Binary Classification of COVID-19 CT Images Using CNN:
COVID Diagnosis Using CT

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ABSTRACT

The COVID-19 pandemic has hit the world with such a force that the world's leading economies are finding it challenging to come out of it. Countries with the best medical facilities even cannot handle the increasing number of cases and fatalities. This disease causes significant damage to the lungs and respiratory system of humans, leading to their death. Computed tomography (CT) images of the respiratory system are analyzed in the proposed work to classify the infected people with non-infected people. Deep learning binary classification algorithms have been applied, which have shown an accuracy of 86.9% on 746 CT images of chest having COVID-19-related symptoms.

KEYWORDS

Convolutional Neural Network, COVID-19, CT Images, Deep Learning, Image Classification

INTRODUCTION

In the current decade, medical facilities are increasing day by day for the betterment of human beings. Medical facilities help human beings prevent and recover from life-threatening diseases (Rajinikanth et al., 2020). Globally, health ailments have been faced with incommunicable and chronic diseases due to various uncontrolled and unavoidable reasons (Chen et al., 2020). Most diseases can be cured through different diagnosis practices if they are identified at their early stage (Krishnan et al., 2010). Diagnosis of the problem can be made through an additional diagnostic method like blood count, CT scan, X-ray, and other tests (Rajpurkar et al., 2017);(Bhandary et al., 2020) to cure or control that disease. But in some scenarios, these tests cannot find the exact problem, and that particular diseases are declared as pandemic diseases. In the different studies, it has been concluded that the lungs are one of the most important organs which help humans to breathe, and infection related to the lungs has an effect on the human body respiratory system, which further leads to death (Syrjala

et al., 2017). Tuberculosis, Asthma, Chronic Obstructive Pulmonary Disease, Chronic Wound, Lung Cancer, and many more are some significant diseases (Chakraborty, 2017), affecting the human body, lungs, and respiratory system (Zech et al., 2018). In the current instance, the whole world is dealing with a pandemic disease named COVID-19, which is declared a contagious disease. COVID-19 is declared a pandemic disease by the World Health Organization (WHO) in March 2020 after the different countries' infected and death rate data (Karim et al., 2020). COVID-19 started its journey by reporting cases with unknown cause from the Wuhan city of China on 31st December 2019 and later became pandemic throughout the world (F. Wu et al., 2020);(Huang et al., 2020);(Organization et al., 2020). This virus is from the corona family, which is termed as SARS-COV-2, and disease-related to this virus is named COVID-19 (Z. Wu & McGoogan, 2020). As of October 29, 2020, there have been 43,766,712 confirmed cases of COVID-19, including 1,163,459 deaths (WHO, 2020). The COVID-19 is human to human transmission disease or communicable disease spreading very fast among the community (Tan et al., 2020);(Zhu et al., 2020);(Li et al., 2020). According to different researchers and doctors, it is becoming difficult to control this pandemic as its transmission medium is still theorized (Qiu et al., 2020). Patients of COVID-19 are assumed to be infected through common symptoms like fever, cold, cough, difficulty in breathing (D. Wang et al., 2020). Medical facilities have increased with time, but still, countries and hospitals are frenzied in improving the facilities to accommodate the COVID-19 patients (Karim et al., 2020). The state-of-art test for COVID-19 is the reverse transcriptase-polymerase chain reaction (RT-PCR) test which is tested through specialized kits in particular laboratories (Ozturk et al., 2020).

The detection of the presence of the COVID-19 virus is a time-consuming task as it is done currently in clinical laboratories. The kits used for the tests are giving inaccurate results or taking more than 24 hours to provide the products. The number of cases being tested is enormous, resulting in the delay of test results. This delay proves fatal at times as a crucial period of treatment is lost. Using the available CNN techniques to classify the CT images for the presence or absence of the virus is less time consuming and tedious than the clinical tests.

The contributions of the proposed work in the area of detection of COVID-19 using the CT images are as follow: (i) A systematic analysis of relevant studies on the state-of-the-art techniques for detecting COVID-19 has been carried out. (ii) Material and methods used for implementation have been discussed in detail. (iii) Binary classifications on the hyperparameters have been used for improving the accuracy of detection. (iv) Applying the algorithm on various epoch size, batch size improved the accuracy of the detection. (v) Integrating the optimizer algorithm, activation function, and loss function with Binary classification using CNN has further improved the detection rate of COVID-19 cases using the CT images, and the findings obtained were analyzed. (vi) The accuracy obtained in the proposed work is better than the existing research work done on the same dataset using various CNN deep learning algorithms (Shalbaf et al., 2020);(Ewen & Khan, 2020). (vii) Numerous problems and concerns with the applied methodology and scope of future work have also been discussed. COVID-19 detection in clinical labs is a tedious and time-consuming process. The proposed technique can provide the detection of COVID -19 in patients in real-time, and the time taken for the process is less than what the lab tests are taking in the present scenario.

The paper is structured as: In related work section it has been summarized the existing work done for COVID-19 detection, the next section describes the material and methods used in the current work for implementation. The result and analysis of implemented work has been discussed in the result analysis and discussion section. Furthermore the challenges of present work and conclusion along with future prespective has been discussed.

RELATED WORK

Bassi et al. has conducted their study on chest X-ray images using the dense CNN classification method. They classify the images in three tags named COVID-19, regular, and pneumonia. The

authors used fine-tuned NN algorithms to train and test their considered Imagenet database and used the NIH chest X-ray14 dataset. Heat maps are created by the author using the Layer-wise Relevance Propagation (LRP) technique. The proposed model used a transfer learning method and concluded that it is a better performer than everyday transfer learning. The author achieved an accuracy rate of 99.4% from their proposed model. According to the author, using the AI Chest X-ray method is cheap and accurate to diagnose the COVID-19. In the future, they offered to conduct a clinical study to fight the COVID-19 pandemic (Bassi & Attux, 2020).

Rahimzadeh et al. proposed a fully automated model to discover the COVID-19 symptoms or causes from the patient's CT scan images. They created their dataset for the study, including 48260 CT scan images of 282 normal persons and 15589 CT scan images of 96 COVID-19 patients in Iran's Negin medical center. First, they applied an image processing algorithm to discard those having high noise and images that are not adequately visible to minimize the false detection rate. Feature pyramid network and ResNet50V2 network is used to classify the dataset into normal and COVID-19 infected. The author achieved 98.49% of the accuracy rate and compared their results with Xception and ResNet50V2 network and concluded that ResNet50V2 with FPN performed well to detect the COVID-19 patients (Rahimzadeh et al., 2020).

Loey et al. presented the GAN class of machine learning to detect the COVID-19 using the X-ray images of patients. Dataset is collected from different sources, and 307 images are gathered from four other classes, which are publically available for the researchers. The dataset consisted of COVID-19, pneumonia bacterial and virus, regular classes' data. The authors used the deep transfer models to conduct their experiment. Googlenet, Restnet18, and Alexnet deep learning models are used by the author in their study to detect coronavirus symptoms. Models considered for this study contain small numbers of layers in their architecture, which reduced the complexity, time, and energy. Three states are taken, in first state, all four classes are considered and achieved testing accuracy of 80.6% through Googlenet. In the second state, three classes are considered and achieved a testing accuracy of 85.2% through Alexnet. Subsequently, in the third state, two categories are considered (COVID-19 and Normal) and achieved 100% testing accuracy and 99.9% during validation through Googlenet. Hence, Googlenet identified the primary deep transfer model (Loey, Mohamed and Smarandache, Florentin, and M Khalifa, 2020).

Mobiny et al. introduced the Detail-Oriented Capsule Networks (DECAPS) architecture to detect corona virus from the CT scan images. Dataset used to experiment contained 746 chest CT images, which is splitted into two groups named COVID-19 and non-COVID-19. The given model has achieved 84.3% precision, 91.5% recall, and 96.1% area under the ROC curve from the model as compared to the other studies considered. The author compared the performance of the given model with three well rich experienced radiologists and found that the proposed model outperformed as compared to other models. The limitation of given work is that larger dataset is required to confirm their future findings (Mobiny et al., 2020).

The authors conducted this study to pre-screening model, which differentiated between the COVID-19 from Influenza pneumonia as both are viral diseases. Out of all the screening cases, healthy cases with pulmonary CT images are done using the DL techniques. To conduct their experiments, they collected the dataset from hospitals of Zhejiang province from Jan 2019 to Feb 2020, in which the total of 618 CT samples were collected. Out of 618 CT samples, 224 CT samples from 224 patients are infected from Influenza, and 219 CT samples from 110 patients are contaminated from COVID-19, and 175 CT images are of the healthy candidate. Infected CT image regions are segmented, and then images are categorized to Influenza, COVID-19, and no infection. All images are provided with confidence scores using location-attention classification, and in the end, they calculated the infection type and confidence score together using the Noisy or Bayesian function. The author achieved an accuracy rate of 86.7% from the proposed model (Xu et al., 2020).

The authors conducted their study to develop a deep learning model to automatically segment and quantification the infected region from the chest CT scan images. To achieve this process, CB-Net

neural network is applied. 549 patient data is used for experimental purposes. Out of these, 249 patient information is used for training, and 300 patient data is used for validation. The infection percentage is used to check the dice similarity coefficient among the automatic and manual segmentation results. The author achieved 91.6%±10.0% of dice similarity and 0.3% POI estimation error for the chosen dataset (Shan et al., 2020).

The authors introduced the model to extract radiological features for COVID-19 diagnosis. The experimental dataset contained 1065 CT images of pathogens. Out of 1065 images, 740 images are viral pneumonia images, and 325 images are confirmed COVID-19 cases. The inception transfer learning algorithm is reframed, which is further followed by internal and external validation. It achieved an accuracy of 89.5% with a specificity of 0.88 and 0.87 of sensitivity from the internal validation. An accuracy of 79.3% with a specificity of 0.83 and 0.67 of sensitivity is achieved from the external validation (S. Wang et al., 2020).

Further, a study is conducted to develop a system for automatic diagnosis for COVID-19 patients. A weakly supervised deep learning model is used for COVID-19 classification and lesion localization. All dataset images are segmented using the pre-trained model that is UNet, and further, these segmented images are fed into the 3D DNN to predict the possibility of COVID-19. In this, 630 images are used to conduct their experiment, and out of these 630 images, 499 were used for training and 131 used for testing purposes. The algorithm achieved 0.959 ROC AUC and 0.976 PR AUC. Changing the probability threshold value to 0.5, an accuracy of 0.901, the positive predictive value is 0.840, and the high negative predictive value is 0.982 has been achieved (X. Wang et al., 2020).

Furthermore, a model has been introduced to detect the COVID-19 using an ensemble deep transfer learning. In this, 15 pre-trained CNN has been taken and further improved on the target task. Based on combining the different deep transfer learning methods, accuracy has been improved. A publicly available dataset of 746 CT images has been taken for experimentation. It achieved an accuracy rate of 85%, precision is 85.7, and recall is 85.4% from the five favorably voted deep transfer learning architectures (Shalbaf et al., 2020).

A self-supervision technique has been presented to enhance the accuracy rate of a small number of labeled data sets. Ten experiments are conducted in this study to compare the classification performance on the variable amount of data. It has been observed that self-supervision has performed better than the non-self supervised counterparts. The accuracy rate of 86.21% has achieved from the introduced model, which is 8% higher than the non-self supervision (Ewen & Khan, 2020).

From the literature, it has been observed that the smaller datasets have been used by most of the models which need larger datasets for experimental purpose and moreover, suchs model has been required to improve their accuracy that can further aid in accurate and efficient diagnosis of corona virus disease.

MATERIAL AND METHODS

Dataset

Image dataset size and its content are the input for the CNN algorithm. In the present work, a dataset of 746 CT images collected from 216 patients. In which 349 are COVID-19 infected images, and 397 are COVID-19 uninfected images. The size of these CT images is different in height and width. In the used dataset, the smallest height of an image is 153, and the maximum height of an image is 1853, and the average height of all images is 491. The smallest width of an image is 153, the maximum width of an image is 1485, and the average width of all images is 383. Wuhan's senior radiologist collected this dataset during the outbreak of COVID-19 patients from January to April 2020 and is publicly available for research (Tongji Hospital, Wuhan, 2020). Sample dataset is illustrated in Figure 1.

Figure 1. Sample Dataset for Training and Testing (Tongji Hospital, Wuhan, 2020)
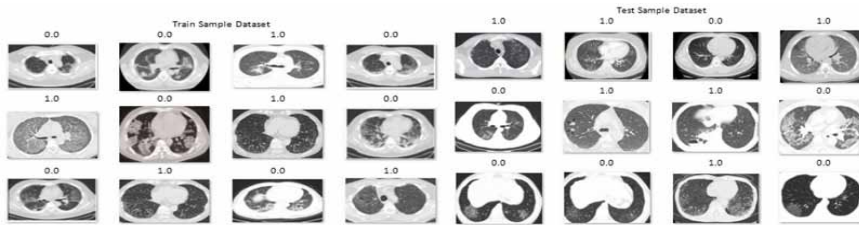

Methods

In this study, a CNN model-based binary classifier has been designed to detect COVID-19 from chest CT images. To implement the model, all images are resized into 150 x 150 and labeled with 0 and 1. Further, the whole dataset is split for training (80%) and testing (20%) and normalize the training and testing dataset between 0 and 1. Binary classification algorithms using CNN on the hyperparameters have been used for improving the accuracy of COVID-19 detection. Implemented the algorithm on various epoch size and batch size to improve the accuracy of COVID-19 detection. After that, integrating the best optimizer algorithm, loss function, and activation function with binary classification using the CNN model achieved an improved accuracy of 86.9%. An implemented method is shown in Figure 2.

Convolutional Neural Network (CNN)

One of the enhanced versions of machine learning is deep learning. Multiple abstraction layers have been employed in deep learning, which works for feature selection and filtering of data (Chakraborty & Gupta, 2016). The machine is then used by the device to learn, which is called training, and finally, make the predictions with accuracy. There are multiple layers, which are called abstractions. The output of one layer becomes the input for the next layer. The neurons do the calculations. Each neuron has a weight associated with it. The weight-adjusted to make the prediction accurately; this method

Figure 2. CNN Model Process Diagram
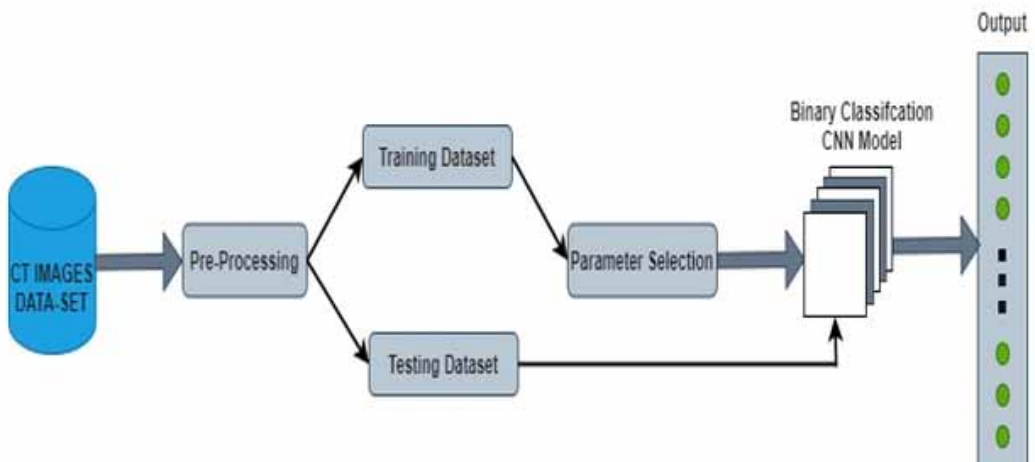
is generally used to predict objects images and videos. There are layers and algorithms related to CNN, which is used in the formation of CNN models. The input and output values are estimated based on these layers and algorithms (S.H. Wang et al., 2020). Deep CNN technique has been used by (Shalbaf et al., 2020) and has achieved an accuracy of 85%. DenseNET CNN technique has been used by (Ewen & Khan, 2020) and has reached an accuracy of 86.2%.

Input Layer

It is the first layer in the Artificial Neural Network. The input image that will be fed to the network is estimated in terms of size. The larger the image's size, the deeper the layers, and the predictor's performance is also high. The higher performance is at the cost of increased CPU, GPU, and RAM of the computer system. If the image is of tiny size, the network is not that deep. It leads to the poor performance of the network. So to use the network optimally, an optimal data entry should be provided.

Convolution layer

It is the second layer in the architecture. Kernels are used to extract the feature from each image. These Kernels can learn about the extracted features. The kernel moves across the image to gather the pixel information and performs a convolution operation. This operation is a mathematical calculation for the next step. After the traversing of the kernel is over, a feature map is extracted. During this process, the padding is also done. The first and the last pixel of the image are conserved with zero spacing between them. The learning process updates the kernel s, and feature extraction is performed, taking the kernels to their optimal level.

Pooling Layer

During the process of feature extraction in the convolution layer, many unnecessary data and parameters are generated. It is based on the size of the image that is fed as an input. In the pooling layer, the parameters to be processed in the network are reduced. It results in the increased speed of the network. Max pooling, Average pooling, Global Max pooling, and Global Average Pooling methods are used for the pooling process. When data/image from the convolution layer to this layer, the features essential in the feature map are conserved, and the rest of the features are discarded. It is done to minimize the data loss in the feature map.

Activation Function and Optimizer Algorithm

The output values of each layer are non-linear. The activation function is used to convert these non-linear values into linear values. Most of the problems that are solved using Deep Learning are non-linear. The activation function used to give linearity to the output depends on the structure of the Network. Still, some commonly used Activation functions, namely Relu, Elu, Sigmoid, Tangent, and softmax. Gradient Descent Algorithm is used to transmit the data from one neuron to another. This algorithm also corrects the errors, thus optimizing the established network. The optimizer algorithms minimize the loss function value.

Fully Connected Layer

A layer of regular neural networks in which the neurons are fully connected is formed. This layer consists of more than one layer of neurons, and each neuron is connected to all the other neurons in the network. This is different from CNN as the neurons in CNN are connected locally, but each neuron is linked to other neurons in the network in this layer. Each neuron layer provides a full connection to different layers, which separates them into classes. The fully connected layers of neurons are directed to the classes required as the final output.

Table 1. Configuration of epoch size

Epoch Size	10	15	20	25	30	45
Loss	0.412	0.2757	0.1359	0.1	0.0716	0.0113
Accuracy	0.797	0.8809	0.948	0.9648	0.9765	1
Val_Loss	0.342	0.2691	0.234	0.19	0.1756	0.169
Val_Accuracy	0.7133	0.74	0.7467	0.7333	0.74	0.7333

Dropout layer

This network of neurons also faces the problem of overfitting. Due to the large size of the image, the neurons processed also allow the layers to memorize the data. It is an undesired activity that needs to be removed so that the class's correct prediction can be carried out. The undesired data created in the CNN layer is randomly eliminated in this layer, thus overcoming overfitting.

Classification Layer

It is the last layer in the network that identifies the class of the data. The training is done in this layer, and the output is a 1xN dimension matrix. Here N is the desired number of output classes. The values in the 1xN matrix fall in the range between 0 and 1. It is done using the activation function.

RESULT ANALYSIS AND DISCUSSION

Implementation to perform training and testing of the dataset was done on the binary classifier based neural network. A total of 746 CT images was used for performance, from which 80% image was used to train the machine, and 20% were used for testing shown in Figure 1. The final output layer gives only one result from 0 to 1. If the final output layer result is close to 0, it reflects the image is parasitized, or if the final output layer result is close to 1, it means the image is uninfected. Implementation has been performed on a machine with 4 GB Ram, ATI Mobility Radeon HD4300 Series graphics card, Intel(R) Core(TM) i5 CPU M430 @2.27GHz, Window 7 Ultimate 64-bit operating system, and 512 GB hard disk. Training took 108 minutes, and the final trained model achieved an accuracy of 86.9%.

Hyper-Parameter Configuration

Different parameters are used to train the machine, and these are needed to optimize at different levels of training. By obtaining and comparing the results at different levels, different changes have been performed on batch size, epoch size, loss function, optimizer configuration algorithm, and activation function. Default configuration parameters are 30, 25, Sigmoid, binary_crossentropy, RMSProp, for batch size, epoch size, activation function, loss function and optimizer configuration. The results based on different epoch size are shown in Table 1.

After training and testing of models on different epoch sizes, it is found that as the number of epochs is increased, training loss values decrease from 0.412 to 0.0113, and accuracy values increase from 0.797 to 1.00, as shown in Table 1. However, Val_Loss values also reduced with the number of epochs increased, and this model achieved the highest Val_accuracy of 74% on 30 epochs.

After achieving the Val_Accuracy of 74%, the parameter of epoch size is set to 30 and trained multiple CNN models with different batch sizes of 32, 64, 96, 128, and 160. Found that model trained and test with 96, 128, and 160 batch sizes are overfitting models, and best possible results are given by 32 and 64 batch sizes model. Table 2 shows that the 32 batch size model achieves the highest accuracy.

In this work, after finding the best epoch and batch size, the dataset is trained and tested on different optimizer algorithms, which are benchmarks in deep learning. Achieved results given by

Table 2. Configuration of batch size

Batch Size	32	64	96	128	160
Loss	0.0677	0.0716	0.1695	0.1871	0.2025
Accuracy	0.9782	0.9765	0.9362	0.9279	0.9279
Val_Loss	0.192	0.2163	0.223	0.265	0.2801
Val_Accuracy	0.7667	0.74	0.7533	0.6467	0.68

different optimizer algorithms are shown in Table 3. After the analysis of results, it is found that the AdaGrad optimizer algorithm training accuracy is less and training loss is high. RMSProp and SGD optimizer algorithms are overfitted models. After examination of the below table based on Val_Loss and Val_Accuracy, it is found that Adam is the best optimizer algorithm after AdaDelta optimizer algorithm for this model.

To improve the classification results, the proposed model is trained and tested on various activation functions, as shown in Figure 3. After the analysis of activation functions, it is found that some activation functions Elu, Relu, and Softmax, are not useful for binary classification, and they can be used for multi-class classification shown in Figure 3. Tanh activation function is given a good Val_Accuracy, but it is an overfitted model. The sigmoid activation function provides the best accuracy of 0.823 with 0.183 Val_loss. Hence, as shown in the Figure 3, it has been concluded that all activation functions cannot perform binary classification.

At last, different loss functions have been used to find the best model. Achieved results by different loss functions are shown in Table 4. After the analysis of Table 4, it is noticed that Categorical Hinge results are inferior as compared to other models. It has been observed that the varied models produced varying results but in a similar value range.The best Val_Accuracy achieved by Mean Absolute Percentage Error is– MAPE (85.13%) and Binary (86.9%) loss functions.

The data set consisted of 746 CT images of the chest, which were of different dimensions. The images were resized to 150X150. A CNN model was prepared to detect COVID-19 cases. The model was tested on the test dataset (20% of the dataset) with variations dome on parameters, namely batch size, size of the epoch, loss function, optimizer configuration algorithm, and activation function. The Epoch parameter was fed with values of 10, 15, 20 and 30. This parameter signifies the number of times the training dataset was provided to the model to train itself. The accuracy obtained for each iteration was checked. The best accuracy has been received with the epoch of value 30. Batch size represents the size of the image that was fed with each epoch to train the model. The best accuracy has been obtained with a batch size of 32. Applying the set of benchmark optimizer algorithms gave us the best accuracy with AdaDelta. Activation functions were applied to the dataset, and the best results have been achieved with Sigmoid. It is because, for the Binary classifier, the sigmoid activation function is best suited. Others are not applicable. The Binary parameter gave us the best accuracy

Table 3. Configuration of optimizer algorithms

Optimizer Algorithms	AdaDelta	SGD	RMSProp	Adam	AdaGrad
Loss	0.312	0.0924	0.0677	0.042	0.2641
Accuracy	0.9141	0.9651	0.9782	0.945	0.8923
Val_Loss	0.183	0.1912	0.192	0.2154	0.918
Val_Accuracy	0.823	0.7892	0.7667	0.791	0.5492

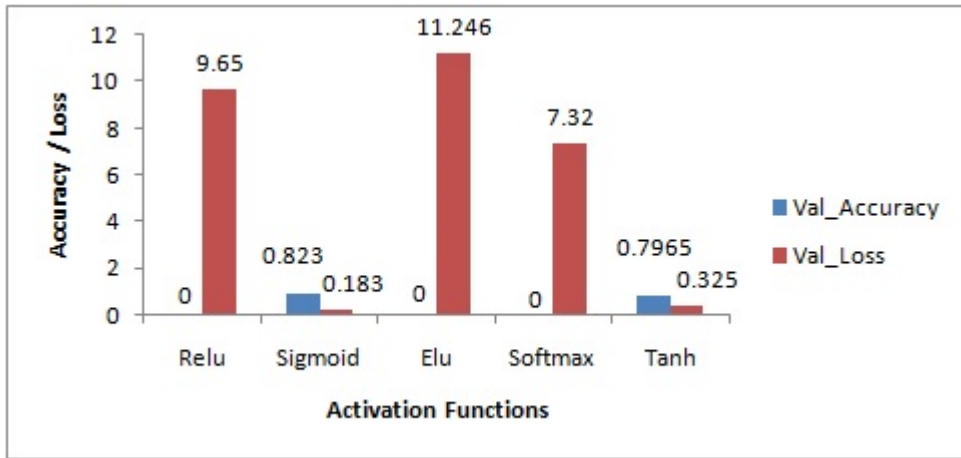Figure 3. Model Accuracy / Loss Values for Different Activation Functions

Table 4. Configuration of loss functions

Loss Functions	Logcos	Ctg_Hinge	Poisson	Binary	MAPE
Val_Loss	0.018	0.0274	0.024	0.213	0.024
Val_Accuracy	0.823	0.4571	0.8412	0.869	0.8513

amongst the benchmark loss functions. It has also been observed that the model may have been ridden with overfitting as the size of the dataset is too small for Deep learning algorithms.

Comparitive Analysis

The accuracy achieved by the proposed work using binary classification using the CNN is 86.9%, which is better than the accuracy (85%) performed on the same dataset (Shalbaf et al., 2020). In (Shalbaf et al., 2020), authors have used deep CNN to conduct their experiments. Images considered in this study are checked for the presence of COVID-19 related features. Hence, binary classification provides more accuracy as the image is only checked for COVID-19 symptoms in the CT images.(Ewen & Khan, 2020) have achieved an accuracy rate of 86.2% with denseCNN in their experiments, which is lower than the present work's accuracy. Comparitve analysis of achieved accuracy is shown in Table 5.

Table 5. Comparitive analysis

Technique	Dataset	Accuracy
Proposed Technique	(Tongji Hospital, Wuhan, 2020)	**86.9%**
Deep CNN (Shalbaf et al., 2020)	(Tongji Hospital, Wuhan, 2020)	85%
DenseCNN(Ewen & Khan, 2020)	(Tongji Hospital, Wuhan, 2020)	86.2%

CHALLENGES

The present work has been applied to the chest CT images. The accuracy of the algorithm on a larger dataset may vary. The epoch's size, batch size, and selection of loss function, optimizer configuration algorithm, and activation function have contributed to the accuracy. In case the epoch, the batch size is changed, then the accuracy and effectiveness of the algorithm may get reduced.

CONCLUSION AND FUTURE SCOPE

In the present work, binary Classification of CT-Images Using CNN for the diagnosis of COVID 19 has been performed. The binary classification has been integrated with the optimizer algorithm. The accuracy of the CNN technique needs to be improved, although the accuracy of 86.9% has been achieved. It is better than the accuracy obtained by (Shalbaf et al., 2020);(Ewen & Khan, 2020), in which investigation has been carried out using the same dataset. It can be further improved by taking a more extensive dataset on which multi-class classifiers can be used. Binary classification gives only a single layer output as it has only one output layer. In the future, a multi-layer approach will be implemented to generate multi-class output. Moreover, augmentation techniques can be applied to the current dataset to increase the dataset size or use a new big dataset. Applying the proposed method on a dataset with more images can be conducted to check the performance and improve detection accuracy. Applying the algorithm to detect other diseases using the CT images can be explored in future work.

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