A Seminar
on

The Deep Learning based Model for COVID-19 Diagnosis and Classification

by

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Abstract

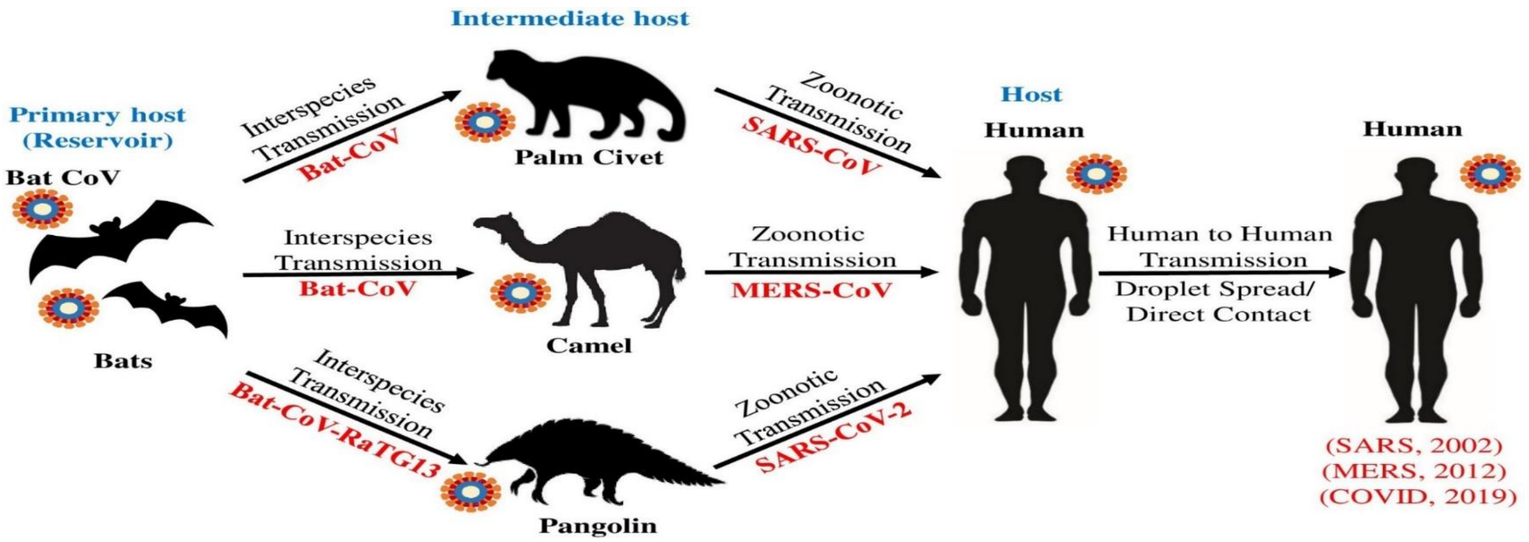
- At present times, COVID-19 has become a global illness and infected people has increased exponentially and it is difficult to control due to the non-availability of large quantity of testing kits.
- Artificial intelligence (AI) techniques including machine learning (ML), deep learning (DL), and computer vision (CV) approaches find useful for the recognition, analysis, and prediction of COVID-19
- Several ML and DL techniques are trained to resolve the supervised learning issue. At the same time, the potential measure of the unsupervised learning technique is quite high. Therefore, unsupervised learning techniques can be designed in the existing DL models for proficient COVID-19 prediction
- In this regard, this study proposed a novel unsupervised DL based Variational AutoEncoder (UDL-VAE) model for COVID-19 detection and classification.

Abstract (cont.)

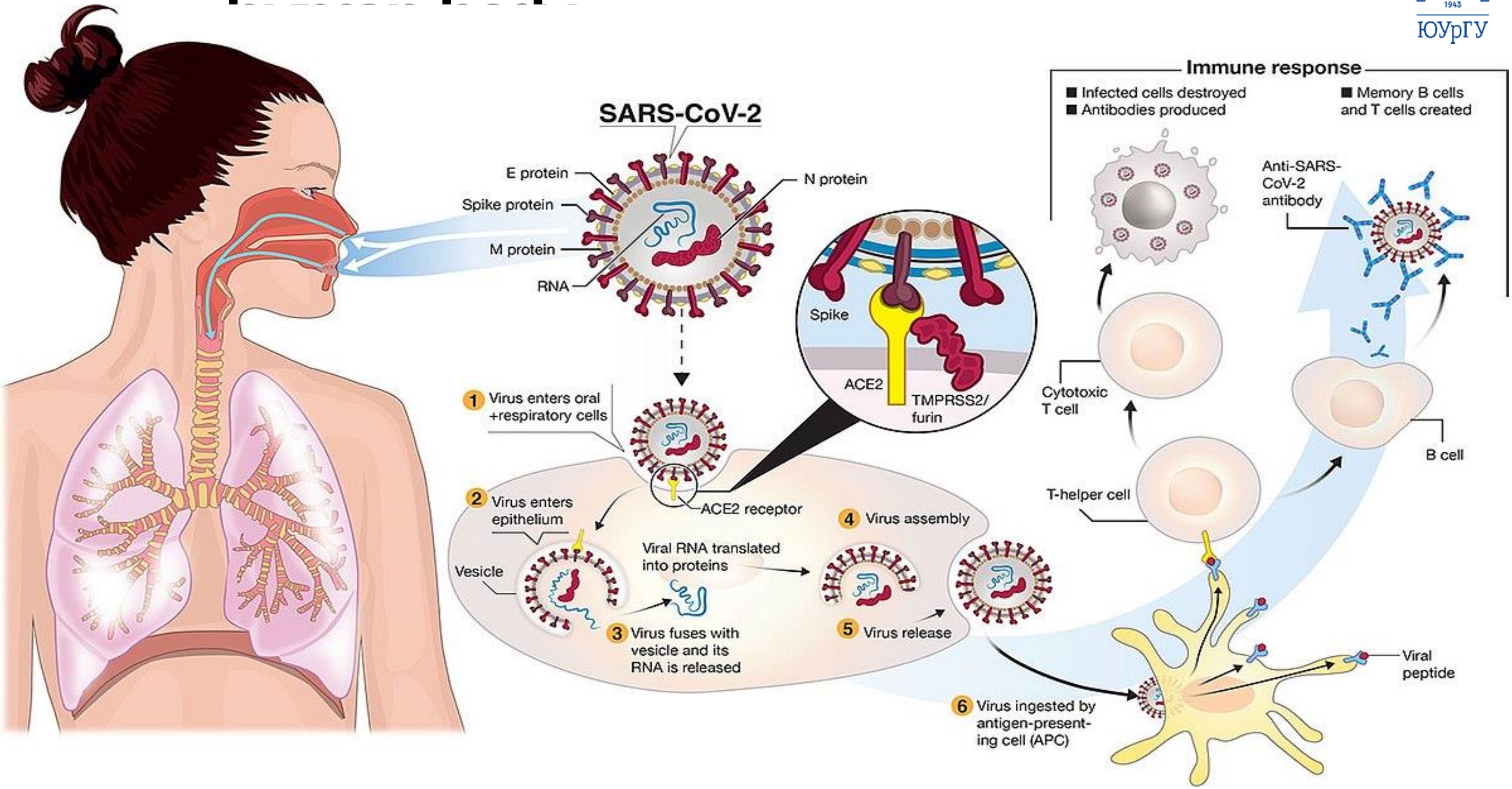
- The UDL-VAE model involved adaptive Wiener filtering (AWF) based preprocessing technique to enhance the image quality
- Besides, Inception v4 with AdaGrad technique is employed as a feature extractor and unsupervised VAE model is applied for the classification process
- In order to verify the superior diagnostic performance of the UDL-VAE model, a set of experimentation was carried out to highlight the effective outcome of the UDL-VAE model
- The obtained experimental values showcased the effectual results of the UDL-VAE model with the higher accuracy of 0.987 and 0.992 on the binary and multiple classes respectively

Background and Introduction

- COVID-19 is Zoonotic: The virus that is usually found in the animals but can be transmitted to the humans through different ways such as animal bites etc
- The primary sources of COVID-SARC family are bats which further infects other animals or humans through bites
- Further, these animals and humans can infects others through different ways:

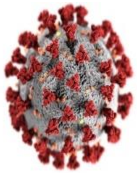


How Covid-Infection starts affecting



Background and Introduction (cont..)

- This type of virus is transferred through respiratory organs from human to human and results in rapid virus transmission.
- It provokes slight infection for most of the patients and some people have severe infection depending on the immunity of a patient
- The most affected part of the human body are the lungs after the COVID-19 infection and that results in breathing issues and partial or full damage of lungs
- The only way to diagnose the COVID-19 is by swab sample collection and sending the sample in the virology lab to confirm the presence of COVID-19



Background and Introduction (cont..)

- As the COVID-19 is highly contagious and number of infections can grow rapidly, the testing and analysis of infected people is very important in controlling the spread

- However, the availability of sample collection kits was a big challenge during the first wave of COVID-19 and also the analysis of samples is expensive and time consuming, therefore, researchers came out with a new solution to detect COVID-19 in COVID-19 suspicious cases

- Every hospital has X-ray imaging device and it is possible to take X-rays test for COVID-19 without any special testing tools.

- The demerits of X- ray testing are that it requires radiological expertize that is time-consuming and experts are not always available

Background and Introduction (cont..)

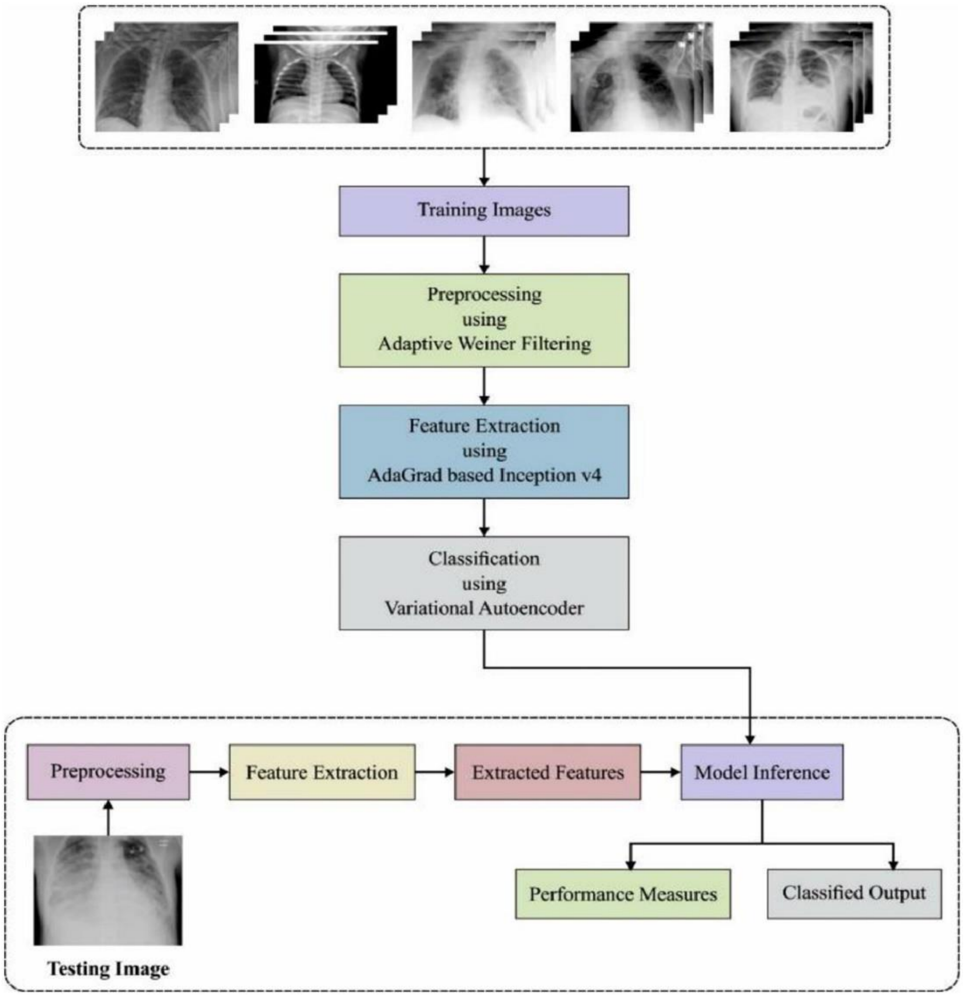
- Therefore, developing an automatic analysis model is extremely significant to limit the overhead of medical professionals
- The deep learning has already shown its potential in medical image diagnosis. Therefore it is very useful technique in analyzing COVID-19 detection using chest x-ray images
- However, the only requirement is the availability of sufficient amount of labelled chest x-ray images for analysis
- Thanks to medical professionals that a good amount of such data is available online to develop more accurate solutions for automatic COVID-19 detection

Background and Introduction (cont..)

The contribution of the study can be defined briefly as follows:

- This study devised an efficient Unsupervised DL based Variational Auto-Encoder (UDL-VAE) model for COVID-19 detection and classification
- The UDL-VAE model performs adaptive Wiener filtering (AWF) based prep-rocessing, Inception v4 with Adagrad based feature extraction, and unsupervised VAE based classification
- The application of Adagrad technique helps to adjust the hyper parameters of Inception v4 model, and thereby the classification performance can be improved
- For facilitating the effective detection performance of the UDL-VAE method, a comprehensive experimental validation takes place to make sure the proficient performance of the UDL-VAE model

Proposed Framework



Training Data

- Data Source:
  - COVID-19 Image Data Collection: Prospective Predictions Are the Future Joseph Paul Cohen and Paul Morrison and Lan Dao and Karsten Roth and Tim Q Duong and Marzyeh Ghassemi arXiv:2006.11988, https://github.com/ieee8023/covid-chestxray-dataset, 2020

- The total number of images used to train the model: 3481
- Number of Classes: [5] Normal, COVID-19, SARS, ARDS, and Streptococcus.
- The total number of images used to test the model: 1173

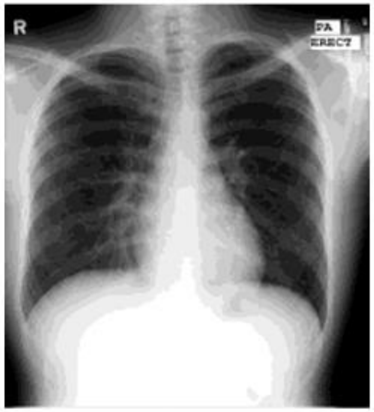
Adaptive Weiner Filter (To enhance the quality of training Images)

- When an image is blurred with the aid of a Low Pass Filter, it's possible to get better the picture by inverse filtering

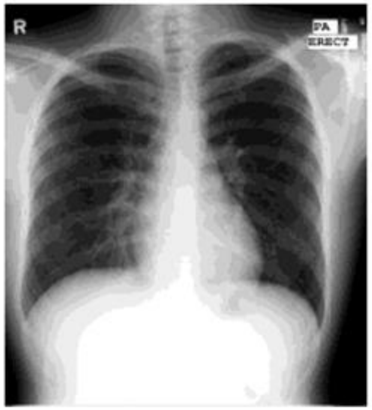
- The Wiener filter gets a balance between inverse filtering and noise smoothening. It reduces the common mean square error. It consists of 2 separate parts:

    1. An inverse filtering part (High pass filter)
    2. A noise smoothening part (Low pass filter)

Original image



Filtered Image



Adaptive Weiner Filter (To enhance the quality of training Images)

- It removes the Gaussian noise and inverts the blurring at the same time

$$W(f1,f2) = H*(f1,f2)P_X(f1,f2)/(|H(f1,f2)|^2 P_X(f1,f2) + P_\eta(f1,f2)')$$

where,

$P_X(f1,f2) + P_\eta(f1,f2)$ is the power spectra of the original chest image with respect to additive noise and $H(f1,f2)$ is the blurring filter

Inception v4 with Adagrad based Feature Extraction

- The preprocessed medical image is subject to feature extraction in which the required features are extracted from given image using Inception v4 method

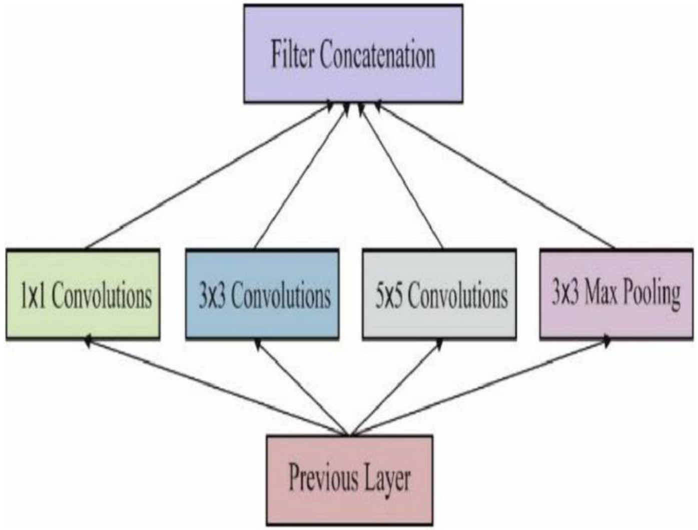
- Basically, CNN is comprised of numerous layers namely, convolutional layers, down-sampling layers, as well as activation layers. The inputs of CNN are determined by means of 1D, 2D as well as 3D

- CNNs having 1D inputs classify the images directly in spectral domain whereas, in 2D, the inputs extract features from adjacent pixels and using neighbors of pixel to be divided as input; and finally, CNNs with 3D inputs filter complicated features from spectral as well as spatial domains

- Then, CNNs with spatial data are capable of accomplishing optimal performance by means of classification accuracy

Inception v4 with Adagrad based Feature Extraction (cont.)

- The Figure shows the structure of Inception module. Here, 2 CNNs were developed on the basis of Directed Acyclic Graphs (DAG) structure in which fundamental layers are defined



- Assume, x as the vector of pixels in input image X, and single neuron computes the process and generates the simulation outcome $a = \sigma(fx + b)$, where f is the weight filter, b is the bias and $\sigma(.)$ is the activation non-linear function

- A neuron is commonly related to a particular spatial position (i, j) and a dimension d. It refers that convolutional block is executed in entire position of spectral dimensionality

Inception v4 with Adagrad based Feature Extraction (cont.)

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- For DAG, the input feature $x \in R^{H \times W \times D}$ is defined as the position (i, j, d) with multi-dimensional filter $f \in R^{H\prime \times W\prime \times D\prime}$ and a bias b, the output $a \in R^{H'' \times W'' \times D''}$ is depicted as follows:

$$a_{i''j''d''} = \sigma(b_{d''} + \sum_{i'=1}^{H'} \sum_{j'=1}^{W'} \sum_{d'=1}^{D} f_{i'j'd} \times X_{i''+i'-1, j''+j'-1, d''})$$

- It is pointed that activation function is performed with square images under different image-processing issues, however, it is operated on random inputs and filters with the top-bottom and left-right paddings $(P_h^+, P_h^-, P_w^+, P_w^-)$ as well as down sampling strides (S_h, S_w).

- The size of the output for convolutional layer in DAG structure is represented as

$$H'' = 1 + [(H - H' + P_h^- + P_h^+)/S_h]$$

Inception v4 with Adagrad based Feature Extraction (cont.)

- In deep learning (DL) networks, the hyper parameters undergo tuning for controlling the effective performance of the model
- The procedure of selecting the hyper parameters is the main feature of the DL approaches
- In this study, the hyper parameters of the Inception-v4 model are tuned by Adagard optimization model
- It refers the parameter-based learning rates and corresponding learning rates of variables that are improvised sequentially as small and large parameters which are upgraded irregularly.
- Hence, update rule for Adagrad is provided as:

$$v_0 = 0 \qquad \text{(initialize squared gradient accumulator)}$$

$$v_t = v_{t-1} + (\nabla J(\theta_{t-1}))^2 \qquad \text{(accumulate squared gradient)}$$

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{v_t} + e} . \nabla J(\theta_{t-1}) \qquad \text{(apply update)}$$

Unsupervised VAE based Classification

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- After the feature extraction stage, the VAE model is applied to allocate the proper class label of the applied medical images. Basically, VAE is relied on the traditional Auto-Encoder (AE)
- In prior to developing VAE, it is crucial to learn the AE process. In general, AE is a type of unsupervised learning method which desires to extract secondary features concealed in the actual data
- The advantage of using unsupervised automated encoder is that it helps to resolve the issue of gradient diminishing
- The gradient diminishing can be defined as the situation when the gradient to update the weight matrix is too small (weight matrix updates marginally only) and it affects NN training and sometimes the training itself seems stopped

Unsupervised VAE based Classification (Cont.)

- VAE is a type of deep Bayesian system which is the combination of NN in conjunction with statistics. When compared with former AE, it enforces the latent codes and follows certain distribution like Gaussian distribution
- Actually, encoder portion of entire NN is developed to imply the conditional probability $q_{\phi}(z|x)$, in which x denotes the actual data, ϕ refers the weights of encoder, and z shows the latent codes
- Inversely, VAE promotes the distribution of latent codes z to the standard normal distribution.

Unsupervised VAE based Classification (Cont.)

- Finally, latent codes z are comprised of stable statistical features which result in better convenience for decoder and efficacy of this model
- Next, decoder manages to reform the actual data by applying latent codes z. Consequently, NN having the weight 0 indicates a conditional probability $p_{\theta}(x|z)$.
- In order to retain the uncertainty within the system, inputs of decoder undergo sampling from scattering of latent codes z.
- Therefore, encoder is modeled in two resultant parameters, mean and variance vector of latent codes z to describe the normal distribution for the sample.

Kullback-Leibler (KL) Divergence

- To make distribution of latent code model for specific distribution, a major problem is to estimate the space among two distribution q and p
- KL divergence is established for estimating the variations among two probability distributions; hence, smaller KL divergence represents the closer distributions
- When there are two unseen distributions p(x) and q(x), then KL divergence is attained by applying the expression

$$D_{KL}((p(x)||q(x)) = \int p(x) log q(x) dx - (-\int p(x) log p(x) dx)$$

$$= p(x) log \left\{\frac{p(x)}{q(x)}\right\} dx$$

This is referred as KL divergence for two distributions p(x) and q(x)

Establishment of loss function (L_{VAE})

- In this model, there are 2 objectives in VAE namely,
  1. To reform the actual data and
  2. To create the latent codes in certain distribution

- Hence, the loss function has been classified into 2 portions:
  1. The initial part is to estimate the distance from produced and actual data
  2. Next, MSE function has been applied and referred as desired value of squared difference among 2 parameters

- MSE is applicable to measure the difference between actual and reformed data

Establishment of loss function (L_{VAE})

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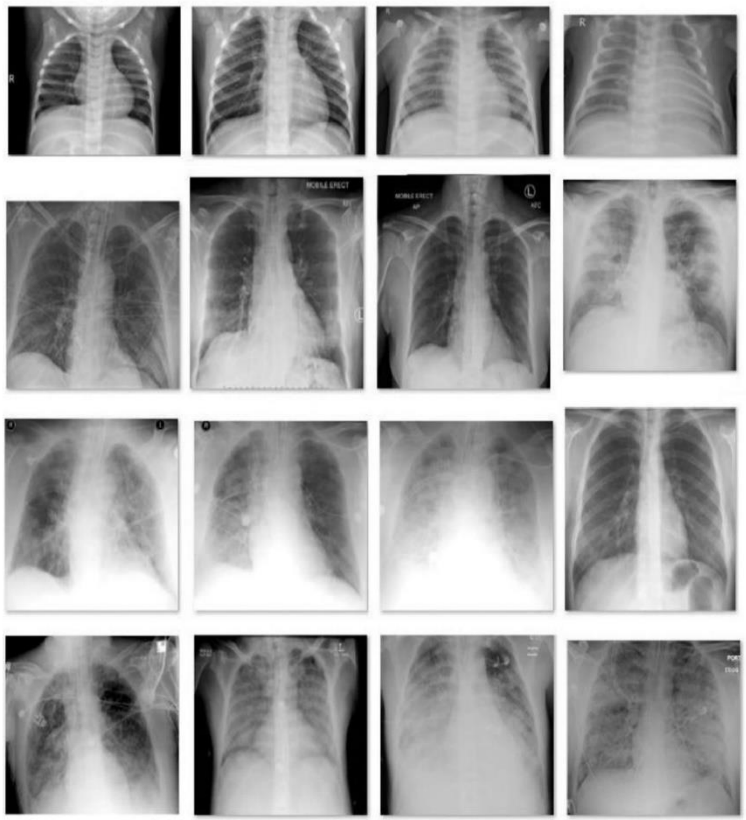
- The latter portion is the loss to relate the distance among distribution of latent code z as well as remarkable Gaussian distribution.
- The KL divergence is used and resulted in final loss process of VAE that can been be devised as,

$$L_{VAE} = \lambda MSE(x, y) + E_{pdata(x)}[-KL(q_{\phi}(z|x)||p(z))]$$

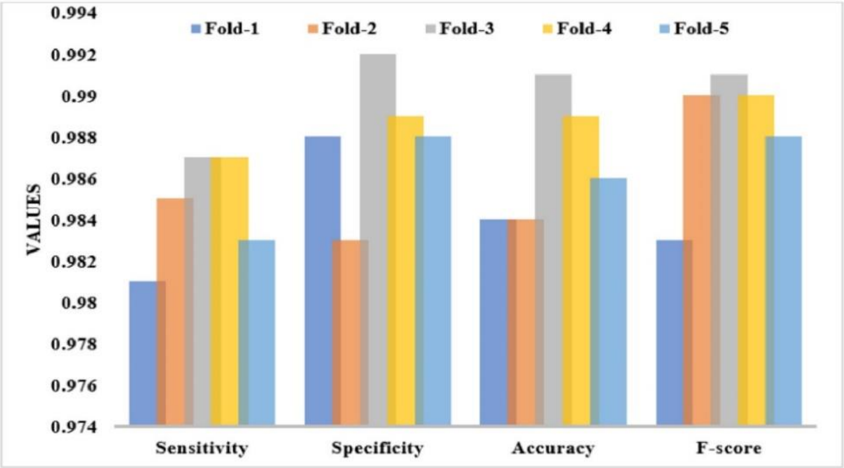
Where,
x indicates the actual data, y defines the reformed data, λ represents a parameter,
$q_{\phi}(z|x)$ defines the distribution of latent codes produced from actual data x by encoding device,
and p(z) depicts the distribution of latent codes
and $E_{pdata(x)}[.]$ demonstrates the numerical expression

Experimental Validation

- The performance validation of the presented UDLVAE model has been tested against COVID Chest X-ray dataset
- It contains the images under distinct classes namely Normal, COVID-19, SARS, ARDS, and Streptococcus
- The parameter setting of the proposed model is given as follows. Batch size: 500, max. epochs:15, learning rate: 0.05, dropout rate: 0.2, and momentum: 0.9
- A few sample test images are illustrated in figure. Besides, the dataset is split in five different folds



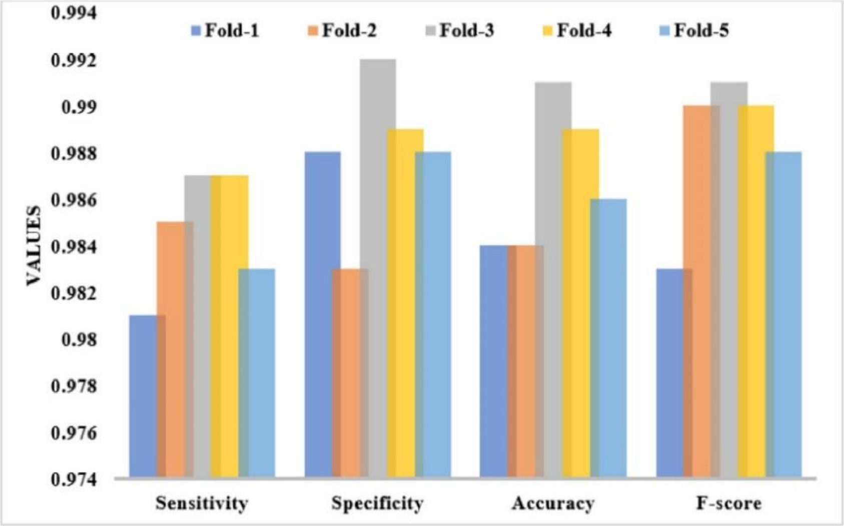
Experimental Validation (cont.)



Cross Folds	Sens.	Spec.	Acc.	F-measure
Fold_1	0.981	0.988	0.984	0.983
Fold_2	0.985	0.983	0.984	0.990
Fold_3	0.987	0.992	0.991	0.991
Fold_4	0.987	0.989	0.989	0.990
Fold_5	0.983	0.988	0.986	0.988
Average	0.985	0.988	0.987	0.988

- The shown Table and Figure illustrates the binary classification results of the UDLVAE model in terms of distinct performance measures with varying folds
- The obtained values denoted that the UDLVAE model has reached to effective classification outcome under diverse folds
- On the applied fold_1, the UDLVAE model has accomplished a sens. of 0.981, spec. of 0.988, acc. of 0.984, and F-measure of 0.983

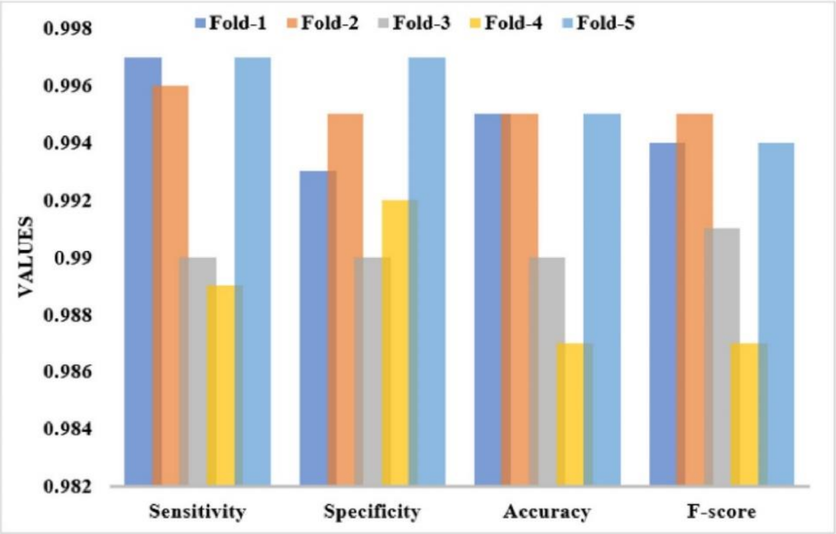
Experimental Validation (cont.)



Cross Folds	Sens.	Spec.	Acc.	F-measure
Fold_1	0.981	0.988	0.984	0.983
Fold_2	0.985	0.983	0.984	0.990
Fold_3	0.987	0.992	0.991	0.991
Fold_4	0.987	0.989	0.989	0.990
Fold_5	0.983	0.988	0.986	0.988
Average	0.985	0.988	0.987	0.988

- Besides, on the applied fold_3, the UDLVAE method has demonstrated a sens. of 0.987, spec. of 0.992, acc. of 0.991, and F-measure of 0.991
- Also, on the applied fold_5, the UDLVAE technique has exhibited a sens. of 0.983, spec. of 0.988, acc. of 0.986, and F-measure of 0.988

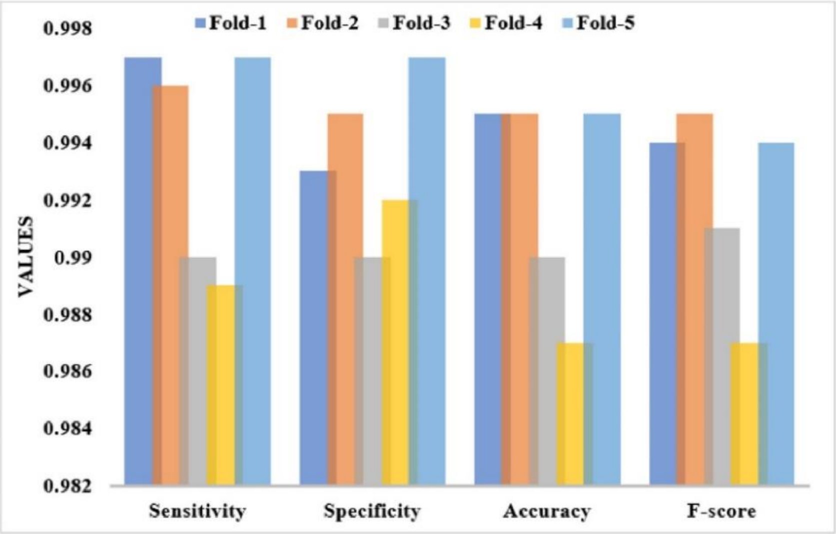
Experimental Validation (cont.)



Cross Folds	Sens.	Spec.	Acc.	F-measure
Fold_1	0.997	0.993	0.995	0.994
Fold_2	0.996	0.995	0.995	0.995
Fold_3	0.990	0.990	0.990	0.991
Fold_4	0.989	0.992	0.987	0.987
Fold_5	0.997	0.997	0.995	0.994
Average	0.994	0.993	0.992	0.992

- The shown Table and Figure illustrates the multi-class classification results of the UDLVAE model in terms of distinct performance measures with varying folds
- The obtained values denoted that the UDLVAE model has reached to effective classification outcome under diverse folds
- At fold_1, the UDLVAE model achieved the sensitivity of 0.997, specificity of 0.993, accuracy 99.5% and F-measure 0.994

Experimental Validation (cont.)

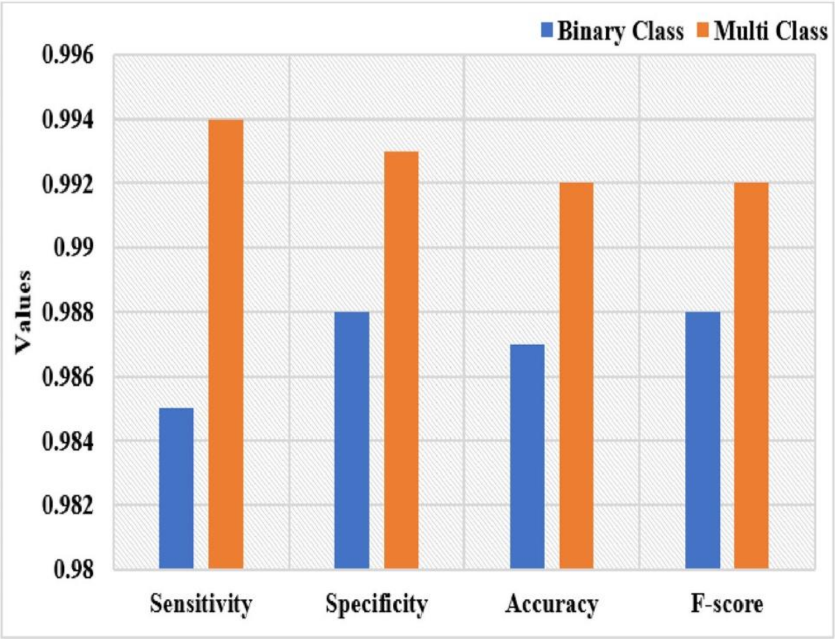


Cross Folds	Sens.	Spec.	Acc.	F-measure
Fold_1	0.997	0.993	0.995	0.994
Fold_2	0.996	0.995	0.995	0.995
Fold_3	0.990	0.990	0.990	0.991
Fold_4	0.989	0.992	0.987	0.987
Fold_5	0.997	0.997	0.995	0.994
Average	0.994	0.993	0.992	0.992

- Additionally, on the applied fold_3, the UDLVAE technique has accomplished a sens. of 0.990, spec. of 0.990, acc. of 0.990, and F-measure of 0.991
- Eventually, on the applied fold_5, the UDLVAE approach has outperformed a sens. of 0.997, spec. of 0.997, acc. of 0.995, and F-measure of 0.994

Experimental Validation (cont.)

- The other existing deep learning models i.e. VGG16, CapsNet, DWS-CNN, FR-CNN, ResNet-50, AlexNet, CovxNet were also developed in order to check the efficiency and potential of the proposed model
- An average classification results analysis of the UDLVAE model with other existing methods takes place, as given in the figure
- The resultant values depicted that the UDLVAE model has accomplished a higher average sens. of 0.985, spec. of 0.988, acc. of 0.987, and F-measure of 0.988 on the classification of binary classes
- On the other hand, the UDLVAE model has resulted in a maximum sens. of 0.994, spec. of 0.993, acc. of 0.992, and F-measure of 0.992



Performance comparison of existing models with the proposed one

Methods	Sensitivity	Specificity	Accuracy	F-measure
UDLVAE (Multi Class)	0.994	0.993	0.992	0.992
DWS-CNN (Multi Class)	0.991	0.992	0.991	0.99
UDLVAE (Binary Class)	0.985	0.988	0.987	0.988
DWS-CNN (Binary Class)	0.984	0.986	0.985	0.986
FR-CNN	0.977	0.955	0.974	0.985
VGG19	0.971	0.96	0.963	0.942
ResNet-50	0.93	0.677	0.896	0.939
AlexNet	0.925	0.714	0.905	0.946
Inception V3	0.91	0.742	0.887	0.933
CovxNet	0.905	0.958	0.917	0.911
Deep Transfer Learning	0.896	0.92	0.908	0.904
CapsNet	0.842	0.918	0.892	0.842

Conclusion

- This paper has developed a novel UDL-VAE method for COVID-19 detection and classification.
- The UDL-VAE model performs AWF based preprocessing, Inception v4 with Adagrad based feature extraction, and unsupervised VAE based classification. Primarily, the medical image quality can be raised by the use of AWF technique
- Then, Inception v4 with Adagrad model extracts out the useful set of feature vectors from the preprocessed image.
- The application of Adagrad technique helps to adjust the hyper parameters of Inception v4 model, and thereby the classification performance can be improved

Conclusion (cont.)

- Next, unsupervised VAE model is applied to define the appropriate class labels of the input medical images
- For facilitating the effective detection performance of the UDL-VAE method, a comprehensive experimental validation takes place to make sure the proficient performance of the UDL-VAE method
- The obtained experimental values showcased the effectual results of the UDL-VAE model with the higher accuracy of 0.987 and 0.992 on the binary and multiple classes respectively

Future plans

- In future, Meta-heuristic optimization based learning rate schedulers can be designed for hyper parameter settings
- In addition, the presented model can be employed to diagnose COVID-19 using other imaging modalities like computed tomography (CT)
- As a part of future extension, it can be incorporated to the internet of things (IoT) and cloud based environment to enable e-healthcare applications

Questions are Welcome!!