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ADVANCED DEEP LEARNING APPLICATION IN COVID-19 DETECTION FROM X-RAYS IMAGES

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ABSTRACT

The COVID-19 virus causes respiratory and pulmonary infection. Coronavirus belongings to the positive sense single standard RNA β family that has similar genetics to SARS. Globally, the exponential increase in Covid19 patients is overwhelming healthcare systems. Getting patients who are infected with coronavirus treated expeditiously and isolated to limit the spread of the illness is a crucial step in combating Coronavirus. As a result, we must use a variety of methods to identify Coronavirus in chest x-ray images. Radiologists examine chest radiographs for visual indicators that can point to Covid-19 infection in severe acute respiratory syndrome (SARS) cases. A chest radiograph is used to detect the virus. We propose, train and test a new Convolutional neural network (CNN) model with 7154 images of affected and non-affected patients with Coronavirus cases. To provide accurate diagnosis of multiple classification system, the proposed model was developed. Too, we propose an image pre-handling stage with image enhancement technique for training and to generate a trustworthy image dataset for testing and upgrade deep learning algorithm models. We direct to diminish undesirable noise in the images by using filters so the deep structured learning models can emphasis exclusively on identifying illnesses by explicit features. To extract deep features, we used pretrained deep Convolutional neural network models. In order to classify, Support Vector Machine (SVM)classifiers were combined with numerous kernel functions, the purpose of Support Vector Machine (SVM) is to solve linear and nonlinear problems. Likewise, the Histogram of Oriented Gradient (HOG) has been used for feature extraction since it is an accepted method that can retrieve features from all areas of an image. A HOG analysis with SVM produced 98.86% accuracy for the Covid-19 infection. The accuracy of our experiment using the CNN model was 99.79%, with 91% sensitivity to identify Coronavirus infections. Though the analysis of chest x-ray information, deep learning is proven to be effective in the recognition of Coronavirus.

***Keywords**: COVID-19(coronavirus); Deep Learning; Chest x-ray images; Convolutional Neural Network models; Image processing*

1. INTRODUCTION

By the 19th of April 2020, the Covid-19 pandemic has killed close to 160,000 humans globally with 2.3 million infections [1]. Our review plans to enlarge a structure for supporting Coronavirus detection with the utilization of image characterization utilizing deep learning model. In addition, this study outlines a pre-handling strategy for further developing image quality for predictions based on deep learning algorithm. The Covid-19 virus causes respiratory and pulmonary infection. As a result of Covid-19 clinical characteristics, patients experience respiratory symptoms, fever, cough and dyspnea and viral pneumonia. These symptoms are the main cause of the main problem since asymptomatic virus infected patients present with these symptoms. Artificial intelligence and radiomics applied to x-ray are helpful tools in the recognition and continuation of the disease [2]. Radiomics characteristics got from chest radiograph and computer-based intelligence would be of extraordinary help with diagnosing Coronavirus. Convolutional Neural Network, which combines deep learning with Artificial neural network, possess demonstrate to be profoundly successful in a wide scope of clinical image classification applications. Recently, chest radiography images are utilized to screen Coronavirus. Deep learning techniques were used to achieve a better performance than customary machine learning approximate. The utilization of Convolutional Neural Network and TL techniques of deep learning makes the performance of COVID-19 detection task more accurate. Through the use of these techniques, the detection of diseases with COVID-19 is reduced. A novel technique is introduced for distinguishing Coronavirus disease using chest radiography images via ML architecture that combines characteristics extracted from Histogram oriented gradient (HOG), Support Vector Machine, and Convolutional neural network and then classified by the Convolutional neural network algorithm. As a brief introduction to this study, we describe recent scholarly works related to it.

2. RELATED LITERATURE

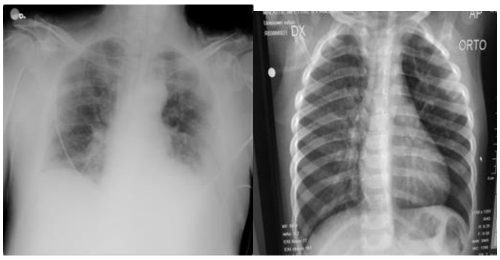
Experts have recently examined and investigated chest radiograph images deep learning to diagnose Coronavirus. The chest radiography images are pre-processed utilizing the Convolutional Neural Network (CNN) method to extract better characteristic, which are taken care of into deep learning algorithm to recognize Coronavirus.

Mangal et al. [3] presented a model that achieved 90.5% accuracy and 100% recall for covid-19 samples. To train the model, she included a random subset of pneumonia cases in each batch. However, the model suffers from many false negatives for normal cases. Linda Wang et al. [4], this paper presents Coronavirus net, space invariant artificial neural networks scheme, intended for recognizing instances of Coronavirus from chest x-rays utilizing deep learning; the model exhibits large parameter truncation on the Covid-19 class and has low inexact negative rate for this class of Coronavirus. Ismail A.M et al. [5] Researchers extracted deep features from 180 covid and 200 normal images with 6 pretrained CNN models, and classified them with SVM,94.7% precision was accomplished with the deep features extricate from the Resnet 50 model and the Support Vector Machine classifier. F.A, Saiz, I Barandiaran et al. [6] In this review, an object recognition architecture is proposed and prepared with dataset images of disease-free and Coronavirus patients as well as pneumonia. It likewise further develops typical image recognition, limits false positives, and accomplishes an accuracy level of 94.92%. T. Ozturk et al. [7] This paper proposes another model for automatic detection of Coronavirus utilizing untreated chest x-rays images. The proposed model gives determination 98.08% precision in binary classification and 87% in multi-class classification by utilizing untreated images. Michael J Horry et al. [8] The researchers proposed a semi-automated pre-processing model for creating image datasets for testing and developing deep learning models, provided an algorithm to remove sampling bias and obtained 93% accuracy. Nur-A-Alam et al. [9] In this review, Histogram oriented Gradient (HOG) and CNN fostered a smart system for Coronavirus distinguishing proof that had high exactness. Most published studies have used chest x-rays images to analyze Coronavirus. In spite of this, irregular characteristics in information control and an absence of extracted features from the images can sometimes undermine performance expectations. To further develop the detection exactness of the Coronavirus, this work suggested combination of features extracted by HOG, CNN, and SVM, as well as ordering utilizing CNN.

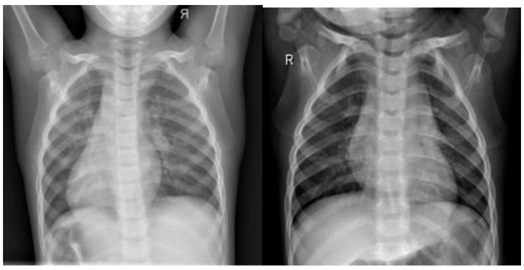
3. MATERIAL AND APPROACHES

Chest X-ray dataset:

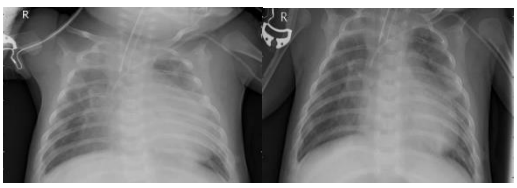
Coronavirus was analyzed in this research utilizing chest radiography images which we have taken from two distinct sources. Enzo et al. [10] ordered a data set of Coronavirus x-ray images from different opensource access hotspot for use in this review. Images from the database are consistently refreshed with images given by scientists all through the world. Images from the chest radiography database provided by Kermany et al. [11] were used to capture images of normal and pneumonia. Our study avoided unbalanced data problems by using 1657 chest x-ray with no findings,4079 chest x-ray with pneumonia, and 2634 frontal covid-19 images randomly selected from this x-ray database. Python was used to execute all necessary experiments. Figure1 shows an example of a few covid-19 cases found in this database.



(a)



(b)



(c)

Figure1. Images of (a) Coronavirus, (b) Normal and (c) Pneumonia dataset

The Coronavirus influences the lungs likewise to pneumonia. The expanded lung thickness causes whiteness in the lungs on radiography. An accomplished radiologist might have the option to affirm the disease by the presence of a ground-glass opacity in the lungs because of the expanded whiteness [9].

4. PROPOSED APPROACH MODEL

Using Deep Learning technique, we strive to achieve better results. Through various deep learning techniques like Convolutional Neural Network (CNN), we have improved the performance of covid-19 detection. COVID-19 was identified by using the input of x-ray images. Image pre-processing is a crucial step as it removes noise from each image and resize it to 224×224 pixels. In order to make this system responsive, the images were first converted to grayscale, and unwanted regions were removed, in order to prepare the input images for use by the system. Then, deep feature extraction was performed with the fusion of HOG, CNN and SVM. We have used two approaches to obtain characteristic vectors from the chest radiography Coronavirus images. Earlier, we have used HOG to extricate features vectors. Next, we used CNN to extract feature vectors from the same image. Then we used SVM to extract useful features and fine -tune a model. From that point forward, the CNN model was trained with VGG19 and the epsilon value of Support Vector Machine (SVM) with linear function was 0.4. Finally, CNN classifier ascertained whether or not it was coronavirus. The figure 2 illustrates the process of developing the proposed approach architecture.

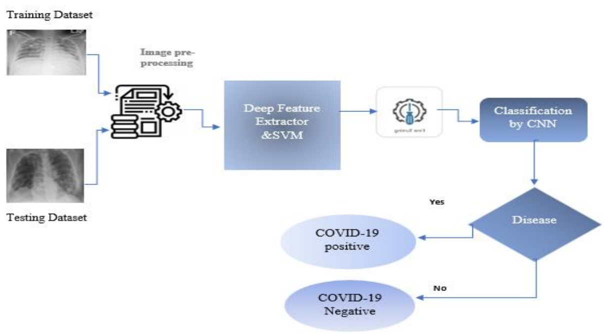


Fig 2. Proposed system architecture

5. INFORMATION PRE- PROCESSING

Image preprocessing is among the main issue in data science community, but developers used a variety of tools and platforms to accomplish it. Python, open cv, karas, tensor flow and pillow are some of the software systems that are used for image pre-processing. In the case of image data, a few problems include complexity, inaccuracy and inadequate, which is why, before using a computer vision model, it is imperative that it is pre-processed to achieve the desired results. We performed image pre-processing to remove noise and deformed pixels from each image in order to achieve accurate classification. we convert the rgb images into grey scale images and resized them to 224×224 pixels. As part of training and testing procedure, the region of interest on the chest radiography was characterized by a district covering fundamentally the lung region. An example image at several stage of pre-processing is illustrated in figure 3. Image segmentation can help to obtain ROI and then pre-processing method can be employed to normalize the image s so that the ROI could be determined independently of the origin. Furthermore, the size effect of the image on system performance will be avoided, and an edge-based image segmentation algorithm will be used to remove unwanted and unnecessary data from the image as shown below.

Fig 3. Image pre-processing

6. DEEP FEATURE EXTRACTOR

Histogram Oriented Gradient:

The Histogram of oriented gradient is one more characteristic descriptor utilized in image synthesis. It distinguishes objects in an image. HOG method obtains features by utilizing a specific number of histogram bins [12]. Histogram oriented gradient characteristics are removed by analyzing the structure or the shape of the object. For area of the image, it makes Histograms involving the size and direction of the angle as displayed in fig 4. In the initial step, resize the information image to 128×64 pixels and calculate HOG features. The gradient of the image was computed using equation 1

$$\mathbf{C_x = L\ (x, y+1) - L\ (x, y-1)} \quad \mathbf{(1)}$$

$$\mathbf{C_y = L\ (x-1, y) - L\ (x+1, y)} \quad \mathbf{(2)}$$

whereas C_x and C_y are horizontal and vertical slope and angle of each pixel is calculated using equations 3 and 4

$$\text{Angle } (\theta) = |\tan^{-1} \left|\left(\frac{C_y}{C_x}\right)\right| \quad (3)$$

$$\text{Magnitude } (\mu) = \sqrt{(C_x)^2 + (C_y)^2} \quad (4)$$

For each block, a 9point histogram is calculated. The gradient image is then normalized by dividing it into 16×16 cells. Four 8×8 cells are then combined into one 16×16 block. The 9point histogram produces a histogram with 9 bins, with each bin having an angle range of 20 degrees.

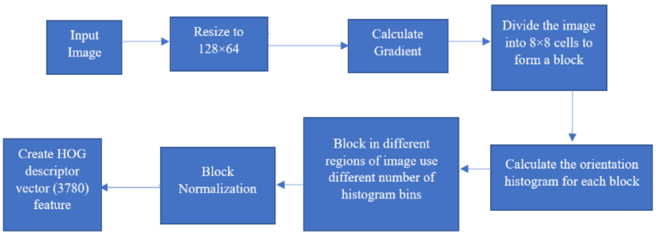


Fig 4. Histogram oriented gradient feature extractor algorithm

Since we are using 9point histograms, we find the following range of angles as:

Number of bins = 9(ranging from $\mathbf{0^0}$ to $\mathbf{180^0}$)

$$\text{Step size } (\boldsymbol{\Delta\theta}) = \frac{\mathbf{180^0}}{\textbf{Number of bins}} = 20 \text{ degree}$$

Scientifically,

$$W_{ai} = [a_1, a_2, a_3\ldots\ldots\ldots\ a_{36}] \quad (5)$$

Values of W_{ai} for each block is normalized by the L_2norm.

$$\boldsymbol{w_{a_i}} \Leftarrow \frac{\boldsymbol{w_{ai}}}{\sqrt{\|\omega_{a_i}\|^2 + \varepsilon}} \quad (6)$$

By adding $\boldsymbol{\varepsilon}$ to the square of $_{Wa}$, a zero-division error is prevented. To normalize Z, the following formula is used,

$$Z = \sqrt{(\boldsymbol{a_1})^2 + (\boldsymbol{a_2})^2 + (\boldsymbol{a_3})^2 + \cdots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (\boldsymbol{a_{36}})^2} \quad (7)$$

$$\boldsymbol{w_{ai}} = \left[\left(\frac{\boldsymbol{a_1}}{\boldsymbol{k}}\right), \left(\frac{\boldsymbol{a_2}}{\boldsymbol{k}}\right), \left(\frac{\boldsymbol{a_3}}{\boldsymbol{k}}\right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \left(\frac{\boldsymbol{a_{36}}}{\boldsymbol{k}}\right)\right] \quad (8)$$

After this normalization is done, 105 blocks of 16×16 are attainable (7×15 blocks of 16×16). Each of these 105 blocks has an equal length, so the total HOG length will be 105×36×1 = 3780. HOG features are then obtained from selected images.

Support Vector Machine (SVMs):

In SVM classifiers, the objective is to make a choice limit that segregates n - dimensional space into classes, which can be combined with various lines on the decision boundary to create the best classification model. The SVM classifiers were created by Vapnik (Widodo and yang, 2007). An optimal hyperplane characterizes a decent decision boundary. The best hyperplane for separating positives from negatives can be found with SVM classifier. The linear detachment of positives and negatives can be taken care of with condition as shown below,

$$\boldsymbol{f(x) = Z_x^L + b} = 0 \quad (9)$$

Where Z^L specify the scalar vector and b is reference value used to decide the place of the hyperplane.

If there exist a function that can calculate the dot product in the same way as when we transform data to a higher dimension, it can be used as a kernel trick. Kernel function can be used to classify non- linearity separable data, while margin can be written as $\frac{1}{|Z^L|}$. SVM objective is reduced to

maximizing the term $max \frac{1}{\|Z^L\|}$, as optimal hyperplane maximizes margin.

$$\boldsymbol{max \frac{1}{\|Z^L\|}} \quad (10)$$

which can be written as, min$\|Z^L\|$. The above equation can be written as

$$\boldsymbol{min \frac{\|Z^L\|^2}{2}} \quad \textbf{(11)}$$

Convolutional Neural Network:

In Convolutional neural network, one system extracts input image features, while another uses the extracted signals to classify the image features. The input image is fed into the feature extraction network, and the extracted feature signal are used by the second neural network for classification [14]. The fundamental structure block of a CNN architecture is made out of convolution, normalization and pooling layers. These layers extract features from the input, applying a pooling layer to lessen the size prior to applying the principal layer, and there are two fully connected layers which contains neural network and create output in view of element information got from the convolutional layer. Furthermore, the result feature map is acquired in equation, where w^{L-1} demonstrates features got from the past layers.

$$\boldsymbol{w_j^L = f \sum_{i\varepsilon M_j} w_j^{L-1} * X_{i_j}^2 + b_j^2} \quad (12)$$

Fully connected layer gives discriminative features to the characterization of the data images into various classes by means of its completely fully connected layer $\boldsymbol{X_{i_j}^2}$ and $\boldsymbol{b_j^2}$ respectively. Bias prevents overfitting during CNN training. Adjustable kernels and training bias can be applied at this layer.

7. CLASSIFICATION AND FEATURE FUSION

A feature vector is produced by combining 1×4096, 1×3780, and 1×4096 with an 81 support vectors by applying the three main feature fusion methods. This feature selection process is mathematically described by equation.[9].

$$f_{HOG1\times N} = \{_{HOG_{1\times2}} + {}_{HOG_{1\times3}} \dots\dots\dots\dots {}_{HOG_{1\times n}}\} \dots\dots\dots\dots (13)$$

$$fVGG19_{1\times n} = Vgg19_{1\times1}, Vgg19_{1\times2} \dots\dots\dots Vgg19_{1\times n------}(14)$$

$$fsvm_{1\times o} = fsvm_{1\times1}, fsvm_{1\times2}, \dots\dots\dots\dots.. fsvm_{1\times m} ----(15)$$

$$(\text{Features Fusion})_{1\times9} = fHOG_{1\times N}, fVGG19_{1\times n}, fsvm_{1\times o} \text{ -(16)}$$

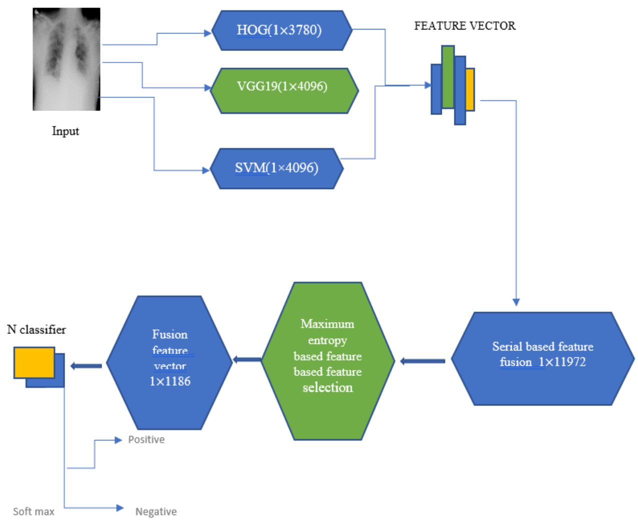


Fig 5 Feature Fusion of HOG, SVM and CNN

11972 features were intertwined with the HOG, CNN and SVM features and 1186 score-based characteristics together elements were chosen with respect to the premise of maximum entropy out of 11972 features to distinguish Covid-19 images. The quality vector got by Histogram oriented gradient and deep learning algorithm were likewise integrate to approve the proposed architecture in this work.

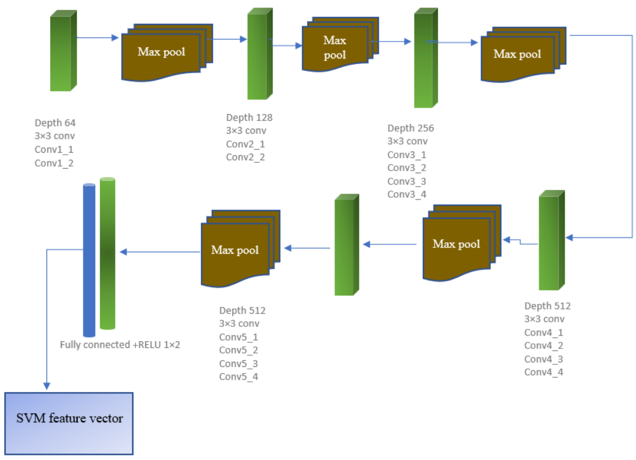


Fig 6 Architecture of VGG19

Our study built Vgg19 architecture consisting of 16 layers of CNN, so it is a sequential model, it includes convolutional layers with gradually increased no of filters such as 8,16,32. SoftMax is included three fully connected layers with one last output layer. The first two layers of the three layers give us 4096 features and 1000 channels respectively. The third layer address the output layer with three neurons (Covid-19, Normal and pneumonia).

8. FINE TUNING

It is important to train the model to fine tune it. To do this requires that not only the CNN architecture is updated, but that it is also retrained to learn new object classes.

9. DATASETS, EVALUATION AND RESULTS

To get a front facing perspectives on chest radiography images with pneumonia, as well as expected lungs, we use information from the Coronavirus chest radiography dataset [10] and the chest radiography pneumonia dataset [11]. Altogether ,1749 chest radiography images were utilized for preparing, testing and approval in this review, as displayed in Table 1 underneath.

Datasets	*Number of images*			*Total*
	Normal	Covid	Pneumonia	
Train	1341	1200	3671	6212
Val	8	1200	8	1216
Test	308	234	400	942

Table 1 Sample wise Data split

A sum of 1341 ordinary and 1200 positive Coronavirus images were utilized in this review for the purpose of training. To prepare the classifier, three kinds of images were required: positive Coronavirus images, as well as normal be expected and pneumonia images. The method incorporates 308 normal images and 234 Coronavirus positive images for testing. It additionally contains 942 validation images for both normal, pneumonia and Coronavirus classes. Three metrices were utilized to assess the method, which are precision, specificity and sensitivity. A few presentation boundaries were utilized to compute metrices for the identification of Coronavirus from chest radiography images. Four unique execution boundaries, including genuine positive (TP1), genuine negative (TN1), bogus positive (FP2), misleading negative (FN2), were utilized to compute the metrices as characterized by equation 17 ,18 and 19.

$$Accuracy = \frac{TP1+TN1}{TP1+TN1+FP2+FN2} \qquad (17)$$

$$Recall = \frac{TP1}{TP1+FN2} \qquad (18)$$

$$Precision = \frac{TP1}{TP1+FP2} \qquad (19)$$

As shown in the figure 7, the confusion matrix addresses a general system performance on the test information. As compared with pneumonia (‘2’) is a class that has a sensitivity value of 0.31, and the sensitivity value for COVID-19 (‘0’) is 0.91, which is different than pneumonia’s sensitivity (recall).

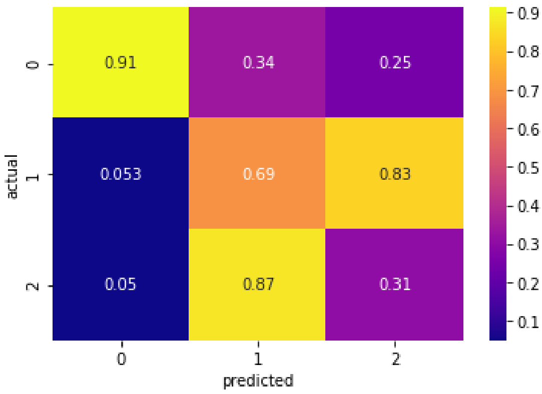


Fig 7. Confusion Matrix for our 3-class configuration

A 99.78% precision rate was accomplished for 3 class characterization setups. The outcome shows that this approach is capable for identifying Coronavirus from x-ray images with a mean AUROC of 0.99 for COVID-19 positive class for 3 class classification as shown in figure 8.

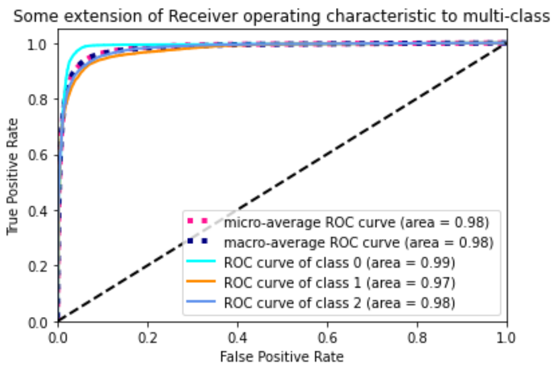


Fig 8. ROC curve for 3-class configuration

Our model performs well at classifying individual classes as indicated by the slightly different ROC and AUC values for each class. In the **Table2** below are the results for AUROC, sensitivity for each class.

Pathology	AUROC	Sensitivity
COVID-19 (0)	0.99	0.91
Pneumonia (2)	0.98	0.31
Normal (1)	0.97	0.69

Table 2. 3- class classification result

10. COMPARISON ANALYSIS

Scientists utilized various strategies, feature extraction methods, and classification procedures to analyze the chest radiography images to contrast our model with existing one. We utilized the significant datasets of chest radiography images to contrast our model and existing model. As shown in the table.3 below shows a comparison of relative classification accuracy for each technique for detecting COVID-19. It is decently plainly that the proposed procedure performed better compared to those proposed in the writing.

Table 3 Examination among existing techniques in the COVID-19 detection

References	Dataset	Methods	Accuracy
Ozturk et al. [7]	625 images (COVID-19 = 125 and Normal = 500)	Convolutional neural network (Dark Net)	98.08%
Mangal et al. [1]	6014 images (Covid-19 = 155, Pneumonia = 4273 and Normal = 1583)	Pre-trained model of Chex Net	90.5%
Ismael et al. [3]	380 images (Covid-19 = 180 and Normal = 200)	Res-Net50+SVM + Fine- tuned ResNet50	ResNet50+SvM achieved an accuracy of 94.7%,
MJ Horry et al.(2020)[9]	60798 images (Covid-19 = 115, Pneumonia = 322 and Normal = 60361)	VGG16 and VGG19 were used.	80%
Linda Wang et al. (2020) [2]	They introduce $Covid_x$ dataset that is comprised of 13975 images	This deep learning model (COVID-NET) was trained with $COVID_x$ dataset.	93.3%
Fatima A.saiz et al.(2020) [4]	1500 images of non-infected patients and infected with Covid-19 and pneumonia	SDD300 model	94.92% of sensibility
Nur-ul Alam et al .[10]	5980 chest X-ray images (COVID-19 = 1979 and normal = 3111)	Fusion Features (CNN+HOG) + VGG19 pretrained model	99.49%
Proposed model	8370 images (Covid-19 = 2634, Pneumonia = 4079 and Normal = 1657)	Fusion Features (SVM+HOG) + Fine tuning of CNN model +VGG19 pretrained model	99.78%

11. CONCLUSION

Convolutional neural network began to gain a tremendous momentum from near 2005 and since then, there have been thousands of highly robust and well performing CNN for almost every possible task. As per my analysis and understanding from previous literature and studies proposed using Convolutional neural network (CNN) one of the major contrastive explanations for various studies on CoVID-19 prediction is the difference in the preprocessing and the enhancements methods used onto images. We direct to diminish undesirable noise in the images by using filters so the deep structured learning models can emphasis exclusively on identifying illnesses by explicit features. To extract deep features, we used pretrained deep CNN models. In order to classify, SVM classifiers were combined with numerous kernel functions, the purpose of SVM is to solve linear and nonlinear problems. Likewise, the Histogram of Oriented Gradient (HOG) has been used for feature extraction since it is an accepted method that can retrieve features from all areas of an image. A HOG analysis with SVM produced 98.86% accuracy for the Coronavirus infection. The accuracy of our experiment using the CNN model was 99.79%, with 91% sensitivity to identify coronavirus infections. However, the examination of chest x-ray information, deep learning algorithms is demonstrated to be compelling in the detection of Covid-19. In addition, this model can be used to discover the rest of the diseases in our body as well.

REFERENCES

[1] WHO. "COVID-19 situation reports." https://protect- au.mimecast.com/s/w3GmCJyBPjF1nJg2uQNMQk?domain=who.int (accessed.

[2] S. Chauvie, A. De Maggi, I. Baralis, F. Dalmasso, P. Berchialla, R. Priotto P. Violino, F. Mazza, G. Melloni and M. Grosso, “Artificial intelligence and radiomics enhance the positive predictive value of digital chest tomosynthesis for lung cancer detection within SOS clinical trial,” European Radiology, p,1-7,2020.

[3] Arpan Mangal, Surya Kalia, Harish Raj Gopal, Kritika Rangarajan, Vinay Namboodiri, Subhashis Banerjee, and Chetan Arora. Covid aid: Covid-19 detection using chest x-ray, 2020.

[4] Wang L., Wong A., COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest radiography images, arXiv preprint arXiv:2003.09871 (2020).

[5] A.M. Ismael, A. Şengür, Deep learning approaches for COVID-19 detection based on chest X-ray images, Expert Syst. Appl. (2021). doi: 10.1016/j.eswa.2020.114054.

[6] Fatima A. Saiz, Iñigo Barandiaran: COVID-19 Detection in Chest X-ray Images using a Deep Learning Approach. Int. J. Interact. Multim. Intell. 6(2): 1-4 (2020)

[7] Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Acharya UR. Automated detection of COVID-19 cases using deep neural networks with X-ray images. Comput Biol Med. 2020; 121:103792.

[8] Michael J Horry, Subrata Chakraborty, Mano Ranjan Paul, Anwar Ulhaq, Biswajeet Pradhan, Manash Saha, Nagesh Shukla: X-Ray Image based COVID-19 Detection using Pre-trained Deep Learning. EngrXiv.pdf

[9] Nur-A-Alam, Mominul Ahsan, Md. Abdul Based, Zulfiqar Haider and Marcin Kowalski: COVID-19 Detection from Chest X-ray Images Using Feature Fusion and Deep Learning. https://doi.org/10.3390/s21041480

[10] Enzo Tartaglione, Carlo Alberto Barbano, Claudio Berzovini, Marco Calandri and Marco Grangetto." Unveiling COVID-19 from chest x-ray with deep learning: a hurdles race with small data". https://doi.org/10.48550/arXiv.2004.05405

[11] Kermany, Daniel; Zhang, Kang; Goldbaum, Michael (2018), "Labeled Optical Coherence Tomography (OCT) and Chest X-ray Images for Classification", Mendeley Data, v2. https://dx.doi.org/10.17632/rscbjbr9sj.2

[12] Xiang, Z.; Tan, H; Ye, W. The excellent properties of a dense grid-based HOG feature on face recognition compared to Gabor and LBP.IEEE Access 2018, 6, 29306-29319 [Cross Ref].

[13] Cleverley, J.; Jones, M.M. The role of chest radiography in confirming covid-19 pneumonia. BMJ 2020, 370. [Cross Ref] [Pub Med]

[14] Gao Huang; Zhuang Liu; Laurens van der Maaten; Kilian q. Weinberger." Densely Connected Convolutional Networks". https://github.com/liuzhuang13/DenseNet