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Speciality: Intelligent Model and Decision (M.I.D)

Subject:

Multimodal Covid-19 classification based on deep neural networks

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Defended on: 03/07/2023

In front of the jury composed of:

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Dedication

I dedicate this modest work to my dear parents, who have been an unwavering source of support, encouragement, and love throughout my journey. Their trust in me and their unwavering support have been crucial in overcoming challenges and achieving my goals. I am grateful to my father, who always encourages me and makes sacrifices to see me succeed. I hold deep respect and affection for them, and I pray that Allah protects them.

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Fadia

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List of Abbreviations

AI	Artificial Intelligence
Adam	Adaptive Moment Estimation
CNN	Convolutional Neural Network
Covid-19	Coronavirus Disease 2019
CT	Computed Tomography
DL	Deep Learning
DNN	Deep Neural Network
ML	Machine Learning
ReLU	Rectified Linear Unit
ResNet	Residual Networks
TL	Transfer Learning
VGG	Visual Geometry Group
X-ray	Radiography

Introduction

Artificial Intelligence (AI) technology has gained significant attention in various domains, including the medical field, where it serves as a valuable tool for assisting physicians and authorities in tasks such as image analysis and disease diagnosis [10]. Within the medical field, AI, along with its subsets of machine learning (ML) and deep learning (DL), covers the extensive survey on various diseases such as alzheimer's, cancer, diabetes, heart disease, tuberculosis, hypertension, and more. Among the most promising areas of health innovation is the application of AI in medical imaging stands out, particularly in image processing and interpretation [28]. Through techniques such as ultrasound (US), magnetic resonance imaging (MRI), mammography, genomics, and computed tomography (CT) scans [22].

1 Background

In late 2019, an outbreak of viral pneumonia emerged in China. This coronavirus pandemic, known as Covid-19, is caused by the Severe Acute Respiratory Syndrome Corona Virus (SARS-CoV-2). It is highly contagious and has been declared a global public health emergency by the World Health Organization (WHO), due to its rapid transmission and devastating consequences [39]. According to the WHO report of May 2023, there have been 766,895,075 confirmed cases and over 6,935,889 deaths [41]. This pandemic has had a significant impact on the world affecting healthcare systems, economies and daily life[21].

2 Problem statement

Reverse Transcription Polymerize Chain Reaction (RT-PCR) is commonly used for Covid-19 diagnosis. However, this method has several limitations, such as time-consuming procedures[5] and the possibility of false-negative results that may arise due to changes in diagnostic accuracy during the course of the disease [35]. In contrast, medical imaging techniques provide visual information that can aid in diagnosis. Chest CT, in particular, outperforms RT-PCR for Covid-19 detection [12]. The integration of AI, particularly Deep neural networks (DNNs), has played a vital role in improving the detection and classification of Covid-19 cases[26].

The objective of this work is to develop effective diagnosis deep neural models that boost the accuracy of both CT-scan and X-ray images.

3 Contribution

In this study, we propose a Covid-19 classification approach that leverages the power of DNNs. By combining two modalities of medical images, our system aims to significantly enhance the accuracy and efficiency of Covid-19 diagnosis. The integration of multiple imaging modalities that complement each other, we anticipate improving the accuracy, and robustness of our classification model.

Furthermore, our main contribution lies in the development of multiple convolutional neural networks (CNNs) models using transfer learning (TL) techniques, employing well-established architectures such as Xception, VGG16, VGG19, and ResNet152V2, to ensure high accuracy. Each CNN model is independently fed with Ct-Scan and X-Ray images, with the goal of improving the accuracy and reliability of Covid-19 diagnosis.

4 Outline of the manuscript

The manuscript is structured as follows:

Chapter 1 provides a comprehensive overview of the basic concepts relevant to the topic.

Chapter 2 presents a detailed literature review encompassing the theme.

Chapter 3 delves into the implementation details of our proposed Covid-19 classification approach, including the methodologies, datasets, and evaluation metrics employed.

Finally concludes the manuscript 3.5 by summarizing the findings, discussing the limitations and future directions of the research, and highlighting the significance of our contributions in the field of Covid-19 diagnosis using DNNs.

Chapter 1

Deep Learning

1.1 Introduction

Artificial Intelligence (AI), introduced by the American scientist John MacCarthy, is a computer science research field focused on developing computers capable of imitating human intelligence in various tasks [10], including radiology, the integration of AI in this field enhances efficiency and time-consuming image analysis by identifying findings detectable or not with the human eye. Key objectives of AI include learning and problem-solving.

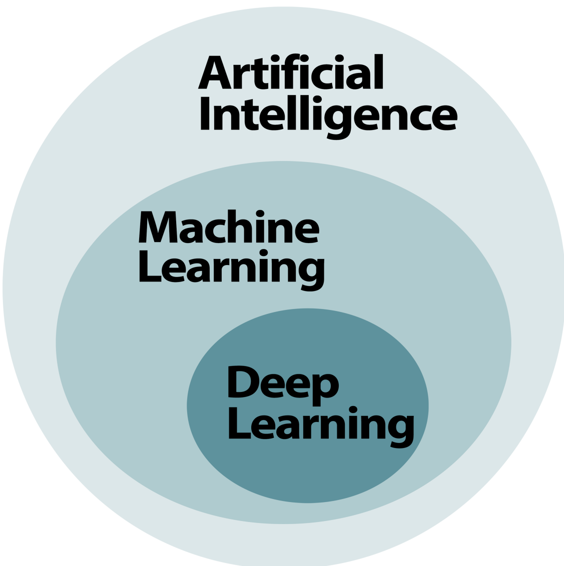

Figure 1.1: AI and its subsets of ML and DL [14].

Machine learning (ML), a subfield of AI introduced by Arthur Samuel in 1959, enables computers to learn from data without explicit programming, incorporates computational models and algorithms that imitate the architecture of biological neural networks in the brain, known as Artificial neural networks (ANNs) [28]. However, traditional ML techniques require feature extraction as a prerequisite, which poses challenges in selecting appropriate features and relies on domain expertise.

DL is a subset of ML (figure 1.1), and addresses the limitation of ML techniques by eliminating the need for pre-selected features (figure 1.2).

Instead, DL automatically extracts significant features directly from raw input for the specific problem at hand [18, 29], DL algorithms such as DNN, which consist of multiple hidden layers of interconnected neurons that are capable of learning and representing complex patterns and relationships in the data [32, 7], DL has led to improved performance and accuracy in various applications, including medical images analysis [34, 29].

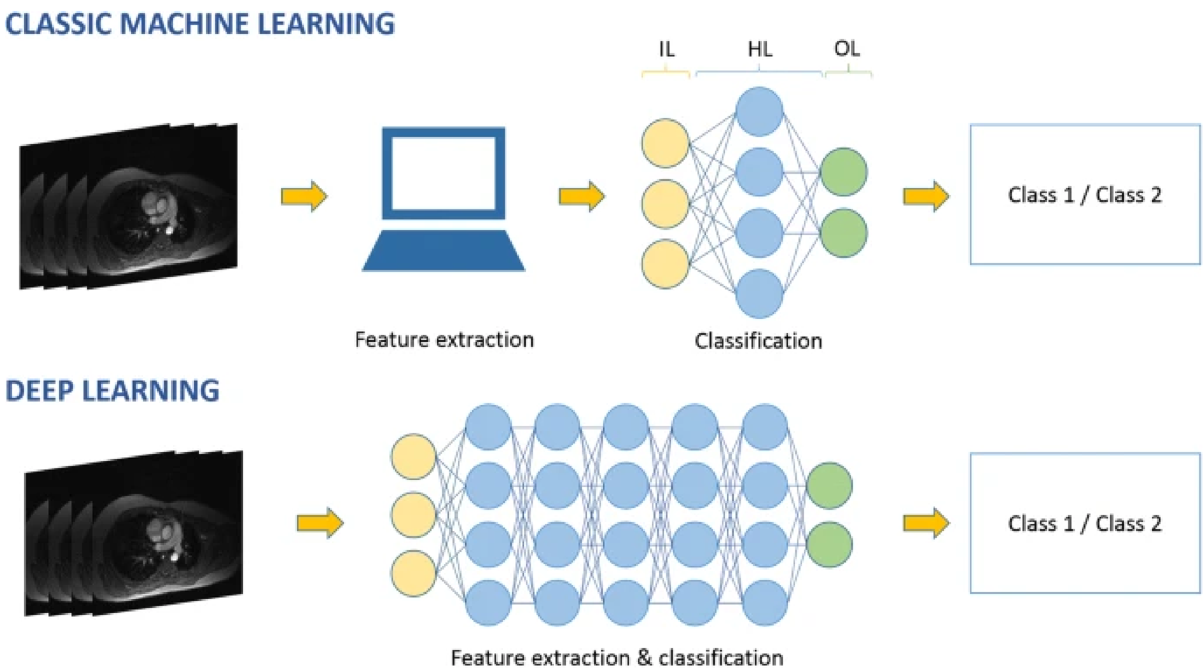

Figure 1.2: A Comparative Analysis of Classic ML and DL Approaches for Classification Tasks: Unveiling the Role of DNNs in Feature Extraction[28].

1.2 Convolutional neural networks

CNNs are widely recognized as the most established algorithm among various DL models [42]. One of the key advantages of CNNs over their predecessors is their ability to automatically identify relevant features without the need for human supervision [4].
Due to their exceptional performance, CNNs have achieved expert-level results in diverse fields, including image classification, object detection, face detection, speech recognition, vehicle recognition, and facial expression recognition [18]. In medical imaging, CNNs have been used to solve classification and segmentation problems in CT images, X-Ray images to diagnose Covid-19, and segmentation of MRI brain images [29, 3, 18].
The architecture of CNNs draws inspiration from the organization of the animal visual cortex, particularly that of a cat's brain [4]. It is designed to learn spatial hierarchies of features in an automatic and adaptive manner, progressing from low-level to high-level patterns[42].

1.2.1 CNN layers

The basic CNN architecture along with its several layers is illustrated in figure1.3. These layers work together to extract features from the input data and perform classification[25].

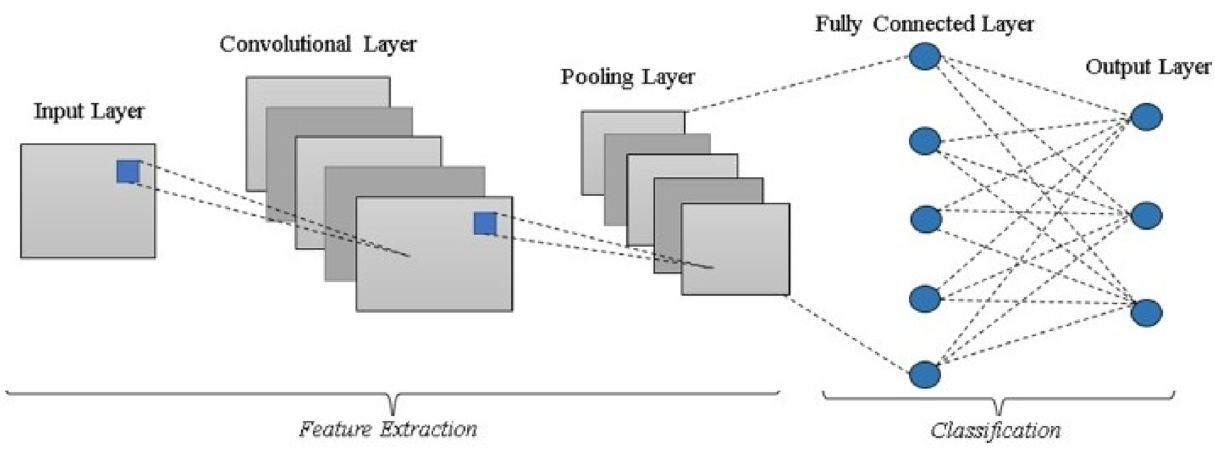

Figure 1.3: The basic architecture of CNN[25].

1.2.1.1 Convolutional Layer

The convolution layer plays a crucial role in the architecture of CNNs that is responsible for extracting features[42].

Kernel: is a small array of numbers, also known as a filter, used for feature extraction in convolutional layers. It is applied across the input tensor, which is an array of numbers representing the input data. The kernel performs a specialized linear operation called convolution.

Convolution operation: convolution is a type of linear operation used in feature extraction. It consists of a set of convolutional filters or kernels, which are applied to the input image to generate the output feature map.
The kernel is applied to the input tensor, and at each position, the values of the kernel and the corresponding elements of the input tensor are multiplied together and then added up. This calculation results in the output value for that specific position in the output tensor, which is referred to as a feature map figure 1.4.
By applying multiple kernels, different feature maps representing different characteristics of the input data can be generated. Each kernel can be considered as a different feature extractor.
The convolution operation is defined by two key hyperparameters:

- the size of the kernel (often 3x3, 5x5, or 7x7).
- the number of kernels, which determines the depth of the output feature maps.

By default, the convolution operation reduces the height and width of the output feature map compared to the input tensor. To address this issue, padding, commonly zero padding, is used to add rows and columns of zeros to the input tensor, to maintain dimensions during the convolution process.

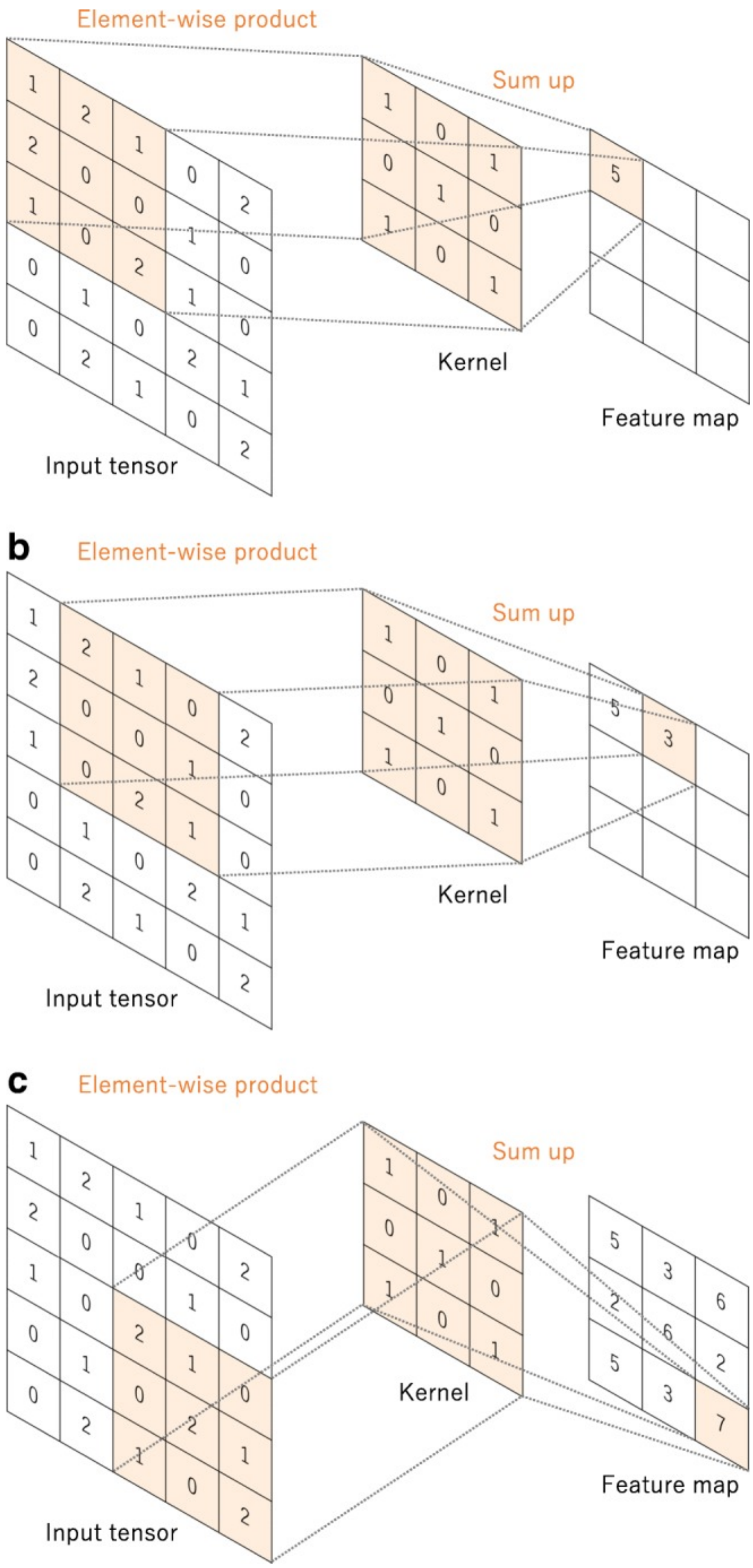

Figure 1.4: Kernel Application and Feature Map Generation in Convolutional Layer [42].

1.2.1.2 Pooling Layer

The main task of the pooling layer is to perform sub-sampling on the feature maps obtained from convolutional operations. This approach reduces the size of the feature maps while maintaining the majority of the important information or features.

The pooling layer follows the convolutional layer as it becomes less significant to precisely locate a feature once it has been detected. One of the significant advantages of using pooling is the notable reduction in the number of trainable parameters, thereby introducing translation invariance. Both the stride and kernel size are initially assigned before executing the pooling operation, similar to the convolutional operation. There are several pooling techniques, such as max pooling, global average pooling (GAP), and global max pooling. Figure 1.5 illustrates these three types of pooling operations.

By incorporating pooling layers, CNNs can efficiently extract relevant features while decreasing computational complexity.[4, 18].

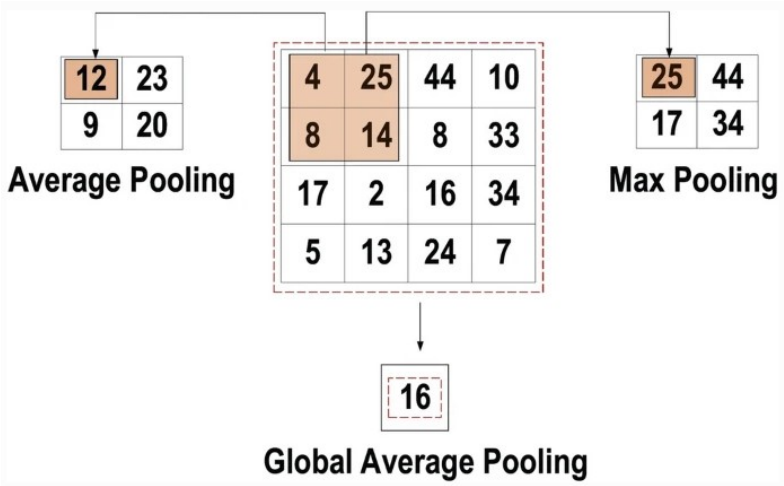

Figure 1.5: Three types of pooling operations[4].

1.2.1.3 Fully Connected Layer

The fully connected (FC) layer, commonly located at the end of a CNN, serves as the classifier. It follows a feed-forward approach similar to a conventional multiple-layer perceptron (MLP) neural network.

Each neuron in this layer is connected to all neurons of the previous layer, known as the FC approach. The input to the FC layer is a vector generated from the flattened feature maps obtained from the preceding pooling or convolutional layers. By computing the dot product of the weight vector and input vector, the FC layer produces the final output of the CNN as illustrated in figure 1.6.

The final FC layer typically consists of the same number of output nodes as the number of classes in classification tasks. Nonlinear functions, such as ReLU, are applied after each FC layer to introduce nonlinearity into the network [4, 18, 42].

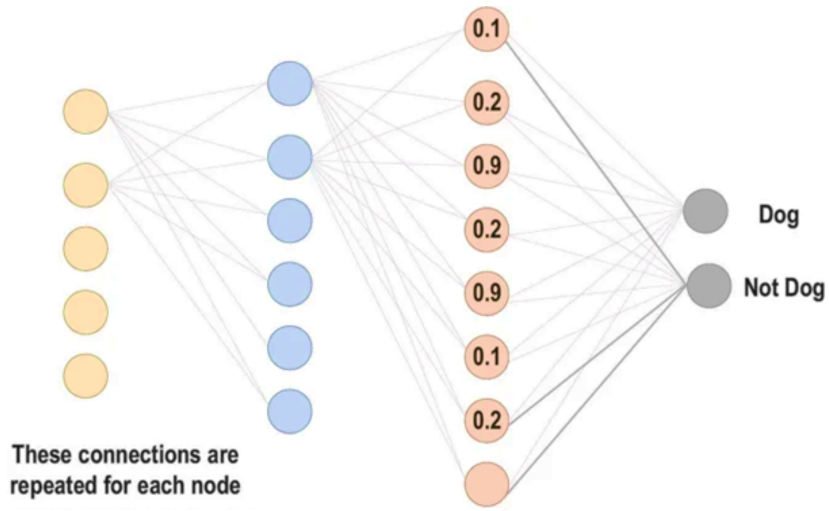

Figure 1.6: Fully connected layer[4].

1.2.1.4 Dropout layer

Dropout layer is a regularization technique, used before the output layers, which randomly discards neurons during training. This helps to prevent overfitting by reducing inter-dependencies between neurons [4, 25].

1.2.1.5 Activation Function

The activation function is the mechanism through which artificial neurons process and transmit information [29]. It plays a central role in neural networks by mapping the input to the output.

It determines whether a neuron should be activated based on the weighted sum of inputs and bias. This decision leads to the creation of the corresponding output.
In CNN architecture, non-linear activation layers are applied after learnable layers, such as FC layers and convolutional layers. These activation layers introduce non-linearity in the mapping process, enabling the network to learn complex patterns. It is essential for the activation function to be differentiable, as it allows error back-propagation for network training [4]. Figure 1.7presents the types of activation functions widely used in neural networks.

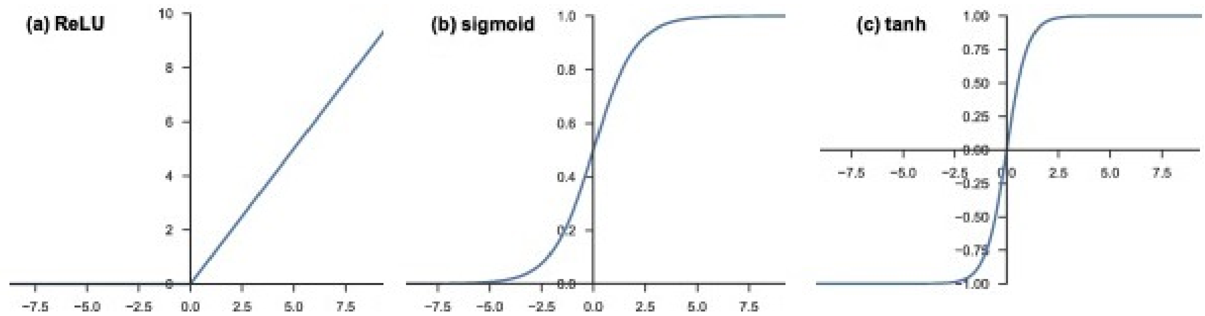

Figure 1.7: Activation functions commonly applied to neural networks [42].

Rectified Linear Unit (ReLU) is the most commonly used activation function in the context of CNNs. It transforms all input values to positive numbers, discarding any negative values. Its mathematical representation can be described as follows 1.1 [4] :

$$f(x)_{ReLU} = max(0, x) \tag{1.1}$$

The ReLU function performs as well as or better than the sigmoid and tanh functions in neural networks.

1.2.2 Training Process in CNN

Training a network is a process that involves the optimization of kernels in convolution layers and weights in fully connected layers to minimize the difference between predicted outputs and ground truth labels on a training dataset.

The commonly used method for training neural networks is backpropagation, which relies on a loss function and gradient descent optimization. By calculating the model's performance using a loss function through forward propagation on a training dataset, the learnable parameters (kernels and weights) are updated based on the loss value using backpropagation and gradient descent [42].

Loss function

A loss function, also known as a cost function, is used to measure the compatibility between the network's output predictions and the ground truth labels. Commonly used loss functions include :

- Cross entropy for multiclass classification tasks.
- Mean squared error for regression tasks.

The choice of the loss function is a hyperparameter that depends on the specific task at hand [42], and plays a central role in all supervised learning algorithms[4].

Learning rate

The learning rate is defined as the step size for parameter updates, it must be carefully chosen to avoid negatively impacting the learning process, despite a hyperparameter [4].

Gradient descent

Gradient descent or Gradient-based learning is a widely employed optimization algorithm that employed to update network parameters in each training epoch (which represents a complete iteration of parameter updates involving the entire training dataset), searching for the locally optimized solution to minimize the training error[42, 4].

The gradient of the loss function provides the direction of steepest increase, and each parameter is adjusted in the negative direction of the gradient, guided by the learning rate hyperparameter[42] (fig1.8). This updating process is facilitated through network back-propagation, where the gradient at each neuron is propagated backward to all neurons in the preceding layer [4]. By iteratively adjusting the parameters based on the gradient, the network aims to converge toward an optimal solution and improve its overall performance.

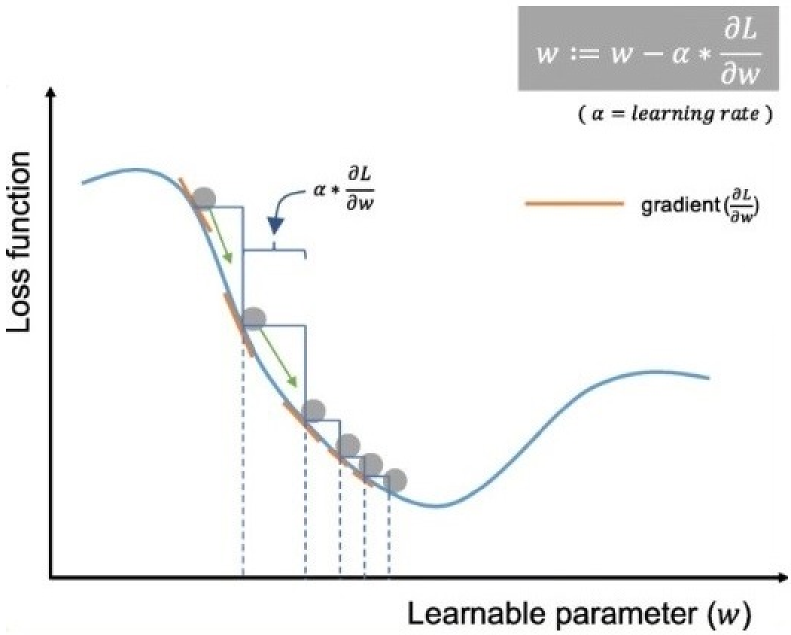

Figure 1.8: Illustration of Gradient Descent[42].

Additionally, various alternatives of the gradient-based learning algorithm are available and commonly employed, such as Stochastic Gradient Descent (SGD), Mini-batch Gradient Descent, Momentum, and Adaptive Moment Estimation (Adam).

Adam

Adam is an optimization technique and learning algorithm that represents the last trends in DL optimization. It combines the benefits of the Momentum and RMSprop, making it suitable for training DNN. The advantage of Adam lies in its improved memory efficiency and reduced computational power.

1.2.3 CNN architectures

Specialized CNN architectures are extensively trained on vast datasets containing numerous categories. These architectures are commonly known as pre-trained CNN models. ImageNet, the dataset on which they are trained, comprises 14 million images across 1000 diverse categories, encompassing animals (dogs, cats, lions, ...), as well as objects (desks, pens, chairs, ...)[13].

1.2.3.1 Visual Geometry Group

The Visual Geometry Group (VGG) network, proposed by Karen Simonyan and Andrew Zisserman [36], presents a powerful solution for large-scale image recognition tasks. Their investigation involves the use of small (3×3) convolution filters and emphasizes the evaluation of networks with depths ranging from 16 to 19 weight layers. Two variants were introduced of the VGG network architecture VGG16, and VGG19 comprising 16 layers and 19 layers respectively.

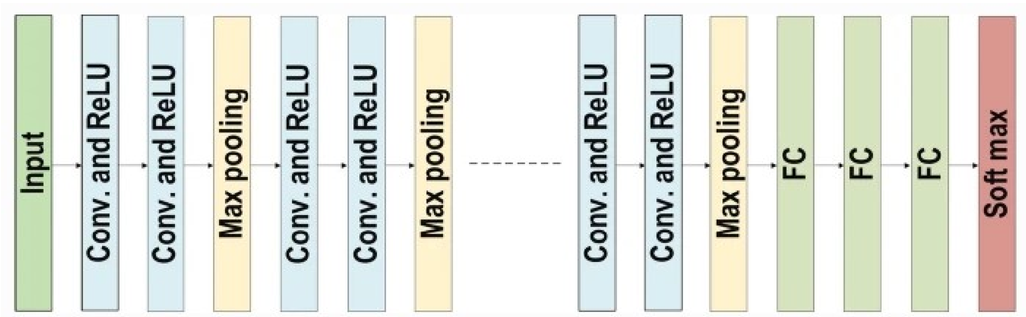

Figure 1.9: the architecture of VGG [4].

1.2.3.2 Xception

Xception[9] is a CNN architecture that utilizes depthwise separable convolution layers as its primary building blocks. The architecture consists of a total of 36 convolutional layers, which are organized into 14 modules. Notably, each module, except for the first and last ones, incorporates linear residual connections. In essence, Xception can be viewed as a linear stack of depthwise separable convolution layers, enhanced by the inclusion of residual connections. This design choice ensures both simplicity and flexibility in defining and modifying the Xception architecture.

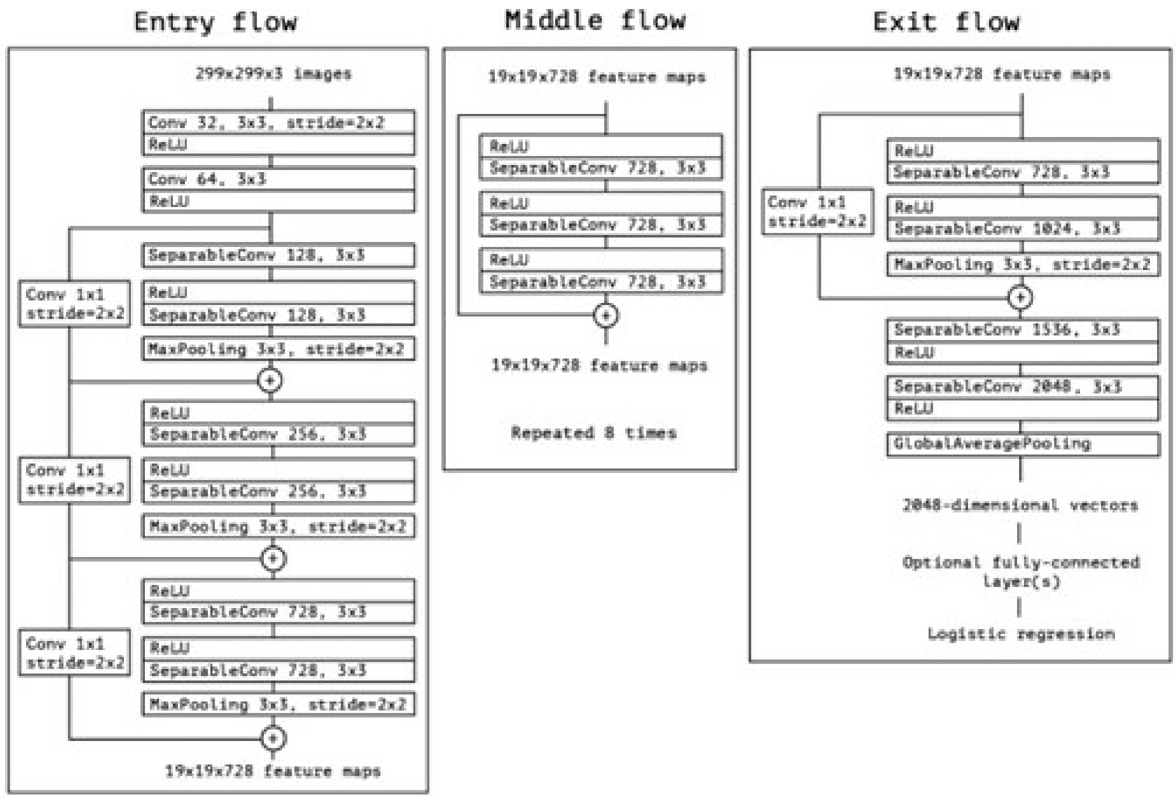

Figure 1.10: The Xception architecture[9].

1.2.3.3 ResNet152V2

Residual Networks (ResNet), a CNN architecture proposed by He et al.[16], offer significant advantages over traditional deep networks. These networks have been extensively evaluated on the ImageNet dataset, demonstrating remarkable optimization capabilities even with depths of up to 152 layers namely ResNet152, which achieves superior accuracy compared to shallower networks, despite its increased depth. This achievement further emphasizes the effectiveness and benefits of leveraging residual connections. The main distinction between (V2) and the original (V1) is the utilization of batch normalization before every weight layer in (V2)[24].

1.3 Transfer learning

Transfer learning (TL), a concept initially derived from educational psychology by psychologist C.H. Judd, involves the ability to apply previously learned knowledge to solve new problems more efficiently or effectively. In the field of ML, TL has gained significant attention since 1995, also known as learning to learn, life-long learning, knowledge transfer, or inductive transfer. Figure 1.11 shows Different Learning Processes between Traditional ML and TL.

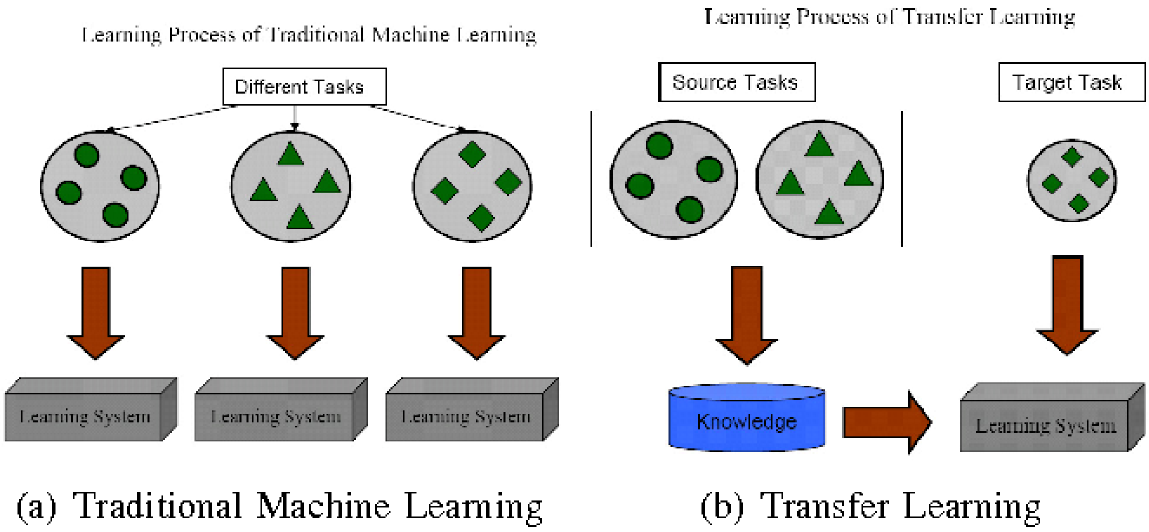

Figure 1.11: Different Learning Processes between Traditional ML and TL [27].

1.3.1 Definition

According to [27, 43] TL is a method that utilizes pre-trained models on large and diverse datasets, allowing the leverage of their general world representations for new and distinct tasks. The motivation behind studying TL stems from the observation that humans exhibit intelligent transfer of learned knowledge.

TL aims to enhance the learning process in the target task by leveraging knowledge from a source task. The effectiveness of TL can be measured in three ways illustrated in figure 1.12 [40].

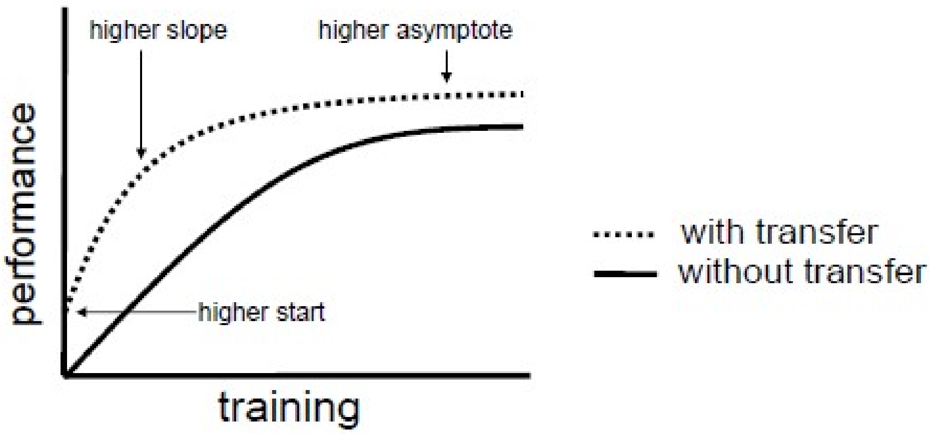

Figure 1.12: Three ways in which transfer might improve learning[40].

- Initial performance: achievable in the target task using only the transferred knowledge is compared to the initial performance of an agent with no prior knowledge.
- Time efficiency: reduce the time required to fully learn the target task by using knowledge, in contrast to learning the task from scratch.
- Final performance: achieved in the target task when compared to learning without transfer.

1.3.2 Deep Transfer Learning

As discussed (1.3.1), TL is a technique that leverages knowledge pre-trained model to solve a new task, with minimal re-training or fine-tuning. This approach is particularly useful for DL because DL models typically require a substantial amount of training data, which can be challenging to obtain, especially in the medical domain, and poses difficulties in creating large-scale, high-quality annotated medical datasets.

Additionally, DL models often require significant computing power, such as GPU-enabled servers. To address these challenges, Deep Transfer Learning (DTL), which is a DL-based TL approach, is introduced. It aims to reduce the demand for training data and time in domain-specific tasks by selecting a pre-trained model, either as a fixed feature extractor or for further fine-tuning [38, 32]. Figure 1.13 represents the main steps of the methodology of a Deep Transfer Learning approach. This approach has gained significant adoption across various fields, including the medical domain, where it has been employed to address diverse needs such as disease classification, notably in the context of Covid-19, utilizing medical images such as CT-scan [20, 23]and X-ray images [1].

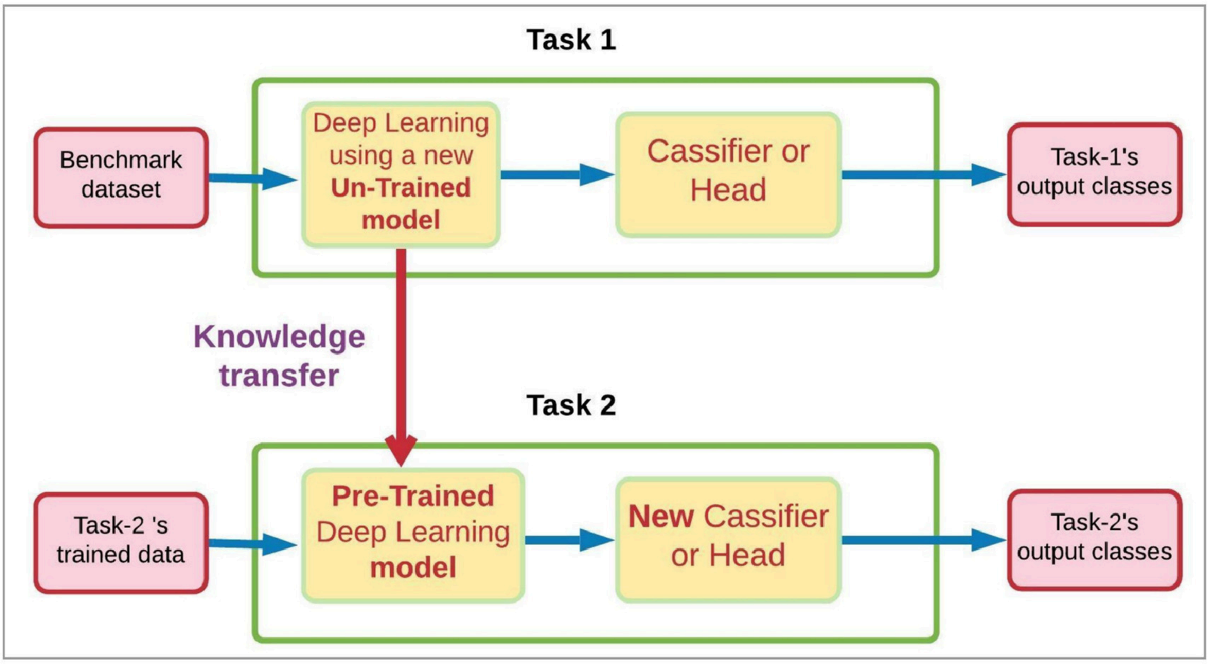

Figure 1.13: Block diagram of an example of Deep Transfer Learning [38].

1.4 Conclusion

In conclusion, DL, particularly CNNs, has revolutionized the field of medical image analysis by enabling automatic feature extraction and achieving high accuracy in various tasks. The use of pre-trained CNN models and transfer learning further enhances the efficiency and effectiveness of deep learning algorithms. With ongoing advancements, deep learning continues to hold immense potential for solving complex problems and advancing the field of AI in healthcare.

Chapter 2

Literature Review

2.1 Introduction

This chapter provides a comprehensive analysis of existing research on Covid-19 classification using deep learning techniques. It aims to explore the advancements and achievements in both unimodal and multimodal Covid-19 classification approaches.

2.2 Unimodal Covid-19 Classification

In this section, we review several studies that focus on the unimodal classification of Covid-19 using various DL models and techniques. Each study utilizes a specific modality, such as chest CT images or X-ray images, to detect and classify Covid-19 cases. The performance and effectiveness of different models are evaluated, providing valuable insights into the capabilities of these approaches.

An automated diagnosis Covid-19 from chest CT images using a TL based convolutional neural network 2022

Baghdad N.A. et al [5] proposes a framework (figure 2.1) for Performing an automatic classification of Covid-19 based on CT lung images using CNN, TL, and Sparrow Search Algorithm (SpaSA). SpaSA optimizes the various CNN and TL hyperparameters to find the best configuration for each pre-trained model. The experiments presented in table 2.1

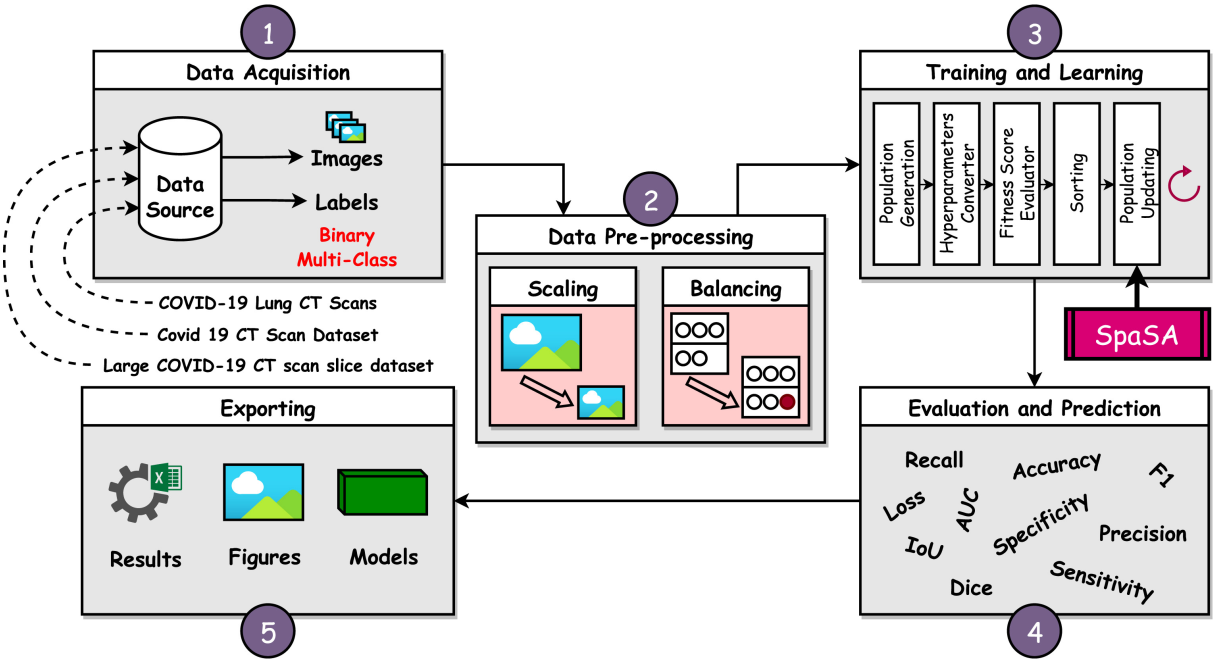

Figure 2.1: The suggested framework [5].

show that the pre-trained CNN models, specifically MobileNetV3Large and SeNet154, deliver optimal or near-optimal results for binary and multi-class classification tasks, respectively.

Dataset	Pre-trained Model	Accuracy (%)	Cross-entropy
Two-classes	MobileNetV3Large	99.74	0.008
Three-classes	SeNet154	98	0.054

Table 2.1: Experimental Results[5].

Deep transfer learning-based classification model for Covid-19 using chest CT-scans 2021

Chikh M.A. et al [23] introduce a deep transfer learning-based classification model, specifically the Densenet201 architecture, for Covid-19 detection in chest CT scan images. The proposed model outperforms other established models, such as VGG16, VGG19, Xception, Inception Resnet-V2, DenseNet121, and DenseNet201, in terms of performance. It achieved a high accuracy of 98.8%. The methodology followed in the study is summarized in the flowchart shown in figure 2.2. Additionally, the visual explanations provided by the Gradient-weighted Class Activation Mapping (GradCam) algorithm improved the interpretability of the model's predictions.

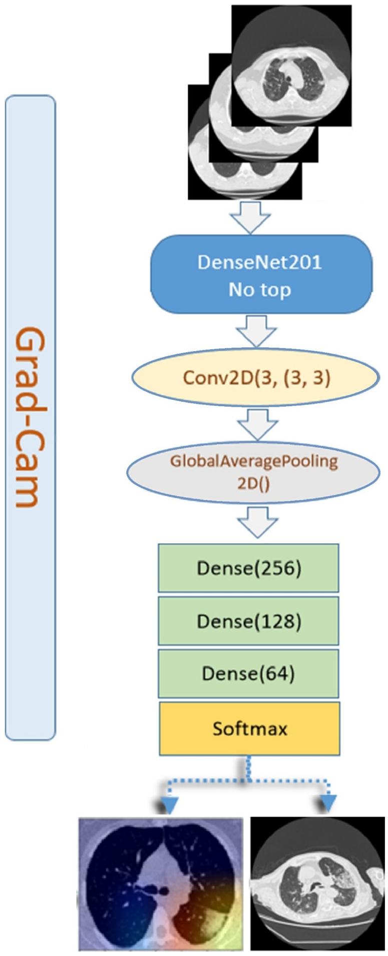

Figure 2.2: Flowchart of the proposed study [23].

A deep transfer learning-based CNN model for Covid-19 detection using CT scan images for medical applications 2023

Kathamuthu N.D. et al [20]conducted a study that compares various CNN-based image classification methods for detecting Covid-19 in chest CT scan images. The Proposed System Architecture is illustrated in figure2.3.Among the CNN models evaluated in the study, the VGG16 model emerged as the top performer, achieving an impressive accuracy of 98.00%. The superior performance of VGG16 can be attributed to its smaller parameter size and faster training time compared to the other CNN models investigated. These advantages allow VGG16 to outperform other models in terms of accuracy and efficiency.

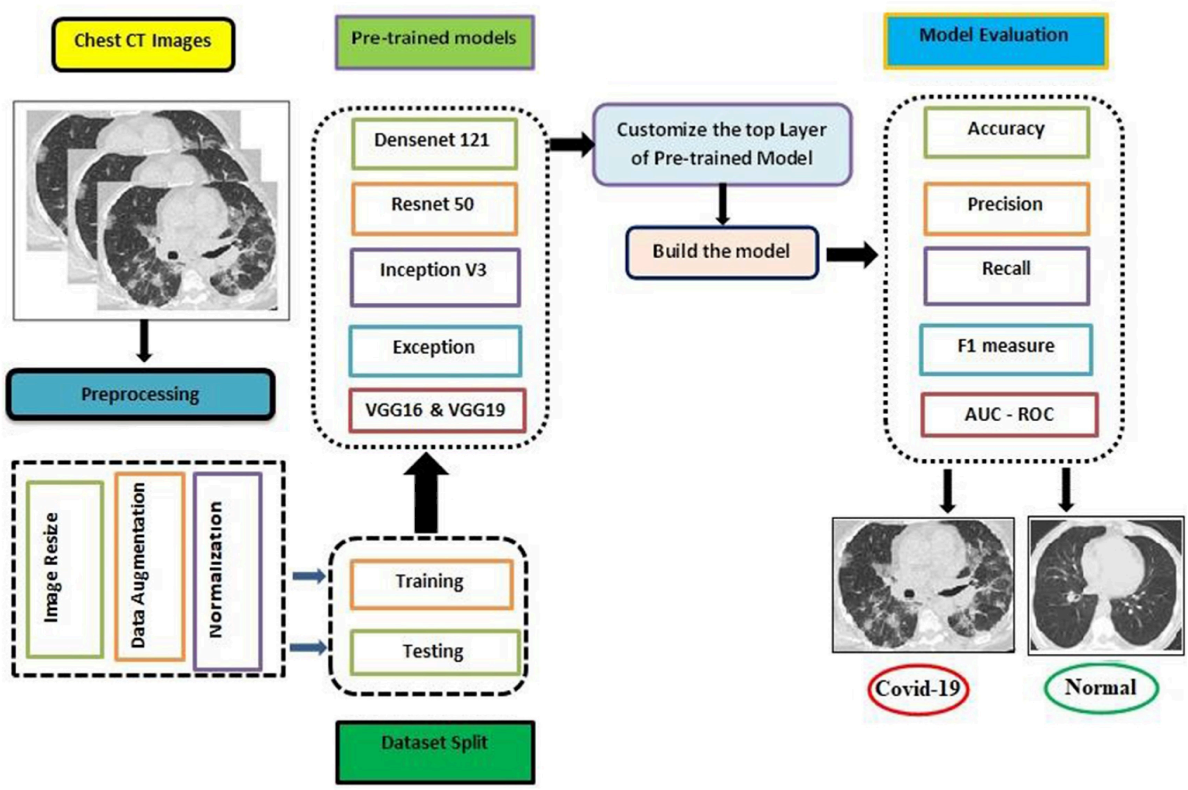

Figure 2.3: Proposed System Architecture [20].

Automated detection of Covid-19 using ensemble of TL with deep convolutional neural network based on CT scans 2021

Gifani P. et al [13] present an automatic methodology for diagnosing Covid-19 based on an ensemble DTL system. The study leverages a total of 15 pre-trained CNN architectures and a publicly available dataset of CT images.

The experimental results indicate that the majority voting of prediction of five DTL architectures with EfficientNetB0, EfficientNetB3, EfficientNetB5, Inception ResNet v2, and Xception has higher results than the individual TL structure and among the other models based on precision 85.7%, recall 85.4%, and accuracy 85% metrics in diagnosing Covid-19 from CT scans.

Transfer Learning Based Method for Covid-19 Detection From Chest X-ray Images 2020

Rashid N. et al [31] present a deep learning-based approach for detecting Covid-19 from chest X-ray images. The study focused on a three-class image classification task using a dataset consisting of chest X-rays from confirmed Covid-19 patients (408 images), confirmed pneumonia patients (4273 images), and healthy individuals (1590 images). To address the dataset's class imbalance, a random under-sampling technique called resampling was applied. Additionally, data augmentation techniques were introduced to enhance the input data. The model architecture and workflow are summarized in figure 2.4.

The proposed method utilized a CNN model with InceptionNetV3. The results demonstrated impressive performance, with an accuracy of 96.33% achieved for the three-class classification task (Normal, Covid-19, Pneumonia) and an accuracy of 99.39% for the two-class (Covid and Non-Covid) classification task.

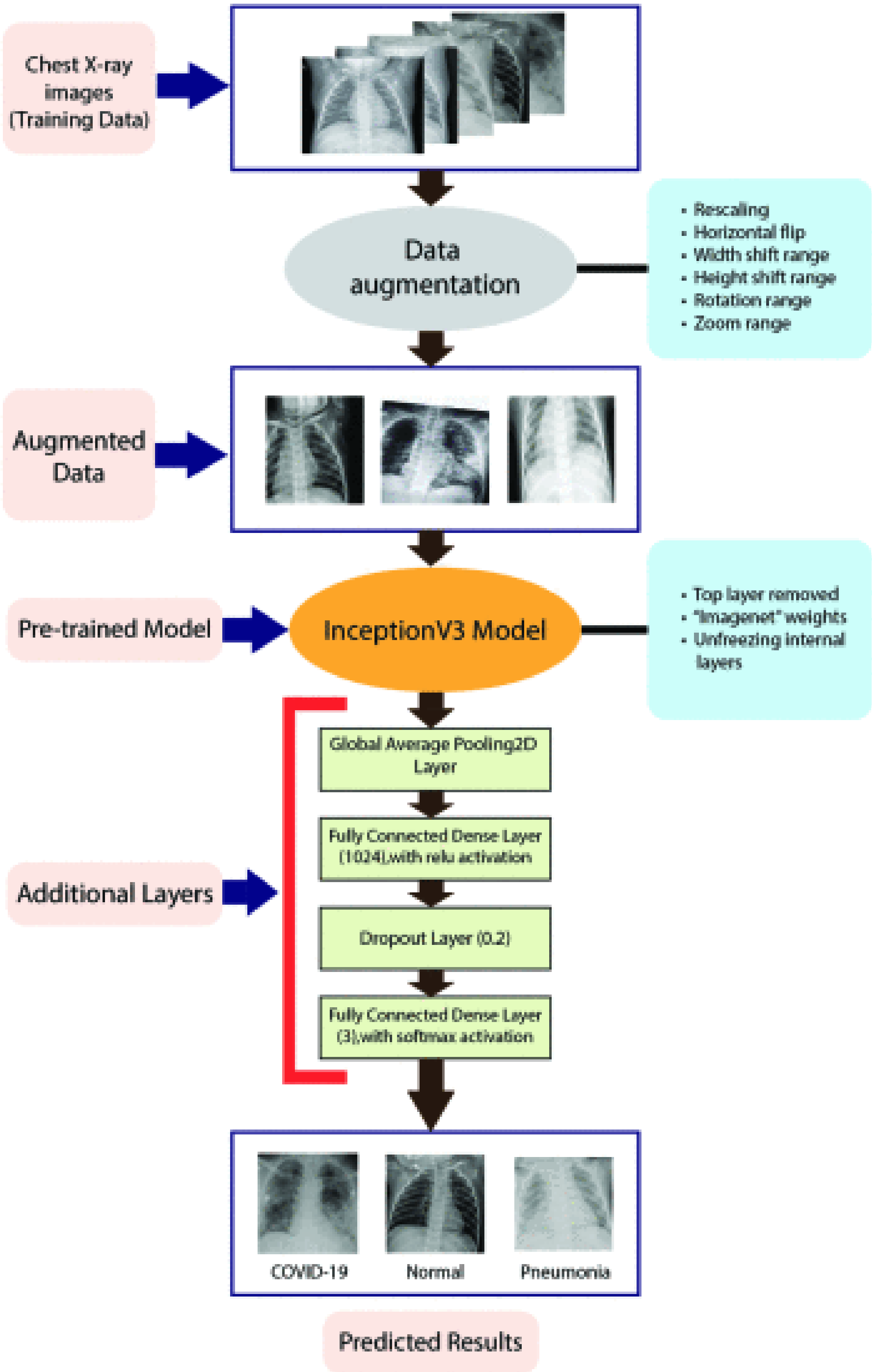

Figure 2.4: The model architecture and workflow [31].

Utilizing Deep Learning Models and Transfer Learning for Covid-19 Detection from X-Ray Images 2023

In this study [1], Agrawal s. et al. compared established Deep Learning models on a new Covid-19 dataset and proposed a ResNet50-based model for easy identification and classification of Covid-19 using X-Ray images. The proposed model illustrated in figure 2.5, achieved an impressive accuracy of 99.20% for binary classification and 86.13% for multi-class classification. The study also compared model interpretation methods such as LIME and Grad-CAM. The results indicated that LIME contours yielded better results compared to the heatmaps generated by Grad-CAM.

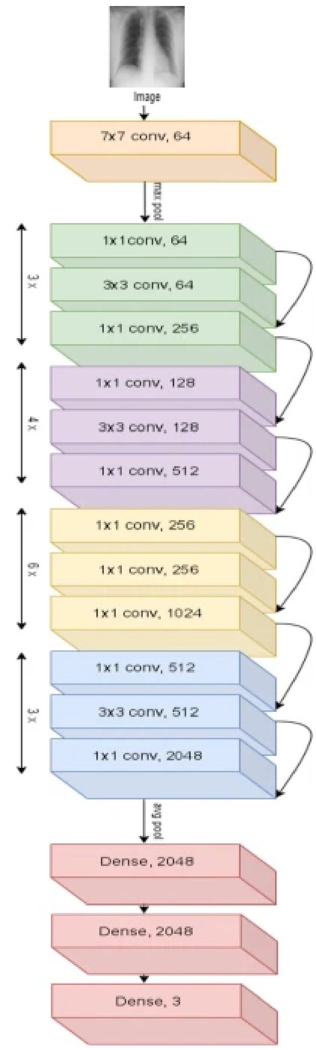

Figure 2.5: The structure of the proposed model [1].

Improved Covid-19 detection with chest X-ray images using deep learning 2022

Gupta, V. et al [15] propose a methodology for detecting the presence of Covid-19 from chest X-Ray images using DNNs. The adopted methodology is presented in figure 2.6. Among four pre-trained DNN models, the baseline architecture of AlexNet demonstrated remarkable performance, achieving an accuracy of 97.6% in identifying Covid-19 cases.

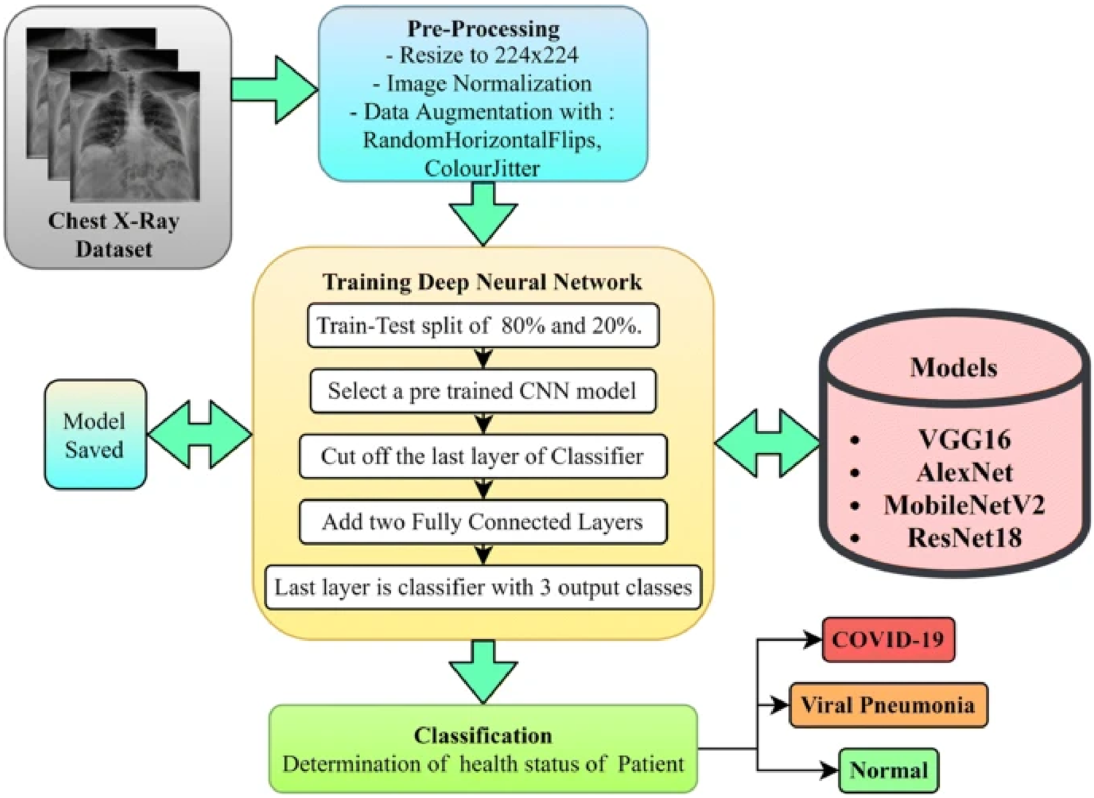

Figure 2.6: Pipelined block diagram of the adopted methodology[15].

2.3 Multimodal Covid-19 Classification

This section discusses several studies, that focus on the classification of Covid-19 using a combination of different modalities, such as X-ray and CT images. These studies employ DL models and techniques to leverage the information from multiple modalities and improve the accuracy and robustness of Covid-19 detection. The performance and effectiveness of various models are evaluated, showcasing their capabilities in multimodal Covid-19 classification.

A lightweight CNN-based network on Covid-19 detection using X-ray and CT images 2022

This study was done by Mei-Ling Huang. et al [17], uses and fine-tunes seven CNNs including InceptionV3, ResNet50V2, Xception, DenseNet121, MobileNetV2, EfficientNet-B0, and EfficientNetV2 on Covid-19 detection. Based on AlexNet and EfficientNetV2, a light-weight convolutional neural network LightEfficientNetV2 is introduced for the classification of Covid-19, Pneumonia, and Normal images. The proposed LightEfficientNetV2 model is a novel deep learning architecture illustrated in Figure2.7. That achieves impressive accuracy of 98.33% and 97.48% on chest X-ray and CT images, respectively. Compared to its predecessors, LightEfficientNetV2 offers significant advantages in terms of computation and running time.
In addition to its outstanding performance on the chest X-ray and CT datasets, LightEfficientNetV2 also exhibits superior performance on three different datasets.

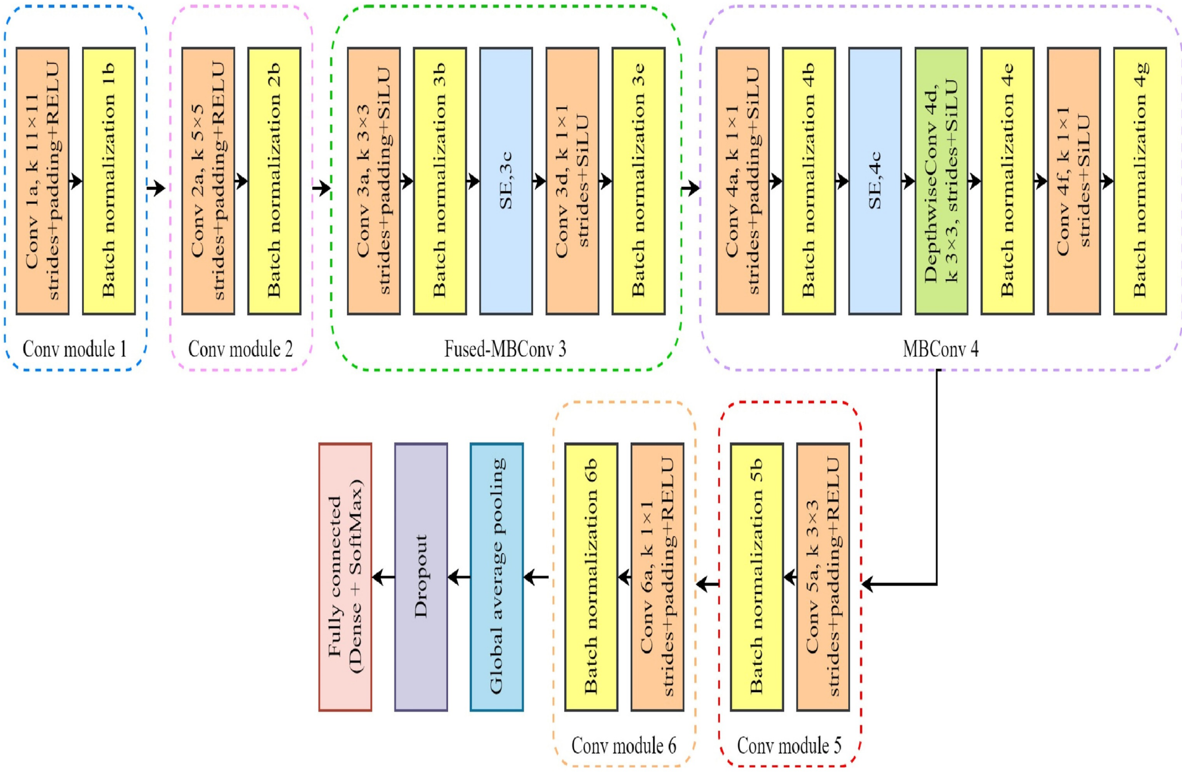

Figure 2.7: Architecture of LightEfficientNetV2 [17].

COVID-19 detection from XRay and CT scans using Transfer Learning 2021

Berrimi M. et al [8] have proposed novel deep learning architectures for the purpose of identification of Covid-19 cases from X-ray and CT chest scan images. The approach involves fine-tuning pre-trained models on two datasets related to X-Ray and CT scans dataset to classify Covid-19, pneumonia, and typical cases. The developed approach outperformed the baseline models, including DenseNet and InceptionV3 models, by at least 12%. The results demonstrate the feasibility and effectiveness of the proposed approach. In particular, InceptionV3 archived an accuracy of 92.35% in recognizing Covid-19, Normal, and pneumonia from X-Ray chest images, while the proposed model New-DenseNet illustrated in figure 2.8, archived an accuracy of 95.98% in recognizing Covid-19 from CT images.

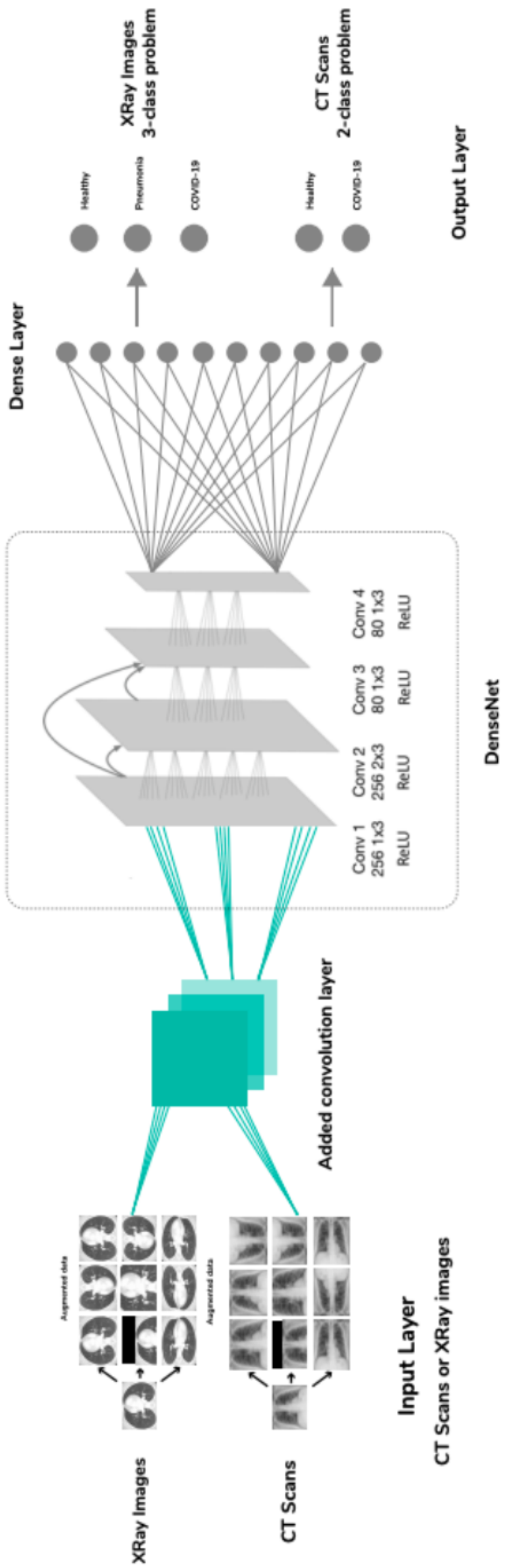

Figure 2.8: Tuned DenseNet for problems of 2-class and 3-class [8].

Classification of Covid-19 based on X-Ray and CT images using DTL 2021

G. Jia et al. [19] propose a dynamic modification method for CNNs to classify Covid-19 Chest X-Ray (CXR) and CT image datasets. Three scenarios of the classification problem are investigated tab2.2. illustrates it. This method establishes connections between

	Model	Classes	Accuracy
X-ray	MobileNet	3 classes Covid-19, Non-Covid-19 infection, healthy	99.7%
		4 classes Covid-19, Non-Covid-19 pneumonia, tuberculosis, healthy	99.6%
		5 classes Covid-19, bacterial pneumonia, viral pneumonia (excluding Covid-19 infection), tuberculosis, healthy	99.6%
CT-scan	ResNet	3 classes Covid-19, Non-Covid-19, Normal	99.22%

Table 2.2: Training models and accuracy scores[19].

various layers of the original CNN architecture using pointwise convolution blocks. The proposed method is compared to six widely used DL algorithms and two recently published models specifically designed for Covid-19 detection. The study proposes modified versions of MobileNet for Covid-19 CXR image classification and a modified ResNet architecture for CT image classification. The implementation of the process is illustrated in figure 2.9.

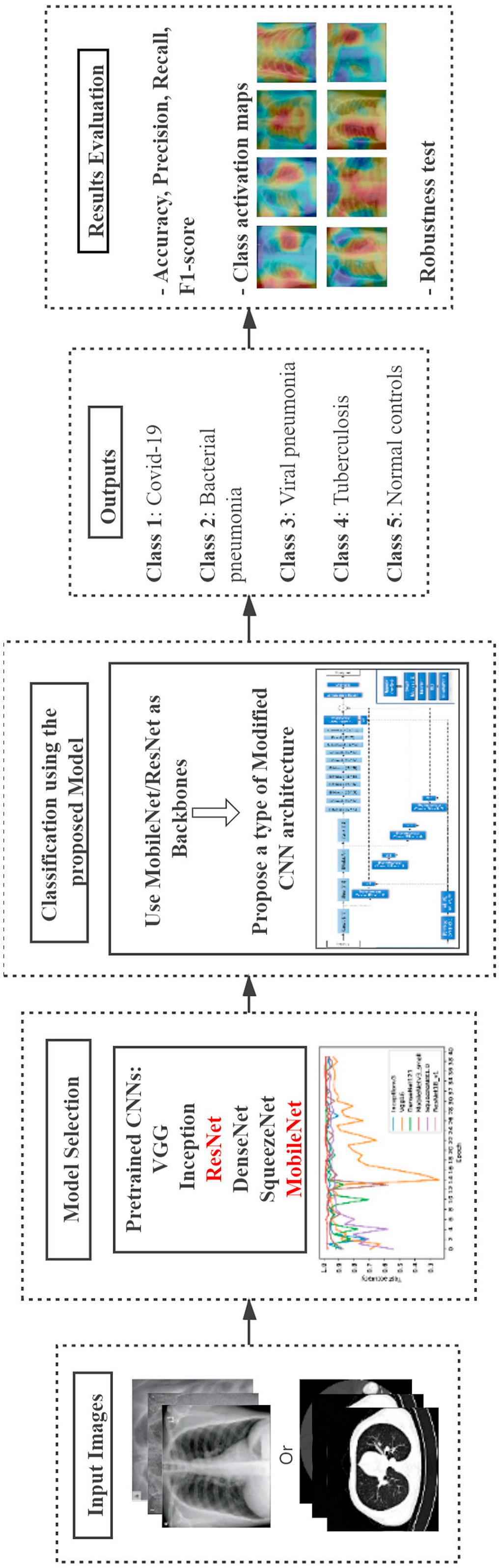

Figure 2.9: Diagram of the implementation process[19].

2.4 Conclusion

In conclusion, this chapter's literature review emphasizes the importance of multimodal Covid-19 classification and its potential for improving the accuracy and reliability of Covid-19 detection. By analyzing the existing research on unimodal and multimodal approaches, we establish the rationale for our study and highlight the significance of our contribution in developing a promising multimodal Covid-19 classification framework using DNNs.

Chapter 3

Experimental study

In this chapter, we present the experimental phase of our study, where we designed and evaluated a promising multimodal imaging classification framework for enhancing the accuracy and reliability of Covid-19 detection. Our methodology, which is based on the insights and methodologies discussed in the literature review, leverages the strengths of different modalities and explores optimal fusion techniques. We provide detailed information about our data collection, preprocessing, and model implementation processes. Through a series of experiments, we thoroughly assess the performance and effectiveness of our proposed system. By analyzing the results, interpreting the findings, and discussing their implications, this chapter provides a comprehensive overview of our experimental phase and contributes to the advancement of our research objectives.

3.1 Data collection and pre-processing

This section focused on the collection and pre-processing procedures of medical images for our experimental study.

3.1.1 Datasets

Our experiment is based on two modalities of medical images widely used for the diagnosis of Covid-19, relying on two different publicly available datasets, one consisting of CT-scan images and the other comprising X-ray images.

SARS-COV-2 Ct-Scan Dataset

SARS-CoV-2 CT scan dataset, which is publicly available [2], was collected by Soares et al [37] from real patients in hospitals from Sao Paulo, Brazil. This dataset has been approved by the Ethical Committee of the Public Hospital of the Government Employees in the same region. Figure 3.1 illustrates the distribution of CT scans in SARS-CoV-2 (Covid-19) infected and non-infected patients.

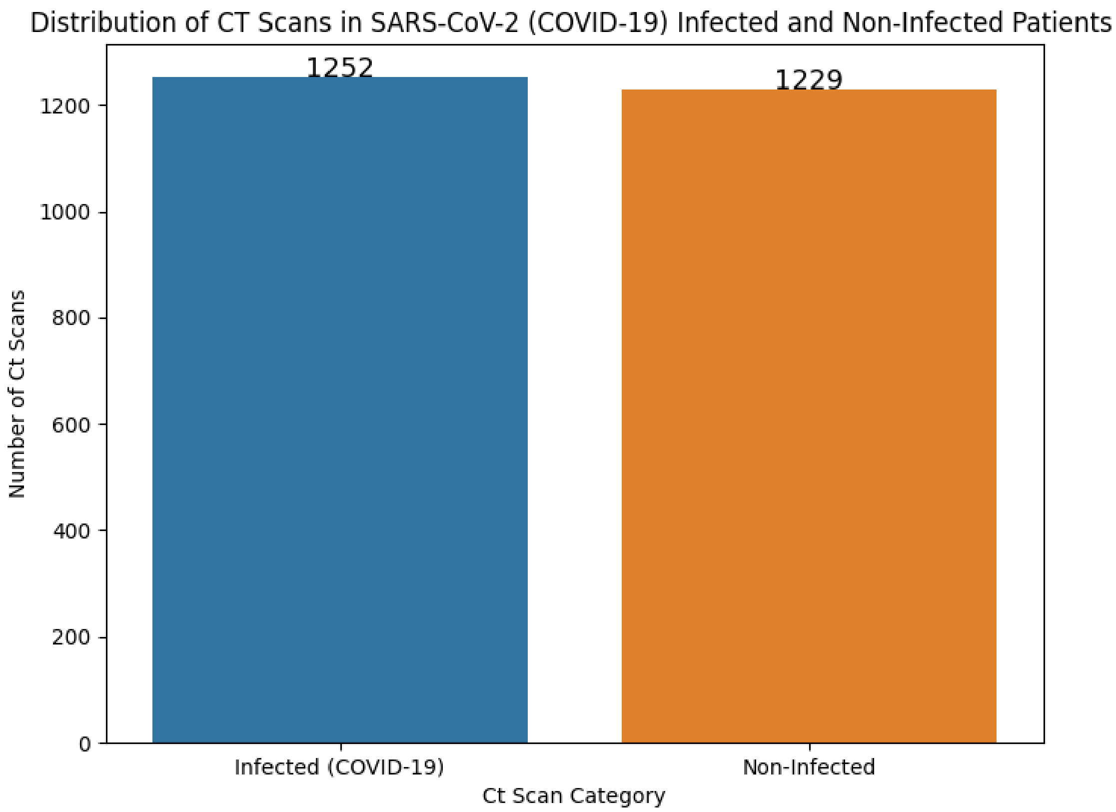

Figure 3.1: Distribution of CT Scans in Covid-19 Infected and Non-Infected Patients.

COVID-19 Radiography Database

A comprehensive database of chest X-ray images available on Kaggle [30], has been developed by a team of researchers from Qatar University, Doha, Qatar, and the University of Dhaka, Bangladesh, in collaboration with their counterparts from Pakistan and Malaysia. This database includes images of Covid-19 positive cases, as well as normal, Lung Opacity, and viral pneumonia cases.

In our experiment, the focus is placed on utilizing two specific classes (figure 3.2) from the dataset out of the four available classes.

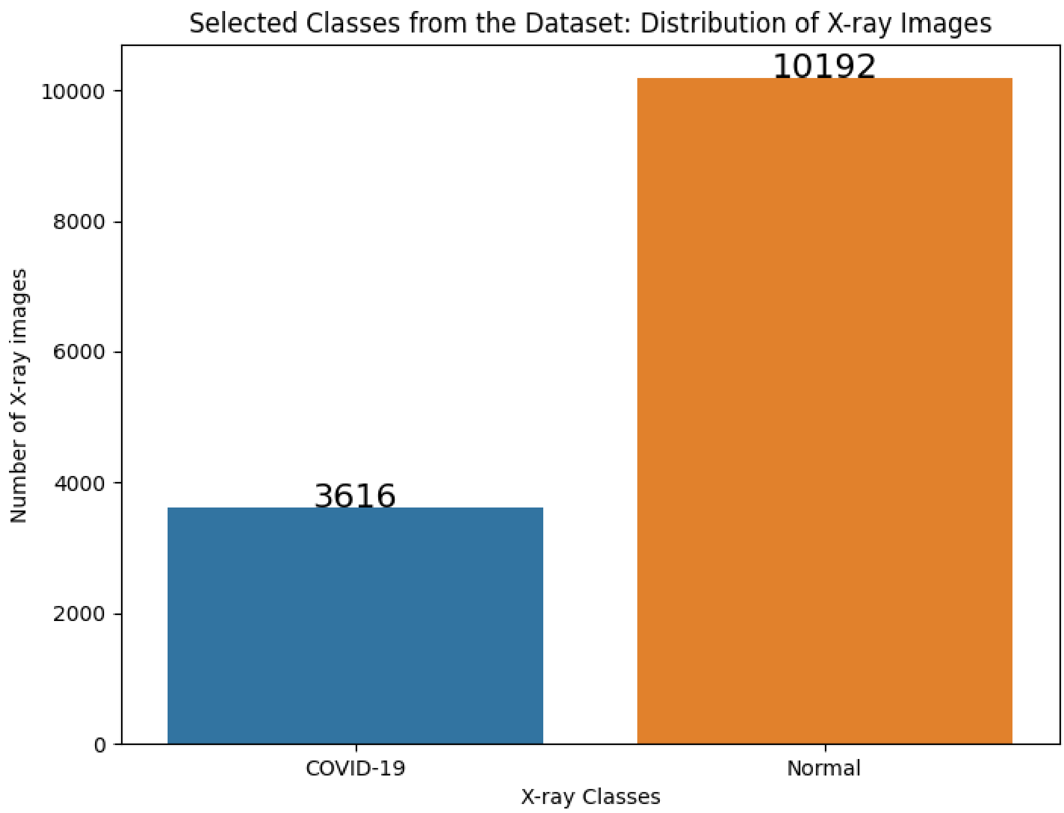

Figure 3.2: Selected Classes from the Dataset: Distribution of X-ray Images.

3.1.2 Data resizing

The original size of the images in the two datasets is varied. To address this, we resize the input images to a fixed size of (224,224) pixels, and the number of channels fixed at 3 (RGB).

3.1.3 Data scaling

A normalization technique is used, which involves scaling the pixel values of the images from the range [0, 255] to the range [0, 1].

3.1.4 Data augmentation

Data augmentation is a technique used to generate new datasets from existing ones and artificially increase the size of a dataset, it aims to reduce overfitting. Commonly used data augmentation techniques include geometric transformation, color space transformation, and random erasing.

However, when working with X-ray imaging datasets for pneumonia classification, it is important to be careful with certain augmentation techniques. For instance, random rotation and reflection along the x-axis are not recommended due to their potential negative impact on classification accuracy [11]. The table3.1 illustrate the transformations applied in our experiment.

Technique	Setting
Zoom range	0.2
Width shift range	0.1
Height shift range	0.1
Shear range	0.2
Horizontal flip	True
Vertical flip	False

Table 3.1: The configurations used for the data augmentation techniques.

Figures 3.3 and 3.4 displayed in the grid demonstrate the application of data augmentation techniques on Covid-19 images, specifically for CT-scan and X-ray modalities.

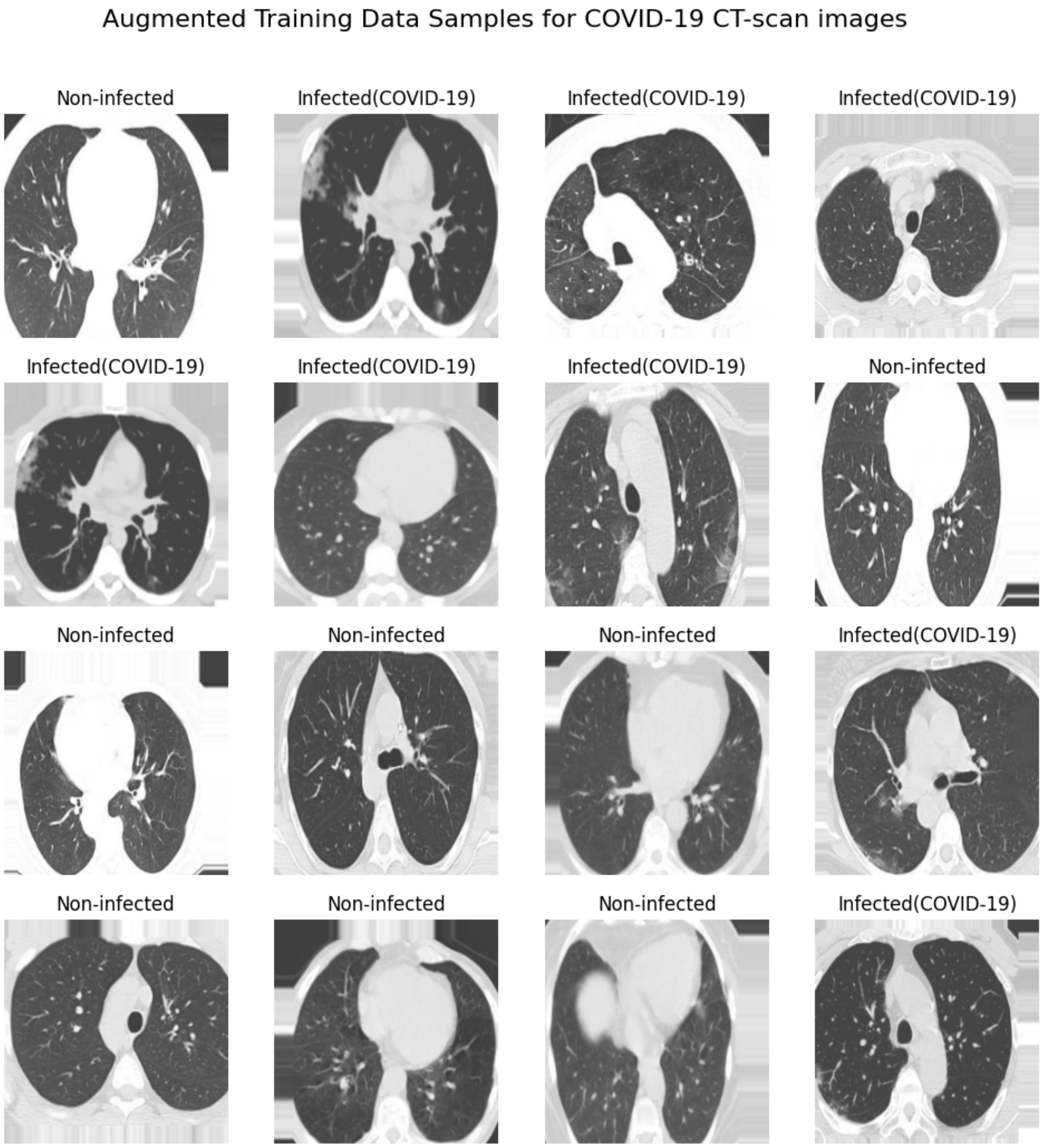

Figure 3.3: Augmented Training Data Samples for Covid-19 CT-scan images.

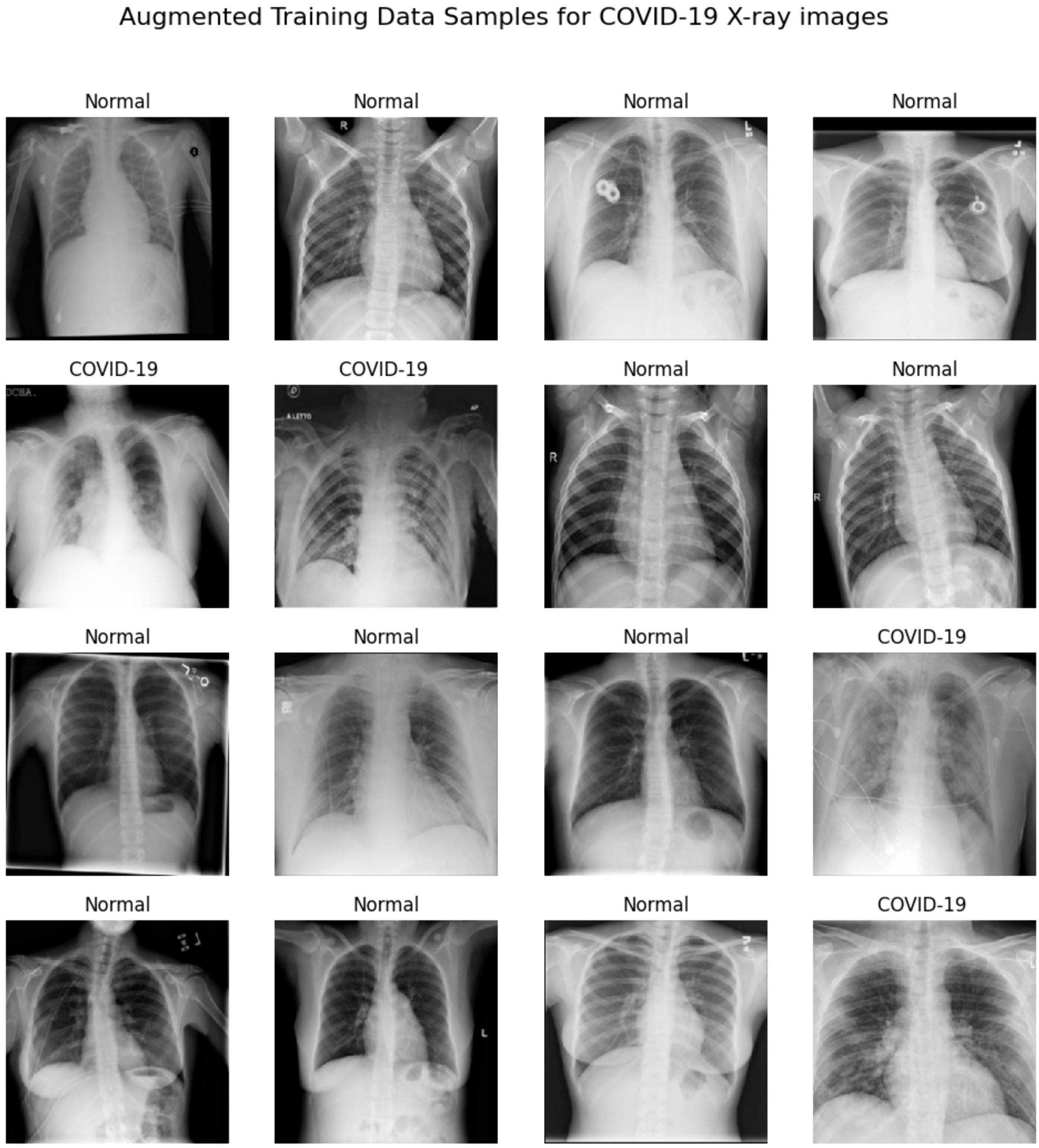

Figure 3.4: Augmented Training Data Samples for Covid-19 X-ray images.

3.2 Proposed system

This section describes the methodology and provides a comprehensive explanation of the process of constructing and fine-tuning the CNN models for Covid-19 classification based on pre-trained architectures including VGG16, VGG19, Xception, and ResNet152V2. These models have shown high top-5 accuracy, indicating their strong performance on the ImageNet validation dataset. These models are developed separately for both X-ray and CT-scan images, using a similar methodology, and therefore, the construction process involves several steps, which are outlined below.

3.2.1 Model Construction and Fine-tuning

The construction of unimodal CNN models involves several key steps that are shared by the two modalities. These steps are as follows:

1. Load the pre-trained with weights obtained from the ImageNet dataset, specifying the input shape and excluding the fully connected layers.

2. Freeze the pre-trained layers by setting them as non-trainable, to preserve the learned features.

3. Define the head of the model by adding new layers on top of the pre-trained layers:
   - Create a new input layer.
   - Pass the input through the pre-trained layers to extract relevant features.
   - Flatten the output to a 1D vector.
   - Add a dense layer with a specified number of neurons and activation function.
   - Include a dropout layer to prevent overfitting, which randomly dropped neurons during training [4].
   - Finally, add an output layer with an appropriate softmax activation function for our classification task.

4. Create the new model by combining the pre-trained layers with the newly added layers is done using the Model function.

Figure 3.5 illustrates the adapted model structure for the CNNs, which involves several key steps as described above. By following these steps, we leverage the knowledge of pre-trained models. Additionally, we performed fine-tuning on the pre-trained models while maintaining their original architecture. This involved adjusting the weights of the models to suit our specific classification task [17]. In particular, we focused on determining the optimal size for the hidden layer, which corresponds to the number of neurons in the dense layer.

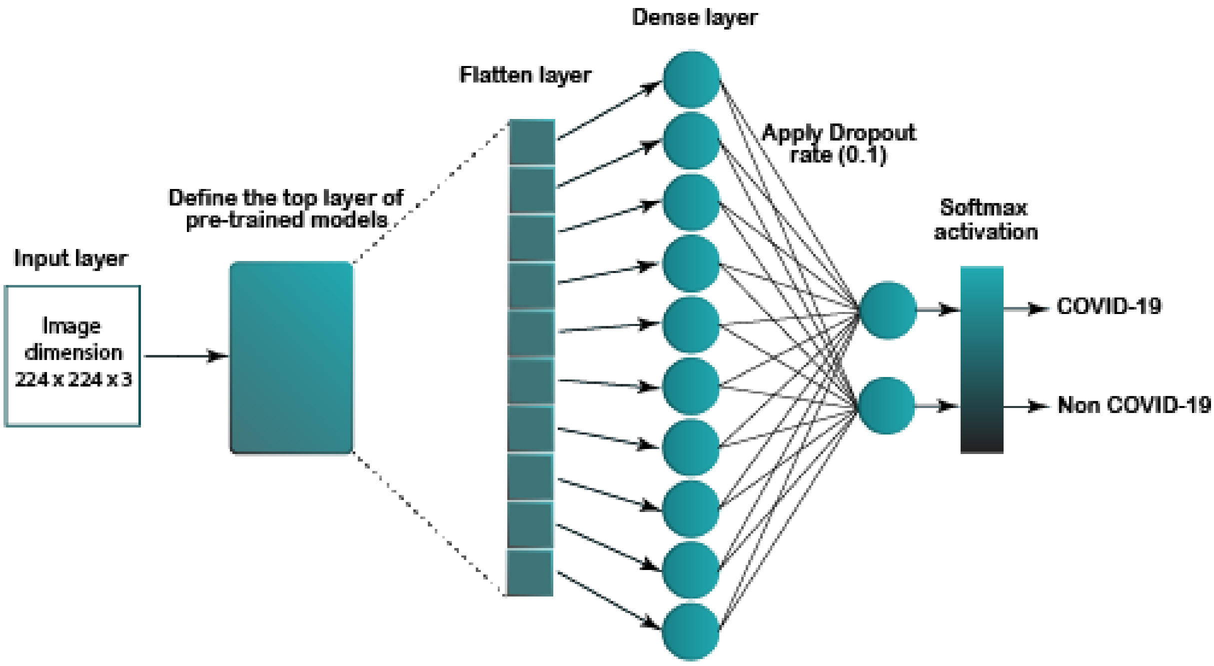

Figure 3.5: Adapted model structure.

Exploring Hidden layer sizes

To explore the optimal hidden layer size, we conducted experiments with different hidden layer sizes ranging from 50 to 1000. This range allowed us to assess the impact of varying hidden layer sizes on the model's performance.

By systematically evaluating the models with different hidden layer sizes, we aimed to find the configuration that achieved the best balance between capacity and generalization ability. This process helps us improve the model's performance and accuracy in Covid-19 classification.

3.2.2 Training procedure

We trained and validated the models with different hidden layer sizes on our datasets. Each dataset was split into 80% for training and 20% for testing. We trained the networks with the training parameters described in table 3.2. Moreover, we employed the ModelCheckpoint function, which saves automatically the model with the best performance on the monitored metric during training, specifically by minimizing the loss on the validation set. This functionality enables us to store the best model obtained for later use.

Training Parameters	Individual Network	
	CT scan	X-ray
Epoch	150	80
Batch size	32	
Optimizer	Adam	
Activation Function	Softmax	
Loss function	Categorical Crossentropy	

Table 3.2: Parameters used in the training phase.

3.2.3 Performance metrics

Confusion matrix, accuracy, and loss are identified as the performance metrics used to evaluate the models.

Confusion matrix

The confusion matrix, a performance measurement, provides valuable insights into the achieved testing accuracy by representing information in a clear and understandable format. It is an extremely useful tool for calculating the accuracy of models, offering a comprehensive overview of classification results [33]. Confusion matrix parameters :

- True Positive (TP): if a Covid-19 infected person is detected as Covid-19.
- True Negative (TN): if a person is correctly detected as NON-Covid-19.
- False Positive (FP): represents incorrect detection where a normal person is detected positive for Covid-19.
- False Negative (FN): represents incorrect detection where a person infected with Covid-19 is detected as normal one.

Accuracy

Accuracy is the fraction of the total predictions that are correct.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + False\ Positives + False\ Negatives + True\ Negatives}$$

3.3 Experimental setup

To conduct our experimental study, we employed two different computing platforms: Google Colab and a high-performance desktop computer. Initially, the experiments were conducted on Google Colab. Subsequently, we utilized a high-performance desktop computer with the following specifications:

- Processor: AMD Ryzen 9 5950x featuring 16 cores.

- RAM: 64 GB.

- Graphics Card: NVIDIA GeForce RTX 3080 with 10 GB of dedicated memory.

- Storage: 1 To SSD drive

The experiments were performed using the Python programming language, leveraging the TensorFlow and Keras libraries for deep learning model development and evaluation.

3.4 Experimental results and discussions

After through the process of fine tuning and exploring hidden layer sizes to find the optimal configuration for our unimodal CNN model. We found a specific hidden layer size that consistently demonstrated the highest performance and ensured accurate predictions independently for CT-scan and X-ray images. To further support our findings, Table 3.3 presents the best hidden layer size for each proposed model on CT-scan and X-Ray images, along with their corresponding accuracy and loss values.

Proposed model	Hidden Layer Size	Accuracy (%)	Loss (%)
CT-scan			
VGG16	450	99.40	1.84
VGG19	300	96.98	11.25
Xception	200	96.58	12.27
ResNet152V2	100	97.99	7.31
X-ray			
VGG16	250	97.10	8.14
VGG19	450	96.41	9.77
Xception	150	95.40	15
ResNet152V2	50	96.31	11.28

Table 3.3: Performance of Proposed Models for Covid-19 Classification on CT-scan and X-ray Images.

3.4.1 CT-scan models

We trained multiple pre-trained models on CT-scan images and evaluated their performance.

VGG16:

Figure 3.6 illustrates the training and validation accuracy and loss curves for CT scan images. The VGG16 model, configured with a hidden layer size of 450, achieved an impressive accuracy of 99.40% and minimal loss of 0.0184 around the 116 epoch. For a comprehensive analysis, the confusion matrix for VGG16 is presented in Figure 3.7.

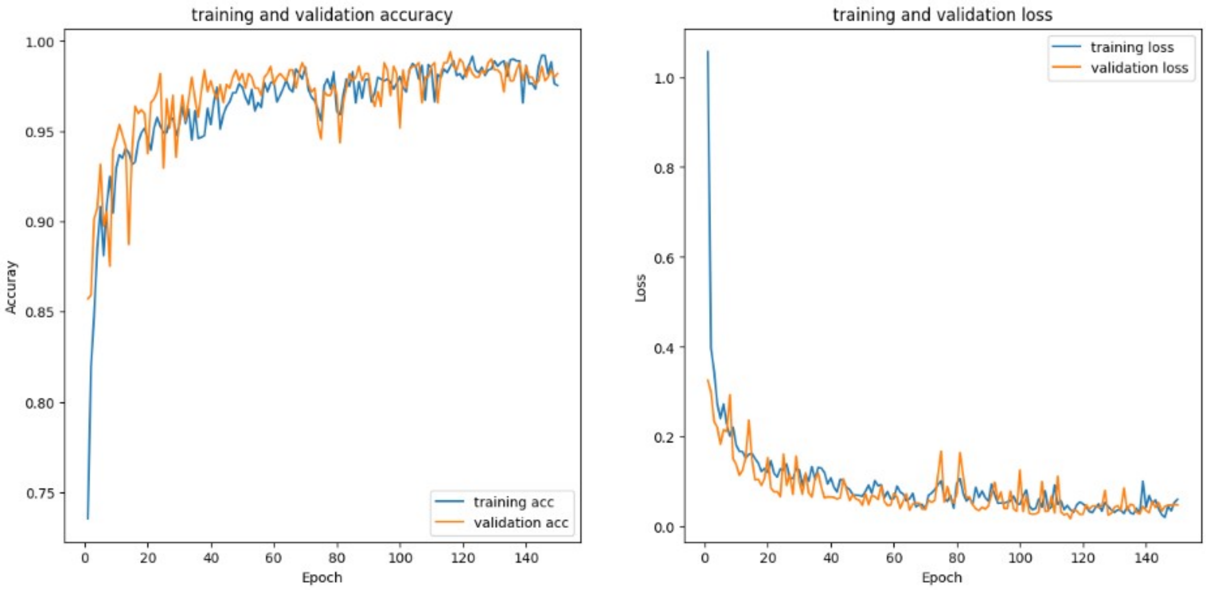

Figure 3.6: Training and validation accuracy/loss curves for VGG16 on CT-scan images.

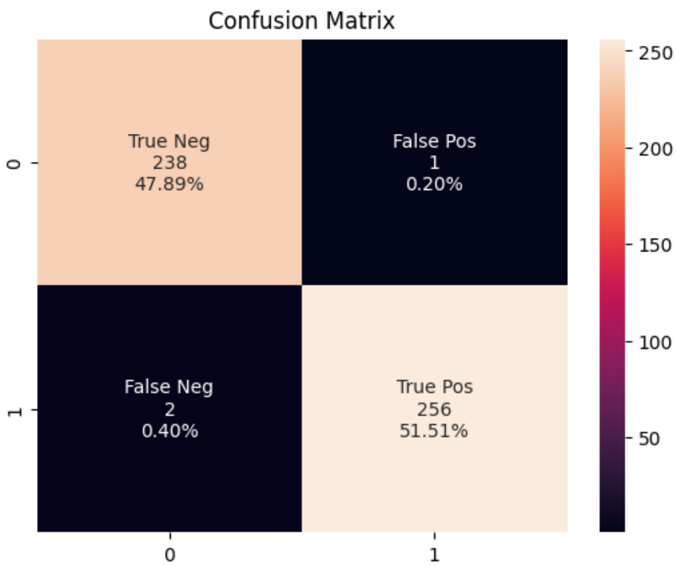

Figure 3.7: Confusion matrix for VGG16 on CT-scan images.

VGG19: The VGG19 model with a hidden layer size of 300 achieved a low loss of 0.1125 and an accuracy of 96.98% at approximately the 135th epoch. Moreover, it demonstrated the highest accuracy of 97.18% with a loss of around 0.1144. However, due to the inclusion of the checkpoint parameter, the performance mentioned earlier was affected. Figure 3.8 displays the training and validation accuracy curves for this model, accompanied by the confusion matrix shown in figure 3.9.

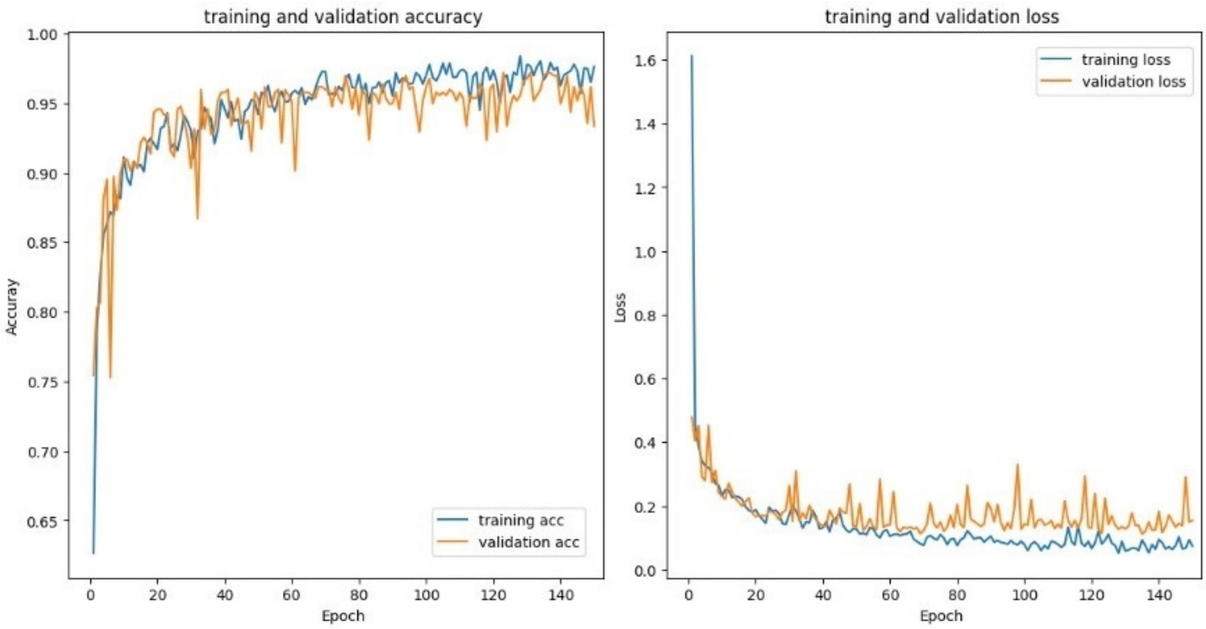

Figure 3.8: Training and validation accuracy/loss curves for VGG19 on CT-scan images.

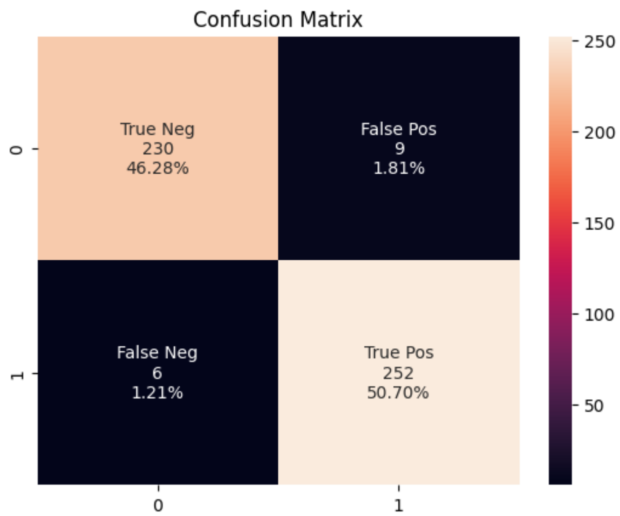

Figure 3.9: Confusion matrix for VGG19 on CT-scan images.

Xception: The Xception model, utilizing 200 neurons in the dense layer, exhibited superior performance compared to other hidden layer sizes. It achieved an accuracy of 96.58% and a loss of 0.1227, obtained on the final epoch (150th epoch). The training and validation accuracy/loss curves for this model can be seen in figure 3.10, accompanied by the corresponding confusion matrix shown in figure 3.11.

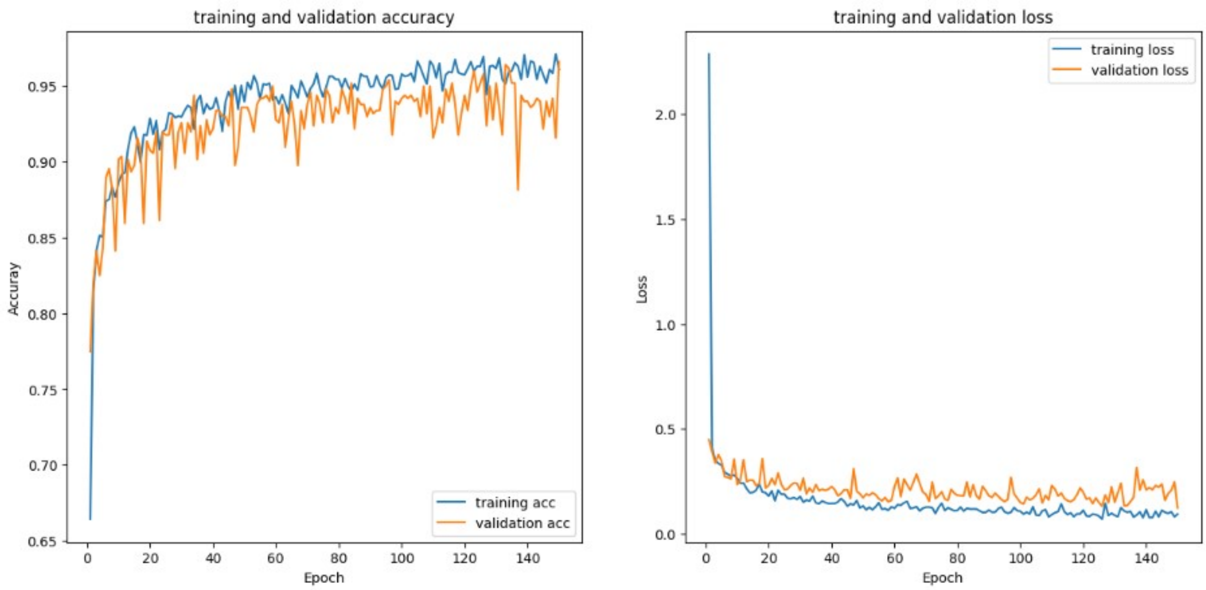

Figure 3.10: Training and validation accuracy/loss curves for Xception on CT-scan images.

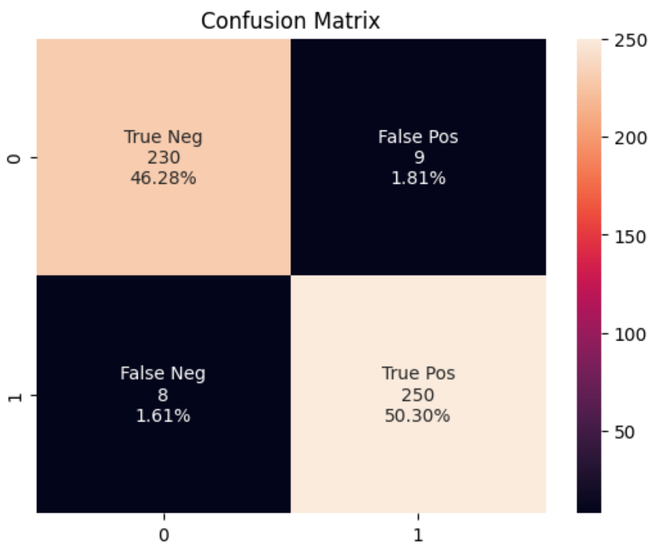

Figure 3.11: Confusion matrix for Xception on CT-scan images.

ResNet152V2:

The ResNet model with 100 hidden layer size, around the 120th epoch, achieved an accuracy of 97.99%, and a loss of 0.073 which is the best performance of the model, as can be seen in the figure 3.13.

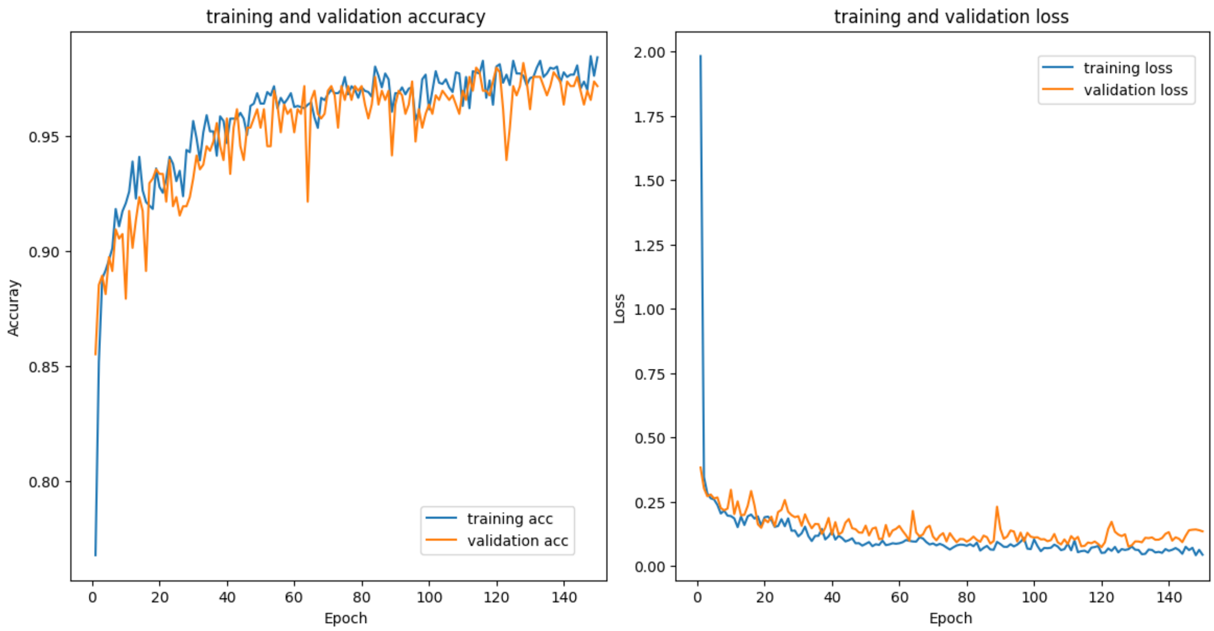

Figure 3.12: Training and validation accuracy/loss curves for ResNet152V2 on CT-scan images.

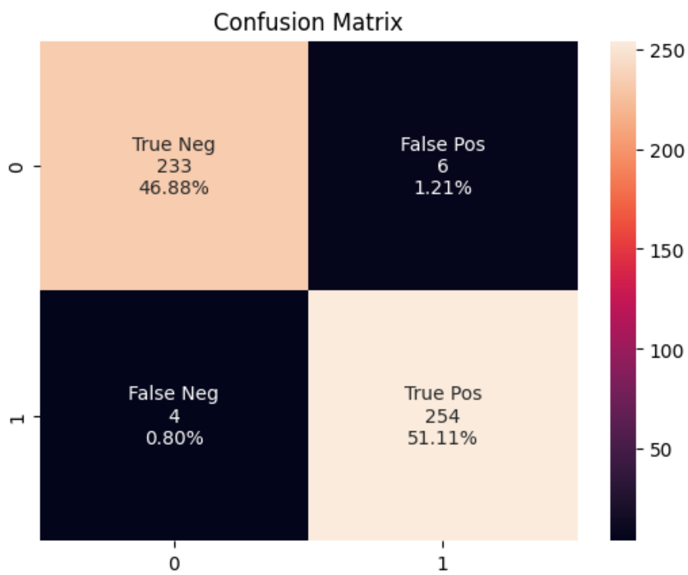

Figure 3.13: Confusion matrix for ResNet152V2 on CT-scan images.

3.4.2 X-Ray models

For X-ray images, we also trained multiple pre-trained models and evaluate their performance individually.

VGG16:

VGG16 model demonstrated good performance in the classification of Covid-19 based on X-Ray images, utilizing a dense layer with 250 units of neurons. It achieved an accuracy of 97.10% and a loss of 0.0815 around the 51st epoch. These results are depicted in figure 3.14, along with the corresponding confusion matrix shown in figure 3.15.

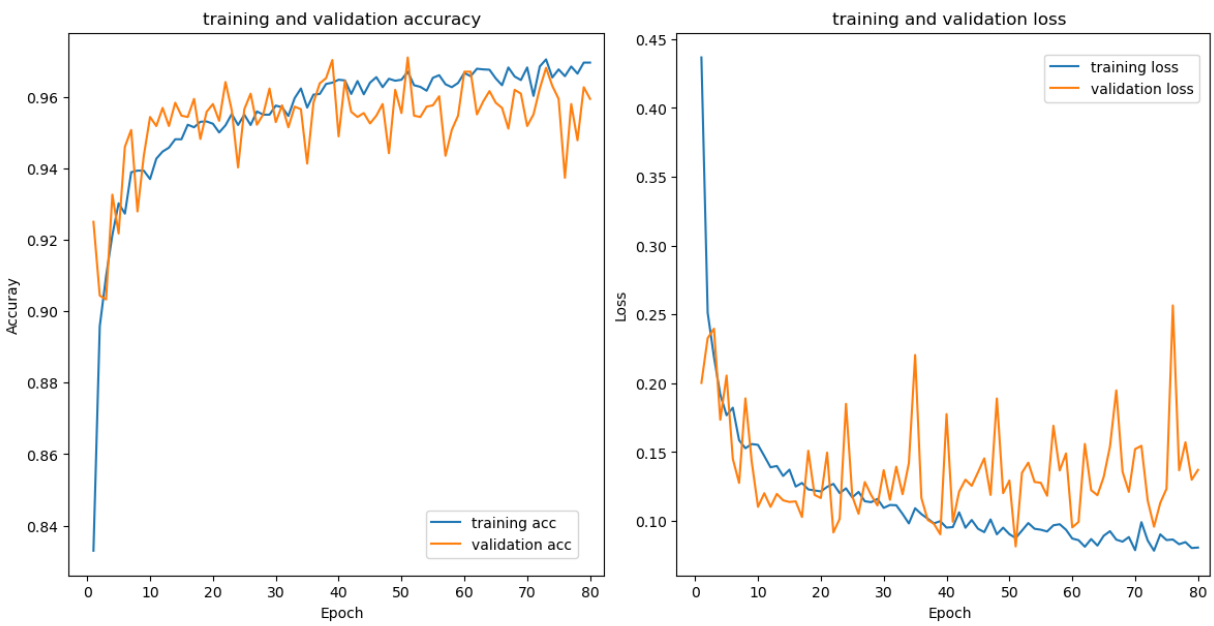

Figure 3.14: Training and validation accuracy/loss curves for VGG16 on X-Ray images.

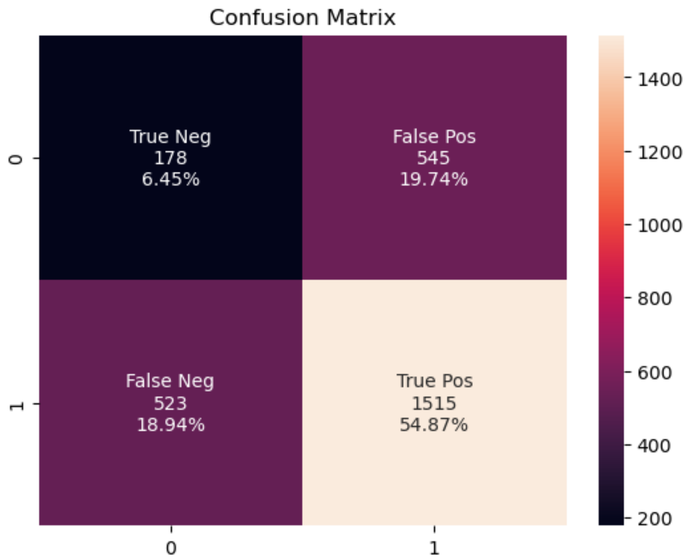

Figure 3.15: Confusion matrix for VGG16 on X-Ray images.

VGG19:

The VGG19 model with a hidden layer size of 450, achieved an accuracy of 96.41% and a loss of 0.0977 on X-Ray images. These results were obtained around the 15th epoch, as shown in figure 3.16. The corresponding confusion matrix is presented in figure 3.17.

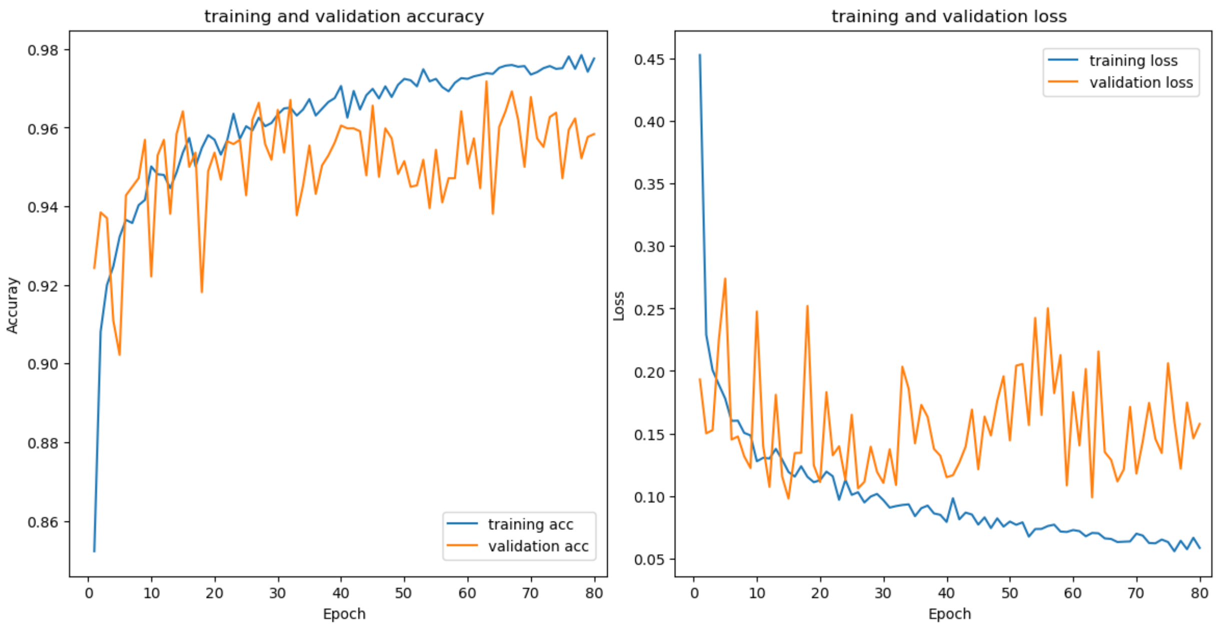

Figure 3.16: Training and validation accuracy/loss curves for VGG19 on X-Ray images.

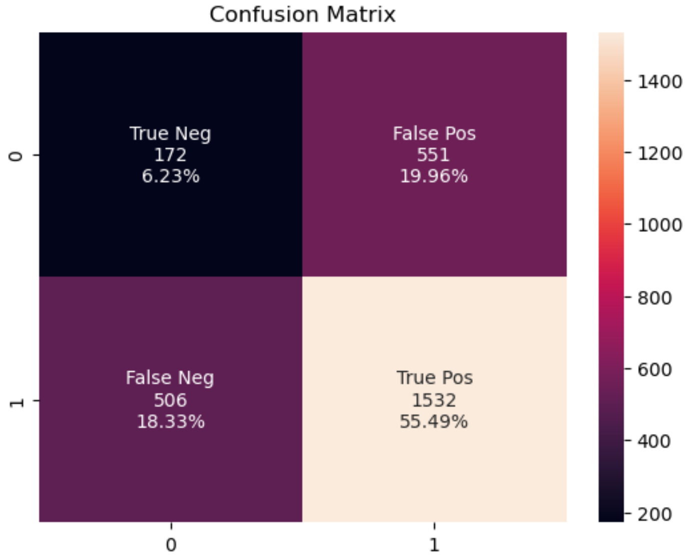

Figure 3.17: Confusion matrix for VGG19 on X-Ray images.

Xception:

The Xception model with a hidden layer size of 150 achieved an accuracy of 95.40% and a loss of 0.1500 on X-ray images. These results were obtained around the 59th epoch, as shown in figure 3.18. The corresponding confusion matrix is presented in figure 3.19.

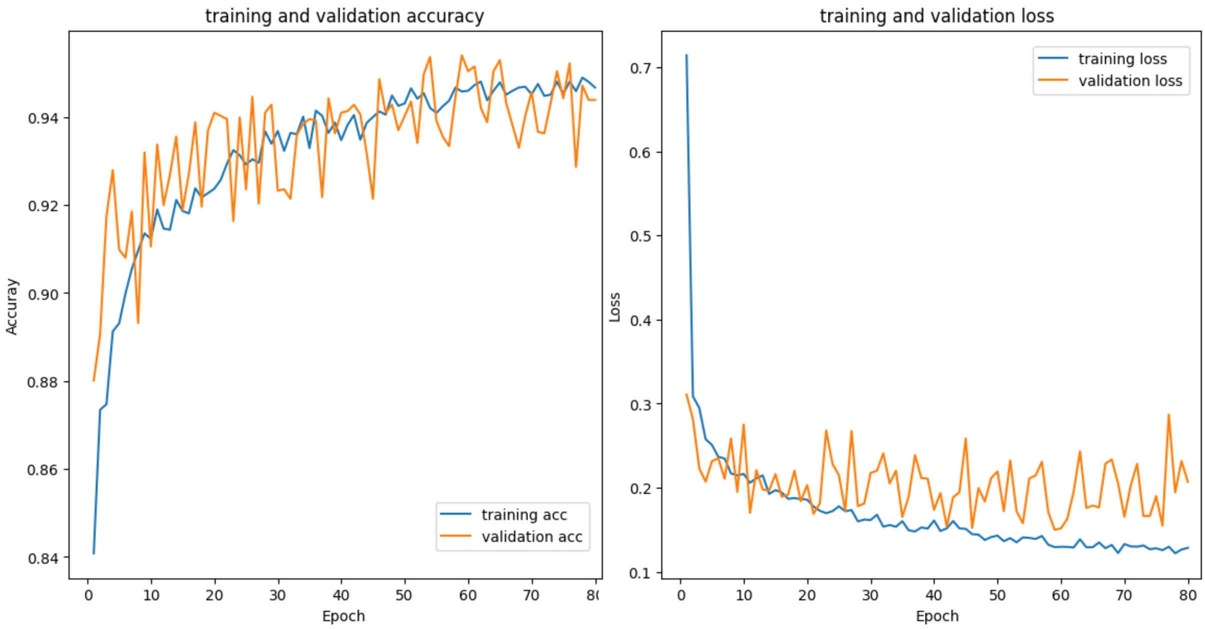

Figure 3.18: Training and validation accuracy/loss curves for Xception on X-Ray images.

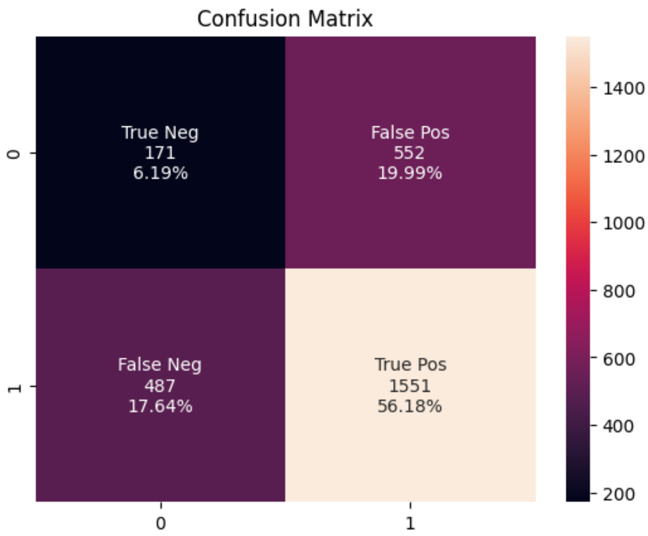

Figure 3.19: Confusion matrix for Xception on X-Ray images.

ResNet152V2:

For the ResNet152V2 model, a hidden layer size of 50 achieved an accuracy of 96.31% and a low loss of 0.1128 around the 44th epoch. Figure 3.20 shows the training and validation curves for this model, while figure 3.21 presents the corresponding confusion matrix.

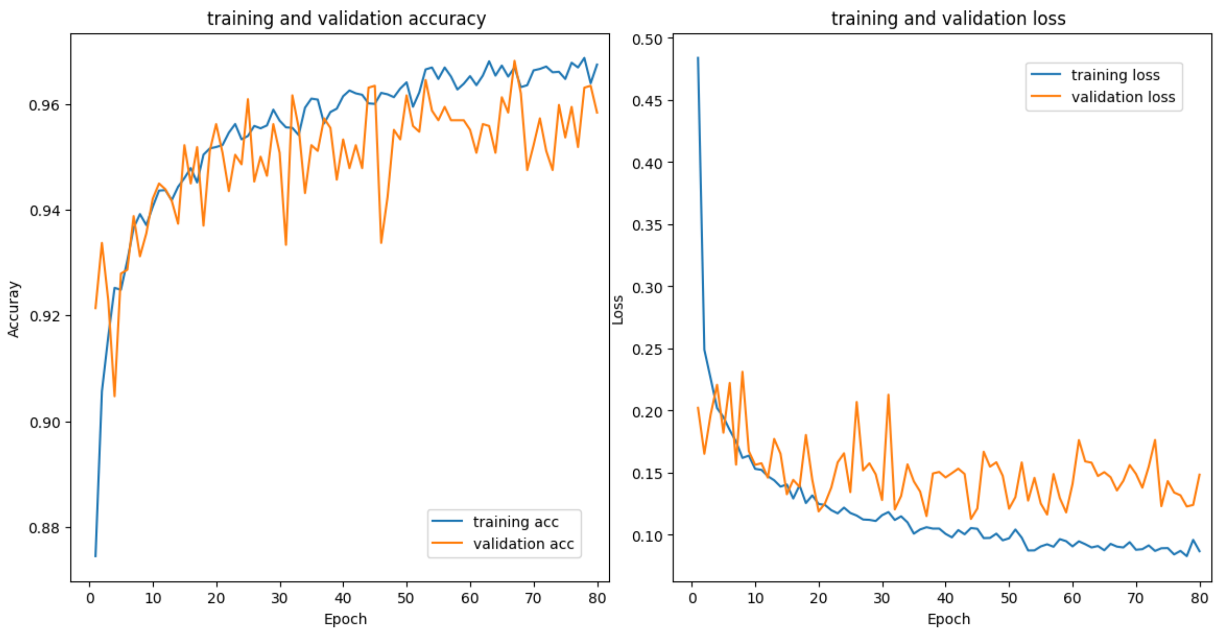

Figure 3.20: Training and validation accuracy/loss curves for ResNet152V2 on X-Ray images.

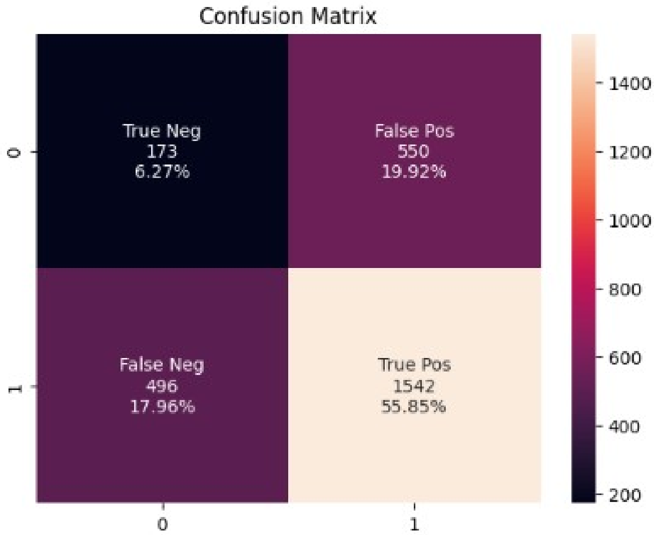

Figure 3.21: Confusion matrix for ResNet152V2 on X-Ray images.

3.4.3 Discussions

The experimental results, as summarized in Table 3.3 above, demonstrate the performance of different proposed models on both CT-scan and X-Ray images for Covid-19 classification. By analyzing the results, we observed that for CT-scan images, the VGG16 model with a hidden layer size of 450 provides the best performance with the highest accuracy of 99.40% and the lowest loss of 0.0184. Additionally, the ResNet152V2 model with a hidden layer of 100, achieved a notable accuracy of 97.99% and a loss of 0.0731.
Furthermore, the confusion matrix of the VGG16 on CT-scan images, reveals its effectiveness in reducing the false negative predictions, as indicated by only two instances of missclassification (figure3.7). This characteristic plays an important role in enhancing the reliability and effectiveness of medical systems [6].
In the cases of X-Ray images, the VGG16 model with a hidden layer size of 250 achieved the best accuracy for Classifying Covid-19 with this modality, about 97.10% and a loss of 0.0814, and the VGG19 model with 450 sizes of hidden layer achieved also a good accuracy of 96.41% and loss of 0.0977. Notably, the ResNet152V2 model with a hidden layer size of 50 achieved an accuracy of 96.31% and a loss of 0.1128.
Overall, the experimental results demonstrate the effectiveness of using pre-trained models

for Covid-19 classification on medical images using both modalities. The high accuracy and low loss values obtained by the models demonstrate their capability in predicting Covid-19 cases accurately. Notably, VGG16 consistently demonstrated strong performance for both CT-scan and X-ray images, making it a reliable choice for Covid-19 classification. The ResNet152V2 model also showed promise, particularly for CT-scan images.

3.5 Conclusion

This chapter described the experimental study conducted to enhance the accuracy and reliability of Covid-19 classification. we conducted a series of experiments covering data collection, pre-processing, and the implementation of the proposed system. The experimental results revealed promising outcomes in terms of accuracy and performance. The VGG16 model emerged as the top-performing model for classifying Covid-19 cases based on both modalities. Furthermore, the ResNet152V2 model exhibited remarkable performance in classifying CT scan images specifically.

Conclusion

Our master thesis aimed to make a significant contribution to the medical field, specifically medical imaging, by developing an intelligent system for the classification of pneumonia diseases, with a particular focus on Covid-19, using DNNs, two modalities of medical images, and TL techniques.

By focusing on the development of a multimodal classification system for Covid-19 using CT scans and X-rays and integrating multiple pre-trained CNN models including VGG16, VGG19, Xception, and ResNet152V2, our work aimed to enhance the accuracy and reliability of Covid-19 classification.

Through the integration of TL techniques and training multiple CNN models independently for each modality, our study achieved high performance in diagnosing the virus. Among the pre-trained models, experimental results revealed that the VGG16 model consistently outperformed others on both modalities, achieving a high accuracy of 99.40%, a low loss of 0.0184 on CT scan images, and a promising accuracy of 97.10% and loss of 0.0814 on X-ray images. These results highlight the effectiveness of the VGG16 model in reducing false-negative predictions, particularly in CT scan classification, and enhancing the readability of medical systems. Although VGG19 and ResNet152V2 also performed well, they were slightly inferior to the VGG16 model.

The proposed system based on CNN models has shown promising results in Covid-19 classification using CT-scan and X-ray images. The optimization of hidden layer sizes and fine-tuning of pre-trained models contributed to the overall performance and accuracy. This research has the potential to reduce costs, aid radiologists in decision-making, and improve the quality of care by reducing false-negative results.

However, it is important to note that the performance of the models may vary depending on the datasets used, the specific configuration of the models, and other factors. Therefore, further analysis and evaluation may be required to validate these findings and ensure their generalizability.

Following our promising results obtained during the implementation of unimodal networks for Covid-19 classification, our goal is to achieve a fusion of the last representation layers of high-performing pre-trained unimodal models, particularly the VGG16 model for both modalities independently, into a bimodal network.

Furthermore, this research has made a significant contribution to the field of Covid-19 diagnosis using DNN, multimodal images, and TL techniques. The findings of this research can contribute to global efforts to combat the pandemic and its variants through early detection. The potential impact extends beyond the Covid-19 pandemic and promises to improve the diagnosis and treatment of various respiratory diseases by providing also a precise interpretation of the infected region. In addition to respiratory diseases, future work can explore the classification of other medical conditions, such as cardiovascular disorders, neurological conditions, and cancer, using similar techniques. Furthermore, efforts can be directed toward enhancing the interpretability of the system's predictions, providing clinicians with valuable information and explanations to aid their decision-making processes.

Appendix A

Business Model Canvas

A.1 Value Proposition

The main objective of this project is to develop and implement an intelligent system, based on Artificial intelligence technologies, to make a significant contribution to the medical field, specifically medical imaging, that aids doctors in diagnosing and detecting pneumonia diseases, including the consequences of Covid-19, by using two modalities of medical imaging namely CT-scan and X-ray images, our system aims to aid doctors by assisting them in their diagnosing and improving their productivity by saving them time, reduce cost, promoting early detection.
We offer a unique opportunity to provide fast, cost-effective, and safe assistance services for the management of patients with Covid-19 symptoms. Furthermore, we plan to extend this prototyping environment dedicated to Covid-19 to other similar pneumonia diseases.

A.2 Customer Segments

Our solution targets the healthcare sector in Algeria, which includes the following customer segments:

- **Public Hospitals**: Our solution is designed to support the needs of public hospitals in Algeria, which play a crucial role in providing healthcare services to the general population. Specifically, we aim to assist public hospitals in enhancing their productivity and aiding in the early detection of pneumonia diseases, including the consequences of Covid-19.

- **Private Medical Clinics**: Private medical clinics and specialized centers, such as respiratory clinics or imaging centers, with their focus on specialized and personalized care, can benefit from our intelligent system to enhance diagnostic capabilities and improve patient outcomes.

- **General Practitioner Offices**: General practitioners and primary care providers play a crucial role in the early detection and management of pneumonia diseases. Our solution can empower these healthcare professionals with advanced diagnostic support, enabling them to detect pneumonia cases more efficiently and make informed decisions about further treatment or referral.

By implementing our advanced technology in these healthcare facilities, we aim to improve medical processes, enhance patient care, and optimize resource utilization, leading to better patient treatment outcomes. With our user-friendly interface and tailored features, our solution is designed to meet the specific needs of hospitals, clinics, and general practitioners, ultimately benefiting the healthcare ecosystem in Algeria.

A.3 Customer Relationships

We plan to market our solution by offering three different value packages to effectively serve our target customers.

- **Basic Package**: This package is the most basic option, that allows interested customers to test the service and engage in a discussion with us. This step involves filling in information about the customer and then providing contact details. With this package, customers can upload and analyze two images using only one available modality.
- **Standard Package**: Designed for customers with limited budgets, such as doctors, this package provides essential features at an affordable price point of 2000 DA per month, costumers will have the opportunity to evaluate up to 10 images using two modalities of medical imaging. this allows doctors to assess the effectiveness of our solution in diagnosing pneumonia diseases.
- **Premium Package**: Tailored for medical centers and hospitals, the premium package is priced at 10,000 DA per month, and offers comprehensive features, enhanced support, and a dedicated account manager. Customers can evaluate up to 50 images for each doctor, using two modalities of medical imaging, and promoting greater interpretability of results and providing a robust solution for accurate diagnosis and decision-making.

By offering these distinct value packages, we aim to address the unique needs and budgets of different customer segments, enabling healthcare professionals to improve productivity, aid in early detection, and enhance patient care through our intelligent system.

A.4 Channels

Our main distribution channel consists of an online platform represented by a website to showcase our solution, its features, and the various available monthly subscription offers available. This approach resembles direct sales, where customers in healthcare can subscribe to an online plan and benefit from our solution. Our e-commerce platform is designed to provide a user-friendly interface, secure payment options, and efficient order

Figure A.1: Summary of Value Packages for Target Customers.

processing.

Additionally, the implementation of an email marketing strategy to reach out to healthcare professionals directly. This can involve sending newsletters, updates, and promotional offers to our target audience, keeping them informed about our solution and its benefits.

Furthermore, the use of Web-based Advertising by Utilizing online advertising channels such as Google Ads or social advertising platforms such as Facebook, Instagram, and Twitter to create a strong online presence, and to target specific healthcare professionals and institutions with relevant ads. This can help increase visibility and attract potential customers to our solution.

It is important to assess the effectiveness of each channel and tailor our marketing efforts to reach our target customers effectively. By leveraging a combination of channels, we can maximize our reach, engage with our audience, and drive the adoption of our solution in the healthcare sector.

A.5 Revenue Streams

Our revenue will be derived from multiple sources, ensuring a diversified and sustainable income stream. These sources include:

Initially, for monthly subscriptions, customers will pay a monthly fee to access our solution based on the selected packages. For example, with 25 doctors subscribing at a rate of 2,000 DA per month and 5 medical centers subscribing at a rate of 10,000 DA per month, our projected revenue would be 100,000 DA.

$$25 \times 2,000 + 5 \times 10,000 = 100,000 \text{ DA}$$

Furthermore, we plan to enhance customer engagement by increasing our content by 30% over the next 6 months. This includes improving our existing content and incorporating additional automation models to provide a more comprehensive and efficient service.

Moreover, annual subscriptions introduce the option for customers to subscribe on an annual basis, offering them a discounted rate compared to the monthly subscription. This provides customers with cost savings and ensures their commitment to using our solution over an extended period.

Furthermore, we plan to explore the potential for advertising partnerships within the healthcare industry. This can involve featuring relevant ads from pharmaceutical companies, medical equipment suppliers, or other healthcare-related organizations on our platform. Advertising can serve as an additional revenue stream while providing value to our customers by showcasing relevant products and services.

By offering monthly and annual subscription options, as well as exploring advertising partnerships, we can generate a diversified and sustainable revenue stream. Additionally, our focus on enhancing customer engagement through content improvements and the incorporation of automation models will contribute to customer satisfaction and retention, further supporting our revenue generation efforts.

A.6 Key Activities

Our management team, consisting of Ms. Chekroun Fadia and Dr. Hadjila Fethallah, possesses the necessary skills to develop this project successfully. To achieve this, we will focus on the following specific objectives:

- **Acquiring Annotated and Expert-Confirmed Databases**: We will actively acquire databases of annotated and expert-confirmed medical images. These datasets will serve as the foundation for training and validating our intelligent system for accurate classification of pneumonia diseases using different modalities of medical imaging.

- **Developing an Intelligent System**: Our team will dedicate efforts to developing a robust and advanced intelligent system. leveraging artificial intelligence techniques, the system will accurately classify pneumonia diseases, incorporating both CT-scan and X-ray images. Our objective is to create a high-performing system that aids healthcare professionals in making reliable and informed decisions quickly.

- **Website Designing and Development**: Designing and Developing a User-Friendly Website that allows healthcare professionals to easily access our solution. The website will serve as a platform for showcasing our features, providing informative content, and enabling efficient decision-making quickly for healthcare professionals.

- **Extending the Prototyping Environment**: Our aim is to expand the functionality of our prototyping environment, which is currently dedicated to Covid-19, to cover other pneumonia diseases. In doing so, we will ensure the interpretability of the decision-making process, allowing healthcare professionals to understand and trust the system's outputs.

In conclusion, our startup's key activities revolve around research and development to create an intelligent system that delivers value to healthcare professionals. We prioritize data acquisition, intelligent system development, website design, and expanding the solution's coverage to address various pneumonia diseases while ensuring transparency and interpretability. By focusing on these activities, we are confident in our ability to develop a successful project that meets the needs of healthcare professionals and positively impacts patient outcomes.

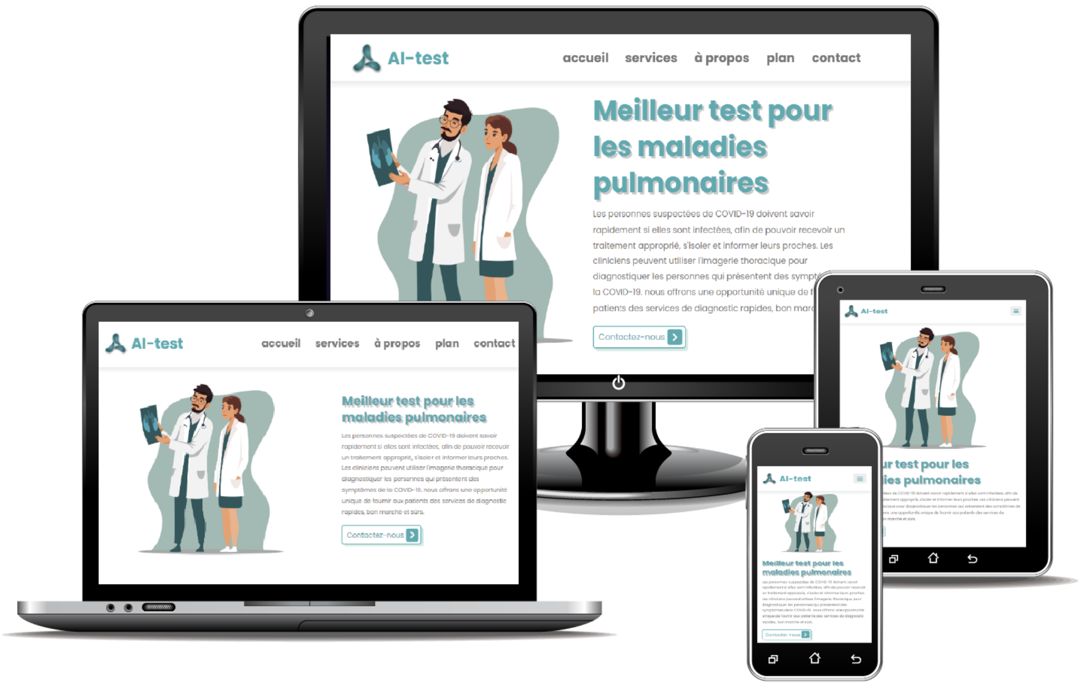

Figure A.2: Responsive Healthcare Decision Support Website.

A.7 Key Resources

In order, to undertake this project successfully, we require the following key resources:

- **High-performance Computer/Server**: A high-performance computer or server is essential for the efficient processing and analysis of medical imaging data. We require a robust system that can handle the computational demands of our intelligent system and provide quick and accurate results. This resource plays a critical role in training our system and running complex algorithms to classify pneumonia diseases accurately.

  - **Processor**: Our high-performance computer/server should be equipped with a powerful processor such as the Intel Xeon or AMD EPYC series. These processors offer multiple cores and high processing speeds, enabling efficient execution of complex algorithms.
  - **Memory (RAM)**: Sufficient RAM is crucial for handling large datasets and ensuring smooth operations. We require a significant amount of RAM, typically 32 GB or more, to accommodate the memory-intensive tasks involved in processing medical imaging data.
  - **Graphics Processing Unit (GPU)**: Incorporating a high-performance GPU, such as NVIDIA GeForce RTX series (e.g., GeForce RTX 3080 with 10 GB of dedicated memory), provides accelerated processing capabilities for AI algorithms. The GPU's dedicated memory and parallel processing capabilities enable faster training and inference times.
  - **Storage**: We need ample storage capacity to store and manage the extensive collection of medical imaging data.

  These specifications will ensure efficient and effective handling of data in our research.

- **Hosting Infrastructure**: Suitable hosting capabilities to ensure the availability, security, and scalability of our online platform.
- **Reliable Internet Connection**: A stable and high-speed internet connection to facilitate data processing, updates, and customer interactions.
- **Marketing Team**: An experienced marketing team is crucial for promoting our solution and reaching our target audience. This team will develop and execute

marketing strategies, including digital marketing campaigns, content creation, social media management, and lead generation. Their expertise will help increase awareness, attract customers, and drive the growth of our business.

By leveraging these key resources, including a high-performance computer/server, hosting infrastructure, and a reliable internet connection, we can efficiently process and analyze medical imaging data, ensuring the accurate classification of pneumonia diseases. These resources form the foundation for delivering a robust and reliable solution to our customers in the healthcare sector.

A.8 Key Partners

To support our project, the partners that we are planning

- **Internet hosting provider**: We will collaborate with a hosting provider to ensure the reliable and secure hosting of our online platform.
- **Medical Professionals**: Collaborating with medical experts, radiologists, and clinicians to acquire annotated medical image databases, validate our system, and gain insights for solution enhancement.
- **Technology Companies**: Temporally we have collaborated with a Pr. who has assisted us with a high-performance desktop computer, we need to collaborate with Technology companies to provide us with access to advanced hardware, software, to support the development and of our system.

A.9 Cost Structure

The cost structure of our project scope encompasses the development of an intelligent system that aims to provide assistance and value to healthcare professionals in the diagnosis of pneumonia diseases. The cost breakdown includes the following:

- **High-performance computer/server**: To ensure the efficient processing and analysis of medical imaging data, we need to acquire a high-performance computer or server that is suitable for our project. As a starting point, we have temporarily provided a high-performance computer, but it's important to have the right equipment in the long term. Getting a dedicated high-performance computer or server may be expensive upfront, but it's crucial for the success of our project. We estimate the cost of acquiring the necessary hardware to be 300,000 DA.

- **Internet connection**: A reliable and high-speed internet connection is crucial for data processing, updates, and customer interactions.

- **Hosting infrastructure**: We need suitable hosting capabilities to ensure the availability, security, and scalability of our online platform.

- **Electricity**: Running a high-performance computer/server will consume a significant amount of electricity.

- **Marketing expenses**: To promote our solution and reach our target audience, we will need to invest in marketing. These expenses include various activities such as digital marketing campaigns, content creation, social media management, and lead generation. The specific cost of marketing expenses will depend on the strategies we employ and the size of our target audience.

- **Development and maintenance of our intelligent system**: This cost structure is specific to the design, development, and continuous improvement of an intelligent system for classifying pneumonia diseases using medical imaging. It includes expenses related to regular updates to enhance the functionality, performance, accuracy, and usability of the system.

- **Maintenance of the website platform**: This includes ongoing maintenance and updates to ensure the smooth functioning of our website platform. It encompasses activities such as regular security updates, bug fixes, and user interface improvements to provide an optimal user experience. Allocating resources to website maintenance is crucial for ensuring the stability and usability of our platform.

Abstract

In recent years, artificial intelligence has emerged as a promising field of health innovation, benefiting both patients and healthcare providers. Medical imaging techniques, play a crucial role in detecting and diagnosing various diseases, including SARS-CoV-2 (Covid-19).

This pandemic highlighted the need for accurate and efficient automated diagnosis methods to ensure timely and reliable virus detection, ultimately improving patient care.

This master thesis focuses on enhancing the accuracy and efficiency of the Covid-19 classification and diagnosis by leveraging deep neural networks. Specifically, we employ two modalities of medical images namely CT scan and X-ray images, and transfer learning techniques.

Multiple convolutional neural network models were considered including VGG16, VGG19, Xception, and ResNet152V2. These pre-trained models were fine-tuned for Covid-19 classification on each modality.

Experimental results consistently demonstrated that the VGG16 model outperformed the others, achieving high accuracy of 99.40% on CT-scan images, and a promising accuracy of 97.10% on X-ray images. This makes VGG16 a reliable choice for Covid-19 classification.

KEYWORDS: Medical imaging, deep neural network, transfer learning, convolutional neural network, Covid-19 classification.

Résumé

Ces dernières années, l'Intelligence Artificielle s'est imposée comme un domaine prometteur d'innovation en santé, bénéficiant tant aux patients qu'aux professionnels de la santé. Les techniques d'imagerie médicale jouent un rôle essentiel dans la détection et le diagnostic de diverses maladies, y compris le SARS-CoV-2 (Covid-19).
Cette pandémie a mis en évidence le besoin de méthodes de diagnostic automatisées précises et efficaces pour assurer une détection rapide et fiable du virus, ce qui améliore finalement les soins aux patients.
Ce mémoire de master vise à améliorer la précision et l'efficacité du diagnostic du COVID-19 en exploitant les réseaux neuronaux profonds, en utilisant spécifiquement deux modalités d'images médicales, à savoir les scanners CT et les images radiographiques (X-ray), ainsi que des techniques d'apprentissage par transfert.
Plusieurs modèles de réseaux neuronaux convolutionnels ont été considérés, notamment VGG16, VGG19, Xception et ResNet152V2. Ces modèles pré-entraînés ont été affinés pour la classification du Covid-19 sur chaque modalité.
Les résultats expérimentaux ont systématiquement démontré que le modèle VGG16 surpassait les autres, atteignant une précision élevée de 99.40 % sur les images CT-scan, ainsi qu'une précision prometteuse de 97.10 % sur les images X-ray. Cela fait du modèle VGG16 un choix fiable pour la classification du Covid-19.

MOTS-CLÉ: Imagerie médicale, réseau neuronal profond, l'apprentissage par transfert, réseau neuronal convolutif, classification du Covid-19.

ملخص

في السنوات الأخيرة، ظهر الذكاء الاصطناعي كمجال واعد في الابتكار الصحي، والذي يعود بالفائدة على المرضى ومقدمي الرعاية الصحية على حد سواء. تلعب تقنيات التصوير الطبي دورًا حاسمًا في اكتشاف وتشخيص العديد من الأمراض، بما في ذلك فيروس كورونا المستجد-2 (كوفيد-19).

أبرزت هذه الجائحة الحاجة إلى طرق تشخيص آلي دقيقة وفعالة لضمان الكشف الموثوق وفي الوقت المناسب عن الفيروس، مما يحسن رعاية المرضى.

تركز هذه مذكرة الماستر على تعزيز دقة وكفاءة تشخيص كوفيد-19 من خلال استخدام شبكات عصبية عميقة، بتوظيف تحديدًا نمطين من وسائط الصور الطبية، وهي الصور المقطعية بالأشعة المقطعية وصور الأشعة السينية ، بالإضافة إلى تقنيات التعلم بالنقل.

تم اعتبار العديد من نماذج الشبكات العصبية الملتفة، بما في ذلك VGG16, VGG19 , Xception ResNet152V2.

تم ضبط هذه النماذج المدربة مسبقًا لتصنيف كوفيد-19 على كل نمط.

أظهرت النتائج التجريبية بشكل متسق أن نموذج VGG16 يتفوق على النماذج الأخرى، حيث حقق دقة عالية تبلغ % 99.40 على صور بالاشعة المقطعية، بالإضافة إلى دقة واعدة تبلغ % 97.10 على صور الأشعة السينية. وهذا يجعل نموذج VGG16 خيارًا موثوقًا لتصنيف كوفيد-19.

كلمات مفتاحية: التصوير الطبي، الشبكة العصبية العميقة، التعلم بالنقل. الشبكة العصبية الملتفة، تصنيف كوفيد19.

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