1. PROJECT REFERENCE NUMBER: 46S_BE_3938

2. TITLE: Fast and Reliable Deep Learning Method to Classify Covid- 19, Pneumonia, and Tuberculosis using Human Chest X-Ray Images

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6. Keywords: Covid-19, Tuberculosis, Pneumonia, MobileNetV2, InceptionV3, Deep Learning Models, Multi-class classification.

6. INTRODUCTION

Deep Learning – which has emerged as an effective tool for analyzing big data – uses complex algorithms and artificial neural networks to train machines or computers so that they can learn from experience, classify, and recognize data/images just like a human brain does. Within Deep Learning, a Convolutional Neural Network(CNN) is a type of artificial neural network, which is widely used for image/object recognition and classification.

The COVID-19 epidemic has a catastrophic impact on global well-being and public health. More than 27 million confirmed cases have been reported worldwide until now. Due to the growing number of confirmed cases, and challenges to the variations of the COVID-19, timely and accurate classification of healthy and infected patients is essential to control and treat COVID-19. We aim to develop a deep learning-based system for the persuasive classification and reliable detection of COVID-19 using human chest X-Ray images.

7. OBJECTIVES

1. To design computer aided detection System that ensure healthy lives.
2. To design system that overcome the false diagnosis of COVID-19 disease using RT PCR.
3. To develop model that overcome the challenges faced by radiologists in differentiating COVID-19 from other ACUTE RESPIRATORY DISTRESS SYNDROME (ARDS) like Pneumonia and Tuberculosis .
4. Covid-19, Pneumonia and Tuberculosis are associated with a lung infection and visually they are very similar. Therefore, a robust Covid-19 identification approach should distinguishable from Pneumonia and Tuberculosis detection system.
5. Deep learning models can be clinically adoptable by radiologists and hospitals. It provides timely assistance and accurate results.

8. METHODOLOGY

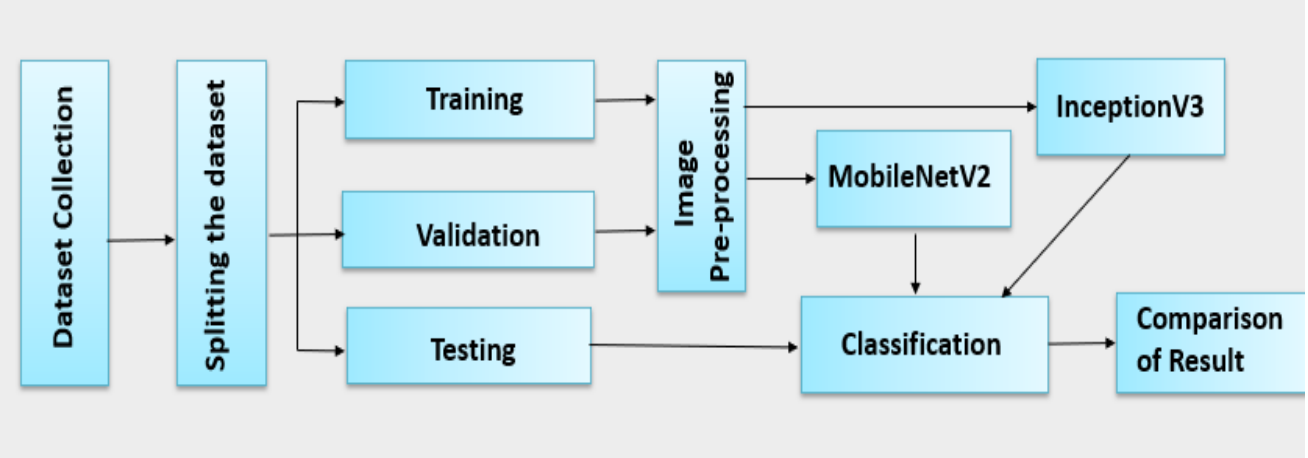

Fig-1 Proposed System Model

The dataset was collected from Kaggle and has 1850 X-ray images which includes Covid-19, Pneumonia, Tuberculosis and Normal chest X-Rays. The normal chest X-Ray depicts clear lungs without any areas of abnormal opacification in the image. The collected chest X-Ray image samples are partitioned into Training, Validation and Testing to ease a model's training process. The training and validation data go through the image pre-processing stage to filter out irrelevant samples and enhance the quality of the samples. The pretrained model was trained with the prepared dataset (Training data and Validation data),iterated over the training data in batches,passing the input samples through the model,training process was monitored by using validation data and hyperparameters are adjusted as needed. After training the model's performance has been evaluated on a separate test dataset to assess its capability. Cross-validation implemented using stratified sampling ensures that the proportion of the feature of interest is the same across the original data, training set and the test set.

Dataset description:

The dataset used for this study consisted of a large collection of chest X-ray images obtained from patients diagnosed with COVID-19, Normal lungs, Pneumonia, and Tuberculosis. The dataset was divided into training, validation, and testing sets, ensuring a balanced distribution of samples across all classes.

Classes	Label_name	Number of images
0	Normal	197
1	Covid	780
2	Pneumonia	698
3	Tuberculosis	175

Table-1 Dataset description table

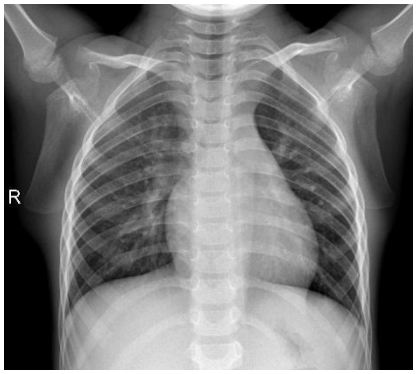

Fig-2 NORMAL CHEST X-RAY

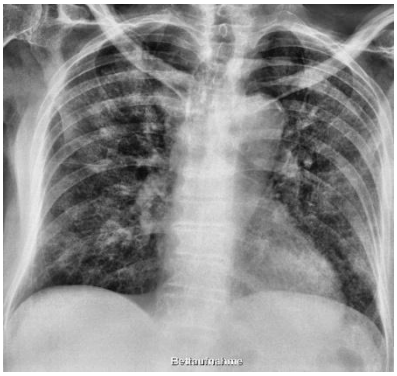

Fig-3 COVID-19 CHEST X-RAY

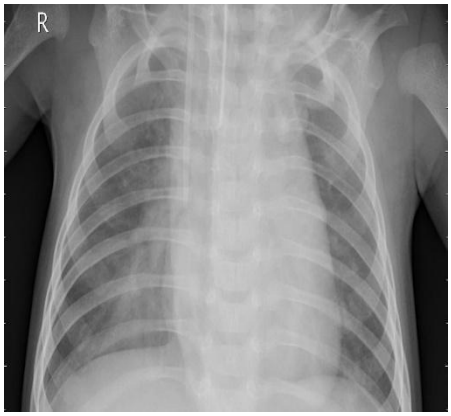

Fig-4 PNEUMONIA CHEST X-RAY

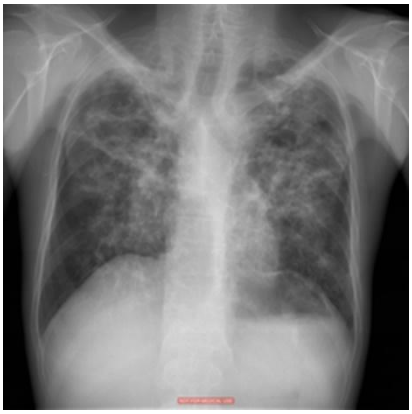

Fig-5 TUBERCULOSIS CHEST X-RAY

MobileNetV2:

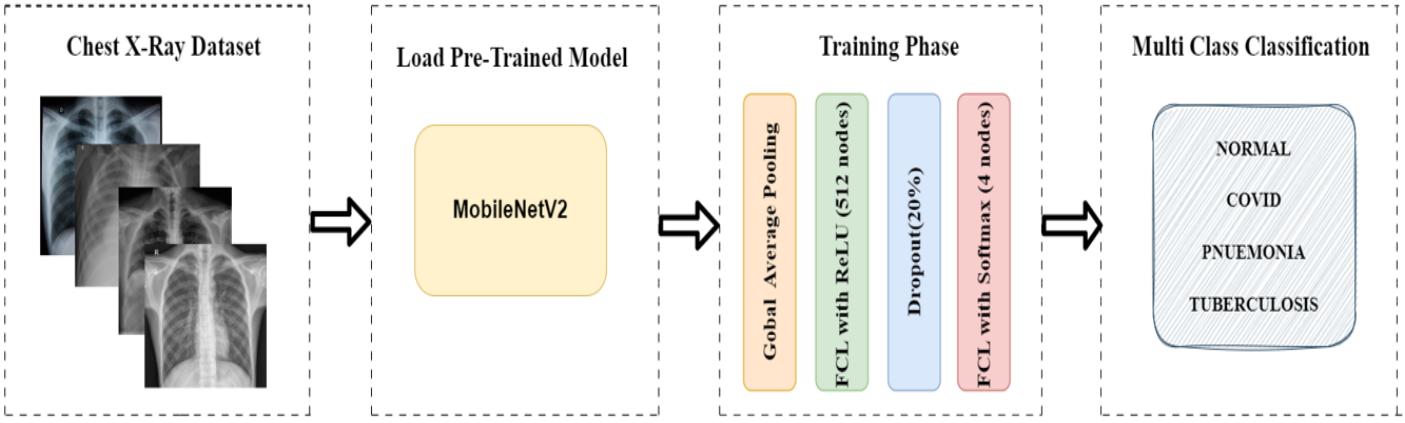

Fig-6 Architecture of MobileNetV2

It builds upon the concepts of depth wise separable convolutions and bottleneck structures from the original MobileNet, while incorporating additional design choices to further enhance performance. It consists of inverted residual blocks which reduces the number of input channels and performs dimensionality reduction and it has depthwise separable convolution that applies depthwise

convolutions to capture spatial information and pointwise convolutions to restore the channel dimensions. It has feature maps which provide low-level and high-level representations. MobileNetV2 introduces expansion and squeezing operations in the bottleneck layers. Expansion increases the number of channels before applying depthwise convolutions, while squeezing reduces the number of channels before the bottleneck layers. It maintains a good balance between model complexity and efficiency.

INCEPTIONV3:

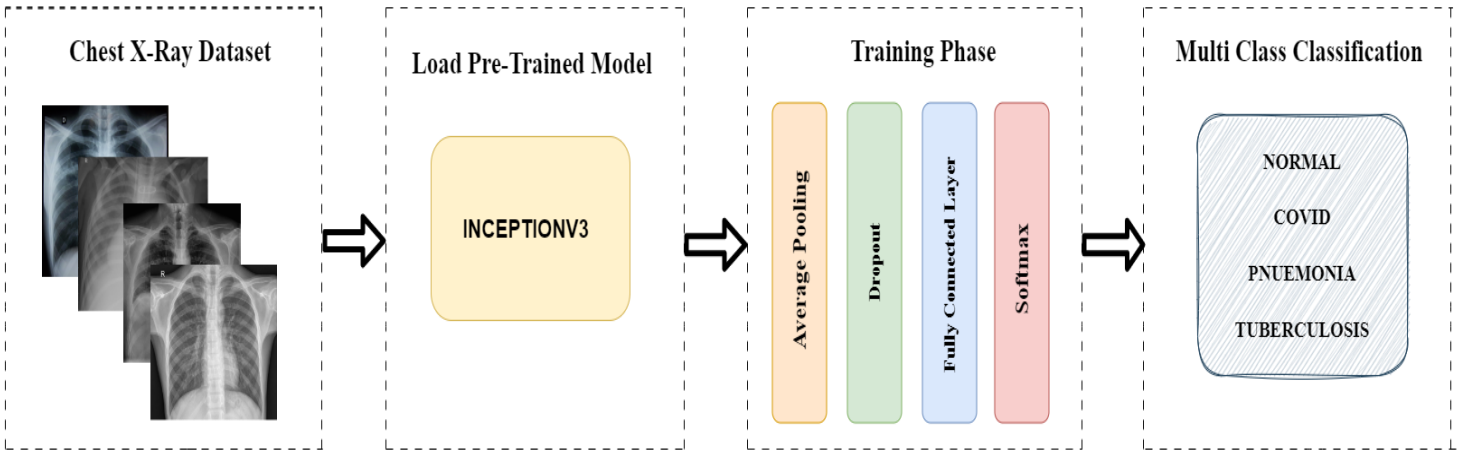

Fig-7 Architecture of InceptionV3

InceptionV3, with its deep convolutional neural network architecture, offers several key features that contribute to its performance and accuracy in computer vision tasks. It consists of inception modules which have parallel branches with different filter sizes. Auxiliary classifiers help combat the vanishing gradient problem during training by providing additional gradients. InceptionV3 can be adapted and fine-tuned on specific tasks or datasets with limited training data, saving time and resources while achieving good performance. InceptionV3 incorporates grid reduction modules at certain points in the network. These modules aim to reduce the spatial dimensions of feature maps while increasing the number of channels. InceptionV3 is known for its ability to capture both local and global features in images.

9. RESULTS AND CONCLUSION:

We aimed to classify medical images into four classes: Normal, COVID-19, Pneumonia, and Tuberculosis. We utilized two popular convolutional neural network (CNN) architectures, namely InceptionV3 and MobileNetV2, for the classification task.

Experimental Results:

After training the models on the dataset, we evaluated their performance on the testing set. The results obtained were as follows:

- InceptionV3 achieved an accuracy of 94.56% in classifying the images. This indicates that the model correctly predicted the class label for 94.56% of the test samples. The precision, recall, and F1-score are detailed in Table-2 below.
- MobileNetV2 outperformed InceptionV3, achieving an accuracy of 96.19%. This indicates that the model accurately predicted the class label for 96.19% of the test samples. The precision, recall, and F1-score are presented in Table-2 below.

METRICS	INCEPTIONV3	MOBILENETV3
Accuracy	94.565%	96.195%
Precision	94.446%	96.277%
F1-Score	94.328%	96.229%

Table-2 Comparison results of models

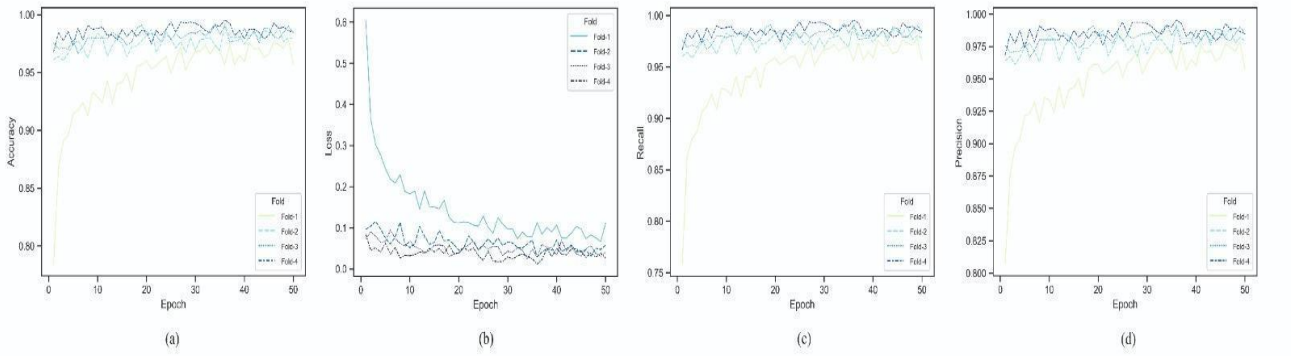

Fig. 8 is shown the InceptionV3 model performance on the validation data using Stratified K-Fold Cross validation for 4 fold. (a) accuracy graph, (b) loss graph, (c) Recall graph, (d) Precision graph.

The validation loss of InceptionV3 model is approximately zero, which indicate results of experiment overcome overfitting problem, Figure 8 illustrates the training and validation loss and it is observed graphs that difference in training and validation loss is very small.

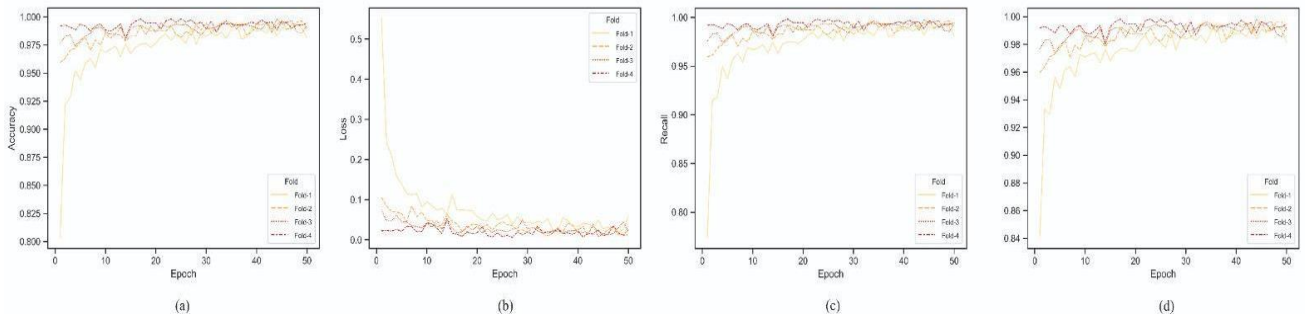

Fig-9 is shown the MobileNetV2 model performance on the validation data using Stratified K-Fold Cross validation for 4 fold. (a) accuracy graph, (b) loss graph, (c) Recall graph, (d) Precision graph.

Figure 9 shows validation loss and accuracy of MobileNetV2 model and it is approximately zero, which indicate results of experiment overcome overfitting problem,

Figure 10 depicts the confusion matrix for the InceptionV3.The first row corresponds to the Normal class. Out of 39 instances of Normal, the model correctly classified 26, while 13 instances were misclassified as Pneumonia.The model correctly identified all 155 instances as COVID-19, with no false positives or false negatives.The third row corresponds to Pneumonia. The model correctly classified 134 instances as Pneumonia. However, it misclassified 4 instances of COVID-19 as Pneumonia.The fourth row represents Tuberculosis. The model correctly classified 33 instances as Tuberculosis, but misclassified 2 instances as Pneumonia.

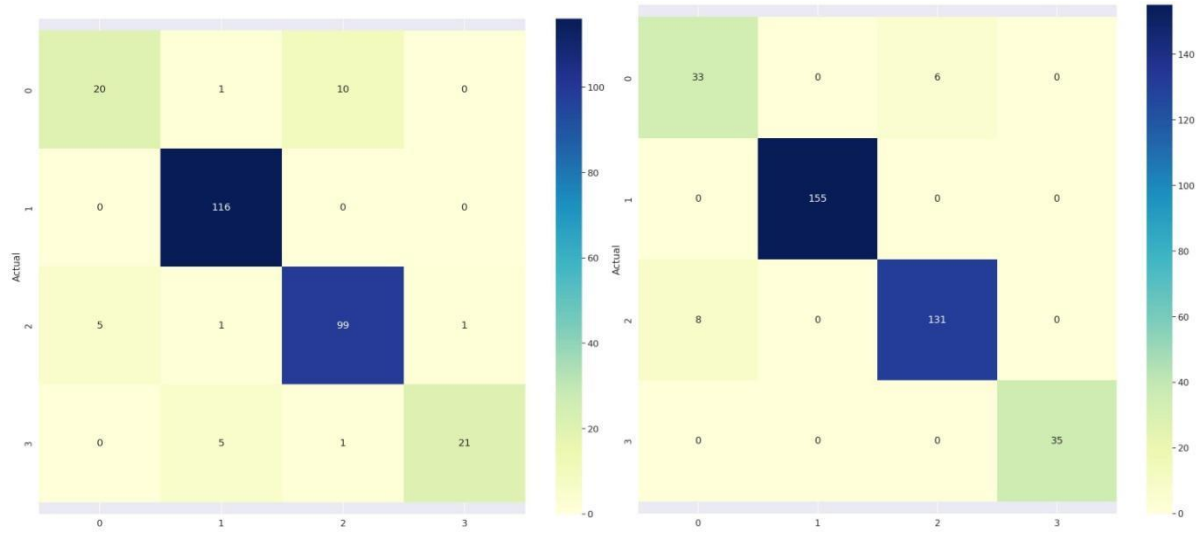

Fig-10 Confusion matrix of InceptionV3

Fig-11 Confusion Matrix of MobileNetV2

Figure 11 describes that the MobileNetV2 model accurately identified 33 out of 39 Normal cases while 6 instances were misclassified as Pneumonia.The model correctly identified all 155 instances as COVID-19, with no false positives or false negatives. Whereas it accurately identified 131 out of 139 Pneumonia cases but misclassified 8 Pneumonia cases as Tuberculosis. The model correctly classified all 35 Tuberculosis cases with no false positives or false negatives.

The results indicate that both InceptionV3 and MobileNetV2 models performed well in classifying the chest X-ray images into the target categories. However, MobileNetV2 exhibited higher accuracy, surpassing InceptionV3 by a significant margin.

In conclusion, the comparative analysis demonstrates that MobileNetV2 outperformed InceptionV3 in the classification of COVID-19, Normal, Pneumonia, and Tuberculosis from chest X-ray images. The higher accuracy achieved by MobileNetV2 highlights its effectiveness in extracting meaningful features and making accurate predictions. These findings suggest that MobileNetV2 can be a preferred choice for similar classification tasks in medical imaging applications.

10. SCOPE OF FUTURE WORK

1. In the future, we hope to acquire more datasets and to train the images using other pretrained deeper neural networks.

2. Classification of COVID-19 variants.

3. In this approach we implemented the classification of ARDS, we will try to implement localization that is to identify the infected regions and lesions.

4. With the relative amount of data, a cross validation approach can be carried out to evaluate the performance of the model.