Multi Scale EfficientNetB0 Backed Convolutional Neural Network for Automated Pneumonia Detection from Chest Radiographs

*Shikhar Agrawal[1] and Bina Kotiyal[2]
Department of Computer Science and Engineering
Graphic Era Hill University,
Dehradun, India
*shikharagrawal023@gmail.com[1] , kotiyalbina@gmail.com[2]

Abstract. Pneumonia is an infection caused by various pathogens, be they bacteria named Streptococcus pneumonia or viruses named Influenza and SARS-CoV-2. It is one of the leading causes of death in the elderly and young population. Traditionally, the diagnosis of pneumonia was done by an experienced physician, which can sometimes be misinterpreted. To tackle this issue, we present a novel multiscale convolutional neural network framework for analysis and detection of pneumonia from the radiographs of the chest of the individual. The model makes use of EfficientNetB0 as its backbone and then multi scale feature extraction is introduced which divides the learning into three parallel convolutional branches, whose output is then concatenated to perform downstream classification. The model is also validated alongside other traditional and state-of-the-art convolutional neural networks named DenseNet121, ResNet50, InceptionV3, VGG16, and base EfficientNetB0. The study was done on the publicly available dataset consisting of 5856 images. Results subsequently show that the proposed and upgraded model provides better accuracy and outperforms other traditional approaches.

Keywords: Deep Learning, Medical Imaging, Multi Scale Architecture, Radiography, Image Classification, Transfer learning.

1 INTRODUCTION

Pneumonia is one of the leading causes of death in the world; it is caused by heavy inflammation in air sacs, called alveoli, which are responsible for transferring oxygen from lungs to blood. There is also an accumulation of pus and fluids during the disease's infection phase, causing high discomfort and resulting in difficulty breathing and pain. The recent study in 2021 [1][2] showed that nearly 2.2 million people died due to pneumonia worldwide, with 1.11 million of them being 70 years or above. Symptoms vary from individual to individual and can range from chest pain, fever, and chills to shortness of breath, confusion and bluish lips, with fatigue and cough being the most common symptoms. The infection can be caused by various pathogens, of which the most common are Streptococcus pneumoniae bacteria, and

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viruses named influenza and SARS-CoV-2, and in rare cases may be due to fungi. In earlier times, analysis was done by a radiologist, and diagnosis was dependent on the experience of the individual, which may lead to incorrect interpretation leading to misdiagnosis, causing harm to the patient. The proposed model helps in tackling the issue of varied experience by having 3 parallel convolutional branches (3x3, 5x5, and depth wise separable) that do feature extraction, and then their output is concatenated to provide final classification.

A. Convolutional Neural Network.

Convolutional Neural Network, or CNN is the basis of modern image classification tasks. Each network consists of numerous convolutional layers that extract spatial features, reduction in dimensionality is performed by pooling layers, and consists of fully interconnected layers that help in classification. Learning happens in layers, with earlier layers responsible for recognizing hierarchical patterns while deeper layers take responsibility for complex shapes. Kotiyal and Pathak [3] displayed the prowess of CNN by making a framework achieve high accuracy along with showing robust performance. CNN removes the need of manual feature extraction, as displayed by Fig. 1, and forms the basis of advanced models like ResNet, DenseNet, and other models.

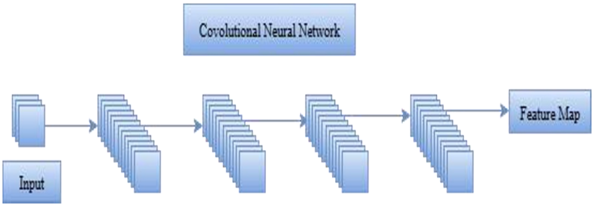


Fig 1: Architecture of Convolutional Neural Network

B. Dense Convolutional Network

DenseNet, or Densely Connected Convolutional Network, is slightly different from the base Convolutional Neural Network, as in this every layer is connected to its succeeding layers. The connection of the output of the previous layer in future layers, as shown in Fig. 2, helps in stronger gradient flow and reduces vanishing gradient issues and in turn also ensures that feature maps are reused thoroughly in the whole network. The variant named DenseNet-121 is used highly, as it is capable of learning both fine and global features due to its dense fishnet like connection. Due to these connections, fewer parameters provide higher accuracy as compared to traditional CNNs.

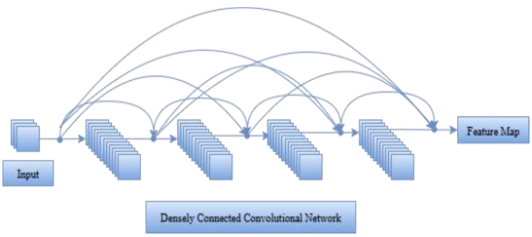


Fig 2: Architecture of Densely Connected Convolutional Network

C. Residual Network

Residual Network, or ResNet, transformed deep learning by introducing a new concept of skip learning, in which information is allowed to bypass layers, making it easier to train deep networks. As displayed by Fig. 3, each layer focuses on learning only the difference between the input and output layers which increases the optimization and makes the network less resource intensive. Generalization is achieved to a higher degree due to its deep and robust design.

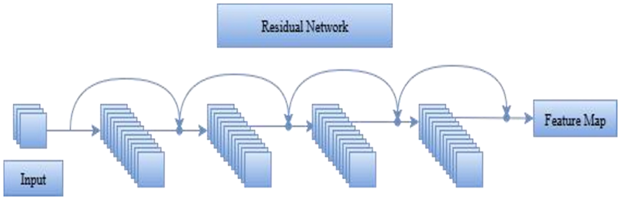


Fig 3: Architecture of Residual Network

D. Deep Convolutional Neural Network

Deep Convolutional Network is an upgraded form of CNNs where instead of linear learning there are multiple convolutional filters (1x1, 3x3, 5x5) working in parallel. Fig. 4, shows Parallel working ensures the capturing of fine and large scale features simultaneously, as well as employs dimensionality reduction and factorized convolution for high accuracy and efficiency. In real time diagnostic application, its optimized computation and generalizability prowess make it one of the most balanced and appropriate architectures to consider. In [4], Y. Wang et al. showed the prowess of Inception V3 as it achieved the highest accuracy from the group of models.

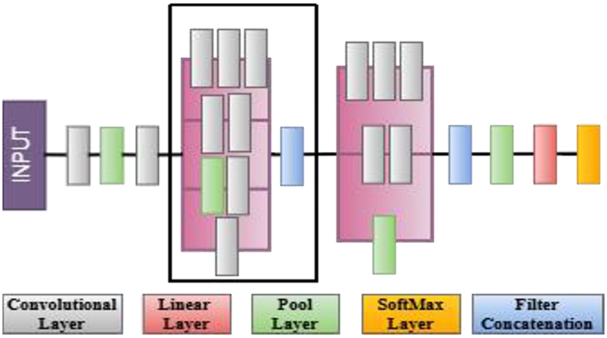


Fig 4: Architecture of Deep Convolutional Neural Network

E. Efficient Network

The compound scaling method of EfficientNet optimally balances the model's depth, width, and resolution to provide higher accuracy with fewer parameters in work. EfficientNet ranges from B0 to B7, which scales up systematically in architecture with principles being similar. Uses Squeeze and Excitation Blocks along with Depthwise Separable Convolutional layers to focus on important photo aspects while being computationally lightweight, as shown in Fig. 5. Amit et al. [5] displayed the flexibility of using multiple embedding strategies and activation functions to enhance the framework.

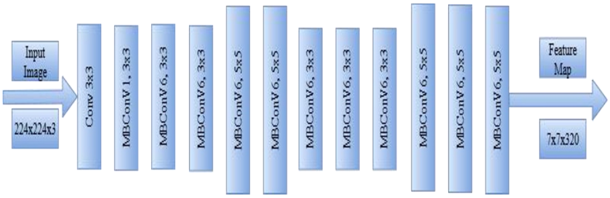


Fig 5: Architecture of Efficient Network

F. Visual Geometry Group Network

The Visual Geometry Group of Oxford created a network that uses small 3x3 convolutional filters stacked sequentially as shown in Fig. 6, and uncovered a foundational model in deep learning research. VGG provides strong and consistent feature extraction but suffers from a serious drawback of being computationally resource intensive. The model proved to be a benchmark for newer models that keep on emerging with research and served as a baseline for comparing modern CNN architectures.

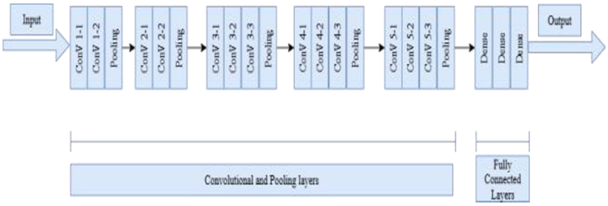


Fig 6: Architecture of Visual Geometry Group Network

2 RELATED WORKS

The detection of pneumonia from chest radiographs has become a benchmark for deep learning research, as there is still a need for a rapid and accurate diagnosis in varied and remote clinical environments. In recent times there are many studies that explore a variety of new convolutional neural networks and transfer learning methodologies, which, even though they provide high accuracy, are held back by limitations like dataset size or single size data and lack of external validation. Numerous studies have explored the use of CNN and its variants for detection due to their ability to learn complex features and classification. Qiuyu An et al. [6] similarly provided a concept in which a combination of EfficientNet and DenseNet was created for advanced attention mechanisms, and that model showcased an outstanding accuracy of 95.1%. On similar turf, A. Alalwan et al. [7] proposed a hybrid model of African Buffalo Optimization and CNN to improve the feature extraction and learning phase, which improved to a peak of 96.95% accuracy and 88% precision. Yanar et al. [8] also proposed a hybrid model and combine 4 state of the art architecture into a single model to achieve a high accuracy of 96% and named it PELM

Rajpurkar et al. [9] presented a ChestXNet Convolutional Neural Network that consist of a dense 121-layer architecture which outperformed an experienced radiologist with an F1 Score of 43%, while the radiologist achieved an F1 score of 38% over 112,000 images, and also achieved state-of-the-art results across 14 different diseases. E. J. Hwang et al. [10] proposed a deep learning based computer aided detection system for detecting Pneumonia from chest radiographs of febrile neutropenia patients, which showcased an improvement in radiologist sensitivity taking it from 75.4% to 79.4%. Nishio et al. [11] put together a deep learning model that does classification in three categories which are COVID-19 pneumonia, non COVID-19 pneumonia and healthy, and achieved an accuracy of 86.67% to outperform six experienced radiologists whose accuracy ranged from 56.6% to 77.3%. Y. Xie et al. [12] chose the enhanced You Only Look Once version 11 as it's deep learning model, the upgradation with the help of C3k2, DCNv2, and DynamicConV modules when applied to a dataset of 4194 images achieved a mean average precision of 97.8%. Visual Geometry Group Network was the consideration of A. Bashar et al. [13] which when applied to a dataset of 21,165 images consisting of healthy, Covid-19, and Viral Pneumonia images showed peak classification accuracy of 95.63%.

Saber et al. [14] suggested the use of the TransUNet model integrating a parameter-efficient transformer module, which showcased accuracy of 92% on Kermany and 95% on Cohen dataset. The Vision Transformer Architecture proposed by S. Singh et al. [15] achieved an accuracy of 97.61% with the help of its own self-attention mechanism which processes images as sequences of patches for better learning. N. Jahan et al. [16] addresses the challenge of tedious manual diagnosis and class imbalance by the help of transfer learning approach with fine-tuning done EfficientNet model pre-trained on ImageNet to finally achieve an accuracy of 96.33% and an area under curve of 0.991. T. Kwon et al. [17] combined two DenseNet based neural networks instead of one which was then trained on 157,016 images from the NIH and KNTA datasets and tested by 212 images from Gachon University Gil Medical Center to finally achieve an area under the curve of 0.983. M. S. A. Reshan et al. [18] suggested the use of a less resource intensive model called MobileNet, which was trained on two datasets comprising of 5856 and 112,120 images each along with eight more pre trained state-of-the-art models, and out of them, MobileNet achieved the highest performance with an accuracy of 94.23% on the larger dataset and 93.75% on the smaller dataset. The study also focused on optimization in batch size and other actors as well. R. K. Sheu et al. [19] introduced a multi modal data analysis for pneumonia discharge status within 7 days; it uses the first 3 days radiographs to predict the possibility and achieved an accuracy of 75% when experimented with almost 4000 patients.

Z. Zhang et al. [20] proposed an improved deep learning model named ResAUNet for detecting and segmenting Covid-19 pneumonia from scans. The model first used U-Net for lung segmentation and then made use of the model's attention modules, residual blocks, and subpixel convolutions to provided a mean intersection over union of 73.4% when done over 100 scans to outperform competing models. Alijuaid et al. [21] did a study comparing 6 neural network models on a balanced dataset and due to the uniform pipeline of VGG19, it achieved an accuracy of 97%. L. Wu et al. [22] gave an anchor free deep learning framework for pneumonia detection using the RSNA dataset, since anchors require extensive tuning, so an anchor free approach with a feature pyramid and two brand detection head to achieved a mean average performance of 51.5%. S. Showkat et al. [23] presented the work by integrating transfer learning with five ResNet models to draw a comparison, in which ResNet101 showed the highest specificity of 94.02%, and highest sensitivity was achieved by ResNet50, which breached 97.1%. R. Kundu et al. [24] speaks about the challenge of subjective variability and data scarcity by utilizing an ensemble of three CNN models named GoogleNet, ResNet18, and DenseNet121. The ensemble showcased accuracy of 98.81% on Kermany and 86.85% on RSNA dataset. Y. Brima et al. [25] highlighted the issue and limitations of RT-PCR and advantages of chest radiography, especially in resource scarce environments. The ResNet50 was found to be the best with an accuracy of 90.4%, and outperformed VGG19 and DeneNet121.

Despite all the research and studies successfully demonstrating the prowess of CNN models for classification, there still exist problems such as limited data diversity and lack of fine grained attention mechanism. To address them the paper proposes a multi scale CNN framework that is designed to enhance the pneumonia detection accuracy and robustness.

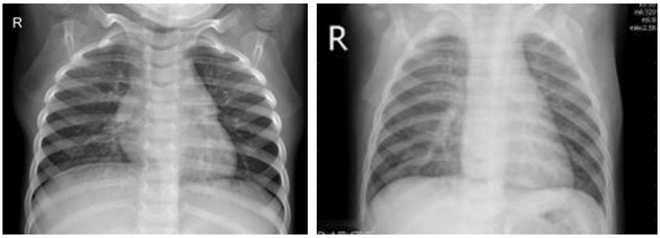
3 METHODOLOGY

The proposed study presented a fresh and optimized Multi Scale Convolutional Neural Network framework for precise and automated detection and classification of pneumonia from the chest radiographs. To overcome the limitations of a single scale CNN model that generally fails to capture all the intricate details appearing at varied scales and limitations was the motivation behind the whole study.

The model follows all the stages, starting from the module import phase, to pre processing and feature learning till final classification. The dataset used is created by Paul Mooney and is publicly available at Kaggle and Fig 7 shows some sample images. It consist of 5,856 images documented in two classes: Normal and Pneumonia. The images were firstly divided into three groups for training, testing and validation with their split amount being 4,496 for training, 663 images for validation, and 696 for testing as illustrated in Table 1. The dataset consists of cases where pneumonia is caused by bacterial as well as viral infection for better and realistic variations. The images were resized to 224x224 pixels and normalized over the range of [0,1] for better uniformity before sending for augmentations.

To prevent overfitting and to improve generalization, the dataset was augmented on some factors, such as horizontal flip, which flips the data along the vertical axis, RandomRotation of 0.2, which rotates the image randomly at 72 degree, RandomZoom of 0.2, which randomly zooms in or out by 20% to help the model recognize objects of different scales and distances; RandomContrast of 0.2, which adjusts the contrast of an image by 20% randomly; and RandomTranslation of

(0.1,0.1), which randomly shifts images horizontally and vertically by 10% each so that the model does not rely on specific object positions.



(a) (b)

Fig 7: Dataset Preview (a) Normal Chest X-Ray (b) Chest X-ray with Pneumonia

Table 1. Dataset Information

Partitions	Normal Case	Pneumonia Case	Total
Training	1089	3407	4496
Validation	259	404	663
Testing	234	462	696

The proposed model as illustrated in Fig 8, is developed by leveraging the use of EfficientNetB0 as its backbone, which is pre-trained on ImageNet and adjusted for binary classification of pneumonia. To capture the fine details and patterns from chest radiographs, EfficientNetB0 is enhanced by a multi scale architecture, which consist of 3 parallel Convolutional Branches learning from the same feature map: Branch 1 is a 3x3 ConV branch that was responsible of extracting and learning medium level details such as textures and opacities. Branch 2 was a 5x5 Conv branch whose responsibility was to extract information from a large lung region to collect contextual data. Lastly Branch 3 was a Depthwise Separable ConV which worked on extracting fine details from radiographs while keeping computations to a minimum. Each branch comprised of Squeeze and Excitation layer to increase feature importance by adaptively readjusting weights of channels. At last the outputs from all three layers were concatenated and passed through additional layers such as convolutional, batch normalization, and dropout to strengthen feature fusion and to prevent overfitting.

The training of the model happens in two phase basis. In the first phase, the first 75 layers of architecture are frozen to retain pre learned features such as textures and edges and run for a total of 20 epochs with 141 steps in each epoch that took 500 ms to 1 sec per step. In phase two, partial unfreezing of deep layers was done, and training happened for 10 more epochs before final completion. The classification head comprised fully connected dense layers with ReLU activation in hidden layers and sigmoid for final classification. Optimizer used for stabilize convergence was the Adam optimizer along with the CoinDecay Learning Rate Scheduler, and loss function was handled by Binary Cross Entropy. The proposed model with all the optimization and refining achieved an outstanding accuracy of 94.4%, along with precision of 87.6%, an F1 Score of 91.3% and a recall value of 95.3%.

All the models used for comparison are also trained on the same dataset with their respective architectures and layer structure and connectivity, which are then finally assessed based on the evaluation metrics of accuracy, precision, F1 score and recall value. The models were deployed in the environment of Google Colab with accelerated GPUs with Keras and Tensorflow, with an initial batch size of 32, an input image size of 224x224x3, and epochs ranging between 20 and 30, as early stopping was applied when validation accuracy plateaued to prevent overfitting, and the learning rate was fixed at 0.0001 for better, smoother, and more stable convergence.

The proposed Multi-Scale CNN architecture consists of approximately 36.5 million parameters, including all trainable, non-trainable, and optimizer parameters from the EfficientNetB0 backbone and optimizer states. The major layers and their parameter counts are summarized in Table 2, highlighting the key computational stages of the model and parameter split.

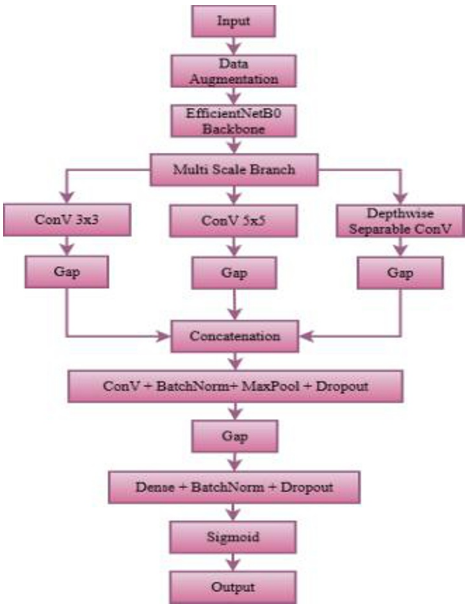


Fig 8: Proposed Model Architecture

Table 2. Layer and Parameter Distribution

Layer Type/ Blocks	Output Shape	Parameters
Input Layer	(224,224,3)	0
EfficientNetB0 Backbone	(7,7,1280)	4,49,571
Conv2D (3x3)	(7,7,128)	14,74,688
Conv2D (5x5)	(7,7,128)	40,96,128
Depthwise Separable Conv2D	(7,7,128)	175,488
Squeeze and Excitation	(1,1,128)	2,184
Concatenate	(3,3,384)	0

Conv2D+BatchNorm+Pooling	(1,1,256)	886,016
Dense (512,256)	(256,)	393,984
Output (Sigmoid)	(1,)	257
Trainable Parameters: 1,21,52,907		
Non-Trainable Parameters: 1087,77		
Optimizer Parameters: 2,43,05,820		
Total Parameters: 36,567,504		

4 RESULTS

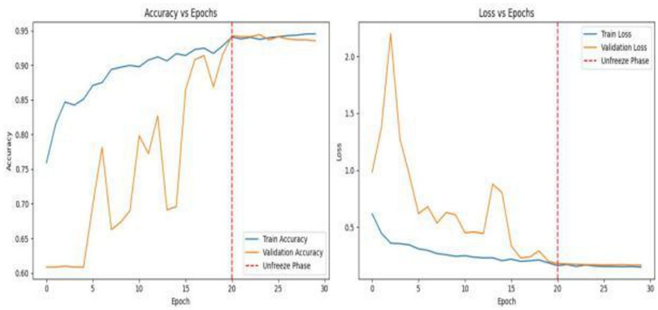
The performance comparison of six deep learning models for pneumonia detection by analyzing chest radiographs is summarized in Table 3. The proposed multi scale CNN model attained the highest accuracy of 94.4%, outperforming all the standard state-of-the-art architectures such as VGG16, which attained 79.3%; ResNet50, with an accuracy of 87.5%; and the base EfficientNetB0, with an accuracy of 90.5%. The model also achieved superior precision of 87.6%, recall of 95.3%, and an F1 score of 91.3%, stating the robustness and prowess of differentiating pneumonia from normal chest X-rays while minimizing both false positives and false negatives.

Table 3. Performance of Neural Networks

Model	Accuracy	Precision	Recall	F1 Score
Multi Scale	94.4	87.6	91.3	95.3
VGG-16	79.3	82	86.3	91
ResNet-50	87.5	65.8	77.9	95.6
DenseNet-121	93.1	82.4	88.9	96.5
EfficientNetB0	90.5	73	83.8	98.2
InveptionV3	93.4	83.7	89.5	96

Comparatively, both DenseNet121 and InceptionV3 showed strong but lower accuracy with 93.1% and 93.4%, respectively. This shows that while deep learning networks capture rich and coherent spatial features, they still lack cross scale sensitivity. N. C. Kundur et al. [26] also devised a custom CNN model based on transfer learning and VGG16 architecture, but was only able to achieve an accuracy of 87.5%, which is surpassed by our multi scale framework. Salehi et al. [27] also did a comparative study of 4 modern day CNN model named DenseNet121, VGG19, ResNet50 and Xception, while each achieved accuracy greater than 83% and DenseNet121 with highest value of 86.8%, they still lack in comparison to the proposed architecture.

The 3-branch feature extraction, along with the squeeze and excitation block that was deployed in multi scale model, enhanced its ability of generalization and its ability to learn fine grained details along with global contextual details. Fig 9. demonstrates the nature of learning achieved during training of 30 epochs with first 20 epochs done with frozen layers and final 10 being done with unfrozen layers.



(a) (b)

Fig 9: Graph between (a) Accuracy vs Epochs, (b) Loss Vs Epochs

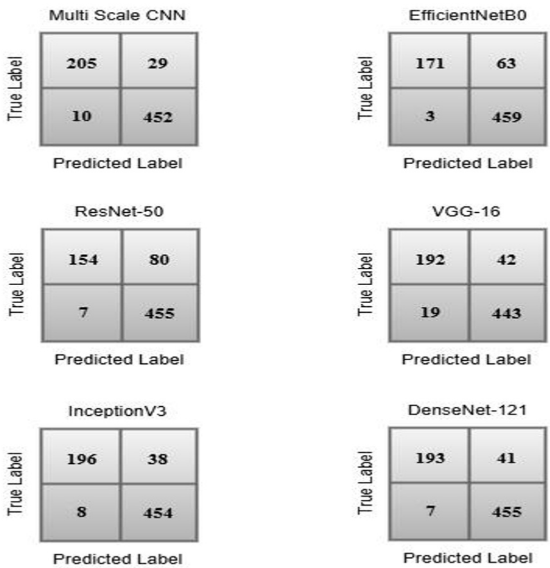


Fig 10: Confusion Matrices of all Neural Networks

The base EfficientNetB0, although computationally efficient with decent accuracy, showed precision of a lower caliber, with only attaining 73%, hence reflecting the trade off between speed and detection capabilities. Fig 10 gives a more detailed insight on the final detection prowess of the proposed architecture. The enhancement and upgradation achieved due the use of a pre trained EfficientNetB0 backbone helped in better feature extraction and better learning, which ultimately helped the model in achieving higher accuracy, precision, and recall values. The results illustrated in Table 3 validate the infusion of multi scale feature learning and attention based refinement, significantly improving the prowess of automated diagnosis of pneumonia in real world clinical environments.

5 CONCLUSION

The proposed multi scale convolutional neural network model displayed exceptional capability in classifying pneumonia from the chest radiographs along with high precision and reliability. Leveraging EfficientNetB0 as a transfer learning backbone, the model evolved with the use of three parallel convolution branches, with each working on learning different features. This architecture allowed simultaneous learning of fine-grained, medium, and large scale spatial features at the same time, enhancing the feature representation. The integration of the squeeze and excitation block and deployment of a two phase training refined the learning process, leading to a stronger discriminative power and improved convergence stability.

Compared to the traditional single level CNN methodology of base EfficientNetB0, the proposed model improved in both textural and global structural understanding. The model achieved an overall accuracy of 94.4%, outperforming conventional state of the art architectures such as VGG16 which achieved 79.3%, ResNet50 with 87.5%, Densenet121 having 93.1%, InceptionV3 peaking at 93.4%, and Base EfficientNetB0 with final accuracy of 90.5%. Additionally, the model also achieved superior performance across precision, recall, and F1 score, demonstrating its robustness against false positives and false negatives. In the broader context of medical imaging, the proposed model provides a scalable, efficient, and interpretable foundation for automated pneumonia diagnosis. With further optimization, the model holds potential for real world deployment, especially in scenarios where rapid diagnosis is critical in resource constrained healthcare environments.

6 FUTURE WORK

Future improvement to the proposed multi scale CNN model will essentially focus on enhancing both scalability and real world applicability. Larger and multi institutional datasets can be employed for a better generalization across more varied demographics and conditions of patients. The framework can be extended beyond binary pneumonia classification to detect multiple diseases like COVID-19, tuberculosis, or even lung cancer. Model optimization for mobile deployment can be explored to support real time diagnosis in remote as well as low resource healthcare environments.

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