B Tech -AIE

21AIE303 SIGNAL AND IMAGE PROCESSING

A HEALTHCARE SYSTEM FOR COVID19 CLASSIFICATION USING MULTI TYPE CLASSICAL FEATURES SELECTION

- Sowmya V (CEN)

Submitted by

Menta Sai Akshay	**- CB.EN.U4AIE20040**
Penaka Vishnu Reddy	**- CB.EN.U4AIE20045**
Sajja Bala Karthikeya	**- CB.EN.U4AIE20065**
Dharavathu Rohith	**- CB.EN.U4AIE20060**
Rachure Charith Sai	**- CB.EN.U4AIE20055**

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ABSTRACT

The coronavirus (COVID19), also known as the novel coronavirus, first appeared in December 2019 in Wuhan, China. After that, it quickly spread throughout the world and became a disease. It has significantly impacted our everyday lives, the national and international economies, and public health. However, early diagnosis is critical for prompt treatment andreducing trauma in the healthcare system. Clinical radiologists primarily use chest X-rays, and computerized tomography (CT) scans to test for pneumonia infection. We used Chest CT scans to predict COVID19 pneumonia and healthy scans in this study. We proposed a joint framework for prediction based on classical feature fusion and PSO-based optimization. We begin by extracting standard features such as discrete wavelet transforms (DWT),discrete cosine transforms (DCT), and dominant rotated local binary patterns(DRLBP). In addition, we extracted Shanon Entropy and Kurtosis features. In the following step, a Max-Covariance-based maximization approach for feature fusion is proposed. The fused features are optimized in the preliminary phase using Particle Swarm Optimization (PSO) and the ELM fitness function. For final prediction, PSO is used to obtain robust features, which are then implanted in a Support Vector Data Description (SVDD) classifier and Random Forest(RF) , Decision Tree (DT), KNN, . The experiment is carried out using available COVID19 Chest CT Scans and scans from healthy patients. These images are from the Kaggle website. For the proposed scheme, the fusion and selection process accuracy is 88.6% and 93.1%, respectively. A detailed analysis is conducted, which supports the proposed system efficiency.

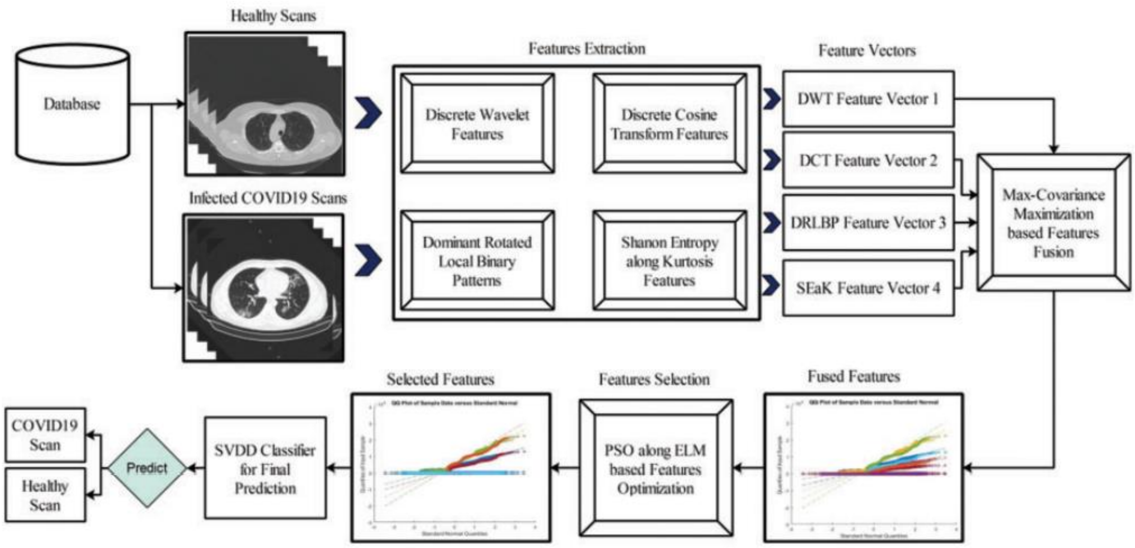
Introduction

The research on coronavirus is going on from the last two decade , however it got much intention by the researchers of Science & Engineering domain in general and Medical Sciences in particular after its spread in Wuhan city, Hubei Province in mainland China . Angiotensin-converting enzyme 2 (ACE2) is a receptor for SARS-CoV, the novel coronavirus that shows the random symptoms like fever, pain, nasal congestion, running nose and acute respiratory syndrome that in some serious situations leads towards death. The major human coronavirus category is SARS-CoV and the novel coronavirus SARS-CoV−2 that causes coronavirus disease in 2019 . Once it has been declared an epidemic, the health sectors of even first world countries were not equipped with necessary medical instruments required to cope with the influx of patients in any specified area . To date, the confirm corona virus cases are 4,253,802, worldwide. The total deaths are 287,250 and United State (USA) is a highly affected with this virus. The need of computer technology arises that provide the medical specialist an intelligent input about the incoming patient so the resources of the hospitals can be intelligently utilized. Keeping in view the great success of artificial intelligence methods in medical imagery a number of scientists undergoes exploitation to these tools in recent Covid-19 situation. In this regard the most recent literature survey is presented.

A predictive performance deep learning models based on neural network has been exploited to distinguished Covid-19 from community acquired pneumonia on chest by extracting the visual features from volumetric chest CT exams. The real time multi-step forecasting of Covid-19 to estimate its spread and its life span across the china is proposed in to help public health planning and policymaking. Identification of Covid-19 cases quickly to reduce spread in susceptible population a machine learning based method is proposed . The applicability of AI methods for detecting infected people using chest radiography images is an alternate quick method of accurate screening proposed in [8] using a deep convolution neural network, although the method required large dataset for better accuracy and reliability of the method. However, currently researchers facing the problem of the availability of Chest CT Scans. In this view, we believe that the employing of classical features like texture and local points are more effective to deal with less number of images. Therefore, we collected 16 patients data which publicly available. The data consists of both normal and confirmed COVID19 Pneumonia CT Scans

Proposed Methodology

In this work, we proposed a new method for prediction of COVID19 from Chest CT scans based on the fusion of multi-type features and particle swarm optimization–extreme learning machine (PSO-ELM) based features optimization. The proposed method is shown in figure below. In this Figure, it is shown that proposed method consists of four principle steps-multiple feature extraction using classical techniques(i.e., DCT, DWT, and DRLBP), Max-Covariance Maximization approach for fusion of all these features, optimization of features using PSO along ELM fitness function, and finally optimized features embed in SVDD classifier for final classification



Obtaining Multi Type Features

Using Discrete Cosine Transform (DCT)

- Image data after applying DCT is transformed into frequency domain where data with high frequency and low frequency can be separated. Low frequency features have high variation and contain useful information suitable for classification problems
- Input image and point (u, v) contain pixel value intensities

$$DCT\,(x,y) = \alpha\,(x)\,\alpha\,(y) \sum_{u=0}^{R-1} \sum_{c=0}^{C-1} Cos\left[\frac{\pi\,x}{2R}\,(2u+1)\right] Cos\left[\frac{\pi\,y}{2C}\,(2v+1)\right] \omega\,(u,v)$$

- R,C = Rows and Columns of the Input Image ; x = 0: N-1 , y = 0: M-1

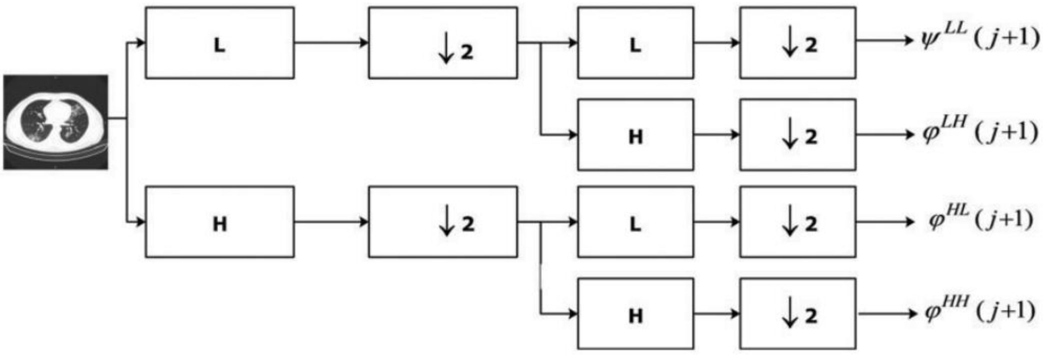
$$\alpha\,(x)\,,\ \alpha\,(y) = \begin{cases} \sqrt{\frac{1}{R}} & for \quad (x,y) = 0 \\ \frac{2}{R} & for \quad (x,y) \neq 0 \end{cases}$$

Using Discrete Wavelet Transform (DWT)

- DWT captures local information present in spatial domain and represents it in requency domain. DWT transforms the input image into four sub-bands at first level of decomposition. In wavelet we are using only Approximation Sub Bands not Detailed Sub Bands because approximation sub bands carry much of the information.

$$Dw\,(j,r,c) = \frac{1}{\sqrt{RC}} \sum_{u=0}^{R-1} \sum_{v=0}^{C-1} \omega\,(u,v)\;\; \psi_{j,r,c}\,(u,v)$$

$$Df\,(j_1,r,c) = \frac{1}{\sqrt{RC}} \sum_{u=0}^{R-1} \sum_{v=0}^{C-1} \omega\,(u,v)\;\; \varphi^{i}{}_{j,r,c}\,(u,v)$$



Using DRLBP

- The DRLBP(Dominant Rotated Local Binary Pattern) computes the feature in a local circular region by taking the difference of the central pixel with respect to its neighbors as presented in equation below:
- g_m and g_n are the gray level values of the middle pixel and its neighboring values

$$DRLBP_N = \sum_{n=0}^{N-1} s\,(g_n - g_m)\,.\,2^{\mathrm{mod}(n-D,N)}, \qquad s\,(g_n - g_m) = \begin{cases} 1 & g_m >= g_n \\ 0 & g_m < g_n \end{cases}$$

$$D = \underset{n\in(0,1,\ldots,N)}{\arg\max}\,(g_n - g_m)$$

Using Shannon Entropy Along Kurtosis

- Shannon Entropy is a measure of uncertainty or randomness of a probability distribution.

- Kurtosis is a statistical measure that describes the shape of a probability distribution. It is a measure of “Peakedness” of a distribution.

$$Kr\,(i) = \frac{E\,(\omega\,(u,v) - \mu)}{\sigma^4},\;\; \sigma = \sqrt{\frac{1}{(R-1)\,(C-1)}\sum_{u=1}^{R-1}\sum_{v=1}^{C-1} |\omega\,(u,v) - \mu|^2}$$

  - R,C = Rows and Columns of the Input Image
  - μ = mean of the image
  - σ = standard deviation the image

$$Kr\,(i) = \begin{cases} \widetilde{kr\,(i)} & for \;\; (x_1 \leq Kr\,(i) \leq x_2) \in \widetilde{Kr\,(i)} \\ Ignore & \quad Other\ features\ Values \end{cases}$$

Maximum Covariance-Based Features Fusion

Maximum covariance based features fusion is a technique used to improve the performance of machine learning algorithms by combining multiple features into one. The technique uses the maximum covariance between features to create a new feature that is more informative than the original features. This new feature is then used to train the machine learning algorithm, resulting in improved accuracy and performance.The process of maximum covariance based features fusion begins with the selection of the features to be combined. The features should have a high covariance so that the new feature created is more meaningful. Once the features have been selected, a model is trained on the data. The model is then used to generate the new feature, which is then used to train the machine learning algorithm.

Initially, We make the equal length of each vector based on their mean padding. After that, calculate the Maximum Covariance among pair of features. The positive maximum covariance value based features are shifted in a fused vector.

$$\mathbb{C} = Cov\,[a_1, a_2]$$

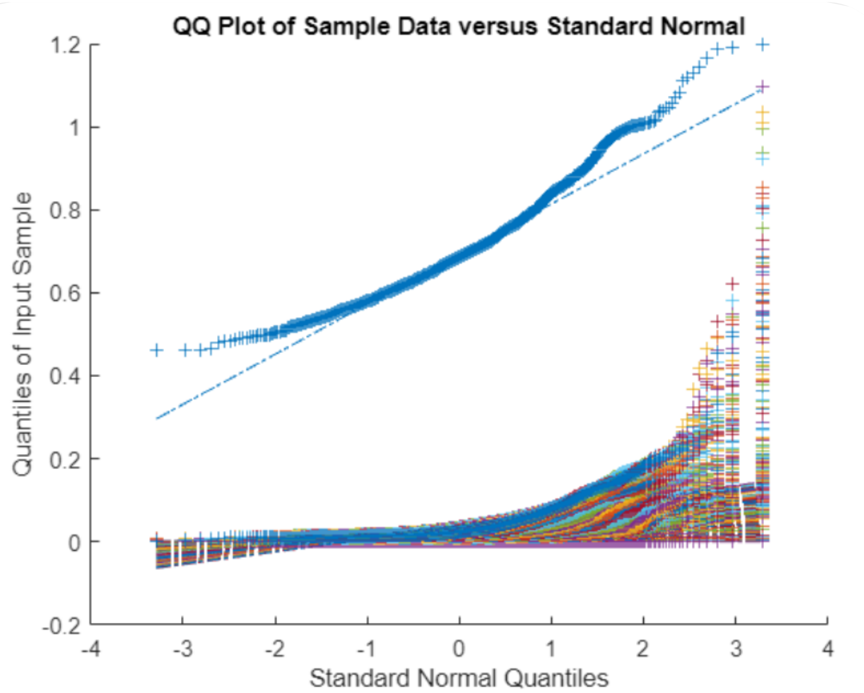
$$= Cov\left[x_1^T \Delta_1, x_2^T \Delta_2\right]$$

$$= \frac{1}{k-1}\left[x_1^T \Delta_1 \left(x_2^T \Delta_2\right)^T\right]$$

$$\mathbb{C} = x_1^T \boldsymbol{C}_{v_1 v_2} x_2$$

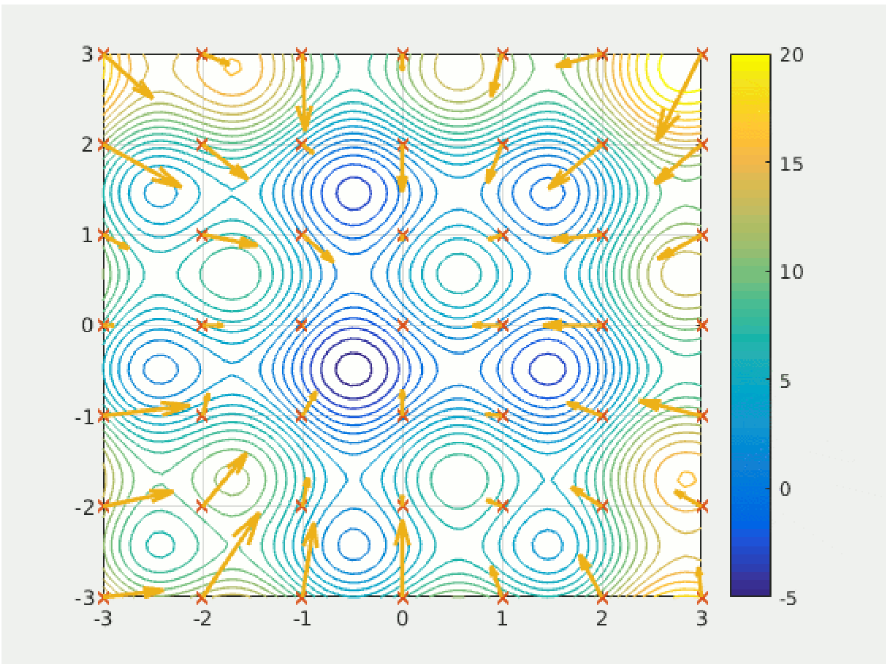
$$\boldsymbol{C}_{v_1 v_2} = \frac{1}{k-1} \Delta_1 \Delta_2^T$$

k represents the sample images that are used for feature extraction



Particle Swarm Optimization (PSO)

PSO is a computational method used for optimization problems in machine learning.PSO uses a population of particles that move through the search space, guided by the best position found so far by any particle in the swarm.The particles are guided by their own best position (pbest) and the best position found by any particle in the swarm (gbest).PSO is a global optimization method, which can find the optimal solution even if the initial conditions are not close to it.



Based on fitness function, if position of kth feature is 1, then taken this feature as a useful feature and if position of kth position feature is 0, then it not chosen. Mathematically, position and velocity of particle k is defined as follows:

Vk = vk1, vk2, ... vkd

Xk = xk1, xk2, ... xkd

Here, value of k = 1, 2, 3, ... n. ELM is employing is a fitness function to calculate the fitness of each particle. Initial best fitness of every particle is also its best so far and is denoted as $P_{best,k}$ and its best fitness function is represented by $fp_{best.}$ The global best position is represented by $g_{best,k}$. The velocity and position of each particle are updated using the following equations:

$$V_k^{t+1} = w\, V_k^t + c_1 r_1 (p_{best,k} - X_k^t) + c_2 r_2 (g_{best} - X_k^t)$$

$$X_k^{t+1} = X_k^t + V_k^{t+1}$$

Here w is weight inertia parameter and is used to control the impact of previous velocity in the new direction.

Algorithm 1: Features selection using PSO along with ELM Fitness Function

Input: Fused Feature Vector of Dimension $N \times K$
Output: Selected Feature Vector of Dimension $N \times \widetilde{K}$
Step 1: Parameter Initialization

- No of Selections = 500
- No of Populations = 100
- Max-Iterations = 500

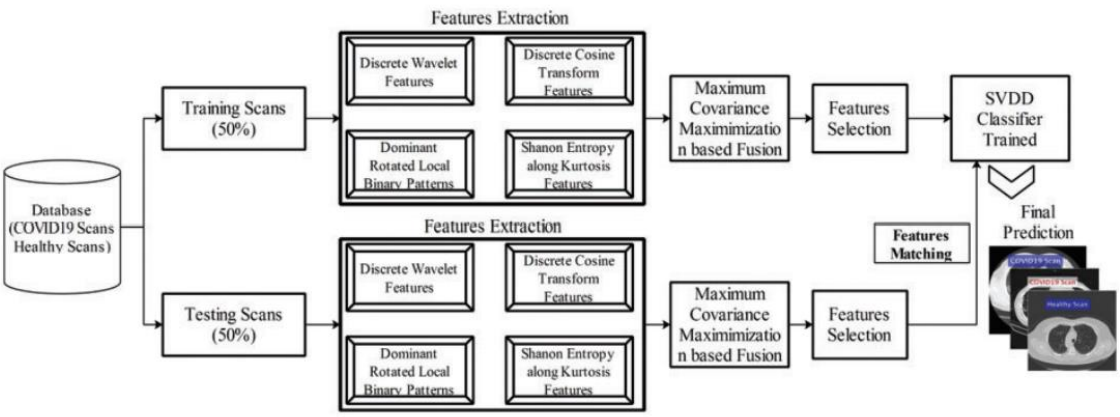
$V_k = v_{k1},\ v_{k2}, \ldots . v_{kd}$

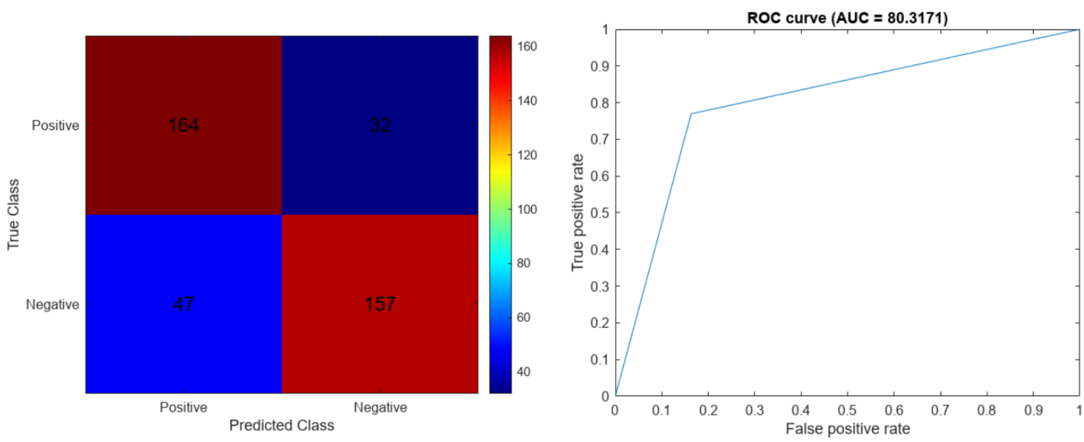
$X_k = x_{k1},\ x_{k2}, \ldots . x_{kd}$

Step 2: Calculate Fitness using ELM
Step 3: While End condition **do**
Step 4: Update $V_k \leftarrow V_k^{t+1}$
Step 5: Update $X_k \leftarrow X_k^{t+1}$
Step 6: Evaluate Fitness using ELM
Step 7: Best particles are updated
Step 8: Features are updated
Step 9: End While
A new informative feature vector is obtained of $\widetilde{K}$ dimension

Embedding Features in SVDD Classifier

The detailed experimental results are presented in this section with detailed quantitative measures and graphical plots. For detailed analysis of proposed results, two steps are followed- fusion of features and most discriminant selected features. The totals of 40 patients Chest CT Scans are utilized to evaluate the proposed method. Several performance measures are considers like sensitivity rate, specificity rate, precision of COVID samples, F1-Score, AUC, error rate in terms of FNR, and Accuracy. These measures are calculated for only testing data. As in this article, we consider the 50% images for training the proposed scheme and rest of them for testing. A detailed training process proposed method as well as testing process is shown in Fig. 7. In this figure, it is shown that the fused features are optimized through PSO and trained SVDD model. After that, testing step is performed and same features are extracted and fused. Later, PSO is applied and optimize features that are passed in trained model. The next step is most important called features matching and in the output, a predicted labeled output is attained.





Accuracy: 83.5

Sensitivity: 77.725

Specificity: 83.06

Precision: 83.67

F1-Score: 80.58

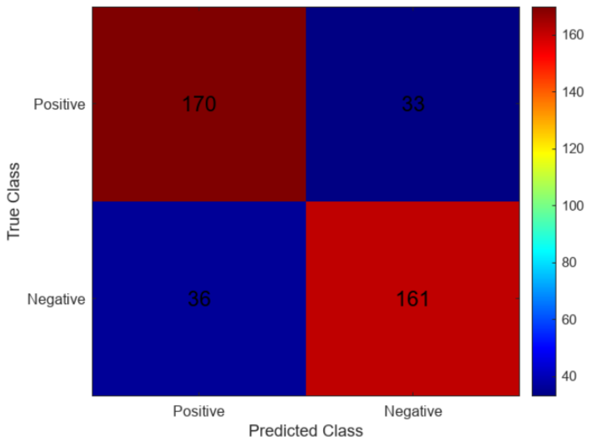
FNR: 22.27

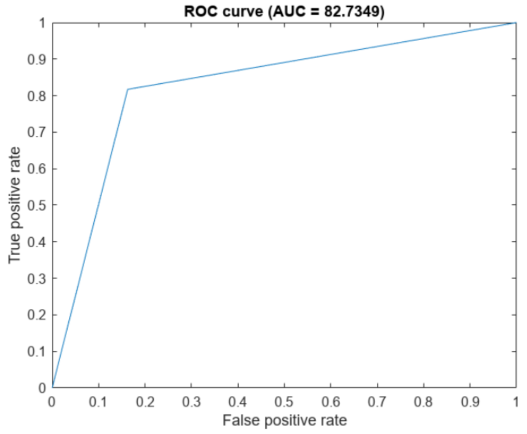
AUC: 80.3

Exploring Other ML Algorithms

We had tried many other machine learning algorithms for the classification and predicting the covid19 from the given image we trained the algorithms and tried to find out the best fitting classifier which id predicting more accurately. We implemented Decision Tree , K Nearest Neighbor , Random Forest , Navie Bayes , and Ensemble method . Here Ensemble method is the algorithm which used five algorithms in it and predicting using all the 5 algorithms accurately, And the Random Forest given the best results as it is the best most powerful algorithm which goes into the roots .

KNN





Accuracy: 82.75

Sensitivity: 82.52

Specificity: 82.98

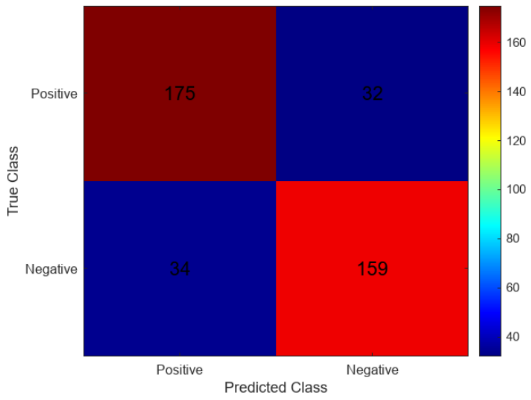
Precision: 83.74

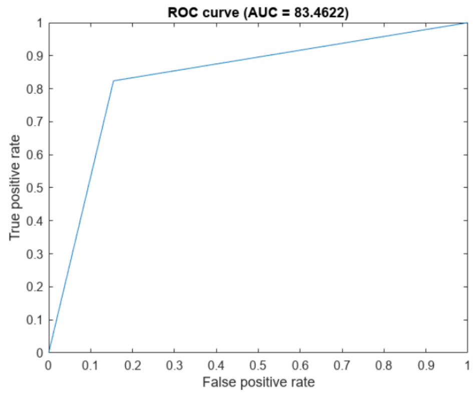
F1-Score: 83.12

FNR: 17.47

AUC: 82.73

Decision Tree





Accuracy: 83.5

Sensitivity: 83.73

Specificity: 84.24

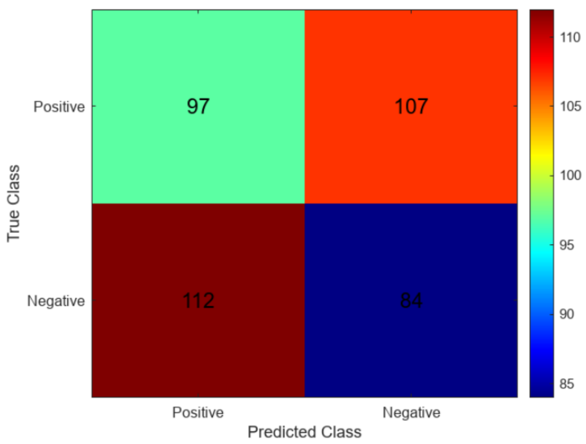
Precision: 84.54

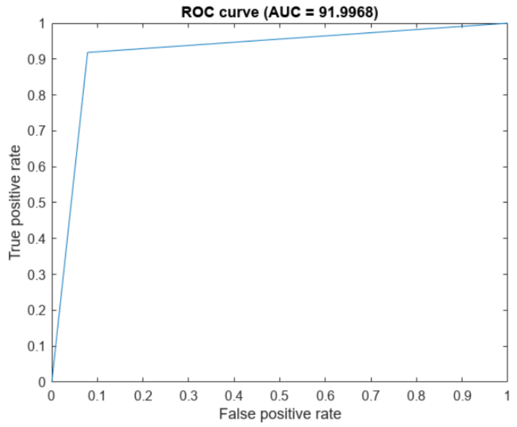
F1-Score: 84.13

FNR: 16.26

AUC: 83.46

Random Forest





Accuracy: 92

Sensitivity: 92.15

Specificity: 91.83

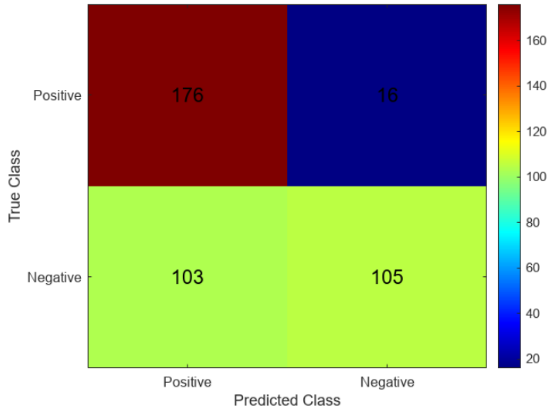
Precision: 92.15

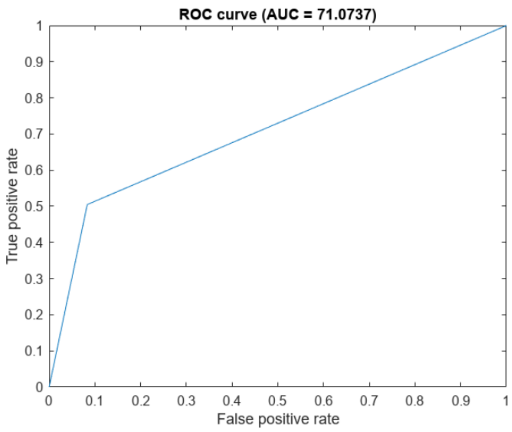
F1-Score: 92.15

FNR: 7.84

AUC: 91.99

Naïve Bayes





Accuracy: 75.75

Sensitivity: 73.08

Specificity: 86.77

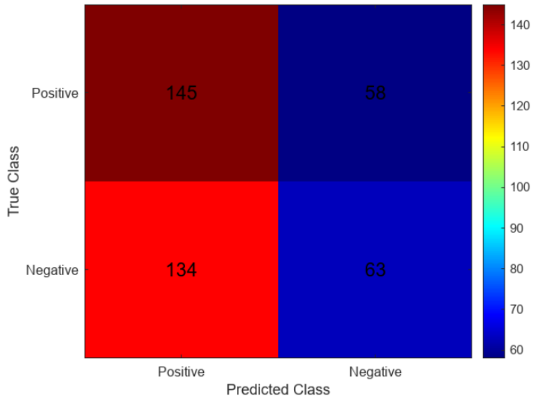
Precision: 91.67

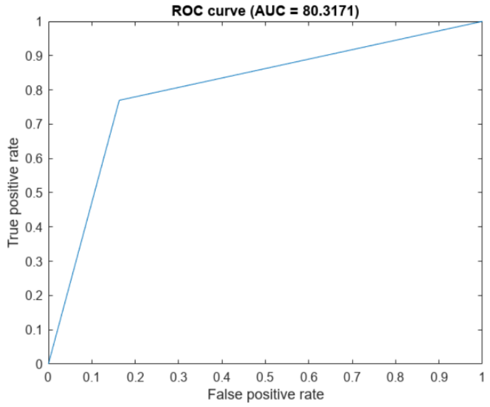
F1-Score: 74.11

FNR: 30.84

AUC: 76.99

Ensemble Method





Accuracy: 80

Sensitivity: 77.725

Specificity: 80.06

Precision: 80.67

F1-Score: 78.58

FNR: 22.27

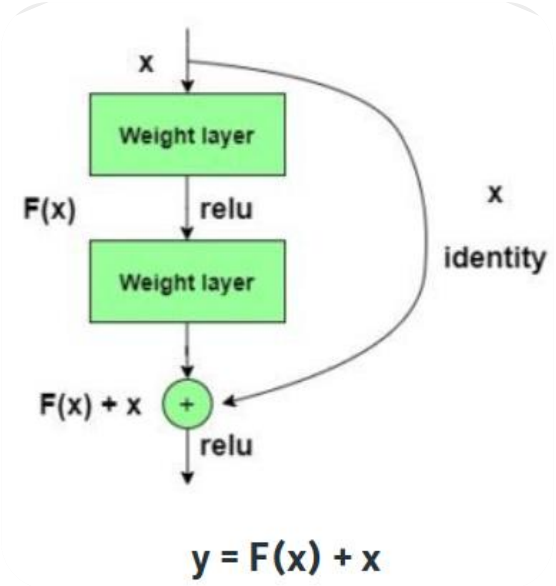
AUC: 80.3

Implementation in DEEP Learning

Deep Neural Networks are becoming deeper and more complex. It has been proved that adding more layers to a Neural Network can make it more robust for image-related tasks. But it can also cause them to lose accuracy. That’s where Residual Networks come into place. The tendency to add so many layers to deep learning practitioners is to extract important features from complex images. So, the first layers may detect edges, and the subsequent layers at the end may detect recognizable shapes.It’s mainly present because of the popular vanishing gradient problem.

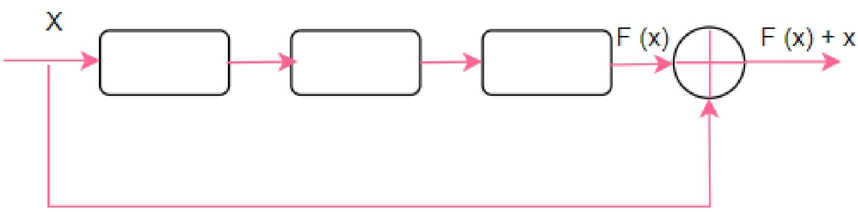
vanishing gradient

Vanishing gradient: a backpropagated error signal typically decreases exponentially as a function of the final layer To avoid this we use skip connections (add original input to the output of convolutional block)



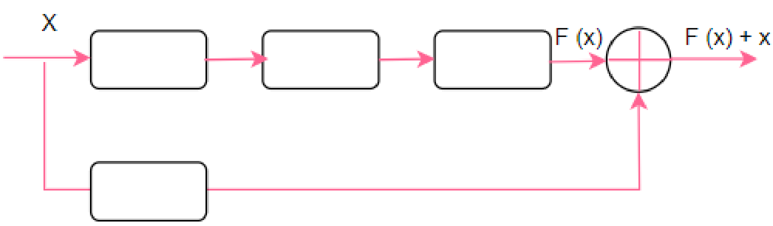
SKIP CONNECTION TYPES

Identity block , Here we just add the input image to the out put so that the vanishing gradient will we over come here it can only be performed if the input and output size is same



Here raise a problem what if the input and output size is not same in this case me just into field

Convolution block , here the convolution will be done in the input image so that the output and input size was matched



RESNET 50

$$\frac{n+2p-s}{s}+1 * \frac{n+2p-s}{s}+1$$

first layer of restnet

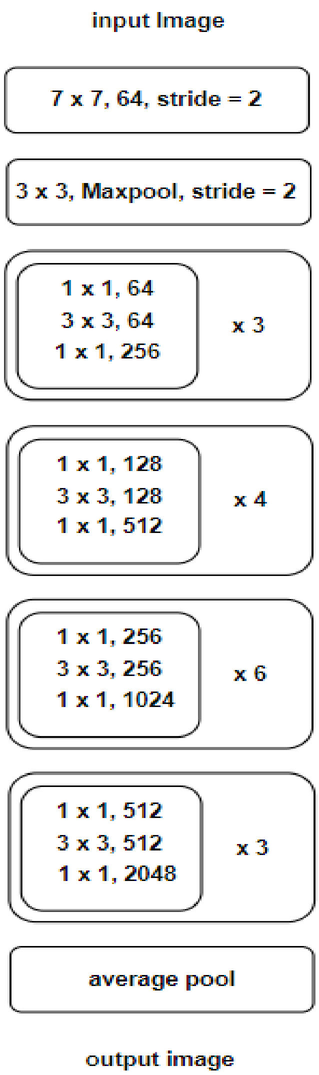
convolution + batch normalization

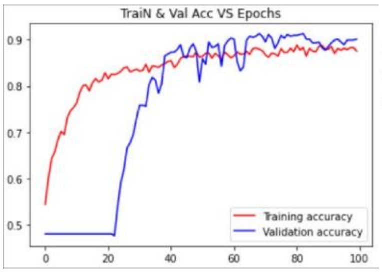
filter size = 7*7, 64 such filters

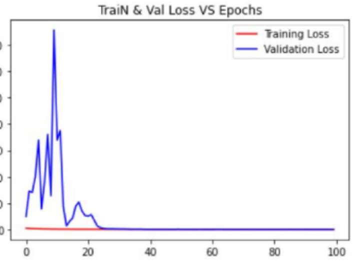
stride = 2

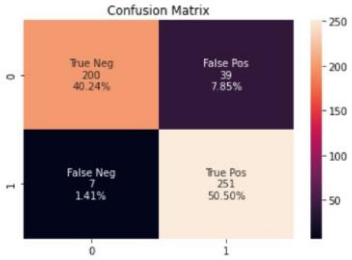
padding = 3

$$\frac{256+2*3-7}{2}+1 = 128*128*64 \text{ (output)}$$





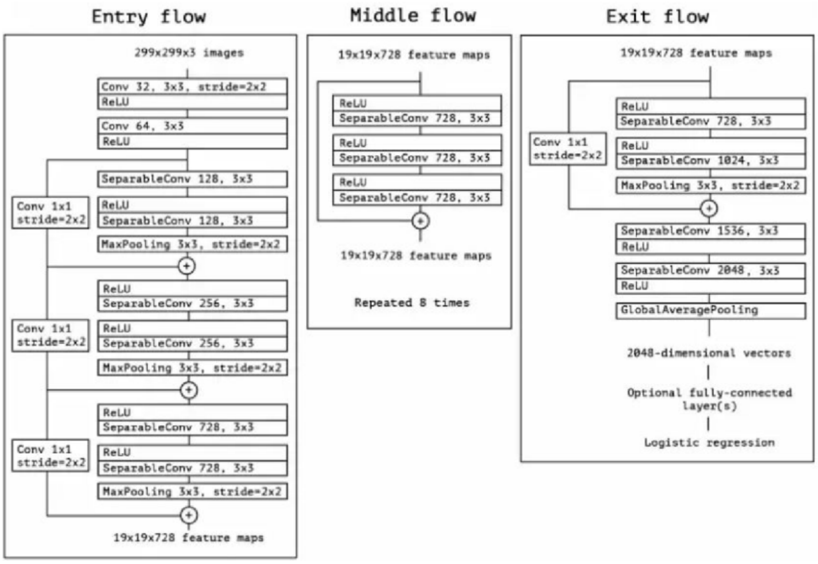


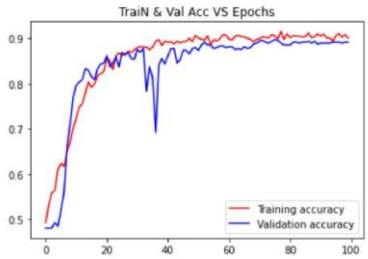


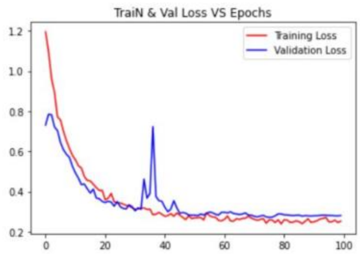
Test accuracy = 90.7444655

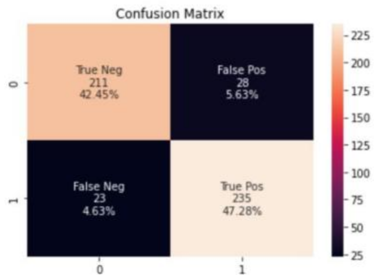
Xception

Xception is a deep convolutional neural network architecture that involves Depthwise Separable Convolutions.









Test accuracy = 90.7444655

Algo	Accuracy (%)
SVDD	83.5
KNN	82.7
Decision Tree	83.5
Random Forest	92
Naïve Bayes	75.75
Ensemble Method	80
RESNET 50(DL)	90.744
Xception (DL)	89.73

Conclusion

This research proposes an automated technique for predicting COVID19 Positive and Healthy Scan using CT images. The procedures are as follows: database setup; multiple feature extraction; feature fusion; selection of most informative features; and prediction. Four types of features are computed along Kurtosis such as DWT, DCT, DRLBP, and Shanon entropy (SEaK). We combined all of these features using the Maximum Covariance technique because they did not provide sufficient accuracy when used separately. Prediction accuracy is improved by the fused feature matrix. It does, however, have a number of unnecessary and undesirable features. An enhanced PSO algorithm is applied to achieve this goal, producing a distinctive feature vector. The final prediction is then made using the SVDD classifier. The result shows how much more accurate the suggested method is. We draw the conclusion from the findings that, while it is not a given that all features are significant, the fusion procedure is crucial to improve the information against a single image for accurate prediction. Additionally, it is found that the selection procedure increases the accuracy of prediction and feature representation.

References

Research paper

Dataset - Kaggle

Covariance, Clearly Explained!!!

Learn Particle Swarm Optimization (PSO) in 20 minutes