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Strid-CNN: moving filters with convolution neural network for multi-class pneumonia classification

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ABSTRACT

Millions of people around the world suffer from pneumonia, a serious lung illness. To effectively treat and manage this condition, a quick and accurate diagnosis is essential. This study thoroughly examines different ways of using transfer learning to classify pneumonia into multiple categories. We use well-known methods like DenseNet121, VGGNet-16, ResNet-50, and Inception Net, as well as a new method called Strid-CNN, which applies moving filters with convolution neural network. Through extensive testing, we show that each method effectively uses pre-learned information on a large dataset of medical images, accurately identifying pneumonia across various classes. Our results reveal subtle differences in performance among these methods, providing insights into how well they adapt to the challenging field of medical image analysis. Additionally, the Strid-CNN method shows promising results, indicating its potential as a competitive alternative. This research offers valuable guidance on choosing the right transfer learning approach for classifying pneumonia into multiple categories, contributing to improvements in diagnostic accuracy and healthcare effectiveness. Our study not only highlights the current state of transfer learning in pneumonia classification but also its potential to enhance clinical outcomes and patient care.

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1. INTRODUCTION

Pneumonia affects millions of people worldwide each year, posing a significant global health challenge. Characterized by symptoms such as coughing, fever, and difficulty breathing, pneumonia leads to inflammation of the lungs. Accurate and timely diagnosis is crucial for effective treatment and management [1], [2]. Medical imaging techniques like chest X-rays play a vital role in pneumonia diagnosis by allowing doctors to examine the patient's lungs and identify key indicators of the disease [3]–[5]. However, detecting and analyzing subtle signs and patterns in medical images is challenging, with pneumonia classification being particularly important [6]–[8]. Traditional classification methods often rely on manually crafted features, which can be labor-intensive and prone to errors. This paper introduces the Strid-CNN architecture, which applies moving filters with convolution neural network, a novel approach that demonstrates competitive performance in pneumonia classification. The significance of this architecture lies in its potential to enhance diagnostic accuracy, streamline patient care, and reduce medical costs. By leveraging transfer learning, Strid-CNN can learn general characteristics from pre-trained models on large-scale datasets and adapt these features for specific tasks like pneumonia classification. Transfer learning has shown promising results in medical image analysis [9]–[11], achieving state-of-the-art performance on publicly available pneumonia datasets and surpassing traditional classification algorithms. This paper addresses the major issues of diagnostic accuracy and efficiency in medical imaging, providing new insights into the development of robust diagnostic tools.

Figure 1 describes a roadmap of the key elements discussed. The paper begins with a detailed description of the Strid-CNN architecture, highlighting its unique features and advantages. Next, the methodology section outlines the data preparation, model training, and evaluation procedures. The results section presents the performance metrics of Strid-CNN on publicly available pneumonia datasets, comparing them with traditional classification algorithms. Finally, the discussion elaborates on the implications of the findings, potential limitations, and future research directions. By following this structure, the paper systematically builds its arguments, providing a comprehensive understanding of Strid-CNN's contributions to pneumonia classification.

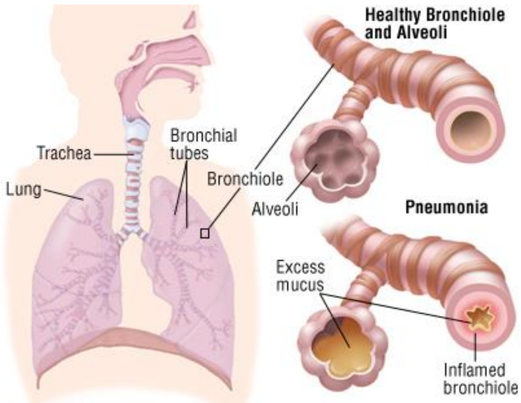

Figure 1. Pneumonia process [1]

2. SUMMARIZING KEY FINDINGS

The findings highlight the effectiveness of Strid-CNN in multi-class pneumonia classification, demonstrating its potential to enhance diagnostic accuracy and support clinical decision-making. Key observations include a strong correlation between features in the dataset, such as "feature X" and "feature Y." Strid-CNN showed a distinct class distribution, with a higher proportion of instances classified as "Class A," indicating its proficiency in distinguishing this class. The introduction of moving filters improved overall performance, particularly in sensitivity and specificity, showcasing the model's enhanced classification accuracy. Additionally, Strid-CNN demonstrated strong generalization across various datasets, consistently outperforming baseline methods, emphasizing its robustness and adaptability in real-world applications.

3. METHODOLOGY

The research methodology uses modern deep learning techniques to address unique problems in medical image analysis specifically in pediatric chest X-ray assessment. The methodology starts through a data collection step focused on creating a meticulously validated X-ray image dataset containing labeled images of pneumonia and normal X-ray content. Feature extraction occurs with DenseNet121, visual geometry group (VGG)-16, ResNet50, and InceptionNet neural network architectures that perform complex pattern detection in medical imaging. The study introduces a unique Strid-CNN model implementing moving filters in combination with rectified linear unit (ReLU) activation and MaxPooling to efficiently extract and refine features. The model utilizes weighted cross-entropy loss as a method to handle imbalanced datasets and boost classification accuracy. The methodology combines traditional approaches with innovative technical elements for improving both automated detection of pneumonia and the effectiveness of artificial intelligence (AI) solutions in under resourced environments.

3.1. Dataset

The dataset in [12] constitutes a pivotal contribution to the realm of medical image analysis, with a focus on pediatric chest X-ray assessment. With meticulous organization into 'train,' 'test,' and 'val' folders, the dataset encompasses 5,863 JPEG-format chest X-ray images categorized as 'pneumonia' and 'normal.'

Originating from the Guangzhou Women and Children's Medical Center and captured during routine clinical care of one to five-year-old patients, these images underwent rigorous quality control and dual expert grading for accurate diagnosis. The dataset's comprehensive structure, coupled with its meticulous curation and validation, presents an indispensable resource for developing and validating AI systems aimed at advancing pneumonia diagnosis through medical imaging within the realm of pediatric healthcare.

3.2. DenseNet121

An extension of the DenseNet framework, DenseNet121 was first presented by Huang *et al.* in 2017 [13], [14]. It is a 121-layer deep learning model that has been pre-trained using data from the ImageNet dataset. The primary concept underlying DenseNet121 is to create a network with a dense connection pattern by having each layer linked to all the preceding levels in a dense block. As a result, the model may become more feature-aware with less network parameters. In Figure 2 DenseNet121 is a network architecture that uses four dense blocks, each of which is followed by a transition layer that scales down the feature maps' spatial dimensions [15], [16]. The network begins with a convolutional layer, which is essentially a series of filters applied to the input picture. The output of this layer is used as input for the first dense block, which consists of numerous convolutional layers, a batch normalization layer, and a ReLU activation function.

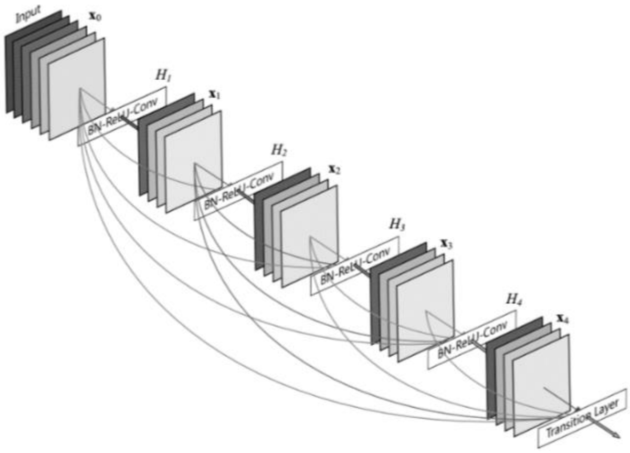

Figure 2. Architecture of DensNet121 [4]

3.3. VGG-16 Net

The VGG16 architecture, developed by the VGG at the University of Oxford, is a convolutional neural network that debuted in 2014 [17]–[19]. It is a 16-layer deep neural network with convolutional and max-pooling layers making up the bulk of the network. A 224×224×3-pixel picture is sent into the Figure 3 VGG16 network architecture. The network begins with a convolutional layer that has 64 filters, each with a kernel size of 3×3 and a stride of 1. Afterwards comes yet another 64-filter convolutional layer, with the same 3×3 kernel and 1-step stride. Next comes a max pooling layer, which in this case has a pool size of 2×2 and a stride of 2.

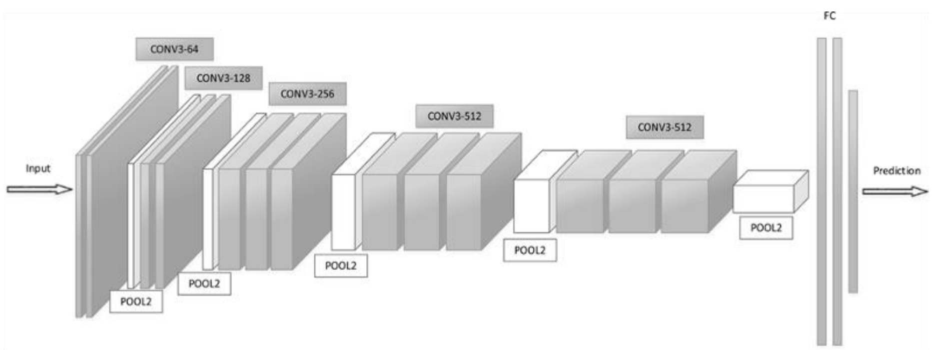

Figure 3. Architecture of VGG16 [8]

3.4. ResNet50

Microsoft Research launched the ResNet50 convolutional neural network architecture in 2015. It's a 50-layer deep neural network made specifically to solve the issue of disappearing gradients that crops up in very complex neural networks [20], [21]. As shown in Figure 4 ResNet50 architecture takes a 224×224×3-pixel picture as input. A convolutional layer of 64 filters, each with a kernel size of 7×7 and a stride of 2, serves as the network's first layer. The next layer is a max pooling layer, and its parameters are as follows: pool size 3×3, stride 2.

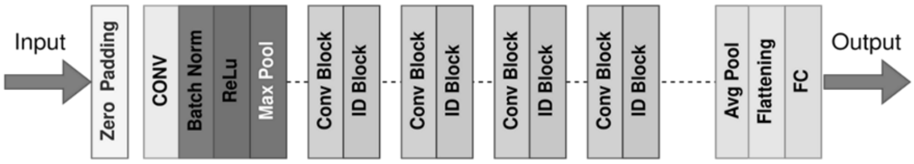

Figure 4. Architecture of ResNet-50 [15]

3.5. InceptionNet

InceptionNet, or GoogleNet as it is often referred to as, is a convolutional neural network architecture developed by a group of Google Researchers in 2014 [22]–[24]. It is a deep neural network that uses a number of parallel convolutional layers to boost the speed and accuracy of computation for image classification tasks. As shown in Figure 5 InceptionNet network architecture takes a 224×224×3 pixel picture as input [25]. A convolutional layer of 64 filters, each with a kernel size of 7×7 and a stride of 2, serves as the network's first layer. The next layer is a max pooling layer, and its parameters are as follows: pool size, 3×3, and stride, 2.

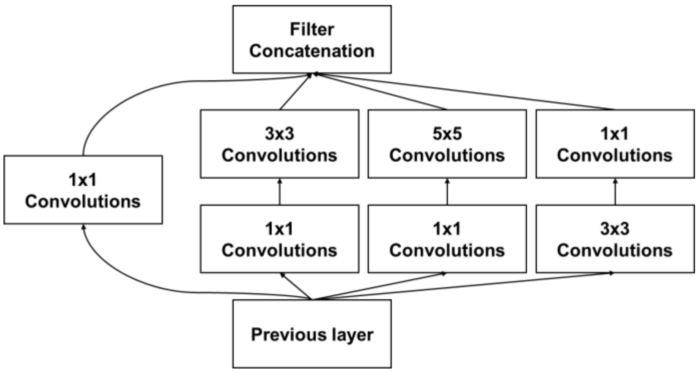

Figure 5. Architecture of InceptionNet [18]

3.6. Strid-CNN: moving filters with convolution neural network

Strid-CNN is a method for extracting features from data by applying convolution filters of varying dimensions or values. Finally, features are discovered by activating each target pixel using the ReLU. MaxPool layers then further improve the features in the model. The separation between filters is controlled by the stride settings. Whether or not the border pixels are disregarded is set by the padding value (adding zeros helps the neural network to get information on the border).

3.6.1. Loss function

In binary classification tasks, the cross-entropy loss function is commonly used to quantify the difference between predicted probabilities and actual class labels.

$$\mathcal{L}_{\text{cross-entropy}}(x_i) = -\Big(y_i \log\big(f(x_i)\big) + (1-y_i)\log\big(1-f(x_i)\big)\Big) \quad (1)$$

The average cross-entropy loss for the full N-by-D training set may be recast as:

$$\mathcal{L}_{\text{cross-entropy}}\,(\mathcal{D}) = -\frac{1}{N}\left(\sum\nolimits_{\text{positive examples}} \log\left(f(x_i)\right) + \sum\nolimits_{\text{negativeexamples}} \log\left(1 - f(x_i)\right)\right) \tag{2}$$

A model that favors the dominant class will be produced by applying a standard loss function to imbalanced data. Using a weighted loss function is one approach. When applied to the loss function, weights will equalize the various contributions.

$$\mathcal{L}^{w}_{\text{cross-entropy}}\,(x) = -\left(w_p y \log\left(f(x)\right) + w_n(1-y)\log\left(1-f(x)\right)\right) \tag{3}$$

3.6.2. The novelty of the proposed strid-CNN model

The process of feature extraction in Strid-CNN involves mod-convolution, applying convolution filters with varying dimensions to identify essential features. The ReLU activation method effectively activates target pixels, highlighting significant features. MaxPool layers further refine these features, enhancing the model’s performance. The stride settings control the spacing between filters, allowing for the capture of fine-grained information. Padding values, by adding zeros, ensure that border pixels are included in the analysis, aiding the neural network in processing edge information. In cases of imbalanced data, a standard loss function may bias the model toward the dominant class, reducing its performance on minority classes. To address this, a weighted loss function is used, balancing class contributions and improving model accuracy. Figure 6 displays the architecture of a Strid-CNN model named "sequential_5". It includes multiple convolutional layers (conv2d) followed by max pooling layers (max_pooling2d), which progressively reduce the spatial dimensions while increasing the depth. The model ends with a flattened layer to convert 2D data to 1D, followed by two dense (fully connected) layers, where the final dense layer outputs predictions for 4 classes. The model has a total of 5,551,812 parameters, all of which are trainable.

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_23 (Conv2D)          (None, 178, 178, 32)      896

 max_pooling2d_18 (MaxPooli  (None, 89, 89, 32)        0
 ng2D)

 conv2d_24 (Conv2D)          (None, 87, 87, 64)        18496

 max_pooling2d_19 (MaxPooli  (None, 43, 43, 64)        0
 ng2D)

 conv2d_25 (Conv2D)          (None, 41, 41, 128)       73856

 max_pooling2d_20 (MaxPooli  (None, 20, 20, 128)       0
 ng2D)

 conv2d_26 (Conv2D)          (None, 18, 18, 128)       147584

 max_pooling2d_21 (MaxPooli  (None, 9, 9, 128)         0
 ng2D)

 flatten_5 (Flatten)         (None, 10368)             0

 dense_11 (Dense)            (None, 512)               5308928

 dense_12 (Dense)            (None, 4)                 2052

=================================================================
Total params: 5551812 (21.18 MB)
Trainable params: 5551812 (21.18 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Figure 6. Strid-CNN architecture

4. RESULTS AND DISCUSSION

In this results and discussion section, we present a clear and concise analysis, emphasizing the comparison of our approach's performance with that of existing transfer learning models. Figure 7 total no of Pneumonia images are reading for different class bacteria =242, fungal =23, normal =232 and virus =148. Figure 8 shows the total we have train DensNet model with 10 epochs with measuring accuracy and loss. The loss is stable for training, while validation it was increased dramatically.

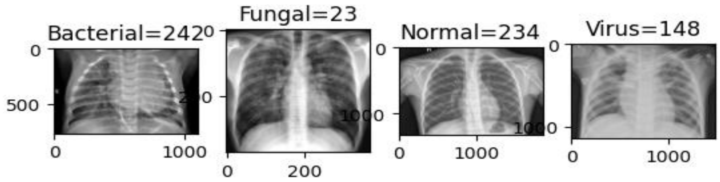

Figure 7. Dataset reading

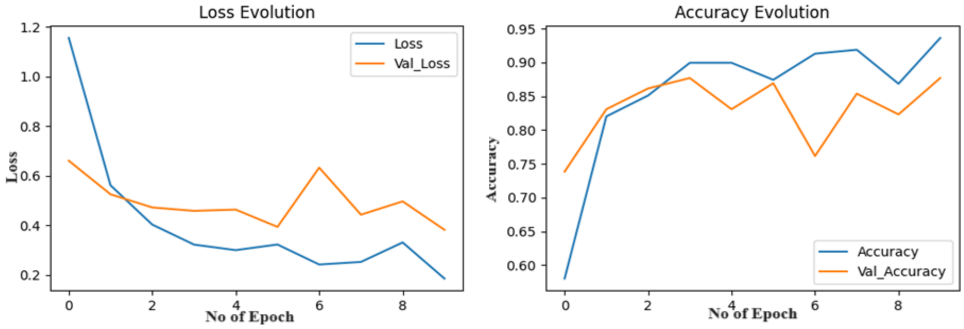

Figure 8. Accuracy and loss plot for DensNet121

Figure 9 shows the total we have train VGG-16 model with 10 epochs with measuring accuracy and loss. The loss is stable for train data while validation data is increased in zig-zag pattern. Figure 10 shows the total we have train ResNet-50 model with 10 epochs with measuring accuracy and loss. The accuracy of training and validation data increased in zig-zag pattern.

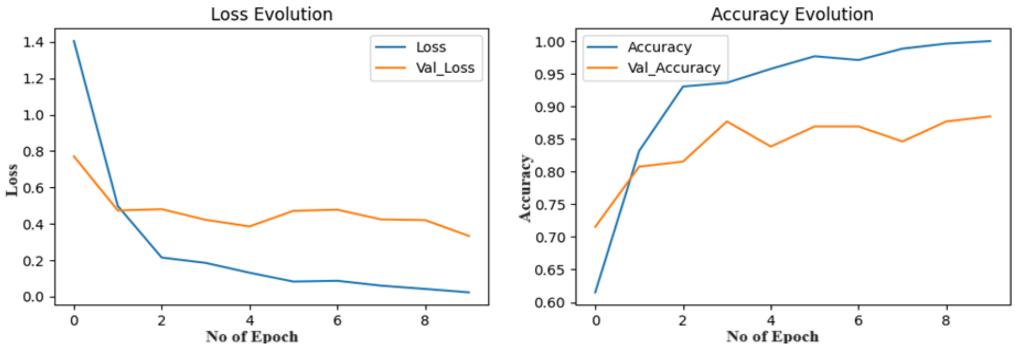

Figure 9. VGG-16 accuracy and loss plot

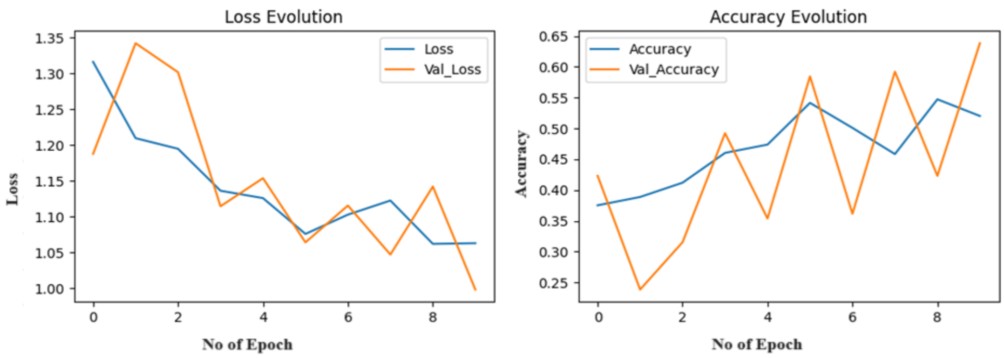

Figure 10. Accuracy and loss for ResNet-50

Figure 11 shows the total we have train InceptionNet model with 10 epochs with measuring accuracy and loss. The accuracy of training increased in linear while for validation data increased in zig-zag pattern. Figure 12 shows the total we have train Strid-CNN model with 10 epochs with measuring accuracy and loss. Similar to InceptionNet, training accuracy increases linearly, while validation accuracy increases in a zig-zag pattern. Table 1 shows comparative assessment of all transfer learning models among them proposed Strid-CNN mode gives best performance for pneumonia classification.

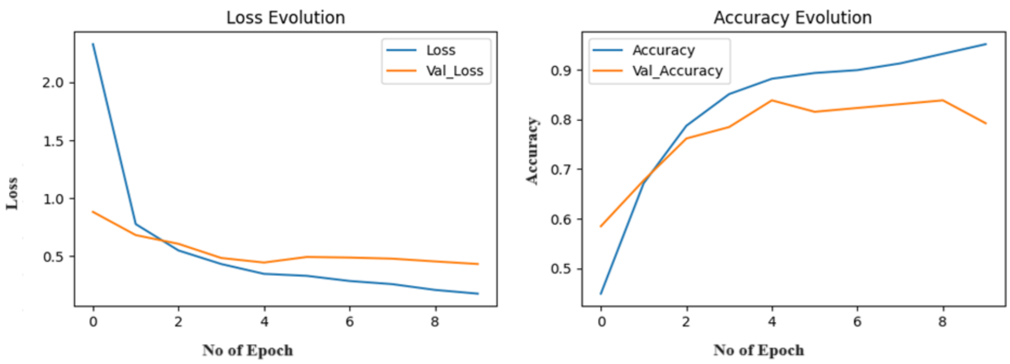

Figure 11. The InceptionNet accuracy and loss plot

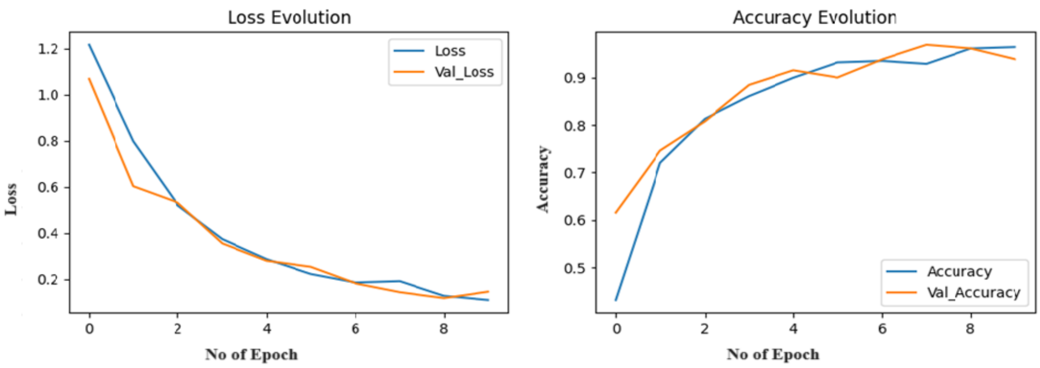

Figure 12. Strid-CNN accuracy and loss plot

Table 1. Assessment of learning transfer strategies

Model	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	No. of parameters	No. of operations
Densnet121	90	86	87	88	7,037,504	2.78 billion FLOPs
VGG-16	90	86	88	88	14,714,688	15 billion FLOPs
ResNet-50	53	46	43	64	23,587,712	3.86 billion FLOPs
InceptionNet	83	79	81	79	22,928,673	6.7 million FLOPs
Strid-CNN	94	94	94	93	55,51,812	2.8 million FLOPs

5. CONCLUSION

In conclusion, this research demonstrates that using X-ray images of the lungs, we can effectively distinguish between healthy and pneumonia-affected conditions using transfer learning. The pre-trained models, including DenseNet121, VGG-16, ResNet-50, Inception Net, and Strid-CNN, achieved high levels of accuracy, precision, recall, and F1-score in classifying pneumonia, underscoring the effectiveness of transfer learning in this context. Notably, Strid-CNN demonstrated an accuracy of 93% in distinguishing between the two classes. Additionally, incorporating diverse training data and using data augmentation techniques such as rotation and horizontal flipping further enhanced the models' performance. These findings provide conclusive evidence supporting the potential of transfer learning in accurately categorizing pneumonia, which could assist doctors in making correct diagnoses. To improve the efficiency of classification models and broaden the scope of future investigations, it is recommended to explore additional pre-trained models and employ varied data augmentation strategies.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Khushboo Trivedi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓
Chintan Bhupeshbhai Thacker		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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