Pre-thesis -1 Report

Medical Image Reader Powered by Artificial Intelligence

by

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Abstract

Medical imaging produces visual representations of areas inside the human body in order to diagnose medical problems and monitor the treatment. Root causes of almost every disease, illness and medical issue arise inside the body. Hence, since its first discovery in 1895, [1] medical imaging has left a massive impact on public health. When the diagnosis is completed, a radiologist analyzes the results and suggests the most appropriate treatment for the patient. Therefore, the faster and more accurate the diagnostic process is, the better the treatment will be. Our proposed project aims towards an interface model using Deep Learning (DL) techniques so that the diagnosis of a medical issue can become faster, easier and more precise. The goal of this research is to find the best suited models to classify different types of medical images, to extract data from an image in order to detect any existence of a medical issue with the best accuracy possible in a general case. Neural Network is one of the most used DL techniques which plays a vital role in analyzing medical images. The initial outcome of the research is some existing modified AI-based models which are already giving accurate results in detecting different kinds of diseases by analyzing different types of medical images, for example, CheXNet for detecting thoracic diseases [5], CoroNet for identifying COVID-19 [11] etc. These models are combinations of a number of various architectures, such as: SVM, Transfer learning, VGG, Inception, DenseNet, CapsNet, ResNet etc. At the conclusion of our research, we try to find and merge these models with the best accuracy in order to identify particular medical issues by analyzing a medical image.

Keywords: Medical Imaging, Deep Learning, Neural Network, CheXNet, Coronet, VGG, Inception, DenseNet, CapsNet.

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Chapter 1

Introduction

1.1 Medical Imaging and Deep Learning

Modern technologies have shadowed every corner of the world. Each and every fundamental of human life including the medical sector is now deeply connected with the new age of technology. Medical sector consists of three broad parts- diagnosis, analysis and treatment. Most diseases and illnesses start their journey from the inner side of the human body. Sometimes the cause of illness can be diagnosed by checking some outer body conditions, such as: high temperature of the body is a symptom of fever, a yellow tinge to the skin, mucous membranes, and the whites of the eyes can be symptoms for Jaundice etc. Nevertheless, there are enormous numbers of medical conditions which need the assistance of technologies to be analyzed, explained and treated. Notably, Medical Imaging is one of the very common and highly used modern technologies in the diagnosis part. In general, one or more medical imaging procedures are performed on a patient's body as per the request of a Radiologist. Radiologists are doctors who are trained to diagnose diseases or injuries or the causes for an illness by analyzing the outputs of the procedures. These outputs are, in fact, images captured on films which contain the information regarding the inner body of the patient. Most common types of medical images are X-ray, Magnetic Resonance Imaging (MRI), Computerized Tomography (CT scan), Ultrasonography, Endoscopy, Tactile Imaging etc. Each of these imaging techniques can help in diagnosis of a wide range of medical conditions. Following is a brief idea about three most common medical images and their scopes of usage:

X-Ray	Thoracic diseases; Bone fractures; Arthritis; Osteoporosis; Infections; Breast cancer; Swallowed items; Digestive tract problems
CT Scan	Injuries from trauma; Bone fractures; Tumors and Cancers; Vascular disease; Heart disease
MRI	Aneurysms; Multiple Sclerosis (MS); Stroke; Spinal Cord disorders; Tumors; Blood vessel issues; Joint or Tendon injuries

In some cases, one procedure alone cannot explain the existence of a disease or abnormality of health. Then, multiple types of diagnostic procedures are performed and by analyzing all the generated medical images, radiologists may be able to diagnose the condition. Availability, knowledge and experience of the radiologists play a key role here in the diagnosis process.

Another component in this modern age of technology is Deep Learning (DL), a subset of Artificial Intelligence (AI). DL has a huge impact upon many sectors of human life as well. Common DL applications are Virtual Assistants (Siri, Alexa, Cortana etc.), Vision for Autonomous cars (Tesla), Facial Recognition, Object Detection and so on. Following is a broad picture of the difference in work-flows between Machine Learning and Deep Learning:

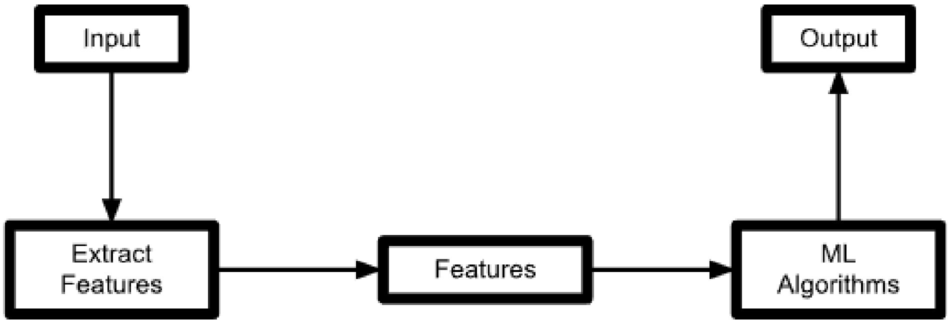

Figure 1.1: Work-flow of Machine-Learning

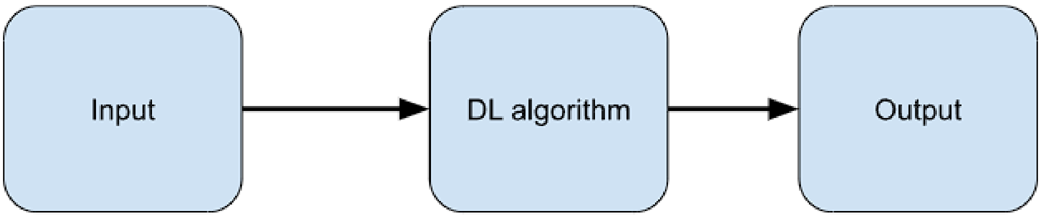

Figure 1.2: Work-flow of Deep-Learning

Among a number of deep learning algorithms, some are very popular and being used in different scopes, e.g: KNN (K-nearest neighbor) method, Convolutional Neural Network (CNN), Deep Neural network (DNN), Generative Adversarial Network (GAN),Restricted Boltzmann Machine(RBM) etc. These algorithms are used in classification, segmentation, processing or analyzing data. Focusing on the medical sector, the accuracy of analyzing medical data by these algorithms is remarkable. More specifically, these data driven classifiers have revolutionized medical imaging fields namely: Image segmentation, computer-aided diagnosis systems, content-based image retrieval image annotation etc. With better technologies, medical data has been more accessible than in the past. Hence, innovating advanced algorithms can take the development of the medical sector to a greater height of success. Consequently, the synergic efforts of data scientists and radiologists would revolutionize the medical sector using the data driven classifiers.

1.2 Problem Statement

According to a research in 2014[3], approximately 12 million people are misdiagnosed annually in the United States; among them, an estimated 40,000 to 80,000 cases lead to death. Almost no disease can be diagnosed without medical imaging procedures let alone starting treatment. There are some factors which don't always come under the light during a medical diagnostic process. As we know, Radiologists are the first to diagnose the condition of an inner body by analyzing a medical image. There are specialized doctors to confirm that. Nevertheless, the availability, knowledge and experience of the radiologists play a major role in the diagnosis. Some countries may not have specialized radiologists, on the other hand, the specialized doctor may not be aware of a disease which may be common in a very distant country. Additionally, there are a lot of emergency cases where the patient needs treatment as early as possible to survive, however, because of unavailability of specialized persons, the diagnosis process becomes lengthy. Hence, misdiagnosis, unavailability of radiologists, low experience of the doctor sometimes lead a patient to even a worse case possible.

In the encounter of these problems, the manpower needs a good amount of time to gain experience. On top of that, to eradicate the issue of unavailability, governments of each country should focus on the radiology department of the hospitals so that more radiologists are hired having a good number of scopes of practice. Still then, there remains many options of errors to be occurred and misdiagnosis to take place. Therefore, the medical sector needs an alternative system which can analyze and identify the existence of a disease or a cause of illness just by reading a medical image as precisely as possible.

1.3 Research Objectives

In the research, we have tried to find as many models as possible in order to identify a number of medical conditions. Most of these models are DL-based models which use combinations of different architectures of Neural Networks Models. The authors of each paper either have found a new model with a great accuracy in detecting one kind of disease or they have shown a comparison of accuracy among few models and architectures for identifying a specific medical problem. We aim to prepare a DL-based interface that can take a medical image as input, analyze it at a human-level or more and finally predict the diseases or problems existing in it as an output. The primary objective of this research is to gather the models for diagnosis of different kinds of diseases. The remaining objectives are as following:

- Increase the number of models for diagnosing various classes of diseases (Thoracic, Cardiac, Neuro, Bone etc.)
- Understanding the use of classification techniques for classifying different kinds of medical images.

- To develop an optimized combination of models with the best accuracy rate in identifying each class of diseases.
- To design the interface model.
- To evaluate the proposed model using collected data.

Chapter 2

Detailed Literature Review

Medical imaging plays a major role in numerous clinical applications like medical procedures used for early detection, diagnosis, observation and treatment analysis of varied medical conditions. In recent times, the utilization of artificial intelligence and machine learning rather than physical observation of humans has created a serious field to figure for the researchers with medical image analysis. To boost the detection of various diseases, several researchers are attempting to use new techniques associated with artificial intelligence and machine learning. By work, it has been seen that Artificial Neural Networks (ANN) and Deep Learning (DL) are essential for understanding medical image analysis in computer vision. Specially, use of Deep Learning Approaches (DLA) are emerging as a fast-growing research field. Many research papers have been published related to DL in the field of medical image analysis. DL is a branch of Machine Learning (ML) that focuses on creating deep neural networks that are modeled after the biological neural networks seen in the human body. There are various deep learning models introduced so far.

2.1 Deep Learning in Medical Imaging

In paper [6], Kenji Suzuki overviewed the area of deep learning in medical imaging. In the beginning, they described the change in machine learning before and after the invention of Deep Learning. After that, they introduced two major Deep-Learning models including a Massive-Training Artificial Neural Network (MTANN) and a Convolutional Neural Network (CNN). Besides, the similarities and differences of the two models were illustrated. Moreover, this review shows that the learning of image data directly without object segmentation or feature extraction is the source of the power of Deep Learning. Because of this, ML with image input can avoid errors caused by inaccurate feature calculation and segmentation. Thus, the performance of ML with image input can be higher than ML with feature input. Moreover, the depth of the model plays an important role. Comparing the two models, for CNN, convolutional operations are performed within the network whereas, for MTANN, it is performed outside the network. In addition, in case of output, CNN consists of class categories whereas MTANN consists of images. Another major difference is that CNN needs a larger number of images to train than MTANN. The authors tested some well known CNNs including AlexNet, the LeNet, a relatively deep CNN, a shallow CNN and a fine tuned AlexNet and a MTANN in focal lesion detection and classification problems. The test result shows that the performance of MTANN is statistically higher than the best performing CNN model stated above. By the following explanation it can be stated that MTANN can get higher performance with less image input compared to CNN. But MTANN outputs an image(a map of continuous values) whereas CNN's output is normally a class. As a result, most of the researchers have used CNN models in classification regarding medical problems.

2.2 Convolutional Neural Network

CNN is a significant artificial visual network for recognizing patterns in medical images. A fully connected neural network's main drawback is that, even for shallow topologies, the number of neurons may be very great, making it difficult to use them for picture applications. In order to solve this problem CNN was introduced which basically reduces the number of parameters, allows a network to be deeper with fewer parameters. In [7], the authors describe that to increase computational efficiency, CNN can reduce the number of parameters automatically. In addition,CNN, a supervised learning model, can effectively process 2D and 3D images with minor modifications. The visual of CNN in process:

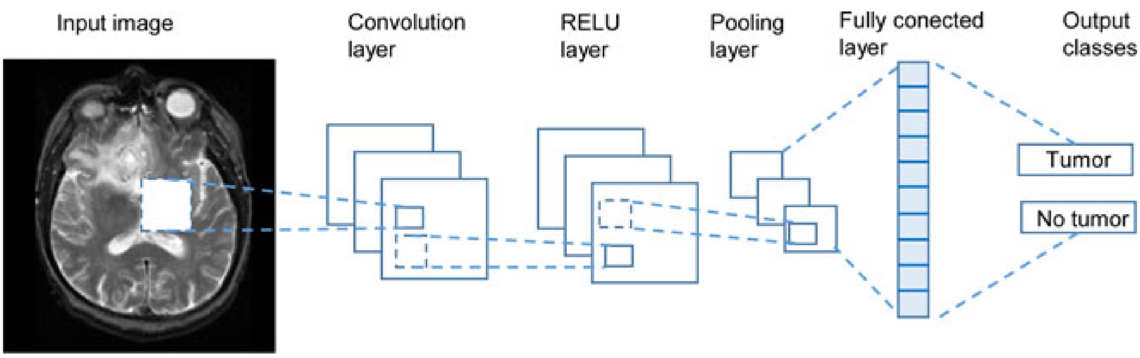

Figure 2.1: Disease classification task, an input image of an abnormal axial slice of a T2-weighted MRI brain is run through a schematic depiction of a CNN. Feature extraction of the input image is performed via the Convolution, RELU and pooling layers, before classification by the fully connected layer.

2.2.1 Convolution layer

A two dimension convolution operation with input I (m, n) and a kernel K (a, b) is defined as:

$$s(t) = \sum_{a} I(a) \cdot K(t-a) \,. \tag{2.1}$$

This equation usually represents input values at a position of image .
Applying the commutative law, the kernel is flipped and then equation looks like:

$$s(t) = \sum_{a} \sum_{b} I\left(a, b\right) \cdot K\left(m - a, n - b\right). \tag{2.2}$$

Implementing the cross-correlation function, we get-

$$s(t) = \sum_{a} \sum_{b} I\left(m + a, n + b\right) \cdot K\left(a, b\right). \tag{2.3}$$

2.2.2 RELU Layer

This is an activation function and this part sets negative input values to zero. The activation function:

$$f(x) = max(0, x). \tag{2.4}$$

2.2.3 Pooling Layer

The main function of this layer is to reduce the number of parameters and it also reduces the size of the image. Max-pooling is the most commonly used parameter in the pooling layer.

2.2.4 Fully Connected Layer

The Fully Connected Layer—the last layer in a CNN defines that every neuron from the layer before is connected to every neuron in the Fully Connected Layer. It typically determines the likelihood of receiving input from the pooling layer and RELU layer.

2.3 Capsule Network

Capsule Network or CapNet was used to classify the brain tumors on MRI images and authors got 86.56% accuracy [9] with a modified CapsNet that reduces the feature maps from the original 256 to 64. Moreover, CapsNet was used to classify breast tissue biopsies from breast cancer histology images with an accuracy of 87%. To classify those datasets the authors embrace the following steps:

- Increase the number of layers in the primary capsule.
- Increase the quantity of capsules in the first capsule layer.
- Combine many models and take the average.
- Modify the loss-scaling factor for reconstruction.
- Increase ConvLayer.
- Examine different activation mechanisms

Usually the capsule network is highly effective for imbalance datasets. In 2016, Hoo-Chang Shin Et al. [2] proposed that deep CNN architectures with 8to 22 layers can be effective in identifying CADe problems when the available data is limited. There are few training datasets available. Previously, CNN models were employed. Increasing the amount of training data should be carefully examined when looking for the best answer to any CADe problem (e.g., mediastinal and abdominal LN detection). Furthermore, limited datasets might be a barrier to future progress of the CADe Building that is gradually expanding.

Moreover, Transfer knowledge from the large-scale annotated natural environment image datasets (ImageNet) have been applied to CADe challenges. Their tests have proven to be consistently useful. This reveals some cross-dataset CNN learning in the medical imaging domain, such as the combination of the ILD and LTRC datasets as proposed in this work. Finally, applications of commercial deep CNN image processing CADe issues' characteristics can be improved by either investigating the performance enhancing qualities of customized features , or CNN training from the ground up and fine-tuning CNNs on the target. This article examined a medical picture collection. They utilize and thoroughly assess three crucial, previously unstudied features on deep convolutional neural networks (DCNN) architecture, dataset characteristics, and transfer learning in this research. CNN performance is evaluated in two computer-aided diagnostic applications: thoraco-abdominal lymph node identification and interstitial lung disease categorization. The empirical assessment, CNN model visualization, CNN performance analysis, and decisive findings may be used to the construction of high-performance CAD systems for additional medical imaging applications.

2.4 Transfer Learning

Whenever we have a small dataset for example: Caltech 101 dataset [15]. In this dataset there are only 101 categories of data that is insufficient to train a model with high accuracy. That is why, using CNN on Caltech is not feasible so a pre-built and pre-trained model using transfer learning can be used here. Basically, transfer learning is training a relatively huge dataset and transferring its knowledge to a small dataset. For example ,small pneumonia dataset, including about five thousand images, achieved an average accuracy of 92.8%, with a sensitivity of 93.2% and a specificity of 90.1%.Transfer learning may aid in expediting patient diagnosis and referral, leading to the introduction of early therapy and an improved cure rate.In Figure: 2.2, the idea of Transfer Learning is illustrated using a diagram.

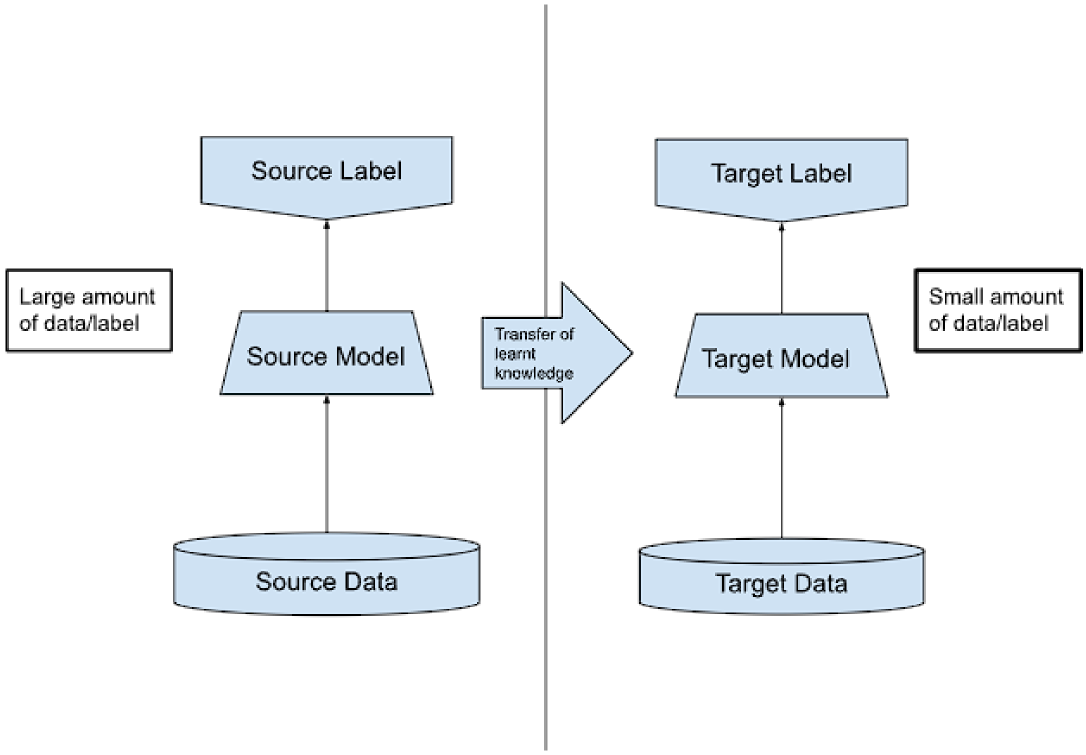

Figure 2.2: Idea of Transfer Learning

2.5 Proposed Models Based on CNN in Medical Diagnosis

In 2017, Pranav Rajpurkar Et al. [11] introduced us with an algorithm called *CheXNet* which is an algorithm that can detect Pneumonia from chest X-rays at a better level than practicing radiologists. Authors used a dataset called *ChestX-ray14* dataset. It contains 112,280 front-view chest X-ray of 30,805 different patients; all labeled up to 14 different thoracic diseases including pneumonia. For this experiment, among the 14 labels, Pneumonia has been selected as a positive label and all the other ones are used as negative ones. Dataset was splitted into training dataset(98637 images) , test dataset (420 images), validation (6351 images) where there is no overlapping patient in these sets of data. Firstly, the images are down-scaled to 224x224 and normalized based on the *ImageNet* Training set.Then, training data is augmented with random horizontal flipping. Pneumonia detection is a binary classification problem, hence, 121- layered Dense Convolutional Network, shortly named as *DenseNet*, is trained on the dataset. Briefly, it optimizes the deeper networks to generate better outputs (check the link in the keyword for better understanding). Four practicing radiologists (with experience of 4,7,25 and 28 years) independently labeled the test set. Finally, the authors used Bootstrap to construct 95% bootstrap CIs. After the F1 score calculation, they found that-

$$F1_{CheXNet} > F1_{Radiologists}$$

HongyuWang Et al. [8] put forward *ChestNet* which is a Deep Neural Network (DNN) model for the computer-aided diagnosis of thorax diseases by reading chest radiography. This model consists of 2 branches-(i) Classification branch and (ii)

Attention Branch. Authors used the same dataset *ChestX-ray14*. At first, the PNG images were rescaled into 1024x1024. Each image had one/multiple labels. These labels were extracted from the radiological reports using Natural Language Processing (NLP). Then, the dataset was split into training and test subsets (80% : 20%). In the classification branch, the *ResNet-152* model has been used since it is pre-trained in the *ImageNet* dataset. This model consists of 152 learnable layers. In order to adapt this model to their project, the softmax layer was removed and the last fully connected layer was replaced with a layer of 14 neurons; each using the sigmoid activation. Outputs of these 14 neurons are defined as Label Prediction Vector. In the attention branch, the relationship between the labels and regions of abnormalities are derived using the analysis of learned feature maps. For this, the input of this branch is the second last residual output from the classification branch. Finally, the output from the attention branch is defined as the Label Confidence Vector. Authors first trained the classification branch (all parameters fixed), then trained the attention branch. Each training process was designed in a way so that the cross-entropy loss can be minimized. The authors of the paper found that their proposed model achieved a better average per-class AUC than the other deep learning methods in diagnosing each of 14 thorax diseases.

In the same year, Paras Lakhani Et al. [4] presented a study on how well Deep Convolutional Neural Networks (DCNNs) operate at spotting Tuberculosis (TB) on chest radiographs. In the first part of the paper, he showed the Materials and Methods of the research, which includes the datasets, methods and statistical analysis. The study used four de-identified HIPAA-compliant datasets, totaling 1007 posteroanterior chest radiographs, that were exempt from institutional review board evaluation. These datasets were separated into Training (68.0%), validation (17.1%), and test (14.9%). AlexNet and GoogLeNet, two separate DCNNs, were utilized to categorize the photos as either having pulmonary TB symptoms or being in good health. On ImageNet, both untrained and pretrained networks were applied, along with a variety of preprocessing methods. Firstly, the chest radiography images were scaled down to a 256x256 matrix and put into the Portable Network Graphics (PNG) format. A high configuration computer with Linux operating system was used. All images were enhanced using the built-in Caffe options of mean subtraction, mirror images, and random cropping of 227 x 227 pixels. Using pseudorandom numbers produced by the random function in the Python Standard Library (Python 2.7.13, Python Software Foundation, Wilmington, Del.), the patients were randomly assigned. The AUCs of the trained models (AlexNet-T, GoogLeNet-T) were higher than those of the untrained models (AlexNet-U, GoogLeNet-U) (P , .001) for both Deep Neural Networks.

In 2020 , Rahul Kumar Et al. [13] introduced a Machine Learning-based classification technique where deep features were extracted using *ResNet152* with COVID-19 and Pneumonia patients on chest X-ray images. To make the model more accurate *SMOTE* (SYnthetic Minority Oversampling Technique) was used which mainly used for embalancing the imbalanced datasets of COVID-19 and normal patients(creates an equal number of samples for each class). The researchers state that this method will help to predict the outbreak of COVID-19 earlier. For classification Machine Learning classifiers like Logistic Regression, k-Nearest Neighbour (KNN), Decision

Tree, Random Forest, AdaBoost Classifier , XGBoost were trained and to compare the performance of this classifiers' accuracy, Sensitivity, Specificity, F1-Score, AUC were checked . After checking, it was clear that XGBoost outperformed all the classifiers. For the training of *ResNet152* model architecture, 5840 images were used with 5216 images for training(1341 for Normal class and 3875 for Pneumonia class) with the remaining 624 (234 for normal class and 390 for Pneumonia class) in testing. Furthermore, for training the Machine Learning classifiers they used images from the chest X-ray Images (Pneumonia) dataset with 2748 images where 1833 (with 42 from COVID-19 patients, 894 in Normal patients and 897 in Pneumonia patients) images for training and 915(with 20 from COVID-19 patients, 447 in Normal patients and 448 in Pneumonia patients) for testing.

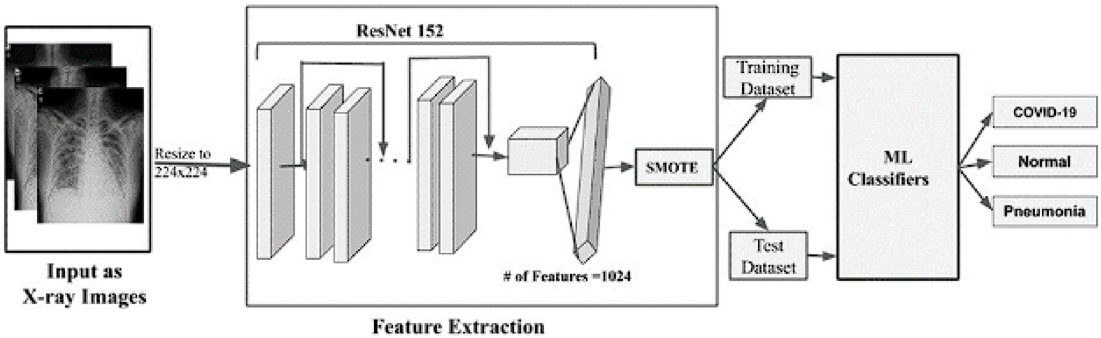

Figure 2.3: Work-flow of SMOTE algorithm

Mohamed Abd Elaziz Et al. [10] in their paper proposed a new ML method to classify people of two classes either COVID-19 patient or non-COVID-19 patient by analyzing their chest x-ray images. For this experiment, the authors used two different datasets. First one is from Github open-source and images gathered from 43 different publications. In this dataset, there are 216 COVID-19 positive images and 1675 negative COVID-19 images. Second one was collected by a team in collaboration with medical doctors. This dataset contains 219 COVID-19 positive images and 1341 negative COVID-19 images. For best accuracy of the classification, two techniques were combined.

First, a new image descriptor namely *FrMEMs*. The second strategy is a modified feature selection method based on *Manta-Ray For-aging Optimization and differential evolution* (MRFODE) . Besides, a parallel multi-core computational framework is utilized to accelerate the computational process. At first, the proposed method gets the features from chest x-ray images using FrMEMs moment. Then, these features are divided into testing and training sets. In order to reduce these features and remove the redundant and irrelevant features, the MRFODE algorithm is used here. The algorithm generates a set of solutions and computes the fitness value for each of them by using the KNN classifier based on a training set with determining the best of them. Furthermore, the operators of MRFO are applied. However, during the exploitation phase, each solution's likelihood is determined using its fitness value. This solution was updated either using DE or the operators of MRFO. The process of updating the solutions stopped when reached to terminal conditions. The

COVID -19 dataset's label was computed using the best method after the unnecessary characteristics were removed from the testing set. In the last step , a KNN classifier was trained and evaluated. To evaluate this new model, various methods were used. Firstly, the feature selection method MRFODE was compared with other MH methods including MRFO, HGSO, HHO, GWO, SCA, and WOA that were used as feature selection models. After comparing, the result indicates that MRFODE has the highest ability to select the optimal subset of features that will increase the accuracy of the two datasets provided in the experiment. Secondly, the proposed model was compared with other CNN models. In this comparison, the proposed model gets higher accuracy than other deep neural networks with use of less features.

In the same year, Asif Iqbal Khan Et al.[12] suggested *CoroNet*, a Deep Convolutional Neural Network model. The suggested model is based on the *Xception* architecture, which has been thoroughly trained on the *ImageNet* dataset and pre-trained on a different dataset. In their proposal, three categories in this Deep Convolutional Neural Network (DCNN) model were Bacterial, Viral, and COVID-19 Pneumonia which are some of the different forms of Pneumonia. Through using CoroNet, after gathering chest X-ray data, they had to generate a dataset containing images from two different image repositories that are open to the public. Images from COVID-19 can be found on an open source Github. They resized all the images to the dimension of 224×224 pixels with a resolution of 72 dpi. After pre-processing being done, they trained the model using the dataset.

In 2021, Chiranjibi Sitaula Et al. [14] proposed an attention-based deep learning model using the attention module with *VGG-16*. There are many papers related to diagnosing COVID-19 by use of CXR-based methods. But these methods have limited performance because they ignore the spatial relationship between the region of interests (ROIs) in CXR images which could identify likely regions of COVID-19's effect in the human lungs. To overcome this problem they used an attention module which basically captures the spatial relationship between the ROIs in CXR images.

For the research of this paper, three datasets were used. First one namely Dataset 1 containing three categories (Covid-19, No findings, Pneumonia); Second one, named as Dataset 2 containin four categories (Covid, Normal, Pneumonia Bacteria, Pneumonia Viral) and the third one named as Dataset 3 contain five categories (Covid, Normal, No findings, Pneumonia Bacteria, Pneumonia Viral). For training and testing this datasets were splitted into 7:3 ratio. The proposed model uses a pre-trained DL model namely *VGG-16*. This model extracts the features at low-level by using its smaller kernel size. Moreover, a fine-tuning approach which is a transfer learning technique is used. For the fine-tuning process, they had used the pre-trained weight of *ImageNet* which helps to overcome the over-fitting problem as there are a limited amount of COVID-19 CXR images. Furthermore, the proposed model also consists of four main building blocks such as Attention module, Convolution module, FC-layers and Softmax classifier. For identifying the performance of the proposed model, it was compared with other advanced models which are based on some pre-trained deep learning models (Incep-V3, ResNet50, DenseNet121, Inception-ResnetV2, MobileNet). The comparison result shows that the proposed model achieves more accuracy then other models on all the three datasets. Besides, they have used Convergence analysis to observe that the proposed model has converged and shown best-fit on all datasets by observing the gap between training and validation accuracy/loss on the datasets. For a better clarification, they have used Class-wise analysis(precision , recall, f-score) of the proposed model which gives an overview about the performance of the modeland Qualitative analysis of convolution and attention modules for five different diseases which basically maps the affected area of the lung.Besides, they used adaptive analysis and shown that VGG-16 performs best if combination of attention and convolution module is used.

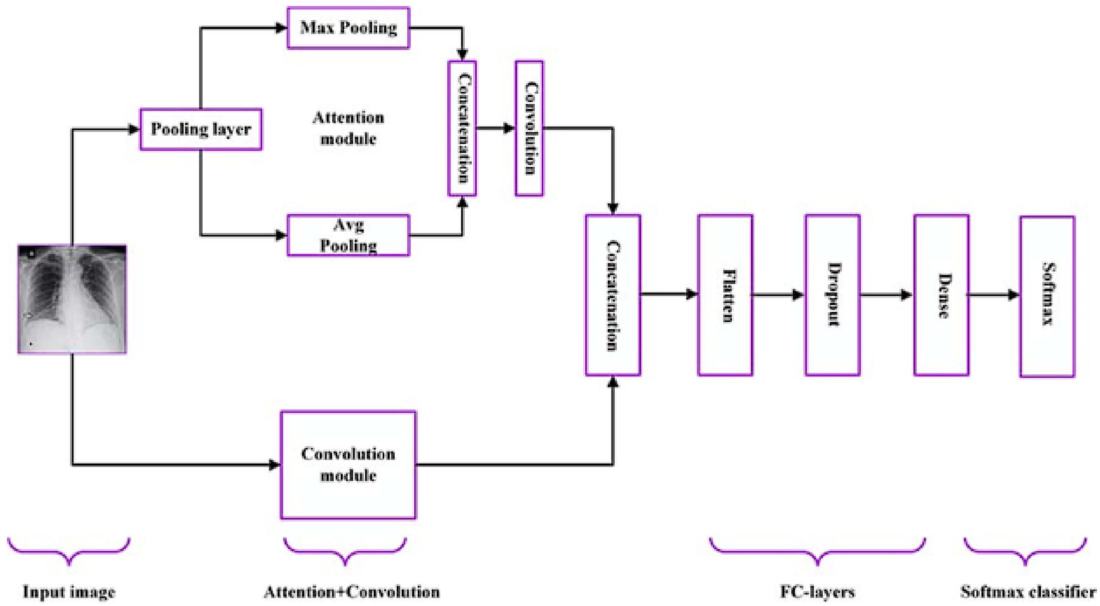

Figure 2.4: Work-flow of attention-based VGG16 Model

Chapter 3

Working Plan

The following flow diagram illustrates our preferred steps to find the best suited models for our proposed project.

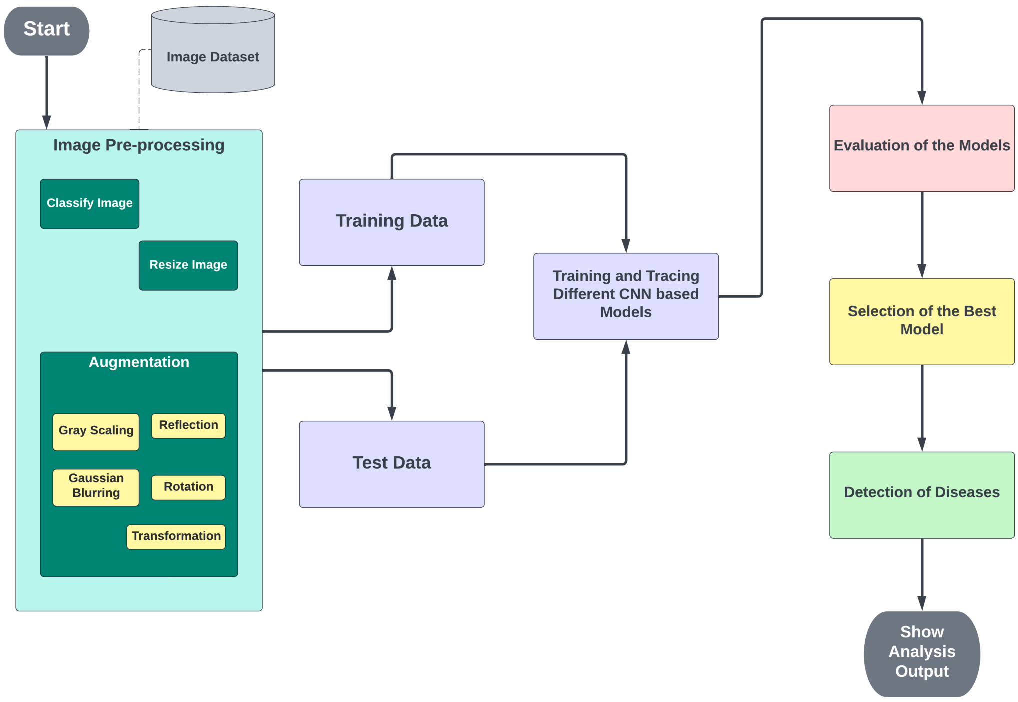

Figure 3.1: Working Plan of the Project

Chapter 4

Conclusion

In this modern era of technology, loss of human lives due to misdiagnosis or unavailability of professionals cannot be accepted. If only in the United States an average of 60,000 people die each year by misdiagnosis, it must be alarming when we will count this number combining the whole population of this world. Therefore, our project aims to help the medical sector by advancing the diagnostic process through the delivery of a human-level analysis of a patient's medical condition. Our proposed model will just need a medical image (X-ray/MRI/CT scan) to detect the presence of any kind of abnormality inside the patient's body. Moreover, the system will be able to analyze the abnormality and show probable diseases or medical problems as output. This system will be able to help in early diagnosis of a disease, in emergency cases of a patient and in advancing the medical study to a greater level. Eventually, these will result in patients to get rid of misdiagnosis and to get the proper path of treatment at an early period of one's deteriorated medical conditions. As a result, plenty of lives will be saved from misdiagnosis all over the world.

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