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Comparative Analysis of Skin Disease in Different Deep Learning Models

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This study examines three CNN architectures-ConvNeXt,ResNet50, and DenseNet121 for skin lesion classification on theHAM10000 dataset. This research employs various techniques such as data augmentation, transfer learning and image segmentation to enhance each model's ability to handle variability in images. This study evaluates the three models on various parameters such as—accuracy, precision, recall, f1-score—to access the strengths and limitations of each model. This evaluation will provide us with the model that provides the most effective approach and efficient results.
Keywords: SkinCancer, Dermoscopy, ArtificialIntelligence, Deeplearning, CNN

1. Introduction

Skin cancer is the most common type of cancer globally.Theincidencerateofskincancerhasbeenincreasingrapidlyoverthedecades;hencetheurgentneedforeffectiveprevention and detection measures. With the advancement in technologies, the survival rates have increased, however precisediagnosis remains crucial for better and optimal outcomes.Melanomaisoneofthedeadliestskincancers.Itisverychallengingtotreatthisdiseasewhendiagnosedlateortolimitedaccess to dermatology specialists due to its high likelihoodof metastasis. If the disease is not diagnosed early, the survivalrateofanindividualpost-diagnosiswillbeamaximumoffiveyears.However,detectingthediseaseatanearlystagenot only increases the survival rates but also offers nearly a100% recovery probability. The slight difference across theskin lesion that can occur due to various factors such as theslight difference in the lighting, difference in skin types, ageofanindividual,andotherenvironmentalfactorsmayleadtomisdiagnosis despite the advancements in detection technologies.Dermoscopy has become an important tool that provides a more detailed and standardized view of skin lesions,improvingthediagnosticaccuracyforhealthcareprofessionals.

Theapplicationofdeeplearninginmedicalimageshasbeenexploredextensively,ashighlightedby(1),JiajiWang(2023)in their survey on deep learning's impact on medical imageanalysis, which outlines the transformative role of CNNs inanalyzingcompleximagedataonskindiseaseclassification.(2),Ismail Oztel (2023) developed a smartphone-compatibledeeplearningmodel,emphasizingtheimportanceofaccessibleandmobilesolutionsfor diagnosisinremoteorresource-limitedsettings.(3),LubnaFarhi(2022),appliedDeepBeliefNetworks for dermoscopic image classification, demonstrating the flexibility and effectiveness of diverse neural architecturesindistinguishingbetweenbenignandmalignantlesions. (4), Cheng-Hong Yan (2021) introduced a deep hybrid CNNmodel specifically designed for melanoma lesion segmentation,illustratingthemodel'scapabilityinenhancingsegmentation accuracy for improved diagnosis. (5),Risheng Wang(2021) provided a comprehensive survey on the use of deeplearning techniques, which has proven instrumental in tasksrequiringpreciseidentificationofaffectedregionsinmedicalimages.

Artificial Intelligence (AI) has emerged as a powerful toolby providing insights on pattern recognition capabilities thatsupport the doctors from identifying potential malignancies.Though AI algorithms have a significance in this context,clinicians still plays a crucial role in validating these findings,incorporatingthepatient'shistoryandlifestyleintothefindings.This integration between AI and the clinical staff notonly optimizes the diagnostic flow but also provides fasterand data-supported insights to patients.Yet, several challengespersistinimplementingeffectiveAI-drivendiagnostictools.Theneedforvast,well-labelleddatasetsisparamount,whichisoneoftheproblems,becauseeachcancertypehasadifferent incidence number as well as image examples, leading to an imbalance between skin cancer classes, especiallymelanoma,leadingtounevendatarepresentation.

Ourresearchaddressesthisproblembytestingthemodelsonastandardizedskindiseasedatasetandevaluatingtheperformance of each model based on its accuracy, precision, sensitivity,specificity,recall,f1-scoreandcomputationpowertoidentify most suitable architecture for accurate and efficientskindiseaseclassification.

2. Background Study

In(6),thestudydemonstratedthatusingwrapper-basedfeature selection, particularly the Grey Wolf Optimization(GWO) algorithm, yielded the highest classification performance, achieving an accuracy of 83.33% on the ISIC 2017datasetand93.50% on the ISIC 2018 dataset.

In (7),the study utilized a Deep Belief Learning (DBL)networkarchitecturethatachievedsignificantimprovementsin classification accuracy, especially on segmented dermoscopicimages,withaccuracygainsrangingfrom8%to47%overothermodelslikeAlexNetandLeeNet.AndsegmentedimagesclassifiedwiththeDBLnetworkalsoexhibitedreduced error rates by 41.5% and faster processing times,focusingonweightdistributionontheclusteredregionsratherthanthewholeimage.

In(8),thestudyhighlightsthatCNN-basedmodels,suchas ResNet and EfficientNet, provide robust results for skinlesionclassification,withaccuracyreachingupto93.65%.

In (9),the proposed hybrid model (a combinationofDeepLabV3+,MobileNetV2,EfficientNetB0,andDenseNet201) achieved an accuracy of 94.42% and an F1score of 93.49% on the ISIC-2019 dataset, and an accuracyof 94.44% on the PH2 dataset, confirming its generalizability.

In(10),themodelusedareEfficientNetv2B0,Regnetx006,InceptionResnetv2.The EfficientNetv2 B0 model achievedthe best overall performance across multiple classificationtasks with an accuracy rate as high as 92.9% for specificbinary classifications, enhancing both sensitivity and specificity.

In(11),themodelusedareResNet-18,EfficientNetb3,MobileNetv2.The study achieved a 74.27% classificationaccuracy on a seven-class skin disease dataset,includingMonkeypox,usingaTensorFlowLiteversionofResNet-18.

3. Methodology

The following sections provide a description of the datasetused, the techniques applied, the architecture of each model,and the structured workflow developed for training eachmodel.

DatasetCollection:ThisprojectutilizestheHAM10000dataset, chosen for its high-quality, dermatologist-reviewedimages, which enhance the reliability of skin lesion classifications.Itincludesadiversecollectionof10,015images,butonly7470uniquelesions,asduplicateimageswereremovedto maintain data integrity and prevent biased training outcomes. The dataset consists of Actinic Keratoses (327 images), Basal cell carcinoma (514images), Benign keratosis (1099 images), Dermatofibroma(115 images), Melanocytic nevi (6705 images), Melanoma(1113images),andVascularlesion(142images),totallingto10,015images.

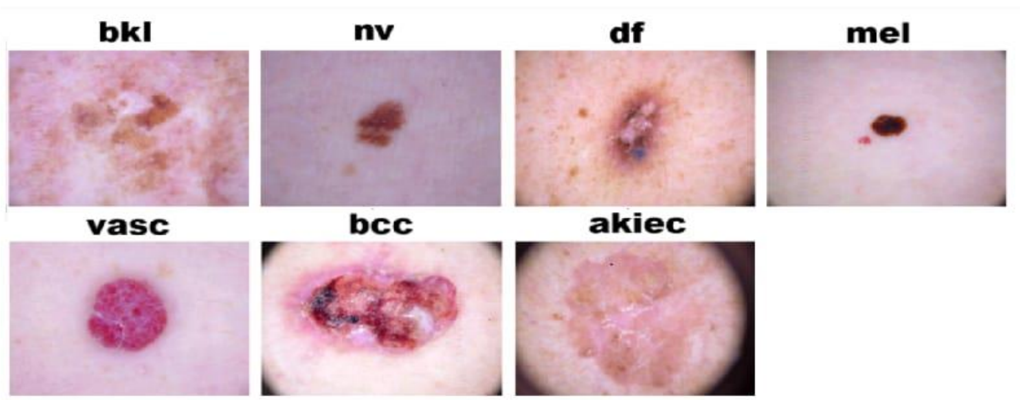

Fig.3.1.SevendistinctskinlesionsinHAM10000dataset.

Preprocessing of Dataset:It is an important step forpreparingrawdatafordeeplearningmodels.

Removing Duplicates: Duplicate images are removed toavoidbias.

Resizing and Rescaling: Adjusting the dimensions of theimagesizeto224x224tofitthemodel.

RemovingNoise:Identifyingandremovinganycorruptor irrelevant images that may affect the performance of themodel.

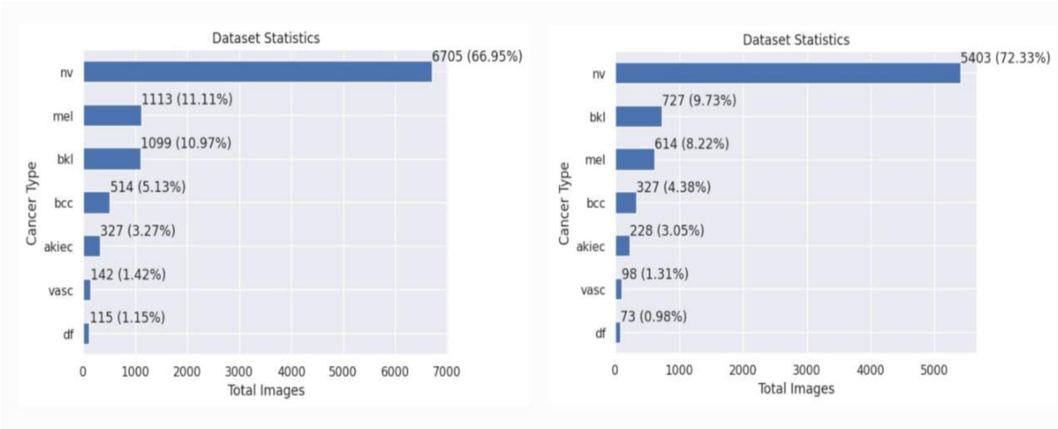

Fig.3.2.Datasetdistributionclasses,ontheleftsidethegraphoftherawdataset,andontherightthere movedduplicateimages.

Data Augmentation: It is the process of artificially expanding the size and diversity of a training dataset by applying various transformations to the images.The various dataaugmentationtechniquesusedare:

Rotation:Rotatingtheimagetospecificangles.

2H-flipandV-flip:Mirroringtheimageshorizontallyandvertically.

Zooming:Randomlyzoomingtheimagesandcroppingtheouteredges.

Shearing:Images being skewed or slanted either along thehorizontalortheverticalaxis.

WidthShift:Horizontalshiftoftheentireimagealongthex-axis.

HeightShiftVerticalshift oftheentireimage alongthey-axis.

ChannelShift:AdjustingtheintensityoftheRGBcolorintheimages.

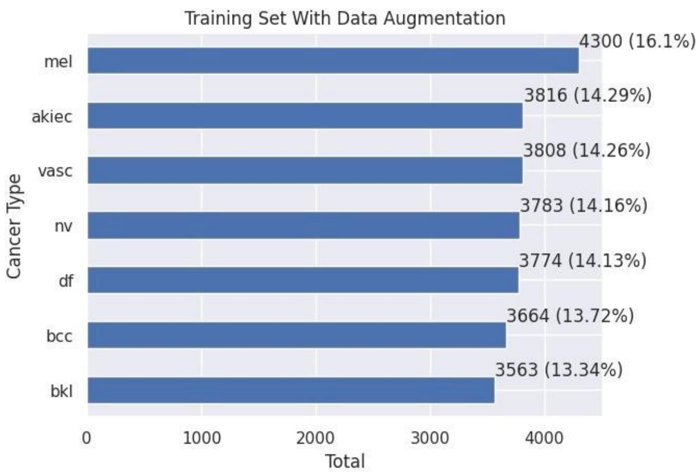

Fig.3.3.Datasetdistributionafterdataaugmentation

TransferLearning:Transferlearningisatechniquethatsolvesrelatedtaskusingapre-trainedmodel.Ithelpsinsolving new problems with smaller datasets by using the knowledge of the model that has been trained on large and diversedatasets. By using these pre-trained weights, transfer learning speeds up the model training process and improves theaccuracy. In this study, transfer learning is used to fine-tunethe models where the original data serves as the foundation.Here, we allow the weights to be adjusted during the training process, thus ensuring that the model adapts itself to thevaried representation of the medical images. This approachhelps in improving the key performance metrics, providingmoreaccurateandefficientdiagnosis.Thefine-tuningofthemodelishighlyeffectiveasithelpsincapturingthedisease-affected feature and enhancing the model’s ability to recognizesubtledifferencesinskincondition.

ModelArchitecture

This project evaluates the performance of three ConvolutionalNeuralNetwork(CNN)architectures:ConvNeXt,ResNet50, and DenseNet121.The details on each of the architectureareprovidedbelow.

ConvNeXt: ConvNeXt wasdeveloped in 2020s, inspired by the design of Vision Transformer.The ConvNeXt architecture has 295 layers, out ofwhich 36 are convolutional layers.This architecture usesapproximately 89 million parameters which enhances themodel’s ability to capture complex patterns in images. ConvNeXt is designed for 224x224 pixel input images whichmakes the model more compatible with a wide range of pre-trainedmodel.Thisarchitectureisveryefficientwhenrobustand high feature extraction is required. The model’s abilitytoprovidehighaccuracylikeVisionTransformersandcomputation powerandsimplicitylikeCNNmakesitanefficientmodelforcomputervision.

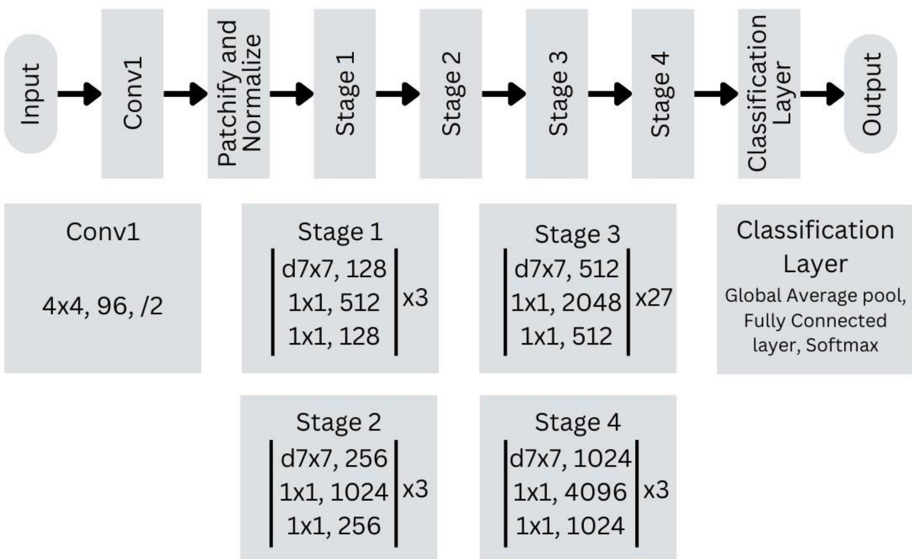

Fig.4.ConvNeXtModelArchitecture

ResNet50:ResNet50 is a variant of ResNet family.ResNet50 comprises of an initial convolutional and poolinglayer followed by four stages of residual blocks, totalling to50layers.ResNet50wasdevelopedtohelpmitigatethevanishinggradientwhichisaproblemthato ccursindeepernetworks. In traditional deeper networks, as layers increase, thegradients decrease during backpropagation leading to difficulty in training.This problem is handled by the residualblock of ResNet50 that incorporates shortcut connection to“skip”certainlayers.Thisarchitectureusesapproximately25.5millionparametersandworkseffi cientlywithimagesat224x224 pixel resolution.Its strong balance between depthandefficiencymakesitaneffectivemodelforimagerecognition.

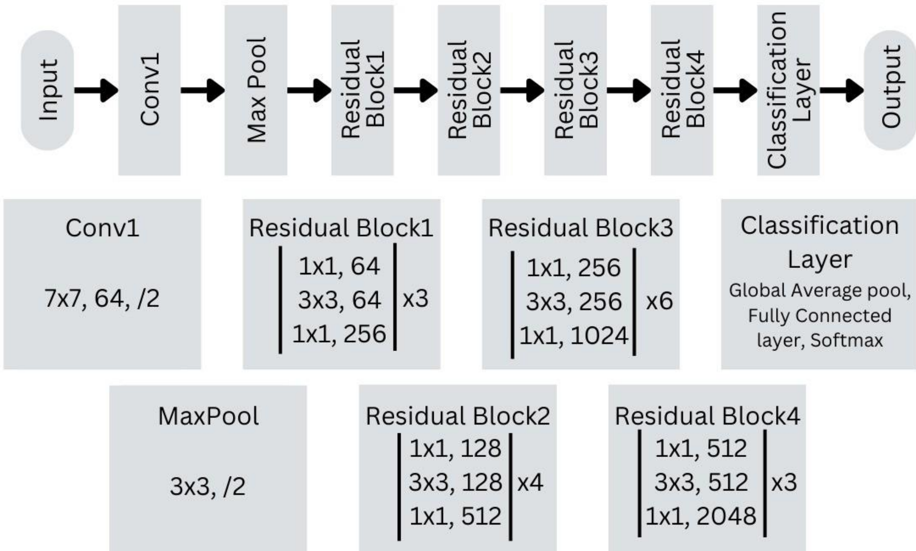

Fig.5.ResNet50ModelArchitecture

DenseNet121: DenseNet121 is a variant of Dense Convolutional Network (DenseNet) architecture. DenseNet 121is known for its innovative design where each layer connects to every subsequent layer, creating a “dense” connectivity pattern, unlike tradition CNN where each layer connects only to the previous and the next layer.Densenet121consistsofaninitialconvolutionalandpollinglayerfollowedbyfourdenseblock sandtransitionlayers,totallingto121 layers.This architecture uses approximately 8 million parametersandworksefficientlywithimagesof224x224pixelresolution.The innovative design of DenseNet121 allowsbetter feature reuse and efficient gradient flow, thus making DenseNet121 an efficient and powerful model for imagerecognitiontasks.

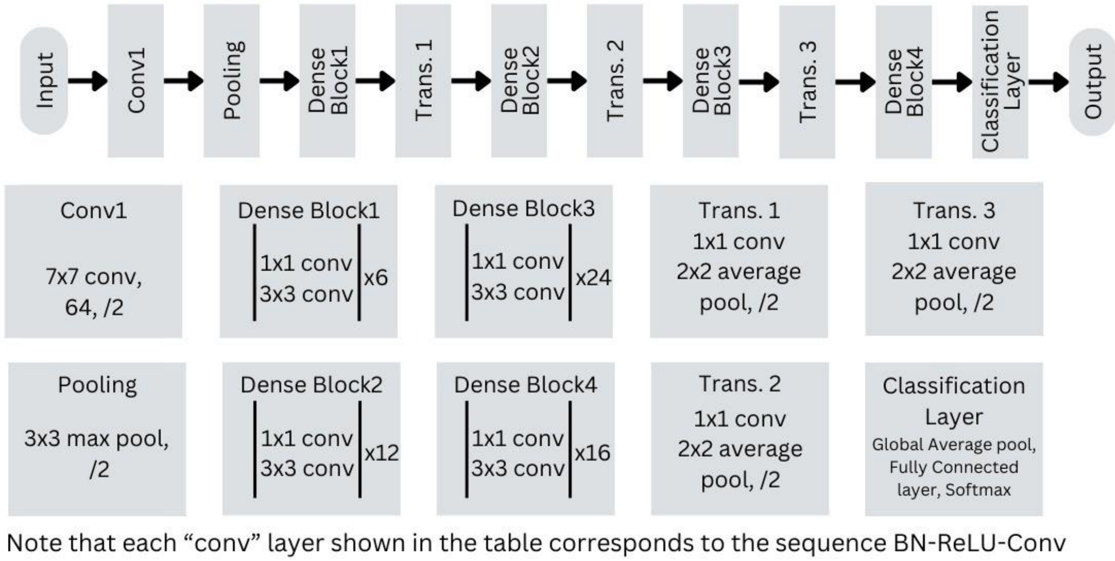

Fig.6.DenseNet121ModelArchitecture

Training:

Aconfigurablenotebookiscreatedforthisproject,tocentraizethemainsettingsforeachtrainingmodel.Eachmodelwastested with the dataset imported via Kaggle’s Dataset, usingonly the TPU to train the model, resulting sub-30 minutes oftrainingtimetoconcludeasingleexecutionofthenotebook.In this stage, the images are divided into three sets: training,validation, and testing with the respective rates: 70%, 10%,and 20%. The exact amount of images for each class is representedintheFig.7:

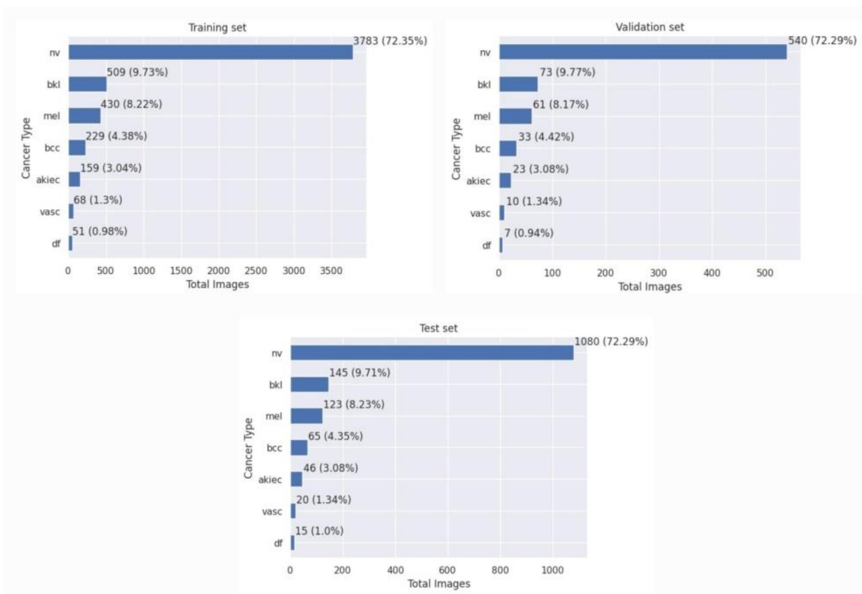

Fig.7.Datasetdistributionbetweentraining,validation,andtestsets

4. Results:

Thisstudyevaluatestheperformanceof—ConvNeXt,ResNet50andDenNet121—onHAM1000datasetusingkey metrics—accuracy, precision, recall,f1-score and specificity—aftertrainingonaugmentedandsegmentedimages.All the three models had a variety of combination andtheoverallperformancemetricsaredisplayedintheFig.

9.Only those combinations are taken that achieved an accuracy of more than 50%.The study revealed that ConvNext achieved the highest accuracy of 96.45% demonstrating robust feature extraction capabilities suitable for complex medical images, followed by ResNet50 with an accuracyof96.03%withitsresidualblockseffectivelyvanishingthe gradient problem, and DenseNet121 achieved an accuracy of 88.62% excelling in its innovative design allowingbetterfeaturereuseandefficientgradientflow.Inconclusion,ConvNeXtwasfoundtobethe mostsuitablearchitectureforhandling variability and complexities in skin lesions, makingitthetop-performingmodelincomparativeanalysis.

Models	Accuracy (%)	Precision (%)	Recall (%)	F1_score (%)	Specificity (%)	ROC_AUC (%)
convnextall	96.39	97.66	97.66	97.66	99.61	98.88
convnextbalancednormtransf	78.94	91.42	91.28	91.34	98.57	96.15
convnextdataaugmentationtransf	96.19	98.02	98.02	98.02	99.67	98.94
convnextdataaugmentationtransfbalanced	96.45	97.99	97.99	97.99	99.66	98.93
convnexttransf	89.27	95.57	95.57	95.57	99.26	97.85
convnexttransfbal	85.45	92.51	92.51	92.51	98.75	96.31
convnexttransfbalseg	85.78	92.35	92.35	92.35	98.72	95.89
densenet121all	80.16	81.61	81.61	81.61	96.93	90.28
densenet121balancednormtransf	74.18	84.84	84.71	84.77	97.47	92.61
densenet121dataaugmentation	79.15	81.58	81.55	81.56	96.93	90.24
densenet121dataaugmentationtrans	78.77	81.7	81.7	81.7	96.95	90.25
densenet121dataaugmentationtransfbalanced	79.76	80.77	80.74	80.75	96.79	89.97
densenet121dataaugtransfbalminmax	56.31	91.34	91.31	91.32	98.55	96.62
densenet121trans	88.62	86.24	86.24	86.24	97.7	92.64
densenet121transbal	84.08	68.5	68.5	68.5	94.75	82
densenet121transbalseg	84.71	71.41	71.41	71.41	95.23	83.81
resnet50all	95.57	96.77	96.77	96.77	99.46	98.41
resnet50dataaugmentationtransf	96.03	97.04	97.04	97.04	99.5	98.44
resnet50dataaugtransfbal	95.64	96.62	96.62	96.62	99.43	98.33
resnet50transf	94.71	97.09	97.09	97.09	99.51	98.66
resnet50transfbal	90.76	92.35	92.35	92.35	98.72	96.15
resnet50transfbalseg	90.43	90.06	90.06	90.06	98.34	94.38

Fig.8.Performancemetricsfordifferentcombinationsofthethreemodels.

5. Conclusion and Future Work

In summary, each model has their unique strengths in skindisease classification with ConvNeXt having the highest accuracyandleadingintermsofoverallperformance.ConvNeXt is a very efficient model where high accuracy andspeed are required. While DenseNet121 and ResNet50 alsoperformed well, their architectures are more suited for environments where memory and computational limitations areless important. To improve further accuracy, future researchcan investigateon model ensembles that incorporates ConvNeXt, DenseNet121 and

ResNet50.It may also involveadding hybrid models that increases the sensitivity to subtle image features.Further broadening the study to a widerrange of skin disease and more diverse dataset can increasetheefficiencyofthemodel.

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