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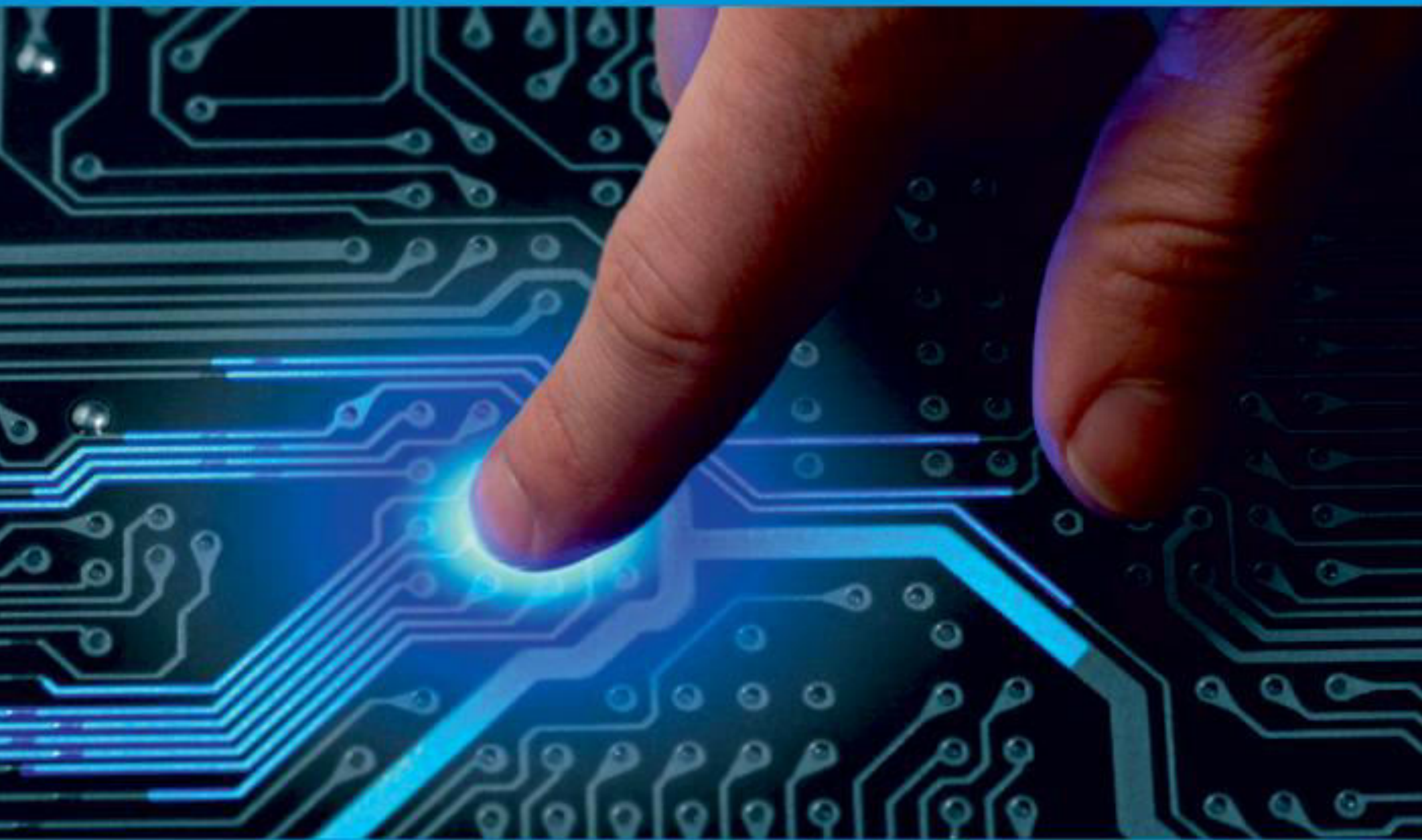

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Detection of Tuberculosis using CNN

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ABSTRACT: This paper explores the usefulness of transfer learning on medical imaging for tuberculosis detection. We show an improved method for transfer learning over the regular method of using ImageNet weights. We also discover that the low-level features from ImageNet weights are not useful for imaging tasks for modalities like X-rays and also propose a new method for obtaining low level features by training the models in a multiclass multilabel scenario. This results in an improved performance in the classification of tuberculosis as opposed to training from a randomly initialized settings. In other words, we have proposed a better way for training in a data constrained setting such as the healthcare sector.

KEYWORDS: Tuberculosis, Detection, Classification, X-Rays, Transfer Learning, Deep Learning, Medical Imaging.

I. INTRODUCTION

Tuberculosis primarily affects the lungs as a bacterial disease. It is a curable and preventable disease affecting developing nations and is one among the top ten causes of death worldwide. Early recognition and management of tuberculosis is very important both in terms of reducing cost of treatment and improving health outcomes [1]. From this, it can be seen that the magnitude of the problem is such that World Health Organization has a separate End TB strategy with the objective of reducing TB related death rates by 95% and TB incidence by 90% before 2035 [2]. In the detection of tuberculosis, there are two pathways that are relevant. One is the patient-initiated pathway where improved awareness of symptoms among people can help early detection and the second pathway being the screening pathway where low cost screenings are required to be systematically done in patient populations of high risk [3]. In the screening process, medical imaging plays a significant role. Chest X-rays are useful in non-invasive diagnosis and screening tools [4]. Tuberculosis is important to be tackled at a global level and is also important for meeting the United Nations sustainable development goals and is of great importance to developing nations as they affect mainly the working population. The development of medical imaging techniques and algorithms for tuberculosis detection is hence of great importance– as the reduction in incidence of tuberculosis and its elimination in turn reduces global poverty and improves healthcare outcomes for people of developing nations. For our work, we seek to look at tuberculosis detection for the large-scale screening from chest X-rays. The systems developed would be able to help in multiple ways. Primarily, by detecting the percentage chance of tuberculosis given a chest X- Ray, it would be possible to determine if more in depth tests are required for the confirmation of the disease. The visualisation makes the models more interpretable and reduces the clinician's overall workload and thereby is useful as a good augmentation strategy in developing nations where healthcare professionals are few in number and stretched on resources.

II. RELATED WORK

In our experiments we primarily use datasets that're accessible, to the public. The following are the datasets being considered Montgomery and Shenzhen datasets [5] and NIH-14 dataset [6] hospital-scale chest x-ray database and benchmarks on weakly- supervised classification and localization of common thorax diseases. Shenzhen dataset [7] consists of chest X-rays taken from Shenzhen No. 3 Peoples Hospital which are 4020 4892 pixels in dimension. Montgomery dataset consists of frontal chest X rays taken from the Department of Health and Human Services in partnership with Montgomery County in the United States. These were taken for the purpose of screening of tuberculosis and is similar in dimension to Shenzhen dataset. For the purpose of the transfer learning experiments we have taken NIH-14 dataset [6] which is a collection of chest X-rays from clinical PACS databases coming under the National Institutes of Health Clinical Centre. It consists of 112,120 chest X-ray images with labels consisting of 14 common chest pathologies. These do not include tuberculosis as a label and is useful for learning the lower level features while transfer learning is done. Jaeger and colleagues (2015) identified characteristics from segmented lung X rays. Utilized various classification techniques to evaluate these traits. In a study, Rajpurkar and team (2018) demonstrated that the NIH 14 dataset could be approached as a classification challenge offering strategies, for applying deep convolutional networks to address the issue.

Additionally, Hwang et al. (2019) have conducted research using the Shenzhen dataset. The effectiveness of class activation maps (CAMs) for visualizing networks was highlighted in a study, by another group (Smith et al., 2020) For the purpose of training, we have augmented the datasets in a manner that is consistent to the ways in which an X-Ray maybe distorted. Rotations, horizontal flipping and perspective transforms are used as augmentation strategies which mirror the real-world scenarios of image flipping, image skew and f lipping which occur while scanning of X-rays. A simple rescaling operation is

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done before feeding to the neural networks to bring the images in the numerical range zero to one. Even though they tried using Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the contrast it didn't actually lead to any improvements, in the results they got.

III. METHODOLOGY

For the detection of tuberculosis, the task is considered to be a binary classification task with the final layer giving the probability that the given X-rays image has tuberculosis. The given set of experiments must deal with answering the following – the effectiveness of using ImageNet weights for transfer learning and methods to improve that performance using pre-trained models. Since the final aim is to develop a system that can be deployable and can be generalized in a much broader sense, in addition to the above, we need to also look at the ideal architectures that can be used, the elements within architectures that are detrimental to the performance for the given task, the selection of loss function such that it can be used for a variety of diseases and finally make the models interpretable for clinical use. The pipeline of the experiments is showed in Figure.

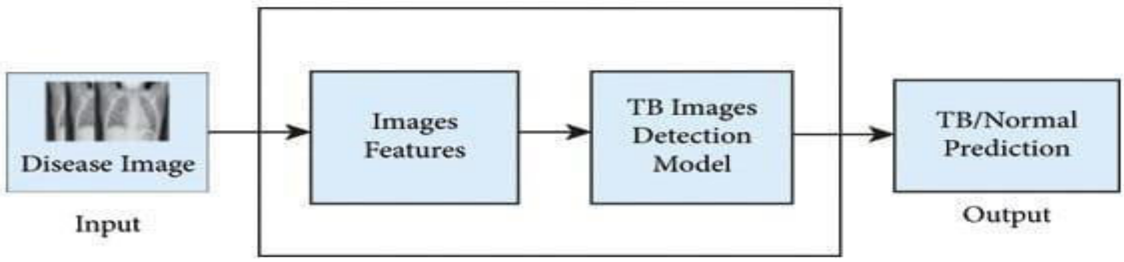

Fig. 1. Workflow diagram of the TB or Normal Image Detection

IV. PROPOSED METHODOLOGY

A proposed system for tuberculosis detection using X-ray images typically involves the application of artificial intelligence and image processing techniques. Here's an overview of how such a system could work:

1. Data Collection: Gather a large dataset of chest X-ray images from patients, including both TB-positive and TB-negative cases. These images should be labeled for training and validation.
2. Preprocessing: Clean and preprocess the X-ray images to enhance their quality and remove any noise. This may involve techniques like resizing, noise reduction, and contrast adjustment.
3. Image Feature Extraction: Extract relevant features from the X-ray images, which could include lung texture, shape, and other characteristics that may indicate the presence .

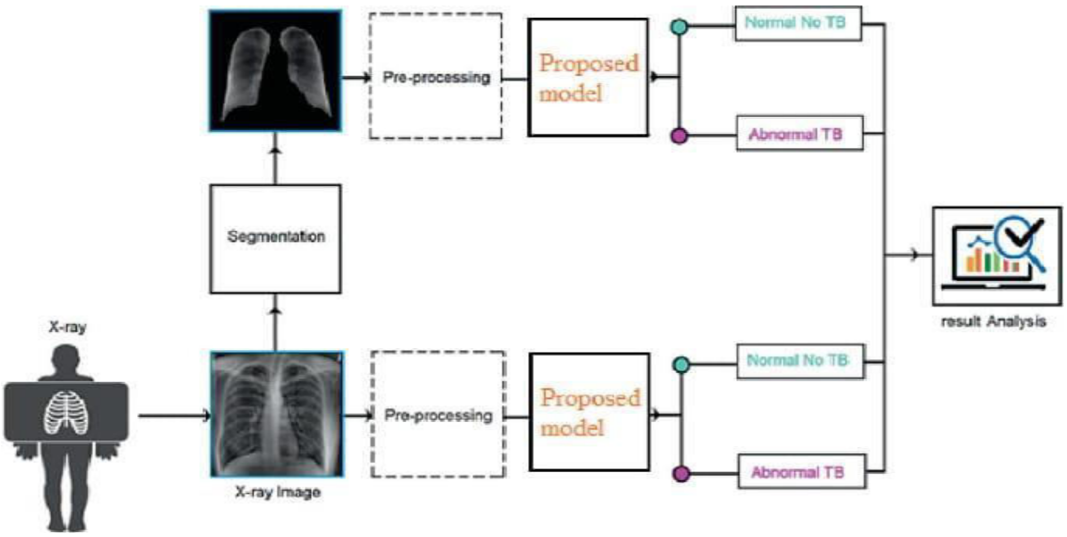

Fig. 2. Block Diagram of the proposed TB Detection System

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V. SIMULATION RESULTS

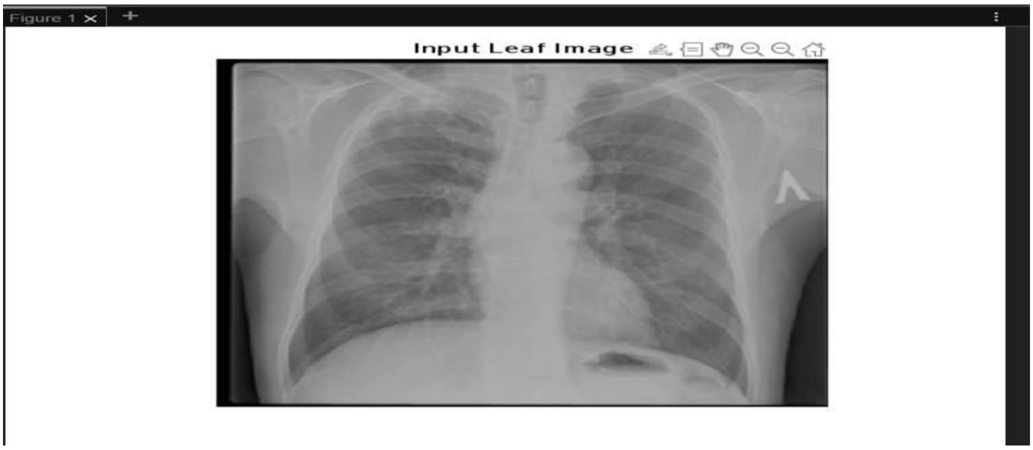
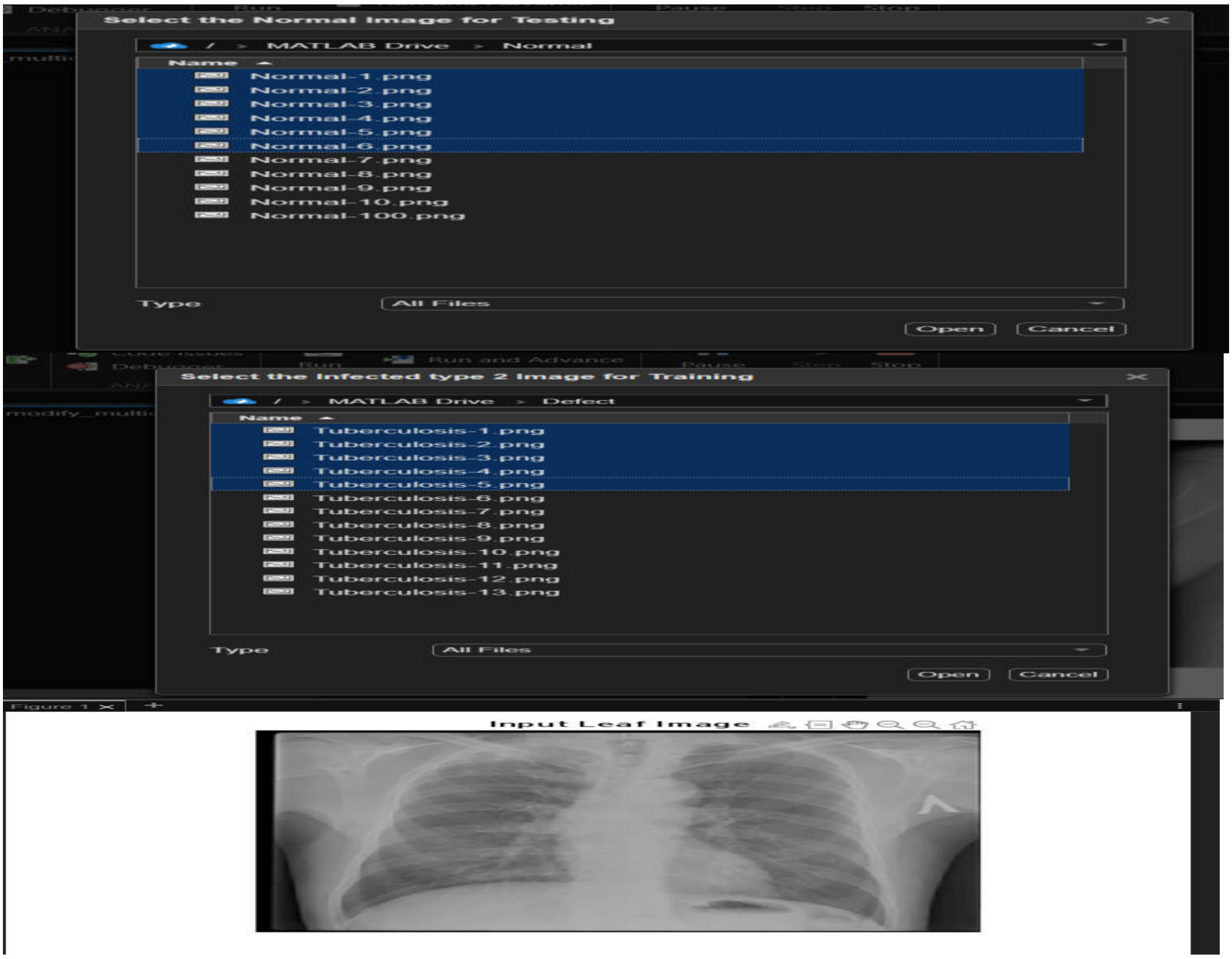


Fig. 3. Output of the TB Detection System

In order to obtain insights from the model, heatmaps were generated using class activations mappings (CAMs) to visualise the regions of the image that has the greatest resemblance of the disease [9]. To generate the CAMs (Figures 3 and 4), an image was input into the fully trained model to extract the feature maps which are then produced by the final convolutional layer. Global Average Pooling in the final feature maps helps us to focus on localization of relevant features and is expressed as class activation map. The pipeline is showed in Fig 2.

OUTPUT:



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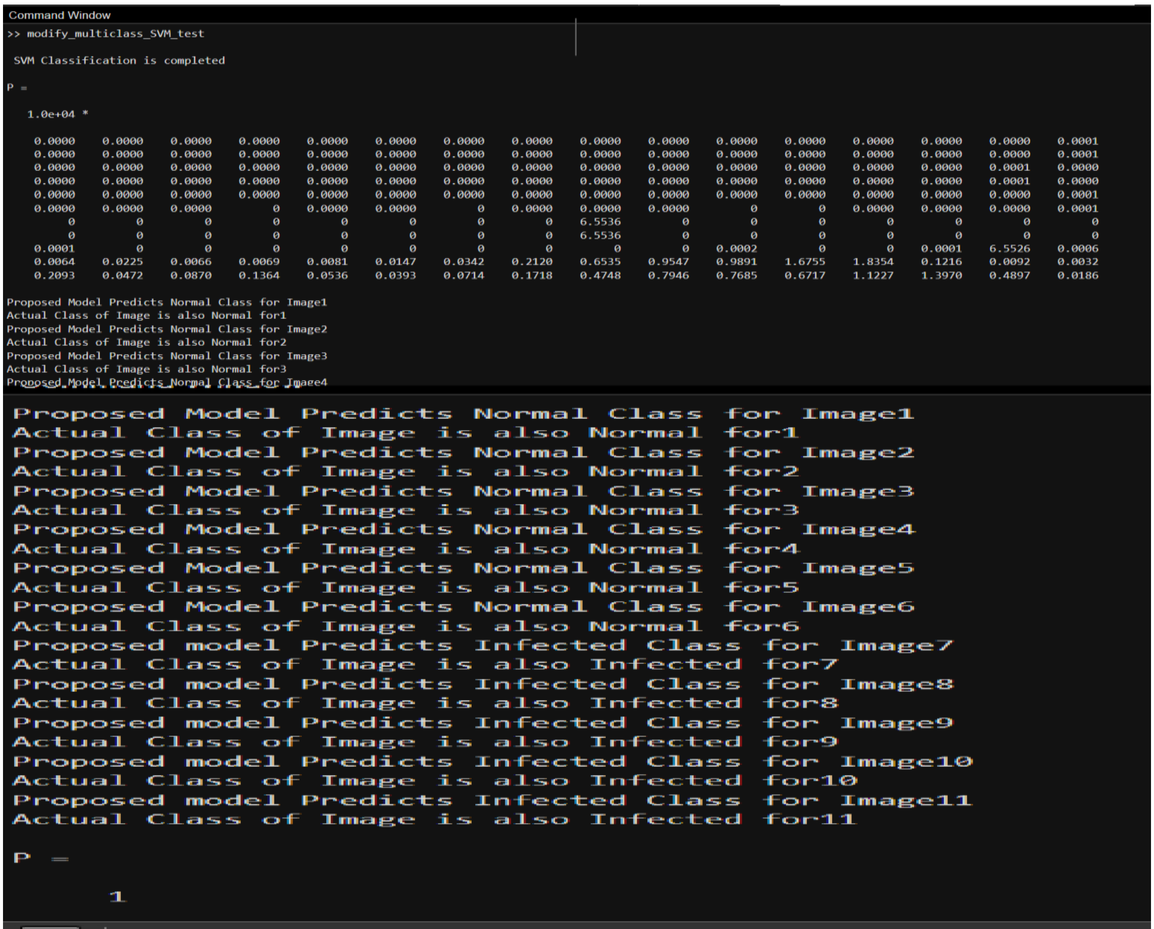

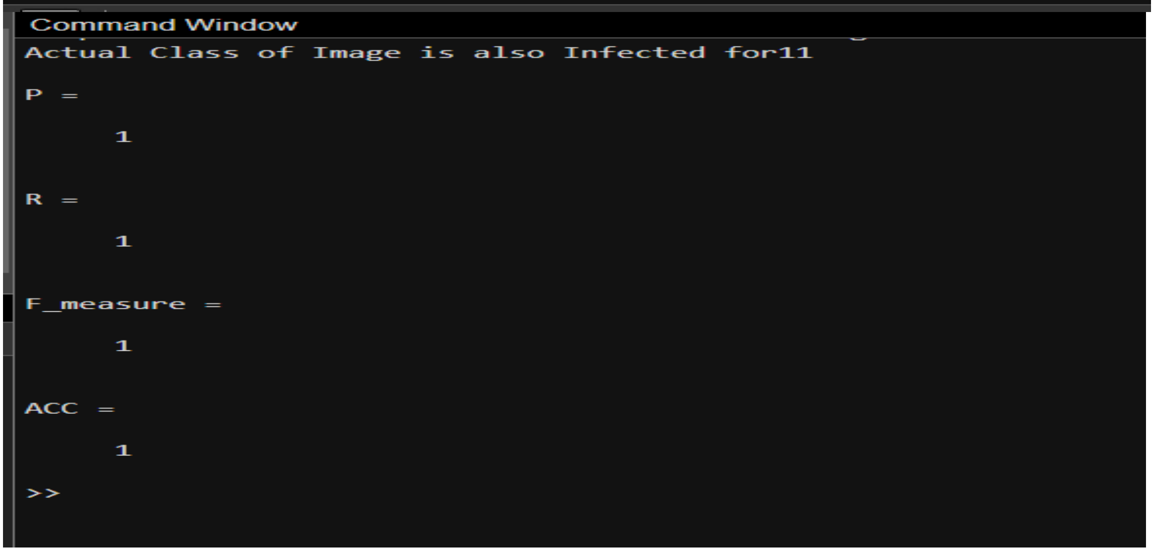

VI. CONCLUSION AND FUTURE WORK

The experiments help understand the nature of transfer learning strategies to be used for medical images. In the process, we also develop an application for screening of patients for tuberculosis and have presented a demo consistent with problem statement presented and with appropriate visualisations. We have also suggested the ideal architectures that can be used and the elements that should be avoided to get better generalization. We show that the ImageNet weights are insufficient and the usage of appropriate data for pre-training is important and makes the entire process more efficient. There can be multiple areas in which this work may be taken forward. One obvious question to be answered is how well the system would perform against human counterparts. A human benchmarking against several of these datasets is required to see both the individual performance and the agreement between various

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clinicians. From inputs of healthcare professionals, we understand that tuberculosis detection is not just limited to examination of X-rays, but can also take as input various things like patient history, lab reports and tests etc. which help improve the final prediction. An interesting area of research would be to combine these sources together and come up with an interpretable model which would make use of clinical inputs as well as the image data. Another way that may improve the performance of the system is applying ensemble learning with different classification algorithms, such as, the support vector machines, random forests, enhanced k-nearest neighbours [14], and kernel dictionary learning [15], on the features at the last fully-connected layer. Solving the spread and incidence of tuberculosis is one which can give great rewards to developing nations. Though the problem has not been that well studied due to lack of financial motivations for private players, the release of new public datasets has helped in recent years to put this as a prominent research problem.

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