Socio-economic Challenges in COVID Detection using Transfer Learning-Based Methods

DITJONA KULE[1], OGERTA ELEZAJ[2], UMESH MEHTRE[2]
[1]University of Tirana,
ALBANIA

[2]Birmingham City University,
UNITED KINGDOM

Abstract: - Healthcare systems are at risk of collapsing unless significant structural and transformative measures are taken. Despite the global economy generating an additional 40 million jobs in the health sector by 2030, the World Health Organization projects a shortage of 9.9 million physicians, nurses, and midwives during the same period (WHO, 2016). The core of innovation in the healthcare industry lies in automation systems, particularly in the realm of image detection. As the ratio of healthcare workers to patients decreases, the integration of robotics and artificial intelligence plays a crucial role in bridging the gap. These technologies not only compensate for the declining workforce but also bring a level of accuracy and precision that eliminates the potential for human error in image detection processes. In this paper we focus on the COVID-19 pandemic that presents significant socio-economic challenges, impacting various aspects of daily life, including health, the economy, and social development. The need for chest X-ray (CXR) scans is rising due to pneumonia being a critical and common complication of COVID-19. Early detection and diagnosis are pivotal in curbing the spread of the virus, prompting the utilization of the reverse transcription polymerase chain reaction (RT-PCR) as the predominant screening technology. Nevertheless, the task's complexity, time-consuming nature, and reported insensitivity in this research emphasize the need for alternative approaches. CXR is a widely employed screening tool for lung-related diseases due to its straightforward and cost-effective application. In this paper, we have deployed different transfer learning methods to detect COVID-19 using chest X-ray images such as VGG19, ResNet-50, and InceptionResnetV2. The findings of our results indicate that the fine-tuned model utilizing the transfer learning and data augmentation techniques enhances the efficiency of COVID-19 detection. We performed a comparison of pre-trained networks and identified the InceptionResNetV2 model as having the highest classification performance with an accuracy of 97.33%.

Key-Words: - Deep learning, COVID-19, Chest x-ray, Transfer learning, Image processing, Explainable artificial intelligence.

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1 Introduction

Shortages of staff in European radiology departments are a longstanding issue and, as per industry experts, have been progressively worsening in recent years. Nevertheless, AI applications are already stepping in to address these gaps by analyzing medical images, identifying pathologies, and assisting healthcare professionals in the decision-making process, among other functions. Numerous AI applications in medical imaging undergo training using extensive collections of medical images. This training equips them to identify clinical abnormalities swiftly and accurately, including conditions like cancer, often surpassing, or matching the proficiency of specialists. The potential implications on health outcomes are substantial, potentially saving lives through enhanced and more prompt diagnoses, alongside associated cost reductions. Annually, the implementation of these measures results in substantial benefits:

Lives Saved: Between 36,000 to 41,000 lives are preserved each year, showcasing the profound impact on public health and well-being.

Financial Savings: The initiative generates significant economic advantages, with savings ranging from €16.1 to 18.6 billion. This includes direct monetary savings and accounts for opportunity costs, as well.

Time Efficiency: One of the main benefits is the total amount of time freed up, totaling between 15.1 to 32.7 million hours. They can benefit from allocating this time for other critical tasks and activities, enhancing overall productivity and effectiveness in various sectors. The impact on healthcare professionals, particularly on healthcare professionals' physical and emotional well-being, is noteworthy.

COVID-19 is a virus that spreads worldwide rapidly. Since 2005, WHO has declared severe pandemics as PHEIC. Six cases, including H1N1 in 2009 and COVID-19 in 2020, have been declared, [1]. Over 599 million COVID-19 cases have been found globally, with almost 6.46 million deaths, [2]. To stop its spread, many countries have imposed lockdowns and other restrictions, impacting the global economy negatively.

The main symptoms of COVID-19 are fever, dry cough, and exhaustion. Some people may also experience aches, pains, or difficulty breathing. Radiologists can identify these symptoms as signs of lung issues and respiratory infections, [3]. RT-PCR, also called real-time polymerase chain reaction, is the most effective method for detecting COVID-19 cases, [4]. However, RT-PCR kits can be costly and can take six to nine hours to confirm a diagnosis. The poor sensitivity of RT-PCR leads to a high percentage of observations that are incorrectly interpreted as negative. It has been determined that radiological imaging techniques, such as chest X-rays, are superior to CT scans to diagnose this condition. The equipment needed for CT scanners is far more expensive than that required for X-ray machines. In addition to this, X-rays emit a lower level of ionizing radiation compared to CT scans. Several radio-logical signals found by COVID-19 can be easily recognized using chest X-rays as a diagnostic tool. Therefore, radiologists are required to investigate these signals very carefully. It is a hard endeavor that requires a significant amount of time investment.

The clinical tests that are used to detect COVID-19 can be quite pricey and time-consuming, which presents several issues for medical professionals. It is crucial to establish advanced systems capable of efficiently and cost-effectively classifying X-ray images. Traditional machine-learning methods face significant limitations in image processing. Deep learning, with its capacity for automatic feature extraction and handling complex, unstructured data, surpasses traditional machine learning approaches in tasks like image recognition. Different neural networks with multiple layers, utilizing convolutional neural networks (CNNs) for image-based data, recurrent neural networks (RNNs) for sequential data, and other advanced architectures designed to enhance the model's ability to learn complex patterns and representations are beneficial to be used.

Deep learning techniques offer a more sophisticated approach, improving accuracy and performance compared to traditional machine learning methods. In 2020, authors in [5], enhanced the VGG19 model for COVID-19 detection in images. Results showed 86% precision on X-ray scans, 100% on ultra-sound scans, and 84% on CT scans. Authors in [6], used the Relief algorithm and pre-trained models for feature selection and extraction. They applied these methods to classify cough acoustic waves, achieving 98.4% accuracy. Authors in [7], used another machine learning method, the support vector machines for early COVID detection in chest images, employing feature selection strategies based on deep features in X-ray images, [8]. The objective of this research is to enhance the accuracy of COVID detection by utilizing various pre-trained transfer learning models, including VGG 19, ResNet50, and InceptionResNetV2. This improvement is achieved through pre-processing the X-ray images and fine-tuning these methods. This study analyzes the practical implementation of various Convolutional Neural Networks (CNNs), transfer learning concepts, and pre-trained algorithms for COVID-19 diagnosis. The approach involves preprocessing with data augmentation and fine-tuning using focal loss, along with the utilization of data augmentation. InceptionResNetV2, ResNet-50, and VGG19, all interrelated, emerge as top picture classification models for identifying COVID-19 cases, [9]. The proposed model builds upon existing healthcare practices, proving to be a valuable tool for physicians and radiologists, to automate the analysis of chest X-rays to streamline and enhance efficiency.

The main contributions of this paper are twofold:
Architectural Evaluation: The study evaluates VGG16, InceptionResNetV2, and ResNet50, architectures to analyze and differentiate between COVID-19 and healthy patients.
Data Handling Techniques: It implements image augmentation to train CNN models with unbalanced data, utilizes a convolutional neural network model for the identification of COVID-19, and integrates performance metrics to address the issue of data imbalance.

The remaining part of the paper is organized as follows. Section 2 presents related work on using deep learning methods for COVID-19 detection from x-ay images. The methodology used is introduced in Sect. 3. Section 4 describes the results obtained by all the experiments, and section 5 sheds light on the discussion of the results. Finally, the conclusions and future work are given in Sect. 6.

2 Related Work

AI is set to revolutionize the interpretation of medical images in digital pathology, encompassing the detection, diagnosis, and monitoring of various pulmonary, cardiac, and oncological pathologies. It extends its impact to image acquisition, reconstruction, video processing for surgical guidance, and 3D imaging.

In the realm of pulmonary pathologies, chest X-rays are pivotal, and AI algorithms in digital pathology prove to be valuable by autonomously detecting pathologies, potentially outperforming radiologists in accuracy. This advancement has the potential to save up to 1,900 lives annually.

In the context of coronary artery disease (CAD), AI excels in early detection. Utilizing machine learning on coronary computed tomographic angiography images and clinical data, algorithms demonstrate superior accuracy in predicting five-year mortality rates for CAD patients compared to standard techniques. This not only enhances patient care but also presents a potential cost savings of €7 billion for the healthcare system. The integration of AI with medical imaging holds great promise for screening, diagnosing, and treating breast cancer. Despite breast cancer remaining a leading cause of death among EU women, with around 85,000 annual deaths, early detection is key to successful treatment. AI has shown substantial benefits in mammography screening, significantly reducing false positives and negatives. Studies reveal that AI software can interpret mammogram results up to 30 times faster than human doctors, with an impressive accuracy of 99%. Additionally, in situations requiring double reading of mammograms, AI can serve as a reliable second reader, particularly beneficial in regions with a shortage of trained radiologists. Collectively, these AI applications have the potential to save up to 16,000 lives and €7.4 billion each year.

Figure 1 illustrates the disparities in the distribution of MRI scanners across specific European regions. Spain and Portugal exhibit comparatively lower levels of MRI scanners per 100,000 people.

Throughout the European Union, a shortage of radiologists is becoming more pronounced, averaging only 12.8 radiologists for every 100,000 people. Even in countries like France, where radiologist numbers are higher, challenges persist due to uneven geographical distribution of staff. Consequently, health systems are actively seeking more efficient methods to provide services.

The scarcity of resources in radiology has intensified the inclination toward outsourcing image reading activities. This shift is driven by health systems grappling with insufficient capacity to meet the rising demand using their current clinical staff.

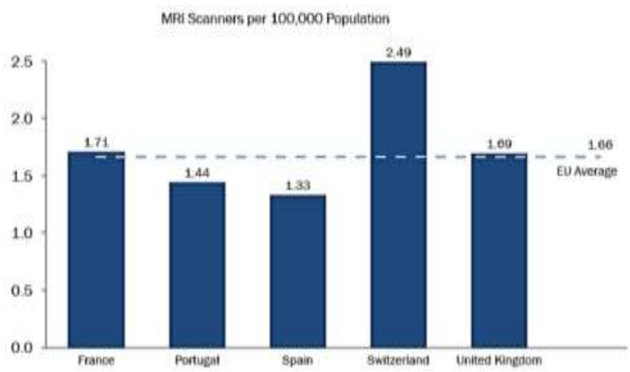

Fig. 1: MRI Scanners, [10]

Artificial intelligence technologies have consistently delivered reliable and accurate results for applications dependent on image-based data. In a literate examination of chest X-ray images by experts, COVID-19 was detected through the utilization of deep learning algorithms.

Authors in [11], introduced a modern COVIDX-Net model designed to assist radiologists in identifying and categorizing COVID-19 in chest

X-ray (CXR) images. They have been using different methods and the results of all these methods have been evaluated and compared. Firstly, during the data pre-processing phase, all the images in the dataset were transformed to a resolution of 224 by 224 pixels. In the second stage, the image labels underwent a one-hot encoding procedure to determine whether each image should be categorized as a positive case with the presence of COVID-19. The images were split into training and testing by an 80/20 ratio, and stochastic gradient descent (SGD) was used in the training of the deep network classifiers. No augmentation techniques were applied to the images. The results of the experiments concluded that the VGG19 model outperformed the other models, achieving the highest accuracy rate at 90%.

Authors in [12], deployed a deep CNN called the Decompose, Transfer, and Compose (DeTraC) aiming at diagnosing COVID by the images, with the primary goal of identifying abnormalities within the images. To substantiate their findings, the authors used Convolutional Neural Network (CNN) features extracted from the pre-trained on ImageNet and ResNet. The COVID-19 image dataset contains a total of 80 chest X-ray samples categorized as normal, with each image having dimensions of 4020 x 4892 pixels. The accuracy achieved was 95.12%. These results underscore the effectiveness of the DeTraC for the classification of COVID-19 chest X-ray images, showcasing its potential to identify abnormalities with a high level of accuracy.

Another study utilized a big dataset of 10,040 samples, with 2,143 cases of COVID-19, 3,674 instances of pneumonia (excluding COVID-19), and 4,223 healthy cases (neither COVID-19 nor pneumonia). This model achieved an accuracy of 96.43% and a sensitivity of 93.68%, [13]. They developed a model capable of analyzing X-ray images, achieving an accuracy of 97% in recognizing COVID-19 cases from a dataset consisting of 3,816 COVID-19 images, 345 pneumonia images, and 192 normal chest X-rays.

Authors in [14], introduced a multi-stage fine-tuning scheme for the pre-trained ResNet-50 architecture, creating the COVIDResNet model. This model achieved an accuracy of 96.23%. The multi-stage fine-tuning approach likely involved adjusting the weights of the pre-trained ResNet-50 layers to enhance the model's performance on a specific task, in this case, the classification of COVID-19-related images. The reported accuracy of 96.23% indicates the effectiveness of their approach in accurately classifying instances within their dataset.

Authors in [15], used a deep convolutional neural network (CNN) to look for COVID-19 in chest X-rays. They trained their model with 13,975 chest X-ray images, mostly from COVID-19-positive individuals, available to the public. The model made correct predictions for 98% of the categories. They also explored how COVID-Net makes predictions using an "explainability" method to identify crucial aspects of COVID cases, aiding doctors in better screening. The researchers ensured COVID-Net's responsible and open use, making conclusions based on relevant data from chest X-ray (CXR) images. The aspiration is for research teams and citizen data scientists to leverage the open-source COVID-Net and guidelines for the COVIDx dataset, aiming to the development of effective and practical deep-learning approaches for the detection and treatment of COVID-19 cases.

In their study, the authors in [16], presented a Deep Learning (DL) model named CoroNet, designed for the automatic classification of COVID-19 disease based on chest X-rays. Their dataset comprised a variety of chest X-ray images, including 310 normal cases, 327 viral pneumonia cases, 330 bacterial pneumonia cases, and 284 COVID-19 cases, sourced from publicly available repositories. The proposed CoroNet achieved a high accuracy of 89.5%. This outcome is particularly important as it addresses the challenge of splitting normal cases from those of COVID-19 and pneumonia. The initial findings of this research hold promise and contribute to the development of an accurate detection system.

Authors in [17], created a dataset known as the "COVID-19 Radiography Database." Widely employed by researchers and practitioners, this dataset has been instrumental in developing and evaluating machine learning and deep learning models for COVID-19 detection using radiography images. The creation of this dataset was a collaborative effort, engaging researchers from Qatar University in Doha, Qatar, and the University of Dhaka in Bangladesh. The dataset contains 18,479 chest X-ray (CXR) images derived from 15,000 patient cases.

Table 1. Accuracy of the models using X-ray images

Paper	Datasets	Methods	Accuracy %
[17]	455 people came up positive for COVID-19 in their testing (GitHub Dr Cohen, Kaggle). The average is 532. Pneumonia caused by bacteria equals 492, while pneumonia caused by viruses other than COVID equals 552.	VGG 16	85
[22]	Training: 2076 Testing: 350	ResNet50	94
[9]	2799 non-COVID examinations used for training, 1194 COVID-19 examinations, and 264 COVID-19 external testing procedures (images of COVID-19 from the record)	FCONet ft ResNet-50	99
[23]	523 for the process of validation, 580 for the process of testing, and 4,698 for the process of training; 3,949 images of pneumonia that were not caused by COVID, and 15,83 shots of healthy individuals	AIDCOV using VGG-16	98.4
[24]	18,479 images	Robust U-Net model lung segmentation	98.63
[25]	3,616 COVID-19, 10,192 Normal	InceptionResNet-v2	96.6
[26]	455 COVID images, 532 Normal cases, 492 Bacterial pneumonias and 552Viral non-COVID pneumonia	VGG-16	
[27]	150 CT images	Wavelet Transform and Support Vector Machine	99.68

The neural networks were trained to identify normal and COVID-19 pneumonia, along with normal, viral, and COVID-19 pneumonia with and without image enhancement. The dataset also included normal and viral pneumonia samples. Four well-known pre-trained algorithms—AlexNet, ResNet-18, DenseNet-201, and SqueezeNet—were used for classification. DenseNet-201 demonstrated outstanding performance, achieving an accuracy of 99.70%.

The remarkably high precision of this computer-aided diagnostic tool holds the potential to significantly expedite and improve COVID-19 diagnostic processes, particularly crucial given the limited resources during the outbreak and the urgent need for preventive measures.

Authors in [18], developed DeepCOVIDExplainer to identify COVID-19 signals in chest X-rays.

The authors used 15,959 chest X-ray (CXR) images from 15,854 patients, covering normal, pneumonia, and COVID-19 cases. Utilizing gradient-guided class activation mappings (Grad-CAM++) and layer-wise relevance propagation (LRP), the model highlights regions in CXR images crucial for class differentiation before employing a neural ensemble method for classification. The explanations for diagnoses are presented in a human-understandable format. The method employed a collaborative strategy, combining image processing and transfer learning. It achieved a classification accuracy of 96.12% for COVID-19 cases.

In a study conducted by researchers [19], transfer learning was used to detect anomalies associated with coronavirus in chest X-rays. The study involved examining 504 images representing healthy individuals, 224 images of confirmed COVID-19 cases, and 714 images of viral pneumonia. The findings indicate that the synergy between deep learning and X-ray imaging holds promise in identifying significant markers related to COVID-19. The obtained accuracy was 96.78%.

These findings imply that Deep Learning, in conjunction with X-ray imaging, can effectively identify crucial indicators of COVID-19. The high accuracy, sensitivity, and specificity of the results suggest that X-rays could be considered as an additional diagnostic tool for COVID-19. Further research may explore the X-ray technique from various perspectives, offering new insights into its diagnostic potential, particularly in scenarios where existing methods may exhibit limitations in accuracy.

Authors in [20], introduced an automated system for COVID-19 detection utilizing chest

X-ray images. They employed Inception V3 w transfer learning to identify infections in patient's chest. The model underwent testing or dataset comprising 1341 normal, 1345 vi pneumonia, and 864 COVID-19 images. T classification accuracy of the model reached 96%.

In their study [21], the authors conducted thorough analysis, evaluating the performance seven deep learning algorithms in detecti COVID-19 in chest X-ray images using a dataset 6087 images. The Inception-ResNetV2 model stc out with an impressive accuracy of 92.12 highlighting its efficacy in accurately identifyi COVID-19 cases. This result signifies the potent applicability of Inception-ResNetV2 in diagnos processes for COVID-19 through chest X-r images. Table 1 summarizes the key accura metrics discussed.

3 Methodology

Figure 2 illustrates the methodology of this resear consisting of six main steps: (i) data pre-processi (ii) splitting the dataset into training and testing; (training the methods; (iv) updating the weig during the training of neural networks; classification; and (vi) model evaluation. The data used in our experiments relies on a chest X-r image dataset from [28] created by the authors, [2 [30].

The Covid-radiography database contains 3,6 COVID-19-positive cases, 10,192 Normal cas 6,012 Lung Opacity (Non-COVID lung infectio and 1,345 Viral Pneumonia pictures. However, our research specifically concentrates on COVID-19 and normal images.

It's important to note that the normal class contains various radiology images, and the term "normal" doesn't automatically imply good health in the lower respiratory system.

The dataset is categorized into a balanced subset with 3,616 images for both Covid and normal classes, and an unbalanced subset with 10,192 images for the normal class and 3,616 images for the Covid class. In the sequential model, the unbalanced dataset is split into 11,047 training images and 2,761 validation images, maintaining an 80:20 ratio. The balanced dataset, is divided into 5,064 training images and 2,168 testing images, following a 70:30 ratio, as shown in Table 2.

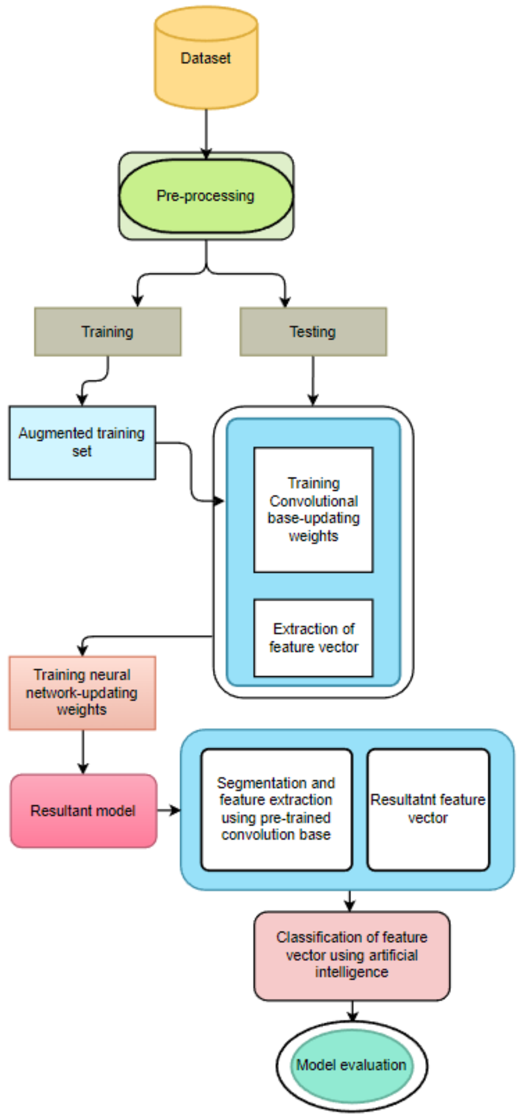

Fig. 2: COVID X-ray images methodology

The images are in PNG format with a resolution of 1024 x 1024 pixels, later scaled down to standard resolutions (244 x 244 pixels for VGG19 and ResNet-50, and 299 x 299 pixels for InceptionResNetV2 in the sequential model) after data augmentation in the transfer learning models. Sample images for both classes, COVID-19 infected and healthy, are shown in Figure 3.

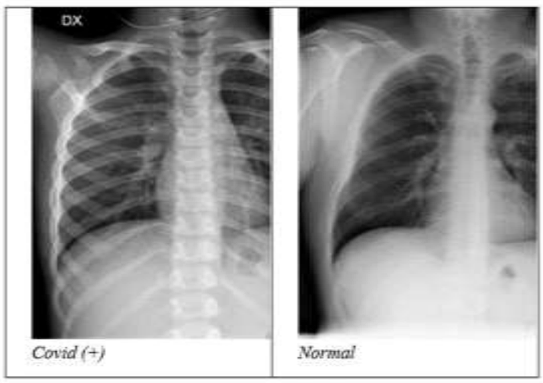

Fig. 3: Sample images from the dataset

Image pre-processing techniques such as data augmentation will enhance the image quality. Multiple transfer learning methodologies, including VGG19, ResNet-50, and InceptionResNetV2, are employed in these tests. The results obtained are compared to several COVID-19 detection methods available in the literature. Classification accuracy, sensitivity, specificity, precision, and F1-score are vital metrics employed to gauge the efficacy of classification algorithms, [31].

Table 2. Number of records

Models	Balanced dataset				Unbalanced dataset			
	Sequential		Transfer learning		Sequential		Transfer learning	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Inception-ResnetV2	5064	2168	6584	3692	11047	2761	12767	3341
ResNet-50	5064	2168	5062	2170	11047	2761	13774	7392

4 Results

In this section, we present an analysis of the key findings derived from each investigation conducted in this study. We provide an overview of the pre-trained and sequential models utilized, along with a discussion of the applied parameters. The study involved the examination of the sequential model and pre-trained models, such as VGG 19, Inception ResNet V2, and ResNet-50, to classify COVID-positive and normal images using two datasets: one balanced and the other unbalanced. The dataset is split into training and validation sets in a proportion of 80% and 20% respectively.

4.1 Sequential Model

The sequential model underwent image augmentation as a preprocessing step, as outlined in Table 3 for all models (VGG19, InceptionResNetV2, and ResNet-50). The focal loss function was applied to handle the imbalanced dataset in the sequential models constructed. Utilizing the "Adam" optimizer with focal loss parameters set at gamma = 2.0 and alpha = 0.20, VGG19 achieved the highest performance (83.63%) on the balanced dataset, followed by ResNet-50 (82.98%) and InceptionResNetV2 (80.49%). Conversely, on the imbalanced dataset, InceptionResNetV2 outperformed (83.82%), surpassing ResNet-50 (83.01%) and VGG19 (82.90%).

Table 3. Comparison of the accuracy for the sequential model balanced and unbalanced dataset

Model	Balanced dataset with data augmentation and tunning	Unbalanced dataset with data augmentation and fine tunning
RESNET-50	Training -79.13% and validation 82.98%	Training -80.30% and validation– 83.01%
INCEPTION-RESNETV2	Training -79.13% and validation – 80.49%	Training– 81.15% and validation 83.81%
VGG19	Training– 79.90% and validation 83.63%	Training– 83.28% and validation– 82.90 %

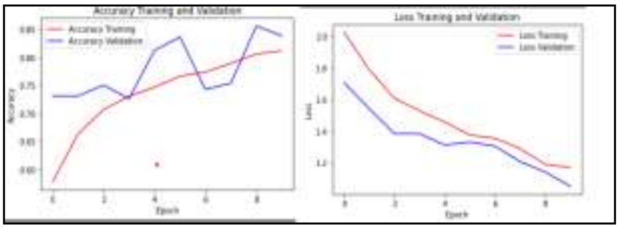

Fig. 4: Accuracy and Loss of VGG19 using sequential model

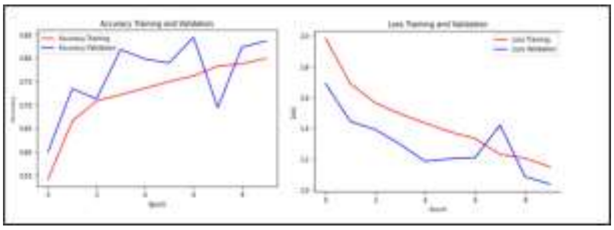

Fig. 5: Accuracy and Loss of InceptionResNetV2 using sequential model

The performance metrics of using sequential model for VGG19 are shown in Figure 4, while those of InceptionResNetV2 are illustrated in Figure 5, offering valuable insights into the evolution of each model's accuracy and loss throughout the training process.

4.2 Pre-trained Model with Binary Cross Entropy

This section explores pre-trained models, including VGG19, InceptionResNetV2, and ResNet-50, utilizing binary cross-entropy to distinguish between COVID and normal images. The dataset was split into balanced and unbalanced subsets with proportions of 70:30 for balanced datasets and 80:20 for unbalanced datasets. After training the model with data augmentation parameters (as detailed in Table 4 for all pre-trained models), "ImageNet" weights were employed for building the pre-trained models with an input shape of 224x224x3. The classifiers utilized activation="sigmoid" with global average pooling 2D and binary cross-entropy before incorporating any pre-trained models. In the balanced dataset, VGG19 achieved the highest score of 91.22%, followed by ResNet-50 with a score of 78.85%. In the unbalanced dataset, InceptionResNetV2 yielded results comparable to VGG19, scoring 73, while ResNet-50 scored 50.92%.

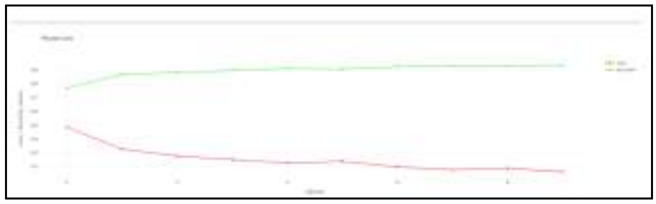
Fig. 6: Accuracy and Loss of VGG19 using Binary Cross-Entropy

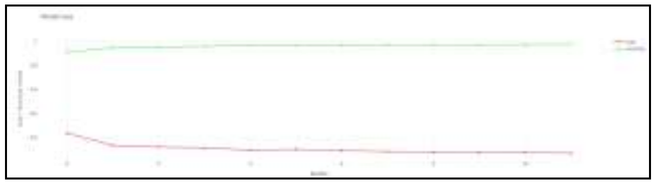
Fig. 7: Accuracy and Loss of InceptionresNetV2 using Binary Cross-Entropy

The performance metrics of using Binary Cross-Entropy for VGG19 are shown in Figure 6, while those of InceptionResNetV2 are illustrated in Figure 7, offering valuable insights into the evolution of each model's accuracy and loss throughout the training process.

4.3 Pre-trained Model with Focal Loss

We explored the application of pre-trained models employing focal loss, including VGG19, InceptionResNetV2, and ResNet-50, to differentiate between normal and COVID images using both balanced and unbalanced datasets. For this investigation, we divided the dataset into balanced and unbalanced subsets with proportions of 70:30 and 80:20, respectively. Subsequently, we trained the model using data augmentation parameters, as outlined in Table 4 for all pre-trained models.

The model utilized in this study, initially developed with binary cross-entropy, was then modified to incorporate the focal loss function. This adjustment aimed to address the imbalanced nature of our dataset, where the weighting of training instances is uneven. Focal loss assigns a lower weight to successfully categorized instances compared to the overall training examples. Consequently, we placed more emphasis on training with challenging-to-classify data, promoting swift and effective classification of the majority class. Simultaneously, we leveraged the attention loss to elevate the relative weight of instances in the minority class, ensuring outstanding accuracy for this class. In defining the focal loss for the pre-trained models, we utilized the "adam" optimizer. Over 10 epochs, the learning rate for all pre-trained models was set at 0.0001 per iteration.

Among the three models on the balanced dataset, VGG19 exhibited the highest performance, scoring 98.70%, followed by InceptionResNetV2 (97.51%), and ResNet-50 (96.64%). Similarly, on the unbalanced dataset, InceptionResNetV2 and ResNet-50 demonstrated high accuracy levels of 97.33% and 95.37%, respectively, comparable to their performance with the balanced dataset.

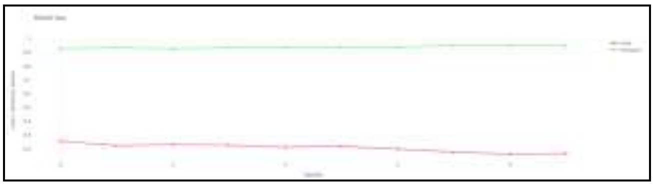

Fig. 8: Accuracy and Loss of VGG19 using Focal loss

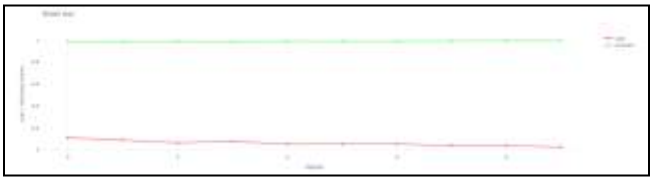

Fig. 9: Accuracy and Loss of InceptionResNetV2 using Focal loss

The performance metrics of using Focal loss for VGG19 are shown in Figure 8, while those of InceptionResNetV2 are illustrated in Figure 9, offering valuable insights into the evolution of each model's accuracy and loss throughout the training process.

5 Main Findings and Discussion

This section discusses the overall performance of various models in COVID-19 detection. It highlights the significance of using unbalanced datasets with specific preprocessing techniques, including data augmentation strategies and focal loss, to enhance the performance of transfer learning methods. The results, presented in Tables 4 and 5, reveal that InceptionResNetV2 stands out with a remarkable accuracy of 99.52% when dealing with an unbalanced dataset. The study introduces three pre-trained deep CNN models—VGG19, ResNet-50, and InceptionResNetV2—used for classifying COVID-19 and normal cases from chest X-ray radiography images. Across balanced datasets, VGG-19 achieved the highest binary classification accuracy at 98.70%, followed by InceptionResNetV2 (97.51%) and ResNet-50 (96.64%). In unbalanced datasets, the models' overall accuracy for binary classification was VGG-19 (95.37%), ResNet-50 (97.33%), and InceptionResNetV2 (99.52%). The focal loss function was employed to address the imbalanced dataset, which is crucial for reducing the oversight of COVID-19 cases. Comparisons with previous studies, summarized in Tables 4 and 5, indicate that the proposed models' performance is competitive or superior.

Notable examples include COVIDX-Net achieving 90% accuracy, DenseNet201 achieving 99.70% precision, and VGG-19 reaching 98.75% accuracy. The study emphasizes the potential of deep learning models, particularly InceptionResNetV2, in swiftly identifying COVID-19 cases from chest X-ray images.

As shown in Table 5, based on our evenly distributed data, the binary classification accuracy of VGG-19, ResNet-50, and InceptionResNetV2 was respectively 98.70%, 96.64%, and 97.51% respectively. According to our unbalanced data, VGG-19, ResNet-50, and InceptionResNetV2, each obtained an overall accuracy for binary classification of 95.37%, 97.33%, and 99.52% respectively. We worked with a dataset that had an uneven distribution and applied the focal loss function to it. This is extremely important because the primary goal of the work being done right now is to reduce the number of COVID-19 instances that are not accounted for, which should be achievable with the models that have been proposed. The results of our research are outlined in Tables 3 and 4, which demonstrate that InceptionResnetV2 achieves the highest level of accuracy for an imbalanced dataset while VGG-19 achieves the highest level of accuracy for a balanced dataset, with scores of 98.70% and 99.52%, respectively.

A new model called COVIDX-Net, to identify instances of COVID-19 using chest X-rays as the data source was proposed, [11]. Their model achieved an accuracy of 90% by utilizing 25 healthy chest X-rays in addition to 25 COVID-19 positives as input. In a different piece of research, a technique for enhancing contrast that was based on transfer learning was used. This collection includes 1579 images of a standard chest X-ray in addition to 423 COVID-19 images, 1485 images of viral pneumonia, and other related images. AlexNet, ResNet-18, DenseNet-201, and SqueezeNet are the names of the four well-known pre-trained algorithms that were utilized in this study. DenseNet201 possesses a precision of 99.70%, an accuracy of 99.70%, a sensitivity of 99.70%, and a specificity of 99.55%. Using transfer learning, in another research, authors investigated 504 typical images, 714 pneumonia cases, and 224 approved COVID-19, [18]. The VGG-19 model that they suggested had an accuracy of 98.75% when applied to binary classification.

With the help of the CVOID-Net model, authors in [14] were able to achieve a classification accuracy of 98% on a total of 13,975 chest x-ray images. It has been demonstrated that other preventative methods, such as wearing cloth face covers, social isolation, and stringent testing, can reduce the spread of COVID-19.

The results underscore the importance of further expanding patient data in training sets for improved model accuracy and reliability in real-world applications. The proposed models have the potential to alleviate the workload for physicians and contribute to efficient COVID-19 diagnosis.

Table 4. A comparison of the accuracy achieved with the pre-trained models while using balanced and unbalanced datasets

	Balanced dataset	Unbalanced dataset
Model	Accuracy	Accuracy
RESNET-50	Training Accuracy using binary cross entropy - 93.97% Test Accuracy using binary cross entropy - 78.85% Training Accuracy using Focal loss - 97.49% Test Accuracy using Focal loss - 96.64%	Training Accuracy using binary cross entropy - 94.15% Test Accuracy of pre-trained model using binary cross entropy tuning- 50.91% Training Accuracy of the pre-trained model using Focal loss tuning- 97.52% Test Accuracy of the pre-trained model using Focal loss tuning- 97.33%
INCEPTION-RESNETV2	Training Accuracy of the pre-trained model using binary cross entropy tuning- 96.95% Test Accuracy of pre-trained model using binary cross entropy tuning- 91.22% Training Accuracy of the pre-trained model using Focal loss tuning- 89.82% Test Accuracy of the pre-trained model using Focal loss tuning- 97.51%	Training Accuracy of the pre-trained model using binary cross entropy tuning- 97.65% Test Accuracy of pre-trained model using binary cross entropy tuning- 95.24% Training Accuracy of the pre-trained model using Focal loss tuning- 99.37% Test Accuracy of the pre-trained model using Focal loss tuning- 99.52%
VGG19	Training Accuracy of the pre-trained model using binary cross entropy tuning- 93.56% Test Accuracy of pre-trained model using binary cross entropy tuning- 96.63% Training Accuracy of the pre-trained model using Focal loss tuning- 94.69% Test Accuracy of the pre-trained model using Focal loss tuning- 98.70%	Training Accuracy of the pre-trained model using binary cross entropy tuning- 73.87% Test Accuracy of pre-trained model using binary cross entropy tuning- 73.77% Training Accuracy pre-trained model using Focal loss tuning- 86.83% Test Accuracy of the pre-trained model using Focal loss tuning- 95.37%

Table 5. Comparison of the results with similar work.

Model	Obtained Accuracy using the whole dataset	Work done by other authors using the same dataset
ResNet-50	97.33%	97.1%
InceptionresnetV2	**99.52%**	96.6%
VGG19	95.37%	98.6%

6 Conclusion

In conclusion, the study aimed to improve COVID-19 detection using transfer learning-based CNN models applied to chest X-ray images. The findings indicate that employing an unbalanced dataset with data augmentation strategies, specifically the Focal loss technique, enhances the performance of transfer learning methods for COVID-19 detection. Among the three pre-trained deep CNN models (VGG19, ResNet-50, and InceptionResNetV2), InceptionResNetV2 stood out with a competitive accuracy of 99.52% when using an unbalanced dataset. Comparative analysis with earlier studies in the field reveals that the proposed models perform on par with or even surpass the accuracy achieved by other models. The significance of the research lies in the potential of these models to identify COVID-19-positive cases, addressing the limitations of current detection methods such as RT-PCR, which is time-consuming and faces challenges of accessibility and cost quickly and accurately. Using pre-trained deep learning classifiers, data augmentation, and transfer learning, the goal of this work is to demonstrate that VGG19 performs best for balanced datasets overall, while inceptionresnetv2 performs best for unbalanced datasets overall, based on the performance results shown in tables 3 and 4. It is feasible to improve both the accuracy of the COVID-19 detecting X-ray image and the time complexity of the process. These findings may prove useful in the data processing and linkage with decision support system procedures required for the development of X-ray image covid categorization systems. The study acknowledges the need for further validation by expanding the patient data used in the training set. Despite the limitations and the necessity for ongoing refinement, the proposed models demonstrate promising results and suggest that deep learning, particularly transfer learning, could play a significant role in containing the global COVID-19 outbreak. The integration of additional images and the implementation of pre-processing methods are identified as potential avenues for further improvement, making the workload less demanding for physicians and enhancing the overall efficiency of COVID-19 detection.

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