# A New Artificial Intelligent Based Deep Learning Model Using IOT For COVID-19 Identification

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**Abstract:**
Since December 2019, the world has been dealing with the COVID-19 epidemic. The importance of a timely and accurate identification of COVID-19 suspected patients in medical treatment cannot be overstated. To combat the COVID-19 outbreak, deep transfer learning-based automated COVID-19 diagnosis on chest X-ray is necessary. Using ensemble deep transfer learning, this work presents a real-time Internet of Things (IoT) system for early identification of suspected COVID-19 patients. COVID-19 suspicious instances can be communicated and diagnosed in real time using the suggested system. InceptionResNetV2, ResNet152V2, VGG16, and DenseNet201 are among the deep learning models included in the proposed IoTframework. Using the deep ensemble model saved on the cloud server, the medical sensors are used to obtain chest X-ray modalities and identify the infection. Over the chest X-ray dataset, the proposed deep ensemble model is compared to six well-known transfer learning models. A comparative investigation demonstrated that the suggested approach can assist radiologists in diagnosing COVID-19 suspicious patients in a fast and effective manner.
**Keywords*:*** Internet of (ings (IoT), diagnosis of COVID-19, deep transfer learning, medical treatment and Artificial Intelligent.

## I. INTRODUCTION

Internet of things (IoT) devices have become widely employed in a variety of applications in recent years, including smart cities, manufacturing, home automation, and medicine [1]. Sensors are employed to collect data about the physical world in these gadgets. The world's healthcare system is currently overburdened as a result of the COVID-19 epidemic. As of December 19, 2020, there had been more than 21 million confirmed active cases, 55 million recovered cases, and 1.6 million deaths reported in 185 countries. To put an end to the outbreak, coronavirus-infected people must be diagnosed as soon as possible. IoT devices are employed to remotely retrieve data from COVID-19 patients for this purpose. This information is shared with healthcare providers in order to diagnose COVID-19 [2]. These devices not only relieve the stress on healthcare staff, but they also identify unexpected patterns in sensor data. Using IoT-enabled devices, healthcare personnel can deliver better treatment for coronavirus-infected people more quickly. There is a need to build an automatic categorization technique that uses data from IoT devices. Deep learning models have recently been used by a number of researchers to support a variety of healthcare applications [3].

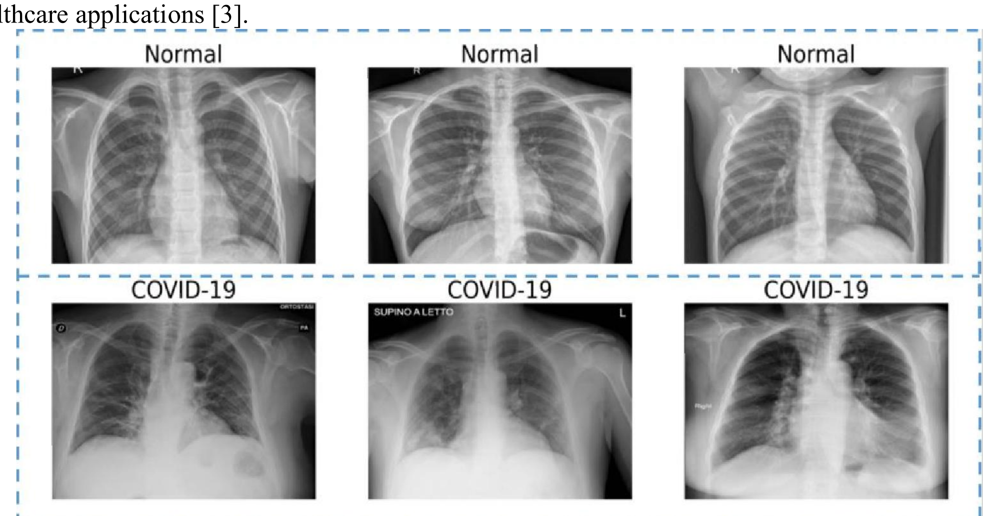


**Figure.1** COVID-19 Chest Xray Images [4]

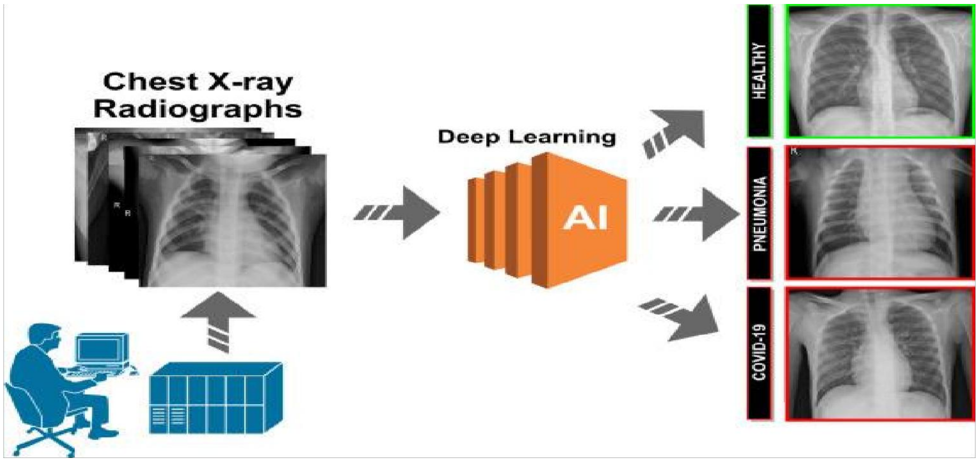


**Figure.2** Conventional Block diagram of COVID-19 identification [5]

The chest X-ray modality can be used to classify the person as COVID-19 (+), pneumonia, tuberculosis, or healthy, according to the literature. It is favoured over other imaging modalities because it is more cost-effective and poses a lesser risk of human radiation exposure. The manual chest X-ray modality analysis for the diagnosis of COVID-19 suspicious participants is shown in Figure 1. It is, however, a difficult and time-consuming task. The radiologists looked at the white patches on the chest X-ray, which indicated infection. However, X-ray modalities contain pus and water, making infection detection difficult and time-consuming. The IoT and deep learning-based coronavirus detection framework is shown in Figure 1. The radiologist can use the deep ensemble model to quickly diagnose infected patients.

The remainder of this paper is organized as follows: the next Section 2 presents the most recent related work, while Section 3 describes the proposed approach. In Section 4, the experiments we have performed to evaluate our system are presented and compared with several methods. Finally, we conclude in Section 5.

## II. LITERATURE SURVEY

For early diagnosis of coronavirus-infected individuals, an IoT-based system has been developed. To diagnose coronavirus suspected cases, researchers used a faster region CNN with ResNet101 (FRCR). The FRCR has a 98 percent accuracy rate [4]. For automatic screening of COVID-19 from chest CT images, an attention-based deep 3D multiple instance learning (AD3D-MIL) method was developed [5]. For efficient learning, AD3DMIL used the Bernoulli distribution of labels. An IoT-based ensemble deep learning framework is built in response to the recent success of deep learning models for automated coronavirus diagnosis. The suggested ensemble model will aid radiologists and medical personnel in determining whether a patient has COVID19 (+), pneumonia, tuberculosis, or is healthy. For the automatic diagnosis of COVID-19 suspicious subjects, an IoT and deep ensemble model-based architecture has been developed. InceptionResNetV2, ResNet152V2, VGG16, and DenseNet201 are all ensembled in a deep ensemble model. The medical sensors gather chest X-ray modalities and use an ensemble deep transfer learning model stored on a cloud server to diagnose the infection. For the experiment, a chest X-ray dataset with four classes (COVID-19 (+), pneumonia, tuberculosis, or healthy) was used.

According to a comparative analysis, the suggested approach will assist radiologists in efficiently and swiftly diagnosing COVID-19 suspicious patients. On 460 CT images, AD3D-MIL was trained and tested. For screening coronavirus-infected people using CT scans, a multitask multislice deep learning system (M3 Lung-sys) was created [6]. Using the generative adversarial network, an auxiliary classifier model was created to generate synthetic chest X-ray pictures (GAN). CovidGAN [7] was the name given to the newly created model. COVID-19 was distinguished from other viral pneumonias using CovidGAN. CovidGAN was put to the test using 192 chest X-ray scans. CovidGAN, on the other hand, does not perform cross-validation. Using ultrasound, X-ray, and CT scan, deep learning models were employed to detect COVID-19 suspicious cases [8]. VGG19 was used to create an automated categorization system. To reduce sample bias and improve image quality, the preprocessing technique was applied. Data fusion strategies, on the other hand, can improve classification accuracy. For the classification of COVID-19 suspicious instances, a CNN-based transfer learning architecture was presented [9]. In this suggested framework, the eight pretrained CNN models ResNet18, Inceptionv3, SqueezeNet, MobileNetv2, ResNet101, CheXNet, DenseNet201, and VGG19 were used. (A total of 423 COVID-19, 1485 viral pneumonia, and 1579 normal chest X-ray images were used to evaluate the framework.) To identify COVID-19 infection from other infections, a 3D convolution neural network (3DCNN) was created [10].

DCNN used a dual-sampling and online attention refining technique. (The infection regions were extracted using this network, and the uneven distribution of pneumonia-infected regions was eliminated.) A total of 2796 CT scan pictures from 2057 patients were used to test DCNN. The accuracy of the affected area, however, is still lacking. To categorise coronavirus-infected people using chest X-ray, a deep learning-based chest radio classification (DL-CRC) system was suggested [11]. To create artificial coronavirus infected X-ray pictures, DL-CRC used a generative adversarial network and data augmentation. Four separate chest X-ray datasets were used to test DL-CRC. The COVID-19 epidemic has been greatly aided by medical IoT devices. Deep learning models based on the Internet of Things have been developed to lessen the labour of medical personnel and doctors. The IoT-based deep learning models that do not address defensive models against adversarial perturbations, on the other hand, are vulnerable to adversarial attacks [12]. To detect COVID-19 suspicious patients, Gianchandani et al. [13] developed an ensemble deep transfer learning model. For COVID-19-infected individuals, Singh et al. [14] developed a deep neural network-based screening strategy. To categorise COVID-19 patients, Singh et al. [15] used highly linked convolutional networks. Although these models produce better results, ensemble modelling can improve them much more.

According to the existing research, present models still suffer from the overfitting problem [16, 17]. Ensemble models, as opposed to individual models, use numerous learning methodologies to produce higher classification performance [18]. When there is more diversity among the deep learning models, the ensembling of deep learning models delivers substantial outcomes. (In the United States, assembling is a meta-approach that combines multiple deep learning models into a single classification model in order to improve prediction (stacking) or reduce bias (boosting) and variation (bagging).

## III. PROPOSED METHODOLOGY

Figure 3 depicts the IoT-based automated coronavirus diagnosis framework's layer-by-layer architecture. Perception, network, data storage and processing layer, and application layer are the four layers that make up the system. Medical IoT devices are first responsible for gathering various types of scans such as X-ray, CT, and ultrasound at the perception layer. (With the help of the network (transmission) layer, these collected scans are then communicated to the data storage layer.) (The collected scans may be transmitted via telecommunications, the Internet, or other means by the network layer.)

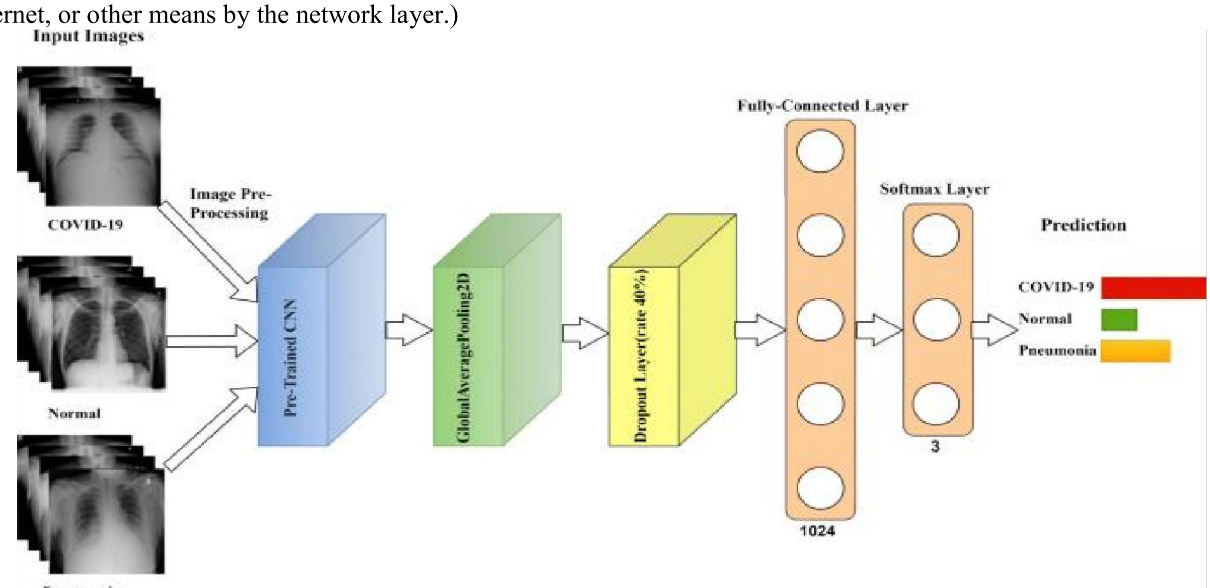


**Figure.3** Proposed Architecture model of this work

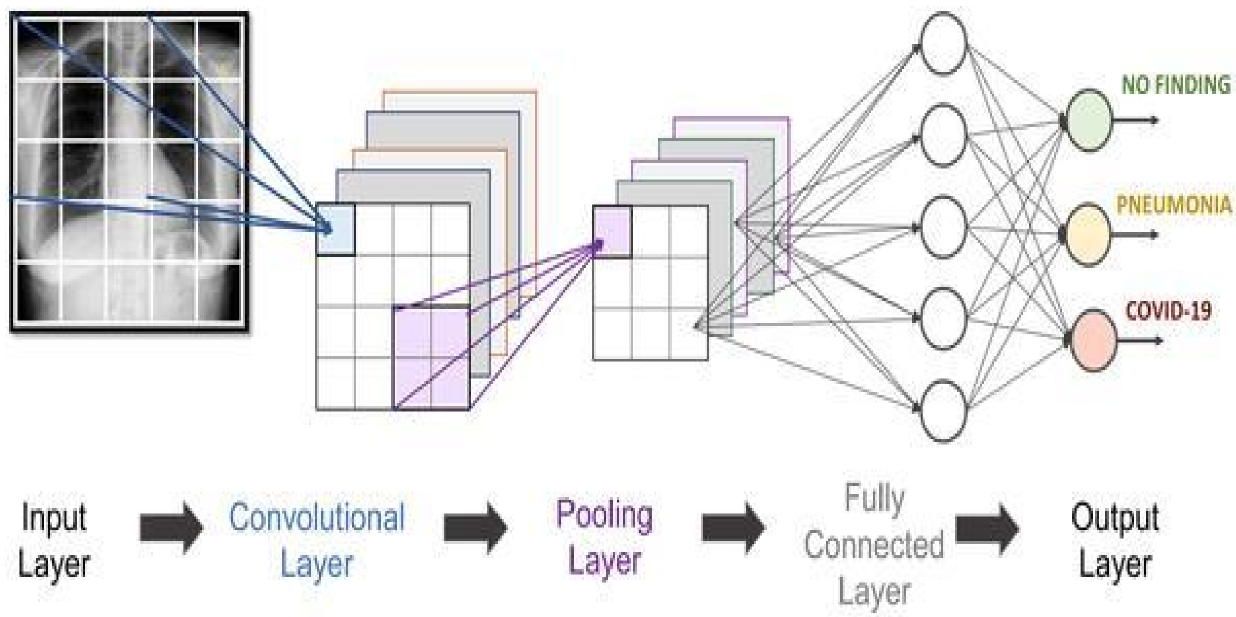


**Figure.4** Proposed AI based Deep Learning Model

The IoT network's data processing/storage layer next uses deep learning models to categorise the people as infected or healthy, and subsequently stores the results. Finally, at the application layer, clients such as patients, doctors, and medical personnel can use the diagnosis results for further treatment or action. (Figure 3 shows a potential ensemble model for COVID-19 diagnosis.) (e suggested model ensembles ResNet152V2 [9], DenseNet201 [9], VGG16 [19], and InceptionResNetV2 [20], four well-known transfer learning models. Only these models were utilised since they achieved good accuracy and diversity among the deployed deep learning models during testing on the provided dataset.

The ensemble of pretrained models produces more efficient results than individual models, according to research. The ensemble method can be used to extract the best features and enhance classification accuracy. The proposed ensemble model for COVID-19 diagnosis is shown in Figure 3. The initial dense layer is made up of 64 neurons. To extract the features, a fine-tuned transfer learning model with multiple layers is used. The softmax activation function is used to solve the four-class classification issue. Using epoch 100 and batch size 10, the models were created. To avoid overfitting, fully linked layers with 64 neurons with dropouts of 0.3 and 0.2 are employed during the first tuning of characteristics. Regularization is also accomplished by taking into account the concept of early halting.

## IV. RESULTS AND DISCUSSION

The four-class CXR dataset is used to test the proposed DenseNet model. The suggested ensemble model is compared to well-known deep transfer learning models that are already in use. The experiments are run on a MATLAB 2020b computer with a core i7 3.80 GHz processor, 32 GB RAM, and 15M cache. To solve the problem of overfitting, this study used 20-fold cross-validation. For training purposes, 70% of the complete dataset is considered.

### *4.1. Database*

The information was gathered by combining four separate datasets. (The first set of data comes from hospitals in So Paulo, Brazil.) There are 1262 COVID-19 (+) and 1230 healthy participants among the 2492 CXR scans [21]. Furthermore, two publicly available tuberculosis datasets from Shenzhen, China, and Montgomery County, USA, were obtained from the National Institutes of Health's National Library of Medicine (NIH). The Shenzhen dataset contains 326 healthy patients and 336 tuberculosis (+) patients. There are 80 normal CXR photos and 58 CXR images of tuberculosis (+) patients in Montgomery County, USA. A total of 1663 COVID-19 (+) patients, 401 pneumonia subjects (viral and bacterial pneumonia), 394 tuberculosis patients, and 2039 healthy person pictures were employed in the study. Random rotation, random cropping, and random blurring are also used to supplement data.

The suggested model's training and validation analysis. It is obvious that the suggested model produces better training and validation outcomes and is unaffected by overfitting problems. The overall accuracy for the COVID-19 class is 99.6%. The suggested deep ensemble model has a 99.2 percent accuracy for healthy patients. The suggested deep ensemble model has an overall accuracy of 99.4 percent for the pneumonia class. The E tuberculosis class has a 99.1 percent accuracy rate. With an overall accuracy of 99.3 percent, the suggested model achieves outstanding overall categorization. As a result, the overfitting problem has little impact on the suggested model. The results show that the proposed framework outperforms existing deep learning models in terms of performance. The suggested approach outperforms existing models in terms of accuracy, Fmeasure, sensitivity, and specificity, among other metrics.

**Table.1** Comparative analysis of performance evaualtion for COVID-19 diagnostic identification using proposed AI-Deep learning model with IOT.

| Model | Accuracy | Sensitivity | Specificity | F-score |
|---|---|---|---|---|
| VGG16 | 96.3 | 96.5 | 95.4 | 96.6 |
| ResNetV2 | 97.1 | 97.3 | 96.2 | 97.9 |
| DenseNet201 | 97.2 | 97.1 | 98.7 | 96.9 |
| Inception V4 network | 97.7 | 97.4 | 98.5 | 98.2 |
| ResNet152V2 | 98.4 | 98.2 | 98.7 | 98.9 |
| Proposed Model | 99.5 | 99.2 | 99.7 | 99.4 |

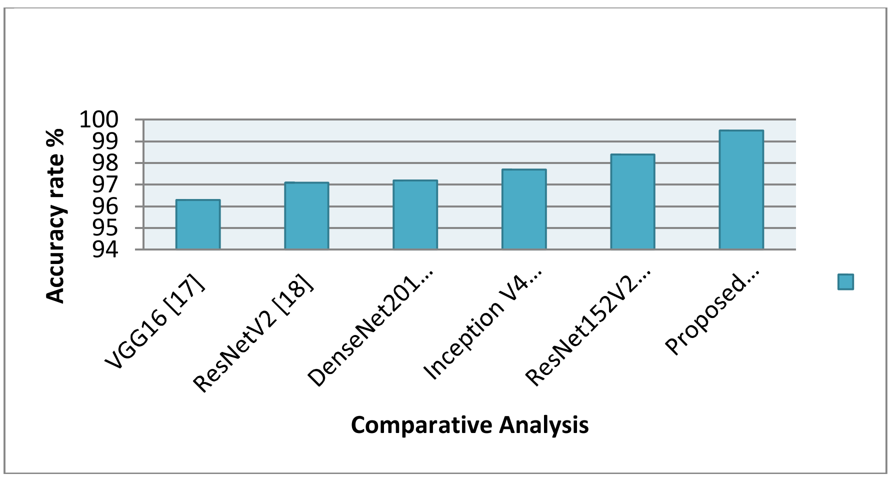


**Figure.5** Comparative analysis of performance evaualtion for COVID-19 diagnostic identification using proposed AI-Deep learning model with IOT for Accuracy.

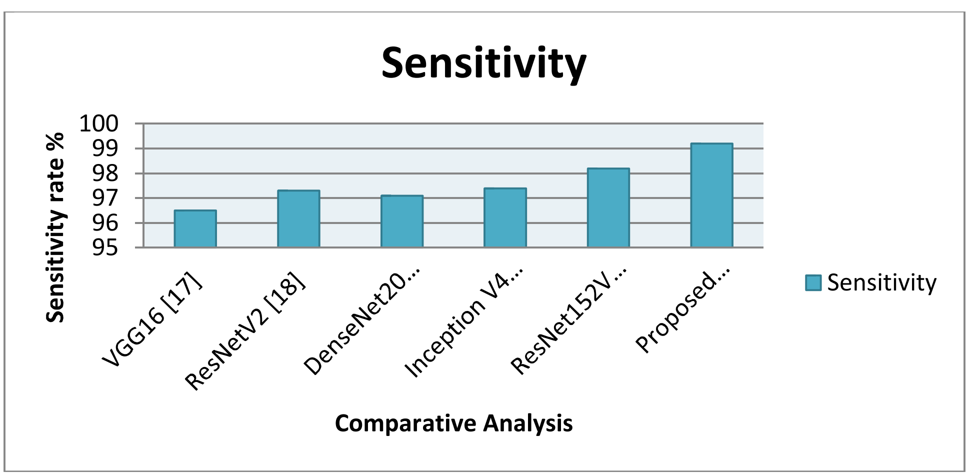

**Figure.6** Comparative analysis of performance evaualtion for COVID-19 diagnostic identification using proposed AI-Deep learning model with IOT for Sensitivity.

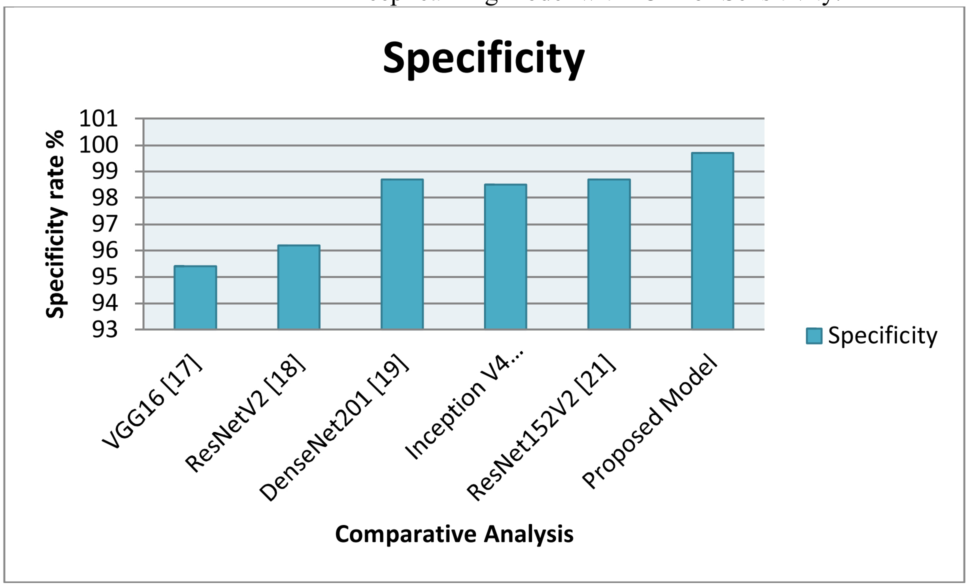


**Figure.7** Comparative analysis of performance evaualtion for COVID-19 diagnostic identification using proposed AI-Deep learning model with IOT for Speficity.

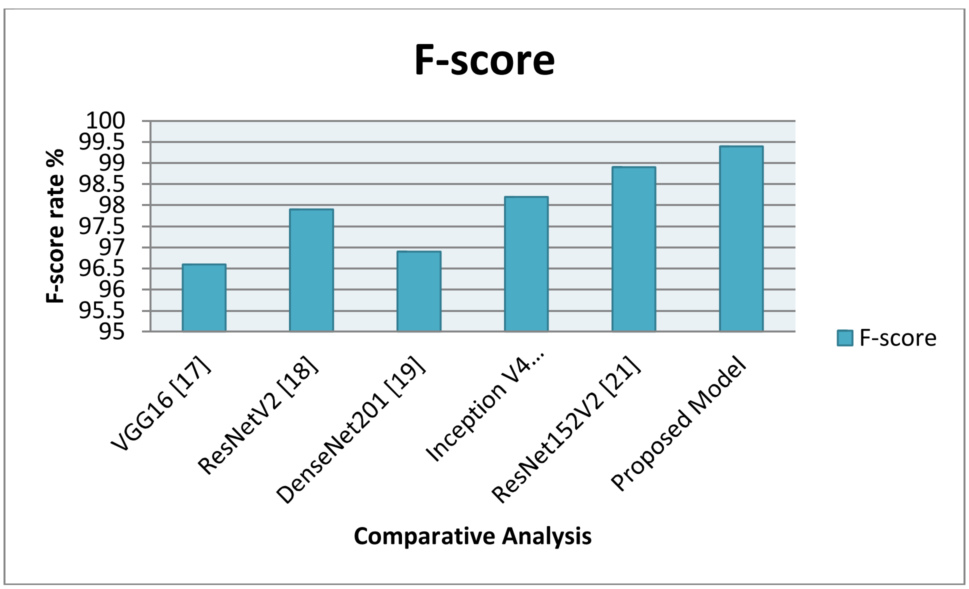


**Figure.8** Comparative analysis of performance evaualtion for COVID-19 diagnostic identification using proposed AI-Deep learning model with IOT for Speficity.

Deep transfer learning models' hyperparameter tuning concerns have yet to be resolved. The results of deep transfer learning models can be improved with effective hyperparameter adjustment. Furthermore, the proposed methodology must be extended to diagnose chest CT and ultrasound pictures. In addition, the proposed approach can be applied to create a multidisease classification model in various disciplines.

## V. CONCLUSION

This paper provides real-time communication and diagnosis of suspected COVID-19 patients. Using ensemble deep learning, an IoT-based automated coronavirus detection system was created. ResNet152V2, InceptionResNetV2, VGG16, and DenseNet201 are among the deep learning models that have been combined in the proposed framework. The suggested model's performance was tested using four-class chest X-ray datasets. A comparative investigation demonstrated that the suggested approach can assist radiologists in diagnosing COVID-19 suspicious patients in a fast and effective manner. The suggested framework outperforms previous models in terms of performance.

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