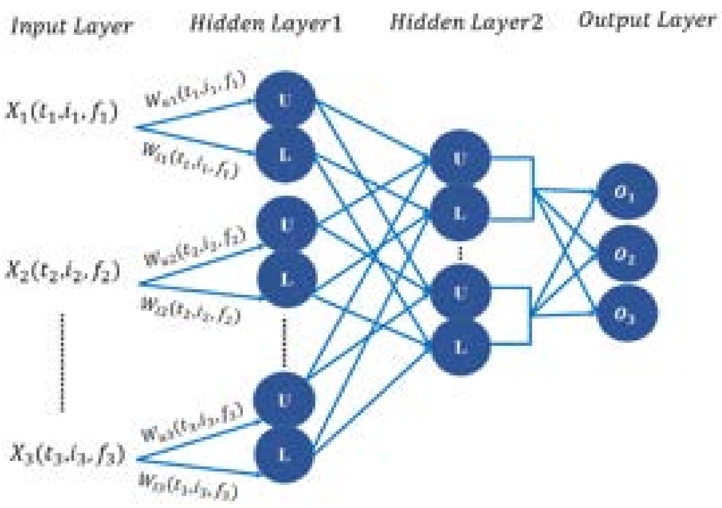

Figure 12. Rough Neural Network (RNN) structure.

Input layer is composed of neuron for each data attribute. The output layer represents the three FHR classes, the hidden layers rough neurons are determined by the Baum-Haussler rule [33].

$$N_{hn} = \frac{N_{ts} \times Te}{N_i + N_o} \tag{11}$$

Where N_{hn} is the number of hidden neurons, N_{ts} is the number of training samples, Te is the tolerance error, N_i is the number of inputs (attributes or features), and N_o is the number of the output.During training process, the normalized input data is multiplied by its weight and computed in sigmoid activation function.

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{12}$$

Step II: Training phase

1. Initialize random (upper, lower) weights of network
2. Feed forward of attribute values and multiply in both direction (Uw, Lw)
3. Compute (IU, IL) of hidden layers by relations:

$$I_{Ln} = \sum_{J=1}^{n} W_{Lnj} O_{nj} \tag{13}$$

$$I_{Un} = \sum_{J=1}^{n} W_{Unj} O_{nj} \tag{14}$$

4. Compute (OU, OL) of hidden layers by relations:

$$O_{Ln} = Min(f(I_{Ln}), f(I_{Un})) \tag{15}$$

5. Check fetus according to comparing between actual output (T) and output value (O), where output represent by

$$O = O_{Ln} + O_{Un} \tag{16}$$

6. If output is error, then use back propagation algorithm, and compute error.

$$\Delta = T - O \tag{17}$$

7. Update (upper, lower) weights of network by derivation of activation function:

New weight = old weight + (Δ * η *derivative* activation of (input)) (18)

where η is learning rate of model

8. Repeat 5, 6, 7, 8 and 8.1 until reduction error as possible as.

Step III: Testing phase Classify new sample of objects and determine the accuracy rate of the model by using relation Accuracy = 1–absolute error, also calculate time consumption in model processing. The proposed model for neutrosophic algorithms and source codes based on the works presented in [34-37] and others.

3.2.3 Classification Performance Analysis

In order to evaluate the performance for each deep learning model in the COVID-X, different metrics have been applied in this study to measure the true and/or misclassification of diagnosed COVID-19 in the tested X-ray images as follow. First, the cross validation estimator was used and resulted in a confusion matrix as illustrated in Table 2. The confusion matrix has four expected outcomes as follows. True Positive (TP) is a number of anomalies and has been identified with the right diagnosis. True Negative (TN) is an incorrectly measured number of regular instances. False Positive (FP) is a collection of regular instances that are classified as an anomaly diagnosis FP. False Negative (FN) is a list of anomalies observed as an ordinary diagnosis [18].

Table 2. Confusion Matrix.

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

After calculating the values of possible outcomes in the confusion matrix, the following performance metrics can be calculated.

A) ***Accuracy:*** Accuracy is the most important metric for the results of our deep learning classifiers, as given in (1). It is simply the summation of true positives and true negatives divided by the total values of confusion matrix components. The most reliable model is the best but it is important to ensure that there are symmetrical datasets with almost equal false positive values and false adverse values. Therefore, the above components of the confusion matrix must be calculated to assess the classification quality of our proposed COVIDX-Net framework.

$$\text{Accuracy}(\%) = \frac{TP + TN}{TP + FP + TN + FN}\ 100\% \tag{19}$$

B) ***Precision:*** Precision is represented in (2) to give relationship between the true positive predicted values and full positive predicted values.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{20}$$

C) Recall: In (3), recall or sensitivity is the ratio between the true positive values of prediction and the summation of predicted true positive values and predicted false negative values.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{21}$$

D) F1-score: F1-score is an overall measure of the model's accuracy that combines precision and recall, as represented in (4). F1-score is the twice of the ratio between the multiplication to the summation of precision and recall metrics.

$$\text{F1} - \text{score} = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right) \tag{22}$$

3.3 Cloud Layer:

Cloud or data-centres layer is the top layer of the IoT architecture in which enabling omnipresent, convenient, and proper network access to shared resources (e.g., storage, and services) over the IoT network. Thus, Cloud perform the heavy services of healthcare data analysis and processing that Fog cannot perform.

3.3.1 Covid-19 Tracer

Interactive tracker offers users map and graphical displays for COVID-19 disease global spread, including total confirmed, active, recovered cases, and deaths. The live dashboard pulls data from the proposed framework as well as the centers for disease control to show all confirmed and suspected cases of COVID-19, along with recovered patients and deaths. The data is visualized through a real-time graphic information system (GIS) as shows in Figure 13 [38].

Figure 13. COVID-19 Tracer

3.3.2 Safe Spacer

Limiting face-to-face contact with others is the best way to reduce the spread of coronavirus disease 2020 (COVID-19). Safe spacer, also called "social distancing," means keeping space between yourself and other people outside of your home. The proposed safe spacer was showed in Figure 14. To practice social or physical distancing using Ultra-wideband technology, Safe Spacer runs wirelessly on a rechargeable battery and precisely senses when other devices come within 2m/6ft, alerting wearers with a choice of visual, vibrating or audio alarm. Each device features a unique ID tag and built-in memory to optionally associate with workers' names for tracing any unintentional contact. To maintain high privacy standards, no data except the device's ID and proximity is stored. For advanced workplace use, an optional iOS/Android app allows human resources or safety departments to associate IDs to specific workers, log and export daily tracing without collecting sensitive data, configure the alarms, set custom distance/alert thresholds and more.

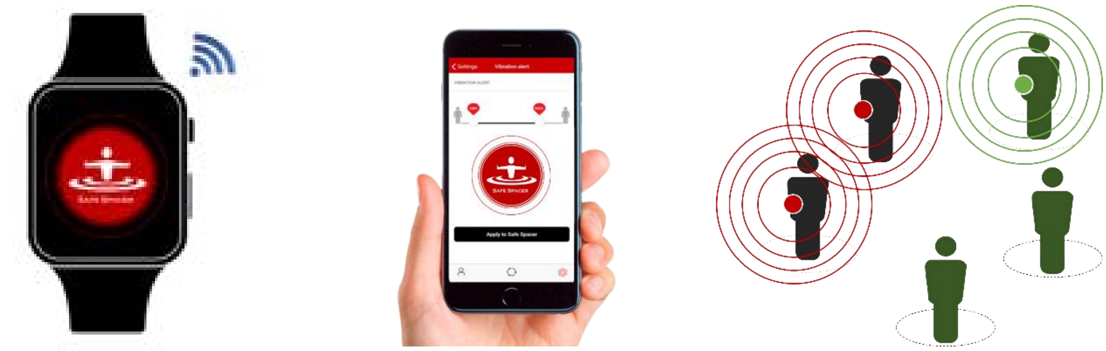

Figure 14. The proposed safe spacer

3.3.3 Health System Response Monitor

The COVID-19 Health System Response Monitor (HSRM) assists healthcare organizations and governments assess patient risk profiles and connects them with virtual care capabilities. It has been designed in response to the COVID-19 outbreak to collect and organize up-to-date information responding to the crisis. It focuses primarily on the responses of health systems but also captures wider public health initiatives. It can be presented the main subsystem in medical system as following:

- ***Medical analysis subsystem*** It records the results of the tests for the patients either manually or automatically by connecting the analytical devices to the system It provides a set of statistics such as: the number of analyzes required by a particular laboratory in a specific period and the number of analyzes that have already been done - analyzes of a particular patient divided according to his medical visits This system is linked to a database that includes all medical analyzes divided by type (chemistry - hematology - microbiology - immunology - pathology) and it is related to a set of applications that record the analyzes of each laboratory and the standard data for these analyzes (Normal Value) according to the kit used in the lab.
- ***Radiology subsystem.*** It records the data of the examination staff, showing the type of radiation required for each of them, along with some clinical data about some of the rays, such as CT-rays and records the radiology report. It contains a system Picture Archiving and Communication System (PACS) that links the radiology devices to the system so that the x-rays are sent to the x-ray. It provides a set of statistics, such as: the number of radiation transferred to a particular x-ray department in a specific period, the number of radiation already done, and the number of x-rays sent. This system is linked to a database that includes all the rays divided by type (therapeutic - diagnostic) or (ultrasound - CT scan - resonance) and it is linked to a set of applications that record the radiation of each section and the standard report for each radiator, as well as determining the work schedule for each section rays.
- ***Medical archive subsystem.*** It provides a set of statistics, such as: the numbers of patients attending a specific clinic in a specific period classified by type or age group or geographically distributed in the governorate, center or city. The system scans patient documents, whether paper documents or x-ray films, with scanners with special specifications. These documents

are stored as part of patient data on dedicated servers. The system contains the ability to record the type of document (x-rays-tests-good checks-surgeries -...) and the document history and some other data that can be used to create statistics for these documents can be added. The system contains a special viewer to display these documents with special capabilities for dealing with these images such as enlarging, reducing or rotating the images. The Digitizer can be used so that x-ray films are stored in the form of dicom files which is the same format that x-ray devices output so that they can be viewed through the PACS Viewer.

3.3.4 Medical Mobile Learning subsystem

Medical Mobile Learning (MML) is an unavoidable alternative during COVID-19. It developed to meet the needs of the education for medical sector, managing all aspects of providing educational, training and development programs with software that looks after administration, documentation, tracking, reporting and delivery. MML denote learning involving the use of a mobile device. It has several advantages and benefits. First, this teaching method can occur at anyplace, anytime, and anywhere and the learning process is not limited to one particular place. Besides, it allows doctors to personalize instruction and allow to self-regulate learning. Generally, mobile learning can helps doctors to develop technological skills, conversational skills, find answers to their questions for any update for COVID-19, develop a sense of collaboration, allow knowledge sharing, and hence leverage their learning.

3.3.5 Robotics and Telehealth system

Health systems broadly, to encompass the full continuum between public health (population-based services) and medical care (delivered to individual patients). When we think about digital transformation in healthcare, we usually think about some new software doctors are using or a new medical imaging machine. However, since doctors are now scrambling to contain the COVID-19 pandemic, they have to do so without endangering themselves as well. The proposed robotics and telehealth system shown in Figure 15. This is where robotics comes in instead of going into the room to see the patient, a robot goes in, and the doctors operate it via an iPad from the other side of the door—this digital innovation in healthcare currently being used in hospitals in Washington and other states. In fact, the robot even has a stethoscope to take the patients' vitals [39].

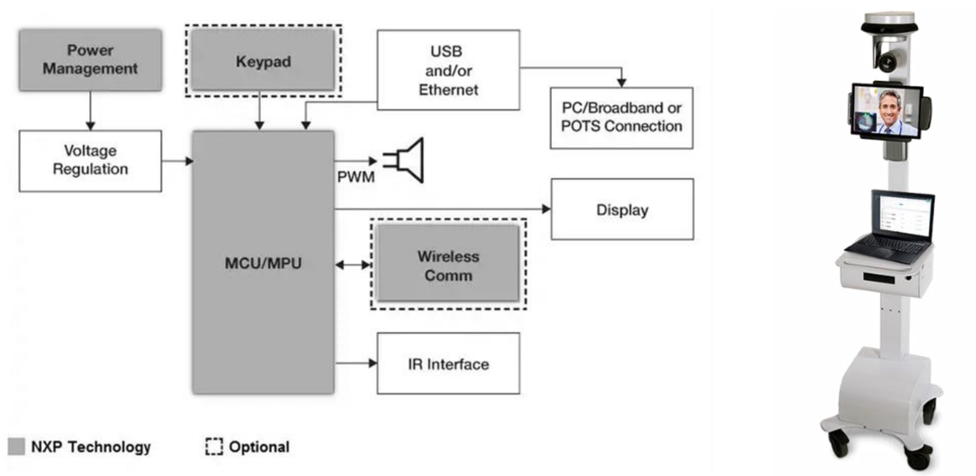

Figure 15. The proposed robotics and telehealth system

4. Limitations

This research is interested in aspects related to Fog computing applied to the healthcare area. In this sense, this paper focuses on the characteristics of fog computing architectures directly related to healthcare, disregarding models. This research is limited in availability of data makes it difficult to process due to the limited hardware availability. Interoperability, data processing, CPU management, memory and disk resources, and big data issues are still weaknesses in architectures that require a large number of heterogeneous devices such as healthcare applications.

5. Conclusion and Future Works

Infectious COVID-19 disease shocked the world and is still threating the lives of billions of people. In this study, a new CVOID-X framework has been proposed to automatically identify or COVID-19 based on deep learning classifiers. Technological developments like edge computing, fog computing, IoT, and Big Data have gained importance due to their robustness. In this retrospective and multi-center study, a deep learning model, COVID-19 detection neural network using Neautrosophic classifier, was developed to extract visual features from volumetric exams for the detection of COVID-19. The proposed system facilitates communication between people and medical centers so that the appropriate COVID-19 patient can be reached just on time. It also integrates the information scattered among different medical centers and health organizations across the country to confrontation COVID-19 Stakeholders are able to use the confrontation as an applications installed on their smartphones or as wearable devices. So the diagnosis of the screening process will be less time consuming and less human interactions that might cause the spreading of the coronavirus faster. It can be concluded that the remote sensing procedures, which provide an assortment of ways to identify, sense, and monitoring of COVID-19, give an awesome promise and potential in order to fulfil the demands from the healthcare system. As part of the future work, the proposed framework can be stimulated and analysis the results for every Thing device/object in Edge layer presented in this work. Moreover, to obtain the most accurate feature which is an essential component of learning, MobileNet, DenseNet, Xception, ResNet, InceptionV3, InceptionRes- NetV2, VGGNet, NASNet will be applied amongst a pool of deep convolutional neural networks. Furthermore, the proposed framework can also be extended towards other important domains of healthcare such as diabetes, cancer and hepatitis, which can provide efficient services to corresponding patients.

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