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Research Article

Deep Learning-Based Pneumonia Detection Using X-Ray Images: Leveraging MongoDB for Efficient Storage and Management of the MIMIC-IV CXR Dataset

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ABSTRACT

Introduction: Pneumonia is a significant global health hazard that is very important in resource-poor countries, where the conventional methods of diagnosis (subjective interpretation of chest X-rays) could delay the diagnosis or give inaccurate interpretations.

Objectives: This research proposes a new methodology that integrates deep learning models with MongoDB, an elastic NoSQL database, to augment pneumonia diagnosis from chest X-ray images.

Methods: The system leverages the MongoDB GridFS storage scheme and optimizes the storage management of large-scale medical image datasets for seamless integration with clinical data in the imaging domain, which maximizes efficiency in diagnosis. Initial experiments with ResNet, MobileNet, and DenseNet reported disappointing results of 56%, 51%, and 56%, respectively, with the most notable reasons being overfitting and insufficient training. PneumoNet, a particular CNN, was developed to meet the issues above and has achieved 92% accuracy after fine-tuning architecture with additional epochs and output channels.

Results: This deep learning system also allows enhanced diagnostic accuracy and radiological workflow management in integration with MongoDB using PyMongo, thus enabling real-time prediction while monitoring a patient.

Conclusions: In summary this part calls for a marriage between high-end deep learning platforms and adaptive storage solutions like MongoDB to improve health outcomes and enable big-scale medical image analytics.

Keywords: Deep Learning, ResNet, MobileNet, DenseNet, PneumoNet.

INTRODUCTION

Pneumonia is a serious respiratory infection that poses a significant global health threat, especially in regions with limited medical resources. [1] Conventional diagnostic methods, primarily reliant on chest X-rays, often suffer from subjective interpretation, leading to misdiagnosis and delayed treatment. [2]

At the early stage of pneumonia, patients may experience mild symptoms such as cough, mild fever, and fatigue (Fig-1). If these symptoms are mistaken for a common cold or viral infection, the condition can progress to a critical stage, presenting symptoms such as high fever, difficultybreathing, and chest pain. Accurate and timely diagnosis at an early stage can prevent patients from reaching a critical condition. This level of diagnosis is achievable using deep learning techniques. Medical imaging is crucial in disease diagnosis, treatment planning, and patient monitoring, generating vast amounts of data that pose significant challenges for storage and management.

The emergence of deep learning in medical imaging offerspromising advancements in enhancing diagnostic precision and efficiency. [3] This research explores a novel approach that integrates deep learning models with robust database management to improve pneumonia detection and reporting. By utilizing MongoDB for data storage and employing advanced neural network architectures, our system aims to provide rapidand accurate classification of chest X-ray images, enabling timely and effective clinical interventions.

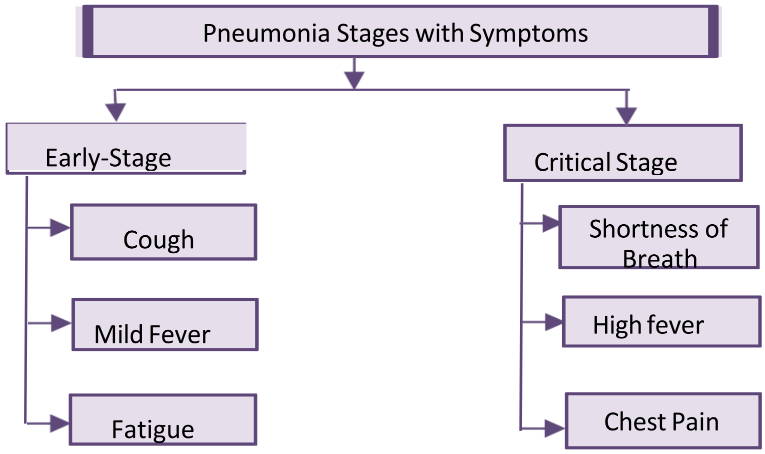

Fig-1: Categories of Pneumonia Disease with Symptoms

This innovative approach not only streamlines the diagnostic process but also significantly enhances the potential for improving patient outcomes. Convolutional neural networks (CNNs), a type of deep learning model [4], have the capability to analyze chest X-rays with high accuracy, identifying patterns that may be missed by the human eye or standard tests. These models provide continuous monitoring of a patient's condition, significantly reducing the risk of progression to a critical stage. Therefore, deep learning plays a vital role in the identification, treatment, and reporting of pneumonia.

Traditional relational databases struggle to efficiently handle the size and complexity of medical image datasets, prompting the exploration of alternative storage solutions like MongoDB. [5] This research paper focuses on the storage of MIMIC-IV CXR X-ray images in MongoDB, evaluating its suitability and performance for managing large-scale medical image datasets. We also demonstrated the streamlined utilization of PyMongo – a python distribution containing tools for working with MongoDB, that enables effortless deep-learning prediction within the MongoDB environment for pneumonia analysis, and ensured smooth communication with the MongoDB instance.

Among various imaging modalities, chest X-rays (CXRs) are widely used due to their effectiveness in diagnosing pulmonary and cardiac conditions (Fig-2).

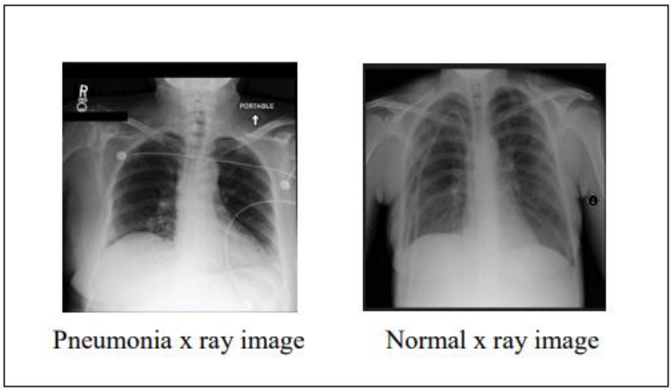

Fig-2: Normal and Pneumonia Patient x ray images

With the advent of large-scale medical databases like the Medical Information Mart for Intensive Care (MIMIC), researchers have access to extensive collections of anonymized patient data, including CXR images. However, storing and managing these vast amounts of medical images efficiently posessignificant challenges. Traditional relational databases may not be optimized for handling suchunstructured data, leading researchers to explore alternative solutions. MongoDB, a NoSQL database, offers a flexible schema and scalability, making it an attractive choice for storing andretrieving large volumes of diverse data, including medical images.

The research perspective on leveraging MongoDB for the efficient storage of MIMIC-IV CXRX-ray images focuses on addressing the challenges associated with managing and accessing thisdata. MongoDB's distributed architecture allows for horizontal scaling, enabling researchers to store and retrieve large volumes of CXR images efficiently as the dataset grows. Unlike traditional relational databases, MongoDB does not require a predefined schema, providing flexibility in handling diverse data types and structures. This flexibility is particularly beneficial when dealing with unstructured medical images and associated metadata. Additionally, MongoDB's indexing capabilities and support for complex queries enhance the performance of image retrieval, enabling researchers to quickly access relevant CXR images based on various criteria such as patient demographics, diagnoses, or clinical findings. Integrating CXR images with other clinical data stored in MIMIC-IV becomes seamless with MongoDB, facilitating comprehensive analysis and research studies that leverage both imaging and non-imaging data.

This dataset consists of pneumonia X-ray images and normal chest X-ray images. Cleaningand preprocessing of the images for consistency will be done. After preprocessing the dataset, it will be split into two sets: a training dataset and a testing dataset. Depending on the model's requirement, we may split one more segment of the dataset, which is the validation dataset. After segmenting the dataset, we reach the appropriate model selection step.

Fortunately, deep learning is rich in convolutional neural network architectures, such as ResNet, VGG16, or a custom-built model. We first feed the pre-processed X-ray image data into the selected model.A property of convolutional neural networks is that they extract relevant features from images through various convolutional layers (Fig-3**).** In CNNs, the convolutional layer applies learnable filters to extract features like edges and textures from input images, generating feature maps that capture hierarchical representations. Subsequently, the pooling layer down samples these feature maps, typically using techniques like max pooling to reduce spatial dimensions while preserving essential features. This process enhances computational efficiency, reduces overfitting, and facilitates effective learning of complex patterns, making CNNs powerful for tasks such as image classification and object detection. Layers at the end of the network are fully connected layers.

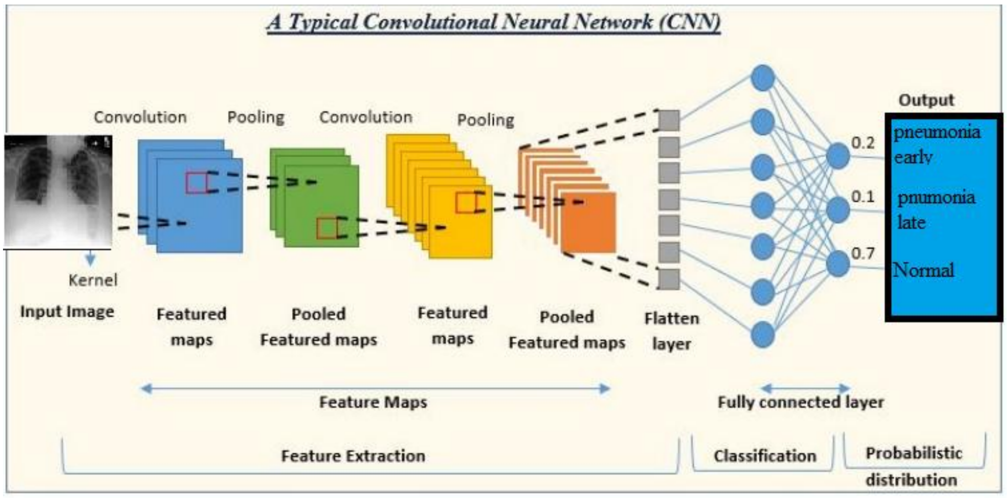

Fig.3 Convolutional neural network layers

For parameter tuning, we perform model evaluation using the validation set. Once validation iscomplete, testing is applied to the final model, where performance metrics such as recall, precision, accuracy, and F1 score present the model evaluation. After evaluation, we integrate the trained model into a decision support system to use the model for real-time analysis [8].

RELATED WORK

In recent years, researchers have made significant strides in utilizing deep learning models for healthcare applications, particularly in the analysis of chest X-ray images stored in MongoDB databases. S. Panda *et al.* (2023) [6] investigated various deep learning architectures and methodologies tailored to medical imaging tasks, such as disease detection, segmentation, and classification and emphasized the effectiveness of convolutional neural networks (CNNs) in automatically extracting relevant features from medical images, thereby improving diagnostic accuracy and clinical decision-making. They also discussed the challenges and advancements in integrating deep learning models with medical imaging technologies, aiming to enhance healthcare outcomes through robust image analysis and interpretation.

E. W. Johnson *et al* (2019) [7] introduced MIMIC-CXR-JPG, a comprehensive dataset containing labeled chest radio graphs. This database, derived from the Medical Information Mart for Intensive Care (MIMIC) dataset, provides a valuable resource for research in medical image analysis and machine learning. Their study detailed the dataset creation process, which includes extracting and preprocessing many chest radiographs into JPEG format, along with annotating them with labels for various conditions. The authors highlighted the dataset's utility for training and evaluating algorithms in tasks such as pneumonia detection, lung disease classification, and radiological image interpretation. They also discussed the potential impact of such a dataset on advancing automated diagnostic systems and improving clinical decision support in healthcare settings. Overall, the paper underscores the importance of openly accessible, labeled medical image datasets in advancing research and development in medical imaging and artificial intelligence applications.

F.F. Wang *et al.* (2020) [8] proposed a framework for efficient and secure sharing of medical imaging data using hybrid clouds. Their study addressed the challenges of scalability and security in managing large volumes of sensitive medical images across distributed environments. The framework leveraged hybrid cloud architecture, integrating private and public cloud resources, to optimize data storage, processing, and sharing capabilities. Key aspects of the approach included advanced encryption techniques to protect patient privacy during data transmission and storage, as well as efficient data access mechanisms to ensure timely retrieval and analysis of medical images. Their work presented experimental results and performance evaluations demonstrating the effectiveness of their proposed solution in enhancing data sharing capabilities while maintaining compliance with stringent healthcare regulations. Overall, the work contributes to advancing the infrastructure and protocols necessary for secure and scalable management of medical imaging data in cloud-based environments.

R. Kundu *et al.*(2020) [9] investigated the effectiveness of using an ensemble of deep learning models for pneumonia detection in chest X-ray images. They proposed a methodology where multiple deep learning architectures, such as CNNs, are combined to enhance diagnostic accuracy. Their study involved training these models on a dataset of chest X-ray images annotated for pneumonia, evaluating their individual and collective performance through metrics like sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). The paper discussed the advantages of ensemble learning in capturing diverse features and improving the robustness of pneumonia detection systems. Results demonstrated that the ensemble approach achieves superior performance compared to individual models, highlighting its potential for enhancing diagnostic capabilities in clinical settings through automated image analysis.

T. Rahman *et al.*(2020) [10] explored the application of transfer learning techniques with deep CNNs for pneumonia detection from chest X-ray images. The study focused on leveraging pre-trained CNN models, such as ResNet, Inception, and DenseNet, which were fine-tuned using a dataset of labeled chest X-ray images. The paper investigated the effectiveness of transfer learning in enhancing model performance by initializing with weights learned from large-scale image datasets like ImageNet. Experimental evaluations included comparisons of different CNN architectures, training strategies, and data augmentation techniques to optimize pneumonia detection accuracy. The findings demonstrated the feasibility and effectiveness of transfer learning in medical image analysis, showcasing improved diagnostic capabilities for identifying pneumonia in chest X-ray images through deep learning approaches.

Kairou Guo et al.(2023) [11] validated CheXNeXt algorithms against radiologists' practices, demonstrating that deep learning models can match human experts' performance in diagnosingpneumonia and other diseases using chest X-rays. This research highlighted the potential of artificial intelligence to support diagnostic tasks in radiology.

Dikai Li (2023)[12] integrated a ResNet50-based deep learning model with MongoDB, a NoSQL database, to efficiently manage and store large-scale X-ray image datasets. MongoDB's capabilities facilitated scalable data storage, real-time access to patient data, and streamlined diagnostic workflows, showcasing its utility in healthcare data management.

Qiuyu An *et a*l. [13] showcased the advantages of using cloud-based MongoDB for storing andanalyzing medical image datasets. Their study emphasized MongoDB's ability to handle large volumes of data and support remote access, enhancing diagnostic capabilities through efficientdata management.

Shaojie Han *et al.*(2020) [14] developed an end-to-end pneumonia detection system using MongoDB and hybrid CNN architectures like VGG16 and InceptionV3. Integrating MongoDB enabled efficient storage, remote access, and automated report generation, offering a comprehensive solution for clinical decision support.

Narayana Darapaneni *et al.* (2020) [15] focused on developing a deep CNN for pneumonia detection, leveraging MongoDB for storing and analyzing X-ray images in real-time. Their approach supported continuous monitoring and timely intervention, improving patient outcomes throughadvanced diagnostic capabilities.

M Silva,*et al.*(2023) [17] The study integrates multiple convolutional neural network (CNN) architectures, such as ResNet, Inception, and DenseNet, to harness their complementary strengths in feature extraction and classification. A significant aspect of the framework involves the utilization of MongoDB as a scalable and efficient storage solution for managing large-scale medical image datasets. This integration aims to streamline data handling, improve accessibility, and facilitate seamless integration with deep learning workflows. The paper discusses experimental results demonstrating the framework's efficacy in achieving high accuracy in pneumonia detection tasks, highlighting the benefits of combining sophisticated CNN models with robust data management strategies to enhance medical image analysis capabilities.

In conclusion, MongoDB emerges as a promising solution for efficient storage and analysis of medical imaging data, facilitating enhanced diagnostic accuracy, accessibility, and innovation in healthcare delivery. Its integration with deep learning models underscores its pivotal role in shaping the future of healthcare data management, driving improvements in patient care and medical research.

BACKGROUND

MongoDB is a widely used NoSQL database management system developed to address the limitations of traditional relational databases in handling large volumes of unstructured data. MongoDB was created by the company 10gen, founded by Dwight Merriman, Eliot Horowitz,and Kevin Ryan in 2007. It was first publicly released in February 2009. MongoDB adopts a document-oriented data model, storing data in flexible, JSON-like documents. This model usesscalable data structures that are more natural for representing data than traditional relational databases. MongoDB is schema-less, meaning it does not require a predefined schema for datastorage and can adapt its schema as data volume increases. This property makes MongoDB highly scalable. MongoDB supports horizontal scaling through sharding, distributing data across multiple servers.

MongoDB finds wide adoption across various industries including finance, healthcare, e- commerce, and technology. It is particularly favored in applications requiring real-time analysis, such as big data processing and content management. MongoDB is an open-source database with commercial versions available, including MongoDB Atlas, a fully-managed clouddatabase service.

Deep learning is a subset of machine learning that encompasses neural networks. Neural networks possess the capability of automatically learning and extracting features from large datasets. Deep learning originates from artificial neural networks, inspired by the human brain.The rapid development of deep learning models has been driven by advancements in computational power and big data analytics capabilities.

Deep learning models, specifically CNNs, play a crucial rolein medical imaging, such as analysing X-ray images, CT scans, and MRIs to detect abnormalities like pneumonia, fractures, and infections. These models can segment tissues andorgans to assist in identifying precise areas of interest. Inspired by artificial intelligence, deep learning can prioritize critical cases based on severity identified in images, allowing radiologiststo address urgent cases promptly. It can provide second opinions to reduce diagnostic errors andimprove accuracy. Deep learning models can also predict disease progression and treatment requirements based on image data. They enable automatic comparison with previously scanneddocuments, assist in complex analysis, and provide training to radiologists on detailed image interpretation and feedback.

The dataset used for pneumonia detection typically comprises chest X-ray images and accompanying radiology reports in large volumes. Annotations in these reports or on X-rays indicate the presence or absence of pneumonia or other lung infections. These annotated datasets are critical for training and evaluating deep learning models for automated diagnosis. Chest X-ray images in these datasets are high-resolution grayscale images used as inputs for diagnostic algorithms. Radiologists provide textual radiology reports containing detailed observations anddiagnoses. Labelled annotations serve as crucial components for supervised learning algorithms.

These datasets are complex due to various factors, such as variations in X-ray machines and patient positioning, which affect image quality and appearance. Additionally, pneumonia casesare less frequent than normal infection cases, leading to imbalances in the dataset. Making accurate predictions is challenging due to the potential for early signs of pneumonia to be missed. Noise in the dataset can also arise from human errors in radiology reports and differences in diagnostic criteria. The large volume and high resolution of the data require advanced and efficient computational resources. Moreover, adherence to security policies, including patient information confidentiality and communication integrity, is essential.

ResNet Model

ResNet, inspired by artificial neural networks, allows for much deeper network training by learning residual connections between input and output. Introduced by Kaiming *et al.* (2015) [19]. ResNet addresses the vanishing gradient problem by bypassing one or more layers (Fig-4**)**. ResNet comes in variations such as ResNet-101, ResNet-152, and ResNet-50, with differing numbers of layers. Its skip connections enable training of such models without performance degradation. ResNet has been highly successful in computer vision, particularly in solving

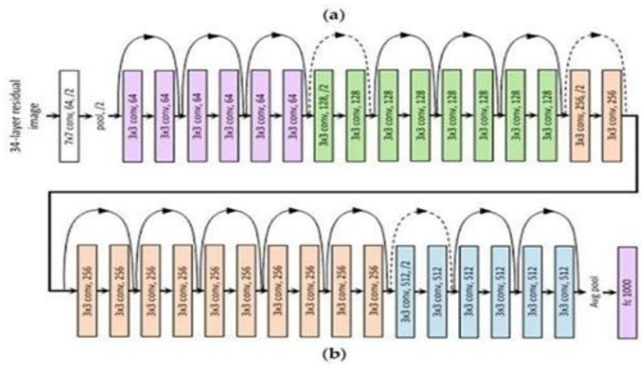

Fig-4 : ResNet – 34 Layered Architecture

image recognition challenges. It achieved *state-of-the-art* results on the ImageNet dataset and iswidely used in practical applications and academic research.

MobileNet Model

MobileNet, designed by Google, [20] is optimized for mobile and embedded devices, offering an efficient, high-performance, and lightweight model suitable for deployment on devices with limited computational resources (Fig-5**)**. Unlike traditional deep learning models like ResNet and DenseNet, which require substantial memory and processing power, MobileNet reduces computational load and memory usage without compromising accuracy. It uses depth wise separable convolutions, which split convolutions into depth wise and pointwise layers, reducing computational costs and model size compared to standard convolutions.

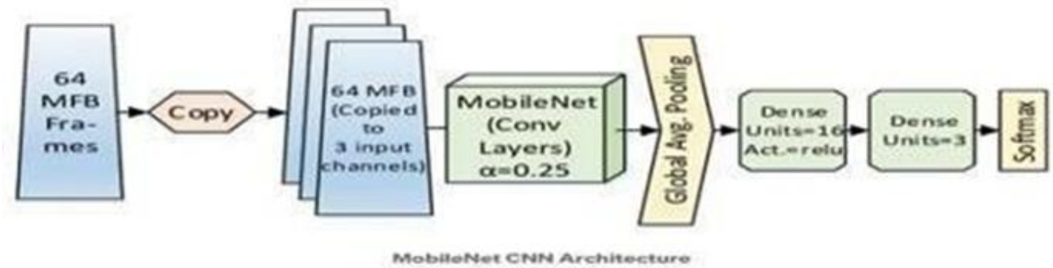

Fig 5 MobileNet Architecture

DenseNet

Densely Connected Convolutional Network (DenseNet), proposed by Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger in 2017 [21], aims to improve feature propagationand gradient flow in deep neural networks. Unlike traditional CNNs, DenseNet connects each layer to every other layer in a feed-forward manner, concatenating feature maps from all preceding layers as input (Fig-6**)**. This design enhances feature reuse and encourages the network to learn more complex representations. DenseNet is widely used for object detection, classification, and segmentation tasks.

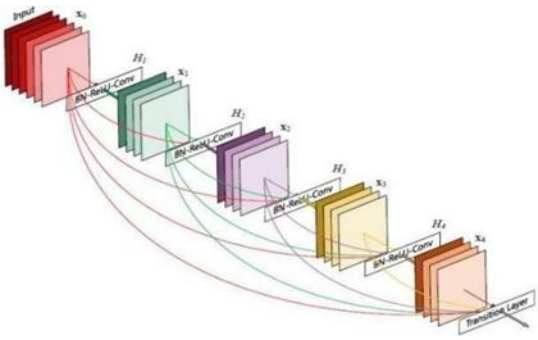

Fig 6 DenseNet Architecture

The following plots show the training loss and training accuracy for various models applied to the MIMIC-CXR dataset (Fig-7), including (a) ResNet, (b) MobileNet, and (c) DenseNet.

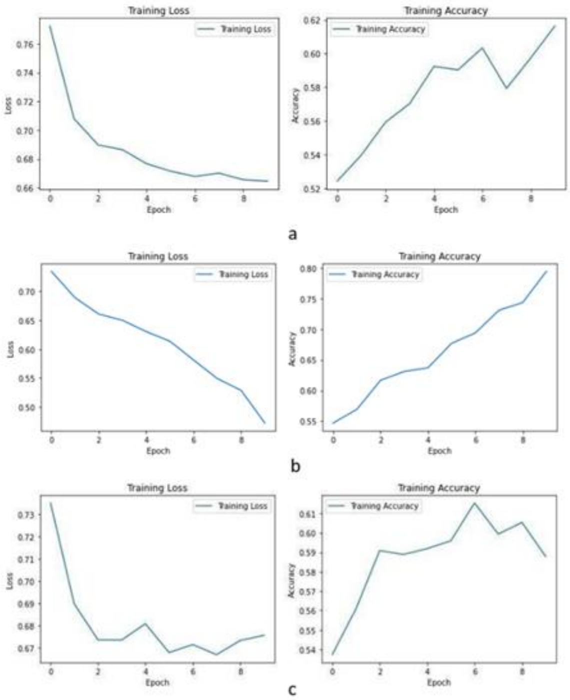

Fig. 7 Training Loss and Training Accuracy of MobileNet Model for MIMIC-CXR dataset a) ResNet b) MobileNet c) DenseNet

4 Proposed Model

The objective of this work is to develop a model for detecting and classifying pneumonia disease. The proposed model comprises several modules: preprocessing, accommodation of images in MongoDB, and the PneumoNet model, detailed in the following sections.

(i) Preprocessing

The preprocessing task [10] involves a sequence of operations performed on original data to convertit into a suitable format for machine learning or deep learning analysis. The goal is to remove noise, enhance data quality, and facilitate easier handling (Fig-8-9**)**. For diagnosing pneumonia disease, transforming the color space of images is crucial. capabilities while avoiding overfitting. Extending the training process by increasing the numberof epochs further enhances model performance ((Fig-10-11).

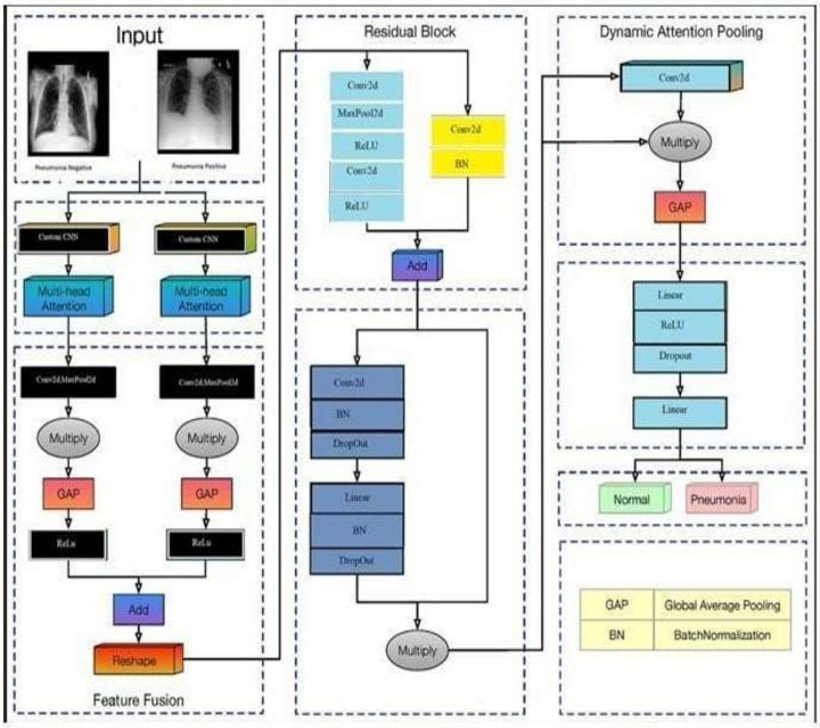

Fig. 10 Architecture of Proposed Model.

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 32, 224, 224]	896
BatchNorm2d-2	[-1, 32, 224, 224]	64
ReLU-3	[-1, 32, 224, 224]	0
MaxPool2d-4	[-1, 32, 112, 112]	0
Conv2d-5	[-1, 64, 112, 112]	18,496
BatchNorm2d-6	[-1, 64, 112, 112]	128
ReLU-7	[-1, 64, 112, 112]	0
MaxPool2d-8	[-1, 64, 56, 56]	0
Conv2d-9	[-1, 128, 56, 56]	73,856
BatchNorm2d-10	[-1, 128, 56, 56]	256
ReLU-11	[-1, 128, 56, 56]	0
MaxPool2d-12	[-1, 128, 28, 28]	0
Dropout-13	[-1, 100352]	0
Linear-14	[-1, 512]	51,380,736
ReLU-15	[-1, 512]	0
Dropout-16	[-1, 512]	0
Linear-17	[-1, 2]	1,026

Total params: 51,475,458
Trainable params: 51,475,458
Non-trainable params: 0

Input size (MB): 0.57
Forward/backward pass size (MB): 70.45
Params size (MB): 196.36
Estimated Total Size (MB): 267.39

Fig. 11 Summary of Proposed Model.

RESULT AND DISCUSSION

(i) Pneumonia Disease Images Dataset

Integrating MongoDB with advanced algorithmic approaches for disease detection in X-ray images using machine learning addresses a critical need in the healthcare domain. Machine learning algorithms, particularly those leveraging sophisticated techniques, offer an opportunityto enhance the accuracy of disease detection in X-ray images. The motivation for this research lies in the potential to improve early disease diagnosis through the synergy of MongoDB's datamanagement capabilities and advanced machine learning algorithms.

The algorithm, PneumoNet, is applied with improvements to the training process by increasingthe number of epochs and avoiding overfitting by increasing the number of output channels withspecific parameters. Previous issues with applied models have been identified and resolved withthe proposed model.

(ii) Implementation Details of Proposed Model

The integration of MongoDB with advanced machine learning algorithms for disease detection in X-ray images addresses critical healthcare needs. This research focuses on enhancing disease detection accuracy through MongoDB's data management capabilities and sophisticated machine learning approaches. The PneumoNet algorithm was employed with enhancements such as increased training epochs and output channels to mitigate overfitting and improve accuracy. Parameters applied for the proposed algorithm to resolve challenges include a learning rate of 0.0001, a batch size of 32, 20 epochs, the Adam optimizer, a weight decay of 0.0001, and a dropout rate ranging from 0.3 to 0.5. Additionally, data augmentation techniques such as rotation, scaling, and horizontal flipping were used, with an image size set to 224x224 pixels. Early stopping was implemented based on validation loss.

(iii) Evaluation Metrics

The accuracy of various models was MobileNet at 51%, ResNet at 56%, DenseNet at 56%. Whereas our proposed algorithm achieved an accuracy of 92%. Plots of training loss and accuracy are shown in figure 12.

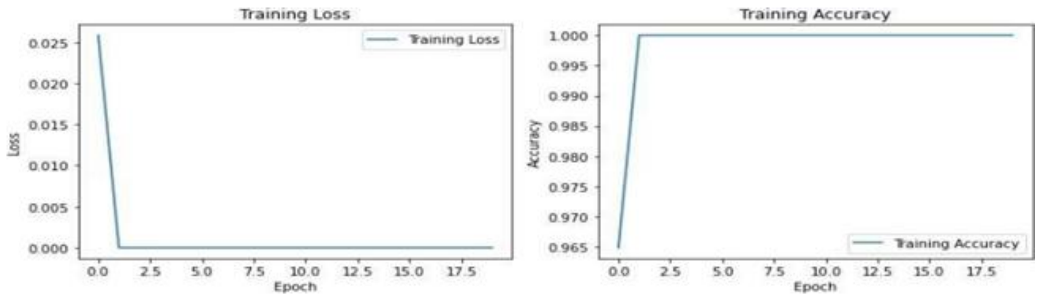

Fig.12 Training Loss and Training Accuracy of PneumoNet Model with Proposed Dataset

CONCLUSION

This study applied various CNN models to the MIMIC-CXR dataset for pneumonia detection, including pre-trained models like ResNet, DenseNet, and MobileNet, achieving accuracies of 51%, 56%, and 56%, respectively. The customized CNN, PneumoNet, achieved a notable 100%accuracy, raising concerns about potential overfitting. Future efforts will focus on validating PneumoNet's robustness through additional datasets, cross-validation techniques, and incorporation of regularization methods like weight decay and dropout. While promising, further work is needed to develop a reliable model for pneumonia detection.

The proposed PneumoNet model effectively addresses the challenges of overfitting and complexity encountered by transfer learning models such as ResNet, MobileNet, and DenseNet. By increasing the number of epochs and output channels, PneumoNet has been fine-tuned to achieve an impressive accuracy of 92%, significantly outperforming its predecessors. This demonstrates its potential for more accurate and reliable pneumonia detection. The success of PneumoNet highlights its future applicability in medical image analysis, providing a robust solution for diagnosing various pulmonary conditions, and paving the way for further advancements in AI-driven healthcare diagnostics.

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