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Medical Image Analysis Using Transfer Learning

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ABSTRACT
Medical image analysis using transfer learning being the foundation of this project, showcases a machine learning technique that saves time and resources in classifying lung diseases. It entails refining an already trained model to classify and extract features from images. initially trained on a diverse dataset. Instead of starting from scratch for each new image classification task, practitioners can fine-tune the pre-trained model for specific applications. We yielded an initial accuracy of 81% through Inception V3 and ResNet models after which with ongoing efforts dedicated; we received better results which reached a remarkable accuracy of 96% on DenseNet121 model.The abstract encapsulates the essence of transfer learning as a dynamic tool amplifying model accuracy and efficiency, exemplified in our pursuit of excellence within the intricate landscape of lung disease detection. This study explores the transformative capability of transfer learning, shaping the future in image analysis for a context to Pre- trained CNN models for specific applications.
KEYWORDS: Accuracy, CNN models, Datasets, DenseNet121, Feature extraction, Features, Medical Image Analysis, Image Classification, Image Net, Inception V3, Pre-trained model, ResNet, Transfer learning

I. INTRODUCTION

In today's technologically fast-paced world the concept of CNN Models and Transfer Learning plays an important role in the sector of medical diagnosis and imaging, highlighting their advantages in accuracy and resource efficiency. It addresses challenges like data diversity and model interpretability, while suggesting future research directions. Ultimately, it underscores the scope in the concept of CNN models and transfer learning to revolutionize medical diagnosis, emphasizing the need for ongoing development to overcome current limitations. The project's primary focus revolves around addressing the scarcity of extensive medical image datasets suitable for training deep neural networks effectively. It aims to develop training methodologies utilizing a diverse aggregated medical image dataset, with the goal of extracting broadly applicable medical features that can enhance performance in analyzing lung diseases.In a broader context, medical image analysis encompasses important processes like object detection, classification of images,segmentation, and description, all which play integral roles in various applications like medical diagnosis, self-driving cars, and security systems. The increasing demand for accurate and efficient image analysis, especially in real- time scenarios like disease detection, symptom understanding underscores the importance of this endeavor.

Existing systems often struggle with accuracy and efficiency due to limited training data and reliance on manually crafted features. However, transfer learning offers a promising solution by enabling the development of precise and efficient systems, even with limited labelled data, while also improvinggeneralization to new tasks and data. In the domain of image analysis, the concept of transfer learning is increasingly recognized as essential for diverse practical applications. A variety of widely used pre- trained models, including Xception, VGGNet, DenseNet121 and InceptionV3 are available for transfer learning in image analysis. Moreover, there are popular open-source frameworks such as TensorFlow Object Detection API, PyTorch Lightning, and Detectron2,which provide robust tools for performing imageanalysis tasks.

II. LITERATURE SURVEY

Inthepursuitofadvancingtransferlearningprocesses,severalimpactfularticlescontributeuniquemethodologies.In[1] thetopicdelvesintothe concept of transfer learning (TL) with CNNfor medical image identification. Examining 425articles,itrecommendsdeepmodelslikeit,Inception,emphasizingtheirefficiencyinovercomingdatascarcity. The [2] titled as "TL-med: A Two-stage transfer learning recognitionmodelformedicalimagesofCOVID-19."Addressestheminimalnumberoflabelledimages by ideating transfer learning model (TL-Med) of two stages. It uses main features fromdiverse data which refines them with large-scalemedicaldata,addressingthechallengeofinsufficient labelled COVID-19 data. The resultson dataset demonstrate a recognition accuracy of93.24%,showingthemodel'saccuracyeffectiveness in detecting disease images. In [3]the authors have studied the concept of CNN andprocess of transfer learning in medical diagnosis,highlightingtheiradvantagesinaccuracyandresource efficiency. It addresses challenges likedata diversity and model interpretability,whilesuggesting future research directions. Ultimately,itshowcasesthepotentialofCNNandtheconceptoftransferlearningtorevolutionizediagnosispractices,emphasizingtheneedforongoingdevelopmenttoovercomecurrentlimitations.
In[4]theauthorshaveaddressedtheglobalimpactofCOVIDwhichfocusesonitschallengesindetection.Itproposesadeeplearning method, specifically using (CNN) withmodels like VGG16. Results indicate VGG16'ssuperiorperformance(98.00%accuracy),showing the use as avaluable tool for effectiveCOVID-19detection,aidinghealthcareprofessionalsindecision-makingforoptimaltherapy with minimal resources. In 2016, Liu andauthors [5] proposed the SSD algorithm for fastobject detection. Both SSD and YOLO are highlyefficient, but SSD uses multi-scale feature mapswhichaiddetectingobjectsatdifferentscales.Asdeepnetworksreducespatialresolution,detectingsmallobjectsatlowresolutionsbecomes challenging, affecting accuracy. YOLOlacksmulti- scalefeaturesandreliesonsmoothing lower-resolution maps. Recent studies applied deepCNNs for COVID-19 pneumonia detection from X-rays,achievinghighaccuracy,precision,andsensitivity.SomeusedtransferlearningwithResNet50 on small 339 instance datasets, obtaining96.2% accuracy models. The disease of COVID wasdetected using the concept CNN in a chest by theauthors of [6]. They have investigated the use ofdifferent approaches for detecting COVID-19 frommedical imaging data like chest X-rays, with mostachievinganaccuracyrangeof90-94%.Theapproach involves fine-tuning the top layers of thepre-trainedmodelswhiletransferringthelearnedlow-level features to the new customized models.OnesuchapproachbyXiao[7]onresidualnetworks and multiple instances learning for binaryclassification of COVID-19 from CT scans. AnotherstudybyPanwaretal.proposedabinaryclassification model using a fine- tuned VGG modeltodetectCOVID-19frominputimages.Additionally,theyemployedGrad-CAMvisualizationtechniquestoprovidecolor-codedexplanations, making the deep learning model

moreinterpretable.Thekeyideaistoutilizethepowerfulfeatureextractioncapabilitiesofpre-trainedmodelslikeResNet50andVGG,whilecustomizing and fine-tuning them for the specifictaskofCOVID-19detectionfromCTimages,aimingtodevelopaccurateandexplainablediagnosticmodels.

III.METHODOLOGY

OurresearchmethodologyfortransferlearninginvolvedtrainingandimplementingaCNNarchitecture, resulting in an accuracy of 96% usingtheDenseNet-121model.Activationfunctionsutilized in this approach were ReLU and Softmax.[8].

3.1 DATASET INFORMATION

TheimagesofCTscansofhumanlungsareincluded in the dataset. CT scan is a type of X-raythat is used to diagnose the sensitive inner organs ofhumanbodyprecisely.Amedicalimagescollectionfromvarioussourcescomprisesthisdataset;asumof17,704images, outof which12,351imagesaredirectedtowardstrainingand5,353 images for the purpose of testing the model.Thedistributionofimagesacrossclassesrevealsthatthedatasetisrelativelybalanced,witheach class having a substantial number of images. The classes include Normal, Mass, Pneumonia, and COVID, with Normal having the highest number of images at 4,685, followed closely by Mass at4,528, Pneumonia at 4,273, and COVID at 4,219.Thetrainingsetdistributionisalso balanced,with Normal having3,280 images, mass having3,170 images, Pneumonia having 2,992images,and COVID having 2,909 images. The testing setdistributionfollowsasimilarpattern,withNormal, mass, Pneumonia, and COVID having1,405,1,358,1,281,and1,310images, respectively.Thisdatasetprovidesacomprehensive and \balanced collection of imagesfor training and testing purposes in the context ofdiagnosing respiratory conditions using medicalimaging.Thedataset’sreliabilityisensuredthroughacquisitionfromreputableorganizations.

3.2 CNN ARCHITECTURE

Our model begins with an input layer, capturingrawpixelvaluesofmedicalimages.Convolutionallayersextractfeatureshierarchically,identifyingpatternslikeedgesandshapes.Werepurposeapre-trainedconvolutional base, facilitating featureextractionfrommedicalimages.Poolinglayersaidinretainingrelevantspatialfeatures,withMaxpooling enhancing focus on critical details. Batchnormalizationstabilizeslearning,particularlybeneficialfordiversemedicaldata.Dropoutlayers prevent overfitting by excluding neuronsduringtraining.Thefullyconnectedlayertranslatesfeaturesintoclassprobabilities,adapting specifically to medical image nuances.Fig.1 represents the 3D CNN architecture ofthe model.

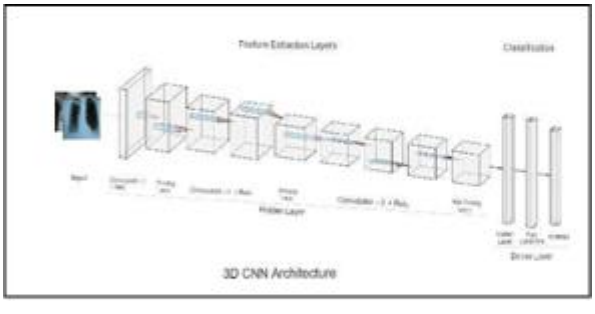


Fig. 13D CNN Architecture

3.3 TRANSFER LEARNING METHODOLOGY

Theusageofpre-trainedCNNmodelssuchasVGG,ResNet50, Xception, InceptionV3, MobileNetV2andDenseNet,weevaluatetheireffectivenesson our dataset. These base models, sourced fromTensorFlow,havetheirclassificationlayersreplaced to match our dataset's four output classes.Whilethepre-trainedweightsareretained,newclassification layer weights are initialized randomly.Unlike freezing the convolutional layers, we fine-tune all layers on our dataset, allowing optimizationfor our specific task. To address the challenge oftraining neural networks with limited data, transferlearning was applied using a tiny training dataset togenerate a feature set for managing lung diseasesand Cancer cases. The dataset, being considerablysmaller, takes greater time to build a perfect model.Fig. 2 given below represents the flowchart ofhowtransferlearningprocesstakesplace.Therefore, the models described were sourced frompre-trained models tohelp identify lung diseases.[9].

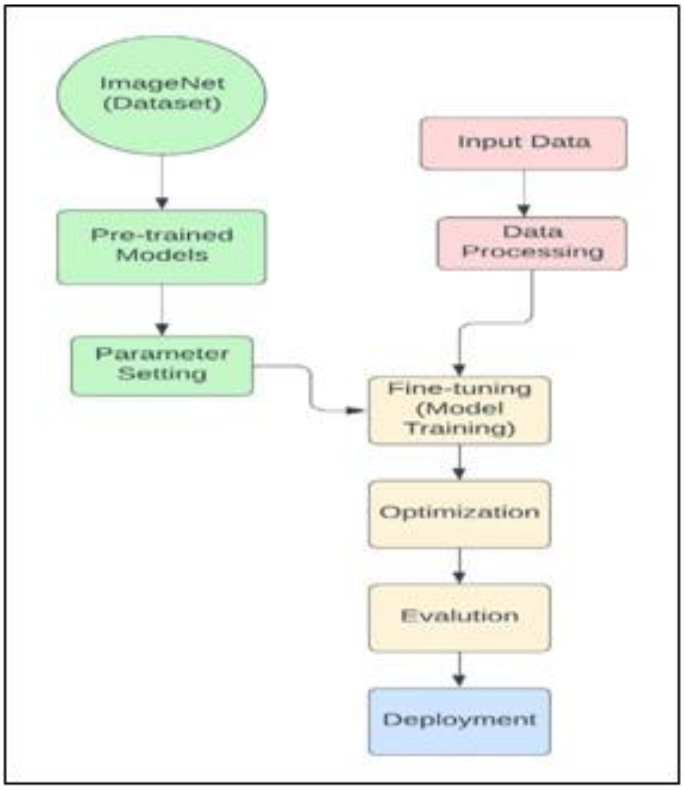


Fig. 2Flowchart of Transfer Learning Process

3.4 MODELS USED

i. DenseNet121

DenseNet121,introducedbyHuang[18],enhancestheResNet50architecturebyunderstandingconnections,ensuring thatevery layer has connections with all theotherlayerspresent.Thiscomputationallybuiltnetworkallowsfortheusageoffeatureswhile allocating and keeping the parametersaslessaspossible.

ii. InceptionV3

InceptionV3 addresses the issue of positionvariabilityinimagesbyincorporatingmultipletypesofkernelsonthesamepedestal,whichresultsinincreasingthenetwork. The Inception contents allow for thesimultaneousoperationofmanykernels.InceptionV3 is an extension of InceptionV2,addressingrepresentationalbottleneckconcerns.

iii. Xception

Xceptionusesdepth-wiseseparableconvolution layers to map spatial and cross-channelcorrelations,decouplingtheminCNNfeaturemaps.Itbuildsonthefundamentaldesignof Inception,with36layers which are divided into modules whereeachmodulehas links.

iv. VGG19

VGG19 consists of more layers than CNNmodelswithlesskernels,makingthemsuitableforunderstandingtheimagecharacteristics,particularlyinthemedicaldomain.

v. InceptionResNetV2(IRv2)

InceptionResNetV2(IRv2)[11]combinestheconceptsofInceptionandResNet,incorporatingresidualconnectionswithinInceptionmodules.Thisarchitectureenhancesfeaturelearningbyenablingthenetworktoleveragebothh theefficientinceptionmoduleandtheresidualconnections,leadingtoimprovedperformancein various tasks.

vi. MobileNetV2

MobileNetV2 is used for devices used in mobile and edge services aiming to provide efficient and lightweightmodelswithoutcompromisingaccuracy.Itdepictsresidualswhichareinverted and the feature of linear bottlenecks tobuilddeepermodelswithfewerparametersmaking MobileNetV2 suitable for where eachmodulehas links.

3.5 ACTIVATION FUNCTIONS

ReLUactivationfunctionintroducesnon-linearityinourCNN,appliedaftereachconvolutional and dense layer.It efficientlyactivates neurons, aiding faster training andmitigatingthevanishinggradientproblem.Softmaxinthefinaloutputlayerconvertslogitsintoprobabilityscores,crucialforinterpretingmodelpredictionsasclassprobabilities.

3.6 TRAINING PROCEDURE

ConvolutionalNeuralNetworks(CNNs)haverevolutionizedimageidentification,especially in tasks likeimage classification.Thesenetworksare typically used to analyzevisualimageryandhavebeenextensivelytrainedusingframeworkslikeKeras[13]withaTensorFlowbackend.ThelargeImageNetdataset,containing1.2millionimages,hasbeenpivotalindevelopinggeneralmodelsforimagerecognition.TransferlearningisoftenappliedtogeneralizethelearningfromImageNettoother datasets, especially when the model ispre-trained. Fig. 3 given below shows themultiplelayersthatareinvolvedinthetrainingprocedureofCNN model.[14]

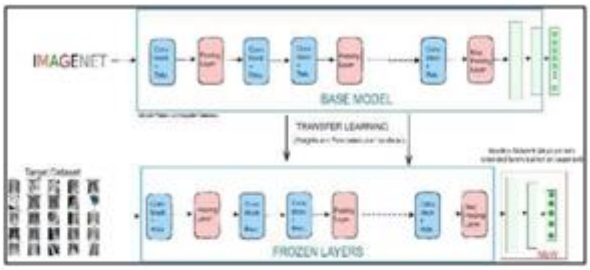


Fig. 3 Layers involved in Training Procedure

For our model, we have used various alreadytrainedmodelssuchasDenseNet121,InceptionV3, Xception, InceptionResNetV2,MobileNetV2,VGG19andmanymore.Adaptingthesemodelsforourbinaryclassificationtaskofdetectinglungdiseasesandnormalcases,weenhancedtheoutputlayerofthemodelintoabinaryclassifier.This involved flattening the output from theearlierlayer to a one-dimensional array andaddingaDropoutlayertopreventoverfitting.

Thefinaloutputconsistedofadenselayerwith a Softmax functionforpredicting classprobabilities.TheAdamoptimizer [20] andcross-entropy for a loss function were used fortraining. Overall, these techniques and modelswerecrucialindevelopinganefficientandaccuratemodelfordetectinglungdiseases.Models undergo 10 epochs of training with abatchsizeof32images,minimizingcategoricalcross-entropyloss.Ifvalidationfailstoimprovebyat least0.001forthreeconsecutive epochs, preventing overfitting andensuring robust performanceon unseen data.

3.7 HYPERPARAMETERS

A learning rate of 0.001 safeguards previouslylearned features during fine- tuning, with theAdamoptimizerchosenfor adaptabilityandefficientconvergence.Abatchsizeof32balancesefficiencyandmemory constraints.10 epochs suffice for fine-tuning, with dropoutregularizationintroducedtopreventoverfitting.ReLUandSoftmaxactivationsareappliedstrategicallythroughoutthenetwork.

3.8 MATHEMATICAL EQUATION

In a completely connected layer, every neuronis connected to other neurons in the previouslayer.ThelayerofoutputYofafullyconnected layercan becalculatedusing thevalue of the input vector X, the weight W, andfinallythebiasvectordenotesbyb.Theactivationfunctionidentifiestheabsenceoflinearityintotheconnection.Oneofthemajorly used activationfunction in this studyis ReLU (Rectified Linear Unit), [15] whichshows the output as it is given it is positive, ifnotthenshowszero.effectivelyintroducing absence of linearity concept to the model. Another majorly absence of linearity concept to the model. Anothermajorlyusedactivationfunctionin this project is Softmax which is important formulti-classclassificationproblems.Softmaxtransforms the raw scores into the probabilities,makingitsuitableforclassificationtasks.Eq. 1 given below represents the formulafor the ReLU that is used in the transfer learningprocess. Along with it theEq. 2 represents the formula for Softmax used in theproject.

$$Y = \mathrm{ReLU}(W \,.\, X + b) \qquad (1)$$

$$\mathrm{Softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}} \qquad (2)$$

IV. RESULTS AND DISCUSSION

ThestudycalculatestheresultsusingtheterminologiesofPrecision,RecallandAccuracy. [19] These parameters are importantforstudyingamedicalsystemforlungdiseases identification.

I) PrecisionValue

Precision is a concept that studies how strongthe modelrecognizes the right samples and isnear to the expected output.The higher the valueof precision shows, the higher is the positivesample. The below Eq. 3 identifies theprecisionforderiving results.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

II) Recall Value

The increased and better accuracy[16] in first identifying the target instance and the value of likelihood bothresult into a greater recall value. The formula to calculate recall is shown in Eq. 4.

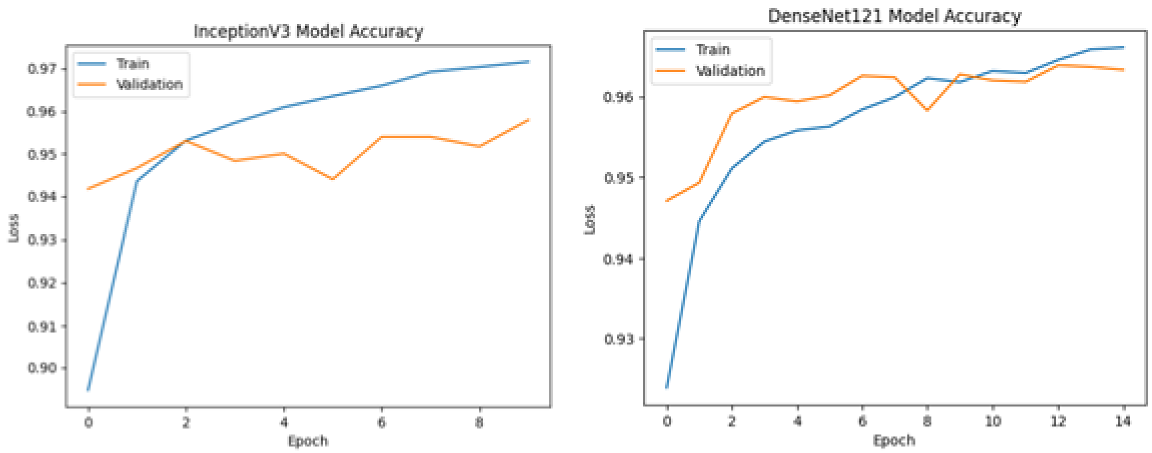
$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (4)$$

III) AccuracyValue

Accuracy can be stated as the ratio of correctpredictions that are made to the value of totalnumberofsamplesusedunderstudy.Eq. 5 is depicting the formula used to find theaccuracy of models in the project.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (5)$$

In the evaluation, DenseNet121 showed the best performance among the tested models. Following closely were VGG19 and ResNet50.[17] Fig. 4 and Fig. 5 given below depict the graphs of Accuracy and Loss Value of DenseNet121 Model respectively.These results highlight the impact of using transfer learning in process of detecting lung diseases in CT scans. By using transformation-based bespoke models, it is possible to further improve the performance of deep CNN models to achieve accuracy levels exceeding 90% across all performance criteria. The low False Positive Rate (FPR) of the proposed method makes it suitable for real-world screening settings.



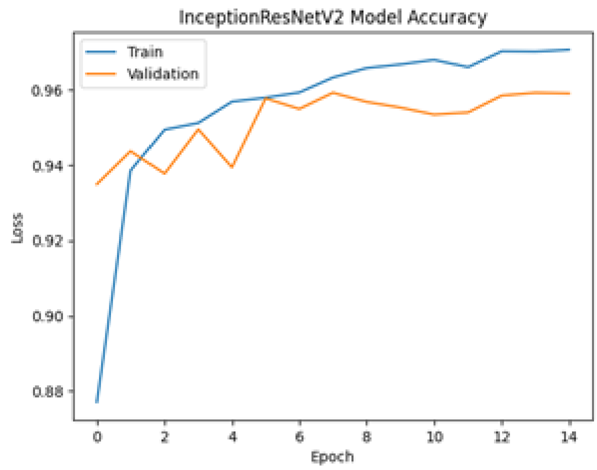
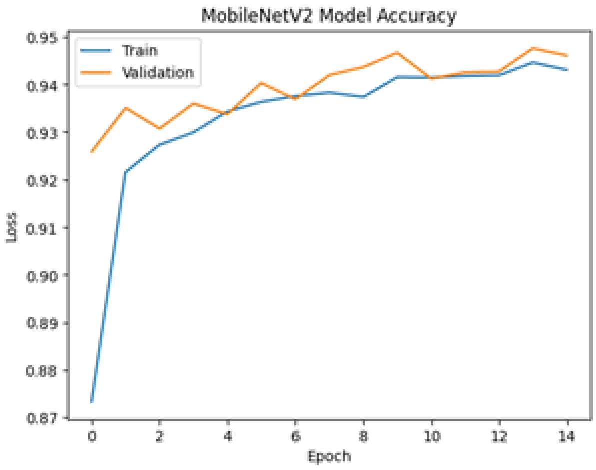
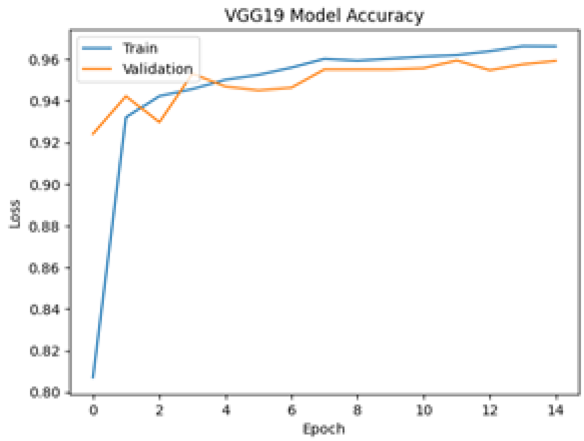
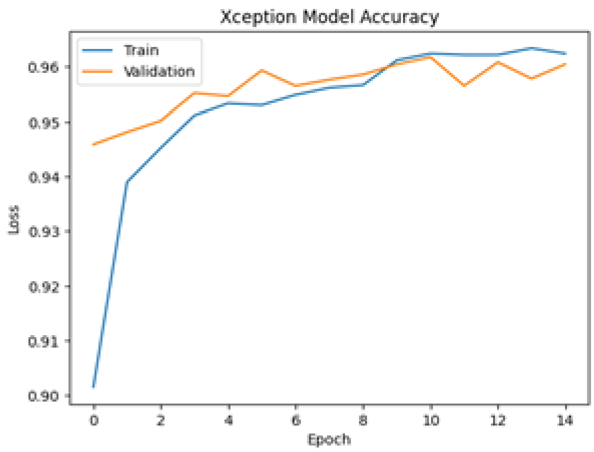
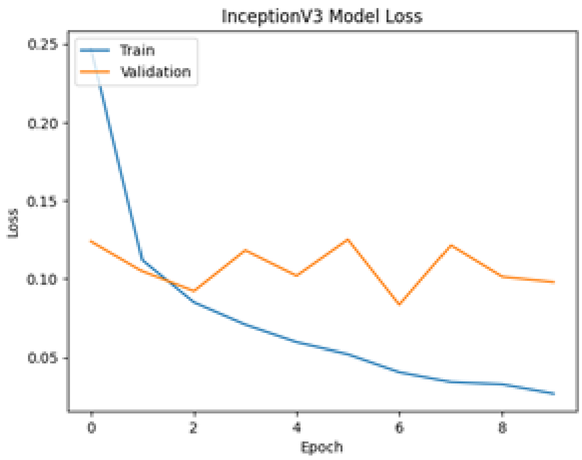


Figure 4: Graph of Results of Accuracy of CNN Models









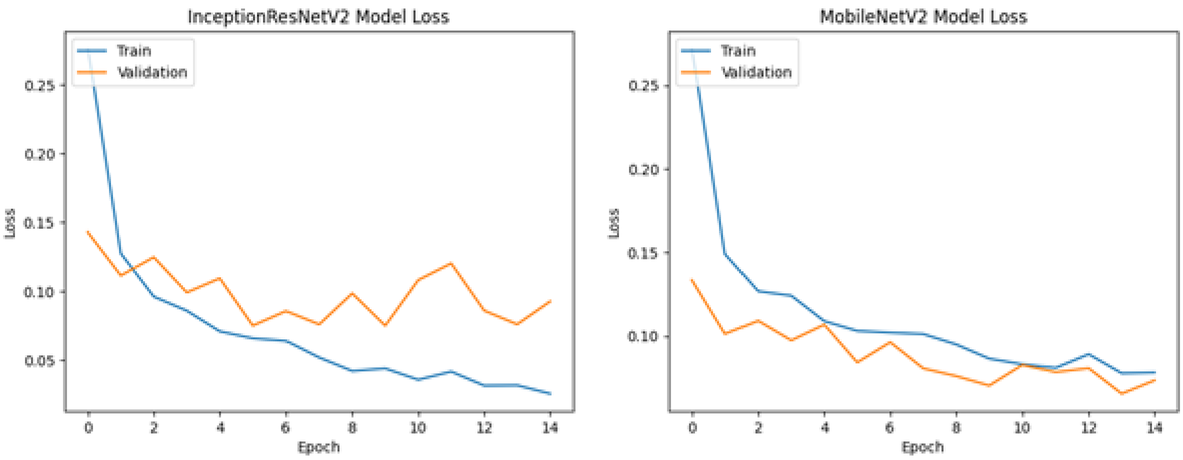
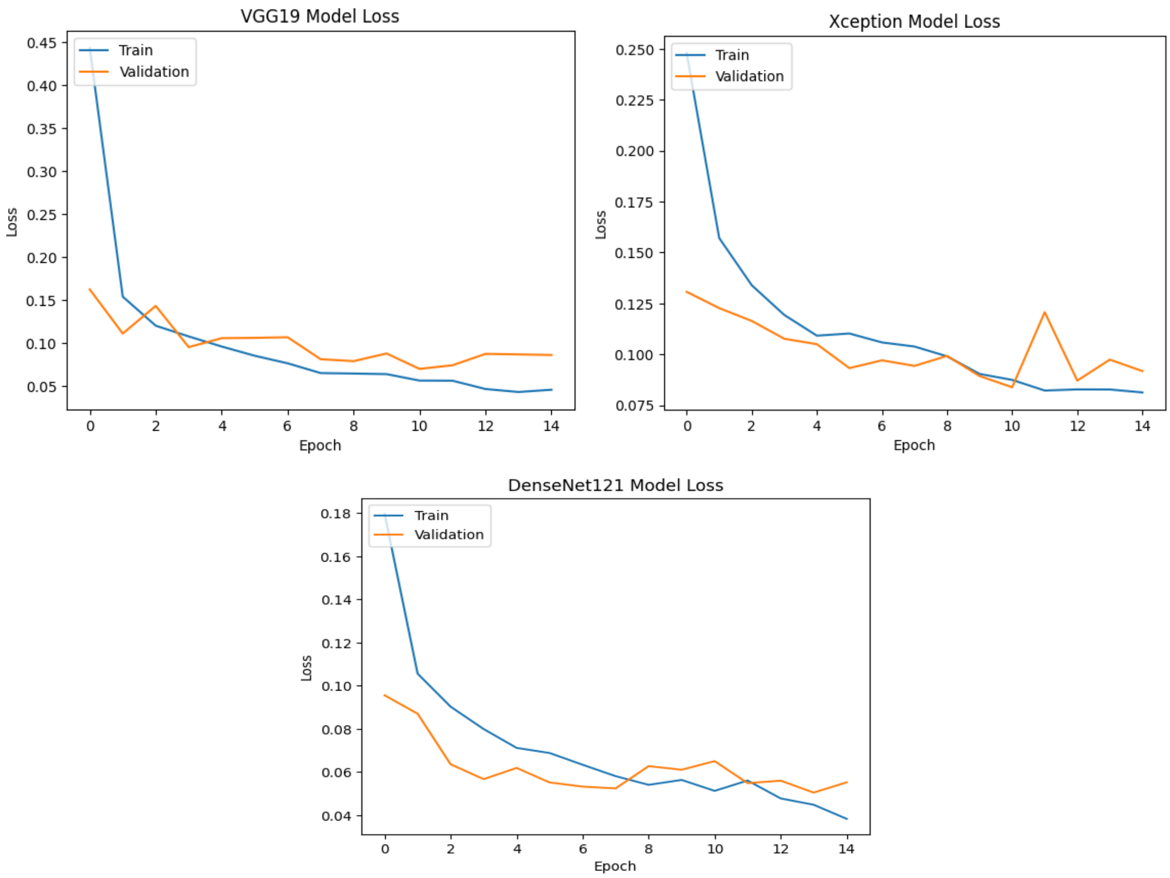


Figure 5: Graphs of Results of Loss Value Models



V. CONCLUSION

This paper serves as a valuable starting point for individuals in the deep learning field who are utilizing transfer learning. It offers guidance on selecting optimal methodologies to improve model accuracy, as evidenced by achieving 96% accuracy using the DenseNet-121 model. Additionally, the study conducts an analysis of different CNN architectures employed in classifying lung diseases from medical images. It showcases how advancements in deep learning algorithms yield promising results, augmenting radiologists' capabilities. The models based on CNN have found an impactful use in the domain of healthcare and medical diagnosis. The study shows usage of multiple CNN image processing and classification models to detect lung diseases using images of CT scan of patients using transfer learning. The findings indicate that the method used achieves exceptional findings, with accuracy percentage exceeding 90% and low false positive rate. The results suggest that CNN-based methods can impact the control of lung disease spread by providing rapid screening. Given the widespread use of DL-based approaches in other medical imaging applications, their implementation in lung disease screening is timely. The analysis highlights DenseNet121 as a standout performer due to its smaller parameter size and minimal training time, surpassing other CNN models. Finally, the study shows the results of transfer learning-based transformations to detect lung diseases in suspected patients using CT scan images.

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