https://doi.org/10.48047/AFJBS.6.13.2024.15-25

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

A TWEAKED DEEP LEARNING MODEL INCLUDING CHEST X-RAY IMAGES for determining CORONAVIRUS DISEASE-19 (COVID-19)

1. Dr Jai Singh W,Associate Professor Selection Grade,School of CSE & Information Science,Presidency University, Bangalore,Karnataka - 560064.

2. Dr.R.K.Kavitha,Assistant professor ,Department of Computer Applications,Kumaraguru College of Technology,Coimbatore 641049

3. Dr. T. Sarathamani,Associate professor,Department of Computer Science and Engineering,Brainware University,Kolkata- 700125

4. .Dr. P.Vijayakumar,Assistant Professor,Department of Computer Applications, Kongu Engineering College,Perundurai-638060

Article History

Volume 6 Issue 13, 2024

Received: 25 May 2024

Accepted : 25 June 2024

doi:10.48047/AFJBS.6.13.2024.15-25

Abstract--- In classical machine learning algorithms, diagnosing patients with Coronavirus Disease-19 (Covid-19) from Chest X-ray images is a major problem. This research proposes to use pneumonia photos to increase the accuracy of various patient categories using Improved Inception ResNet-v2. An Inception-ResNet-v2-based multiscale channel attention module is shown to provide network recognition and target detection in the face of drastic scale shifts. At the beginning of the model, the effective receptive field and the convolution kernel of the network stem layer are both larger. The activation function is made smaller and the SiLU activation function is utilized rather than the ReLU activation function in order to prevent the model from being overfit. In order to solve the problem of the Chest X-ray dataset having less data, the input image

Keywords: X - Ray Image Processing; COVID – 19, Deep Learning; Medical Image Classification; Computer Aided disease Diagnosis.

1. Introduction

Reverse transcription polymerase chain reaction (RTPCR) detection kits were the major diagnostic tool used in the early stages of the COVID-19 pandemic; nevertheless, a significant false negative rate in nucleic acid detection was caused by a combination of poor kit quality, improper sampling practices, and disease evolution strategies. Clinicians now acknowledge chest X-ray image diagnosis as a crucial component of the early detection and follow-up of newly diagnosed coronary pneumonia because of the objectivity and ease of use of medical imaging. The use of deep learning in medical imaging has expanded in recent years due to the dedication of numerous scientists and healthcare professionals to sharing chest X-ray image data of patients who have developed new cases of coronary pneumonia.

In order to diagnose new cases of coronary pneumonia, the researchers created a number of deep learning diagnostic models and successfully classified medical images with a high accuracy rate. Two modules are designed in this research to enhance the ConvNeXt network. In order to modify channel relationships, a Converged Attention Module (CGMB) is first proposed. Secondly, multiple small convolutions are used in place of large convolutions in spatial attention. This technique replaces large convolutions with fewer parameters and more nonlinearity, improving feature map learning. The suggested GlstNet is more adept at combining local and global data thanks to the CGMB design. When the LSTM layer is eventually introduced to the network, it remembers the prior data, connects it to the present data, and emphasizes interaction.

2. Related Works

Dastider et al considered the spatial and temporal characteristics of Lung Ultrasound (LUS) frames, and introduced a Convolutional Neural Network (CNN) with a long short-term memory network (LSTM) to improve classification performance. Islam et al developed a combined deep CNNLSTM network to automatically diagnose COVID-19 cases using three types of chest X-ray images. Among them, CNN extracted complex features from the image, and LSTM was used as a classifier to obtain better detection results. Naeem et al proposed a multi-level feature extraction method, which reduces the training complexity of CNN and helps to accurately and stably identify the lesion area of the new coronary pneumonia.

Hassanien et al applied the ConvNeXt network to the study of malignant breast tumors, and used the visual interpretation module to generate heat maps on ultrasound images to help explain the deep learning model and achieved good results. Ketu et al used convolutional layers to extract feature information and trained and learned from time series data. This network enriched the functions of the LSTM layer, and experiments proved that using additional convolutional layers in the LSTM layer will improve the performance of the detection model. Inspired by the above research, combining global and local information can improve the performance of the network for X-ray image classification of new coronary pneumonia.

Yang et al [1] At the time of writing (December 22, 2022), the number of cases of the novel coronavirus infection COVID-19 reached 700 million. Through comprehensive measures that include early diagnostic entry, the spread of disease and, therefore, deaths can be prevented and reduced. The main method of laboratory diagnosis is reverse transcription polymerase chain reaction. During the height of the first wave of the coronavirus pandemic, the implications of this approach were laid bare: high false positive rates, limited availability, and long result runs.

Rubin et al [2] Meanwhile, patients with symptoms of COVID-19 on chest computed tomography (CT scan) may receive false negative results. According to Russian and international recommendations, radiological diagnostic methods for COVID-19-associated pneumonia include X-ray photography and CT scanning. For chest X-ray photography, the sensitivity for the diagnosis of viral pneumonia is low, so CT scan plays an important role in the diagnosis of COVID-19-associated pneumonia and its complications.

Lei et al [3] During the pandemic, the widespread use of CT scanning has created problems related to high radiation exposure to populations. During hospitalization, CT scans were performed within a short period of time to assess the progression of the disease, because a significant change in the CT scan with a shrinking tendency was one of the criteria for discharge. For patients with suspected COVID-19, 1–2 CT scans can be performed in the outpatient clinic to detect symptoms of the disease.

Shiri et al [4] However, the main approach to noise reduction is the use of iterative reconstruction, which allows CT studies with lower radiation doses and similar signal-to-noise ratios compared to standard data reconstruction techniques. A promising direction is to use neural networks for image reconstruction. According to the literature reviewed, the following conclusions can be drawn: In order to reduce the radiation dose, it is reasonable to reduce the tube current, while, in order to optimize the signal-to-noise ratio, use a reconstruction filter that eliminates the difference between adjacent pixels (soft tissue) and Iterative reconstruction is reasonable.

Feng et al [5] In the new crown pneumonia epidemic, the main technology for diagnosing new coronary pneumonia is the reverse transcription polymerase chain reaction (RTPCR) detection kit, but the sampling technology, kit quality and disease evolution method will all lead to the false negative rate of nucleic acid detection. Due to the collection and high-level nature of medical imaging, detector X-ray image diagnosis has become an important part of the early detection and collection of new coronary pneumonia recognized by clinicians. In recent years, many researchers and medical workers have contributed to COVID-19. The disclosure of X-ray image data of hamster patients has made the application of deep learning in medical imaging more extensive.

The researchers designed a variety of deep learning diagnostic models related to new coronary pneumonia, and achieved a high accuracy rate in medical image classification. Dastider et al. [6] considered the spatial and temporal characteristics of lung ultrasound (LUS) frames, and introduced a convolutional neural network (CNN) with a long short-term memory network (LSTM) to improve classification performance.

Islam et al. [7] developed a combined deep CNNLSTM network to automatically diagnose COVID-19 cases using three types of chest X-ray images. Among them, CNN extracted complex features from the image, and LSTM was used as a classifier to obtain better detection results.

Naeem et al. [8] proposed a multi-level feature extraction method, which reduces the training complexity of CNN and helps to accurately and stably identify the lesion area of the new coronary pneumonia. Applied the ConvNeXt network to the study of malignant breast tumors, and used the visual interpretation module to generate heat maps on ultrasound images to help explain the deep learning model and achieved good results.

Li et al [9] In late December 2019, a new type of coronavirus, severe acute respiratory syndrome coronavirus 2 (severe acute respiratory syndrome coronavirus 2, SARS-CoV-2), first broke out in Wuhan City, Hubei Province. 2019 coronavirus disease (corona virus disease-19, COVID-19). SARS-CoV-2 is highly contagious, and the population is generally susceptible. It generally manifests as fever, cough, chest tightness, and fatigue. In severe cases, it can rapidly progress to acute respiratory distress syndrome and multiple organ failure, leading to death. Due to the poor understanding of SARS-CoV-2, coupled with the very rapid epidemic and spread across the country, the diagnosis of COVID-19 has brought great challenges. Nucleic acid detection is the gold standard for diagnosis, but its specificity and sensitivity are greatly affected by the reagent itself and sampled samples, and false negative results are prone to occur.

FANG et al [10] Therefore, the role of imaging examination is increasingly prominent. At present, some literatures have described the chest imaging characteristics of COVID-19 patients. We found that the chest imaging manifestations of patients will change dynamically with the progress of the disease.

Jin et al [11] The author retrospectively analyzed the chest CT imaging data of 52 patients diagnosed with COVID-19 in the First Affiliated Hospital of Zhejiang University School of Medicine, in order to deepen the understanding of COVID-19. -19 Changes of lung tissue lesions in patients.

MAMOM et al [12] this research aims to develop an early detection system for COVID-19 through X-ray thorax reading, using deep learning Convolutional Neural Network (CNN) technology. CNN is a deep learning application method that can detect and recognize an object in a digital image. This method is claimed to be the best model for solving object detection and object recognition problems. It is a development of the Backpropagation method and does not require large computations in the process.

In this study, the successful detection speed was obtained by Panwar et al. [13] will be fixed. Besides, object detection methods such as that of Ozturk et al. will also be developed using a similar model. The object detection model used in this research is Single Shot Detection (SSD) MobileNet. The SSD MobileNet model was chosen because it is lightweight to be implemented in mobile applications.

Many researches have successfully detecting COVID-19 in many ways. Several studies have been successfully conducted COVID-19 detection based on chest X-rays using CNN. Research conducted by Mahmud et al. [14] developed a CNN architecture called CovXNet that can detect COVID-19, normal, and pneumonia (virus and bacteria) conditions with an accuracy of 90.2%.

Another study conducted by Varela-Santos and Melin et al [15] found the effect of the amount and quality of chest X-ray data on the detection accuracy using CNN with an accuracy of 91.53%.

3. Proposed Method

The Multi-Scale channel attention Module (MSM) is introduced into the network, and the initial features are fused and alternately integrated with another attention module, which enables the network to dynamically and adaptively fuse the received features to improve the accuracy of the model, so as to focus on the differences in images of different types of patients with pneumonia, and suppress the impact of other redundant information. Increase the size of the convolution kernel in the early stage of the network to increase the effective receptive field of the network. Prevent network overfitting by reducing the use of activation functions. The amount of data is enhanced by performing data pre- processing and data enhancement on the patients's pneumonia image dataset to help the model extract and classify images.

3.1 Inception-ResNet-v2

The Inception network was first started by Google in 2014 after Google Net. The original Inception-v1 used convolution kernels of different sizes to capture features of different scales, removed the last fully connected layer of the network, and changed it to a global average pooling layer, greatly reducing the number of parameters and speeding up training. It also achieves the effect of reducing overfitting. Inception-v2 proposes the famous Batch Normalization (BN) layer, which speeds up the training speed and convergence speed of the model. Inception-v3 splits the two-dimensional convolution into two smaller one-dimensional convolutions, which reduces the number of parameters and plays the role of expanding nonlinear transformation.

Inception-v4 uses a more complex stem module than the previous network. The stem module uses a parallel structure and an asymmetric convolution structure, which can reduce the amount of calculation when the information loss is small enough. Inception-ResNet combines Inception and ResNet, and uses the Inception structure to fit the residual structure. There are two versions, Inception-ResNetv1 and Inception-ResNet-v2. Inception-ResNet-v1 adds ResNet to Inception-v3, Inception-ResNet-v2 adds ResNet and the corresponding residual network to Inception-v4, and the network converges faster. Inception-ResNet-v2 is stacked by stem, Inception-ResNet-A, Reduction-A, Inception-ResNet-B, Reduction-B, Inception-ResNet-C and other modules. Inception-ResNet-v2 can not only accelerate training to prevent gradient dispersion, but also obtain sparse or non-sparse features of the same network layer. Its structure is shown in Figure 1.

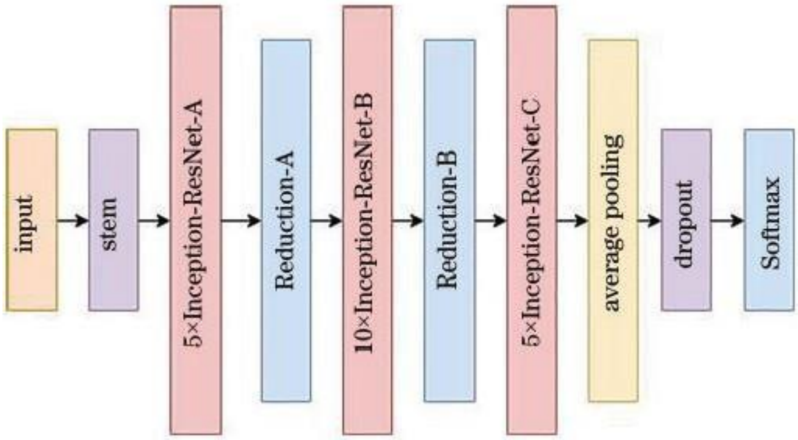


Figure. 1 Inception-ResNet-v2 model

3.2 Attention Mechanism

The attention mechanism is used to automatically learn and calculate the contribution of the input data to the output data. Its essence is to locate the information of interest and suppress useless information. Since the data set has a lot of noise, the difference between patient's viral pneumonia and Covid 19 is not obvious, which requires the network itself to be able to extract more useful information, so as to make more accurate judgments. The proposed method adds an Iterative Attention Feature Fusion Module (IAFF) between the Inception-ResNet layer and the Reduction layer, and adds MSM to the Inception-ResNet, as shown in Figure 2.

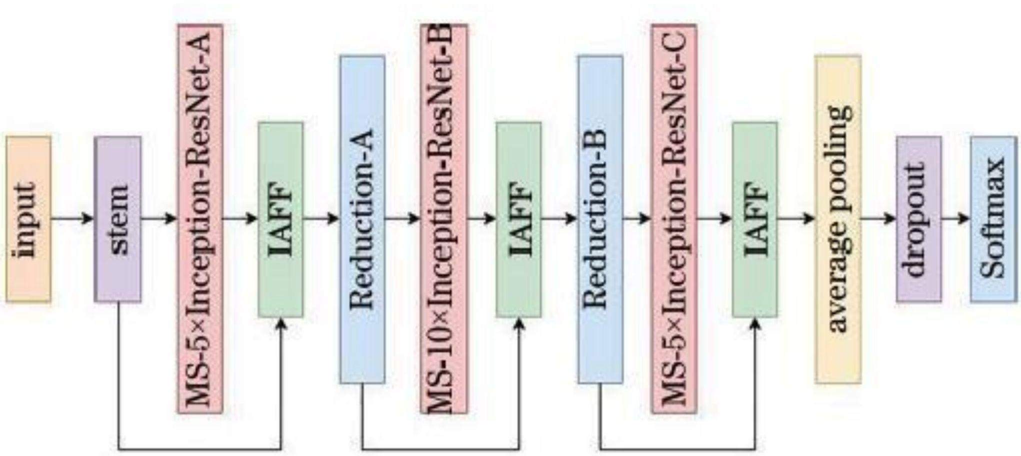


Figure. 2 Improved Inception-ResNet-v2 model

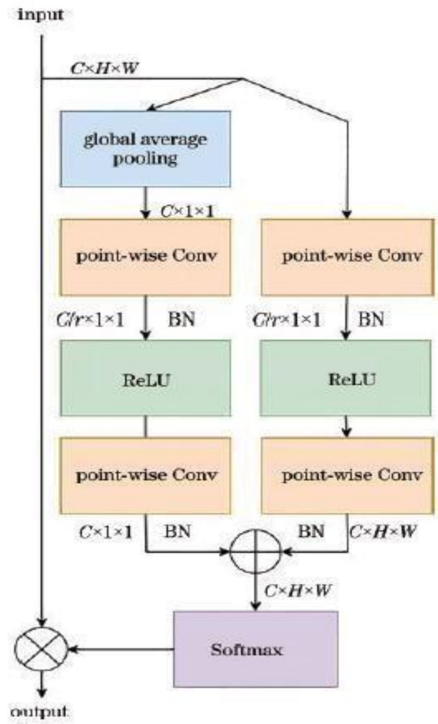
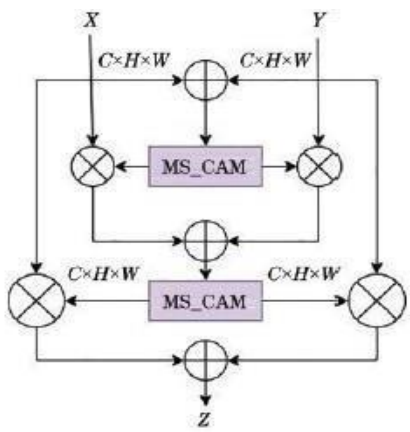


Figure 3. Multi-Scale Channel Attention Module structure

In recent years, most of the attention mechanism modules introduced in the network are based on the full-channel attention mechanism, which dynamically weights and averages multiple groups in the same layer. Although this attention mechanism provides nonlinearity for feature fusion, their initial integration is too single and lacks the ability to integrate attention features of different scales. The MSM used can not only effectively solve the problem of inconsistency of attention features at different scales, but also emphasize large objects distributed globally and small objects prominently distributed locally, so as to promote network recognition and detection of targets under extreme scale changes. Its structure is shown in the figure 3 shown.

Nowadays, many feature fusions use simple summation or concatenation, and it is still impossible to achieve cross-layer feature fusion. However, this only provides a linear aggregation of a fixed feature map. It is completely unknown whether this combination is suitable for a specific object, making the model performance limited. The proposed method uses the IAFF module to fuse various feature fusion scenarios using a unified method, and IAFF achieves cross-layer feature fusion, which improves the quality of the fusion features of the network at different feature scales and the generalization of the



network. The IAFF structure as shown in Figure 4.

Figure4. IAFF structure

3.3 Improved Stem Layer

The first three layers of the stem layer use a convolution with a convolution kernel size of 3×3. After the first data splicing, the left branch uses a 1×1 convolution followed by a 3×3 convolution, and the right branch first the first layer and the fourth layer use 1×1 convolution and 3×3 convolution, which reduces the number of parameters to a certain extent, but the effective receptive field is actually not large. Due to the high resolution of images in the data set and the small variance of image pixel values, a larger 7×7 convolution is selected. Through multiple experiments, the convolution kernel size of the first three layers of the stem layer was changed from 3×3 to 7×7, and the left branch was changed to two convolution kernels with a size of 7×7 after the first data splicing. Convolution, the first layer and the fourth layer of the right branch are also replaced by 7×7 convolution. The above modifications greatly enhance the effective receptive field of the model at the initial stage, making the obtained global features better.

3.4 Modification of the Activation Function

In the original Inception-ResNet-v2, each convolution and Inception-ResNet layer will finally introduce the ReLU activation function . Although the activation function can bring nonlinearity to the model and can better map the input image to the output, it must be Too many activation functions will make the model more complex, leading to overfitting. The proposed method removes the activation function after each convolution on the basis of the original Inception-ResNet-v2, which reduces the complexity of the model and speeds up the convergence of the model. In the last layer of the original Inception-ResNet layer, the SiLU activation function is used to replace the original activation function. SiLU has the characteristics of no upper bound, lower bound, smoothness, and non-monotonicity, especially in deep networks, it has a better effect than ReLU activation function.

4. Experiment and Result Analysis

4.1 Experimental Platform

This experiment is carried out using the PyTorch deep learning framework based on the Python language, and the experiment is based on the Ubuntu platform.

4.2 Dataset

The data set used in this experiment is Chest X-ray [16], which is a public data set based on the X-ray scan database of patients aged 20 to 50 in Guangzhou Women and Children's Medical Center. The dataset contains a total of 5856 chest X-rays labeled covid and pneumonia, and the image format is JPEG. According to the type of pneumonia marked in the data set, it was divided into viral pneumonia and covid. The specific distribution is shown in Table 1. In the experiment, the ratio of 8:1:1 was used to divide the data set, in which 80% of the pneumonia images were used as the training set, 10% of the pneumonia images were used as the test set, and 10% of the pneumonia images were used as the verification set. A picture sample is shown in Figure 6.

Table 1 Number of grades of pneumonia in patients

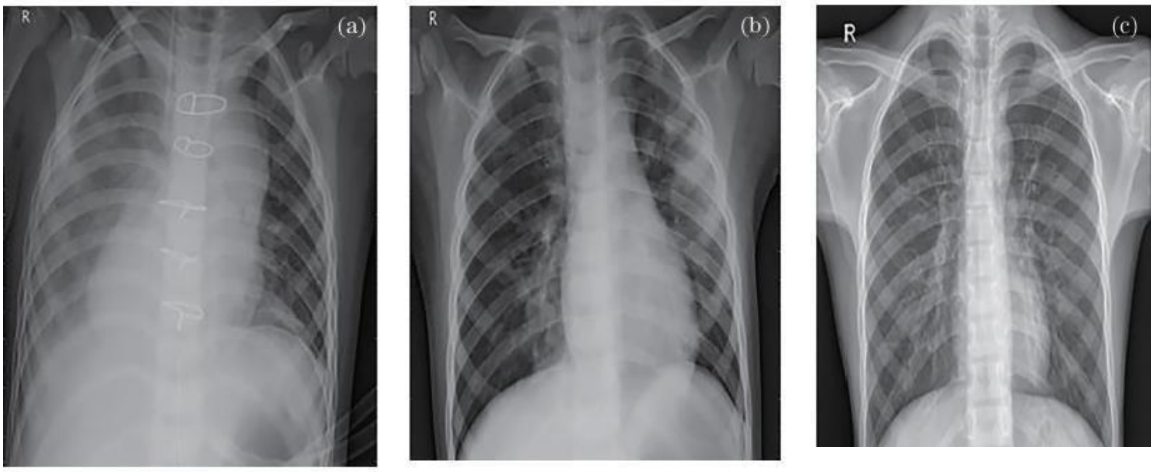
Category	Types of pneumonia	Quantity
0	Covid - 19	3780
1	Normal	1684
2	Viral pneumonia	1595

4.3 Model Training Strategy

In order to adapt to the input of Inception-ResNet-v2, the image size is adjusted to 299×299, and the method of flipping and random angle rotation is used in the training set for data enhancement.

4.3.1 Optimizer

The optimizer is used in the neural network to update and calculate the network parameters that affect the model training and model output, so choosing an appropriate optimizer is very important in model construction. Due to the large noise in the data set used, the Adaptive Moment Estimation (Adam) [25] optimizer is used. Adam can avoid local optimal solutions while speeding up the training. In the Adam optimizer, the gradient is g, the first matrix estimation and the second matrix estimation are m and v, the parameter variable is θ, and the parameters are optimized after setting the initial learning rate α



(a) Covid - 19 (b) Viral Pneumonia (c) Normal

Figure 5. Diseased and Normal X – Ray Images

4.4 Evaluation Index

In order to verify the effect of the proposed improved Inception-ResNet-v2 algorithm, the accuracy (R_{accuracy}) , precision $R_{\text{precision}}$), recall R_{recall}), specificity $R_{\text{specificity}}$ and confusion matrix are used to further evaluate the performance of the model. The calculation formula is,

$$R_{\text{accuracy}} = \frac{N_{\text{TP}} + N_{\text{TN}}}{N_{\text{TP}} + N_{\text{FP}} + N_{\text{FN}} + N_{\text{TN}}}, \quad (1)$$

$$R_{\text{precision}} = \frac{N_{\text{TP}}}{N_{\text{TP}} + N_{\text{FP}}}, \quad (2)$$

$$R_{\text{recall}} = \frac{N_{\text{TP}}}{N_{\text{TP}} + N_{\text{FN}}}, \quad (3)$$

$$R_{\text{specificity}} = \frac{N_{\text{TN}}}{N_{\text{TN}} + N_{\text{FP}}}, \quad (4)$$

Where: NTP is the number of true positives; NFP is the number of false positives; NFN is the number of false negatives; NTN is the number of true negatives. The confusion matrix is a summary of the prediction results of the classification problem. The sum of each row represents the number of real samples of this category, and the sum of each column represents the number of samples predicted as this category.

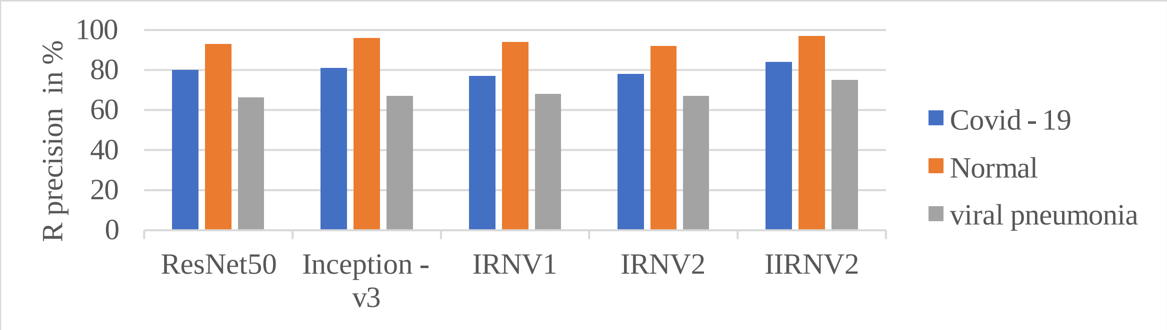


Figure 6. Evaluation of Precision

In above chart shows that $R_{precision}$ value of IIRNV2 is 5 times better than ResNet50 in Covid 19 condition and nearly 3.7 times better than Inception -v3 in Covid 19 conditions. At the same time normal condition Rprecision value of IIRNV2 is 3.1 times better than IRNV1 and nearly 5.3 times better than IRNV2.

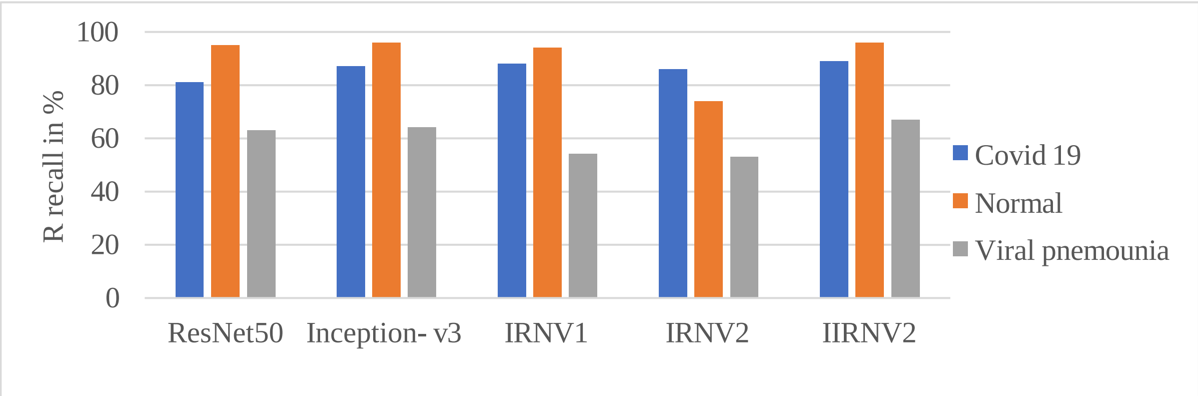


Figure 7. Evaluation of Recall

From Figure 7, it shows that R_{recall} value of IIRNV2 is 3.4 times better than IRNV2 in Covid 19 condition and nearly 1.1 times better than IRNV1 in Covid 19 conditions. At the same time viral pneumonia condition R_{recall} value of IIRNV2 is 6.3 times better than ResNet50 and nearly 5.3 times better than Inception-v3.

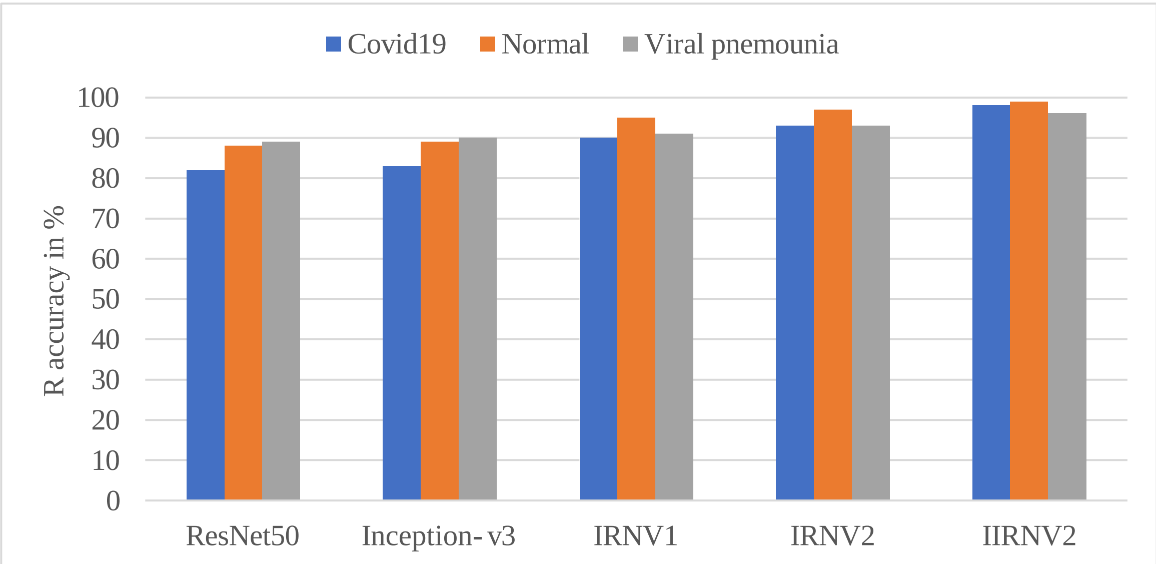


Figure 8. Evaluation of Accuracy

From Figure 8, it shows that R $_{accuracy}$ value of IIRNV2 is 20 times better than ResNet50 in Covid 19 condition and nearly 18 times better than Inception in Covid 19 conditions. At the same time viral pneumonia condition R $_{accuracy}$ value of IIRNV2 is 5.4 times better than IRNV1 and nearly 3 time better than IRNV2.

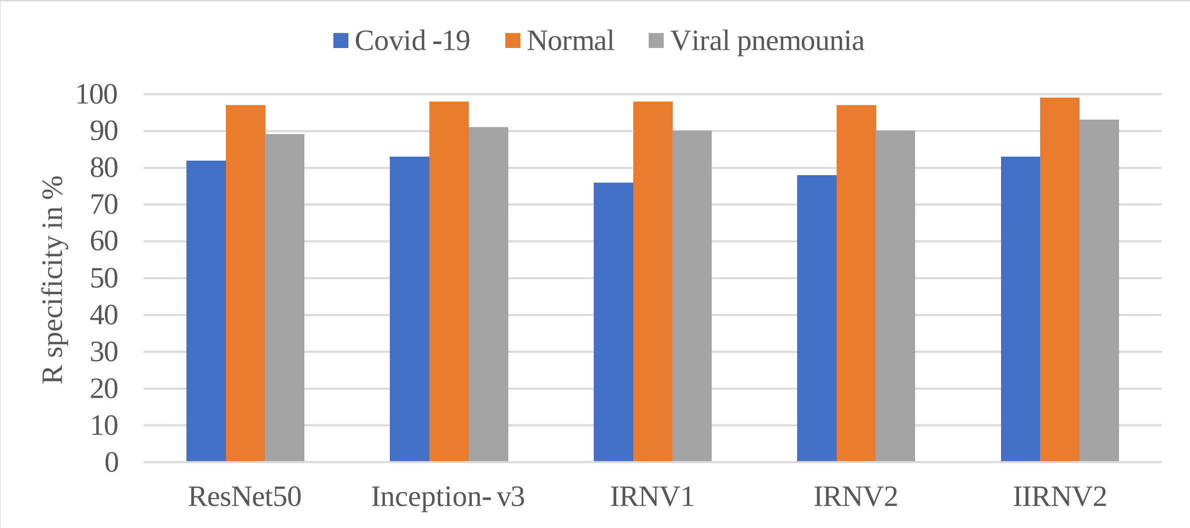


Figure 8. Evaluation of Specificity

From Figure 8, it shows that R $_{specificity}$ value of IIRNV2 is 6.4 times better than IRNV2 in Covid 19 condition and nearly 9.2 times better than IRNV1 in Covid 19 conditions. At the same time normal pneumonia condition $R_{specificity}$ value of IIRNV2 is 2 times better than ResNet50 and nearly 1 time better than Inception-v3.

5. CONCLUSION

An improved Inception-ResNet-v2 classification algorithm is proposed for the detection of patient's pneumonia images. By fusing the multi-scale channel attention module, the model's ability to extract features of different scales is effectively improved. Increase the size of the convolution kernel of the stem layer to increase the effective receptive field of the model. Reduce the use of activation functions and use data augmentation methods to prevent model overfitting. The experimental results show that, compared with other methods, the proposed method has improved in all aspects of the two-category and three-category tasks of patient's pneumonia, and has better generalization. However, a complete classification system has not been formed during the experiment. In the follow-up work, we will try to develop all the experimental processes into a complete auxiliary system.

REFERENCES

[1]. Yang Y., Yang M., Shen C., et al. Evaluating the accuracy of different respiratory specimens in the laboratory diagnosis and monitoring the viral shedding of 2019-nCoV infections // medRxiv. 2020. doi: 10.1101/2020.02.11.20021493

[2] Rubin G.D., Ryerson C.J., Haramati L.B., The role of chest imaging in patient management during the COVID-19 Pandemic: A multinational consensus statement from the fleischner society // Radiology. 2020. Vol. 296, N 1. P. 172–180. doi: 10.1148/radiol.2020201365

[3] Lei DP, Fan B, Mao J, et al. The progression of computed tomographic (CT) images in patients with coronavirus disease (COVID-19) pneumonia: Running title: the CT progression of COVID-19 pneumonia. J Infect. 2020;80(6):e30–e31. doi: 10.1016/j.jinf.2020.03.020

[4] Shiri I, Akhavanallaf A, Sanaat A, et al. Ultra-low-dose chest CT imaging of COVID-19 patients using a deep residual neural network. Eur Radiology. 2021;31(3):1420–1431. doi: 10.1007/s00330-020-07225-6

[5] Feng Y B, Qiu D W, Cao H, et al. Research on coronavirus disease 2019 (COVID-19) detection method based on depthwise separable DenseNet in chest X-ray images[J]. Journal of Biomedical Engineering, 2020, 37 (4): 557-565.

[6] Dastider A G, Sadik F, Fattah S A. An integrated autoencoder-based hybrid CNN-LSTM model for COVID-19 severity prediction from lung ultrasound[J]. Computers in Biology and Medicine, 2021, 132: 104296.

[7] Islam M Z, Islam M M, Asraf A. A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images[J]. Informatics in Medicine Unlocked, 2020, 20: 100412

[8] Naeem H, Bin-Salem A A. A CNN-LSTM network with multi-level feature extraction-based approach for automated detection of coronavirus from CT scan and Xray images[J]. Applied Soft Computing, 2021, 113: 107918.

[9] LI Q, GUAN X, WU P, et al. Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia[J]. N Engl J Med, 2020. DOI: 10.1056/NEJMoa2001316.

[10] FANG Y C, ZHANG H Q, XU Y Y, et al. CT manifestations of two cases of 2019 novel coronavirus (2019-nCoV) pneumonia[J]. Radiology, 2020. DOI: 10.1148/radiol.2020200280

[11] Jin Yinhua, Chen Bin, Zhang Jingfeng, et al.Value of chest CT imaging in prevention and control of novel coronavirus pneumonia epidemic[J]. Modern Practical Medicine, 2020，32（2）

[12] MAMOM, J. (2020) Digital Technology: Innovation for Malnutrition Prevention among Bedridden Elderly Patients Receiving Home-Based Palliative Care. Journal of Hunan University Natural Sciences, 47 (10), pp. 165-169.

[13] PANWAR, H., GUPTA, P.K., SIDDIQUI, M.K., MORALES-MENENDEZ, R., and SINGH, V. (2020) Application of deep learning for fast detection of COVID-19 in X-rays using nCOVnet. Chaos, Solitons and Fractals, 138, 109944.

[14] MAHMUD, T., RAHMAN, M.A., and FATTAH, S.A. (2020) CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization. Computers in Biology and Medicine, 122, 103869.

[15] VARELA-SANTOS, S. and MELIN, P. (2021) A new approach for classifying coronavirus COVID-19 based on its manifestation on chest X-rays using texture features and neural networks. Information Sciences, 545, pp. 403-414.

[16] Kermany D S, Goldbaum M, Cai W J, et al. Identifying medical diagnoses and treatable diseases by image-based deep learning[J]. Cell, 2018, 172(5): 1122-1131.