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The Development of Deep Learning Algorithm for Identifying the Patients With Suspected Coronavirus

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Abstract: Throughout the globe a new infection named as coronavirus, that is spreading among human being very fast and intensely. Due to the fast spread of this virus since December 2019, the financial activities across the whole world are deteriorating. There was a lockdown in the whole world because of which the world's biggest stock markets have collapsed. Unemployment in the whole world has increased in a large number and the trade between the countries stopped. To stop the spread of virus between person to person, the World Health Organization (WHO) has advised the people to adopt the home isolation. The main challenge in this pandemic is to identify the infected people from this virus. The present method which are commonly used are measuring of body temperature and doing blood test. However, body temperature detection and lab testing of the blood is complex and intrusive. The current challenge is to develop some technology to non-intrusively detect the suspected coronavirus patients at crowded places through the COVID alike symptoms of cough, sneezing and flu. Another, challenge to conduct the research on this area is the difficulty to obtain the data set due to limited number of patients to give their consent to be part of the research study. Looking at the efficacy of Artificial Intelligence (AI) in healthcare systems, it is a great challenge for the researchers to develop an AI algorithm which can assist health professionals and government officials to automatically identify and segregate the people having coronavirus symptoms such as cough and flu. Hence, this paper proposes a novel proof of concept system using ML-DCNNet to identify the Coronavirus infected people through facial expression (FE) recognition. The proposed algorithm takes the facial expressions of the people and identifies the facial expressions linked with normal health, cough, sneezing and flu. The data of the facial expressions have been collected through market places, medical clinics and quarantine centers in India. The working of the developed algorithm has been divided into dual stages, at the first stage, the suspected COVID infected patients are classified using Expression-Net on the basis of FEs and in the second stage, intensity level is checked using Intensity-Net to segregate the suspected people with cough, sneezing and flu symptoms. The proposed prototype of ML-DCNN is used to measure the people infected with COVID-19 with their symptoms intensity estimation has been carried out by using the COVID-19 datasets. The proposed system will act as a COVID alert system about the presence of suspected Coronavirus infected people with symptoms of cough, sneezing and flu. It is the first kind of study to analyze the facial expressions and behavioural measures (coughing, sneezing, flu and hand movements). This is study is a proof of concept which can be viable solution in future to detect the suspected COVID patients. However, this needs to be tested on larger dataset. It has been foreseen that the proposed method will demonstrate a distinguished performance as contrast to the situation of the skill methods being used currently.

Keywords: Artificial Intelligence; COVID19; Pandemic; Health Prognostics; Suspected Infection

1. Introduction

The Coronavirus has become a pandemic and the whole world is hugely affected by this pandemic. Coronaviruses are enveloped and widely spread in humans and other mammals by non-segmented positive sense RNA viruses belonging to the Corona viridae family and the order Nido virales. More than 10,000 combined cases of extreme acute respiratory syndrome coronavirus (SARS-CoV) and Middle East respiratory syndrome coronavirus (MERS-CoV) have caused mortality rates of 10 percent for SARS-CoV and 37 percent for MERS-CoV, while most human coronavirus infections are mild [1]. In Wuhan , China, a pneumonia related to the 2019 novel coronavirus (2019-nCoV) appeared in December , 2019. The older men are more likely to be affected with co occuring of the 2019-nCoV infection, because of which serious respiratory deasese like acute respiratory distress syndrome can occur. The model for early warning prediction of pneumonia viral mortality is MuLBSTA , and the patients who died were consistent with the multilobular infiltration, hypo-lymphocytosis, bacterial coinfection, smoking history, hyper-tension and age (MuLBSTA) score. The deaths caused due to COVID-19 is calculated using MuLBSTA score methods, the authenticity of this method is required to be checked [2]. In [3] the author has explained about human conjunctival epithelium that gets quickly infected by bacterial droplets and body fluids.

So far, 184 countries and patients exceeding 2.79 million globally have been affected by this coronavirus disease (COVID-19) pandemic. In the last eight months, around 47,585,097 total cases has been registered and more than 1,215,180 deaths have been related to it, with over 237,177 deaths in the United States alone. Prevalent pulmonary manifestations symptoms are well acknowledged. The deases related to cardiac also involved as well. The most prominent cardiac deases like sever heart attack, is detected in patients even they are not having any previous history of heart problem. SARS-CoV-2 contamination occurs in the case of respiratory droplets and aerosols released by coughing and sneezing. Till October 31, 2020 there were 86,070 confirmed cases and 4634fatalities in China. It has become a big public health problem in the international community. This virus and its predecessors were possibly obtained from animals and modified or reunified in a way that infected, induced bacteria, and passed from one individual to another. COVID-19 virus are enfold RNA infections that are mostly spread between persons , different creatures, making contagious, enteric, hepatic, and neurological diseases. The persons having less immunity can easily cause cold symptoms which are caused due to four viruses, 229E, OC43, NL63, and HKU1. [4-8].

A study held in china Maternal and Child Health Information System by the authors and they found out that between the month of January and March 2020, around 11,078 womens having pregnancy and giving single births were checked for coronavirus infection in which 65 are diagnosed with the virus COVID-19. 206,000 (95 percent credible interval, 178,100-231,000) more people died in 21 industrial countries from mid-February to May 2020 than if the pandemic had not happened. In most countries, the number of excess deaths per 100,000 adults, and comparitive rise in mortality can be compared between male and female. For example, a model has been developed that can be used for early COVID-19 pneumonia screening and the model can be used to distinguish between COVID-19, influnza, viral pneumonia and stable cases using deep learning techniques by respiratory computed tomography (CT) images. The AI-based analysis was used in the screening of COVID-19 to obtain high precision. They also tested the efficacy of the AI algorithm for disease burden quantification and monitoring. [9-13]

The AI diagnostic algorithm was concluded to have the benefits of high performance , high repeatability and simple large-scale deployment[14]. The availability of computational computing technologies such as Big Data, Deep Learning, Internet of Things (IoT) and Artificial Intelligence (AI) and others have brought major improvements in medical operations, personal medicine and epidemiology to their subsequent use in healthcare worldwide, and this is expected to continue to improve precision in this area , especially in diagnostic accuracy[15].

In busy areas, the identification of potential corona patients has been a big problem for governments and health organizations. The available tools used are to detect the individual's body temperature and to conduct blood sample laboratory research. Complex and invasive approaches are the detection of body temperature and laboratory testing of blood. In addition, those strategies are time-consuming and require a lot of money. Therefore, the contribution of this paper is to create an algorithm based on Artificial Intelligence (AI) to non-intrusively diagnose suspected coronavirus patients via the effects of cough, sneezing and flu in crowded areas. It examines a person's emotions and can be used to determine a person's emotional motives at a certain level. With the use of image detection and recognition systems , different approach work using the Internet of Things (IoT) in the field of computer, observing setup, observation, confirmation or validation of persons and home automation system formed on digital face recognition system. In these applications, the state of art is to detect FE by its level of strength. Due to the dynamic nature of FE, which is correlated with emotions and disease symptoms such as cough, sneezing and flu, it is an attention-seeking issue. For this aim, it is important to build a new extensive learning prototype to check and calculate the FE depth level to check the doubt the persons infected with the new virus from congested places such as airports, markets and Mosques. To perform this, a ML-DCNNet has been evolve in this research to realize the FE, their severity level and to separate the people doubt with cough, sneezing and flu symptoms.

The rest of the paper has been organized as follows: Section II gives a detailed theoretical framework of the Multi-Level Deep Convolutional Neural Network. Section III presents the results and analysis and finally, Section IV provides the conclusions.

2. Data Collection

The data for this study was collected from the clinics in Pakistan and India. The images of the people visit the clinic were taken after their written consent. A total of 346 images were taken. The 68 images were taken for the people who have no symptom of flu, cough or sneezing. These people were named as healthy people. The 67 images were taken for the people who have symptoms of flu only. The 68 images were taken for the people who were having sneezing and the 143 images were taken for those people who were suffering with cough. The images were saved in jpg format and each image has the dimension of 120*100*3. This study was conducted after getting ethical approval from the Najran University Research and ethical committee.

3. Development of ML-DCNN

The least quantity of filters and peak time difficulty of the new facial expression detection techniques are present [18-24]. The research done in this paper is to solve this issue by using ML-DNN based image classification. It is connected to a typical neural network with a mixture of separate neurons, rates of learning and different variables. As shown in figure 1 one used to separate two CNN methods for the selection of network. Expression-Net, known as the first CNN used the FE of a patient to classify the patient that whether it is COVID infected or not. The second CNN known as Intensity-Net is used to classify the suspected COVID-19 intensity into three stages: coughing, flu and sneezing. After every convolutional layer there is a max-polling layer to control the overfitting and other parameters. The image input layer takes image having pixel values with width, height and three color channels for RGB. The convolutional layer will figure out the output regions that are connected in input sections, each one calculating a dot product of their small weights regions connected in the input layer. The pooling layer performs down-sampling operations with spatial dimensions (width and height) resulting in some volume. The fully connected layer will calculate the class scores resulting in a volume of some classes, in our work it returns the three classes for segments. This layer is fully connected to activations in all the layers. The soft-max layer is implemented just before the output layer. It takes the same no of nodes as the output layer and performs normalization. The classifying layer is a complete linked layer where the input from other layers is flattened and transforms to the output layer.

The CNN experiments were implemented in MATLAB. The developed algorithm was evaluated on the COVID-19 dataset whose details are shown in Table 2 and Fig 2. To train the multi-level neural network, the dataset is separated into three groups: training, testing and authenticating groups. As shown in Table 3, the instruction and investigation datasets are distributed into 70 percent and 30 percent ratios of the overall COVID-19 data file.

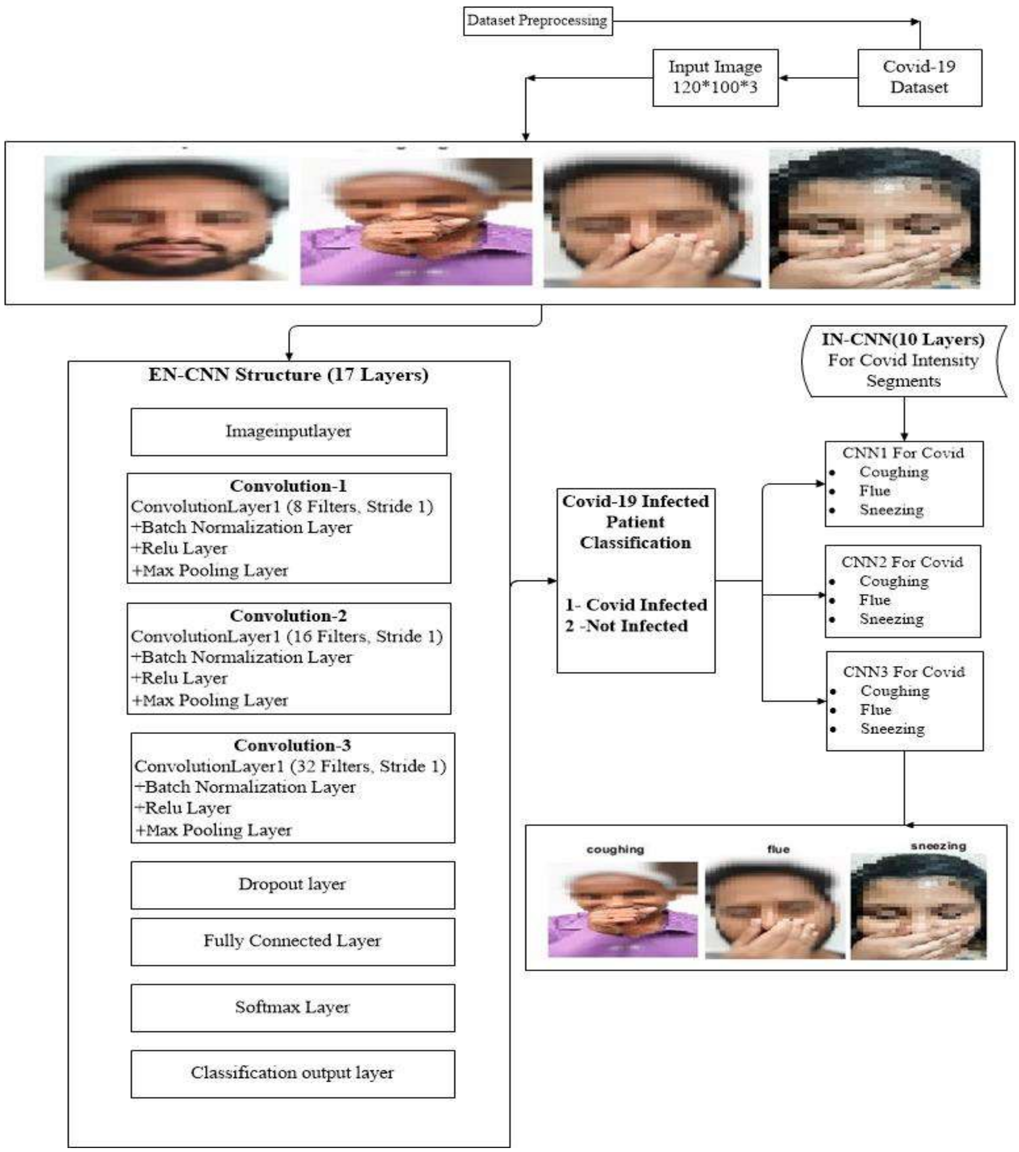


Figure 1. ML-DNN Architecture.

Figure 2. Dataset types.

Table 2. Details of the dataset for COVID-19.

Data set	Initial Size	Format	Healthy	Flu	Sneezing	Coughing	Total
Covid-19 images dataset	120*100	JPG	68	67	68	143	346

Table 3. Distribution of images in the training, testing and validation sets.

Group	Training	Validation	Testing
Health	68	68	30
Flu	67	67	30
Sneezing	68	68	30
Coughing	143	143	70
Total	**346**	**346**	**160**

4. Results and Discussions

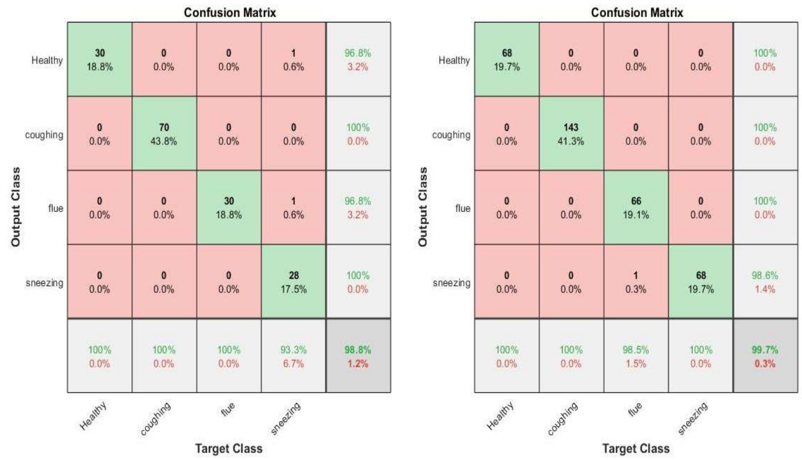
In this section, the experimental results obtained from Multi-level deep Neural Network have been described. The experiments are divided into two phases. In the first phase, one can recognize the image sequences and classify them into suspected COVID patient and Non-COVID patient categories using CNN. The second phase is related to find the values of the intensity value of suspected COVID patients by using another CNN. The values have been divided in three segments coughing, flu and sneezing.

The confusion matrix in Fig 4 displays the effects of the different classes' recognition rate for both the test (A) and training (B) set of data. The output values are represented by rows of the classes and columns in this confusion matrix to illustrate the target values of the classes. In diagonal and off-diagonal cells the examination are shown for accurately and inaccurately classification. The total number of examination and their percentages are depicted by the individual cell. The percentage of total expected classification values is displayed on the right-hand side of the confusion matrix. These values are often referred to as precision rates. The bottom row shows the percentages of all the observations that are classified as correct and incorrect. These standards are also known as true-positive and false-negative values, respectively. The overall exact value is shown at the bottom-right cell in the confusion matrix. Table 4 presents the classification results for testing and training datasets and overall, both shows 98.8 % and 99.7 % average accuracy, respectively. Fig 5 shows the validation and training accuracies and losses for the Covid-19 testing (A) and training (B) dataset. The validation of precision and loss is shown by the dotted line in figure 5, while the training accuracy and loss is shown by the smooth line, respectively.

The justification of the superiority of the proposed Multi-Level Deep Neural Network algorithm over other existing AI methods in image classification has been proved through a comparison of the accuracies of each method, as given in Table 5. It has been observed that the proposed Multi-Level Deep Neural Network algorithm gets better accuracies as compared to the other techniques for recognition and classification of different images.

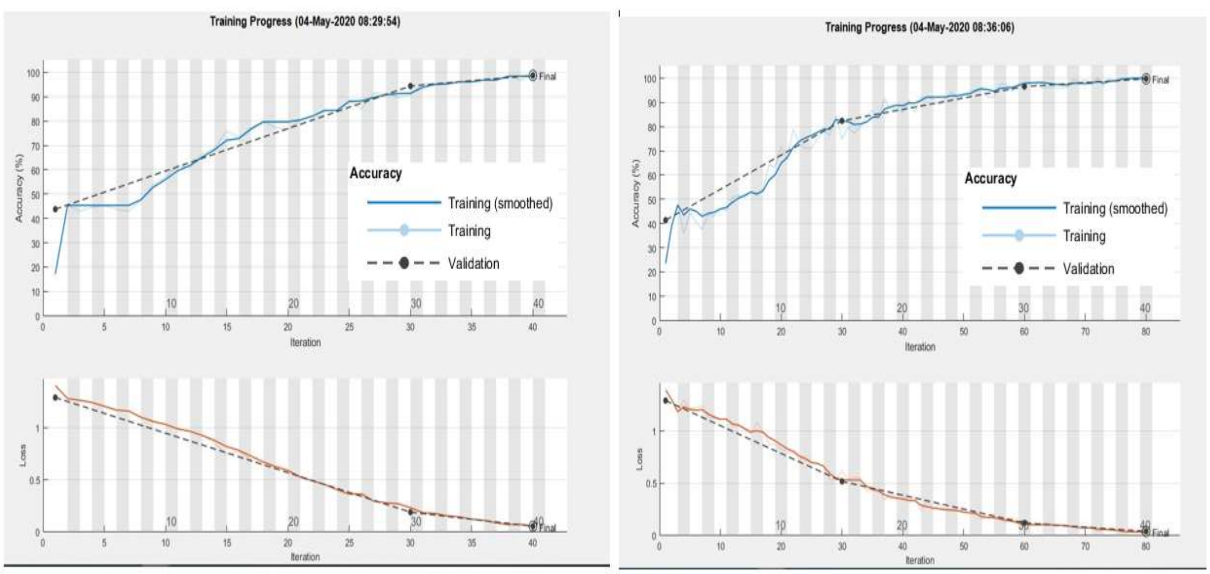
Table 4. Classification Accuracy of Multi-Level Deep Convolutional Neural Network on COVID-19 Dataset.

Segments	Testing Accuracy (%)	Training Accuracy (%)
Healthy	96.8	100.0
Coughing	100.0	100.0
Flu	96.8	100.0
Sneezing	100.0	98.6
Average Accuracy	**98.8**	**99.7**



A B

Figure 4. Confusion Matrix of Covid-19 Testing (A) and Training (B) Dataset.



A B

Figure 5. Validation and Training Accuracy and Loss for Covid-19 Testing (**A**) Training (**B**) Dataset.

Table 5. Collation of précised value (%) of the presented method with the state of the art methods.

Cited	Methodologies	Dataset Type	Accuracy (%)	Year
[19]	CNN	ORIGA and SCES	83.00	2015
[20]	Feed-Forward neural network	PPGVFs and OAG	92.00	2016
[21]	Support Vector Machine	UNICAMP	87.00	2016
Proposed Multi-Level deep neural network (Coughing, Flu, Sneezing)		**Covid-19 dataset**	**99.7**	**2020**

5. Conclusions

An algorithm based on Multi-Level Deep Neural Network has been developed and implemented to identify the suspected COVID-19 infected people from crowded places. The face images dataset has been acquired from market places, clinics and quarantine centers in Pakistan and India. The data set contains the face images of the healthy people,

people having symptoms of cough, sneezing and flu. The proposed algorithm has shown the classification accuracy of 99.7 %, which is quite satisfactory. It has been reported in the literature that the mass testing in laboratories is a time-consuming process and lack of test kits is a major problem to identify and isolate the Coronavirus infected people. The proposed technique is a novel contribution that will assist the private and public medical institutes to isolate the people having symptoms of cough, sneezing and flu from the crowd and then only those isolated people will go through the laboratory testing for the confirmation of coronavirus infection. It is the first kind of study to analyze the facial expressions and behavioural measures (coughing, sneezing, flu and hand movements). This is study is a proof of concept which can be viable solution in future to detect the suspected COVID patients. However, this needs to be tested on larger dataset. It has been foreseen that the implementation of the proposed method on the business places such as airports, markets and shopping malls will assist the authorities to run the business smoothly with an alert system to search and isolate the people having symptoms of COVID-19.

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