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Iot And Cloud Computing Platform For Covid-19 Detection And Monitoring In Healthcare

[1]Dr Vijayasaro V, [2]Dr Ugranada Channabasava, [3]BSH. Shayeez Ahamed, [4]Santhi Karuppiah, [5*] Dr. J. Balamurugan, [6]Dr. R. Senthamil Selvan, [7]Dr.Uvaneshwari.M

[1]Associate professor, Department of ECE,Guru Nanak Institute of Technology, Telangana, Orchid: 0009-0006-2947-4519, viji.saro17@gmail.com

2Associate Professor, Department of Artificial Intelligence and Data Science, Global Academy of Technology, Bangalore, channasan11@gmail.com

[3]Assistant Professor, Department of CSE (AI and ML), Madanapalle Institute of Technology and Science, Madanapalle, shayeezahamedbsh@mits.ac.in

[4]Professor, Department of Computer Science and Engineering, Vel Tech High Tech Dr Rangarajan Dr Sakunthala Engineering College, Avadi, Chennai- 600062 Tamilnadu, gracecathrine3@gmail.com

[5*]Assistant Professor and Research Supervisor, Department of Management Studies, St. Joseph's College of Engineering (An Autonomous Institution), Old Mahabalipuram Road, Chennai, Tamilnadu, orcid.org/0000-0002-3093-5611, drjbalamuruganpdf@gmail.com

[6]Associate Professor, Department of ECE, Annamacharya Institute of Technology and Sciences (Autonomous), Tirupati, A.P, orcId: 0009-0008-6500-5255, selvasenthamil2614@gmail.com

[7]Assistant Professor, Department of Computer Science and Design,Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Avadi,Chennai, Tamilnadu, druvaneshwarim@veltech.edu.in

Abstract
Global attention has been focused on COVID-19, a contagious sickness. Modelling illnesses may greatly improve the prediction of their consequences. While traditional statistical modelling may be effective, it may not fully capture the difficulty of the data. Automatic COVID-19 discovery using computed tomography (CT) scans or X-rays is successful, but healthy system design is problematic. This paper suggests a smart healthcare system using IoT-cloud technology. This design employs smart connection devices and deep learning (DL) for smart city decision-making. The sophisticated technology provides real-time patient tracking and affordable, high-quality healthcare services. DL experiments are used to assess the feasibility of the suggested COVID-19 detecting system. Sensors are used to capture, convey, and monitor healthcare data. IoT sensors electronically transmit patient CT scan pictures to the cloud, where the cognitive unit is kept. The technology determines patient status from CT scan images. The cognitive module of the DL makes real-time decisions on potential actions. Assigning information to a cognitive module, they apply ResNet50, a cutting-edge DL-based classification algorithm, to determine whether patients are healthy or sick with COVID-19. To ensure its robustness and efficacy, the approach is validated using two public datasets (Covid-Chestxray and Chex-Pert). Initially, 5000 photos are gathered from the two datasets. The suggested method was trained on pictures from 80% of datasets and tested on 20%. Tenfold cross-validation is used to evaluate the presentation. The system achieved 99.7% accuracy, 99.3% specificity, 98.4% sensitivity, and 98.88% F1 score. This suggested approach has great accuracy, specificity, sensitivity, and F1 score. Comparing the proposed system to state-of-the-art systems reveals superior performance. The system offered will aid medical diagnostic research and healthcare systems. Additionally, it will aid COVID-19 showing professionals and provide a valued second perspective.
Keywords: *COVID-19, CT scan, Deep Learning, Internet of things, Healthcare System.*

1. INTRODUCTION

A new coronavirus, known as COVID-19, has been spreading from Wuhan to many regions inside China. Worldwide, about a million people lost their lives, and over a million instances were officially documented. Due to the lack of a vaccine or therapy for COVID-19, early detection is crucial to isolate the patient effectively. In a healthy population, it lowers the chance of infection. Respiratory or blood samples were subjected to gene sequencing or reverse-transcription polymerase chain reaction (RT-PCR) as the primary COVID-19 screening procedures. Many healthy people get the virus from undiagnosed patients since the total RT-PCR positive rate for throat swab samples is predicted to be 35 to 65%. Quick

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and easy illness diagnosis is possible using chest X-ray imaging; this technique is also used to diagnose pneumonia. Additionally, comparisons between chest X-ray pictures and CT scans reveal visual indices associated with COVID-19, while CT scans have better diagnostic sensitivity.

Chest imaging revealed multilobar participation and peripheral airspace opacity. Ground glass (58%) and mixed attenuation (30%) are the most often measured opacities. The early stages of COVID-19 include ground glass patterns on the pulmonary vessel edges, which are hard to detect visually. Asymmetrical patches or diffuse territory opacities are also seen in COVID-19. Perception of minor irregularities is limited to specialists in radiology. Automated systems may enhance early detection rates and improve accuracy in identifying illnesses due to the high number of suspicious individuals and limited skilled radiologists. Automation using machine learning (ML) is an efficient solution for such issues.

Research on automated COVID-19 identification utilising chest CT scans or X-ray pictures has shown underwhelming results owing to the absence of public image files of patients. Currently, researchers may use a limited dataset of COVID-19 X-ray pictures for automated diagnostic training. Scans from research articles showing COVID-19 findings utilising X-ray and CT scans. A panel of radiotherapists reviewed the whole picture database. Limited pictures were kept after analysis, and labelled by radiologists as COVID-19 patients. Figure 1 shows images related to COVID-19 and affected areas. The COVID-19-contaminated areas in the pictures are highlighted. Afterwards, we used a subset of the ChexPert dataset photos to serve as examples of negative COVID-19. Covid-Xray, a dataset consisting of five thousand photos, was created using the two existing datasets, the Chex-Pert dataset and the Covid-Chestxray dataset. The number of photos used for testing is 1100 out of 5000, whereas 3900 images are utilised for training purposes.

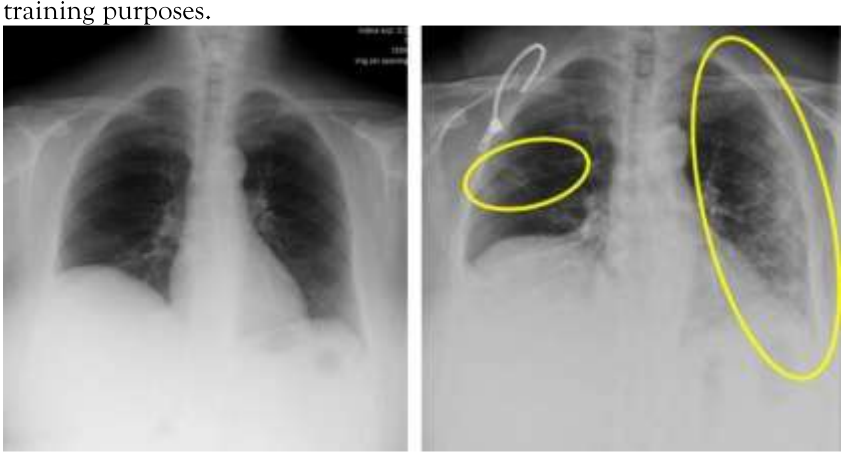

Figure 1 Image Connected to COVID-19 and Affected Areas

This research presents a suggested ML-based approach for COVID-19 discovery in chest X-ray pictures. In contrast to the traditional method of manually extracting characteristics and classifying medical photos, it utilises a deep learning-based end-to-end forecast system to detect COVID-19 instances directly from the input pictures. Among the several deep learning models, a convolutional neural network (CNN) has shown to be the most actual in numerous applications. Local connection and weight sharing are two key characteristics of this artificial neural network type. Because of these benefits, it is suitable for use with photos and other high-dimensional data. Use cases for them include segmentation, feature extraction, classification, and other image-enhancing issues. They built a deep learning-based pattern recognition system to identify COVID-19. Figure 2 provides an overview of the system under question.

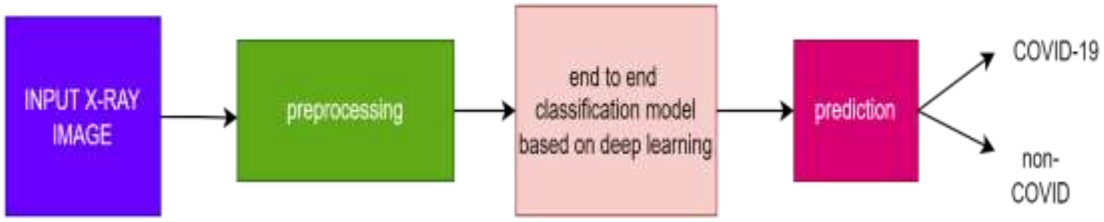

Figure 2: The suggested system architecture

This research assesses the effectiveness of a cutting-edge ResNet50 CNN model in detecting COVID-19. X-ray pictures for COVID-19 are few, hence two methodologies are used in this study: Using data augmentation, the dataset size is increased by a factor of 5. To achieve this, they employ slight rotation, flipping, and slight distortion. They optimised the ResNet50 CNN model's last layer using Image Net instead of starting from scratch. The model may be trained with fewer samples of each class.
Two ways resulted in a network with great performance on 1100 photos by using accessible images. As COVID-19 pictures are few, they calculate the confidence interval (C.I) for performance measures. A receiver-operating characteristic (ROC) curve is used to estimate the concert of the ResNet50 model. Therefore, in a smart medical setting, the suggested system extracts features and classifies them using deep learning from CT scan images. The following are the primary benefits of this research:

- Suggest a smart healthcare architecture that incorporates cloud and Internet of Things technology
- Gathered 5,000 photos to use as a dataset. A qualified radiotherapist labels the COVID-19 photos, and they are only utilised for research reasons with a distinct mark.
- To distinguish between COVID-19 patients and healthy individuals, use the cutting-edge ResNet50 CNN model. The ResNet50 model was trained using 3900 photos, and its performance was evaluated using 1100 images. The suggested approach has shown a 99.7 per cent accuracy, a 98.4 per cent sensitivity, a 99.3 per cent specificity, and an F1-score of 98.88%.
- Extensive experimental analysis. They employ the histogram of suggested ratings, ROC curve, accuracy, specificity, sensitivity, and F1-score for this purpose.
- Utilised tSNE plot to identify distinguishing characteristics between groups.

The following of the paper's structure. Section 2 explains the Framework for Intelligent Healthcare. Section 3 contains the findings and explanation of the experiments. The paper is concluded in Section 4.

2. Framework for Intelligent Healthcare

The suggested COVID-19 detection technique and Internet of Things cloud-based smart healthcare infrastructure are detailed in this section.

2.1 Scenario for Smart Healthcare

In a smart city, healthcare systems are designed to function together. Through the use of smart sensor devices, it enables residents, stakeholders, and doctors to track their health. They have 24/7 access to their electronic health records because of cloud and IoT technologies. Decisions made with high cognitive capacity are both accurate and intelligent. Patients can choose the optimal course of therapy because of the cognitive system's real-time analysis, integration, and tracking of data. Medical professionals may access patients' health records remotely using the cloud, allowing them to better advise their patients.
The smart healthcare system's top goals include accurate diagnosis, affordable treatment, reduced patient expenses, easy access, and better health in general. A healthcare system centred on IoT-cloud technologies is what it's proposing to achieve these aims. For a smart city's infrastructure to function, inhabitants must sign up for its services. Residents and healthcare professionals can communicate securely via the registration procedure. With this feature, authorised users may access patients' medical data and information securely via the cognitive module. The cognitive system orders the patient's vitals and sends the CT scan's image to a cloud-based cognitive module for analysis using deep learning. To get the results of the binary classification, the deep learning module must first identify COVID-19. This research indicates that the brain is already planning what it will need to do next. These findings are shared with medical experts in the form of reports so they may examine them in detail. A smart mobile or ambulance healthcare facility can quickly trace the patient after receiving alerts and messages from the cognitive gadget in the case of an emergency. Additionally, the smart transportation system enables emergency services to reach the site via the quickest route possible. Cognitive smart healthcare delivers all citizens access to essential healthcare services via digital means.

2.2 System Design

Figure 3 shows the blueprints for the smart health scheme that is being considered. Internet of Things (IoT) smart sensors interconnect the CT scan images. The LAN is made up of interacting gear that operates at a low range. This layer is accountable for relaying the signals received from the smart Internet of Things sensors and the device to a different layer known as the hosting layer. Handheld multimedia players and signal-transmitting laptops are examples of the intelligent gadgets that make up the hosting layer. A wide area network (WAN) links all of the smart devices together, allowing them to send data to the cloud. To transmit data to the cloud instantly, the WAN layer makes use of specialised networking networks like Cell LAN, 4G, or 5G. Before sending patient data to the deep learning cognitive module, the cloud manager verifies the data. For data transfer, smart IoT sensors are used. The patient's environment could include any of these sensors. Other Internet of Things devices may also be connected to this device. Zigbee, LoWPAN, and Bluetooth are all short-distance networking technologies that make up the LAN.

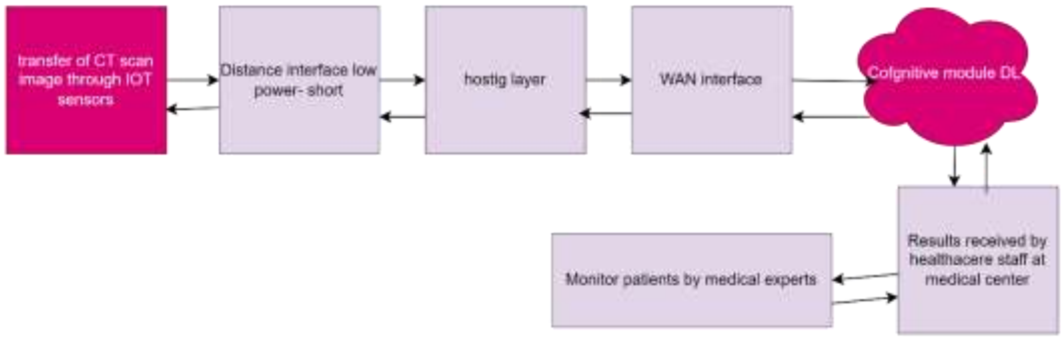

Figure 3: Smart COVID-19 detection healthcare framework

In the hosting layer, find smart devices such as hypermedia smartphones, tablets, laptops, and even human digital supporters. Specialised software on these devices calculates the signals received and stores data locally. Users can get preliminary and broad health assessments from these compact processing units. The WAN layer is responsible for transmitting data to the cloud computing unit. The cloud layer consists of a deep learning and cloud management cognition unit. The cloud executive supervises data flow and authenticates all participants in the intelligent city. Following patient verification, the DL cognitive unit assesses the patient's illness via data analysis. CT scan pictures are used to make informed judgements on COVID-19 detection. Deep learning models provide identification findings to the cognitive module, which finalises the patient's position and informs shareholders. Hospital professionals analyse clinical data, and results, and continue patient monitoring.

2.3 Detecting and Classifying COVID-19

The purpose of the DL cognitive unit is to provide a deep-learning solution for detecting COVID-19. Deep learning displays superior performance compared to older methods using hand-engineered features. They will utilise deep learning to create the suggested technique. This section outlines the suggested technique.

2.3.1 Data Set

This research prepares a 5000-image dataset from two datasets. The dataset consists of both training and testing sections. The training set has 3900 photos while the testing set has 1100 images. This research makes use of many datasets, one of which is the newly published COVID chest X-ray dataset, which contains some pictures captured by Joseph Paul Cohen for use in his COVID-19 papers. This database contains a mix of images from a chest CT and an X-ray scan. This dataset included 260 radiographs of COVID-19 patients beginning in June. For this research, 185 out of 260 photos were chosen because they perfectly identify COVID-19 patients. Updates to this dataset are ongoing. Each patient's age and gender are examples of the information included in this dataset. By using additional photos from the ChexPert dataset, they were able to reduce the amount of non-COVID pictures in the collection.

2.3.2 Pre-Processing

The pictures in this collection have a constantly changing resolution. There are both low-resolution and high-resolution photos in the COVID-19 class. The suggested model is more suited to this variance because, upon training, it produces superior results regardless of the difference in sample picture quality or image capture method. It is not practical to gather data in an extremely regulated setting, such as when taking high-resolution cleaning or pictures of the information after pre-processing. There has been a

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recent uptick in the growth of complex frameworks and models within the machine learning public to improve performance in uncontrolled settings, where factors like small-scale labelled datasets, variations in sample picture size and quality, and other similar issues are increasingly common. The original dataset provider supplies the COVID-19 class with photos sourced from several sources. Consequently, they normalised the training pictures before training the model to address the issue of image resolution. This means that the model is less affected by variations in resolution since all the photos fall into the same distribution.

2.3.3 Transfer Knowledge

To distinguish between COVID-19 patients and healthy controls, this research used the cutting-edge ResNet50 convolutional neural network (CNN) model. Trained a ResNet50 CNN model using the transfer learning method to achieve this goal. This method involves taking a model that has been trained for one work and applying it to another that is similar. Utilising the Image Net model for picture classification allows implementing task-specific learning on a more manageable dataset. One famous model that uses millions of tagged photos is the Image Net. Medical photos linked to different illnesses are one example of a job where transfer learning might be useful since there aren't enough suitable examples to train a model. For really complicated models that call for a plethora of parameters during training, this method may be useful. Models trained using transfer learning start with strong baseline values and need just little tweaks to perform better when faced with novel problems.

There are primarily two applications for the pre-trained model. In the first approach, features are removed using the pre-trained model, and a classifier is then trained using it to categorise the data. The second method involves fine-tuning either a subset or the whole model network according to the new goal. The training process will include making adjustments to the pre-trained model weights, which will serve as the starting points.

Due to the limited sample size of the COVID-19 class, this work used pre-trained models to extract discriminative structures and fine-tuned the CNN's final layer. The results of the ResNet50 model are subsequently assessed. In the part that follows, they address the problem's implementation and the ResNet50 model's architecture. Figure 4 shows the design of the ResNet50 CNN-type model.

Figure 4: Architecture of REsNet50 CNN

2.3.4 Covid-19 Identification Using Resnet50 CNN Model

A pre-trained ResNet50 CNN model was used in this investigation. The popular Image Net dataset served as the basis for training this model. The ResNet50 model, which won the 2015 Image Net competition, is among the most widely used convolutional neural network (CNN) designs for more reliable training. Using the identity shortcut link to bypass layers and speed up learning is the idea behind the ResNet50 design. A direct connection in the network is made possible for the basic levels by this design. Because of this, updating the gradients in the first layers will be a breeze.

2.3.5 Training Models

The research makes use of the cross-entropy loss function in conjunction with the suggested ResNet50 model. The objective is to minimize the deviation between the actual and goal probability values, and this loss function helps with that. The following formula is used to describe it:

$$L_{ce} = \sum_{i=1}^{N} P\, p_i \log q_i \qquad (1)$$

where the expected and actual probability values for each sample picture are denoted by pi and qi, respectively. Next, minimize the loss function by using the random gradient descent procedure.

3. RESULTS AND DISCUSSION OF THE EXPERIMENT

3.1 Parameters of the model

The experiment fine-tunes the ResNet50 model and optimizes the loss of cross-entropy function. Optimizer settings were established for beta-1 and beta-2 learning rates. The network received all photos with the same resolution.

3.2 Evaluation metrics

Tenfold cross-validation was performed to assess the suggested approach on a tenfold dataset. Ninefold (80% of the data) are trained and onefold is tested each time. This is performed for each fold for generalisation. Thus, training and testing employ all folds. The training set was split into 80% for model training and 20% for validation. The following metrics assess the proposed system's performance:

$$Accuracy\ (Acc) = \frac{TP + TN}{Total\ Sample} \qquad (2)$$

$$Specificity\ (Spec) = \frac{TN}{TN + FP} \qquad (3)$$

$$Sensitivity\ (Sens) = \frac{TP}{FN + TP} \qquad (4)$$

$$F1 - Score = \frac{2 * TP}{(2 * TP + FP + FN)} \qquad (5)$$

The system identifies COVID-19 images as FN (false negatives), TN (true negatives), TP (true positives), and FP (false positives) as COVID-19.

3.3 Model's expected scores

This research detects COVID-19 using ResNet50 CNN. Every input picture receives a probability score from the proposed model, representing its COVID-19 class probability. This number may be compared to a threshold to determine whether the input picture is related to COVID-19 or not. An ideal model estimates the odds of all non-COVID samples being near to 0 & COVID-19 samples being close to 1. ResNet50's test image anticipated likelihood score distribution. Normal and COVID-19-infected participants make up the non-COVID class in this research. Figure 5 shows that the likelihood rating of the normal class (non-COVID) is less than that of other illness classes. Images of various illnesses are distinguishable from the normal class, but harder to distinguish from the COVID-19 class due to high likelihood ratings. Overall, non-COVID photos from other and normal illness classes had lower likelihood ratings than COVID-19 images. This shows that the model can differentiate between COVID-19 and non-COVID pictures.

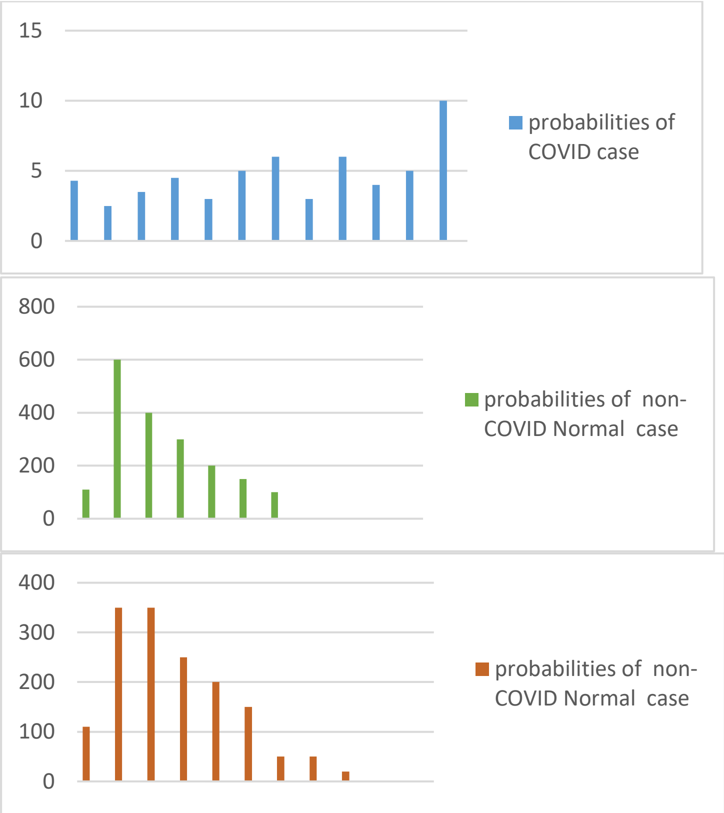

Figure 5: Probability predictions from the ResNet50 CNN model

3.4 Findings and Analysis

The ResNet50 probability score classifies the test picture as COVID-19 or non-COVID. The input image's COVID-19 status may be determined by comparing these scores to a threshold value. Projected labels determine model sensitivity and specificity. Four threshold values were employed in this investigation. These four threshold settings showed that ResNet50 performed best with 0.15. Table 1 shows the average performance. Since there are only 100 photos to be tested in the COVID-19 class, the suggested system's sensitivity and specificity are not very dependable due to the limited sample size.

Table 1: CNN model ResNet50 performance

comparing COVID-19 with non-COVID	
Performance indicators	CNN ResNet50 Model
Accuracy	99.7%
Sensitivity	98.4%
Specificity	99.3%
F1-Score	98.88%

Test pictures labelled with COVID-19 are needed to assess sensitivity and specificity rates more accurately. One may also calculate the 96% CI of the specificity and sensitivity numbers. Estimating C. I check the specificity and sensitivity of test examples for each class. Define the C. I as:

$$r = \sqrt[z]{\frac{accuracy(1 - accuracy)}{N}} \qquad (6)$$

where z is C. I's significance level and N is the class's total instances. The research used C.I. therefore, z shows accuracy value. A solid COVID-19 detection model is essential. ResNet50 model sensitivity of 98.4% is used as the cutoff criterion. COVID-19 diagnosis requires a sensitive model; thus, they set the ResNet50 CNN model's threshold value at 98.4% sensitivity and compared its specificity rates. C.I. for sensitivity is 2.5% and for specificity, it is 1.4%, as shown in Table 2. Since there are 1100 non-COVID test pictures in the sample, the sensitivity C.I. is greater than the specificity C.I.

Table 2: ResNet50 CNN model specificity and sensitivity

Model	Specificity	Sensitivity
ResNet50	99.3% - 1.4	98.4% -2.5

The testing data ROC curve is shown in Figure 6. The graph shows that the system's AUC is 0.99. COVID-19 and non-COVID courses may be distinguished by the model. Table 3 illustrates the testing data confusion matrix, which contains three errors by categorizing four COVID-19 photos as non-COVID and nine errors by categorizing fourteen non-COVID pictures as COVID-19. The confusion matrix indicates that the suggested system accurately classifies test data. Figure 7 shows the tSNE plot of features, showing COVID-19 and non-COVID groupings. The two classes' traits are clearly distinguished in this plot. Only a few photos in both types are misclassified. The tSNE graphic proves the suggested system's supremacy.

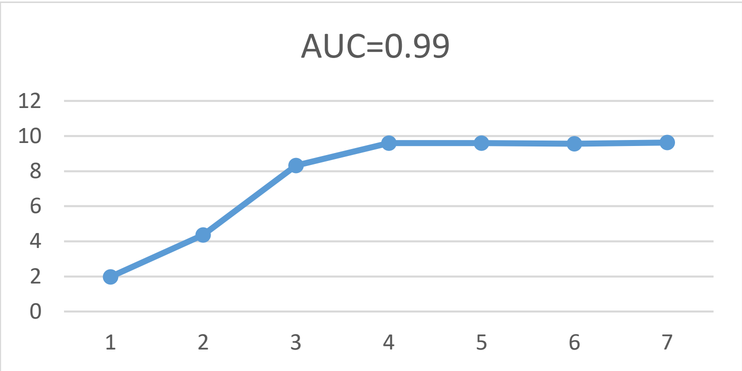

Figure 6: Proposed system ROC curve

Table 3: Model ResNet50 confusion matrix

Real class	predicted class	
	COVID-19	Non-COVID
COVID-19	98	4
Non-COVID	14	1088

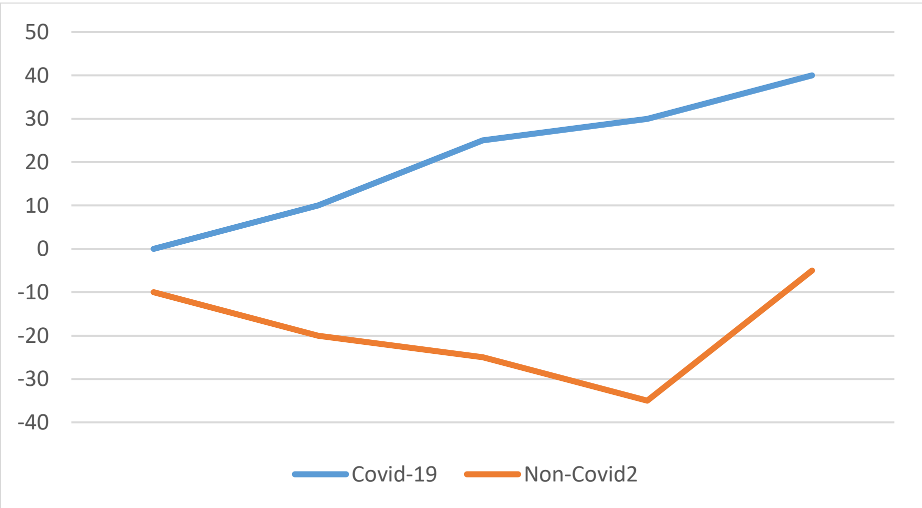

Figure 7: COVID-19 vs. non-COVID tSNE plot for features visualization

3.5 Analysis

Deep learning was used to create a cutting-edge COVID-19 identification framework for chest X-ray images. This required fine-tuning the pre-trained ResNet50 CNN framework on the training set. 5000 photos are used in this investigation. The complete experimental study evaluates the ResNet50 CNN model's accuracy, specificity, sensitivity, and F1 score. The suggested model has an average specificity of 99% for a 98% sensitivity. These findings provide positive outcomes when X-ray pictures are used to identify COVID-19, which is very encouraging. Data used in this analysis come from two publically accessible sources: one with 530 COVID-19 photos and the other with 4470 COVID images. A 99.7% accuracy rate, 98.4% sensitivity, 99.3% specificity, and 98.88% F1 score were all provided by the suggested approach. The results demonstrate that the suggested system outperforms the current one.

3.6 Future work

COVID-19 identification from chest X-rays is difficult and still needs improvement. Future directions for the suggested study are varied. Accuracy improvement is likely the biggest future problem. To build a more robust and versatile model want to increase the model's depth in the future and observe the effect on accuracy. The goal of creating these models is to use cutting-edge, complex learning approaches. Two datasets that are accessible to the public are used in this investigation. Adding additional pictures to the COVID-19 detection issue is one way to go in the future. Further research on the possibility of multi-class or category identification for COVID-19 detection should be considered in the future. Despite performing well on a publically accessible dataset, the suggested solution is not yet ready for real-time healthcare implementation. Another fascinating issue is whether additional people in the studies improve or worsen classifier performance as data rises. The suggested DL-based approach will aid medical diagnostic research and healthcare systems. It will complement COVID-19 screening specialists and provide a valued second perspective.

4. CONCLUSION

A smart healthcare system using IoT-cloud technologies to identify and categorise COVID-19 is presented in this research. Medical imaging data is collected via smart sensors. Cloud-stored photos are utilized to evaluate patients. The system recommends patient-requested facilities and medical care. To perform follow-up processes, the deep learning cognition module recognizes COVID-19 in the picture and notifies all stakeholders. The DL cognition module proposes a top-notch deep learning system for COVID-19 detection. ResNet50 CNN was fine-tuned using Chest X-ray images for training. Both the Covid-Chestxray and Chex-Pert datasets are publically accessible to test the proposed system's resilience and efficacy. Starting with Covid-Chestxray and Chex-Pert datasets, 5000 pictures are created. Train the suggested system to gather photos from 80% of datasets and test with 20%. Results demonstrate that the strategy performs well. A tenfold cross-validation method is used. The suggested system's performance is examined in this paper via a comprehensive experimental investigation. With an F1-score of 98.88%, specificity of 99.3%, sensitivity of 98.4%, and accuracy of 99.7%, the findings show that the suggested approach is quite effective. When compared to the current systems, the suggested system outperforms them. Research into medical diagnoses and healthcare systems would benefit from the DL-based approach that has been suggested. Additionally, it will help medical specialists with COVID-19 screening and perhaps main to a valued second opinion.

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