School

of

Electronics and Communication Engineering

Course Project Report

on

Identify And Localize COVID-19 Abnormalities on Chest Radiographs

By:

1. **Nikhil N. Akalwadi** USN:01FE18BEC088
2. **Aditya Krishna Vamsy M.** USN:01FE18BEC006
3. **Manali V. Hiremath** USN:01FE18BEC074
4. **Manish Pujar** USN:01FE18BEC076

Semester: VI, 2020-2021

Under the Guidance of

Priyadarshini Patil

K.L.E SOCIETY'S
KLE Technological University,
HUBBALLI-580031
2020-21

SCHOOL OF ELECTRONICS AND COMMUNICATION ENGINEERING

CERTIFICATE

This is to certify that project entitled " **Identify And Localize COVID-19 Abnormalities on Chest Radiographs"** is a bonafide work carried out by the student team of **"Nikhil (01FE18BEC088), Manish (01FE18BEC076), Aditya (01FE18BEC006), Manali (01FE18BEC074)"**. The project report has been approved as it satisfies the requirements with respect to the course project work prescribed by the university curriculum for BE (VI semester) in School of Electronics and Communication Engineering of KLE Technological University for the academic year 2020-21.

Your Guide	**Dr. Nalini C. Iyer**	**Prof. N.H.Ayachit**
Priyadarshini P.	**Head of School**	**Registrar**

External Viva:

Name of Examiners **Signature with date**

1.

2.

ACKNOWLEDGMENT

The feeling of fulfillment that lies within the effective completion of Identifying and localizing COVID-19 abnormalities in chest radiographs using Deep learning, would have been unfinished without citing the names of the individuals who helped us generously enough in the process of achieving the goals of the project, with their consistent directions, encouragement brought about in it's realization. We are thankful to our esteemed institute KLE Technological University, Hubballi, which has provided us this opportunity to fulfil the most cherished desire to reach our goal. We also express our deep sense of appreciation and gratitude to the School of Electronics and Communication, Nalini Iyer, the Head of Department, and the faculty at Embedded Intelligent Systems course for guiding us and, encouraging us throughout the completion of this project. Finally we would like to thank all those who either specifically or indirectly helped us, in achieving the goals and objectives in regards with the project.

-The project team

ABSTRACT

The COVID-19 pandemic has affected each and every corner of the world. This strain of the coronavirus with basic symptoms like fever and common cold can prove to be fatal. Although RT PCR COVID-19 tests are used in clinical settings, times for COVID-19 test results range from 3 to more than 48 hours, and probably not all countries will have access to those test kits that give results rapidly. One of the main alternate recommendations for the RT PCR tests is to use chest radiography for patients with COVID-19 symptoms. The detection of severe acute respiratory syndrome coronavirus 2 (SARS CoV-2), which is responsible for coronavirus disease 2019 (COVID-19), using chest X-ray images has life-saving importance for both patients and doctors. In addition, in countries that are unable to purchase laboratory kits for testing, this becomes even more vital. In this study, we aimed to present the use of deep learning for the high-accuracy detection of COVID-19 using chest X-ray images. X-ray images available in the Kaggle competition (1583 healthy, 4292 pneumonia, and 225 confirmed COVID-19) were used in the project, which involved the training of deep learning classifiers. Then an object detection model is trained for localization of the area of infection in the X-Rays. These models are integrated into an android app where the X-Ray images are given as input and the prediction is displayed on the interfacing screen.

Contents

List of Figures

Chapter 1

Introduction to Identification and localization of COVID-19 From Radiograph Images

Identifying and Localizing COVID-19 infections from other pneumonia viruses is a task of object detection and multi-class image classification at the core. Meaning, given any input image of a chest radiograph image, the algorithm classifies the image as positive for COVID-19, or negative, or pneumonia, and then localizes the area of infection in the radiograph, or the X-Ray as we call it, by adding a bounding box over the area of infection. We use the BIMCV-COVID19 dataset [1] for the tasks. The architectures are discussed briefly over in the further parts of this research work, but to put it down in few lines, MobileNetV3Large is used as the classifier coupled with YOLOv5 as an algorithm for predicting the bounding boxes for the classified images, making it easier to quickly identify the area of infection. We then focus on deploying the models on Android platform. We make use of Android Studio to perform the task. The app will feature a minimalist user interface, that will take an input image from the image gallery of the device, then classify it.

1.1 Motivation

- The pandemic hit the world. Said to be more than five times stronger than normal flu, COVID-19 virus is said to bring significant morbidity and mortality in some cases.
- COVID-19, much like other pneumonias, pulmonary infections, brings inflamation and fluid in the lungs.
- Since the coronavirus looks similar to other pneumonias in the chest radiographs, it is very difficult to diagnose.
- The proposed architecture, along with a coupled Android application is intended to help doctors diagnose COVID-19 quickly, and confidently.

1.2 Objectives

- Localize the area of infection in the input image of the chest radiograph
- Classify the localized image
- Optimize the trained models for edge devices
- Deploy the models on the Android platform

1.3 Literature survey

- **Searching for MobileNetV3 [2] by Andrew Howard et. al.,** encorporates combinations of depth-wise seperable convolutions which was earlier introduced in MobileNetV1 as an efficient replacement for the traditional convolutional layers, linear bottleneck and inverted residual structures which was introduced in MobileNetV2 and lightweight attention modules based on squeeze and excitation into the bottleneck structure which was originally from the MnasNet which inturn is based on the MobileNetV2. In MobileNetV3, the layers are also upgraded with modified swish nonlinearities by replacing the sigmoid with hard sigmoid. The blocks for residual structures and MobileNetV3 are shown below.

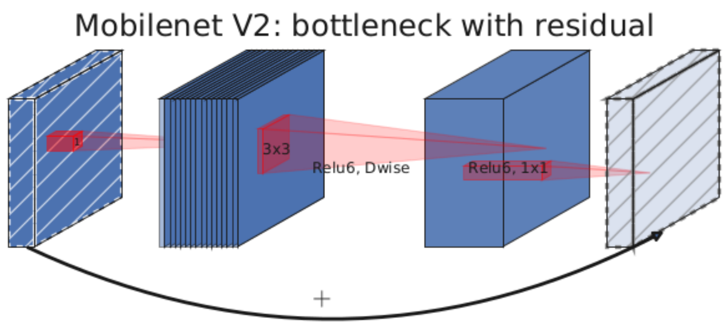


Figure 1.1: MobileNetV2 layer (Inverted Residual and Linear Bottleneck)[2]

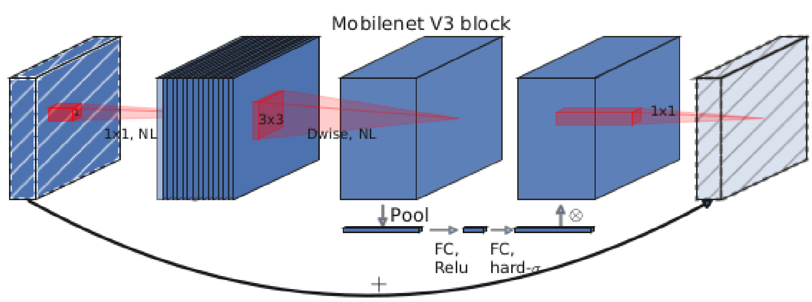
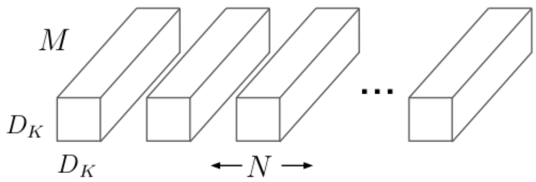
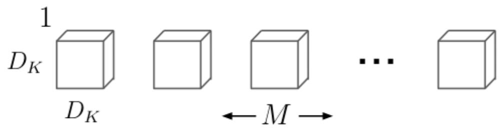


Figure 1.2: MobileNetV2 + Squeeze-and-Excite [2]

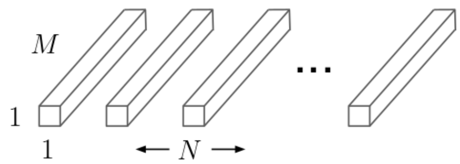
- **MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications [3] by Andrew G. Howard et. al.,** proposed efficient models known as MobileNets, which are useful in mobile and embedded vision applications. These networks are based on depth-wise seperable convolutions that make up the light weight neural networks, ideal for mobile deployment. For MobileNets the depthwise convolution ap- plies a single filter to each input channel. The pointwise convolution then applies a 1×1 convolution to combine the outputs the depthwise convolution. A standard convolution both filters and combines inputs into a new set of outputs in one step. The depthwise separable convolution splits this into two layers, a separate layer for filtering and a separate layer for combining. This factorization has the effect of drastically reducing computation and model size. Figure below shows how a standard convolution 1.3a is factorized into a depthwise convolution 1.3b and a 1×1 pointwise convolution 1.3c



(a) Standard Convolution filters



(b) Depth-wise Convolution filters



(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

- **YOLOv3: An Incremental Improvement [5] by Joseph Redmon et. al.,** proposed changes in the original YOLO algorithm. It's a little bigger than the last version of YOLO but more accurate. It's still fast at 320×320 YOLOv3 runs in 22 ms at 28.2 mAP, as accurate as SSD but three times faster. When we look at the old .5 IOU mAP detection metric YOLOv3 is quite good. It achieves 57.9 AP 50 in 51 ms on a Titan X, com- pared to 57.5 AP 50 in 198 ms by RetinaNet, similar perfor- mance but 3.8× faster.

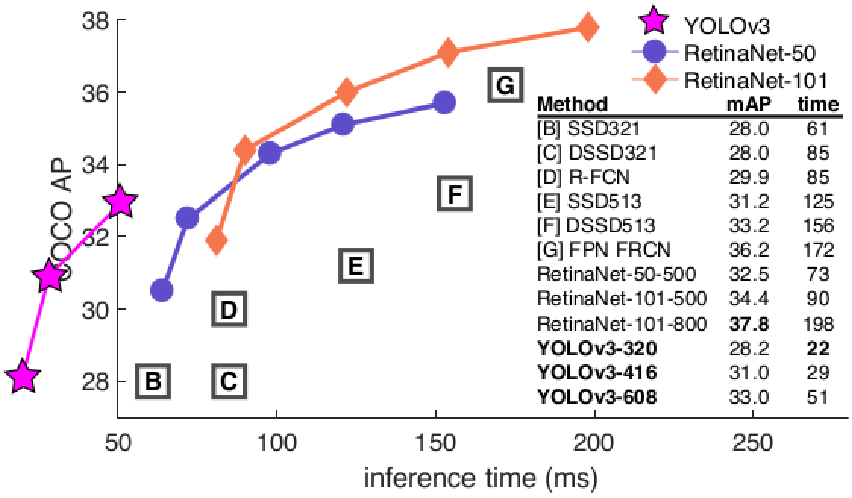


Figure 1.4: Inference time comparison against other algorithms [4]

- **Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks [6] by Shaoqing Ren et. al.,** proposed State-of-the-art object detection networks depend on region proposal algorithms to hypothesize object locations. The authors futher proposedRegion Proposal Network (RPN) that shares full-image convolutional features with the detection network, thus enabling nearly cost-free region proposals. An RPN is a fully convolutional network that simultaneously predicts object bounds and objectness scores at each position. The RPN is trained end-to-end to generate high-quality region proposals, which are used by Fast R-CNN for detection. We further merge RPN and Fast R-CNN into a single network by sharing their convolutional features—using the recently popular terminology of neural networks with "attention" mechanisms, the RPN component tells the unified network where to look.

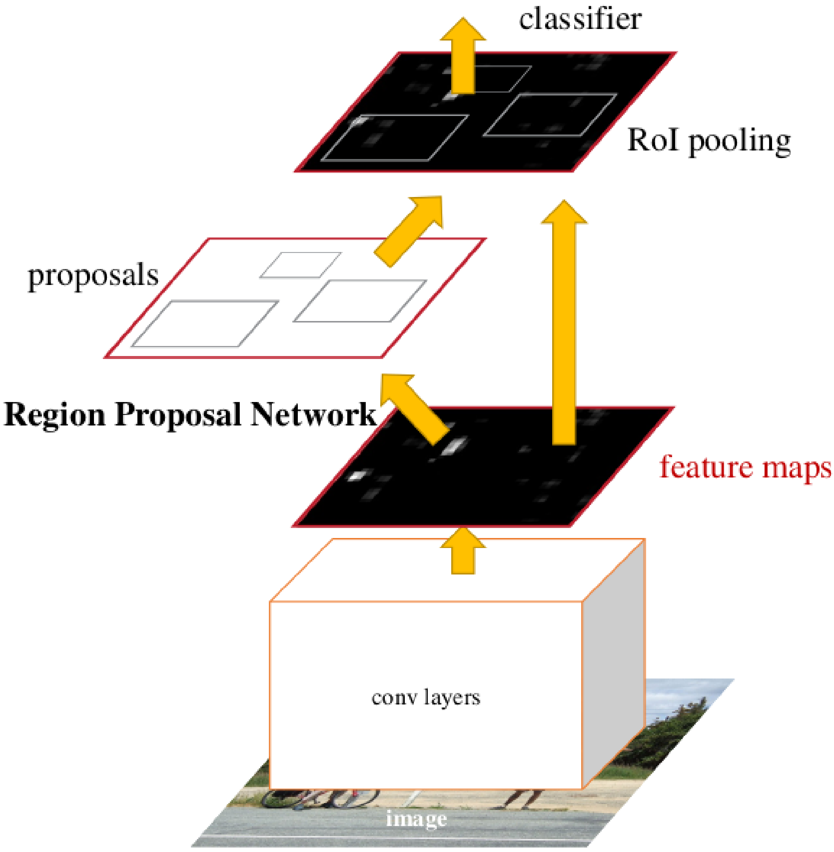


Figure 1.5: Faster-RCNN [6]

1.4 Problem statement

Build an android application with an algorithm that can identify and localize the area of infection and the type of flu, to which the input shall be an image of a chest radiograph.

1.5 Organization of the report

In chapter 1, we breifly discuss over the literature survey, methods, and the overall objectives towards achieving the goal of the problem statement. In chapter 2, we move ahead with the proposed system design, block diagram. Further in chapter 3, we talk more on the proposed design. Results are analysed and discussed over in chapter 4. We then conclude the project in chapter 5 with future scope of the project.

Chapter 2

System Design: Identification and localization of area and type of infection in the chest radiographs

In this chapter, we describe about the proposed system architecture along with the functional block diagram and other details.

2.1 Functional block diagram

Here we describe the block diagram for our proposed methodology.

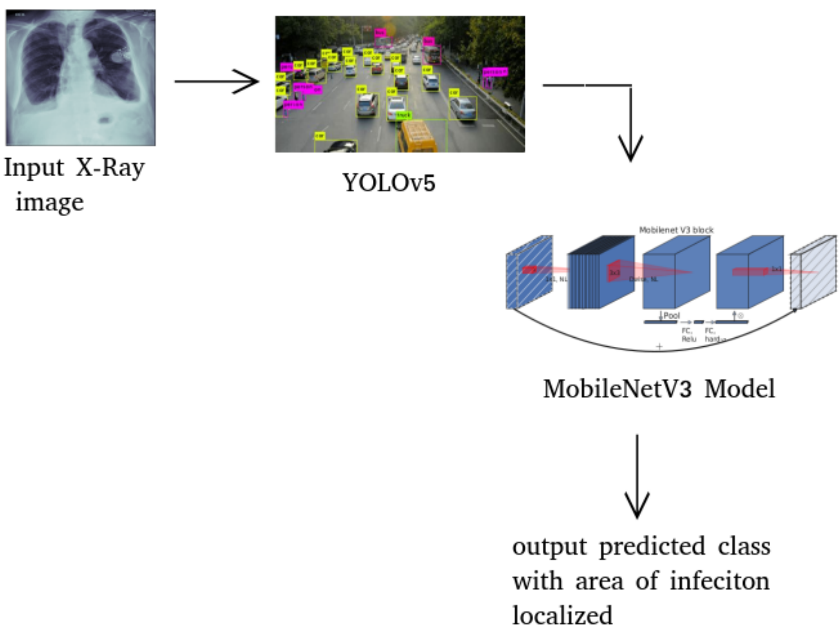


Figure 2.1: Functional block diagram for the proposed design

2.2 Alternate Design Approaches

In this section we throw light on the alternative design approaches towrads acheiving the goals of this project.

- Faster-RCNN: the network was trained on the COVID-19 dataset, but was not as efficient in predicting the bounding boxes.
- YOLOv5: the network was trained on custom dataset, and was found to be more efficient than Faster-RCNN.
- For classification the other alternatives for MobileNetV3 would be EfficientNetB7, Xception, Inception V3. All the networks were trained on the dataset of COVID-19 and evaluated individually. MobileNetV3 was able to classify the input with decent accuracies and was light weight to be ported to Mobile devices while EfficientNetB7 was able to acheive much better results than MobileNetV3, but was not as light weight, hence MobileNetV3 was opted for porting on the edge devices.

Chapter 3

Implementation details

In this section we discuss in detail about the architecture we propose towards Identifying and Localizing the Abnormalities in the Chest Radiograph images.

3.1 Specifications and system architecture

There are several concepts and methodologies used to achieve the goals of the project. We will discuss the same in this section.

- **Dataset Analysis:** The train dataset comprises 6,334 chest scans in DICOM format, which were de-identified to protect patient privacy. All images were labeled by a panel of experienced radiologists for the presence of opacities as well as overall appearance. The total size of the dataset is 120GB. The dataset also contain ground truth labels, along with the bounding box information and other meta data.

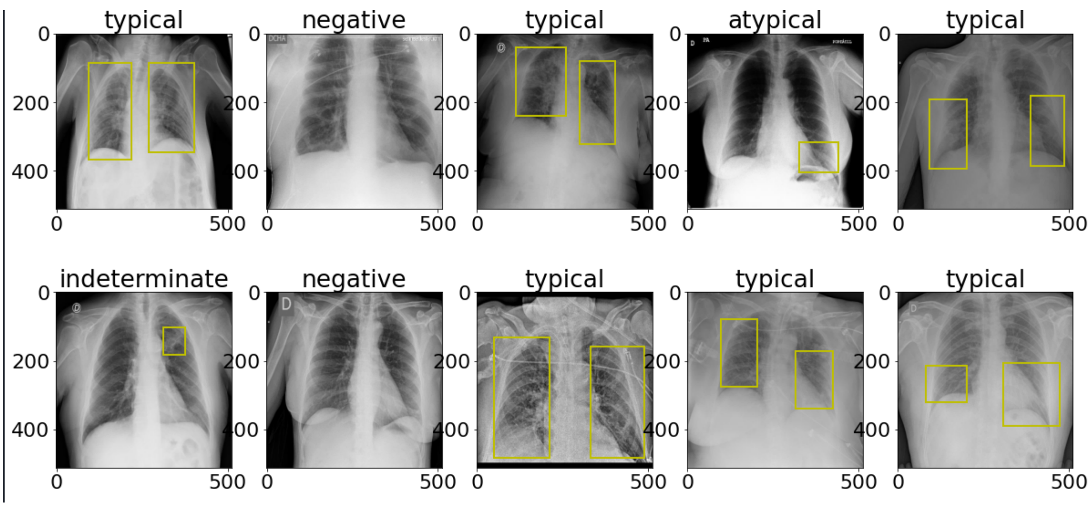


Figure 3.1: Few samples from the dataset

- **Data Pre-processing:** The dataset is highly imbalanced. There are uneven number of samples for each class. We calculated the weights for each class and used weighted losses during the training.

- **Fine Tuning the MobileNetv3[8] Network:** since MobileNetV3 is based on depth-wise convolutions, which are for a fact light weight for mobile applications, but we found that it was not performing well during the initial training phases. Since the classes in the dataset were highly imbalanced, the model was not learning efficiently. We experimented various things including weighted losses, different epochs and learning rates, but the model was able to acheive a maximun of 79% training accuracy and 77% of classification accuracy.
- **Model Ensembling[9] during training:** Since the performance was not as expected, we tried ensembling five models trained with different configurations, to predict the outputs and later merged the outputs in the output csv file. We performed model ensembling during testing and not training.

3.2 Algorithm for identifying and localizing covid abnormalities in chest radiographs

Algorithm 1: Load Dataset

Result: train, test images loaded
initialization;
while *end of directory* **do**
    read train, test images;
end

Algorithm 2: Data Preprocessing

Result: processed images
initialization;
while *end of images* **do**
    convert images from .dcm to .png;
    resize images;
    initialize data generators;
end

Algorithm 3: Predicting bounding boxes

Result: images with bounding boxes
initialization;
while *end of images* **do**
    predict bounding boxes using YOLOv5;
end

Algorithm 4: Predicting classes

Result: predicted class
initialization;
while *end of images* **do**
    predict classes for each image using MobileNetV3;
end

3.3 Flowchart for identifying and localizing covid abnormalities in chest radiographs

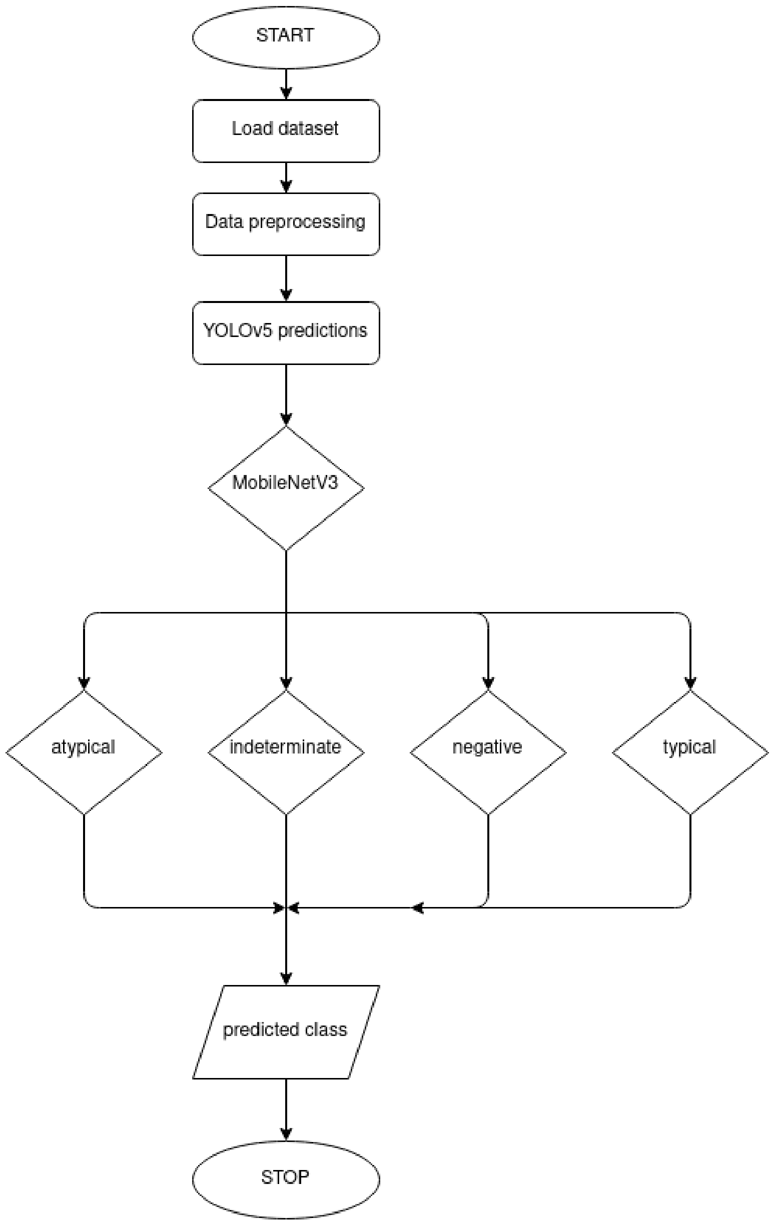


Figure 3.2: working flowchart for the proposed architecture

Chapter 4

Results of the proposed architecture to identify and localize covid abnormalities in chest radiographs

In this chapter we will discuss about the acheived results of the proposed methodlology.

4.1 Result Analysis

4.1.1 Results of YOLOv5

We trained the YOLOv5 network on the dataset of covid-19 radiograph images. We were able to achieve a training accuracy of about 89%

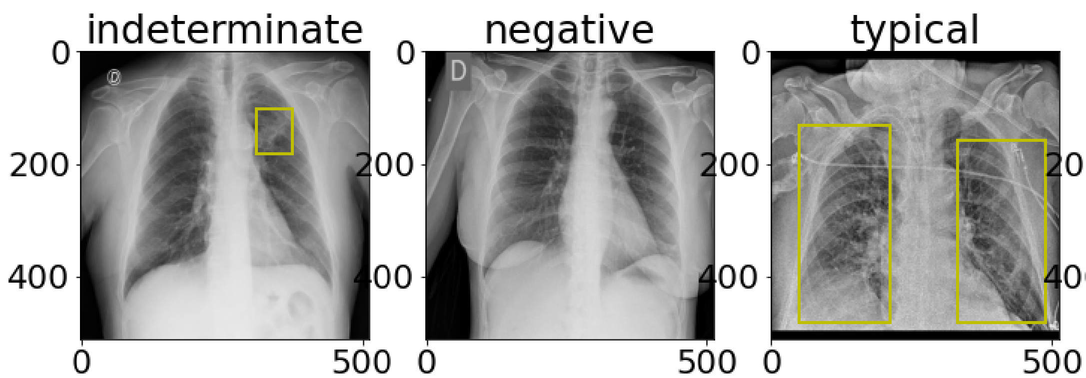


Figure 4.1: few samples of YOLOv5 predicting the bounding boxes for the given images

4.1.2 Results of MobileNetV3 classification

The network was trained on the entire dataset, with training accuracy of 79% and classification accuracy of 77%

4.1.3 Results of Android Application

The trained models were converted to TensorFlow Lite, which is suitable for porting neural networks onto edge devices. Note that five models were ensembled during the testing phase, but only one model with the best accuracies was ported onto the android application to reduce computational expenses. The prediction results are shown in figure below.

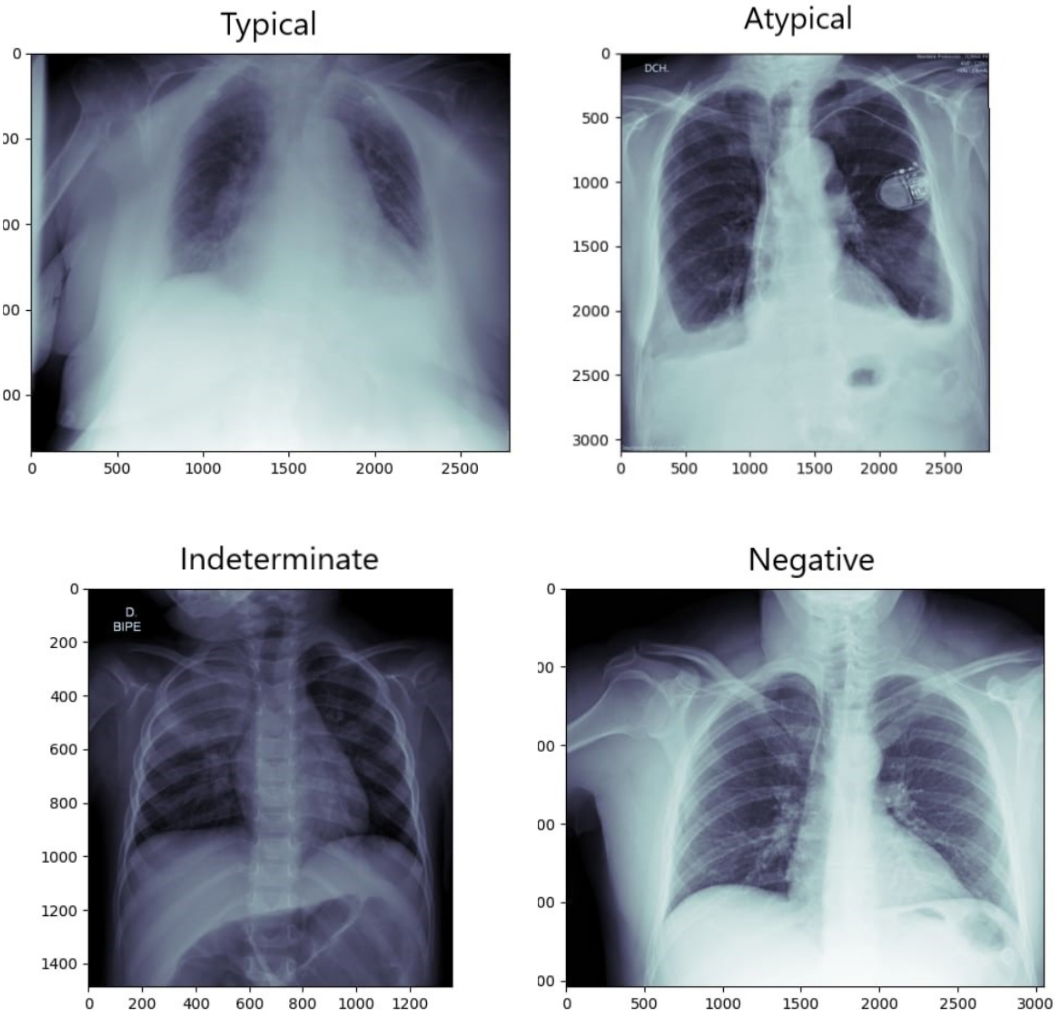


Figure 4.2: Ground Truth images, and their corresponding class labels

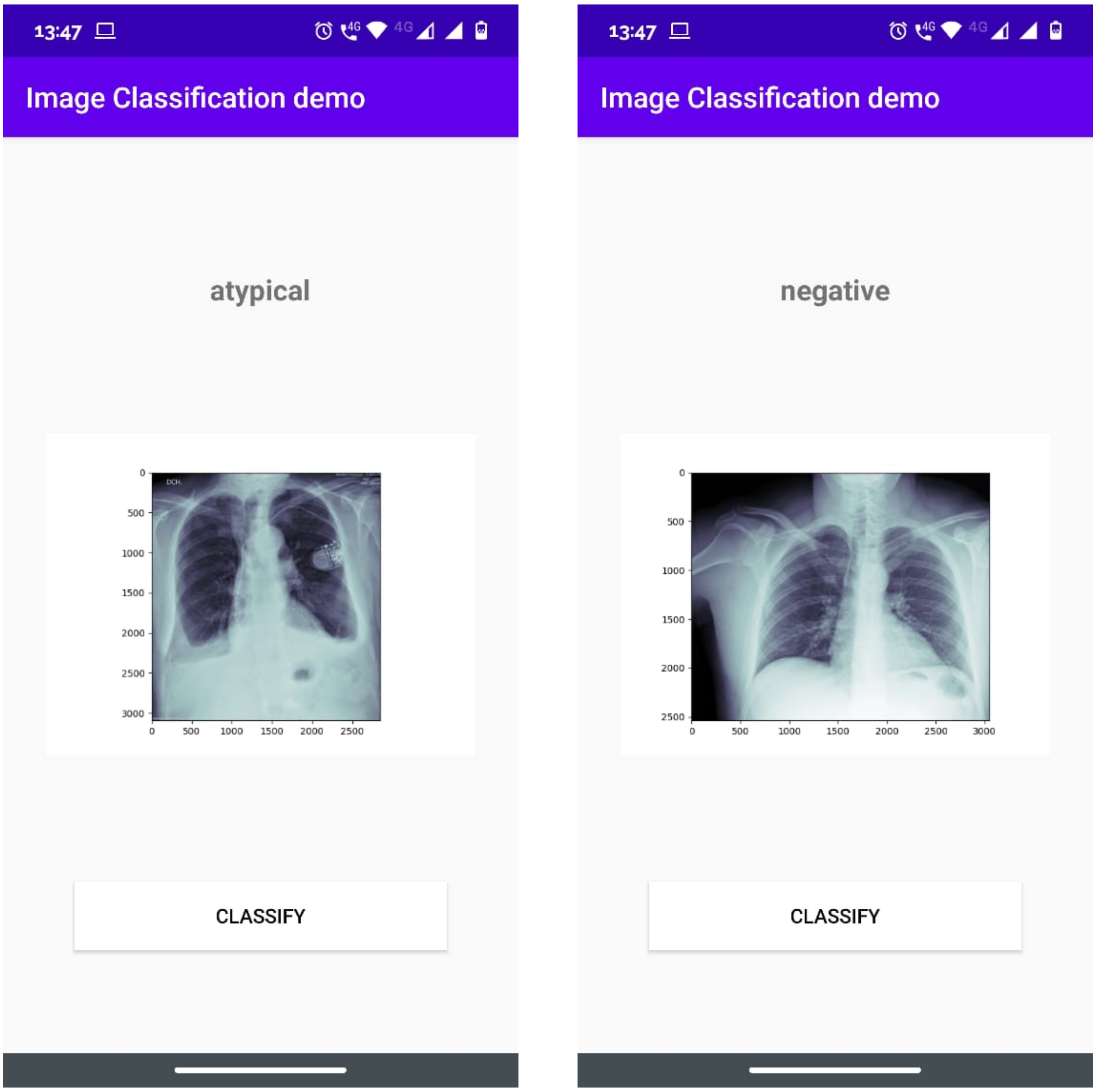


Figure 4.3: Atypical and Negative predicted as Atypical and Negative

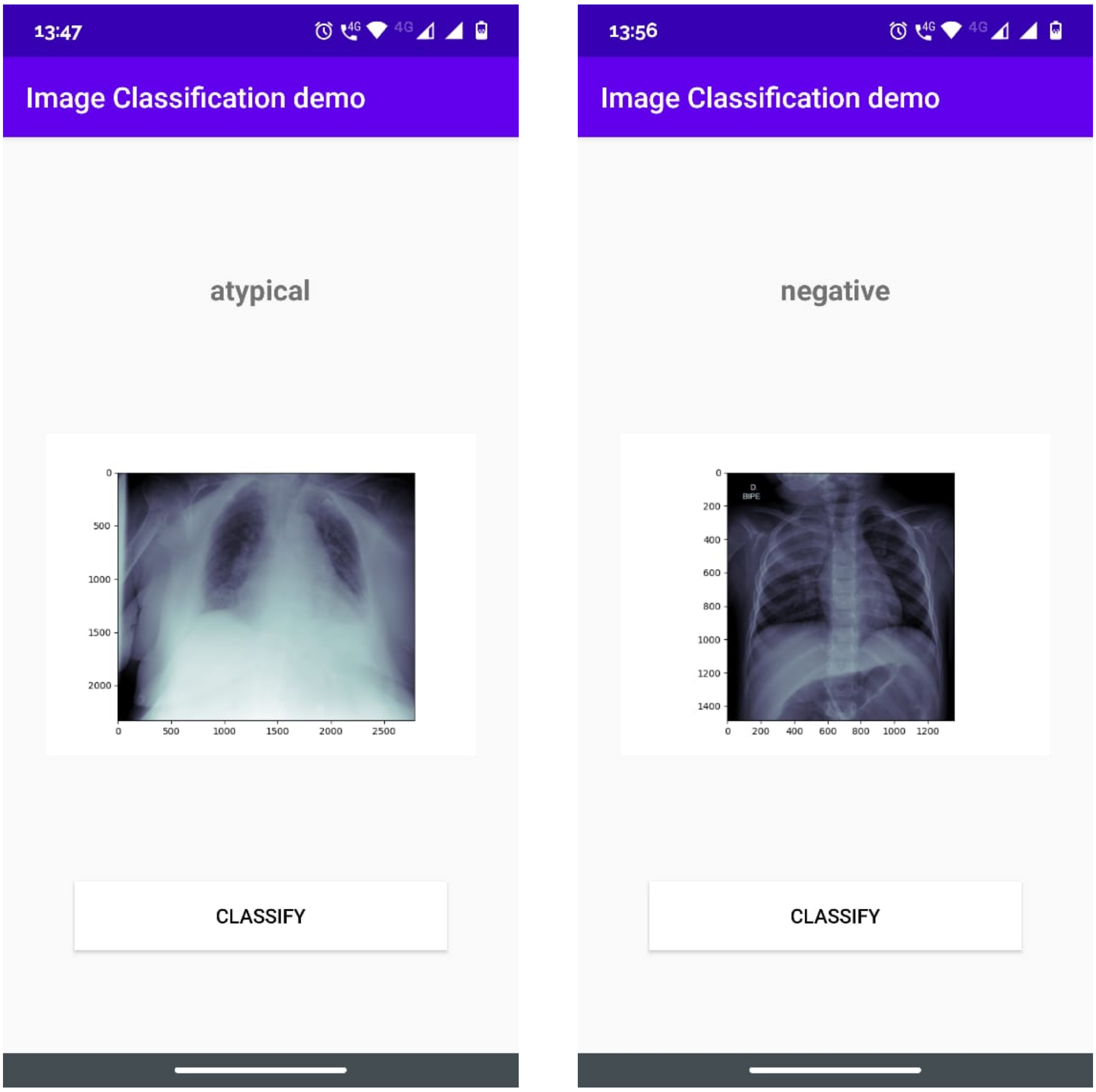


Figure 4.4: Atypical and Negative predicted as Atypical and Negative

Chapter 5

Conclusions and future scope

5.1 Conclusion

The architecture proposed was able to localize and classify the abnormalities in the chest radiographs. However, since the dataset was highly imbalanced, we could not unlock the full potential of the networks.

5.2 Future scope

The performance can be improved by using other better networks like EfficientNetB7[7] or ResNets.

5.2.1 Application in the societal context

The developed model is deployed onto Android platform which can be very convinient to remotely classify abnormalities in the radiographs of chest, for easy and quick diagnosis.

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