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Chapter

COVID-19 Data Analytics Using Extended Convolutional Technique

Anand Kumar Gupta, Asadi Srinivasulu, Kamal Kant Hiran, Tarkeswar Barua, Goddindla Sreenivasulu, Sivaram Rajeyyagari and Madhusudhana Subramanyam

Abstract

Health care system, lifestyle, Industrial growth, economy and livelihood of human-beings worldwide effected due to triggered global pandemic by COVID-19 virus originated and first reported from Wuhan city, Republic Country of China. COVID cases are difficult to predict and detect on its early stages due to that its spread and mortality is uncontrollable. RT-PCR (Reverse Transcription Polymerase Chain Reaction) is still first and foremost diagnostic methodology accepted worldwide, hence it creates a scope of new diagnostic tools and techniques of detection approach which can produce effective and faster results compared to its predecessor. Innovative through current studies that complements to the existence of COVID-19 to findings in Chest X-ray snap shots, the proposed research's method makes use of present deep getting to know models (U-Net and ResNet) to method those snap shots and classify them as the positive patient or the negative patient of COVID-19. The proposed technique entails the pre-treatment phase through dissection of lung, getting rid of the environment which does now no longer provide applicable facts and can provide influenced consequences; then after this, preliminary degree comes up with the category version educated below the switch mastering system; and in conclusion, consequences are evaluated and interpreted through warmth maps visualization. The proposed research method completed a detection accuracy of COVID-19 round 99%.

Keywords: COVID-19, classification algorithms, CNN, feature selection, ECNN, data pre-processing

1. Introduction

The disease referred to as “the extreme acute breathing syndrome coronavirus 2 (SARS-CoV-2)” was determined in year end of 2019. As per reports, this disease was originated in China, have become the reason of disorder referred to as “Corona Virus Disease 2019” or “COVID-19”. The WHO (World Health Organization) has declared

this disorder as a “deadly disease” in March 2020 [1, 2]. As per the reviews delivered and up to date with the aid of using worldwide health organizations, authorities/entities and governments, pandemic has affected tens of thousands and thousands of human beings globally [3]. The maximum severe contamination due to COVID19 is associated with the lungs which include pneumonia. The signs and indications of the disorder may range & consist of excessive body temperature (high fever), dyspnea, coryza and cough. These instances can be normally recognized through the usage of lung x-ray evaluation of the irregularities [4].

Throughout this hasty period, several scholars have tried towards expand numerous transmission gear and diagnosing systems. Such as, the RT-PCR (Reverse Transcriptase-Polymerase Chain Reaction), which is still the vital testing technique to discover extreme severe breathing disease SARS-COV2 [1, 2, 4] and in addition to COVID-19 [3]. Though RT-PCR is considered to be the best method of screening so far, it still has limitations. The working system of Reverse Transcriptase-Polymerase Chain Reaction (RT-PCR) is complex and time-consuming [2, 4–11]. Thus, attempts were attempted to detect COVID-19 thru lung x-ray images which include CT (Computed Tomography) or lung x-beam photographs. It is said the investigative significance and accurateness of CT lung photographs over RT-PCR in COVID-19 [2] are highly accepted. The discoveries display that a lung CTs are an excessive sensitivity for the analysis of COVID [2].

2. Literature survey

The call for quicker analysis of COVID-19, more than one research carried out to focus on layout answers and clinical records concerning this exceedingly transmittable disease. Some picture identification, examination, clarification, and conclusion strategies were indexed on this segment. The DL (Deep Learning) method [12] has been projected and has efficaciously received satisfying outcomes in phrases of accurateness in diverse arenas [3, 13–17]. The instance research of COVID-19 examination of CT-scans had been offered with the aid of using authors together with Xu et al. [18], Srinivasulu [19], Qing et al. [20], Srinivasulu and Gangadhar [21]. Authors Xu et al. [18] mentioned that the COVID-19 well-known shows its’ traits can change from different varieties of virus-related pneumonia, like viral influenza-A pneumonia. The study’s goal has become to the broaden a preliminary testing outline for COVID-19 with the aid of using automatic respiratory CT-scans (CT photographs) of COVID-19, pneumonia, and ordinary instances. They hired 628 CT-scans test pattern photographs earlier than expansion, and their version acquired the accurateness of 90%. The writers’ approach consists of the image pre-processing, dissection of more than one region (patches) accepting V-Net (Volumetric Network) [22] based separation version V-Net-IR-RPN [23], that has skilled for pulmonic tuberculosis resolution.

Our method includes 3 essential experiments to assess the overall performance of the predication and determine of an effect on of the distinctive levels of the procedure. Respective test follows the workflow. The distinction among trials are the dataset used from various repositories. In all occurrences, identical photographs of COVID-19 effective instances had been used. Meanwhile, 3 distinctive datasets for poor instances had been utilized. In that direction, Experiment 1 and 2 included

comparing effective vs. poor instances datasets, and Experiment three entails Pre-COVID generation photographs (photographs from 2015 to 2017).

3. System methodology

3.1 Existing system

There are approachable in superficial learning strategies, for example, The Convolution Neural Organization and Intermittent Neural Organization. CNN computation Drawbacks: The disservices are:

- Little precision
- In flood time complexity
- In flood executing time
- In flood fault prone
- Insignificant data size

Computation downside:

- Little precision
- In flood time complexity
- In flood execution time
- In flood fault prone
- Little data size

3.2 Proposed system

There are available in deep learning method like Extended Convolutional Neural Networks i.e., in Deep Learning Technique.

ECNN algorithm advantages:

- In flood accurateness
- Fewer time consumption
- Little performance time
- Little mistake degree
- Big data scope

4. Results

Basic idea is to execution, is to assure that the Omicron disease severer affected role collected statistics functioned in the way that can compel preparation, subdivision from their first outlook.

4.1 ECNN algorithm

Two trials of one or the other CC or MLO seen should be adjusted utilizing the picture enlistment method. At that argument, a dissimilar picture was received by removing the former trial out of the existing trial and subsequently scaled to the full-range force. The territorial pictures from the refined district proposition are trimmed from the three pictures and scaled to $224 \times 224 \times 3$ for each picture, which are utilized for ECNN is floodlight extraction. The three channels are rehashed from one-channel grayscale pictures (e.g., the current sweep of $224 \times 224 \times 1$) since the pertained ECNN and ECNN models expect 3-channel pictures. Multi-measurements of three-state in floodlights (from earlier sweep, current output, and contrast pictures) are made to prepare a CNN model. For instance, The ECNN is floodlights utilizing ResNet-60 V3 of 2048×3 measurements for each view (CC or MLO) of a subject's side (left or right bosom). Remember that earlier sweep consistently relates to the ordinary (sound) status in any event, for a destructive subject. Assume we code sound and carcinogenic as 0 and 1 individually, at that point the ground realities (yields) compared to the three states (earlier, current, distinction) of the destructive view are [0 1 1]. This coding instrument can be handily stretched out to at least two earlier sweeps.

4.2 Algorithm

The following is the ECNN algorithm steps:

The Omicron disease infection data index, i.e., the absolute 522 pictures, our experiment involved the related following steps:

1. Introduces mandatory collection.
2. Introduces training dataset.
3. Executes in the floodlight ordering of change data.
4. Alignment with 70-time segments and 2 yield.
5. Introduces Keras (Keras is a Deep Learning library).
6. Resets ECNN.
7. Enhances ERNN part & about regulation of loss calculation function.
8. Improvement of yield part.
9. Adds the ECNN.



Figure 1.
 Input dataset of the projected prototype for COVID-19 disease detection.

10. Adjusts ECNN in the assessment dataset.
11. Loads the Omicron disease infection test image data of the year 2020.
12. Become a predicted Omicron disease infection in Dec 2019.
13. Imagine aftereffects with anticipated or genuine Omicron disease infection.

INPUT DATASET: Here the input dataset is having 16 columns with target class, i.e., severity level of the COVID-19 disease consisting the database of 282 sample x-ray images (**Figure 1**).

5. Results: here are the result of in finding COVID-19 disease detection by integrating ECNN

Figure 2 shows the execution flow of the ECNN code on COVID-19 database analyzing time taken, accuracy, loss, Val_Loss, Val_Accuracy with respect to epochs.

The proposed model achieve the accuracy of 99% on the database collected and used from Kaggle, and UCI repositories (**Figure 3**).

Figure 4 displays the CPU and related resources occupancy of computer during ECNN code execution on COVID-19 database.

5.1 Evaluation methods

The following are measurements of evaluation methods or metrics.

```

testenv_breastcancer - cnn.py
Found 242 images belonging to 2 classes.
Found 40 images belonging to 2 classes.
Epoch 1/50
13/13 [=====] - 26s 2s/step - loss: 2.4999 - accuracy: 0.5289 - val_loss: 0.6683 - val_accuracy: 0.5000
Epoch 2/50
13/13 [=====] - 25s 2s/step - loss: 0.6866 - accuracy: 0.6901 - val_loss: 0.6593 - val_accuracy: 0.5250
Epoch 3/50
13/13 [=====] - 26s 2s/step - loss: 0.6827 - accuracy: 0.7273 - val_loss: 0.3266 - val_accuracy: 1.0000
Epoch 4/50
13/13 [=====] - 27s 2s/step - loss: 0.4777 - accuracy: 0.7934 - val_loss: 0.2487 - val_accuracy: 0.9500
Epoch 5/50
13/13 [=====] - 28s 2s/step - loss: 0.5805 - accuracy: 0.7769 - val_loss: 0.3245 - val_accuracy: 0.9750
Epoch 6/50
13/13 [=====] - 27s 2s/step - loss: 0.5446 - accuracy: 0.7851 - val_loss: 0.5356 - val_accuracy: 0.7000
Epoch 7/50
13/13 [=====] - 28s 2s/step - loss: 0.4425 - accuracy: 0.8182 - val_loss: 0.2214 - val_accuracy: 0.9500
Epoch 8/50
13/13 [=====] - 29s 2s/step - loss: 0.3808 - accuracy: 0.8512 - val_loss: 0.1425 - val_accuracy: 0.9500
Epoch 9/50
13/13 [=====] - 29s 2s/step - loss: 0.3889 - accuracy: 0.8182 - val_loss: 0.7783 - val_accuracy: 0.7000
Epoch 10/50
13/13 [=====] - 30s 2s/step - loss: 0.3872 - accuracy: 0.8140 - val_loss: 0.1977 - val_accuracy: 0.9000
Epoch 11/50
13/13 [=====] - 50s 4s/step - loss: 0.3278 - accuracy: 0.8512 - val_loss: 0.1087 - val_accuracy: 0.9750
Epoch 12/50
13/13 [=====] - 41s 3s/step - loss: 0.3249 - accuracy: 0.8512 - val_loss: 0.0817 - val_accuracy: 1.0000
Epoch 13/50
13/13 [=====] - 34s 3s/step - loss: 0.4135 - accuracy: 0.8760 - val_loss: 0.1185 - val_accuracy: 0.9750
Epoch 14/50
13/13 [=====] - 28s 2s/step - loss: 0.3174 - accuracy: 0.9008 - val_loss: 0.0610 - val_accuracy: 0.9750
Epoch 15/50
13/13 [=====] - 27s 2s/step - loss: 0.2440 - accuracy: 0.9132 - val_loss: 0.0350 - val_accuracy: 0.9750

```

Figure 2.
ECNN code execution flow.

```

testenv_breastcancer - cnn.py
Epoch 38/50
13/13 [=====] - 31s 2s/step - loss: 0.0827 - accuracy: 0.9711 - val_loss: 0.1827 - val_accuracy: 0.9500
Epoch 39/50
13/13 [=====] - 28s 2s/step - loss: 0.1577 - accuracy: 0.9298 - val_loss: 0.0032 - val_accuracy: 1.0000
Epoch 40/50
13/13 [=====] - 29s 2s/step - loss: 0.1524 - accuracy: 0.9628 - val_loss: 0.0646 - val_accuracy: 0.9750
Epoch 41/50
13/13 [=====] - 32s 2s/step - loss: 0.0706 - accuracy: 0.9711 - val_loss: 0.0311 - val_accuracy: 1.0000
Epoch 42/50
13/13 [=====] - 30s 2s/step - loss: 0.0973 - accuracy: 0.9752 - val_loss: 0.0236 - val_accuracy: 0.9750
Epoch 43/50
13/13 [=====] - 27s 2s/step - loss: 0.1287 - accuracy: 0.9628 - val_loss: 0.0040 - val_accuracy: 1.0000
Epoch 44/50
13/13 [=====] - 27s 2s/step - loss: 0.0806 - accuracy: 0.9545 - val_loss: 0.0016 - val_accuracy: 1.0000
Epoch 45/50
13/13 [=====] - 27s 2s/step - loss: 0.1444 - accuracy: 0.9587 - val_loss: 0.0096 - val_accuracy: 1.0000
Epoch 46/50
13/13 [=====] - 27s 2s/step - loss: 0.0929 - accuracy: 0.9628 - val_loss: 0.0039 - val_accuracy: 1.0000
Epoch 47/50
13/13 [=====] - 26s 2s/step - loss: 0.2147 - accuracy: 0.9587 - val_loss: 8.2552e-04 - val_accuracy: 1.0000
Epoch 48/50
13/13 [=====] - 26s 2s/step - loss: 0.1039 - accuracy: 0.9752 - val_loss: 0.0045 - val_accuracy: 1.0000
Epoch 49/50
13/13 [=====] - 26s 2s/step - loss: 0.0523 - accuracy: 0.9917 - val_loss: 0.0010 - val_accuracy: 1.0000
Epoch 50/50
13/13 [=====] - 27s 2s/step - loss: 0.3372 - accuracy: 0.9463 - val_loss: 0.0073 - val_accuracy: 1.0000
2/2 [=====] - 1s 641ms/step - loss: 0.0073 - accuracy: 1.0000

Accuracy: 1.0
Loss: 0.0072827329859137535

```

Figure 3.
Final results of COVID-19 using ECNN approach.

$$Quality = \frac{BP + VM}{BP + VP + BM + VM}$$

$$Precision = \frac{BP}{BP + VP}$$

$$Callback = \frac{BP}{BP + VM}$$

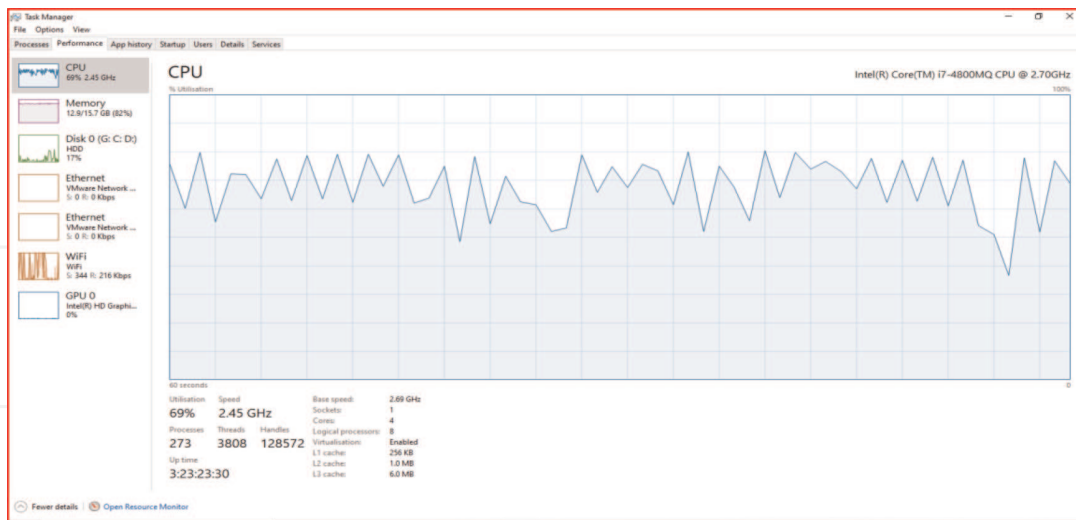


Figure 4.
 Processor and related resources occupancy of computing device.

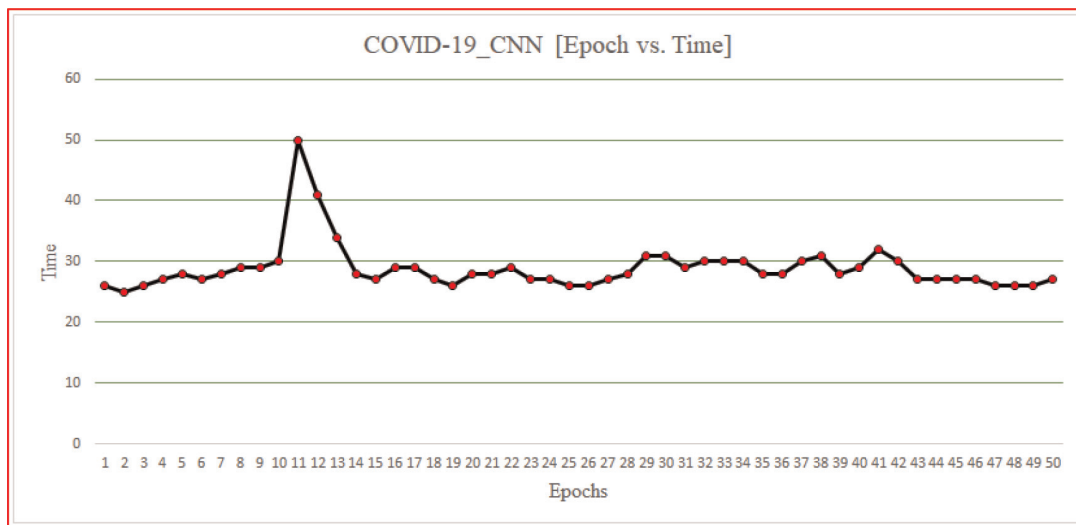


Figure 5.
 COVID-19 ECNN graph comparing epochs vs. time.

$$F - measure = \frac{2 \times Precision \times Callback}{Precision + Callback}$$

Data Input: Our experiment was carried over on a database of 282 x-ray images.
Figure 5 demonstrates the time taken to complete iteration of epochs.
 Explains the loss ratio with respect to each epochs during execution (**Figure 6**).
 Demonstrates the accuracy achieved against each epochs during execution (**Figure 7**).
 Demonstrates the loss reduction and accuracy gain of the training model of ECNN with respect to each iteration (**Figure 8**).
 Value loss and value accuracy gained of the ECNN model during training (**Figure 9**).
 At a glance representation of the comparison among epochs, loss, accuracy of the ECNN model (**Figure 10**).

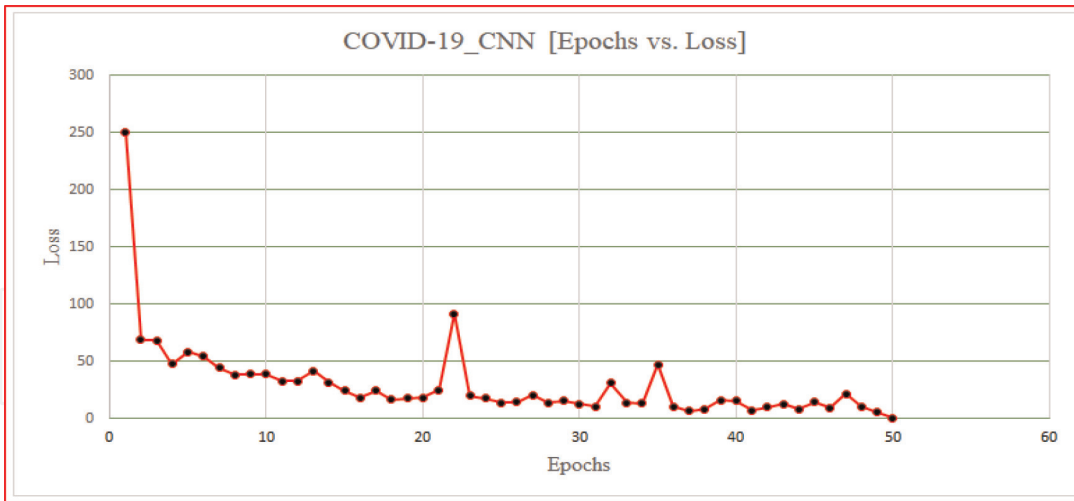


Figure 6.
COVID-19 ECNN graph comparing epochs vs. loss.

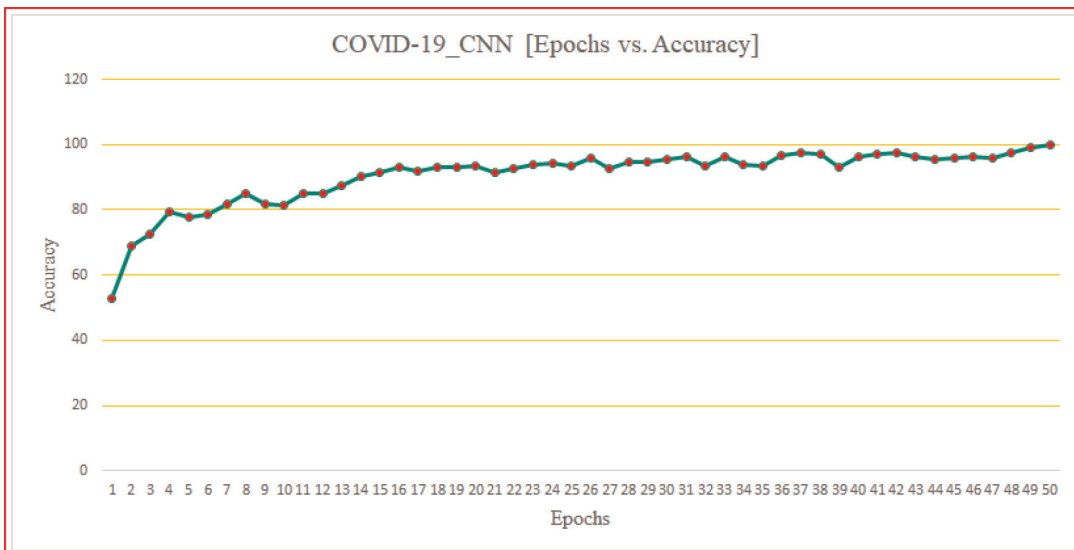


Figure 7.
COVID-19 ECNN graph comparing accuracy vs. epoch.

6. Conclusions

This method suggests how the present prototype may be beneficial for more than one tasks, specifically if it's far taken into consideration that the modified U-Net prototypes do now no longer have higher overall performance. Also, is proven how x-ray images' noise may produce predisposition withinside the prototypes. Most metrics display photographs without dissection as higher for categorizing COVID infections. Additional evaluation suggests that even though benchmarks are higher, those prototypes are primarily created on totally seen diagnosis throughout lung's x-ray as clean proof of COVID, so actual correct prototypes ought to be centered on lungs elements for classification. In this situation, dissection is desired for dependable outcomes through lowering this bias. Transfer getting to know changed into crucial of the outcomes offered. As proven categorized models, the use of this approach wants among 40 and 50 epochs to converge, even as segmentation prototypes without

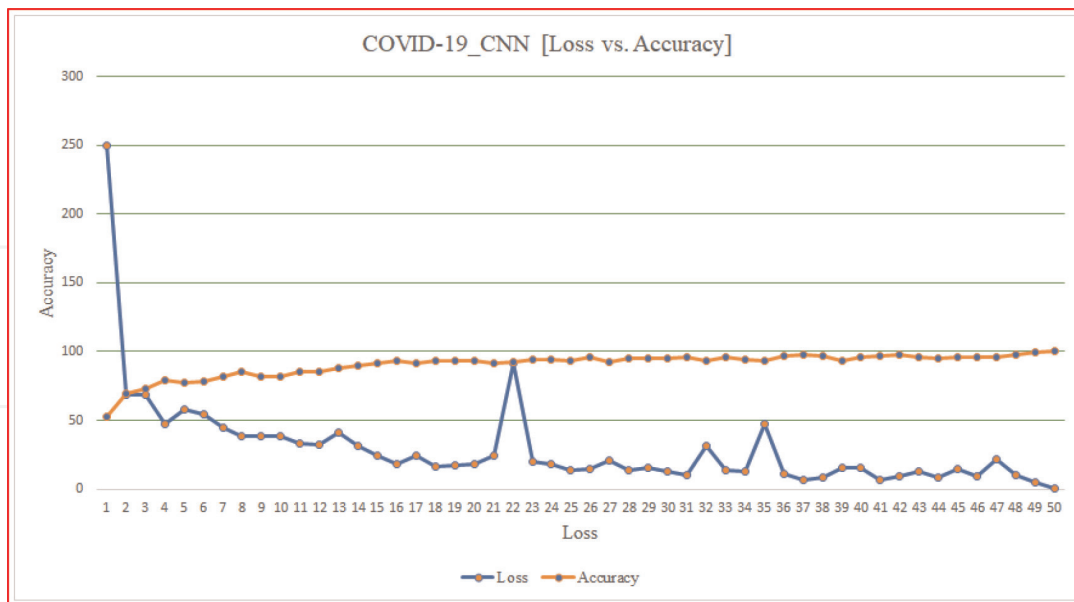


Figure 8.
 COVID-19 ECNN graph comparing loss vs. accuracy.

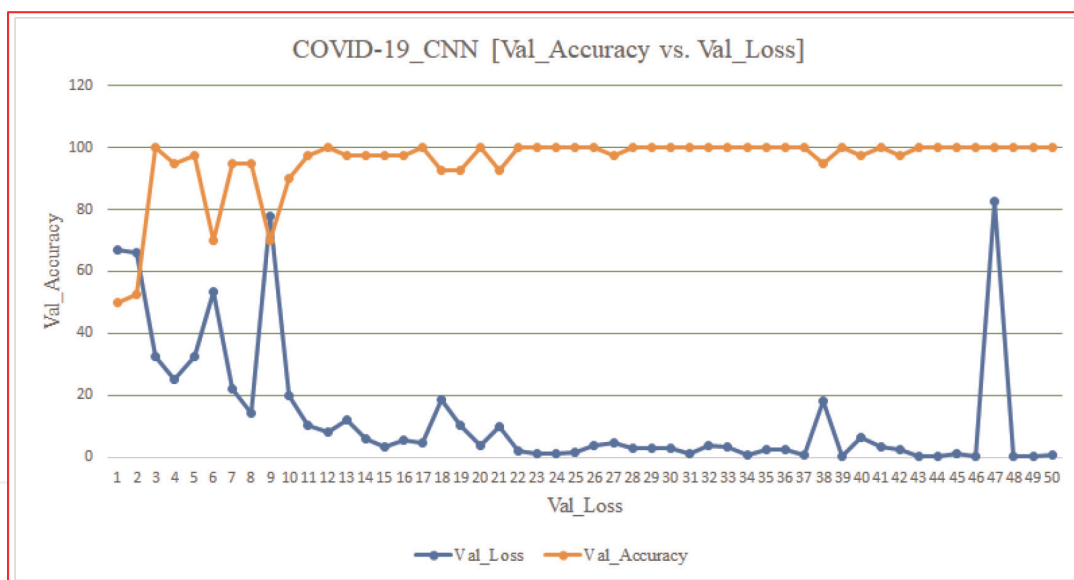


Figure 9.
 COVID-19 ECNN graph comparing Val_Accuracy vs. Val_Loss.

modification was approximately 282. The sequence of prototypes was obtainable to decide COVID-19 Disease in Chest X-ray photographs with a general accuracy of 99% through categorizing COVID-positive and COVID-negative images. In the meantime, solitary for the COVID label, the method achieved an average of 98.58% accuracy withinside the take a look at the database for a threshold of 0.4. Changing the edge suggests a growth withinside the accuracy of prototypes as much as 99%.

The segmentation work suggests an excessive opportunity of imparting more statistics to element in the all experimentations, concluding the unconventional out-comes through dissecting lungs and including statistics mixed with surrounding noise. The noise is related to wires used in medical equipment's, patient's gender and/or age, making photographs without lungs have extra information for classification in those

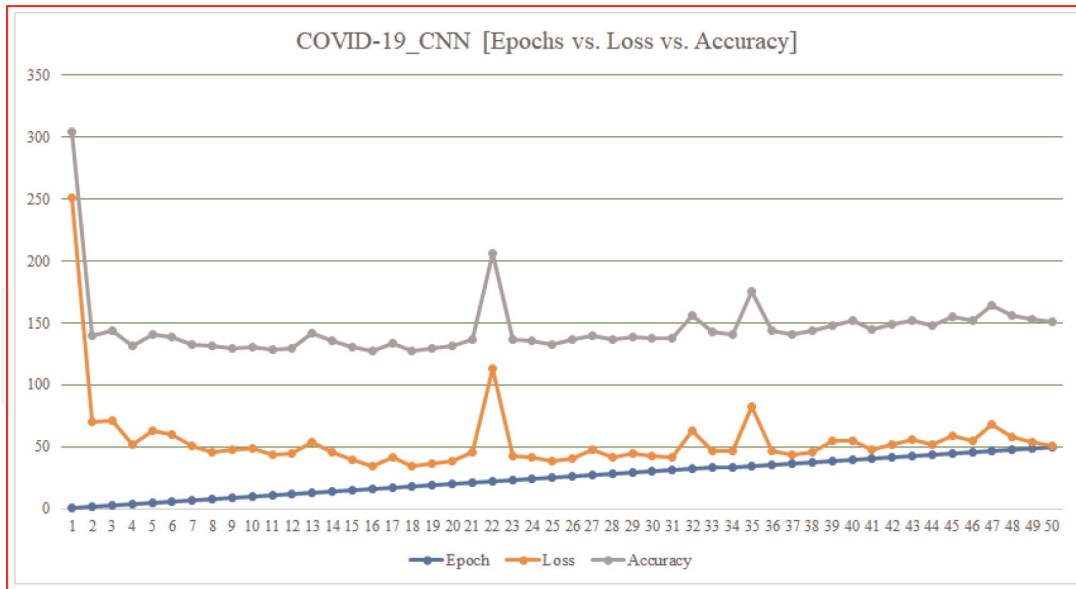


Figure 10.
COVID-19 ECNN graph comparing epoch vs. loss vs. accuracy.

situations. Either destiny efficacy or the use of prototypes without lungs should have to be the very best possibilities of mislabeling photographs due to errors. Further researches are required of section diagnosis recognized by the expert radiotherapist to make sure that any noise is a causing object for biased results. It is likewise critical to spot that the outcomes offered do now no longer always suggest the identical overall performance in each database. For example, the used database was collected of Asian victims; different international sufferers might also additionally display minor facts seize modifications or diagnosis, assuming a higher type is wanted the use of international databases. In addition, setting apart the databases through gender will offer extra statistics at the prototype's scope, because the tiny tissues of the chest might also additionally cover elements of the lungs, & it is far unidentified in case or not that it is taken into consideration a partiality with inside the forecast of the prototypical.

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