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# Detection of Covid-19 using Deep Learning Techniques

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***Abstract*: -** The text discusses the global impact of infectious diseases, emphasizing COVID-19 as a significant example. It proposes using medical imaging (such as Chest X-ray and CT scans) and deep transfer learning to detect COVID-19 cases. The methodology focuses on employing pre-trained deep neural networks (ResNet50, InceptionV3, VGGNet-19, and Xception) along with data augmentation techniques. The study reveals that VGGNet-19 performs best when considering CT scans, while the refined Xception model excels with CXR images, achieving high precision, recall, F1-score, and accuracy values. When combining both modalities, VGG-19 presents the most favorable overall scores, showcasing the potential to automate the analysis of chest CT scans and X-ray images with high accuracy, particularly useful in situations with limited RT-PCR testing and resources.

***Keywords***: *Covid-19, CT Image, X-Ray Image, Deep learning*

## 1. Introduction

The text delves into various aspects of coronaviruses, particularly the impact of COVID-19, covering transmission, symptoms, high-risk factors, testing limitations, and the urgent need for better diagnostic methods. It emphasizes using medical imaging (like chest X-rays and CT scans) as non-invasive tools for identification. Furthermore, it proposes employing artificial intelligence, specifically deep learning models, to address the complexity of interpreting medical images for COVID-19 diagnosis. The article is structured to encompass sections from related work to proposed experiments, aiming to offer more precise and effective diagnostic solutions for the current pandemic.The article emphasizes the potential of medical imaging, such as chest computed tomography and X-rays, as a non-invasive means of identifying COVID-19 and addressing false negative PCR cases. However, it acknowledges the complexity of pneumonia-related images and the time-consuming nature for radiologists to interpret them.

The article advocates employing artificial intelligence, particularly deep learning models, to tackle challenges in diagnosing COVID-19. This approach capitalizes on the models' superior accuracy in analyzing medical images. The aim is to adapt existing deep learning structures to create an automated tool proficient in identifying and diagnosing COVID-19 from chest X-ray and CT images. Leveraging pre-trained models, the intent is to refine and reconfigure these systems to specialize in detecting COVID-19 indicators within medical scans, thereby aiding healthcare professionals in quicker and more accurate diagnoses. This AI-based tool intends to streamline the diagnostic process, offering a faster and potentially more reliable means of identifying COVID-19 through imaging, which could significantly assist healthcare providers in managing and treating the disease.

The article is structured in distinct sections covering various key aspects related to the development of enhanced COVID-19 diagnostic tools. It begins by exploring previous works in this field, identifying gaps and laying the groundwork for their proposed framework. The focus then shifts towards the meticulous creation of a dataset crucial for the research. The article further details the experimental approaches adopted, emphasizing the integration of cutting-edge technology to meet the pressing need for improved diagnostic capabilities in the context of COVID-19.

Throughout the article, the central goal remains the urgent enhancement of diagnostic tools for the virus. The authors weave a narrative that addresses the significance of leveraging advanced technology to meet this pressing need. By offering a comprehensive understanding of related work, proposing a framework, detailing dataset creation, experimental methodologies, and concluding with the ultimate aim of bolstering COVID-19 diagnostic tools, the article succinctly encapsulates a holistic approach toward this crucial issue in the scientific community.

## 2. Objectives

1. To collect the large amount of Covid 19 dataset.
2. To apply the Deep Learning models.
3. Attain and maintain a high level of accuracy in disease detection.
4. Optimize the computational efficiency of the system for real time medical applications.

**Literature survey**

The diagnosis and early detection of diseases with high infection is a major challenge for health officials and researchers in order to reduce the suffering of patients. Recently, several scientific papers have been published on the application of deep learning and CNN approaches in the field of detection of COVID-19 cases using different medical imaging modalities mainly the CXR and CT images. This analysis helps overcome the problems encountered by others and opens a new approach in the design and development of a precise solution to fight against the COVID-19 pandemic and limit its transmission.

1. The authors of Xu et al. (2020) created a predictive algorithm to differentiate COVID-19 pneumonia from influenza. Deep learning algorithms were used to create viral pneumonia. For such predictions, the CNN model was used. The prediction model's highest level of precision was 86.7%.

2. Apostolopoulos and Mpesiana (2020) proposed to evaluate the performance of convolutional neural network architectures developed in recent years (VGGNet-19, MobileNet-v2, Inception, Xception and Inception ResNet-v2) using medical image classification techniques as a tool for automatic detection of coronavirus disease. The authors adopted a procedure called ''Transfer Learning'' because it achieves good performance for the detection of various anomalies in small datasets of medical images. They used a dataset of 1,442 X-ray images of patients: 714 images with bacterial pneumonia and viral pneumonia, 224 images with confirmed COVID-19 disease, and 504 images of normal incidents. The results show that VGGNet-19 and MobileNet-v2 achieve the best classification accuracy. They claimed to have an overall accuracy rate of 83.5%. The non-COVID-19 class had the lowest positive predictive value (67.0%), whereas the normal class had the highest (95.1%).

3. For the categorization of COVID-19 chest radiographs into COVID-19 and normal classes, Aı¨ et al. (2020) built a CNN based on the InceptionV2, Inception-ResNetV3, and ResNet50 models. They discovered a strong link between the CT imaging results and the PCR method.

4. InceptionNet was used by Wang et al. (2020) to detect anomalies related to COVID-19 in lung CT scan images. On 1065 CT images, the InspectionNet model was evaluated, and 325 contaminated people were identified with an accuracy of 85.20%.

## 3. Methods

Recent advancements in Deep Learning (DL) have excelled in image processing and computer vision tasks, encompassing segmentation, detection, and classification. This study focuses on categorizing CT scans and CXR images into two classes: COVID-19 positive or normal. To accomplish this, four DL algorithms—VGGNet-19, ResNet50, Xception, and InceptionV3—are recommended. The study introduces a proposed methodology for COVID-19 screening via CT scans, detailed within this section. Unfortunately, specifics from Figure 1 cannot be described. This approach represents a critical step toward leveraging DL techniques for accurate classification of medical images, contributing to efficient COVID-19 screening and diagnosis.

### 3.1 Dataset

The research conducted on image recognition and computer vision used datasets sourced from Dr. Jkooy's GitHub repository, consisting of 3,000 Chest CT scans (3,000 normal, 623 COVID-19). Specifically, 408 normal and 325 COVID-19 CT scans were utilized. Additionally, 500 normal and 500 COVID-19 Chest X-ray images from Kaggle were included. The dataset contained samples of both CT scans and X-ray images, with Figure 2 displaying selected examples.

Pre-processing and data augmentation

The study conducted by Sakib et al. (2020) highlighted the prevalence of noise in collected data due to various intrusions during imaging and data collection processes. Preprocessing techniques were employed to mitigate this noise, making the input data compatible with model requirements. Images were standardized by resizing to dimensions of 224x224 pixels, in a 3-channel (224x224x3) JPEG format.

To adapt the original images' RGB values (ranging from 0 to 255) to suit model comprehension, a scaling process was implemented, rescaling the values to a range between 0 and 1 (by dividing by 255). The study differentiated normal images (tagged as 1) from COVID-19 images (tagged as 0).

Due to a relatively small dataset, data augmentation was employed to artificially expand the training data. This augmentation technique helps improve network efficiency and generates additional samples, contributing to more robust model training. Various traditional data augmentation methods like rotation, shifting, flipping, zooming, and transformations were applied using the 'Keras ImageDataGenerator' during training. The specifics of these geometric transformations, such as scaling, rotating, shifts, and flips, were outlined in Table 1 of the study.

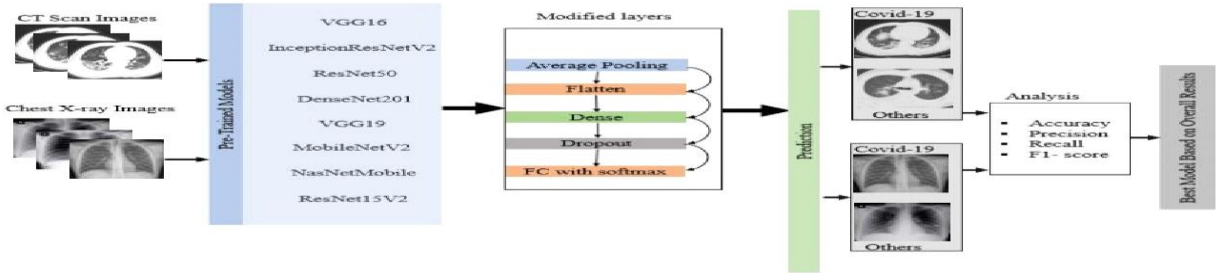


**Fig 1:Overviw of proposed method**

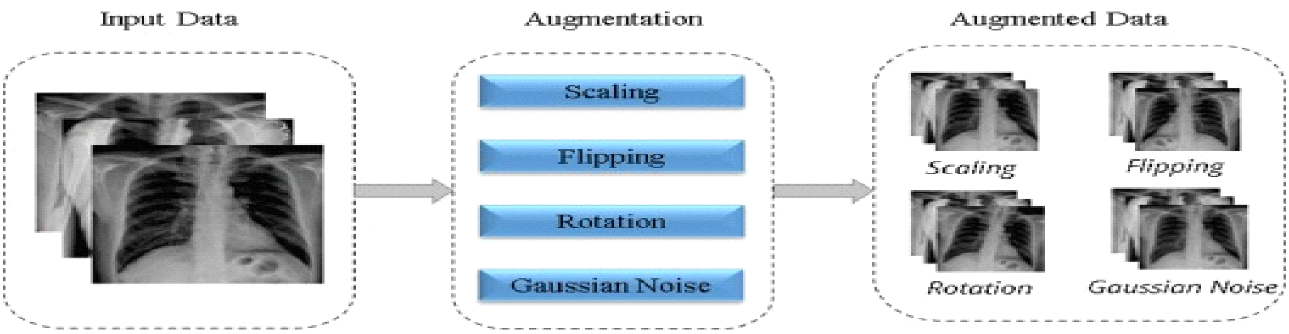


**Fig:2 pre-processing and Data Augmentation**

**Dataset splitting**

The dataset was divided into two distinct sets: one designated for training, encompassing 80% of the data, and another for testing, which held 20% of the data. This division was implemented to allow for distinct and independent sets for the purposes of training and evaluating the model. The larger training set, comprising 80% of the data, was utilized to train the model, enabling it to learn patterns and relationships within the dataset. Following this, the model's performance and generalization capabilities were assessed using the separate and distinct 20% testing set. This methodology helps in validating the model's effectiveness by evaluating its performance on unseen data, thereby ensuring its ability to generalize beyond the information it was trained on.

**Table 1** Data augmentation used

| Name | Prob. | Other |
|---|---|---|
| Random Cropping | 100 | Resize: 300x300 Crop: 224x224 |
| Mirroring | 50 | - |
| Rotation | 30 | Angle: Random [-10,10] |
| Scaling | 50 | Scaling factor: Random [1,1.3] |
| Color jitter | 30 | Jitter: Random [-0.05,0.05] |
| Saturation and value jitter | 20 | Jitter: Random [-10,10] |

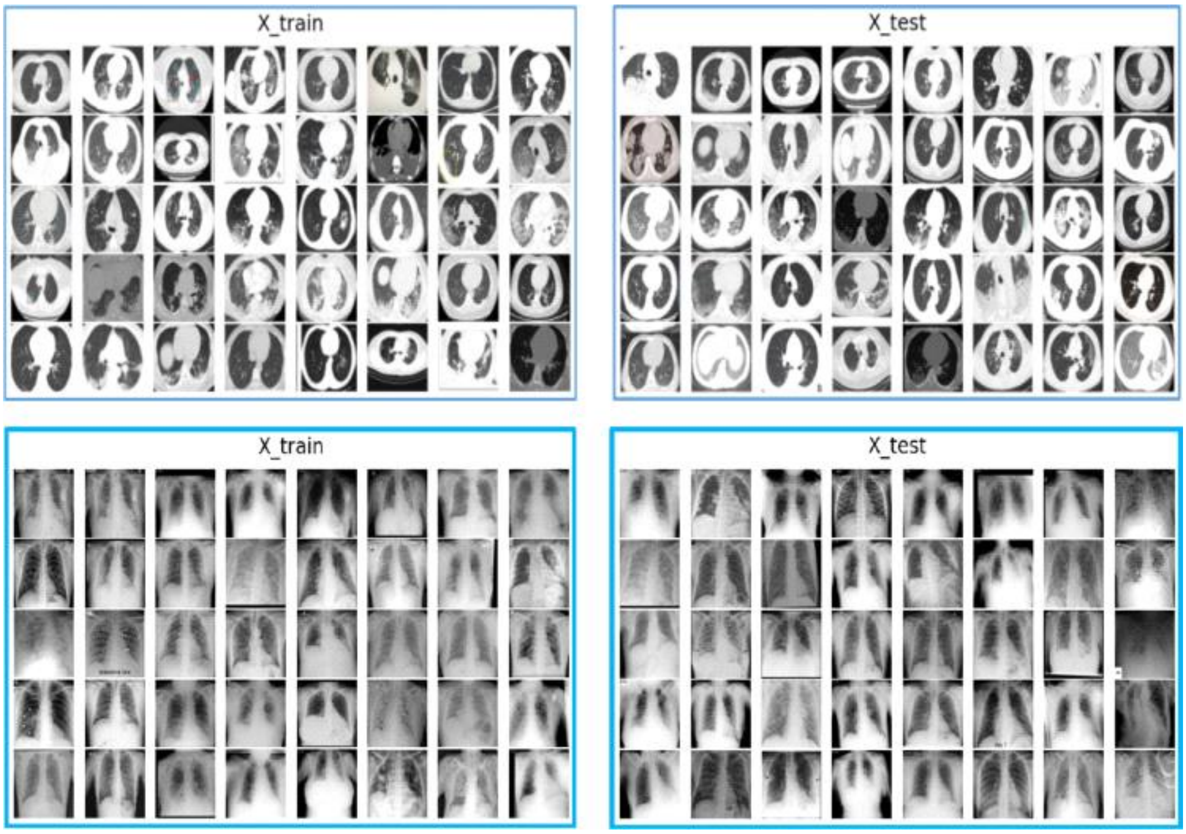


**Fig:3 Example of training and testing images**

**ResNet50 Classification**:

ResNET50 or Residual Networks, is a deep neural network extensively applied in various computer vision tasks. It was developed in 2015 and gained recognition by winning the ImageNet competition (He et al., 2016). It marks a significant advancement in CNN architecture by introducing residual learning, enhancing the training methodology for networks.

The proposed method for COVID-19 detection employs the ResNet50 model, primarily structured with residual blocks. Unlike conventional shallow neural networks where layers are linked, ResNet's design includes connections between residual blocks. Each layer is interconnected, with 2 to 3 skips between them, allowing the flow of information throughout the network.

A notable advantage of the residual connections in ResNet is their ability to retain learned knowledge during training. These connections aid in accelerating model training by boosting network capacity and facilitating the flow of information.

In this particular study, the researchers used ResNet50 as the foundational model architecture, adapting and refining it to address the specific requirements of their classification problem, likely aimed at COVID-19 detection.

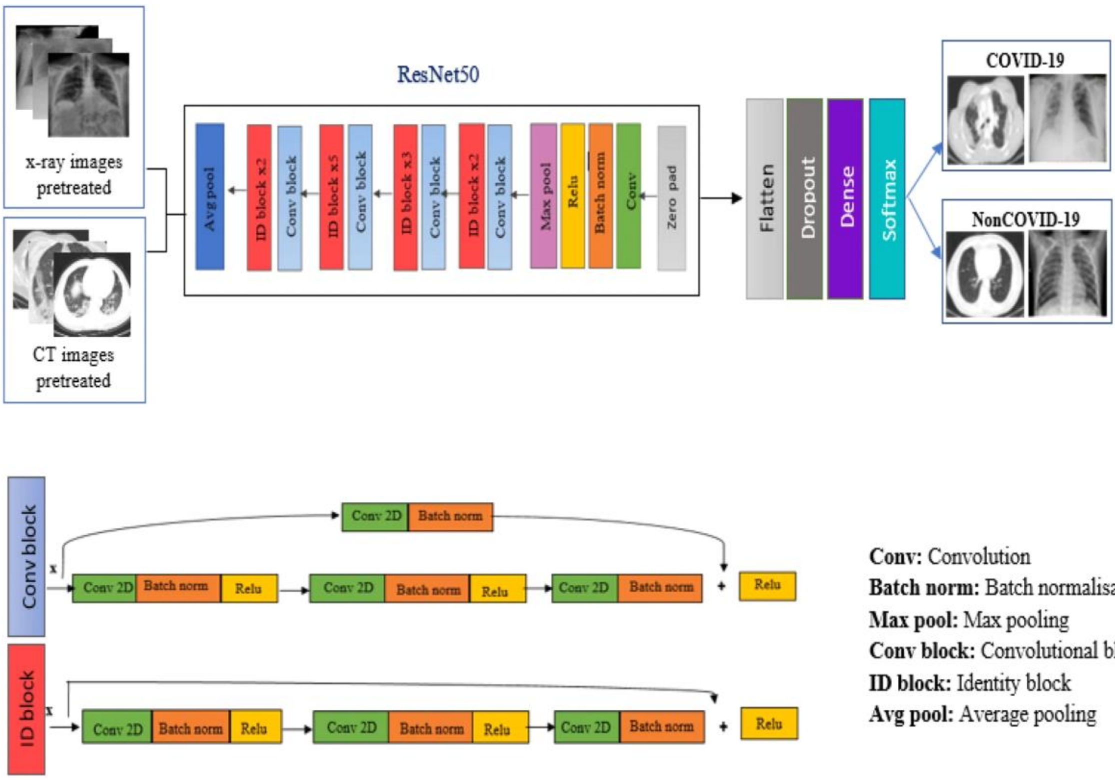


**Fig. 5 Proposed method for the detection of COVID-19 using the ResNet50 model**

**Confusion Matrix:**

**True Positive (TP):** the context of machine learning and medical diagnostics, the accurate identification of COVID-19-infected instances is crucial. When a model correctly classifies a patient as having COVID-19, it demonstrates the ability to discern specific patterns or features within the data that align with the characteristics of the disease. This correct classification often involves a comprehensive analysis of various symptoms, lab results, and potentially imaging data to distinguish COVID-19 from other illnesses.

Accurate classification implies that the model effectively recognizes key markers or combinations of symptoms unique to COVID-19, such as fever, cough, shortness of breath, and specific laboratory findings like abnormalities in white blood cell count or certain inflammatory markers. Achieving a high rate of correctly classified cases showcases the model's proficiency in differentiating COVID-19 from similar conditions or healthy cases.

Successful identification of COVID-19-infected instances demonstrates the model's ability to contribute to timely and precise diagnoses, enabling healthcare professionals to initiate appropriate interventions, isolation, and treatment strategies promptly. Such accurate classifications play a pivotal role in the overall management and control of the disease by aiding in containment efforts and healthcare resource allocation.

Moreover, ensuring high accuracy in classifying COVID-19 cases contributes to the reliability and trustworthiness of the AI system in clinical settings. It enhances the confidence of healthcare practitioners in utilizing these tools as supportive aids in decision-making processes, especially in scenarios where rapid and accurate diagnoses are essential.

However, achieving and maintaining high accuracy in classifying COVID-19 cases demand constant validation, updating, and refinement of machine learning models to adapt to evolving clinical data and changes in the virus's manifestations. Continual improvement is necessary to ensure the models remain robust and dependable in identifying COVID-19 cases accurately.

**True Negative (TN):** machine learning for medical diagnosis, correctly identifying instances as not infected with COVID-19 is as critical as identifying positive cases. When a model accurately classifies a patient as not having COVID-19, it signifies the system's ability to discern patterns or indicators that distinguish the absence of the disease. This involves analyzing various symptoms, tests, and clinical data to differentiate between COVID-19 and other health conditions.
Correctly classifying cases as not infected with COVID-19 implies the model's capability to recognize a lack of specific symptoms or markers typically associated with the disease. It involves considering a range of factors, such as absence of fever, cough, or abnormalities in diagnostic tests, that collectively suggest the absence of COVID-19.
Accurate identification of cases without COVID-19 showcases the model's efficiency in differentiating between the virus and other respiratory illnesses or healthy cases. This accuracy is crucial for preventing misdiagnosis and unnecessary treatment, thereby optimizing healthcare resources and reducing unnecessary isolation or interventions for patients.
Successful classification of instances as not infected with COVID-19 demonstrates the model's reliability in aiding healthcare professionals to rule out the disease accurately. This contributes to more efficient and effective patient care by ensuring that non-COVID cases receive appropriate diagnosis and treatment for their specific conditions.
However, maintaining high accuracy in classifying cases as not infected with COVID-19 requires continual model validation and updates to adapt to new clinical data and emerging knowledge about the virus. Ongoing improvement and refinement of these machine learning models are essential to ensure their reliability in accurately identifying cases without COVID-19.

**False Positive (FP):** In the realm of machine learning applied to medical diagnostics, instances wrongly classified as COVID-19 infected refer to cases where the model inaccurately identifies individuals as having the virus when they are, in fact, not infected. These misclassifications can occur due to various reasons, such as similarities between symptoms of COVID-19 and other respiratory illnesses, leading to confusion within the dataset.
Misclassifications might result from the model misinterpreting certain symptoms or lab results, leading to an incorrect inference of COVID-19 presence. Factors like atypical presentations of the disease or insufficient training data representing diverse patient profiles can also contribute to these misclassifications.
Incorrectly labeling cases as COVID-19 positive could lead to unnecessary anxiety, treatment, isolation, or strain on healthcare resources. These errors might result in individuals receiving unwarranted medical attention or isolation measures, impacting their overall well-being and burdening healthcare systems.
Reducing misclassifications necessitates ongoing model refinement, continuous learning, and a diverse, comprehensive dataset that encapsulates various presentations of the disease. Regular updates and validations are crucial to improving the model's ability to discern between COVID-19 and similar conditions accurately.
Enhancing the accuracy of identifying COVID-19 cases involves a constant process of fine-tuning the model's algorithms, considering a broader array of symptoms, and incorporating new information about the virus's manifestations to reduce misclassifications and increase the model's reliability in clinical settings.

**False Negative (FN):** Instances incorrectly classified as not infected with COVID-19 refer to cases where the model mistakenly identifies individuals as free from the virus when they are actually infected. These misclassifications can stem from various factors, such as overlapping symptoms between COVID-19 and other health conditions, leading to confusion or ambiguity in the data.
The model might overlook or misinterpret certain symptoms, test results, or patient profiles, resulting in the false classification of individuals as not having COVID-19. Factors such as atypical presentations of the disease

or inadequacies in the training data—failing to represent diverse patient profiles—can contribute to these misclassifications.

Mislabeling cases as not infected with COVID-19 can have serious implications, potentially leading to delayed treatment, inadvertent spread of the virus, and a false sense of security for individuals who might actually be infected. It could impact public health measures, potentially leading to inadvertent exposure and transmission.

Addressing these misclassifications requires continual model improvements, ongoing learning from diverse and comprehensive datasets, and frequent validation to refine the model's ability to accurately distinguish COVID-19 cases from other conditions. Regular updates and adaptations based on emerging knowledge and clinical data are essential to enhance the model's accuracy in identifying cases of COVID-19.

**Performance Measures:**

**Accuracy:** Accuracy, a fundamental metric in assessing the performance of a model, gauges its overall correctness by considering both true positive (TP) and true negative (TN) instances over the total instances. The accuracy formula, expressed as (TP + TN) divided by the total number of instances (TP + TN + FP + FN), quantifies the model's precision in correctly identifying both positive and negative cases.

It provides a comprehensive view of the model's effectiveness in making accurate classifications, encompassing the instances correctly identified as well as those correctly ruled out. This metric evaluates the model's ability to accurately discriminate between positives (cases of interest, like COVID-19 infections) and negatives (instances where the condition is absent).

However, while accuracy is an essential measure, it might not be sufficient when dealing with imbalanced datasets or when the costs of false positives or false negatives are significantly different. In such cases, other metrics like precision, recall, or F1 score might be necessary to gain a more nuanced understanding of the model's performance in specific areas. Overall, accuracy serves as a foundational gauge of a model's general correctness in classification across positive and negative instances.

$$Accuracy = TP + TN/(TP + TN + FP + FN)$$

**Precision:** Precision is a crucial metric used to assess the accuracy of positive predictions made by a model. It measures the ratio of correctly predicted positive observations (true positives) to the total predicted positive instances. The precision formula, expressed as TP / (TP + FP), focuses specifically on the model's ability to precisely identify instances it has labeled as positive.

This metric is particularly valuable in scenarios where the cost of false positives is high. It ensures that the model's positive predictions are reliable and accurate. A high precision score indicates that among the instances predicted as positive, a significant proportion are indeed true positives.

Precision is an essential metric in various fields, including healthcare and fraud detection, where correctly identifying positive cases is critical. However, it should be considered alongside other metrics such as recall and accuracy to gain a comprehensive understanding of the model's performance, especially in cases of imbalanced datasets or when the consequences of false positives versus false negatives differ significantly.

$$Precision = TP /(FP + TP)$$

**Recall (Sensitivity):** Recall, also known as sensitivity or true positive rate, is a significant metric measuring the model's capability to identify all positive instances. It calculates the ratio of correctly predicted positive observations (true positives) to the total actual positives. The recall formula, expressed as TP / (FN + TP), focuses on the model's effectiveness in capturing all actual positive cases.

This metric is crucial in scenarios where missing positive instances (false negatives) can have serious consequences. A high recall score indicates that the model can successfully identify a larger proportion of actual positive cases.

In fields like healthcare, where correctly detecting all cases of a particular condition is vital, recall serves as a key metric. It's important to interpret recall alongside precision and accuracy to gain a more comprehensive understanding of the model's performance, particularly in situations where the cost of missing positive instances significantly outweighs the cost of false positives.

$$Recall = TP/ (FN + TP)$$

**F1-score:** The F1 score, often referred to as the harmonic mean of precision and recall, serves as a consolidated measure that balances both precision and recall into a single value. It is calculated as 2 * (Precision * Recall) divided by (Precision + Recall). This metric seeks to find a compromise between precision, which evaluates the accuracy of positive predictions, and recall, which assesses the model's ability to identify all positive instances.

The F1 score is particularly valuable in situations where there is an imbalance between false positives and false negatives, as it combines these two metrics to provide an overall assessment of the model's performance. This single value represents a trade-off between precision and recall, where a higher F1 score indicates a better balance between the precision and recall values of the model. However, the F1 score might not be suitable in all scenarios, and its interpretation should be considered in conjunction with other metrics based on the specific context and objectives of the problem being addressed.

F1-Score = 2 * precision * recall/ precision +recall

**Table 2 classification of Accuracy,Recall,precision**

| Models | Training set | | | | Test set | | | |
|---|---|---|---|---|---|---|---|---|
| | Precision | Recall | F1-score | Accuracy | Precision | Recall | F1-score | Accuracy |
| DUGRU | 0.97 | 0.97 | 0.97 | 97.90% | 0.96 | 0.96 | 0.96 | 96.65% |
| DULSTM | 0.97 | 0.97 | 0.97 | 97.92% | 0.96 | 0.96 | 0.96 | 96.41% |
| CNN | 0.96 | 0.96 | 0.97 | 97.57% | 0.95 | 0.96 | 0.95 | 96.42% |
| NN | 0.95 | 0.96 | 0.96 | 96.15% | 0.94 | 0.95 | 0.95 | 95.39% |

**4. Results obtained by using CT images and CXR images**

The objective was to automate the classification of CT and CXR images. To prepare the data, images were resized to 224 x 224 pixels, and the Keras Augmentor API was applied for input image augmentation. The resultant images were used to train deep learning models. The training employed a batch size of 32, and the models were fine-tuned across different epochs—specifically, 100, 200, and 300.

Python 3, in combination with the Keras framework, was utilized to construct these models. Development and training took place on Google Colab, a cloud-based platform for coding and computation.

The process involved preparing the images, creating deep learning models, and fine-tuning them over multiple epochs in the pursuit of automating the classification of both CT and CXR images.

The models underwent evaluation using metrics such as precision, recall, accuracy, and F1-score, enabling comparison of their performances within the dataset for both CXR and CT techniques in detecting COVID-19 and non-COVID-19 cases. The confusion matrices for the four models with CXR images across different epochs are displayed in Figs. 16, 17, 18, and 19. Furthermore, the loss and accuracy trends during training and validation phases across various epoch counts are represented in Figs. 19, 20, 21, and 22.

Specifically focusing on the Xception model's classification of CT images over different epochs:Across varying epoch counts, the model's performance in classifying 147 images fluctuated. At 100 epochs, 115 out of 147 images were correctly classified, with 32 misclassifications. With 200 epochs, the correct classifications increased to 128, while misclassifications reduced to 19. However, at 300 epochs, the correct classifications decreased to 119, while misclassifications rose to 28. The model's accuracy varied with the number of epochs, showcasing improvements initially from 100 to 200 epochs in terms of correct classifications and reduced misclassifications. However, at 300 epochs, the model's performance declined, with a decrease in correct identifications and an increase in misclassifications. These fluctuations indicate the sensitivity of the model's performance to the number of training iterations (epochs), suggesting that an optimal balance needs to be found between underfitting and overfitting to achieve the best classification results for the given dataset.

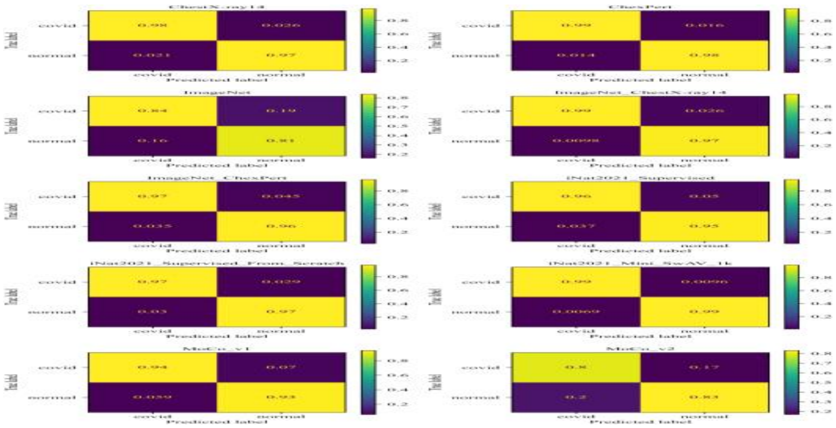

**Fig. 10 Confusion matrix obtained by the Resnet50 model after a 100, b 200 and c 300 epochs**

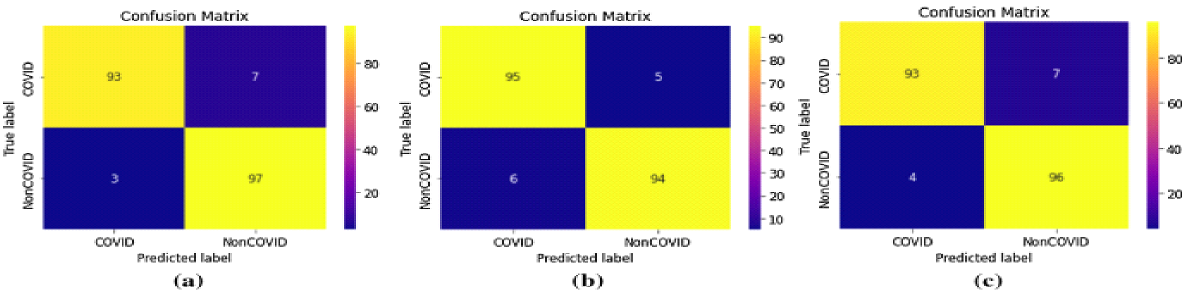


**Fig. 11 Confusion matrix obtained by the Resnet50 model after a 100, b 200 and c 300 epochs**

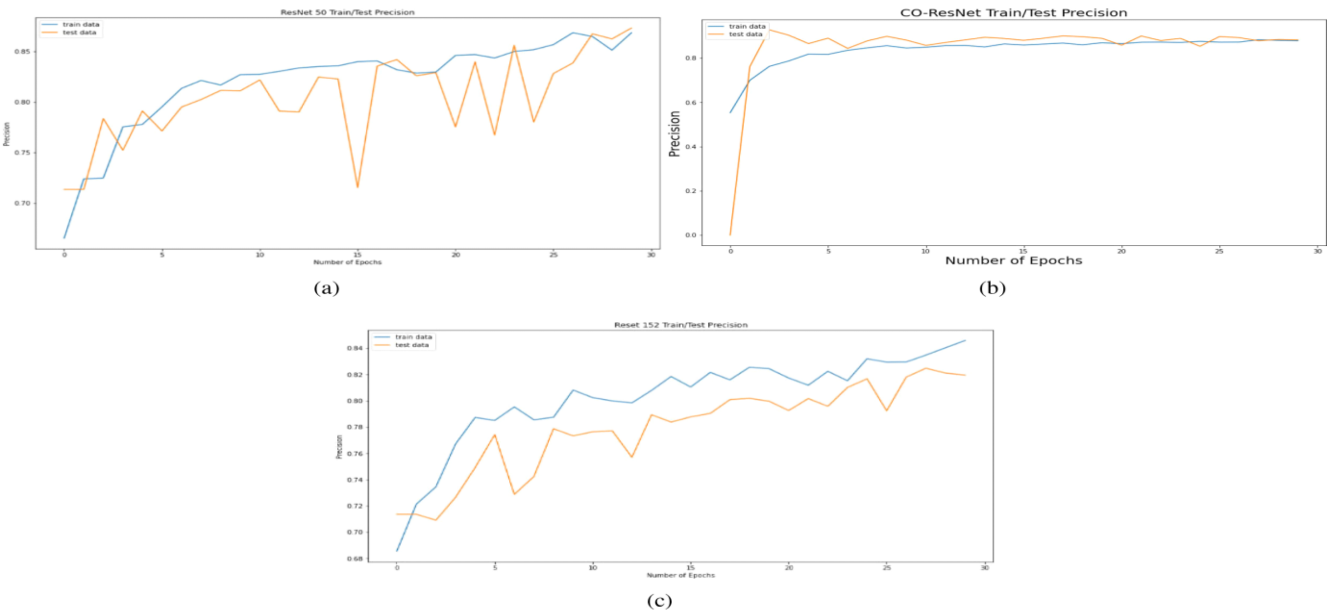


**Fig. 12 Precision and loss plots on training and validation sets for the Resnet101, model after a 100 epochs, b 200 epochs, c 300 epochs**

**Conclusion**

Deep learning models have shown considerable promise in detecting COVID-19 from both CT and CXR (chest X-ray) images. The ongoing research, alongside extensive data collection and collaborative efforts among diverse teams, remains crucial. These initiatives are vital for refining the accuracy, reliability, and interpretability of these models. Continuous development and improvements in these technologies hold the potential to significantly enhance patient outcomes and strengthen healthcare systems on a global scale. The ability of these models to offer timely and precise diagnoses of COVID-19 cases represents a significant step forward in more effective pandemic management. Their contributions are pivotal in aiding healthcare professionals to swiftly and accurately identify cases, thereby improving patient care and optimizing resource allocation in the face of the ongoing global health crisis.

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