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Low-risk covid-19 detection using a novel deep learning network

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ABSTRACT

Computer Science is a field of deep knowledge, of which Artificial Intelligence has an imminent role in unraveling solutions to complex real-life situations. With technological advancements, we have been able to accomplish many said to be impossible tasks in the past, and are striving to achieve more and more everyday. Artificial Intelligence, being a sophisticated and advanced field of study, has revealed many techniques which can be used in various sectors of our society. One of such vital sectors is healthcare. Amidst many epidemics and pandemics, our human race has survived countless decades. Artificial Intelligence and its disciplines have proven to aid human beings when it comes to a healthy well-being. Among various disciplines, deep learning has assisted us in the most notable manner. In the current scenario where we are struggling to overcome a global pandemic, deep learning has led us to a breakthrough, which could possibly help us all in a positive manner. The proposed network utilizes deep learning to construct a feasible solution to detect COVID-19 with the help of CXR images(Chest Radiographs). COVID-19, being a respiratory disease, is said to accumulate in the lungs of the patients, and hence we can detect the virus' presence at an early stage with this methodology. Our novel deep learning network is procured from the traditional Convolutional Neural Network, the working of which is similar to that of the structure of a human's brain. Neural networks are said to function like a brain, analyzing and computing at faster rates than most of the existing networks. This network processes the image dataset consisting of chest radiographs to detect the presence of COVID-19 virus with the help of a novel neural networking model, which is said to have higher accuracy than the existing models.

Keywords: *Computer Science, Artificial Intelligence, Deep Learning, Chest Radiographs, COVID-19, Convolutional Neural Network*

INTRODUCTION

Amidst the major global pandemics this world has experienced, COVID-19 has proven to be the earnest of all, causing mayhem amongst the human race. The virus, being a variant of severe acute respiratory syndrome coronavirus (SARS CoV-2), is extremely transmissible and needs to be addressed immediately with high attention. The statistics dated 07th March 2021 indicate that 116 million cases have been reported worldwide, with a death count of 2.59 million and 65.8 million recovered cases. These numbers indicate that the traditional methods have not been efficient enough in handling such a dangerous pandemic. We know that reverse transcription polymerase chain reaction (RT-PCR), a type of qualitative test which is done on the nucleic acid to detect the presence of virus genome is one of the most commonly used traditional techniques. However, we cannot ignore the fact that this technique requires physical presence of the patients, thereby increasing the risk of disease spread. Several other methods such as Antigen tests, Antibody tests and Isothermal amplification assays also require human presence. We require a testing methodology to detect the virus' presence with minimalistic physical contact. Thus comes the idea of introducing the computational capabilities of deep learning networking models, which can help in a great way to reduce human contact. It is clear that laboratorial tests are much more efficient than computerised tests, but the requirement of physical labour is a major problem. The main reason to choose CXR images was the revelation of the fact that pneumonia is one of the major symptoms in the early COVID-19 patients. The radiology department is the only one which has work when it comes to obtaining Chest radiographs, which also does not involve physical contact of the supposedly affected patient. That being said, we can make use of digital methods to reduce the human efforts and ease up the process of detecting disease-causing viruses in humans. Several neural network models have been modified and used for detection of many diseases such as malaria and pneumonia in human races.

From the models developed so far, we propose a system that is low-risk and is useful for the early detection of Coronavirus in human beings. The existing system uses only a limited number of dataset so the model trained using this dataset is not much efficient and rather than being accurate with the values it is based on majority voting. In the system we propose the limitations in the existing model have been resolved and it gives results of better accuracy which is essential for the precise detection of Coronavirus in the human beings. The deep learning model that we have in the proposed model has learning algorithms embedded in it which trains on its own without the help of humans. This feature of the proposed model scales images and eliminates errors on its own. With this said, the proposed model has better efficiency and accuracy than the model that is existing.

RELATED WORK

Traditional approach

Traditionally, many methods have been discovered, to deal with various diseases, but all required physical contact. During the evolution of technology, we were able to find newer methods that were technology driven such as clustering methods, classification methods etc. Late in the 1980's image processing systems for processing digital X-ray images which was a great advancement considering the early times.

Deep learning-based approach

Hosny et al reciprocated the usage of Artificial Intelligence in Radiology. Pranav Rajpurkar et al elaborated a methodology that involved Computer Vision and Pattern Recognition for processing X-ray images and detecting pneumonia. Various methodologies have been adapted to cope with the growing medical needs in our society.

MATERIALS AND METHODS

Dataset and data pre-processing

The images constituting our dataset were retrieved from the world's largest data science community, Kaggle and National Institute of Health (NIH). The images were already assigned labels, for ease of usage, by various people working under these organizations. The images are classified into three cub-categories: test dataset, train dataset, and Val dataset. These images are used for testing, training and validation respectively. Prior to categorizing these images, we had to manually remove many pediatric images, as they would give biased outputs.

For the purpose of pre-processing, we incorporated various techniques. Which resulted in an efficient dataset for our model. Since the dataset is globally limited, we have only 25608 images for our purpose. The same is interpreted in the table below.

Dataset used in the existing model

The table 1 gives a detailed description of the number of images included in the dataset of the existing model:

TABLE 1: Number of dataset of existing model

Dataset	Normal	Pneumonia	COVID-19	Total
Training	8651	5812	160	14623
Validation	100	100	10	210
Testing	100	100	10	210
Total	8851	6012	180	15043

Dataset used in the proposed model

The table 2 gives a brief explanation about the number of images in our dataset:

TABLE 2: Number of images in the proposed model dataset

Dataset	Normal	Pneumonia	COVID-19	Total
Training	14732	9876	520	25128
Validation	100	120	20	240
Testing	100	120	20	240
Total	17405	10116	560	25608

Proposed model

Our proposed model uses a novel deep learning model, different from the regular convolutional model used in the existing method to scan the images present in the dataset. Our methodology includes training the model with the help of convolutional neural networks Figure 1, ensemble learning and support vector machines. Our sole purpose of introducing ensemble learning is to improve the efficiency of the neural networking model and help predict the date more accurately.

Ensemble learning is highly useful to reduce the variance of a convolutional network, as complex convolutional networks have high variance due to multiple layers and large inputs. One of the most commonly used ensemble learning methodologies is the multi-layer perceptron network. It is a subset of Artificial Intelligence and utilizes a feed forward mechanism. Generally, a multi-layer perceptron network comprises three layers namely a layer of input, a hidden layer and an output layer. This network usually propagates backwards to learn the features from the dataset. This network uses a non-linear activation function which helps in mapping the inputs to the outputs in a better manner.

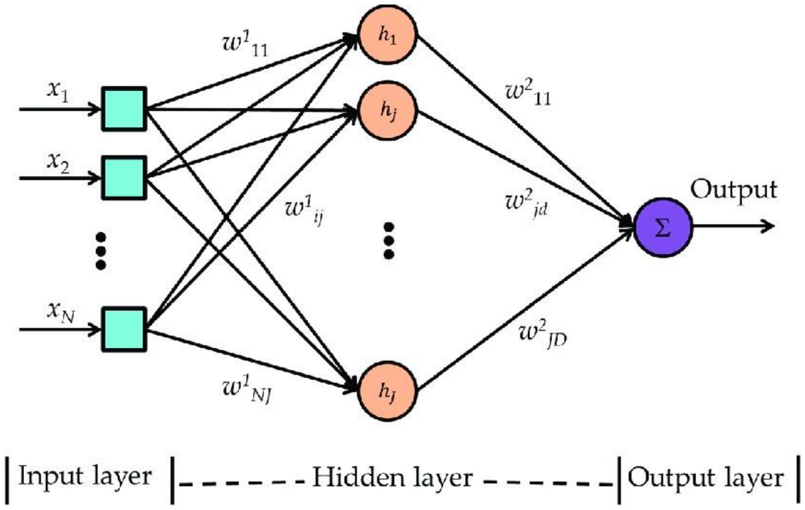

FIGURE 1: Structure of Neural Network

The convolutional network used in this model consists of three layers of convolutions as given in the Figure 2, each having a kernel size of 3 X 3. Kernels are one of the many hyperparameters used to tune the neural network. Other hyperparameters include padding size and stride which decide how the network convolves around the input.

It also includes an activation function which defines the network's functionality in determining the output for the given dataset. Generally, ReLU, or as we can elaborate it, a rectified linear unit, is used as an activation function for the convolutional neural network.

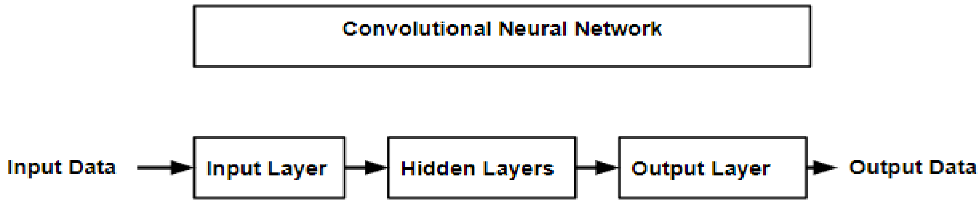

FIGURE 2: Layers of Convolution Neural Network

In addition to it, a support vector machine as shown in Figure 3 is included for improving efficiency of proposed model as it involves data with high dimensional spaces. Support vector machines are said to learn in a statistical manner, classifying the input data into classes with the help of a non-probabilistic binary classifier.

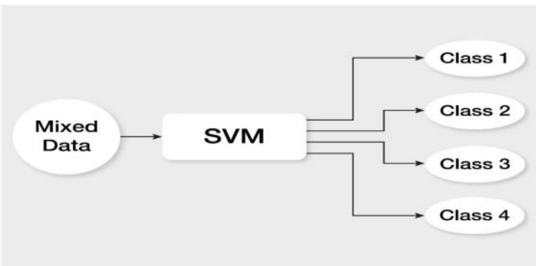

FIGURE 3: Support Vector Machine

Incorporating these layers into the traditional convolutional neural network increases the capabilities of the model in making decisions without any supervision, thereby learning on its own as shown in Figure 4.

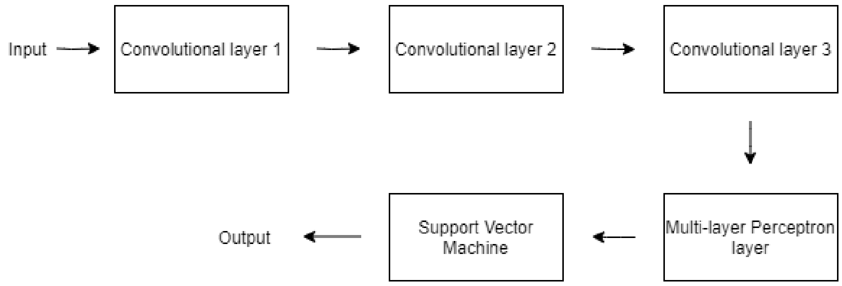

FIGURE 4: Proposed Model Architecture

Algorithm

Proposed model

Step 1: Input images for testing and training individually. The images are stored in the form of a pixelated data matrix.
Step 2: Adjust the height and width of the images for the purpose of training and testing.
Step 3: Next, store the image data as numerical arrays using the NumPy library for faster and efficient processing.
Step 4: To avoid any similarity in the stored data, the arrays are shuffled.
Step 5: Categorize the data into testing data and training data to feed the neural network.
Step 6: The input is passed into the convolutional neural network first, where the input data passes through three layers of convolution and gives an output.
Step 7: Now the input data passes through the multi-layer perceptron layer and the output is now passed onto the last layer, support vector machine.
Step 8: The summary of the model is displayed at the end for viewing the results.

Neural network

Step 1: The images that have been processed for reduction in sizes are inputted into the first layer of convolution. Here the images are processed using a kernel size of 3 to extract features from the images with an area of 3 X 3 at a time.

Step 2: The obtained output is fed into a multi-layer perceptron network, which consists of three Dense layers which propagate the input of the previous layer to all the succeeding layers.

Step 3: The last layer is the Support Vector Machine layer, which is used to classify the input data into classes, for better efficiency and higher accuracy of the final output.

EXPERIMENT AND RESULT

Experiment setup

The dataset containing the images of chest x-ray images are segmented into training and testing subsets. We intend to calculate the accuracy, precision and recall of our proposed neural network model using the given formulae:

Accuracy = TN + TP / TN + TP + FN + FP (1)

Where,

TP = True Positives, TN = True Negatives, FP = False Positives, and FN =False Negatives.

Precision = TP / TP + FP (2)

Recall = TP / TP + FN (3)

True Positives are the values which the model predicts accurately from the positive class. True Negatives are the values which the model predicts accurately from the negative class.

False Positives are the values which the model predicts inaccurately from the positive class.

True Negatives are the values which the model predicts inaccurately from the negative class.

To ensure that all the data does not go for training, we set 33 % of the data for testing. Similarly, we define different parameters for training the neural network namely epoch, optimizer, batch and learning rate. These values are set to their optimal values and tested for checking the accuracy of the proposed network and later will be fine-tuned for achieving higher accuracy. As stated before, we add three layers of convolution at the start of the network, followed by a layer of multi-layer perceptron network and a support vector machine at the end. The network is tested on Keras version 2.4.3. It relies on TensorFlow-GPU 2.3.0. The network is coded in Python 3.7.6 with a Windows operating system. The system contains 16 GB RAM, 8th Gen Intel i5 Processor, and a NVIDIA GTX 1050 GPU.

Comparison with other models

We compared our model with state-of-the-art models that exist in the medical field for verifying our model's performance. We use Accuracy, Precision and Recall for evaluating our model.

The Table 3 depicts the different metrics that are used to determine the performance of different models. U-Net gives an accuracy of 85.9, a Recall of 82.3 and Precision or 95.3. FC DenseNet67 shows 81.8 Accuracy, 73.1 Recall and 91.5 Precision. COVID-Net gives 82.7 Accuracy, 80.1 Recall and 91.2 Precision. FC DenseNet103 depicts an Accuracy of 88.9, Recall of 83.4 and Precision of 96.4. Our proposed method gives an Accuracy of 91.1, Recall of 86.6 and Precision of 97.2.

TABLE 3: Performance Analysis

Networks	Accuracy	Recall	Precision
U-Net	85.9	82.3	95.3
FC DenseNet67	81.8	73.1	91.5
COVID-Net	82.7	80.1	91.2
FC DenseNet103	88.9	83.4	96.4
Proposed Method	91.1	86.6	97.2

When compared to the existing method, we could see that the existing model gave an accuracy of 70.7, Recall value of 92.5 and Precision of 89.7. Our proposed method depicted an accuracy of 91.1, Recall value of 86.6 and Precision of 97.2 and that is given in the Table 4.

TABLE 4: Number of images in the proposed model dataset

Networks	Accuracy	Recall	Precision
Existing Method	70.7	92.5	89.7
Proposed Method	91.1	86.6	97.2

RESULTS

We can see that our model performed really well compared to the other models. We can see that we have achieved a high accuracy of 91.1, recall of 86.6 and precision of 97.2. To obtain such positive results, we had to train our model using different patch sizes, and determine which patch size best fit the mode for achieving high results. We used 112 X 112, 224 X 224, and 448 X 448 as different patch sizes.as given in the Table 5.

The graph in the Figure 5 shows the Accuracy vs Proportion of Data. We could see that as we gradually increased the dataset, accuracy was increasing and our model was performing well. This determined that a large dataset could possibly be of more help in our case

TABLE 5: Number of images in the proposed model dataset

Patch size	Accuracy	Recall	Precision
112 X 112	81.2	77.3	94.4
224 X 224	91.1	86.6	97.2
448 X 448	94.3	83.2	96.6

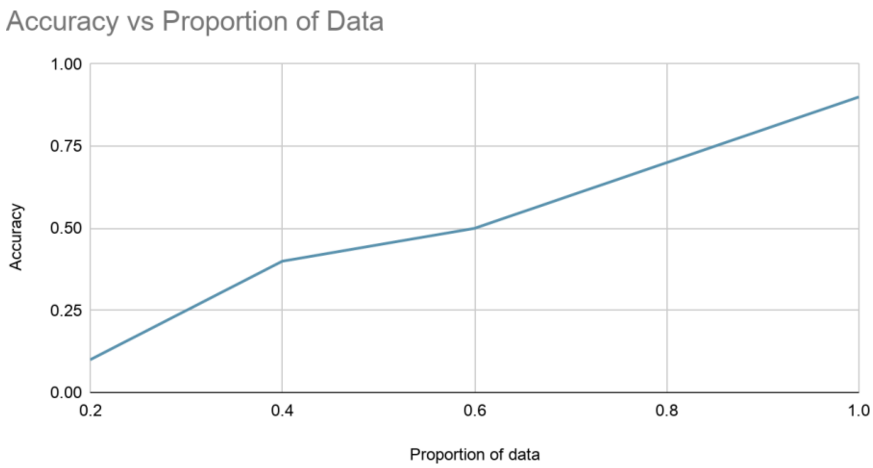

FIGURE 5: Proposed Model Architecture

CONCLUSION

We have witnessed a disastrous pandemic amidst the human race, which is terrorizing each and everyone, taking the lives of millions as we still suffer with it. It needs to be taken care of in every aspect of our life, and take utmost precautions all the time. Our proposed method would not only reduce the physical contact, but also yield higher accuracy and detect the presence of COVID-19 at an early stage which would help many people to seek treatment and become better, saving many lives of innocent human beings. We propose to make more changes in our model, to cope with the medical field. We wish to add more images to our dataset which would help in efficient training of our model. Moreover, we would like our model to be accessible to everyone, so that we can help each and every one in this pandemic.

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