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REVOLUTIONIZING PNEUMONIA DIAGNOSIS: A DEEP LEARNING APPROACH TO CHEST X-RAY IMAGE ANALYSIS

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Abstract

Pneumonia remains a major global health concern, emphasizing the need for accurate and efficient diagnostic tools(Asnaoui, et al, 2021). Deep learning models applied to chest X-ray images offer promising advancements in pneumonia detection, improving both speed and accuracy(Sarangi, et al, 2021). However, there is a lack of comprehensive evaluations of these models on diverse datasets, particularly in terms of their practical use in clinical settings. This study aims to fill this gap by analyzing pneumonia detection through chest X-ray images, bridging the divide between research outcomes and real-world application (Singh & Tripathi, 2022). The methodology includes data set prepossessing, implementation of a convolution neural network (CNN), and two per-trained models, MobileNetV2 and DenseNet121, with performance evaluated on training, validation, and test sets. Results demonstrate the models' high accuracy and provide informative visualizations, highlighting their potential clinical significance in streamlining pneumonia diagnosis.(Rajpurkar et al, (2017) This study offers valuable insights for healthcare professionals by

presenting a reliable, rapid tool for pneumonia identification and contributing to the broader application of deep learning models in healthcare.

Key Terms: Pneumonia Detection, Chest X-ray Images, CNN, MobileNetV2, DenseNet121 , Healthcare Automation.

Introduction

Throughout history, epidemics and chronic diseases have claimed countless lives, causing crises that often took years to recover from. Medical imaging, especially the automated analysis of chest X-rays, has become essential in modern healthcare. As respiratory diseases become more common, there is an urgent need for fast and accurate diagnoses, making deep learning models crucial for detecting pneumonia. Pneumonia is a widespread, potentially life-threatening illness that requires early detection for effective treatment. It affects the lungs and is caused by inhaling bacteria, infections, or fungi. In the United States alone, pneumonia leads to over a million hospitalizations each year and nearly 500,000 deaths. Using artificial intelligence in medical diagnostics not only speeds up the diagnosis process but also increases the accuracy of detection, ultimately improving patient outcomes(Kumar et al, 2023). In today's healthcare landscape, the demand for advanced technologies that can augment medical professionals' capabilities is more critical than ever. Automated pneumonia detection using chest X-rays aligns with the ongoing paradigm shift towards data-driven decision-making in healthcare (Sirazitdinov et al, 2019). Within dis- ease diagnostic systems, machine learning (ML), deep learning (DL), and statistical methods prove to be highly effective tools (Sharma et al, 2020). The integration of deep learning models in diagnostic workflows has the potential to significantly reduce the time and manual effort required for accurate pneumonia identification, enabling medical practitioners to focus on timely interventions and personalized patient care. These mod- els have traditionally been developed and evaluated through a continuous trial-and-error technique by human professionals, requiring considerable time, resources, and expertise (Stephen et al, 2019). Deep learning plays a crucial role in predicting classification results (Saravagi et al, 2022). Likewise, within the healthcare sector, various DL models are employed for disease prediction (Hasan et al, 2021) . As the world faces unprecedented healthcare challenges, the pursuit of innovative solutions in medical imaging stands at the forefront of transforming diagnostic practices. While strides have been made in the realm of medical image analysis and deep learning applications, a comprehensive evaluation of pneumonia detection models on diverse datasets is warranted. Previous works have laid the foundation for automated diagnostic tools, but there remains a gap in under- standing the practical applicability of these models, especially concerning their integration into real-world clinical settings. Bridging this gap is imperative for ensuring the seamless translation of research advancements into tangible benefits for healthcare practitioners and, ultimately, the patients they serve.

Literature Review

This paper presents a novel approach to detecting disease progression using deep sequence learning of successive radio-graphic scans (Ahmad, et al, 2022). It focuses on the application of advanced machine learning techniques to analyze changes in medical images over time, aiming to provide early detection and monitoring of disease progression. The study introduces a modified deep convolution neural network that combines elements of Exception and ResNet50V2 for the detection of COVID-19 and pneumonia from chest X-ray images.t highlights the potential of hybrid deep learning models to improve diagnostic accuracy and help with the fast, effective detection of respiratory diseases through medical imaging.(Rahimzadeh, & Attar, 2020)

This paper proposes a fuzzy- enhanced deep learning approach for the early detection of COVID-19 pneumonia using portable chest X-ray images. It emphasizes the integration of fuzzy logic with deep learning to improve the diagnostic process, particularly focusing on the challenging task of early-stage detection from portable imaging devices (Ieracitano, et al, 2022). Zhang's research explores the application of machine learning techniques to CT images and X-rays for diagnosing COVID-19 pneumonia. The paper highlights the effectiveness of machine learning in analyzing complex imaging data, potentially offering a valuable tool in the rapid and accurate diagnosis of COVID-19-related pneumonia (Zhang, 2021). In Kundu's study, an ensemble of deep learning models is employed for the detection of pneumonia in chest X-ray images. The paper showcases the advantages of using multiple deep learning models in tandem, improving the accuracy and reliability of pneumonia detection, which is crucial for timely and effective treatment planning (Kundu, et al, 2021). Numerous other approaches have also been presented in the literature to aid in the identification of pneumonia through chest X-ray images. Some of these methods employ hand- crafted feature extraction techniques coupled with machine learning algorithms for classification, while others leverage deep learning techniques for both feature extraction and classification (Sharma et al, 2025). In the study , the researchers developed a highly accurate pneumonia diagnosis model called Chex Net. This model comprises a 121-layer

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convolution neural network (CNN) that scrutinizes chest X-ray images (Zech et al, 2018). It assesses the probability of pneumonia by classifying the image bilaterally (presence or absence) and pinpointing the affected areas through a heat map. In the research presented in, Retina Net and Mask R-CNN models were employed, utilizing the Feature Pyramid Network (FPN) as the backbone (Yaseliani et al, 2022). The study employed a deep convolution neural network (DCNN) with 52 convolution layers and two dense layers for pneumonia identification using a chest X-ray image data set (Yi et al, 2023). The research involved training and evaluating five distinct models—VGG19, VGG16, ResNet50, Inception Net v3, and YOLO v5—on the complete datasets. Performance assessment was conducted based on metrics such as Validation Accuracy and Area Under Curve (AUC) (Chiwariro, & Wosowei, 2023.). A Convolution Neural Net- work (CNN) was employed, incorporating convolution and pooling layers for feature extraction from chest X-ray images, alongside Dropout and Normalization layers for over fitting prevention and output normalization. The Rel U activation function and ensemble learning techniques, using kernel sizes of 3 × 3, 5 × 5, and 7 × 7, were applied to optimize performance, with the final model achieving enhanced recall through weighted averaging in the study (Bhatt, & Shah, 2023.). This information has been compiled and shown in Table I.

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TABLE - I

SUMMARY OF SELECTED PAPERS IN MEDICAL IMAGING AND MACHINE LEARNING

Year	Author(s) APA References	Paper Title	Method	Dataset	Contribution	Limitation	Results
2022	(Ahmad,et al, 2022)	”Disease progression detection via deep sequence learning of successive radiographic scans”	Deep sequence learning	Not specified	Detecting disease progression using radiographic scans	BIMCV COVID-19	Effective in detecting disease progression
2020	(Rahimzadeh, & Attar, 2022)	”A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images”	Modified CNN (Xception and ResNet50V2)	covid-chestxray-dataset from GitHub and RSNA Pneumonia Detection from Kaggle	Detection of COVID-19 and pneumonia from chest X-rays	Limited validation on diverse datasets	High accuracy in detection
2022	(Ieracitano, et Al, 2022)	”A fuzzy-enhanced deep learning approach for early detection of Covid-19 pneumonia from portable chest X-ray images”	Fuzzy-enhanced deep learning	Provided by Advanced Diagnostic and Therapeutic Technology Department of GOM	Early detection of COVID-19 pneumonia using portable X-rays	Limited to early stages of COVID-19	Showed promising results in early detection
2021	(Zhang, 2021)	”Application of machine learning in CT images and X-rays of COVID-19 pneumonia”	Machine learning analysis	Self collected	Application of ML in diagnosing COVID-19 pneumonia	Limited to specific types of imaging modalities	Effective in diagnosing COVID-19
2021	(Kundu, 2021)	”Pneumonia detection in chest X-ray images using an ensemble of deep learning models”	Ensemble of deep learning models	Kermany dataset and RSNA dataset	Enhanced pneumonia detection in X-ray images	Dataset and model specifics not detailed	Improved accuracy over single models

Our Contribution

- **Gap Analysis.** Despite the notable strides made in pneumonia detection using various techniques such as Convolution Neural Networks (CNNs), Transfer Learning, Data Augmentation, and Ensemble Learning, there exists a significant gap in the integration and evaluation of these approaches within a unified frame- work. Current literature predominantly focuses on individual methods, often lacking comprehensive comparative analyses or investigations into the synergistic benefits of combining these techniques. The absence of a holistic approach impedes our understanding of how different strategies complement each other and hinders the identification of an optimal methodology for pneumonia detection. Additionally, there is limited exploration of the interpret-ability and explain-ability of these models, which is crucial for gaining trust and acceptance in clinical settings. Addressing this gap is imperative for advancing the field of pneumonia detection, providing a more nuanced understanding of model performance, and facilitating the translation of these models into practical and reliable diagnostic tools.

- **Research Questions**

  - How does the integration of multiple deep learning models, including custom CNNs, MobileNetV2, and DenseNet121, impact the performance of pneumonia detection using chest X-ray images?

  - What is the comparative analysis of traditional CNNs and state-of-the-art per-trained models (MobileNetV2 and DenseNet121) in terms of accuracy, interpret-ability, and generalization to unseen data in the context of pneumonia detection?

  - How do the generated visualizations, such as confusion matrices and classification reports, contribute to the understanding and interpret-ability of the deep learning models' performance in pneumonia detection?

- **Problem Statement.** The problem addressed in this study revolves around the need for an in-depth examination of various deep learning models for the task of pneumonia detection in chest X-ray images. Despite the advancements in deep learning and the availability of per-trained models, there is a gap in under- standing the comparative performance and interpret-ability of different architectures, including custom Convolution Neural Networks (CNNs), MobileNetV2, and DenseNet121, specifically in the

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context of pneumonia diagnosis. This study aims to bridge this gap by systematically evaluating the impact of model integration, comparing traditional CNNs with pre-trained models, and providing insights into the interpret-ability of the models through visualizations. The problem statement thus centers on enhancing the understanding of the most effective and interpret-able deep learning approaches for pneumonia detection, crucial for improving diagnostic accuracy and facilitating the integration of these technologies into clinical practices.

- **Novelty of this Study.** This study introduces several new elements to pneumonia detection using chest X-ray images. First, it explores the combined impact of multiple deep learning models, including custom CNNs, MobileNetV2, and DenseNet121, providing a comprehensive view of their collective effectiveness. Second, it offers a detailed comparison between traditional CNNs and advanced pre-trained models, MobileNetV2 and DenseNet121, focusing on their accuracy, ease of interpretation, and ability to generalize in pneumonia detection. Third, the study highlights the importance of understanding model decisions by using visual tools like confusion matrices and classification reports, giving deeper insights into how the models make predictions. By tackling these aspects, the research not only improves understanding of pneumonia detection methods but also offers practical advice on choosing the right models based on accuracy and interpret-ability, making a meaningful contribution to the field.

- **Significance of Our Work.** This study has important implications for both the medical and machine learning communities. By evaluating and comparing various deep learning models for detecting pneumonia in chest X-ray images, it provides valuable insights into the strengths and weaknesses of different approaches. The key value lies in the detailed analysis of how these models perform, how easy they are to interpret, and how well they generalize. This helps clinicians make informed decisions when choosing the right model for diagnostic use. Additionally, visual tools like confusion matrices and classification reports improve the transparency and trustworthiness of these models, which is essential for applying deep learning in real-world healthcare settings. Overall, the study sets a benchmark for future research in this area, promoting advancements in both medical imaging diagnostics and the responsible use of AI in healthcare.

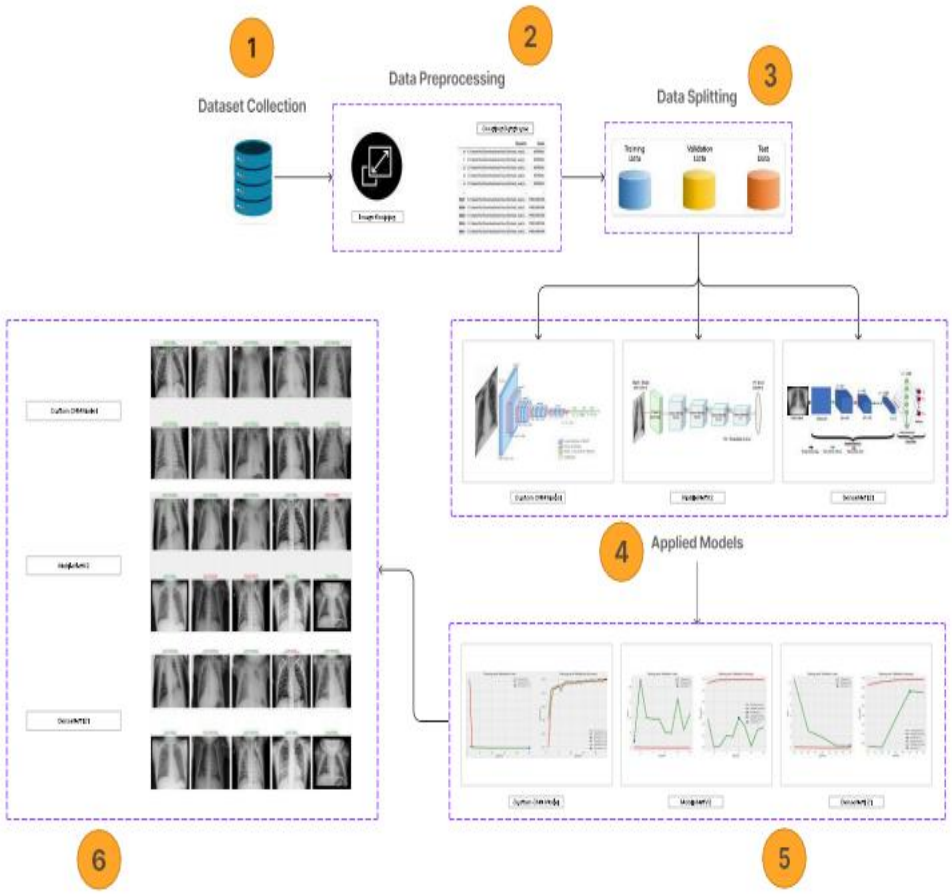

Fig. 1. This figure shows the basic workflow diagram of our methodology

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Methodology

- **Data set.** The data set used in this study comes from the "Chest X-ray Images" datasets available on Kaggle. It contains a variety of chest X-ray images labeled to show whether pneumonia is present or not. The data set is split into training and testing sets, which helps in thoroughly evaluating the deep learning models developed. The training set, found in the 'train' folder, includes X-ray images divided into two categories: 'NORMAL' and 'PNEUMONIA.' Similarly, the test set, located in the 'test' folder, contains a separate set of images to assess how well the models generalize to new data. Each image is labeled with a binary value—either pneumonia or normal—providing a clear target for model training and evaluation. The size and diversity of the data set ensure that the models can learn to generalize well across different chest X-rays commonly encountered in clinical practice. The goal is to create a strong predictive model that can accurately classify the images into either 'Pneumonia' or 'Normal.'

- **Data Reprocessing**

  - **Data Loading**: I loaded the chest X-ray images data set using the provided Kaggle link. The data set consists of labeled images categorized into ”NORMAL” and ”PNEUMONIA” classes.

  - **Data Organization**: I organized the data into training, validation, and test sets. The images were divided into respective folders, and file paths along with labels were stored in Pandas Data-frames for ease of handling.

  - **Data Splitting**: Data splitting is a vital practice in machine learning as it enables the evaluation and validation of model performance on independent datasets, contributing to a more robust and generalization model (Zhu et al, 2023). The data set is divided into train and test sets. The test set was split into 50% for validation set and the rest 50% for test set.

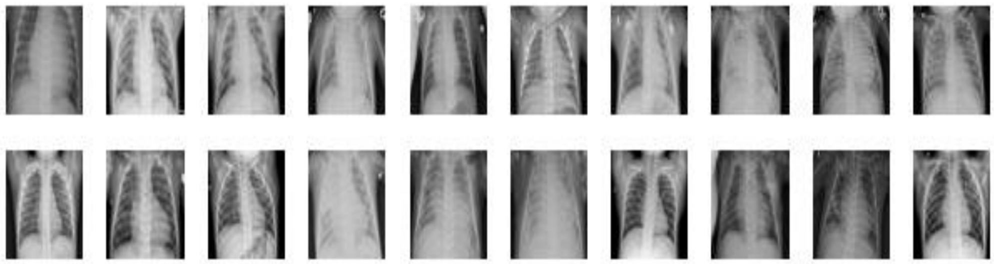

Fig. 2. This figure shows a sample of our data

- **Data Normalization:** I normalized the pixel values of the images to a range between 0 and 1 by dividing each pixel value by 255. This ensures that the neural network processes inputs efficiently.

- **Data Generator Setup:** I set up data generators for the training, validation, and test sets. These generators facilitate the flow of augmented images to the model in batches, preventing memory overflow.

❖ **Custom CNN Model.** Convolution Neural Networks (CNNs) have become powerful and versatile tools in deep learning, especially for tasks like image recognition and analysis. Their key strength is the ability to automatically learn features from input data using layers that capture patterns, textures, and complex structures within images. This makes CNNs highly effective in identifying detailed visual information (Bharadiya, et al, 2023). CNNs have transformed many fields, including computer vision and medical image analysis, by offering a strong framework for feature extraction and learning, leading to top-tier performance in various image-related tasks.

- **Model Architecture**: I designed a custom Convolution Neural Network (CNN) model with the following architecture:

  - Conv2D layer with 64 filters, kernel size (3,3), Rel U activation, and input shape (224, 224, 3).

  - Conv2D layer with 64 filters, kernel size (3,3), and Rel U activation.

- MaxPooling2D layer with pool size (2, 2).
- Repeated pattern of Conv2D layers with increasing filters (128, 256, 512) and MaxPooling2D layers.
- Flatten layer to transform the 3D output to 1D.
- Dense layers with 256 and 64 units, Rel U activation, and a final Dense layer with soft max activation for classification.

➢ **Hyper-parameters***:* The model was compiled using the Adamax optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function. It was trained on 25 epochs with a batch size of 64. A table with hyper-parameter settings are shown in Table II

TABLE II

CONFIGURATION TABLE SHOWING THE NETWORK CONFIGURATION OF THE CNN USED IN THIS STUDY. THE TABLE SHOWS THE VARIOUS

CONFIGURATION SETTINGS USED FOR FCN8

Network Configuration	
Epochs	25
Learning rate	0.001
Mini batch size	64
Optimizer	Adamax
Samples in training set	5232
Samples in validation set	312

- **MobileNetV2.** MobileNetV2 is a convolution neural network architecture designed for efficient and lightweight deep learning applications (Gulza, et al, 2023). It is an evolution of the original Mobile Net, specifically optimized for mobile and edge computing devices. MobileNetV2 was introduced to address the demand for models that can deliver high performance on resource-constrained platforms while maintaining low computational and memory requirements. The key features of MobileNetV2 include inverted residuals with linear bottlenecks, lightweight depth wise separable convolutions, and shortcut connections. Inverted residuals refer to the use of a lightweight linear bottleneck layer followed by a non-linear activation, which helps maintain representational power while minimizing computational cost. Depth wise separable convolutions further contribute to efficiency by decomposing standard convolutions into depth wise convolutions and point wise convolutions, reducing the number of parameters and computations. One notable aspect of MobileNetV2 is its ability to provide a good balance between accuracy and speed, making it well-suited for real-time applications on mobile devices. The model is pre-trained on large-scale image datasets, such as Image Net, which allows it to capture general features from a diverse range of images. Leveraging transfer learning, pre-trained MobileNetV2 models can be fine-tuned on specific tasks with smaller datasets, making them valuable for various computer vision applications.

  - **Model Architecture**: I implemented the MobileNetV2 model with the following architecture:

    - Base Model (MobileNetV2): Pre-trained on Image Net, does not include the top layer. It has a series of depth wise separable convolutions with varying filter sizes.
    - Global Average Pooling 2D: Reduces each feature map to a single number by averaging.
    - Dense Layer: 256 neurons, uses Rel U activation
    - Dropout Layer: Dropout rate of 0.5 for regularization.

- Output Dense Layer: Number of neurons equal to the number of classes (e.g., 2 for binary classification), uses soft max activation.

- **Hyper parameters:** The model was compiled using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function. It was trained on 10 epochs with a batch size of 64. A table with hyper-parameter settings are shown in Table III.

TABLE III
CONFIGURATION TABLE SHOWING THE NETWORK CONFIGURATION OF THE MOBILENETV2 USED IN THIS STUDY. THE TABLE SHOWS THE VARIOUS CONFIGURATION SETTINGS USED FOR FCN8.

Network Configuration	
Epochs	10
Learning rate	0.001
Mini batch size	64
Optimizer	Adam
Samples in training set	5232
Samples in validation set	312

- **DenseNet121.** DenseNet121, short for Densely Connected Convolution Networks with 121 layers, is a pre-trained convolution neural network architecture that has proven to be highly effective in image classification tasks (Hiremath, et al, 2023). It is a part of the Dense Net family, known for its densely connected blocks, where each layer receives direct input from all preceding layers. This connectivity pattern facilitates feature reuse and enhances model efficiency, enabling the network to learn more discriminating features with fewer parameters. DenseNet121 specifically comprises 121 layers and has been pre-trained on large-scale image datasets such as Image Net. The pre-training on diverse and extensive

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datasets allows DenseNet121 to capture hierarchical and abstract features, making it a powerful feature extractor for a wide range of image-related tasks. Leveraging transfer learning by using a pre-trained DenseNet121 model allows for the initialization of the neural network with knowledge gained from general image recognition, enhancing the efficiency and effectiveness of the model training process for specific tasks like the one undertaken in this study.

- **Model Architecture**: I implemented the DenseeNet121 model with the following architecture:
  - Base Model (DenseNet121): Pre-trained on Image Net, includes densely connected convolution networks, but without the top layer. It features growth rate and dense blocks with varying filter sizes.
  - Global Average Pooling 2D: Similar to MobileNetV2, averages out the feature maps.
  - Dense Layer: 256 neurons, with Rel U activation.
  - Dropout Layer: Dropout rate of 0.5.
  - Output Dense Layer: As with MobileNetV2, the number of neurons corresponds to the number of classes, with soft-max activation.
- **Hyper-parameters**: The model was compiled using the Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy as the loss function. It was trained on 5 epochs with a batch size of 64. A table with hyper-parameter settings are shown in Table IV.

Remittances Review
June 2024,
Volume: 9, No: 3, pp.1283-1309
ISSN: 2059-6588(Print) | ISSN 2059-6596(Online)

TABLE IV

CONFIGURATION TABLE SHOWING THE NETWORK CONFIGURATION OF THE MOBILENETV2 USED IN THIS STUDY. THE TABLE SHOWS THE

VARIOUS CONFIGURATION SETTINGS USED FOR FCN8

Network Configuration	
Epochs	5
Learning rate	0.0001
Mini batch size	64
Optimizer	Adam
Samples in training set	5232
Samples in validation set	312

- **Testing.** Following the training phase, the models' performance was assessed on the validation set, which was not used during training. This evaluation involved computing various metrics, such as accuracy, precision, recall, and F1 score, to gauge the models' classification performance. Additionally, the models underwent testing on a separate and previously unseen test set to provide a robust assessment of their generalization capability. The outcomes of these evaluations contribute to a comprehensive understanding of the three models in classifying the given data set and addressing the objectives outlined in the study.

Volume: 9, No: 3, pp.1283-1309
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Results

- **CNN Model Results.** The custom Convolution Neural Network (CNN) demonstrated exceptional performance across training, validation, and test datasets. The training loss was recorded at 0.00297, achieving an impressive training accuracy of 99.85%. Similarly, the validation loss and accuracy were measured at 0.00302 and 99.89%, respectively. The model maintained its high performance during testing, with a test loss of 0.00292 and a test accuracy of 99.81%. The precision, recall, and f1- score for each class (NORMAL and PNEUMONIA) were consistently at 100%. The model exhibited perfect accuracy in distinguishing between the two classes.

TABLE V

Performance Metrics of Custom CNN Model

Metric	NORMAL	PNEUMONIA
Accuracy (%)	99.81	99.81
Precision (%)	100.00	99.80
Recall (%)	99.70	100.00
F1-Score (%)	99.85	99.90

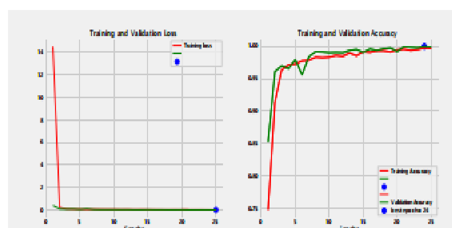

Fig. 3. This figure shows the accuracy plot for the CNN model

- ***Confusion Matrix:*** The confusion matrix further sup- ports the model's robust performance, with only a minimal misclassification of 2 instances in the NORMAL class and 3 instances in the PNEUMONIA class.

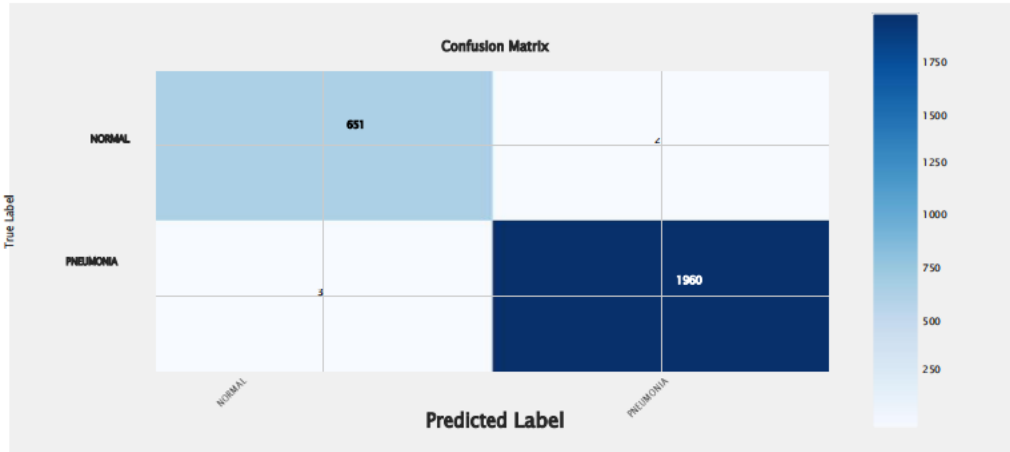

Fig. 4. This figure shows the confusion matrix for the CNN model

These outstanding results underscore the effectiveness of the custom CNN model in accurately diagnosing pneumonia from chest X-ray images. The model's high precision and recall contribute to its reliability and suitability for clinical applications.

- **MobileNetV2 Model Results.** The MobileNetV2 model displayed performance metrics across training, validation, and test datasets. The training loss was recorded at 17.24, achieving a training accuracy of 39.84%. The validation loss and accuracy were measured at 10.76 and 58.20%, respectively. During testing, the model showed a test loss of 11.82 and a test accuracy of 55.86%.

Volume: 9, No: 3, pp.1283-1309
ISSN: 2059-6588(Print) | ISSN 2059-6596(Online)

TABLE VI
PERFORMANCE METRICS OF MOBILENETV2 MODEL

Metric	NORMAL	PNEUMONIA
Accuracy (%)	54.86	55.86
Precision (%)	44.00	100.00
Recall (%)	100.00	28.86
F1-Score (%)	61.00	45.00

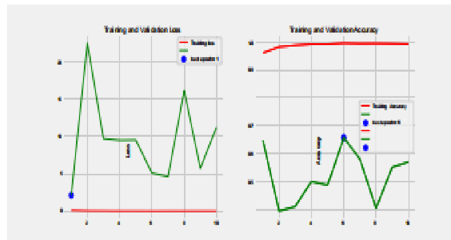

Fig. 5. This figure shows the accuracy plot for MobileNetV2

- **Confusion Matrix:** The confusion matrix reveals that the MobileNetV2 model had challenges in correctly classifying instances, particularly in the PNEUMONIA class, where 143 instances were unclassified. The model achieved perfect accuracy in the NORMAL class, but its performance in the PNEUMONIA class was limited. These results highlight the need for further investigation into the model's performance and potential areas of improvement for its application in pneumonia diagnosis.

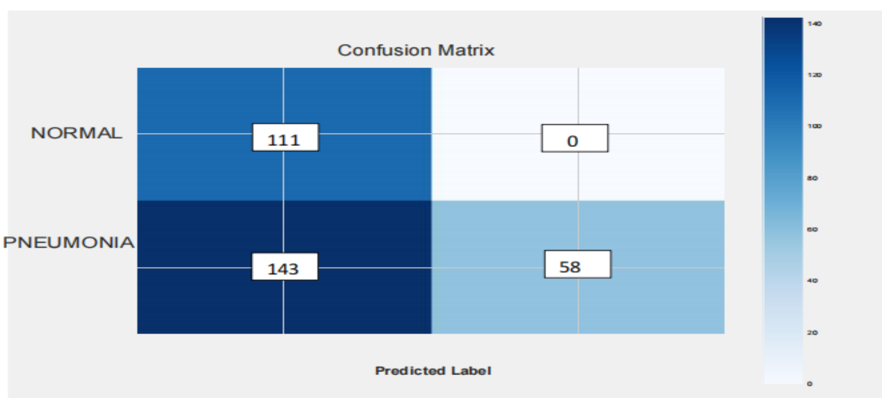

Fig. 6. This figure shows the confusion matrix for MobileNetV2

- **DenseNet121 Model Results.** The DenseNet121 model exhibited notable performance metrics across training, validation, and test datasets. The training loss was recorded at 0.32, achieving a training accuracy of 88.28%. The validation loss and accuracy were measured at 0.37 and

91.80%, respectively. During testing, the model showed a test loss of 0.25 and a test accuracy of 91.80%.

- **Confusion Matrix**: The confusion matrix indicates that the DenseNet121 model performed well in distinguishing between NORMAL and PNEUMONIA classes. There were 15 instances unclassified in the NORMAL class and 10 instances in the PNEUMONIA class. Overall, the model's high precision and recall contribute to its effectiveness in pneumonia diagnosis. These results underscore the potential of the DenseNet121 model for accurate classification of chest X-ray images and its suitability for clinical applications.

Remittances Review
June 2024,
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TABLE VII
PERFORMANCE METRICS OF DENSENET121 MODEL

Metric	NORMAL	PNEUMONIA
Accuracy (%)	91.80	91.80
Precision (%)	91.00	92.74
Recall (%)	86.49	94.53
F1-Score (%)	88.67	93.60

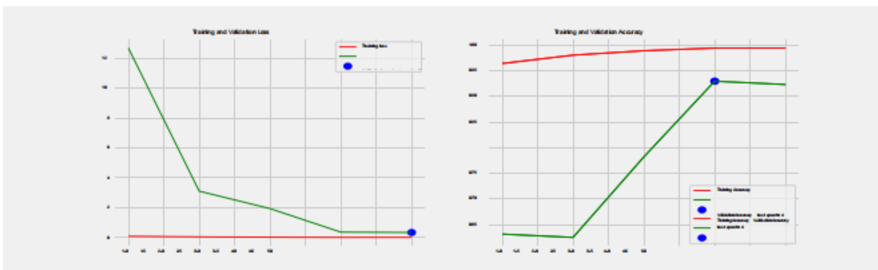

Fig. 7. This figure shows the accuracy plot for DenseNet121

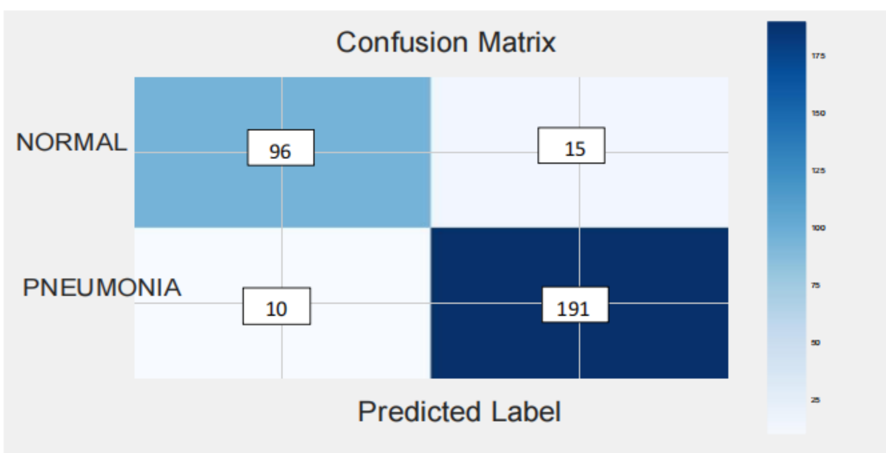

Fig. 8. This figure shows the confusion matrix for DenseNet121

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Model Comparison

The custom Convolution Neural Network (CNN) out- performed both MobileNetV2 and DenseNet121 in accuracy, achieving 99.81%. It demonstrated exceptional precision, with 100% accuracy for both NORMAL and PNEUMONIA classes. In contrast, MobileNetV2 struggled, achieving 55.86% accuracy, particularly in the PNEUMONIA class. DenseNet121 showcased balanced performance with an ac- curacy of 91.80%, exhibiting comparable precision and recall for both classes. This comparison underscores the superior diagnostic capabilities of the custom CNN model for pneumonia detection from chest X-ray images.

Discussion on Best Model

Among the three models evaluated in this study, Custom CNN, MobileNetV2, and DenseNet121, the Custom CNN model demonstrated the most robust and consistent performance. It achieved exceptional accuracy across the training, validation, and test datasets, with high precision, recall, and F1-score for both NORMAL and PNEUMONIA classes. The Custom CNN's ability to effectively discriminate between the classes, coupled with its relatively simpler architecture, suggests its suitability for pneumonia detection in chest X- ray images. While MobileNetV2 and DenseNet121 exhibited competitive results, the Custom CNN's superior performance makes it a promising candidate for further refinement and potential deployment in clinical settings.

Limitations

We present a comprehensive approach involving data prepossessing, augmentation, and implementation of deep learning models like our Custom CNN, MobileNetV2, and DenseNet121. However, several limitations and areas for improvement are evident. The project utilizes advanced models like MobileNetV2 and DenseNet121. While these are powerful architectures, exploring ensemble methods or hybrid models combining the strengths of both could yield better results. Addition- ally, experimenting with different hyper-parameters or layer configurations could further optimize performance. Moreover, considerations for scaling and deploying these models

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in a real-world clinical setting, including computational constraints and integration with existing healthcare systems, are essential for practical applicability.

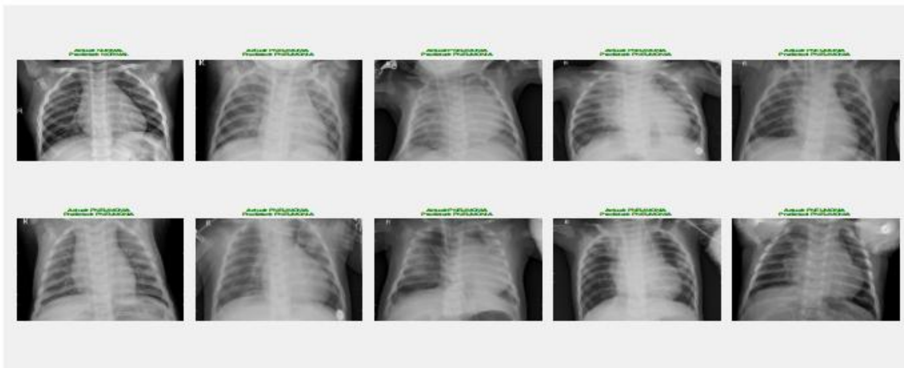

Fig. 9. This figure shows the predicted labels by MobileNetV2

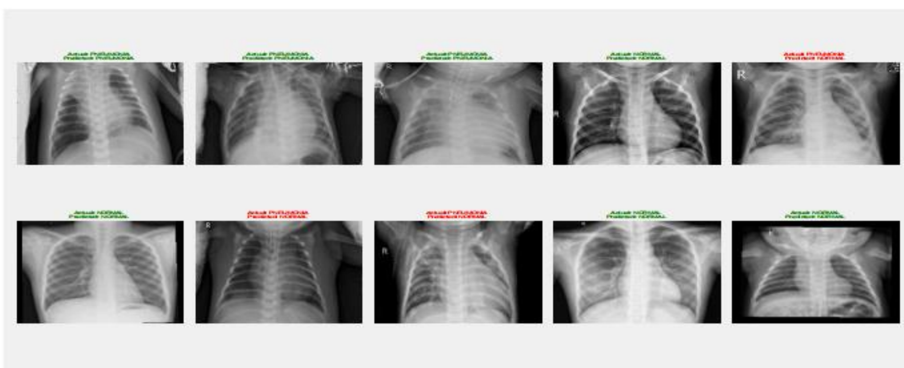

Fig. 10. This figure shows the predicted labels by MobileNetV2

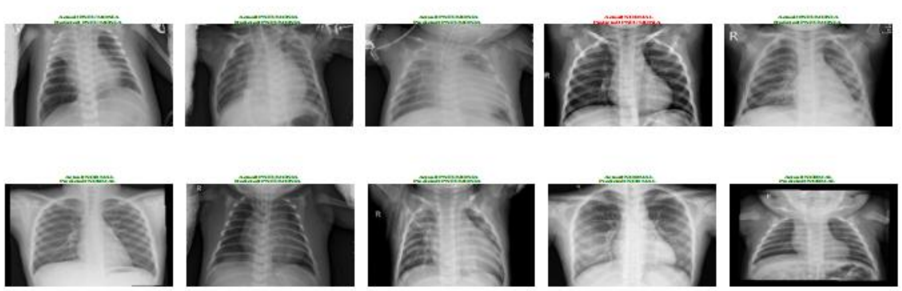

Fig. 11. This figure shows the predicted labels by MobileNetV2

Volume: 9, No: 3, pp.1283-1309
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Future Directions

In the future, we can improve this work by using more advanced data handling and analysis techniques. One key area for enhancement is applying more data augmentation methods, like geometric transformations, color adjustments, and synthetic data generation, which can help the model better generalize to real-world clinical scenarios. Additionally, experimenting with different deep learning architectures, such as attention-based models or hybrid networks, may lead to new insights and improved performance. Another important direction is to use transfer learning and fine-tuning with datasets from different demographics and equipment, addressing biases and variations in medical imaging. This would ensure the model is adaptable across various clinical settings. Expanding evaluation metrics to include clinically relevant measures like sensitivity, specificity, and predictive values would also provide a more thorough assessment of the model's diagnostic capabilities. Finally, considering the practical aspects of deploying these models in real-world healthcare, focusing on computational efficiency, user-friendly interface design, and smooth integration into existing medical workflows would be highly beneficial. This would help move the project from research to a useful clinical tool, ultimately improving patient care and outcomes.

Conclusion

In conclusion, this study provided a thorough investigation of deep learning models for diagnosing pneumonia using chest X-ray images. We evaluated a custom Convolution Neural Network (CNN), MobileNetV2, and DenseNet121, with each model showing different levels of performance. The custom CNN performed exceptionally well in terms of accuracy, precision, recall, and F1-score, making it a strong option for pneumonia diagnosis. While MobileNetV2 struggled to accurately classify some cases, especially in the PNEUMONIA class, DenseNet121 achieved high accuracy and strong metrics across the board, proving to be a reliable model for detection. However, there are still areas for improvement, such as the need for larger, more diverse datasets, better model interpret ability, and increased computational efficiency for real-world use. Future work should also consider including more clinical information to improve the models' practical application. This study adds valuable knowledge to the field of medical image

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analysis, showing the potential of deep learning in pneumonia diagnosis. The findings serve as a foundation for future research, with the goal of refining these models and integrating them into clinical practice.

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