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Transfer Learning Technique for Covid-19 Screening from CT-Scan: An Empirical Approach

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ABSTRACT- As a result of the Covid-19 pandemic, the field of Medical Sciences has been challenged with new challenges and benchmarks for development. Front line workers are overcoming the Covid-19 challenge with four steps: Screening and Diagnosis, Contact Tracing, Drug and Vaccine Development, and Prediction & Forecasting. Following the above segments carefully can save millions of lives. Artificial Intelligence has proven invaluable in predicting critical factors in many fields. With the ability of AI to process huge databases and conclude with high precision, we are motivated to use AI to screen and diagnose the Covid-19 pandemic. This paper examines the strategic use of Transfer Learning for screening and diagnosis of Covid-19 Patients. The Xception model is used to categorize Covid-19 infected patients. Our proposed Xception model has achieved better Accuracy, Sensitivity and Specificity as compared with state-of-the-art models.

General Terms: Xception Model, Transfer Learning, Healthcare
Keywords: Covid-19; Transfer learning; Xception model, CT-Images

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1. INTRODUCTION

At the onset of Coronavirus Disease 2019 (Covid-19), which is caused by severe acute respiratory syndrome Coronavirus 2 (SARS-Cov-2), the Medical Science Community is shook terribly. Covid-19 caused millions of deaths throughout the world and post covid diseases to thousands of patients. As time has passed, frontline workers have identified effective ways to deal with the pandemic by utilizing the existing modern technology. There are four steps in dealing with the Corona'19 Pandemic. The first step is to screen and diagnose patients having normal to savior symptoms. By doing this, the Covid-19 patients can be immediately separated from the general population. As a result, the patients can receive immediate treatment and be saved. A second step involves tracing the contacts the identified patients had with others. In this way, the Corona Virus spread can be limited. Moreover, this step allows one to determine the number of patients who were in close contact with Covid Positive, and this information is used to forecast the estimated amount of medical resources to be needed in the near future. Thirdly, dedicated teams work on developing drugs and vaccines that can be used.

To deal directly with Covid-19 today, there is no clear solution, even after this. Because of the dynamic behavior of the virus and its severity in virulence, blunt measures were adopted to safeguard lives, such as public movement bans, lockdowns, and restricted access. Thus, it has become rational to use modern technological resources to help in achieving better results at a lower cost to society. Collecting and analyzing large amounts of data to get precise results is the first and foremost challenge. Data science plays an important role in this process. People in the frontline who are working in the first two phases are working at the front end, while those working in the last two phases are working at the back end.

The main contribution to the study is the use of Transfer Learning in the diagnosis and screening of patients infected with COVID-19. It highlights the importance of using AI to process massive databases and address the challenges that medical professionals face during the outbreak. By utilizing Transfer Learning, the proposed Xception model can improve its accuracy and sensitivity when compared to existing models. This method helps the model learn from large datasets, which can aid in capturing important COVID-19 features. Through the use of accumulated knowledge, the model can also demonstrate better specificity, sensitivity, and accuracy.

In this paper, a novel screening and diagnosis technique is presented. Data Science is used to implement the proposed technique using Transfer Learning Approach. In addition, the model is implemented using Xception modeling, pretrained on ImageNet data. Python and Keras Deep Learning Library are used to describe the model. Models designed with this configuration are scalable, they increase speed, they are

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reliable, and they perform at a higher level without human involvement once trained and developed. Afterward, the paper conducts a detailed review of the known techniques, presents a proposed model, and concludes with discussion of the results.

2. LITERATURE REVIEW

Disease is defined as a harmful variation that adversely impacts a person's health. Coronaviruses are among the most virulent pandemics in the history of mankind. Coronavirus safety precautions include keeping the contaminated person away from others and isolating them from the rest of the population. Coronavirus end period can be predicted using reproduction number and case casualty rate. The authors examined several methods for examining and presenting coronavirus data. Moreover, the authors [Mishra, 2021] developed an algorithm for approximating the virus transmission rate in several regions. We present a novel algorithm for predicting when the coronavirus pandemic will end using data from infected and recovered people. A final experimental analysis is presented in order to estimate the impact of transmission possibility, contagiousness, and the estimated number of people affected by the Coronavirus.

Coronavirus was first discovered in Wuhan, China, in December 2019 and has since spread rapidly around the world. World Health Organization declared it a global epidemic within a very short amount of time. Several regions of Indonesia where the positivity rate of Coronavirus is high are examined in this paper. It is difficult to predict the outcome when a person shows no symptoms of Coronavirus. To approximate and expand Coronavirus, the authors proposed two methods [Burhanuddin, 2021]. We compare the outputs of the proposed methods to determine the probability of the maximum spread of the Coronavirus in several regions.

Using the first method, the maximum spread for the day is predicted to be 168 and using the second method, it is predicted to be 167. This difference is impacted by an alpha factor, which is based on coronavirus initiation.

A recent Coronavirus outbreak has frightened all human communities. During this epidemic, authorities often have to take quick decisions in order to save the lives of people. Public mobility is restricted during lockdowns and curfews to reduce COVID-19 spread. Among the most important factors contributing to the spread of Coronavirus disease is public mobility. The study [Parvathavarthini,2021] applies the fuzzy clustering-based cross alternative to investigate mobility patterns in the preferred region by identifying the best features. Depending on the results, there may be a need to restrict areas with high public mobility. Moreover, a detailed analysis is done to determine if there is a correlation between changes in public mobility during the lockdown and after it to the Coronavirus outbreak. In the area of interest, the risk of public mobility is categorized into low-, average-, and high-risk areas.

In 2020, COVID-19 was discovered in China and quickly spread throughout the world. A lack of vaccine against Coronavirus continues to cause an increase in Coronavirus patients. Coronavirus disease triggers life anxiety and results in the loss of quality of life as a result. Teaching-learning processes are conducted online in the education sector. Inequality occurs because it is more difficult to detect Coronaviruses and the demand for Coronavirus tests has increased rapidly. Using machine learning is one of the best solutions to reduce this critical situation. In [Sangidong, 2021], the authors proposed a simple machine learning technique based on Coronavirus Networks. When compared to other machine learning models, the proposed approach requires less training time. It also achieves 97.98% accuracy.

Globally, COVID-19 is a public health emergency whose spread must be curtailed immediately. Identifying and isolating the infected individual for at least 15 days is the most effective way to reduce the rapid spread of the Coronavirus. As an analytical tool, X-ray scanning of the chest can be used to detect coronaviruses. One of the most difficult jobs is to differentiate the features of the coronavirus disease from other diseases having the same characteristics outputted from the X-ray of the chest. Machine learning with CAD is the most effective way to eliminate this problem and increase accuracy. Using X-ray images, artificial intelligence-based machine learning systems can be used for analyzing and accurately identifying coronavirus infected persons. The authors [Fitriasari,2021] proposed two convolutional neural network-based structures to identify confirmed Coronavirus cases by categorizing them into different classes. By incorporating these structures into the system, it becomes more effective at detecting characteristic patterns.

With the rise of the internet of things, new researchers are gathering and transmitting data to the cloud in order to increase system efficiency and speed up decision-making processes in the medical field. Today, everyone is aware of the coronavirus diseases which are rapidly spreading around the globe. researchers are working on ways to gather, transmit, and continuously monitor the infected person's data remotely in order to minimize disease transmission. The authors developed an application based on the Internet of things to eliminate the risk of transmission of Coronavirus disease from one individual to another. In the proposed system [Hanoon,2021], some parameters such as heart rate, body temperature, and oxygen level can be detected and measured while doctors observe the data from a distance. These parameters can be recorded by an embedded device that connects to a cloud server.

There is a huge impact of the Coronavirus on Indonesia's population. Everyone today wonders when this epidemic situation will end, so that human life can return to normal. Author [Kurniawan,2021] suggested a novel graph fitting procedure for finding the probability of the time and the overall infected person information based on period series information without considering the recovery rate and lockdown period. Based on the experimental result and evaluation of the normal graph, the proposed technique predicted that the epidemic coronavirus disease would last about two years since it began. In regards to the open lockdown and other strategies related to social needs; the calculated predictions can assist the authorities in making the right course of action.

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Due to the rapid increase in deaths and infected cases due to Coronavirus, it is now necessary to continuously monitor the physical condition constraint of an infected person. Due to the growing number of infected people, the healthcare system is in trouble. The three most important parameters that need to be monitored during COVID-19 are pulse rate, breathing rate, and blood oxygen level. Pulse rate and blood oxygen are the two parameters that are most frequently used by doctors to detect pneumonia. Pulse rate and blood oxygen measurements are available in many nations, but their costs are high. A sensor kit based on an Atmega Atmel for the measurement of pulse rate and blood oxygen has been designed and developed by the authors. Based on a comparison with a commercially available pulse oxygen meter, a variation of 0.78 percent for pulse rate and 0.39 percent for blood oxygen was found, which suggests the proposed method is efficient [Ahmed, 2021].

Coronavirus disease is still a worldwide epidemic, and numerous expert interventions are already in place to detect infected patients with Coronavirus disease. A machine learning technique based on cough acoustic examples was proposed by the authors [Vrindavanam, 2021] for identifying people infected with Coronavirus. There are three categorization models established, and the best model is identified amongst these three. The characteristics are selected based on grade dissimilar scores using the characteristics selecting approach. By using the proposed technique, front-line employees can reduce their workload and have enough time to work with healthcare professionals. Both coronavirus-infected and healthy subjects are studied in the experiments, and the results are encouraging.

The city of Wuhan in China is known as the birthplace of the epidemic Coronavirus which spread rapidly throughout the world. COVID-19 adversely affects pulmonary tissues in humans, therefore chest X-rays can be helpful for detecting COVID-19 early on. Fixed X-ray systems reduce COVID-19 infectivity, so portable X-ray systems are a better alternative. However, portable X-ray systems have lower quality images. A new technique has been proposed to artificially enhance the quality of X-ray images to detect Coronavirus disease [Moris,2021]. A rotation generative adversarial arrangement structure is used for sampling purposes without the requirement of paired information. This portable X-ray system is capable of detecting Coronaviruses with an efficiency of 96%.

Supervisory testing is the most important method of reducing the spread of Coronavirus disease. CRISPR and qualitative reverse transcription polymerase chain reaction testing are alternative methods that are frequently used since they are faster, easier and cheaper. In order to improve the CRISPR detection technique, the authors have designed and developed a convention processor vision application that works in conjunction with fluorescence images of the detected examples and gives the test results. Experimental results indicate the computed features are related to the example pictures, which are important for determining the transmissibility and severity of infection. CRISPR detection of Coronavirus diseases could be made more effective using the proposed method depicted in *figure 1*.

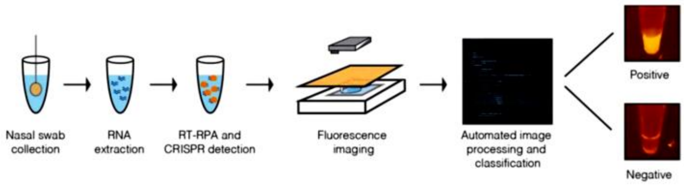

Figure 1: Coronavirus detection using CRISPR testing

The World Health Organization has classified the Coronavirus diseases as an epidemic for which the search for an accurate treatment is still on. Coronavirus diseases are challenging to identify because they spread rapidly through physical contact. Fever, headaches, coughs, and a loss of taste and smell are the most common symptoms. Based on circulatory blood indicators, the authors [Darapaneni,2021] have proposed an analytical tool for detecting highly infected Coronavirus disease persons. Analysis of this kind can help authorities to take care of highly infected people and to conduct frequent examinations on less infected people. In order to optimize the utilization of hospital beds for highly infected patients, the proposed application can aid hospital management.

Coronavirus is a life-threatening infection that is characterized by severe, sensitve respiratory symptoms. Therefore, early detection and treatment of Coronavirus disease are essential. A variety of techniques are used to detect Coronaviruses, including computerized tomography and X-rays. Coronavirus detection requires professional knowledge and takes a lot of time. In [Shrivastava, 2021], the authors propose a max choice supported group learning technique. Learning and testing are carried out using the available information set of computerized tomography and X-ray tests. In terms of sensitivity, efficiency, and correctness, the proposed methodology can achieve an average of 98%.

In many ways, the entire world is affected by the Coronavirus. Some people have lost their loved ones, most people have lost their jobs, and almost all people are struggling with financial crises. Efforts to find out the correlation between coronavirus disease-related infections and death rates are continuously being made by experts to identify the main causes of infection and death rates. A number of recent studies have focused on two prospective studies. The first is to identify the causes of disease and preventative measures to be used; the second is to recognize the link between the deaths and existing diabetes and heart conditions. The purpose of the present paper is to establish a correlation between Coronavirus disease and the eating habits of citizens. Data has been collected from supermarkets regarding consumers' purchasing habits. The health-related information was collected from the information center. Following a detailed analysis, we conclude that foods containing alcohol, fat, and carbohydrates may be associated with Coronavirus disease [Algbear, 2021].

As a result of this Coronavirus outbreak situation, hospital health staff cannot identify the serious patients from the normal ones, which results in poor personal outcomes. Using novel communication techniques and sensor-based expertise, the authors are able to supervise the home-isolated Coronavirus-infected patient frequently. During the Coronavirus epidemic,

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[Maghraby, 2021] software was proposed to solve the problem of hospital overloading. A wristwatch is used in the proposed software to constantly check some parameters like body temperature and pulse rate and transmit them to a computer via Bluetooth. A notification is sent to the hospital staff and patient family member when symptoms of a patient worsen without human intervention.

3. PROPOSED SCREENING MODEL

In this paper, the proposed model is described using the Python programming language. The code is interpreted, meaning it is executed immediately rather than compiled and then executed. A byte-code is used to convert the high-level language. In comparison to compiler-based language platforms, it makes it one of the fastest open-source scripting languages. Programming language Python has dynamic semantics. Additionally, open-source libraries need to be incorporated for individual application development. Consider, for instance, the development of a scientific application, where additional libraries are used like SciPy, Pandas, and NumPy; the development of web applications uses libraries like Django, Pyramid, and Flask. Also, an open-source deep learning library, Keras, is used for applications related to Deep Neural Networks. *Figure 2* explains the proposed methodology flow.

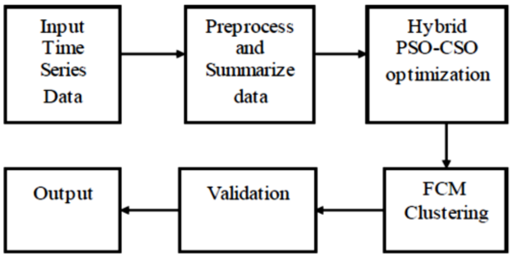

Figure 2: Proposed Methodology

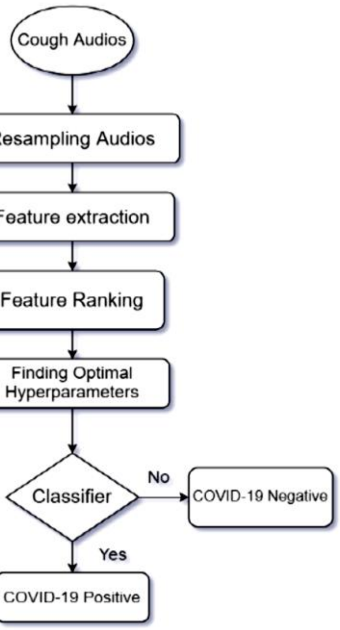

Figure 3: Flowchart of Proposed Methodology

We used Convolutional Neural Network (CNN) fundamentals to develop the screening model as it is the most effective tool for extracting patterns and details from low resolution and critical images like CT scans. A camera image can be input to the system in real time, or an image downloaded from a local disk can be input. Training and validation are two separate parts of the system. During the testing phase, the input images are used to train the screening model. In the validation phase, the input images are checked for accuracy. In the proposed training model, the input images are fed through the local disc. *Figure 4* and *figure 5* discloses sample Covid and Non-Covid CT Scan Images.

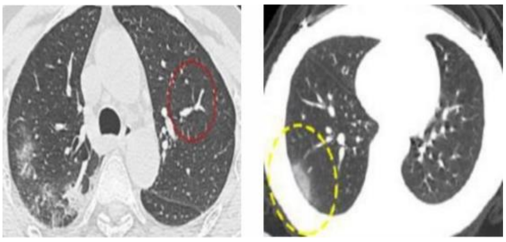

Figure 4: Sample Covid CT Scan Images

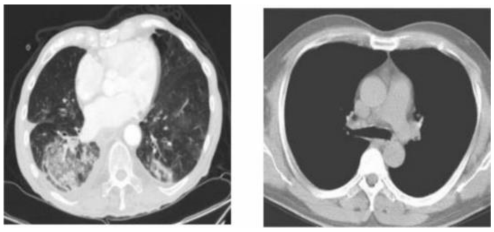

Figure 5: Sample Non-Covid CT Scan Images

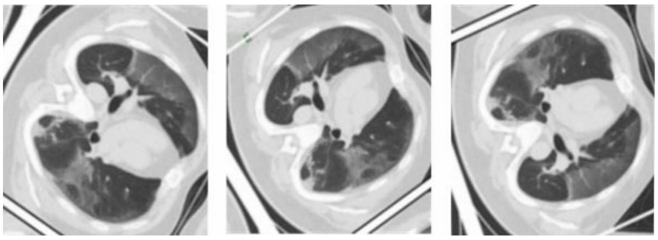

Figure 6: Outcome after Pre-Processing: Horizontal Flip, 10% Zoom and 0.1^0 Rotate

We used a data set of 3445 CT scan images for the training and validation process. There are 1571 positive Covid CT Scan images in this data base and 1784 negative Covid CT Scan images. Generally, 80% of the database, or 2756 samples, are used for training the screening model, and 20% of the database, or 689 samples, are used for validation.

An additional step is the Pre-Processing of the input images. This process involves various operations like resizing, rotating, labelling, and others. For the classification statements, pre-processing reduces the training time and results in better classification of the input samples. An example of the outcome after pre-processing is shown in *figure 6*.

Following preprocessing of the training dataset, 20,863,536 samples are generated. There are only 2049 trainable samples from these samples, while 20,861,487 non-trainable samples are discarded. We analyze these samples and train the model based on 20 epochs. A training accuracy of 94.1% and a validation accuracy of 95.8% are observed when these constraints are used. Fine tuning is performed with 10 epochs in the following step. By resetting the constraints, 20,863,536 samples become 20,809,001 samples and the non-trainable samples become 20,863,536 samples. Fine-tuning the Xception model involves taking into account various parameters, such as the learning rate, batch size, optimizer settings, and the mode of operation. In addition, the optimization techniques and loss functions can be considered.

After resetting the constraints, the trainable samples become 20,809,001, while the non-trainable parameters remain at 54,535 out of 20,863,536. The training accuracy is thus almost 99%, and the validation accuracy is almost 97.6%.

4. RESULTS AND DISCUSSIONS

After the experimentations are performed, the outcome observed in the form of Confusion Matrix is shown in *figure 7*.

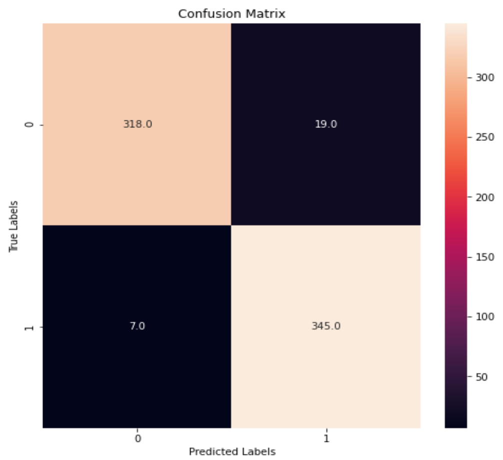

Figure 7: Confusion Matrix

The values of True Positives (TP), False Positives (FP), True Negatives (TN) and False Negatives (FN) are as follows:

TP = 318, FP = 19, TN = 345, FN = 7

Based on values of TP, FP, TN and FN, following ascendency parameters are computed as follows:

Accuracy:

Accuracy= (TP+TN)/(TP+TN+FP+FN) = (318+345)/ (318+345+19+7) = 96.22%

Precision:

Precision=TP/TP+FP=318/ (318+19) = 94.36%

F1 Score:

F1 Score= (2*TP) / (2* TP+FP+FN) = (2 *318) / (2*318+19+7) = 96.07%

Sensitivity/Recall/True Positive Rate:

Sensitivity= TP/ (TP+FN) = 318/ (318+7) = 97.64%

Specificity/True Negative Rate:

Specificity= TN/ (TN+FP) =94.78%

Training Time: The training time per epoch is provided through the jupyter notebook console. For 20 epochs of the training, the training time is:

Training Time = 46.05 minutes

Fine Tuning Time: After execution of the training process, the fine tuning is carried out. As per the jupyter notebook console, for 10 epochs of fine tuning, the time required is:

Fine Tuning Time=80.03 minutes

Further, Covid class prediction and non-Covid class prediction precision can be calculated by executing classification report command. Accordingly, the Covid Class prediction precision is 98% and non-Covid Class prediction precision is 95%. Considering this average classification precision is 96.5%. In a nutshell, the following statistical results are observed as shown in *table 1*.

Table 1: Overall Statistical Analysis of the Proposed Model Using Xception Modelling

Sr. No.	Parameter	Formula	Value
1.	TP	-	318
2.	TN	-	345
3.	FP	-	19
4.	FN	-	7
5.	Accuracy	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$	96.2264 %
6.	Precision	$Precision = \frac{TP}{TP+FP}$	94.3620 %
7.	Average Class Precision	-	96.5 %
8.	F1-Score	$F1\ Score = \frac{2*TP}{2*TP+FP+FN}$	96.0725 %
9.	Sensitivity/ Recall/ True Positive Rate	$Sensitivity = \frac{TP}{TP+FN}$	97.6481 %
10.	Specificity/ True Negative Rate	$Specificity = \frac{TN}{TN+FP}$	94.7802 %
11.	Training Time	-	46.05 min
12.	Fine Tuning Time	-	80.03 in

4.1 Comparative Analysis of different Modelling Style

Different researchers prefer to implement the prediction model for Covid-19 disease using different algorithms. The subsequent *table 2* discloses the performance evaluation with respect to the modelling style that is algorithms used for implementation of their model. In the subsequent table, application for which the model is designed, preferred algorithm and performance metrics like accuracy, sensitivity and specificity is disclosed.

Table 2: Performance Evaluation with respect to Modelling Style

Ref. No	Application	Algorithm	Performance
[Sethy,2020]	COVID-19 detection by SVM based on deep feature using X-ray images	ResNet50+ SVM	Accuracy: 0.95 Sensitivity: 0.97 Specificity: 0.93
[Narin,2021]	Binary classifications with four classes: COVID-19, normal, viral and bacterial pneumonia	Deep CNN ResNet-50	Accuracy: 0.96
[Apostolopoulos, 2020]	COVID-19 detections from X-ray binary and 3-class classification using 2 datasets	VGG-19 and MobileNet v2	Accuracy: 0.97 Sensitivity: 0.99 Specificity: 0.97
[Song,2021]	Pneumonia classification, COVID-19 diagnosis and localization of the main lesions from X-ray	DRE-Net (ResnNet50 + FPN)	Accuracy: 0.86 Sensitivity: 0.96
[Zheng,2021]	Weakly-supervised software system to detect COVID-19 from 3D CT volumes	UNet+DeCoVNet (3D DNN)	Accuracy: 0.91 Sensitivity: 0.91 Specificity: 0.91
[Xu,2020]	Distinguish COVID-19 pneumonia from Influenza-A viral pneumonia (IAVP)	ResNet-18	Accuracy: 0.87 Sensitivity: 0.87 Specificity: 0.81
[Mei,2020]	Rapid diagnosis for COVID-19 combined with clinical info	ResNet18 + MLP	Accuracy: 0.92 Sensitivity: 0.84 Specificity: 0.83
[Hurt,2020]	Probability maps to augment COVID-19 diagnosis from CT images	U-Net17	Accuracy: 0.81 Sensitivity: 0.83 Specificity: 0.73
[Li,2020]	Identify COVID-19, CAP non-pneumonia from chest CT	COVNet	Sensitivity: 0.90 Specificity: 0.96
[Wang,2021]	Prediction of COVID-19 on CT images	M-Inception	Accuracy: 0.83 Sensitivity: 0.81 Specificity: 0.8
[Hemdan, 2020]	Automatically diagnose COVID-19 in X-ray images	COVIDX-Net	Accuracy: 0.92 Sensitivity: 0.10 Specificity: 0.99
[Wang,2020]	Detection of COVID-19 cases from chest X-ray images	COVID-Net	Accuracy: 0.92 Sensitivity: 0.91
Proposed	**Proposed Model**	**Xception Model**	**Accuracy: 0.9623** **Sensitivity: 0.9764** **Specificity: 0.9478**

Accuracy is the means by which we can represent like how much our model is doing right prediction. The subsequent depicts the comparative analysis of the proposed Xception model with the previously reported, different algorithms. As it is observed from the *figure 8*, if the classification model is implemented using ResNet 50 algorithm the performance is comparable and the proposed model still performs better than the ResNet 50. Whereas if the classification model is implemented using VGG-19, the model performs slightly better than the Xception model.

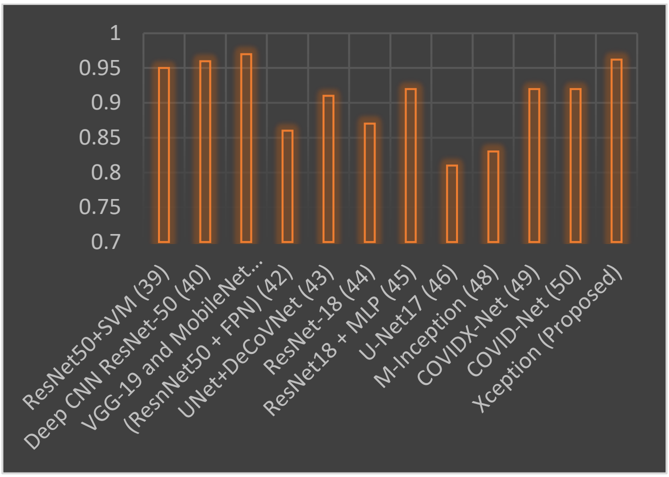

Figure 8: Performance Evaluation with Respect to Accuracy

Sensitivity is the metric which indicates how much the model is sensitive in predicting the true positive samples. It can also be interpreted as measure of actual cases which are predicted as positive. As per the graph shown in the *figure 9*, the proposed model is 97.64% sensitive in predicting the positive samples. This performance is slightly better than the ResNet-50 algorithm, if it is combined with SVM or FPN. Further, the model performance is comparable with the performance of the model designed using VGG-19 algorithm.

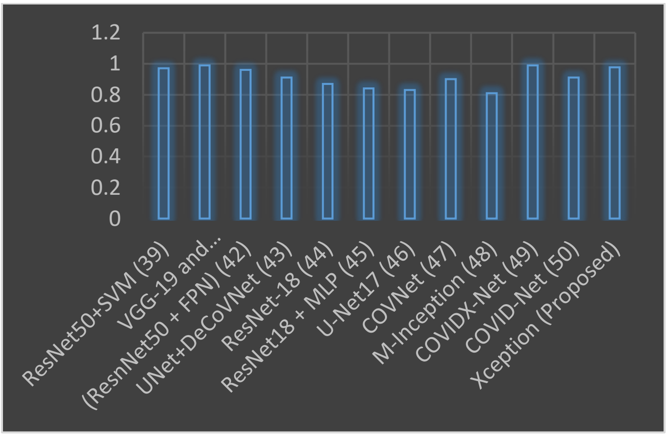

Figure 9: Performance Evaluation with Respect to Sensitivity

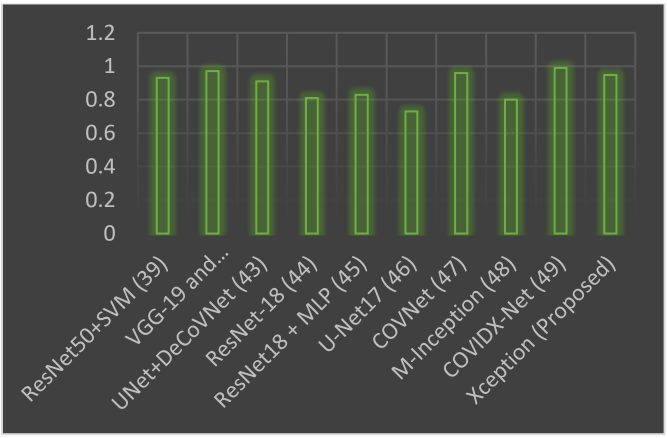

Figure 10: Performance Evaluation with Respect to Specificity

Specificity is the measure which indicates the proportion of negative samples which are actually classified as the negative samples. The performance evaluation with respect to the specificity is disclosed in the *figure 10*. As shown in the graphical representation, the specificity is the much better than the other techniques except the VGG-19 and Covidx-Net.

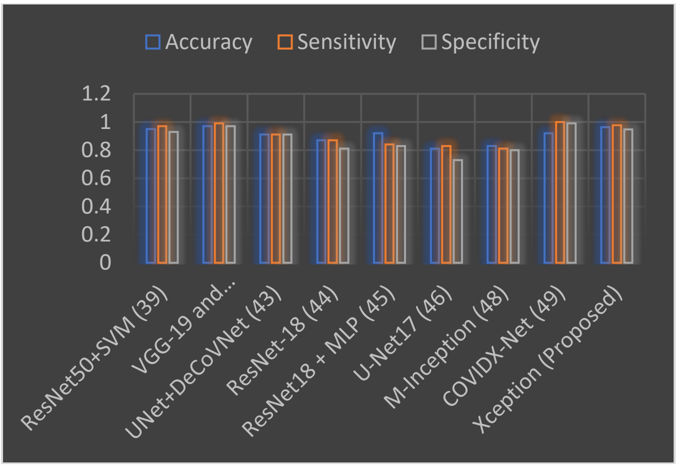

Figure 11: Cogent Analysis

The overall performance of the different classifier with respect to the accuracy, sensitivity and specificity, are depicted in the *figure 11*. The model classifier is designed using Xception model which is pretrained on ImageNet database. The proposed model performs better than the all of the previously reported models. Considering the above specified ascendency parameters, VGG-19 performs better than the proposed model architecture. But the VGG-19 performance is slightly better than the proposed model. This slightly better performance as compared to the proposed model is at the cost of the dealing with the large number of weight parameters, heavy model and long inference time of the VGG-19 model. The proposed model is also light weight model and takes comparatively less time for training and validation of the samples with distinct parameters attainments.

4.2 Comparative Analysis of different CT Scan Database

In another approach of performance analysis, the comparative analysis can be carried out to with respect to the CT-Scan database. In this approach, different researchers who used CT-Scan database for implementation of the model using different algorithms. The subsequent table discloses the statistical analysis of the same.

Table 3: Statistical Analysis of Model of different CT-Scan Database

Reference	Accuracy	Sensitivity	Specificity
UNet+DeCoVNet (43)	0.91	0.91	0.91
M-Inception (48)	0.83	0.81	0.8
Xception (Proposed)	0.9623	0.9764	0.9478

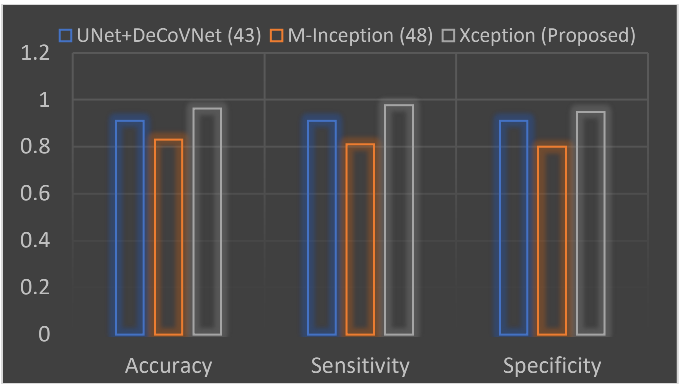

Figure 12: CT-Scan Database Specific Analysis

In the cogent analysis, out of the reported statistical analysis in the previous section, two of the citations are using CT-Scan database for training and validation of the model. Since we are also using the CT-Scan database for modelling the architecture, separate analysis is carried out clearly indicating the performance of the model if CT-Scan database is used.

As depicted in the *figure 12*, the authors have used UNet+DeCoVNet and M-Inception algorithms for designing the model. In our case, the model is designed using Xception modelling technique and superior performance is observed in terms of Accuracy, Sensitivity and Specificity for database of CT-Scan images.

5. CHALLENGES & CONTRIBUTIONS

During deciding the research problem this pandemic have threaten the world and there were no sources of data available. With the evolvement of technology such as machine learning and AI identifying which model will perform better on CT scan or Xray for diagnosis of COVID -19 was real challenge also disadvantage of RTPCR was time consuming. In order to predict this disease, we have used a model based on Transfer learning Xception.

The prime objective of this research work is to identify the model classifier for screening and diagnosis of the Covid-19 disease. For screening and diagnosis Antigen, RT-PCR, X-Ray Scan and CT-Scan is techniques are preferred worldwide. Antigen and RT-PCR technique are the lab testing techniques whereas X-Ray scan and CT-scan needed radiology expertise. On the technical front, this research work is demonstrating the use of machine learning for implementation of the effective diagnosis technique of Covid-19 disease. For this development, true and valid database is fetched from Covid-19 Research Resource Repository, maintained by National Digital Library, Ministry of Education, Government of India. Then the database is preprocessed, in which it is sorted, labeled, encoded, augmented and segmented into training and testing dataset. Soon after this, the xception model is configured with different constraints like batch size, number of epochs for training, compiler, optimizer and activation function. Subsequently, the training of the model is carried out for predefined number of epochs and with segmented database of training. Then, for increasing the accuracy, fine tuning of the model is carried out.

This assures accurate prediction with balanced sensitivity and specificity. Accordingly, different ascendency parameters like accuracy, precision, sensitivity, specificity, F1-score, training time and fine-tuning time is computed.

The cogent analysis is carried out by comparing the statistical results with the previously reported outcomes. The cogent analysis is carried out by comparing the results with respect to the algorithm used for implementation of the model and with respect to the database used.

While comparing the outcomes with respect to the algorithm used, the proposed model performs much better as compared to the model which are designed using ResNet50+SVM, Deep CNN ResNet, ResNet50 + FPN, UNet+DeCoVNet, ResNet-18, ResNet18 + MLP, U-Net17, M-Inception, COVIDX-Net and COVID-Net algorithms. This better performance is assessed with respect to the accuracy, sensitivity and specificity. The model performance is comparable with the model which is designed using VGG-19 algorithm. But VGG architecture has large number of weight parameters, it is bulky and hence it has long inference time.

On the other hand, when the performance is evaluated by considering the models which are using only CT-Scan database for modelling, the proposed model outperforms the rest of all the algorithms. Hence, it can be concluded that, an efficient model for screening and diagnosis of the Covid-19 disease can be designed using Xception model.

6. CONCLUSION

A screening model for identifying patients with Covid-19 disease has been developed through the aforementioned research work. We use Deep Neural Network Concepts and the CT-Scan database to create the screening model. During the process, image preprocessing, image analysis, and fine tuning are done. Models are configured using Python. A training accuracy of 94.1% and a validation accuracy of 95.8% were observed after 20 epochs. After fine tuning, at 10 epochs, the training accuracy reaches to 99% and validation accuracy reaches to 97.6%.

The proposed method can be applied to various population groups and demographics with comparable accuracy. The Transfer Learning approach used in the Xception framework allows the model to learn from a wide variety of data sets, which makes it adaptable to address the varying needs of different people. But, it's important to ensure that the model's accuracy is maintained on diverse sets of information. The proposed method can handle various biases in the data collected by the system, such as those related to CT scans and imaging protocols. Through Transfer Learning, the model can learn from a set of pre-existing data that includes different protocols. But, it's important to note that the training data must also contain variations in CT scans and imaging protocols to minimize the model's biases. The proposed method can only be effective if the data it requires is labeled properly with respect to Covid-19. This issue can affect its generalizability and performance. It might also be hard to implement due to the computational resources required and the size of the data set. Validate the model's capabilities on different datasets and take into account any limitations or biases that may arise from the data being used for training and assessment.

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