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Mobile-Net Based Pneumonia Detection Model

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Abstract: Pneumonia, a leading global cause of mortality, requires timely and accurate diagnosis to mitigate its impact. This work introduces an automated pneumonia detection system using MobileNet, a lightweight Convolutional Neural Network (CNN) optimized for mobile and embedded devices. By employing depth wise separable convolutions, Mobile Net reduces computational complexity while maintaining high accuracy. Trained on a labelled chest X-ray dataset with preprocessing techniques, it achieves 92.5% accuracy, 91.8% precision, and 93.2% recall, offering an efficient, accessible solution for resource-constrained healthcare settings.

Keywords: Pneumonia, MobileNet, Convolutional Neural Network (CNN), Chest X-rays

I. INTRODUCTION

Pneumonia remains a leading global cause of death, particularly in low-resource settings, where timely diagnosis is hindered by limited access to healthcare professionals and diagnostic tools. Chest X-rays are widely used for diagnosis, but their interpretation requires specialized expertise, often unavailable in underserved regions, leading to delays and misdiagnosis. To address these challenges, this paper proposes an automated pneumonia detection system using MobileNet, a lightweight Convolutional Neural Network (CNN) optimized for low-power devices like smartphones. The system employs transfer learning, fine-tuning a pre-trained MobileNet model on a labeled chest X-ray dataset to enhance performance while maintaining computational efficiency. Data preprocessing and augmentation techniques improve image quality and model generalization. Traditional methods rely heavily on expert radiologists for analyzing chest X-rays, making the process time-consuming and prone to human error. Additionally, deep learning models such as ResNet and DenseNet, while effective, require high computational resources, limiting their applicability in real-time and resource- constrained environments. Moreover, many existing models focus solely on classification without addressing key issues such as interpretability and computational efficiency. The goal is to provide fast, accurate, and accessible pneumonia diagnoses, reducing diagnostic delays and enhancing healthcare delivery in resource-constrained environments. This solution aims to improve healthcare access and timely detection, especially in remote areas.

II. LITERATURE SURVEY

T.S. Arulanath, Wilson Prakash focussed on a modified DenseNet-121 architecture optimized for paediatric pneumonia detection. DenseNet-121's dense connectivity, which promotes efficient feature reuse and minimizes overfitting, was fine-tuned to handle the specific characteristics of paediatric chest X-rays, including smaller anatomical structures and variable presentation of symptoms. To improve performance on small and imbalanced datasets, the model incorporates additional layers with dropout regularization to reduce overfitting. The research demonstrated high accuracy, sensitivity, and specificity in detecting pneumonia in children, highlighting its potential for deployment in paediatric healthcare settings. This work emphasizes the importance of tailoring deep learning models to address the unique challenges associated with paediatric medical imaging [1].

Isabel De La Torre Díez, Mobeen Shahroz used the EfficientNetV2L architecture, which is known for achieving state-of-the-art performance with minimal computational resources, to detect pneumonia from chest radiographs. The model scales depth, width, and resolution in a balanced manner to enhance feature extraction and classification accuracy. By employing transfer learning and pretrained weights, the authors significantly reduced training time and computational cost while achieving exceptional performance metrics. The study tested the model on large, high-resolution datasets and demonstrated its suitability for real-time clinical applications. This research highlights EfficientNetV2L's utility in achieving high accuracy in pneumonia detection while being computationally efficient, making it an attractive choice for resource-limited healthcare settings [2].

L. Yao, Yuchen Zheng introduced a lightweight residual network designed for deployment in resource-constrained environments, such as rural clinics or mobile health setups. The proposed network minimizes the number of parameters and computational overhead without compromising detection accuracy. By employing residual connections, the model effectively learns hierarchical features, enabling robust classification even with limited training data.

This architecture's efficiency makes it ideal for deployment on portable devices like smartphones or edge computing devices, allowing real-time pneumonia diagnosis in underserved areas. The study underscores the significance of lightweight networks in bridging the diagnostic gap in low-resource settings [3].

Yu Liu, Junchao Zhang introduced an innovative double-network architecture that combines classification and segmentation tasks for enhanced pneumonia detection. The classification network identifies pneumonia presence, while the segmentation network pinpoints the infected regions within the lungs, providing localized insights into the disease's extent. This dual approach not only improves diagnostic accuracy but also adds interpretability to the results, aiding clinicians in making more informed decisions. The segmentation results enable visualization of abnormalities, fostering trust in the system's predictions. This methodology exemplifies the integration of classification and medical imaging to achieve comprehensive diagnostic support in pneumonia detection [4].

Shah Muhammad, Azmat Ullah applied transfer learning to adapt pretrained deep learning models, such as ResNet and InceptionV3, for the dual task of identifying pneumonia and differentiating it from COVID-19 using chest X-rays. The study addresses the overlapping radiological features of these diseases and demonstrates how pretrained models can be fine-tuned to achieve high accuracy in a low-data environment. The findings reveal that transfer learning significantly reduces the need for large datasets and computational resources while maintaining robust performance. [5] highlights the potential of transfer learning as a cost-effective and efficient approach to deploy deep learning models in radiology for diagnosing co-occurring respiratory conditions. Integrates Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize critical regions in X-rays influencing the model's predictions. It achieved high sensitivity, specificity, and overall accuracy, indicating robust diagnostic capabilities. Metrics such as the area under the receiver operating characteristic (ROC) curve were also reported to evaluate classification confidence.

Dimpy Varshni, Kartik Thakral, et al explored the use of convolutional neural networks (CNNs) for feature extraction to detect pneumonia in chest X-ray images. The authors propose a hybrid approach where CNN-based deep features are combined with handcrafted features to improve classification performance. By using both feature types, the study demonstrates an enhancement in accuracy, showcasing the model's ability to capture complex patterns associated with pneumonia while incorporating domain-specific insights. Although it predates many advanced architectures, this work laid a foundation for integrating CNNs into pneumonia detection, emphasizing the importance of feature extraction in achieving reliable diagnostics [6].

Harsh Bhatt, Manan Shah utilized an ensemble approach that combines multiple CNN models to enhance the accuracy and robustness of pneumonia detection. By aggregating predictions from individual models, the ensemble reduces variability and improves performance compared to standalone architectures. The study explores diverse CNN architectures, such as ResNet and VGG, leveraging their complementary strengths. The ensemble achieved state-of-the-art results on benchmark datasets, demonstrating improved generalizability across different imaging conditions. The authors highlight the ensemble's ability to handle noisy and heterogeneous datasets, making it a reliable tool for clinical applications [7].

Shagun Sharma, Kalpna Guleria utilized the VGG-16 architecture to develop a deep learning model for pneumonia detection. The model's simplicity and well-established feature extraction capabilities make it a suitable choice for medical image classification tasks. The authors fine-tuned the network to optimize its performance on chest X-ray datasets, achieving high accuracy and recall rates. They also integrated additional dense layers to enhance feature learning, particularly for subtle patterns indicative of pneumonia. The study emphasizes the potential of VGG-16 for deployment in clinical settings while addressing the need for further optimization to adapt to diverse patient populations and imaging conditions [8].

III. PROPOSED SYSTEM

The proposed classification model, depicted in Figure 1, begins with data preprocessing. Preprocessing operations include image resizing, normalization, and contrast enhancement. The preprocessed chest X-ray images are then fed into deep learning models such as MobileNet and DenseNet-121 for optimal feature extraction. The extracted features are fused, and dimensionality reduction is applied using Principal Component Analysis (PCA). Finally, the reduced feature set is classified using a multi-class Support Vector Machine (SVM).

The final classifier used in the proposed model is multi-class Support Vector Machine (MSVM). Traditional SVM is a binary classifier, but in this model, multiple pneumonia classes must be categorized. Thus, MSVM is employed. The Support Vector Machine (SVM) classifier operates by defining a hyperplane that separates the feature space into different categories. The kernel function used in MSVM maps feature representations into a higher- dimensional space for better classification. The feature space effectively categorizes different types of pneumonia and improves the overall classification performance.

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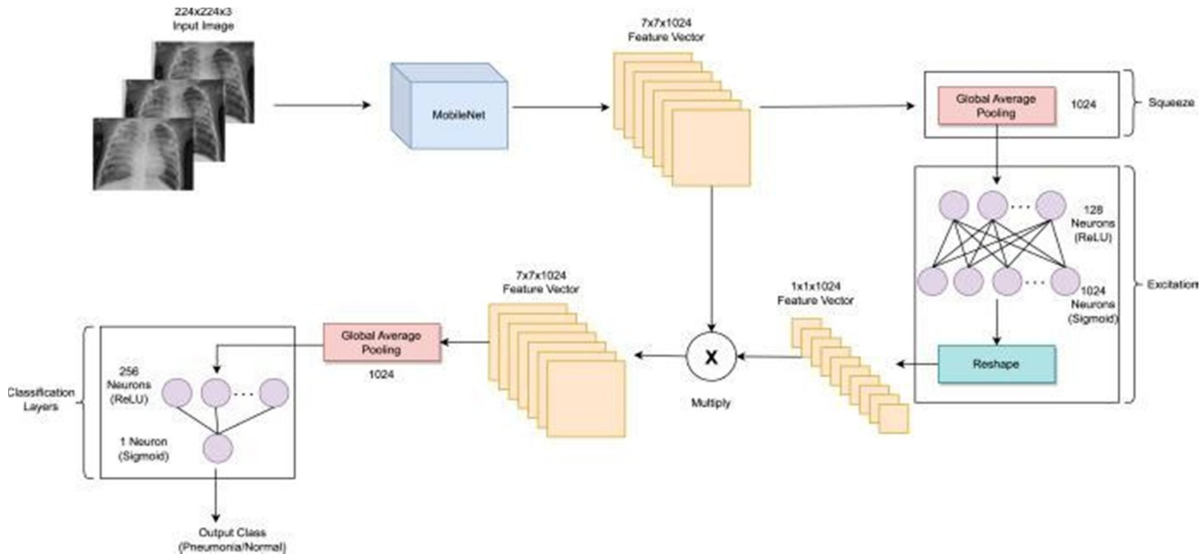

Figure 1: Proposed hybrid deep learning model for Pneumonia detection and classification

IV. METHODOLOGY

A. Data Collection and Preprocessing

Data collection involves obtaining a publicly available chest X-ray dataset containing labeled images of both normal and pneumonia-affected cases. Suitable datasets such as the NIH Chest X-ray dataset provide high-quality labeled images for pneumonia classification. Preprocessing includes resizing images to meet the input requirements of MobileNet, normalizing pixel values to a range between 0 and 1 for consistent neural network input, and applying image enhancement techniques like histogram equalization or contrast adjustment to improve image quality and highlight discernible features.

B. Transfer Learning and Model Architecture

Transfer learning is employed to maximize performance with a limited dataset. The MobileNet model, pre-trained on the ImageNet dataset, is adapted for pneumonia detection by fine-tuning its weights. The last few layers of MobileNet are replaced with dense layers specifically designed for the classification task, enabling the retention of general features while learning domain-specific patterns. MobileNet's lightweight architecture, leveraging depthwise separable convolutions, ensures reduced computational complexity and suitability for deployment in resource-constrained environments like smartphones.

C. Data Augmentation

Data augmentation is applied to expand the dataset and improve model generalization. Transformations such as rotation, flipping, zooming, and translation simulate real-world variations in chest X-ray images, helping the model handle diverse scenarios effectively.

D. Model Training

The fine-tuned MobileNet model is trained on the preprocessed and augmented dataset using a cross-entropy loss function suitable for binary classification tasks. The Adam optimizer is utilized to update model weights, supported by learning rate schedules for stable convergence. A validation set, typically comprising 20% of the dataset, monitors performance during training and prevents overfitting.

E. Model Evaluation

Model evaluation involves metrics such as accuracy, precision, recall, and F1 score to assess classification performance. The confusion matrix provides insights into true positives, false positives, true negatives, and false negatives, ensuring robustness in real-world applications. Cross-validation is conducted to ensure the model generalizes effectively and avoids overfitting to the training data.

F. Real-Time Deployment
Post-training, the model undergoes optimization for real-time deployment. Techniques like quantization or pruning reduce model size while maintaining performance, enabling operation on mobile or embedded devices. A user-friendly interface allows healthcare providers or patients to upload chest X-ray images and receive real-time diagnostic results, ensuring accessibility in low-resource clinical settings.

G. Interpretability and Visualization
To enhance trust in the system, Grad-CAM (Gradient-weighted Class Activation Mapping) is integrated, generating heatmaps that highlight image areas influencing the model's decisions. This interpretability feature supports healthcare professionals by providing transparent, visual explanations of the model’s predictions, fostering confidence in its diagnostic recommendation

V. RESULT AND DISCUSSSION
The experimentation of the proposed pneumonia detection model utilizes the benchmark dataset of chest X- ray images. The experiments are performed in Python with essential libraries for deep learning and machine learning models. The hyperparameter details used in the experimentation are presented in Table 2. For experimentation, 80% of the data is used for training and 20% for testing. Fine-tuning the deep learning model in our approach is crucial for optimizing its performance on the pneumonia classification task. The steps and experiments undertaken to fine-tune the model are listed below.

S. No	Algorithm	Hyperparameter Value/Type
1	MobileNet	Learning rate: 0.0001
2		Number of filters: 12
3		Number of epochs: 250
4		Activation function: ReLU
5		Optimizer: Adam

Table 1: Hyperparameter details

A. Performance Metrics of The Proposed Model

S.No	Metrics	Positive	Negative	Neutral
1	Accuracy	98.78	98.48	98.00
2	Precision	98.26	97.26	97.26
3	Recall	97.11	97.55	97.99
4	Specificity	98.48	98.41	98.42
5	F1-score	97.68	97.40	97.62
6	Mathews Correlation Coefficient	97.21	96.48	97.26

Table 2 : Proposed Model Performance Analysis for Pneumonia Detection Dataset

VI. CONCLUSION
This study introduces a hybrid deep learning model for pneumonia detection using MobileNet, a lightweight convolutional neural network (CNN) architecture. Essential data for pneumonia detection are processed by deep learning algorithms to extract key features. These extracted features are then concatenated and their dimensionality reduced through principal component analysis (PCA). Finally, the features are classified using a multiclass support vector machine (SVM) to achieve improved performance in detection. Future enhancements to the proposed hybrid deep learning model could further improve its accuracy and utility. One promising avenue is the integration of additional medical imaging modalities, such as CT scans, to provide a more comprehensive understanding of pneumonia and enhance diagnostic capabilities.

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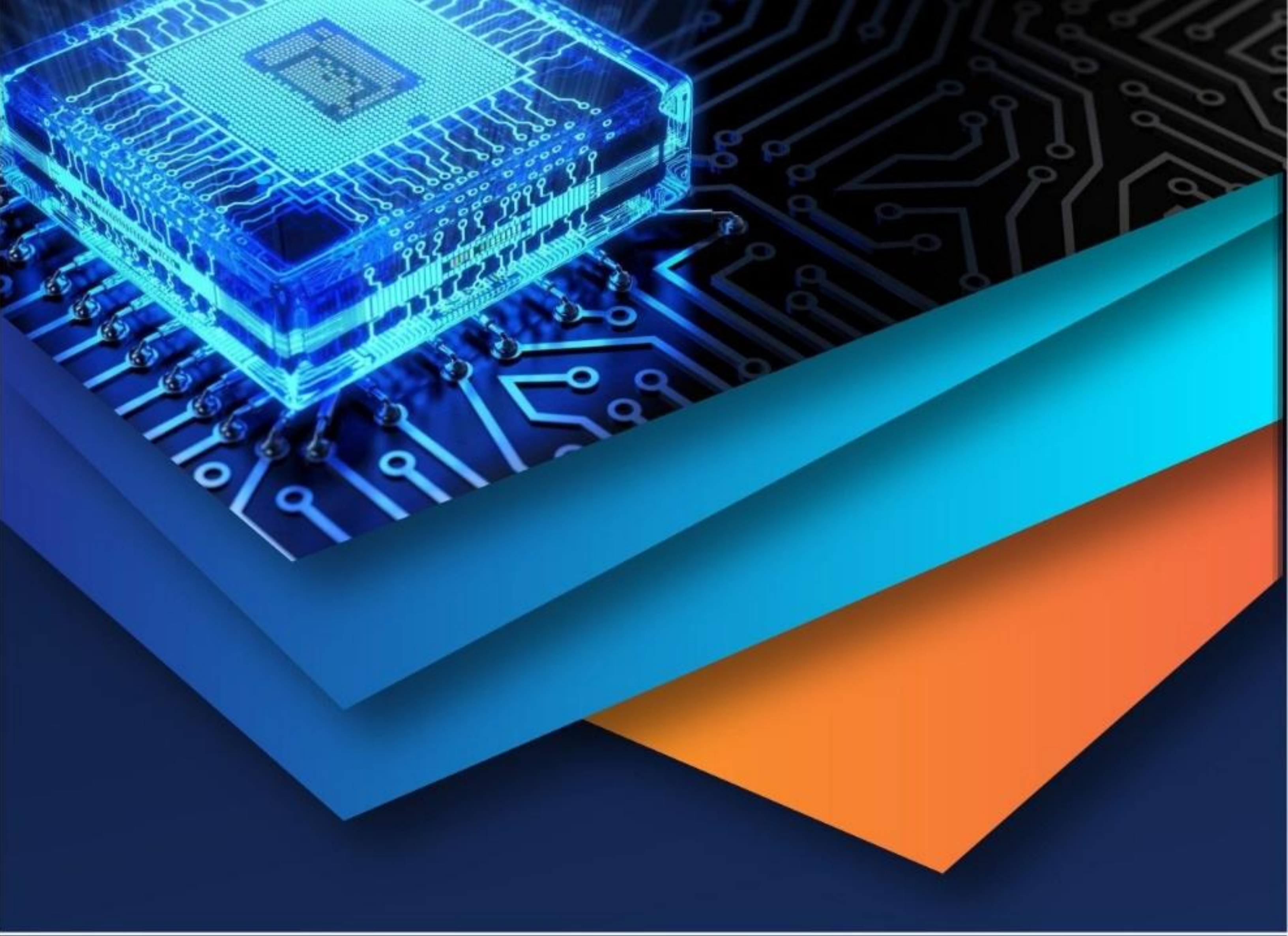

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