International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

COVID-19 Diagnosis System

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ABSTRACT

The coronavirus disease is rapidly spreading around the world. The design and implementation of COVID-19 testing kits remains an open research problem. Several findings attained by the use of radiology imaging approaches recommend that the images comprise important data related to corona viruses. The radiological imaging finds useful to precisely detect and classify the disease. The proposed model comprises major processes namely pre-processing feature extraction and classification. The u-net segmentation model incorporates the deep learning (DL) features utilizing convolutional neural network (CNN) based technique. To further improve the performance of learning rate scheduler using u-net has been applied. At last, multilayer perceptron (MLP) is employed to carry out the classification process. The experimental validation of the proposed model takes place using chest x-ray dataset and the experimental outcome defined the superior performance.

INTRODUCTION

The coronavirus disease is rapidly spreading around the world. The COVID-19 pandemic is rising in an exponential rate, with the accessibility of restricted number of rapid test kits. So, the design and implementation of COVID-19 testing kits remains an open research problem. Several findings attained by the use of radiology imaging approaches recommend that the images comprise important data related to corona viruses. Corona virus has showed its rapid evolution from 28 January 2020. At that time, there were around 4600 COVID -19 affected cases in many countries and 160 mortalities in 15 February 2020. Now, these cases get increased to 9 9.94 million and 497000 mortalities. Wuhan city in China has been quarantined in 23 January 2020 without transportation inside and outside the city. These primary measures were prolonged in the subsequent days to the nearby cities of Huanggang, Zhijiang, chibi, Jingzhou and Ezhou. Common symptoms of this virus are dry cough, fever, and breath shortness. Also, muscle pain, sputum production, and sore throats are mild symptoms of the COVID-19. Protect yourself and others from infection by staying at least 1 metre apart from others, wearing a properly fitted mask, and washing your hands or using an alcohol-based rub frequently. Get vaccinated when it's your turn and follow local guidance. The virus can spread from an infected person's mouth or nose in small liquid particles when they cough, sneeze, speak, sing or breathe. The radiological imaging finds useful to precisely detect and classify the disease. DL is one of the common research domains in AI which allows creating end to end technique to attain assured outcomes utilizing intake data without the help of manual feature extraction. DL method have been effectively used in number of issues like such as segmentation, pneumonia detection from chest X-ray images. The virus is quickly raising the needed for knowledge in this domain. It has improved the awareness in evolving the automatic detection technique based on AI method. It is a risky process for providing physicians to all hospitals because of inadequate radiologists count. Thus, the modest, precise, and fast AI methods might be useful for overcoming this issue and give support to patients in correct time.

This paper introduces an effective fusion model of hand crafted with deep learning features called radiomics model for COVID-19 diagnosis and classification. The proposed model comprises major processes namely feature extraction and classification.

IMAGE PROCESSING TECHNIQUES

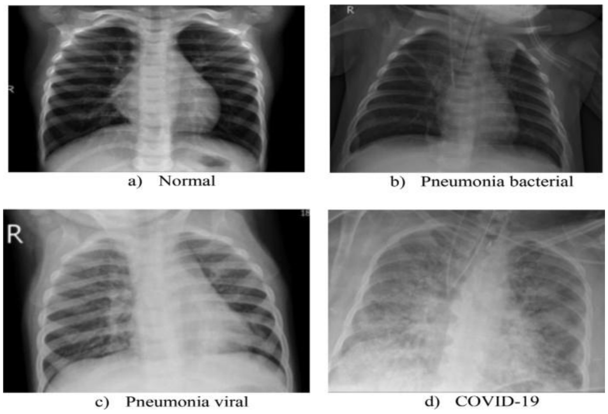
Digital image processing comprises the manipulation of images by the use of digital computers. In past decades, images have been exponentially increased. Some of the image processing applications are medical imaging. An image can be treated as a function ff (xx, yy) of two continuous variables x and y. For processing the digital images, it has to undergone sampling and transformation of the data into a matrix of numbers. Image analysis models allow processing of images for extracting the information in an automated way. Some instances of image analysis are image segmentation, edge extraction, texture and motion analysis. A significant feature of images is the requirement of large quantity of information to represent them.

Feature Descriptors

The feature extraction using radiomics model and text. The model has extraction for image analysis and resize and shape. Classification usingKernel ELMmodel, this classification using parameter of input weight and hidden randomly with simple kernel function. Unet use the segmentation of image for best method in CNN based technique.To further improve the performance of learning rate scheduler using u-net has been applied. At last, multilayer perceptron (MLP) is employed to carry out the classification process. The experimental validation of the proposed model takes place using chest x-ray dataset and the experimental outcome defined the superior performance.

Data set

The collecting image obtained from Kaggle repository "chest x-ray image". Image contains in radiologic type. Dataset available image collection by covid, normal, Pneumonia Bacterial, PneumoniaViral. The dataset consists of 320 covid ,446 normal,449 pneumonia bacterial and 424 pneumonia viral. Then using resize image in dataset.



Sample of chest x-ray image

LITERATURE REVIEW

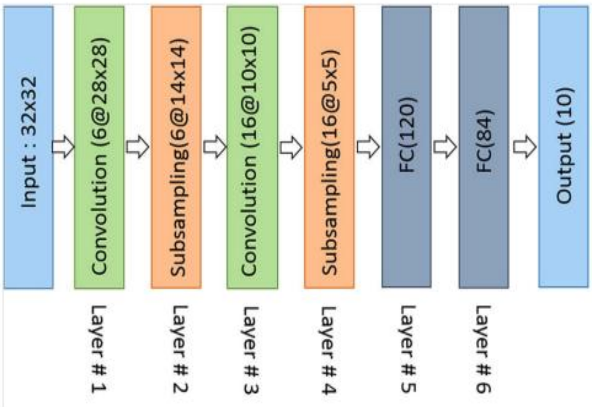
The research carried out on covid 19 detection. in December 2019, the first infectious new Coronavirus case (COVID-19) was discovered in Hubei, China. to emphasize the relevance of artificial intelligence (AI) using many methods. This article proposes an Artificial Intelligence-based solution to fight the infection (AI). To achieve this aim, Deep Learning (DL) approaches such as Generative Adversarial Networks (GANs), Extreme Learning Machine (ELM), and Long/Short Term Memory (LSTM), etc.

Long /short term memory (LSTM)

A Recurrent Neural Network (RNN) is widely utilized for dealing with variable-length sequence inputs. This method using hidden vector repossible for storing the long-distance historymodel to solve N instability and gradient vanish problems d to compute a balanced summation of input signa. This model accuracy value is 73.9%.

LeNet

Hence, LeNet has been presented in 1990s with restricted ability in performing the operation which has the influence to execute any functions. Lenet a CNN including back-propagation technique and implemented on handcraft digital database in order to attain the accuracy in state-of-the-art. Thus, the projected CNN architecture is as familiar as LeNet-5.



LeNet Architecture

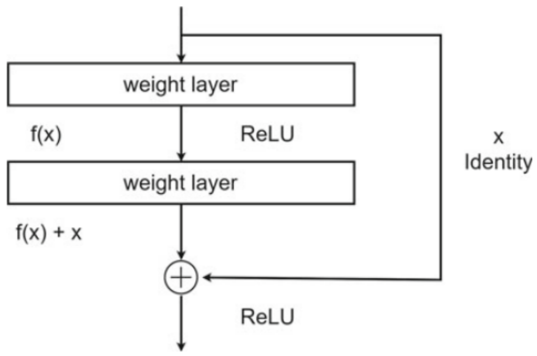
The basic structure of LeNet architecture has two convolution layers, two sub-sampling layers, two FC layers and single output layer along with Gaussian association. Therefore, amount of weights as well as multiply and Accumulates (MAC) are said to be 431k and 2.3M correspondingly. Since the hardware function is enhanced in terms of ability, CNN has been developed for performing efficient learning technique with respective to computer vision and ML concepts.

Alex Net

Alex net presented a CNN method when compared to LeNet, it has a complex ImageNet problem in recognizing visual object which is named as ImageNet Large Scale Visual Recognition Challenge (ILSVRC). it is an important factor in the domain of ML and computer vision which is mainly used for visual recognition and classification tasks which leads to rapid improvement in DL. This model accuracy value is 80.2%.

Resnet

This model very important in CNN architecture. Resnet is small limited in data size, which have a large number of parameters in train. The specific classification model in image using image net. This model accuracy value is 85.4%.



Coronet

Coro net presented a CNN method when compared to Resnet. the model is based on Xception architecture pre-trained on ImageNet dataset and trained end-to-end on a dataset prepared. Thismodel, using results with minimum pre-processing of data, not using non -trainable parameter.This model accuracy value is 83.5%.

PROPOSED SYSTEM

U-net segmentation is a convolutional neural network that was developed for image segmentation . The major processes namely feature extraction and classification.

U-Net architecture

U-NETmodel using image understanding and segmentation. Image used feature extraction and classification image in u-net segmentation.

METHODOLOGY

Convolution layer

Convolution layer gets varied from a NN where not all pixels are linked to upcoming layer with a weight and bias, however the whole image is divided into tiny regions and weights and bias are used. Such weights and bias are named as filters or kernels that are convoluted with all small regions in the input image that offers a feature map. Such filters are referred as simple ‘features’ which can be explores from input image in this layer. The count of parameters is essential for this convolution task might be lower as similar filter is traversed across the whole image for a single feature. The count of filters, size of local region, stride, and padding are referred as hyper parameters of convolution layer. According to the size and genre of an input image, the hyper parameters undergo tuning in order to accomplish optimal outcomes.

Activation function

Diverse activation functions were applied over different structure of CNN. Nonlinear activation functions have shown optimal outcome than former sigmoid or tangent functions. Such nonlinear functions are applied to enhance the training speed. Thus, various activation functions were applied and ReLU is remarkable than alternate models.

A CNN learning method is relied on the vector calculus and chain rule. Assume z be a scalar (i.e., $z \in R$) and $y \in R^H$ be a vector. Thus, when z is a function of y, the partial derivative of z interms of y is a vector can be determined as:

$$\left(\frac{\partial z}{\partial y}\right)_i = \frac{\partial z}{\partial y_i}$$

In particular, $\left(\frac{\partial z}{\partial y}\right)$ is a vector containing the similar size as y, and its i-th element is $\left(\frac{\partial z}{\partial y}\right)_i$. And, it is noticeable that $\left(\frac{\partial z}{\partial y^T}\right) = \left(\frac{\partial z}{\partial y}\right)^T$. In addition, assume $x \in R^W$ is another vector, and y is a function of x. After that, the partial derivative of y interms of x is determined by:

$$\left(\frac{\partial z}{\partial y^T}\right)_{ij} = \frac{\partial y_i}{\partial x_i}.$$

In the fractional derivative is a $H \times W$ matrix, it is accessed at the juncture of the i-th row and j-th column is $\frac{\partial y_i}{\partial x_i}$. It can be simple to see that z is a function of x in a chain-like argument. Also, a function maps x to y, and another function maps y to z. The chain rule is utilized to compute as follows:

$$\left(\frac{\partial z}{\partial x^T}\right), \text{as} \left(\frac{\partial z}{\partial x^T}\right) = \left(\frac{\partial z}{\partial y^T}\right)\left(\frac{\partial z}{\partial x^T}\right)$$

The cost or loss function is utilized for measuring the difference among the prediction of a CNN x^L and the goal t, $x^1 \to w^1, x^2 \to \cdots, x^L \to w^L = z$, utilizing a simplistic loss function $z = \|t - x^L\|^2$. The predictive outcome is seen as $\text{argmax}_{x_i} x_i^L$. A convolution method is represented as follows:

$$y_{i^{l+1},j^{l+1},d} = \sum_{i=0}^{H}\sum_{j=0}^{W}\sum_{d=0}^{D} f_{i,j,d} \times x^L_{i^{l+1}+i,j^{l+1}+j,d}$$

The filter f has size $(H \times W \times D^l)$, so that the convolutional contains the spatial size of $(H^l - H + 1) \times (W^l - W + 1)$ with D slices and implies that $y\left(x^{l+1}\right)$ in $R^{H^{l+1} \times W^{l+1} \times D^{l+1}}$, $H^{l+1} = H^l - H + 1$, $W^{l+1} = W^l - W + 1$, $D^{l+1} = D$.

The possibility of all labels $k \in \{1, \ldots K\}$ is applied to train instance is calculated by $P(k|x) = \frac{\exp(z_k)}{\sum_i^K \exp(z_i)}$, where z is a non-normalized log possibility. A ground truth shared over labels $q(k|x)$ is normalized, in order that $\sum_k q(k|x) = 1$. During this method, the loss is provided by cross-entropy as defined below:

$$l = \sum_{k=1}^{K} \log\left(p(k)\right) q(k)$$

The cross-entropy loss is differentiable in terms of the logit z_k and so it is utilized to gradient training of deep methods, as the gradients has the easier form $\frac{\partial l}{\partial z_k} = p(k) - q(k)$, bounded among −1 and 1. Generally, if the cross entropy gets minimized, it implies that the log-possibility of the accurate label is maximized. Inception V3 is regarded as shared above labels independent of training instances $u(k)$ with a smooth parameter ϵ, as to a train instance, the label shared $q(k|x) = \delta_{k,y}$ is easily returned by:

$$q^{'(k|x)} = (1 - \epsilon)\delta_{k,x} + \frac{\epsilon}{K}.$$

Otherwise, these are interpreted as cross-entropy as given below:

$$H(q', p) = -\sum_{k=1}^{K} \log(p(k))\, q^{'(k)} = (1 - \epsilon)H(q', p) + \epsilon H(u, p).$$

So, the label-smoothing regularization is same for executing a single cross-entropy loss $H(q, p)$ with a couple of losses $H(q, p)$ and $H(u, p)$, with the second loss penalizing the variation of the forecast label shared p from the prior u with comparative weight $\frac{\epsilon}{(1-\epsilon)}$.

MLP based Classification

MLP network consists of 3 layers namely, input, hidden, and output layers. An MLP network is capable to have massive hidden layers by activating the network to hold processing abilities to produce system outputs. Fig. 4 implies an MLP network with 1 hidden layer, which has few weights connecting among layers. The final outcome scores would be determined by the given procedures. Initially, the addition of weights is estimated in the following:

$$S_j = \sum_{i=1}^{n} w_{ij} x_i + \beta_j,$$

where x_i denotes an input variable, w_{ij} defines the weight among input variable x_i and neuron j, and β_i depicts the input variable's bias term. Then, neurons' final values in hidden layers are produced from obtained values of weighted summation (Eq. (17)) by an activation function. A well-known choice of these functions is said to be a sigmoid function in the following:

$$f_j(x) = \frac{1}{1 + e^{-S_j}},$$

where f_j represents the sigmoid function for neuron j and S_j refers the sum of weights. As a result, the result of neuron j is determined in the following:

$$y_j = \sum_{i=1}^{k} w_{ij} f_j + \beta_j,$$

where y_j signifies the result of neuron j, w_{ij} denotes the weight from output variable y_i and neuron j, f_j indicates the activation function for neuron j, and β_i depicts the final variable's bias term.

The work technique for U-net segmentation. The u-net is convolutional network architecture for fast and precise segmentation of image, it is best method for image.

Feature Extraction:

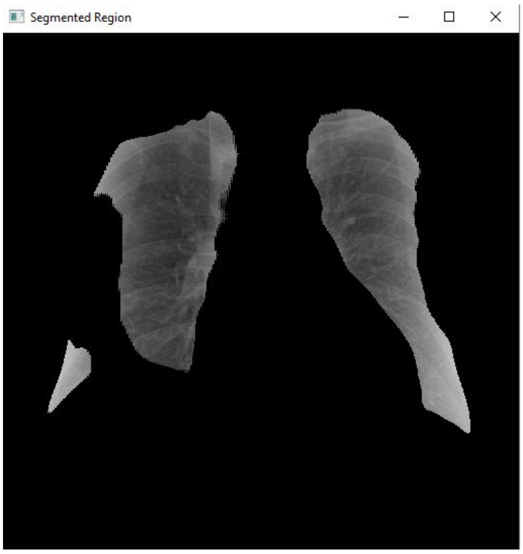
The radiomic feature can be divided into group like size and shape. Thistechnique used to extract a large number of quantitative features from radiography image. It is most easily as "Image analytics".

Classification

Extreme learning machine (ELM) is essentiallya single hidden layer feed forward neural network (SLFN). It determines the initial parameter of input weight and hidden biases randomly with simple kernel function.

Lung Mask

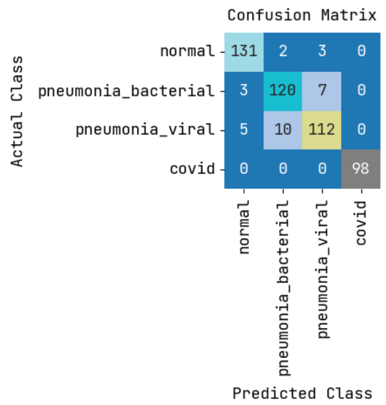
Mask Draw

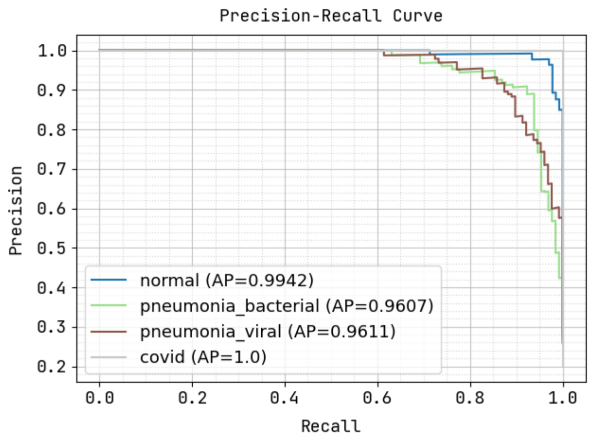


Segmented Region

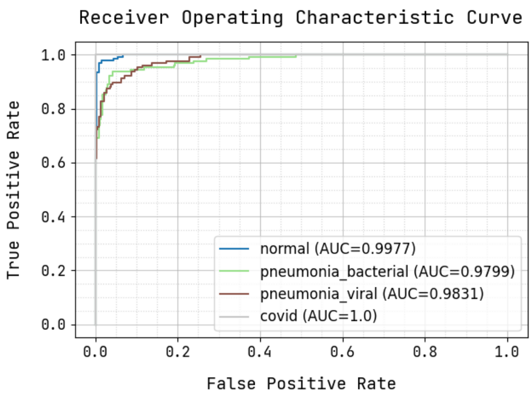
Results

The dataset used chest x-ray image. The proposed model using u-net segmentation for image. The requirement for package is tensor flow is backend for image.segmented use for mask draws in image. The performance of the model confusion matrix. The measure the performance Accuracy,92.74, Precision 93.23, Recall 93.17, F1-Score93.12. finally proposed model compare between the covid and normal and pneumonia bacterial and pneumonia viral. The result is covid disease will be positive or negative.





Confusion matrix **Recall curve**



Receiver operation characteristic curve

CONCLUSION

The coronavirus disease is rapidly spreading around the world. The dataset using chest x-ray image. The U -net developed for image segmentation. The model has been trained and testing on dataset and image prepared for pneumonia case and covid case and normal case.The major processes namely data preparation, segmentation, feature extraction and classification. The proposed model better accuracy in image.

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