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Detection of COVID-19 from radiology modalities and identification of prognosis patterns

G. JayaLakshmi[a,*], Haitham Abbas Khalaf[b], Abolfazl Farhadi[c], Shokhan M. Al-Barzinji[d], Sawsan dheyaa Mahmood[e], Saif Al-din M. Najim[d], Maha A. Hutaihit[f], Salwa Mohammed Nejrs[g], Raghda Salam Al.Mahdawi[h], Azmi Shawkat Abdulbaqi[d]

[a]*Department of IT, V R Siddhartha Engineering College, India*
[b]*College of Medicine, University of Anbar, Ramadi, Iraq*
[c]*Department of Medical Sciences, Shirvan Branch, Islamic Azad University, Shirvan, Iran*
[d]*Department of Computer Science, College of Computer Science and Information Technology, University of Anbar, Ramadi, Iraq*
[e]*Department of Electricity Engineering College of Engineering, University of Tikrit, Tikrit, Iraq*
[f]*Department of Communication Engineering Collage of Engineering, University of Diyala: Baqubah, Diyala, Iraq*
[g]*Directorate of Private University Education, Ministry of Higher Education, Baghdad, Iraq*
[h]*Department of Computer Engineering Collage of Engineering, University of Diyala: Baqubah, Diyala, Iraq*

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Abstract

SARS-CoV-2 and the consequential COVID-19 virus is one of the major concerns of the 21st century. Pertaining to the novelty of the disease, it became necessary to discover the efficacy of deep learning techniques in the quick and consistent discovery of COVID-19 based on chest X-ray and CT scan image analysis. In this related work, Prognostic tool using regression was designed for patients with COVID-19 and recognizing prediction patterns to make available important prognostic information on mortality or severity in COVID-19 patients. And reliable convolutional neural network (CNN) architecture models (DenseNet, VGG16, ResNet, Inception Net)to institute whether it would work preeminent in terms of accuracy as well as efficiency with image datasets with Transfer Learning. CNN with Transfer Learning were functional to accomplish the involuntary recognition of COVID-19

*Corresponding author

Email addresses: jaya1123@vrsiddhartha.ac.in (G. JayaLakshmi), med.haitham.alakidi@uoanbar.edu.iq (Haitham Abbas Khalaf), Farhadi_1967@yahoo.com (Abolfazl Farhadi), shokhan.albarzinji@uoanbar.edu.iq (Shokhan M. Al-Barzinji), sawsan.d.mahmood@tu.edu.iq (Sawsan dheyaa Mahmood), saifaddin.r@uoanbar.edu.iq (Saif Al-din M. Najim), mahaabbashutaihit@uodiyala.edu.iq (Maha A. Hutaihit), salwamn@uomisan.edu.iq (Salwa Mohammed Nejrs), raghdasalam@uodiyala.edu.iq (Raghda Salam Al.Mahdawi), azmi_msc@uoanbar.edu.iq (Azmi Shawkat Abdulbaqi)

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from numerary chest X-ray and CT scan images. The experimental results emphasize that selected models, which is formerly broadly tuned through suitable parameters, executes in extensive levels of COVID-19 discovery against pneumonia or normal or lung opacity through the precision of up to 87% for X-Ray and 91% intended for CT scans.

Keywords: convolutional neural network, transfer learning, COVID-19, X-ray, CTscan, deep learning.

1. Introduction

COVID-19 pandemic takes modified lives round the world. This can be the present scenario as of 2020/09/26, per United Nations agency. To avert the spread of COVID-19, many nationwide governments have presented 'lockdown' to live 'social distancing' and 'isolation' pointers that bound the undertaking of individuals. The coronavirus symptoms will vary after cold to fever, in addition as acute disease. The infection of coronavirus is spread preponderantly via precipitations. Time of evolution, numerous diseases like diabetes, heart disease, liver disorder, breast cancer, COVID-19, etc. caused unembellished and severe actions on human health, then artificial intelligence-based systems illustration better performance to recognize those diseases. Fighting in contradiction of COVID-19, modern technologies are playing substantial roles in the progress of a smart healthcare system CT scans are accustomed screen and diagnose COVID-19, particularly in areas wherever swab take a look at resources are severely lacking. The goal of this information challenge is to diagnose COVID-19 victimization chest CT scans [2]. Therefore, we want to make a classification model which will classify patients to COVID or NonCOVID supported their chest CT scans, as accurately as doable. Comparatively even range of COVID and NonCOVID pictures ar provided to coach the model. The competition additionally needs that the model's coaching with provided information should take but one hour. Coaching information set contains 251 COVID pictures and 292 NonCOVID pictures. Meta-information: patient data, severity, image caption, etc. It's necessary to notice that the challenge is to tell apart between COVID and NonCOVID CT scans, instead of COVID and traditional scans. In fact, there could also be some NonCOVID CT scans that belong to different respiratory disorder patients.

Related to RT-PCR, CT scan pictures have a high understanding in designation then detection cases with COVID-19; but, their specificity remains low. This suggests that CT scan is a lot of correct in relations of COVID-19, however fewer correct in cases of noncontagious respiratory illness. A related work conducted on the designation of patients in urban center, China, presented that consolidation besides groundglass opacities (GGO) weren't determined in CT scan imaging in Bastille Day of the pictures, which means that Bastille Day of the conclusive cases of COVID-19 stayed misdiagnosed as utterly healthy supported their CT scan tests. Out of eighteen patients through COVID-19 UN agency obligated GGO with consolidation, solely twelve had GGO and, as a consequence, no consolidation or malady was ascertained. Despite the presence of consolidation while not the arrival of GGO in several cases, it absolutely was troublesome besides nearly not possible towards notice COVID-19.

The current medical applications of deep learning approaches are attracting growing attention. specifically, the presentations of metric capacity unit approaches have attracted consideration for the uncovering of pulmonic menace, active TB, abnormal condition, in addition respiratory disease in metal pictures. Previous analysis has incongestible the clinical effectuality of the metric capacity unit algorithmic program in terms of its capability to enhance speed and accurateness in image reading. If the metric capacity unit algorithmic program achieves a performance that's similar to that achieved by physicians within the discovery of metal with COVID-19 respiratory disease, the automated construal of the metal with metric capacity unit approaches will considerably cut back the problem on clinicians and radiologists in an exceedingly unforeseen heave of assumed COVID-19 patients.

2. Related Work

Medical image classification is a subfield of image classification. Several approaches in image classification can be used. Many image improved methods to develop the discriminable features for categorization [3]. Conversely, as CNN is a last part to end result for image classification, it will be trained the feature by own. Consequently, the works concerning by what means to choose and augment features in the health image is not revised. The study principally focuses on the relevance of conventional techniques and CNN based transfer learning.

The traditional system has severalstructures and classifying approaches which can be assessed and notrestated due to lack of time. For CNN created transfer learning (TLCNN), the layer of reinstructed ConvLayer, the complication of classification layers, the withdraw rate has important properties on the ending result [4, 7].

3. COVID CT-Scan and X-ray-Dataset

In this review, X-ray images acquired from deuce sources were used for the identification of COVID-19 [3, 6]. The X-ray database consists of127 X-ray images analyzed with COVID-19 with 43 female and 82 male cases that were found to be positive and 500 no-findings and 500 pneumonia category avoid the unbalanced data problem. Where in the SARS-CoV-2 CT-scan datasetcomprises of 2482 CT scans from 120 patients, among 1252 CT scans of 60 patients contaminated by SARS-CoV-2 from males as well as females, and 1230 CT scan images of 60 non-contaminated patients by SARS-CoV-2 from males as well as females, but their other pulmonary ailments [5].
Figure 2 illustrations some of the COVID-19 diagnosed X-ray images along with pneumonia, lung opacity, and normal. Figure 3 shows COVID-CT dataset has elevated typical for image extent as well as disparity [8].

A prognostic model for predicting COVID-19 critical disease has been proposed as **COVID-19 extrapolativetool** to approximation transience rates in patients byCOVID-19 which in turn has been adapted from CDC materials. By evaluating the above parameters, we can evaluate results and conclude with diagnosis or treatment of the disease using COVID prognostic tool. This is a demonstration study of a prognostic model for the forecast of COVID-19 critical disease where significant disease was distinct as the following:

1. Age?
2. Heart Disease?
3. Diabetes?
4. Chronic Respiratory Disease?
5. Hypertension?
6. Cancer?
7. Prior Stroke?
8. Chronic Kidney Disease?

Validation was executed with an arbitrary sample of patients with COVID-19 also non COVID-19.

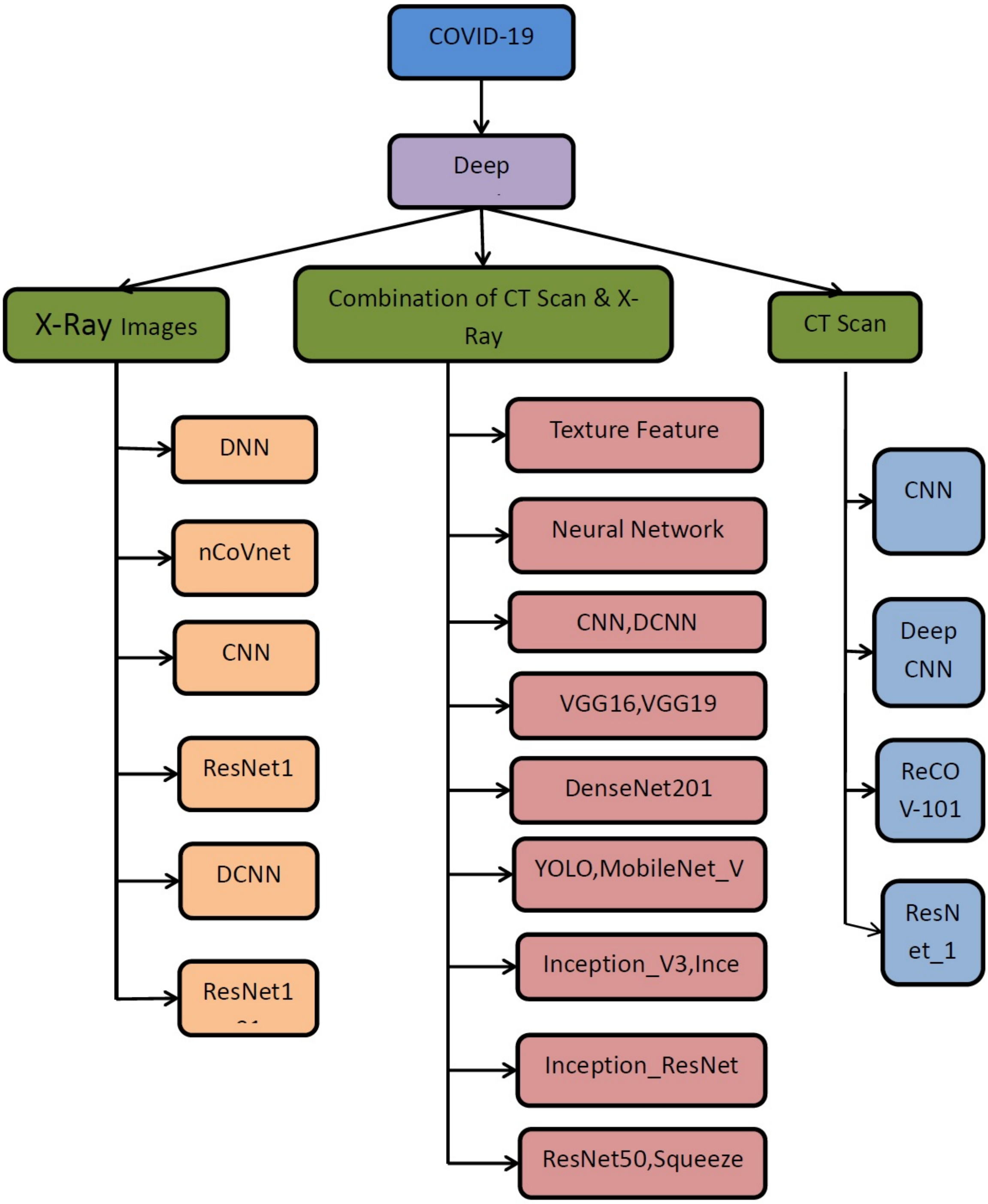


Figure 1: Deep Learning Techniques for Detection of COVID

Table 1: Related Work

Year	Datasets	Algorithms/Techniques Used	Remarks	Links
2021	COVID-19 CT-Scan Images	Inception V3, DNN	Limitation is to improve the model performance for different lung diseases as well.	https://ieeexplore.ieee.org/document/9331029 [5]
2021	COVID-19 Datasets	U-Net, DSS, EGNet, PoolNet	it failed only on 0.8% images.	https://ieeexplore.ieee.org/document/9357961
2021	CT-Scan Dataset	ReCOV-101	ReCOV-101 has possible and is probable to outpace its currently accessible form.	https://www.sciencedirect.com/science/article/pii/S2542660521000214
2021	CT-Scan Dataset	ResNet18	It needs to be explored on the higher set of COVID-19 positive CT scan of patients	https://link.springer.com/article/10.1007/s10489-020-01826-w
2021	Chest X-Ray besides CT-Scan COVID-19 Dataset	VGG19, CNN, ResNet152V2, GRU, Bi-GRU	VGG19+CNN loss value is high compared to others	https://www.sciencedirect.com/science/article/pii/S0010482521001426
2021	COVID-19 Dataset X-Ray Image Dataset	CNN, YOLO	The performance of YOLO is average	https://ieeexplore.ieee.org/document/9343918
2021	Custom Chest CT scan	ResNet50	In dataset, there are only few samples to build Deep learning	https://ieeexplore.ieee.org/document/9376253
2021	COVID-19 Dataset	Bi-LSTM and CRF	Limiting the situation to the binary token layer as it could get misleading suggestions on the presentation of the diverse layers comprising the model.	https://ieeexplore.ieee.org/document/9335570
2021	Chest X-Ray Image Dataset	CNN, SqueezeNet	The approaches have used a imperfect number of images and have not described the other classification presentation parameters	https://www.sciencedirect.com/science/article/pii/S1568494621001617
2021	COVID-19 Dataset	CNN	The lungs of kids are not fully developed, it is problematic to forecast the diseases by means of their scan image	https://www.sciencedirect.com/science/article/pii/S0208521621000036
2021	Chest X-Ray CT-Scan Dataset	DNN, Inception V2, ResNet, Inception V4, VGG16, MobileNet	Due to the confines of the COVID-19 examples, a clinical authentication study based on a higher dataset with further COVID-19 samples is desirable to patterned the routine of the projected network	https://www.sciencedirect.com/science/article/pii/S1110016821000144
2020	X-Ray Image Dataset	DarkNet Model, YOLO	A restraint of this learning is the use of a imperfect number of COVID19 X-ray images	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7187882/
2020	Trained-ImageNet Dataset COVID-19 Datasets	nCOVnet, CNN	Since nCOV netenvis ages with a assurance measure we can use the RT-PCR testing in the few belongings where nCOVnet is not poised about to decrease the probabilities of errors.	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7254021/
2020	Medical Images Custom Dataset	Texture Extraction, CNN	Sometimes misclassification of images had happened.	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7513693/
2020	COVID CT scan dataset	Deep CNN, VGG16, Inception V3, ResNet50, DenseNet121, DenseNet201	The maximum average Accuracy, AUC, and F1-Score of 0.8834, 0.8832, and 0.867 All algorithms have shown less accuracy when compared to DenseNet121.	https://www.hindawi.com/journals/jhe/2020/8843664/
2020	CXR Dataset Segmentation Network Dataset JSRT Dataset MC Dataset	ResNet18, DeepCNN, ResNet	This paper performs miss-classification of images for all classes except for COVID and viral. Use of less training images.	https://pubmed.ncbi.nlm.nih.gov/32396075/

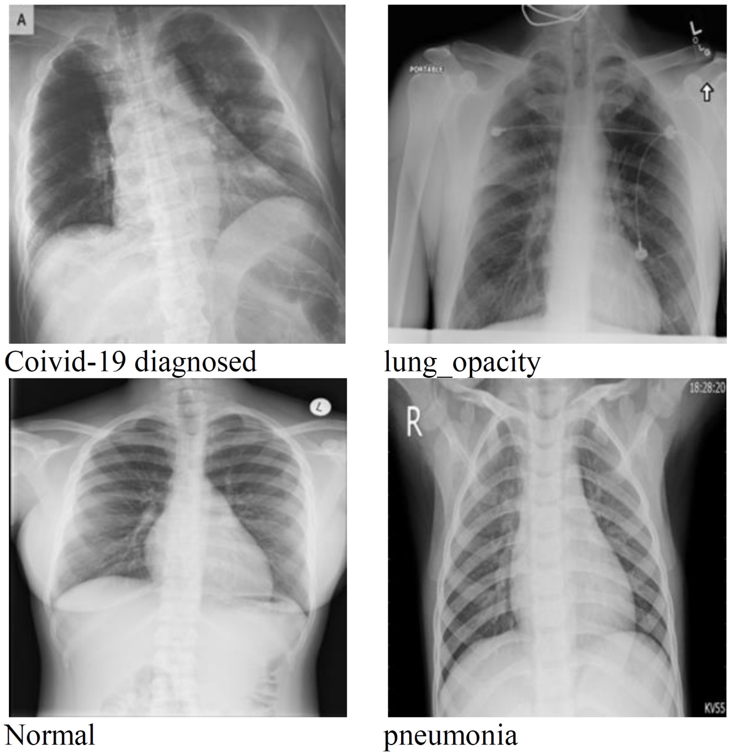


Figure 2: Instances of X-Ray images: positive for COVID-19 and other lung alignments.

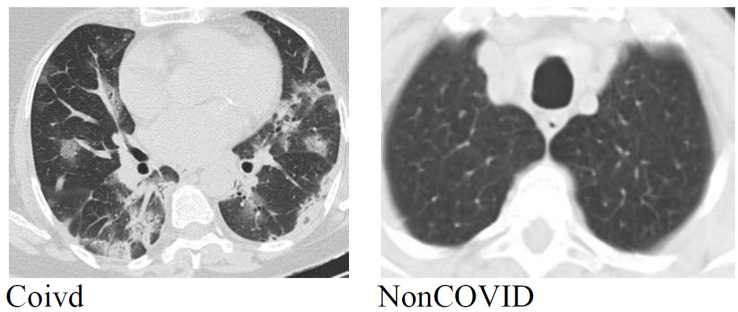


Figure 3: Instances of CT scanimages: positive for COVID-19 and non-COVID-19

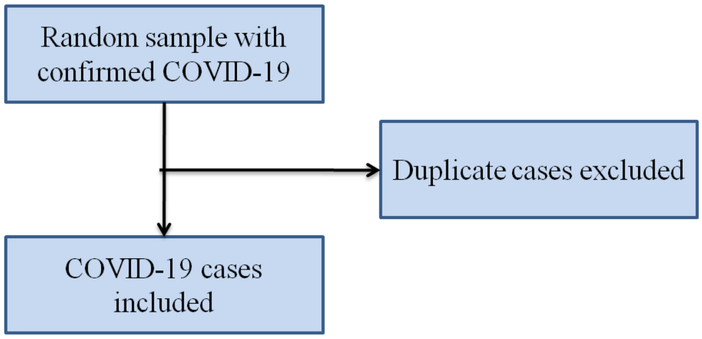


Figure 4: Using Prognostic Tool for Fatality Rate

4. Transfer Learning

Transfer learning is machine learning with a supplementary source of information distant from the typical training data: knowledge from individual or additional related tasks [9]. In an inductive learning job, the purpose is to bring a predictive representation from asituate of training patterns. By definition, Transfer learning is a Domain D consists of 2 parts: a space for the feature X and a distribution P marginal (X). That is= $\{X, P(X)\}$, in other words. And the symbol X denotes a set of instances defined as $X = \{x/xi \ to \ X, \ i = 1, ..., n\}$.
Some machine learning models actually produce the predicted instance conditions'
$(xj) = \{P(yk/xj)/yk, \ k = 1, ..., \mid Y \mid\}$ In this case, $f(xj)$. In practice, numerous instances with or without the label information often observe a domain.

5. Proposed Methodology

In this segment, the projected methodology for COVID-19 showing based on X-ray and CT scans is obtainable. Here the methodology has been proposed for both prognosis and diagnosis.

5.1. Covid-19 Prognosis

We present a model which correctly predicted COVID-19 important disease risk using fatalities and presenting imperative signs and laboratory standards, on descent and validation cohorts from random sample of population. If more validated on supplementary cohorts of patients, this model may provide useful tool of significant care needs. COVID-19 extrapolative tool was built based on custom baseline parameters to forecast unsophisticated disease sequence to support the pronouncement for an earlier discharge.

5.2. Covid-19 Diagnosis

As transfer learning is a prevailing technique for training neural networks, we considered Convolutional Neural Networks (CNNs). The proposed work is to investigate the transfer learning usage and models generalization improvement with the limited datasets. Pre-trained network's convolutional layers are used as feature extractors to reduce parameters numbers which are to be learnt from the network [11]. The feature extraction comprise of convolution i.e., image filtering, ReLU activation i.e., feature detection within filtered image and maximum pooling i.e., image condensing for enhancing the features. Dense Net, VGG16, ResNet, Inception Net models are used on the both datasets [10].

Table 2:

Model	Architecture
DenseNet	• The first layer is associated to the 2nd, 3rd, 4th etc. • The second layer is associated to the 3rd, 4th, 5th etc.
ResNet	• The skip connection omits training from a a small number of layers and connects straight to the output to improve performance
InceptionNet	• Presents sub-networks called inception modules
VGG16	• Blocks of 2 or 3 convolutional layers trailed by a pooling layer, and a final solid network collection of 2 hidden layers in addition to one output layer. • Only 3x3 filters have been used.

By means of convolution filters with dissimilar extents or values results in dissimilar features extracted. Features are after that detected by means of the reLu activation on every target pixel. The convolution receives the identical size of standards from the foundation image, and then proliferates the weighted principles of the $H \times H$ window to the filtered standards of basis pixels. The filtering is repetitive over the basis image by changing the window. Components of the participation and filter are distinct as $p_{i,j}(1 \leq i \leq M, 1 \leq j \leq M)$ and $q_{x,l,n}(0 \leq x \leq H-1, 0 \leq 1 \leq H-1, 1 \leq n \leq N)$, correspondingly.

$$c_{i,j,n} = \sum_{x=0}^{H-1} \sum_{l=0}^{H-1} q_{x,l,n} y^{\wedge}_{i+m,j+1} + a_n \tag{5.1}$$

We utilize a rectified linear unit (ReLU) by means of the activation function (f), which can decide on positive inputvalues appropriate to an advance in the alteration of a matrix, as articulated in the subsequent equation

$$f_{i,j,n} = f1(c_{i,j,n}) \tag{5.2}$$

For transfer learning, after ruling the near dataset, the subsequent step is transferring the knowledge from preceding runsin source dataset to the latest dataset. We decide on four best performing models and hyperparametersituations on the adjoining dataset. The motive we choose the four best performing settings is tokeep away from bias.

We identified an appropriate Convolutional Neural Network (CNN) prototypical all the way through preliminary comparative study of numerous prevalent CNN models. We after that augment the chosen models DenseNet, VGG16, ResNet, InceptionNet for the image modalities to demonstrate how the representations are able to be used for the extremely infrequent and difficult COVID-19 datasets [12].

6. Experimental Results

6.1. Covid-19 Prognosis

The most important outcome was the efficacy of different parameters for early on prognostication of patients with COVID-19 and all reasons for mortality or it is replacement. Factors influencing the prognosis are shown in Table 3. Patients were categorized into three groups. We analyzed features of various patients to determine potential biomarkers that may influencethe prognosis and supervision of these patients.

COVID-19 can happen in any age group. By the outcomes of prognostic tool,meekillness appears in those under 40 years of age. Older individuals build up higher levels of sternness of disease.

Table 3: Baseline Characteristics with Mortality of Patients for COVID-19

Parameter	**Age**	**Results**	**Parameter**	**Age**	**Results**	**Parameter**	**Age**	**Results**
Age?	<40	0.2%	Age?	40-49	0.4%	Age?	50-54	Age Specific Fatality Rate : 1.3%
Cardiovascular Disease?	No		Cardiovascular Disease?	No		Cardiovascular Disease?	Yes	Cardiovascular Disease Specific Fatality Rate : 10.5%
Diabetes?	Yes	Patients with no described underlying medical situations had an inclusive case casualty of 0.9%	Diabetes?	Yes	Patients with no describedcausal medical situations had an inclusive case casualty of 0.9%	Diabetes?	Yes	
Chronic Respiratory Disease?	No		Chronic Respiratory Disease?	No		Chronic Respiratory Disease?	No	
Hypertension?	No		Hypertension?	No		Hypertension?	Yes	Diabetes Specific Fatality Rate : 7.3%
Cancer?	No		Cancer?	No		Cancer?	No	
Prior Stroke?	No		Prior Stroke?	No		Prior Stroke?	No	
Heart Disease?	No		Heart Disease?	No		Heart Disease?	Yes	
Chronic Kidney Disease?	No		Chronic Kidney Disease?	No		Chronic Kidney Disease?	No	Hypertension Specific Fatality Rate : 6.0% Comorbidity Information : Heart disease has been linked with increased COVID-19 illness sternness and contrary outcomes.

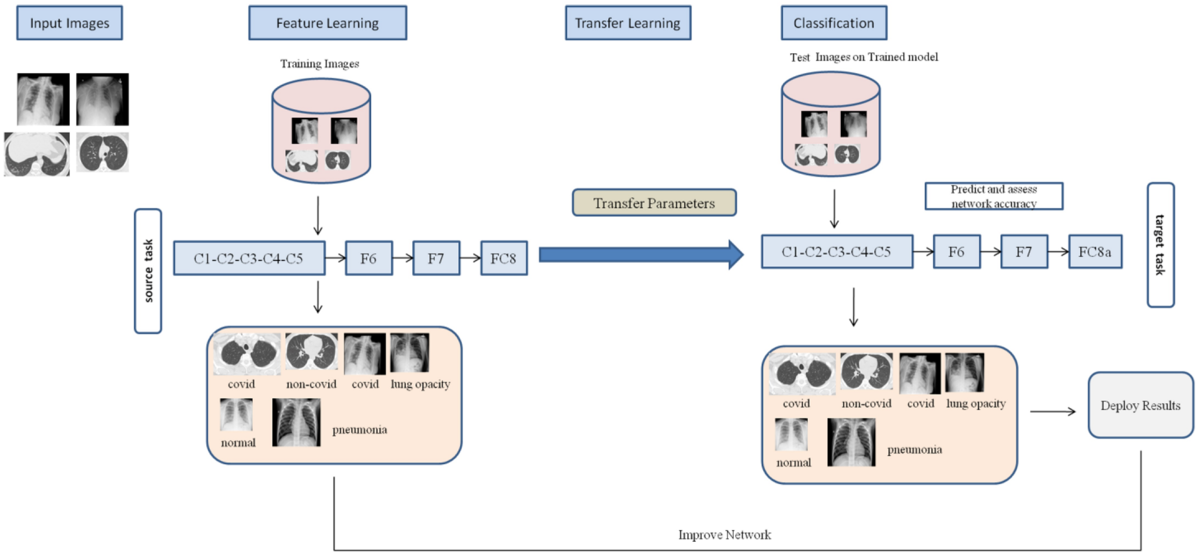


Figure 5: Proposed Architecture for Transfer Learning with appropriate CNN

When experimented prediction of incidence of ICU admission, automatic ventilation, or demise of COVID-19hospitalized patients, the results are shown in Figure 6.

A novel transfer learning through convolutional neural network as classifier was developed by means of a simplified programming method and a dataset containing of 21,165 chest X-ray images which was fragmented into training test, validation subgroups. Pixel value distribution was investigated to investigate the spreading of pixel intensities in the image [13]. Modification of images to suit training of convolutional neural network using ImageDataGenerator by which data preprocessing and data augmentation such as random horizontal flipping of images is performed. To have mean value 0 and standard deviation 1, values in each batch are transformed using generator. This generator converts X-ray/CT scan image which is a gray scale image to a three channel format [14]. New generator was build for testing and validation datasets as we normalize as we process one image at a time, incoming test data using statistics computes from the training set [15]. The dimensions of the X-Ray image are 180 pixels width and 180 pixels height, one single color channel. The maximum pixel value is 3.0183 and the minimum is -2.7502. The mean value of the pixels is -0.0000 and the standard deviation is 1.0000.And the dimensions of the CT scan image are 229 pixels width and 321 pixels height, one single color channel. The maximum pixel value is 1.0000 and the minimum is 0.2000. The mean value of the pixels is 0.7248 and the standard deviation is 0.3009.
To build a CNN model, imbalance data on loss function was calculated using the following

$$L_{crossentropy}(p_i) = -(q_i \log(f(px_i)) + (1 - q_i) \log(1 - f(p_i))) \tag{6.1}$$

On the whole average cross-entropy loss above the complete training set S of size N is rewritten as:

$$L_{crossentropy}(S) = -\frac{1}{N}(\sum_{positive} \log(f(p_i)) + \sum_{negative} \log(1 - f(p_i))) \tag{6.2}$$

To avoid bias toward the dominating class, we used a weighted loss function which balanced the contribution in the loss function as following

$$L^u_{crossentropy}(p) = -(U_s p \log f(p)) + U_n(1 - p) \log(1 - f(p)) \tag{6.3}$$

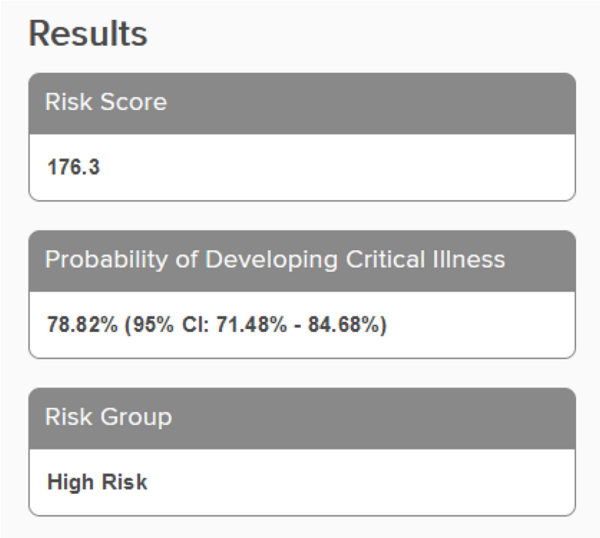


Figure 6: Results of extrapolativetool forCOVID-19 critical infirmity prediction

Autonomously, 4 varieties of pre-trained CNNs model: DenseNet, VGG16, ResNet, InceptionNet on ImageNet datasets are adjusted on taken dataset of X-ray and COVID19-CT images, through the objective of relocating the evidence into our mission that consumes inadequate training facts.

6.2. Algorithm TL-CNN

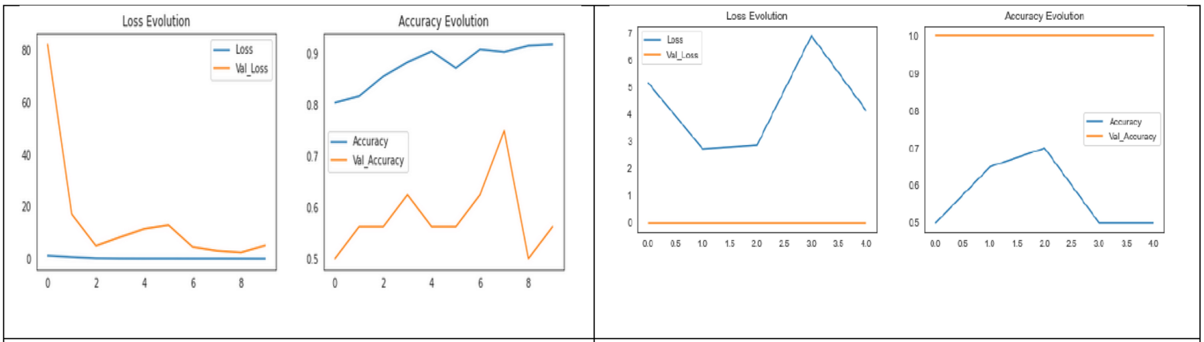
1. perform modifications to use pre-trained model by fine-tuning
2. $learning\_rate < training\_learning\_rate$
3. fine-tuning:
   feature extraction by means of pre-trained model and remove the output layer
   fix feature extractor for entire new dataset
   architecture usage of the pre-trained model while initializing model and training the model
   train the model partially and retain some weights of frozen initial layers
4. develop skillful model for first task
   reuse the model based on the source task
   fine_tune the model on the input-output pair data available
5. retrain specific features on a fresh target dataset is necessary to progress performance.

The class weights extracted for X-ray and CT scan are Weight for category 0: 0.74, Weight for category 1: 0.26 and Weight for category 0: 0.50, Weight for category 1: 0.50. The steps_per_epoch=100, validation steps=25 were considered loss evolution and accuracy evolution for both X-ray and CT scan in the training groups for modification of diverse pre-trained CNN models, correspondingly and are depicted in Figure 7.

The results of classification metrics, support, precision, recall, and F1 score are illustrated in Table 4.

The consequences of transfer learning by means of different structures are demonstrated in Table 5 by mutual classification system of measurement, accuracy, precision, recall, F1 score in addition-support.

To develop the classification accurateness, a proposed method has been established, where diverse architectures of transfer learning with CNN productivities as singular classifiers are merged [16].It was pragmatic that the proposed method using transfer learning with CNN models using preponderance



(a) (b)

Figure 7: (a) X-ray loss evolution and accuracy evolution (b) CT scan loss evolution and accuracy evolution

	0	1	accuracy	macro avg	weighted avg
precision	0.956522	0.647255	0.658654	0.801888	0.763230
recall	0.094017	0.997436	0.658654	0.545726	0.658654
f1-score	0.171206	0.785066	0.658654	0.478136	0.554868
support	234.000000	390.000000	0.658654	624.000000	624.000000

(a)

	0	1	micro avg	macro avg	weighted avg
precision	0.0	0.483113	0.483113	0.241557	0.233398
recall	0.0	1.000000	0.483113	0.500000	0.483113
f1-score	0.0	0.651485	0.483113	0.325743	0.314741
support	352.0	329.000000	681.000000	681.000000	681.000000

(b)

Figure 8: (a) X-ray: Classification system of measurement on the test dataset using the dissimilar architecture of proposed transfer learning with CNN. (b) CT scan: Classification system of measurement on the test dataset using the dissimilar architecture of proposed transfer learning with CNN [1]

Table 4:

	Model	Precision	Recall	F1-score	Accuracy		Model	Precision	Recall	F1-score	Accuracy
X-Ray Image Dataset	DenseNet	0.607(± 0.03)	0.608(± 0.6)	0.607(± 0.05)	0.61(± 0.04)	**CT scan Image Dataset**	DenseNet	0.728(± 0.03)	0.728(± 0.02)	0.728(± 0.03)	0.74(± 0.02)
	VGG16	0.755(± 0.04)	0.745(± 0.07)	0.745(± 0.04)	0.75(± 0.02)		VGG16	0.708(± 0.06)	0.709(± 0.09)	0.708(± 0.03)	0.71(± 0.04)
	ResNet	0.810(± 0.03)	0.806(± 0.7)	0.806(± 0.05)	0.81(± 0.04)		ResNet	0.79(± 0.04)	0.789(± 0.06)	0.788(± 0.03)	0.79(± 0.03)
	InceptionNet	0.825(± 0.03)	0.814(± 0.05)	0.815(± 0.03)	0.82(± 0.03)		InceptionNet	0.825(± 0.03)	0.814(± 0.05)	0.815(± 0.03)	0.82(± 0.03)
	Proposed Model	0.87(± 0.02)	0.868(± 0.05)	0.869(± 0.01)	0.87(± 0.01)		Proposed Model	0.91(± 0.01)	0.91(± 0.02)	0.91(± 0.02)	0.91(± 0.01)

voting format for ultimate forecast is improved than entity representations with elevated precision, recall and accuracy as 0.87, 0.868 and 0.87 for X-ray image dataset and for CT scan image dataset precision, recall and accuracy as 0.91, 0.91 and 0.91.
The multi-class classification routine of the proposed prototypical has been estimated for every fold, and the typical classification routine of the approach is considered [17, 18]. Related confusion matrix is formed using the quantity of confusion matrices attained in the entire folds. Sensitivity, specificity, correctness, F1-score, and correctness canons are shown in Table 5.

From the Table 5,the proposed model has accomplished an average accuracy of 88.15% and 86.286% for X-ray and CT scan image datasets.

7. Conclusion

Currently, there are not any obvious treatment alternatives for COVID-19. A great deal of the treatment hinge on knowledge, laterally with indicative and helpful care.The healthiness position and virus vulnerability of a patient are significant influences that require to be measured to expand a prediction of the disease. Elderly people, patients with cardiac disease and individuals with chronic fundamental diseases have deprived prognosis. As lockdown limitations all through the creation ease, the severity of the pandemic tranquil requires adjacent study, in directive to progress its prognosis. Accurate analysis of COVID-19 using a elementary deep learning method is practicable using open-source X-ray and CT image statistics. We have described how different models are inputted to CNN based transfer learning and inspected how this method makes classifications by attempting to achieve deeper insights into significant factors connected with COVID cases, which can assist clinicians in enhanced screening as well as advance trust and precision when leveraging CNN with TL X-ray and CT imaging.

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Table 5: Proposed Model Sensitivity, specificity, precision, F1-score, and accurateness values for respectively fold of X-ray and CT scan image datasets.

X-ray Dataset					
Folds	Performance Metrics				
	Sensitivity	Specificity	Precision	F1-Score	Accuracy
1-fold	85.83	92.75	89.71	87.57	90.97
2-fold	84.83	91.14	89.38	86.8	87.1
3-fold	82.61	92.75	89.71	87.57	87.11
4-fold	85.83	92.29	84.57	84.57	88.00
5-fold	83.9	90.61	89.71	92.75	87.57
Average	**84.6**	**91.908**	**88.616**	**87.852**	**88.15**
CT scan Dataset					
Folds	Performance Metrics				
	Sensitivity	Specificity	Precision	F1-Score	Accuracy
1-fold	86.83	91.76	91.1	83.75	89.01
2-fold	84.16	82.24	88.12	88.7	86.5
3-fold	83.13	91.65	87.21	85.0	89.22
4-fold	83.0	91.12	84.2	82.1	79.8
5-fold	85.3	87.9	87.12	90.8	86.9
Average	**84.484**	**88.934**	**87.55**	**86.07**	**86.286**

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