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# Early Diagnosis of Covid-19 using Advanced Learning Algorithms

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**Abstract:** COVID-19 is called as corona virus firstly discovered in Wuhan city, china and this spreads all over the world very fastly since January 2020. This is very dangerous chronic disease that created the panic situation in many countries across the world. Still many countries are facing health issues with COVID-19. It is very difficult to detect this disease in the early stages with the traditional tests. Testing of this disease becomes more complicated in the beginning. To diagnosis COVID-19 the reverse transcription-polymerase chain reaction (RT-PCR) is most widely used by the labs. Symptoms such as fever, body pains, dry cough etc. Some of the symptoms that is non-specific such as headache, no taste or smell, vomiting etc. This disease will transmit from person to person very fastly. Still there is lack of accuracy in results. It is very important to diagnose the CT scan images for accurate results. In this paper, a decision based learning approach is introduced to improve the accurate results. The performance is calculated by using Precision, Recall, Accuracy, Cohen kappa score (CKP), Pearson coefficient (PC). The proposed approach shows the huge accuracy.

***Keywords:*** Covid-19, RT-PCR, CKP, PC.

## Introduction

Coronavirus is called as COVID-19 firstly identified in Wuhan the city of China and fastly spread the entire world. The World Health Organization (WHO) [1] announced that COVID-19 becomes the pandemic and becomes the more emergency situation for the people. If the person affected with COVID-19 then he can face the respiratory ailment [2]. Some of the common symptoms are fever [3], body pains, dry cough etc. Some of the non-specific symptoms are headache, no smell and taste vomiting etc [4]. These symptoms will take 5-6 days [5] in the starting period but now these becomes more fast based on the availablity of the testing kits. Some people are recovering very fast if they are having mild symptoms [6]. People suffering with other health issues such as diabeties or any heart issues may become more complex if they effected with COVID-19.

Still now also for the testing of corona virus it is taking more than two days. Sometimes these tests may fail to get the accurate results. Experts are trying to diagnose the accurate results by using the CT scan analysis. This will shows the better results for the experts [10]. In this paper, a decision making approach is developed to analyze the corona virus affected regions by using deep learning approach called as CNN.

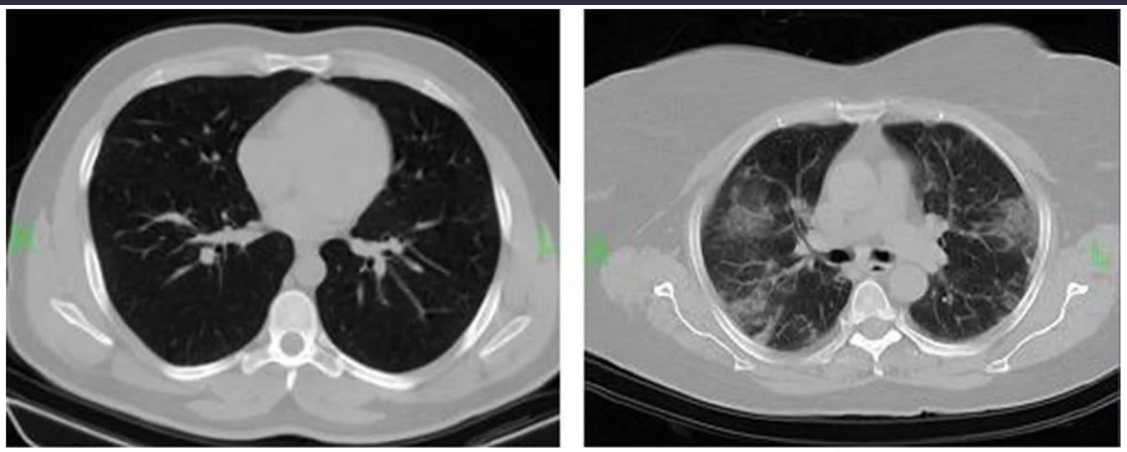


**Figure 1: Sample CT images from patients with suspected COVID-19 (a) and confirmed (b)**

In some cases, the infected are not possibly recognized on time and do not receive suitable treatment. The infected can be assigned sometimes as COVID-19 negative because of a false-negative result [12]. Hence, automated analysis of the thorax CT pictures is desirable to save the valuable time of the medical specialist staff. This will also avoid delays in starting treatment.

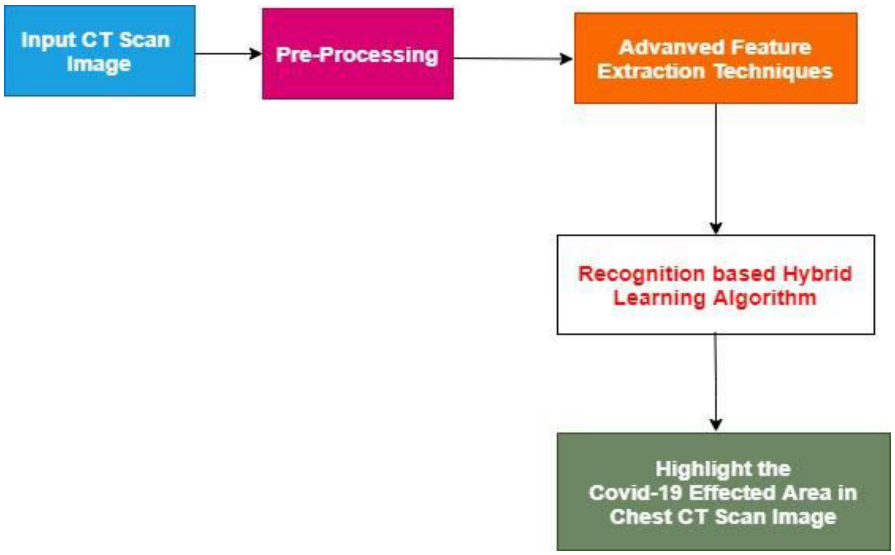


**Figure 2: System Architecture**

## Literature Survey

A few researchers' works have been completed in the field of determination from clinical images like computed tomography (CT) filters utilizing man-made reasoning and deep learning. DenseNet design and repetitive brain network layer were consolidated for the examination of 77 minds CTs by Grewal et al. [15]. RADnet shows 81.82% discharge expectation

precision at the CT level. Three sorts of profound brain organizations (CNN, DNN, and SAE) were intended for a cellular breakdown in the lungs ordered by Song et al. [13]. The CNN model was found to have better exactness when contrasted with different models. Utilizing profound learning, explicitly CNN examination, Gonzalez et al. [14] could distinguish and organize chronic obstructive pulmonary disease (COPD) and predict acute respiratory disease (ARD) occasions and mortality in smokers.

During the episode of COVID-19, CT was viewed as helpful for diagnosing COVID-19 patients. The central issue that can be pictured from the CT filter pictures for the discovery of COVID-19 was ground-glass opacities, solidification, reticular example, and insane clearing design [15]. A review was finished by Zhao et al. [16] to research the connection between chest CT discoveries and the clinical states of COVID-19 pneumonia. Information on 101 instances of COVID-19 pneumonia was gathered from four establishments in Hunan, China. Fundamental clinical qualities and definite imaging highlights were assessed and looked at. A review on the chest CTs of 121 suggestive patients contaminated with Covid was finished by Bernheim et al. [17]. The signs of COVID-19 disease as seen on the CT filter pictures were two-sided and fringe ground-glass and consolidative aspiratory opacities. As it is challenging to get the datasets connected with COVID-19, a publicly released dataset COVID-CT, which contains 349 COVID-19 CT pictures from 216 patients and 463 non-COVID-19 CTs, was worked by Zhao et al. [18]. Utilizing the dataset, they fostered an AI-based conclusion model for the finding of COVID-19 from the CT pictures. On a testing set of 157 worldwide patients, an AI-based mechanized CT picture investigation instruments for discovery, evaluation, and following of Covid was planned by Gozes et al. [19]. The exactness of the model created was 95%. The normal chest CT discoveries of COVID-19 are various ground-glass darkness, combination, and interlobular septal thickening in the two lungs, which are for the most part conveyed under the pleura [20]. A profound learning-based programming framework for programmed COVID-19 discovery on chest CT was created by Zheng et al. [21] utilizing 3D CT volumes to recognize COVID-19. A pre-prepared UNet and a 3D profound brain network were utilized to anticipate the likelihood of COVID-19 contaminations on a bunch of 630 CT filters. Out of 1014 patients, 601 patients tried positive for COVID-19 in light of RT-PCR and the outcomes were contrasted and the chest CT. The awareness of chest CT in proposing COVID-19 was 97% as shown by Ai et al. [22]. In a progression of 51 patients with chest CT and RT-PCR tests performed in something like 3 days by Fang et al. [23], the responsiveness of CT for COVID-19 disease was 98% contrasted with RT-PCR awareness of 71%. An AI framework (CAD4COVID-Xray) was prepared on 24,678 CXR pictures including 1540 utilized distinctly for approval while preparing. The radiographs were freely broken down by six perusers and by the AI framework. Utilizing RT-PCR test results as the reference standard, the AI framework accurately characterized CXR pictures as COVID-19 pneumonia with an AUC of 0.81 [24].

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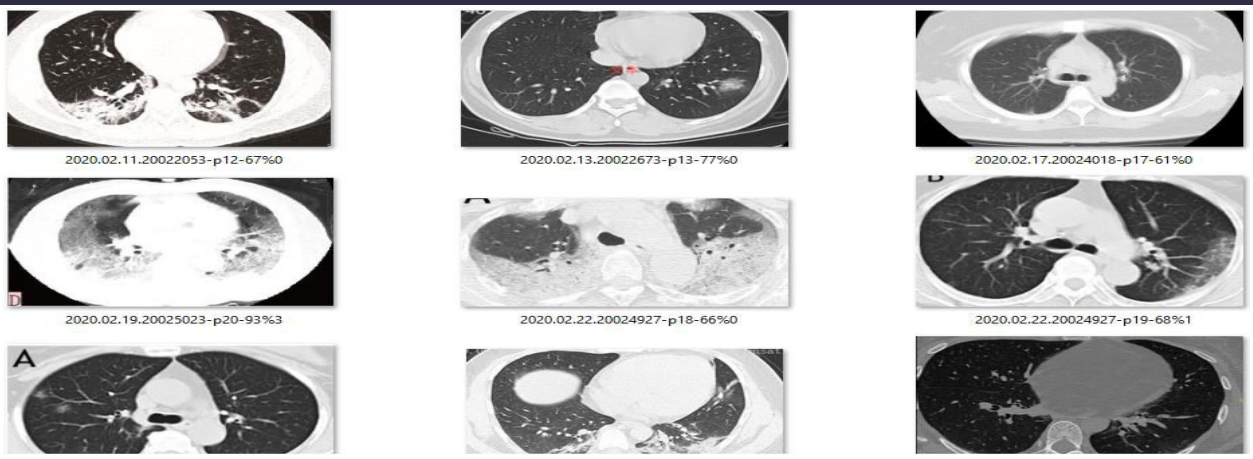


**Figure 3: Covid-19Positive affected Images**

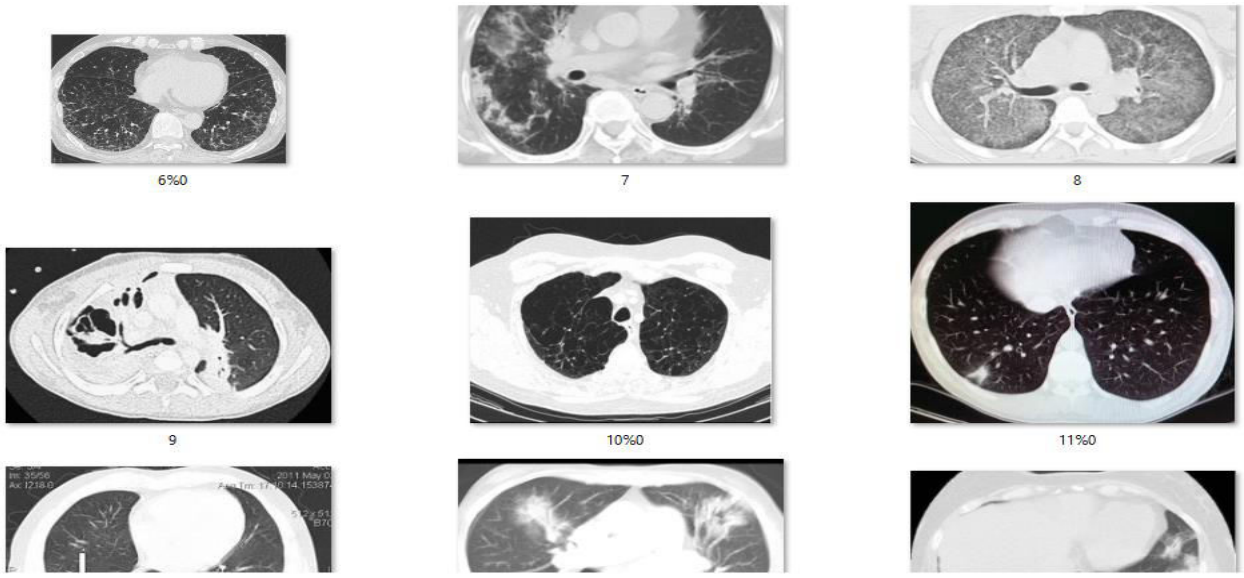


**Figure 4: Covid-19 Negative (Normal) Images**

**Advanced Feature Extraction Technique**

In this paper, to achieve better results feature extraction is adopted with the CNN approach. Pre-trained models such as VGG-16 are used to integrate and used to analyze the accurate results. Every input image is shown as the array of the pixel that will depend on the resolution of an image. The proposed CNN approach contains multiple layers such as convolutional and pooling layers. Another approach that is used in this paper is data augmentation integrated into the convolution layer. The convolutional layer is applied to the input image and this will identify the region of the image and the values of the pixels in the specific region and convert them into the required value.

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$$E(x,y) = \sum_{a=-K}^{K} \sum_{b=-K}^{K} I(a,b)F(x-a,y-b) \quad (1)$$

Where E (x, y) represents the values of pixels at (x, y) after the convolution measure; I (a, b) represents the values of pixels at (a, b) in input matrix and F(x-a, y-b) represents the value of pixel at (x-a, y-b) in filter (Kernel) matrix and K represents the kernel size of the filter matrix.

The size of the output convolution layer is represented by using Eq (2).

$$M = \frac{I - F + 2P}{S} + 1, \quad (2)$$

M represents the output matrix, I represent the input matrix, F represent the convolution filter size, P represents the padding and S represents the stride values. The dimensionality reduction is used in the max-pooling layer. The process of this layer works as a down sample without losing the significant data. By finding the high value neuron the specific area of the affected image is identified and the output layer from the before the layer is represented as:

$$E(x,y) = \sum_{a=-M}^{a=M} \sum_{b=-M}^{b=M} \max(E(a,b) \quad (3)$$

Where P(x, y) is the value of pixel at (x, y) after pooling operation is performed; E (a, b) is the value of pixel at (a, b) of preceding layer's output and 'M' is the size of previous layer's output grid. The output size of the max-pooling layer is given in Eq (4).

$$N = \frac{M - F}{S} + 1 \quad (4)$$

Where N is the size of the output matrix, M is the size of the previous layer's matrix, F is the size of the pooling filter, and S is the stride value same as what was chosen for convolution operation. Relu acts as activation for convolutional and max-pooling layer as given in Eq (5)

$$F(x) = \max(0, x) \quad (5)$$

Where x is the input value provided to activate the neuron. Thus, all the parameters which were extracted from the series of convolution and pooling operations from all the pre-trained models that were used for feature extraction only.

**Evaluation metrics**

The evaluation metrics include accuracy, F1 score, precision, recall, Cohen kappa, Pearson coefficient.

**Accuracy:** This is very important parameter that initializes the total number of exactly classified data instances over the total number of data instances.

$$\text{Accuracy} = \frac{TN + TP}{TN + FP + TP + FN}$$

**Precision:** When the FP is high the precision helps. If the precision is low, then the patients will be told that they are affected with lung infection; this may show some mistakes within the tests.

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

**Recall:** Recall is calculated when the false negatives are high.

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

**Cohen Kappa score (CP-score):** It is the statistical measure that calculates the quality of the result. The CP score is calculated as:

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$$k = \frac{p_0 - p_e}{1 - p_e} = 1 - \frac{1 - p_0}{1 - p_e}$$

**Pearson coefficient:** This is used to calculate the strength of the linear association between two images (input images). The image with positive represented as r=1 and negative image is represented as r=-1.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

Where r represents the correlation coefficient
$x_i$ represents the x
− variable values within given input
$\bar{x}$ represents the x − variable mean values
$y_i$ represents the y
− variable values within given input
$\bar{y}$ represents the y − variable mean values

**Experimental Results**

The experiments are conducted on https://mosmed.ai/en/datasets/ by applying the Recognition based Hybrid Learning Algorithm on each and every image. The dataset consists of 360 Covid-19 infected CT scan images and 400 normal images; among this the training is conducted with 500 coid-19 and normal images. Python programming language is used to show the results with more accuracy of detecting COVID affected area. Libraries that are used to improve the performance of proposed algorithm. Keras and pandas are main libraries that are used in this implementation.

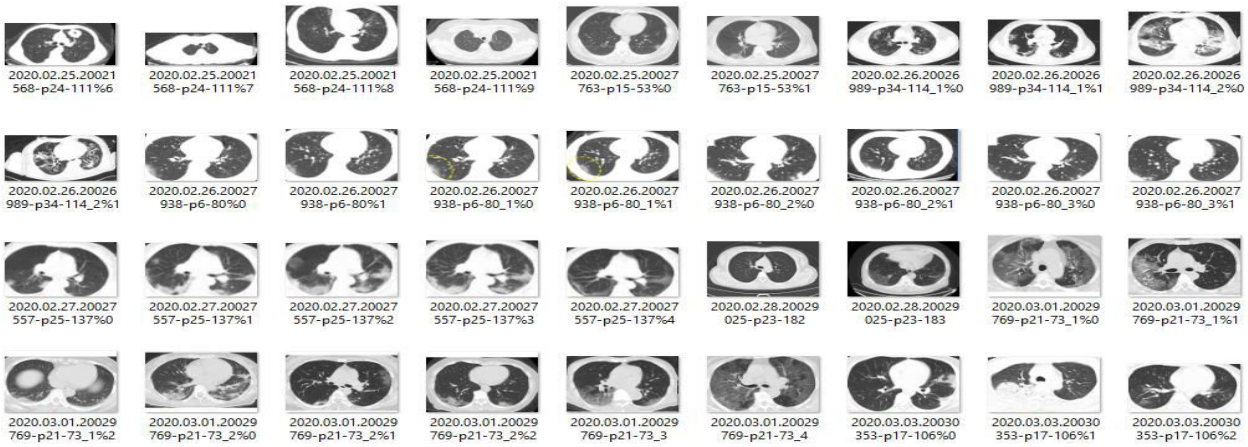


**Figure 3: Dataset Images**

| | C3D | DeCoVNet | Decision Based Learning Approach |
|---|---|---|---|
| Precision | 94.6% | 95.65% | 96.52% |
| Recall | 95.21% | 96.45% | 97.72% |
| Accuracy | 96.17% | 97.78% | 98.98% |
| Cohen kappa score | 97.92 % | 97.92% | 98.99 % |
| Pearson coefficient | NA | NA | 99.80% |

**Table 1: shows the comparative results of several algorithms for COVID-19**

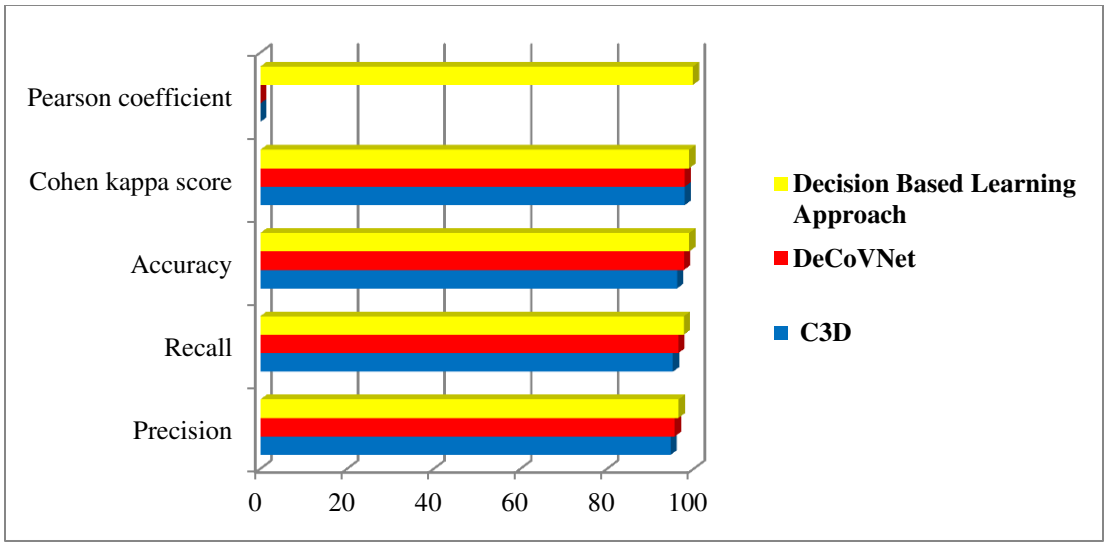


**Figure 4: Performance Graphs**

## Conclusion

Detection and diagnosis of COVID-19 disease with the CT scan images becomes more complex, so the proposed methodology is focused on diagnosis of COVID-19 in the early stages. Efficient feature extraction is utilized in this paper which is integrated with the a decision based learning approach that can work very efficiently. Compare with other approaches such as C3D and DeCoVNET. The C#D got the accuracy of 96.17% and DeCoVNET obtain the 97.78%. The proposed approach obtained the 98.98%.

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