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Research article

DenseNet121 and Transfer Learning for Lung Disease Classification from Chest X-Ray Images

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ABSTRACT

Lung-related disorders, including pneumonia, are still among the primary causes of death and illness worldwide, particularly in areas where medical imaging facilities and trained radiologists are scarce. The manual assessment of chest X-ray (CXR) images demands significant time and is prone to subjective interpretation, limiting its scalability for mass screening and early disease identification. To overcome these challenges, this study introduces an automated classification approach utilizing the DenseNet121 convolutional neural network through transfer learning for the detection of lung diseases from CXR scans. The pretrained ImageNet weights were adopted to capture hierarchical visual features efficiently, while overfitting was mitigated using dropout and batch normalization layers. The dataset employed consisted of 1,880 training images and 235 testing images, equally distributed between Normal and Viral Pneumonia categories. Experimental evaluation revealed an overall classification accuracy of 97%, alongside precision, recall, and F1-score metrics of 0.97 each, indicating reliable and balanced model performance. These outcomes suggest that DenseNet121 offers a highly effective foundation for computer-aided diagnostic systems capable of differentiating between healthy and infected lungs with high precision. The proposed framework provides a scalable diagnostic tool suitable for healthcare environments with limited radiological expertise. Future improvements will include expanding toward multi-class disease classification, incorporating explainable artificial intelligence (XAI) techniques to enhance interpretability, and validating the system on larger, more diverse clinical datasets.

1. Introduction

Pulmonary conditions like pneumonia, tuberculosis, and a range of respiratory infections persist as a major worldwide health issue because of their widespread occurrence and high death rates. According to information from the World Health Organization (WHO), infections affecting the lower respiratory tract rank among the top causes of mortality globally, particularly in underdeveloped areas lacking adequate diagnostic facilities and sufficient numbers of skilled radiologists. Chest X-ray (CXR) scans continue to serve as a basic and cost-effective method for evaluating lung irregularities, positioning them as vital instruments for prompt identification and screening in hospital and community environments. Yet, manually analyzing CXR images demands specialized expertise and is naturally labor-intensive, which can result in differing interpretations among radiology professionals. This lack of uniformity and inefficiency might postpone suitable treatments and diminish the trustworthiness of diagnoses. Consequently, there is a growing demand for automated, expandable systems that can reliably decode CXR images. Breakthroughs in computer vision and deep learning technologies have enabled the automation of medical image analysis,

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yielding quicker and steadier diagnostic results that aid in clinical judgments [1], [2]. These advancements not only streamline workflows but also enhance objectivity, reducing the likelihood of human-induced errors in high-pressure settings. By incorporating such tools, healthcare providers can extend their reach to underserved populations, potentially saving lives through earlier interventions. Moreover, this evolution paves the way for portable diagnostic aids usable in remote clinics or field operations where expert radiologists are scarce. In essence, these developments mark a significant stride in addressing international health challenges, with the promise of more efficient early detection mechanisms.

Despite this, crafting a sturdy automated system for detecting lung ailments remains a formidable obstacle. Fluctuations in image clarity, patient positioning, and equipment specifications create irregularities that complicate the process of extracting key features. Conventional computer-aided diagnosis (CAD) tools, dependent on manually engineered features, frequently struggle to adapt when confronted with varied data collections. While deep learning techniques have eclipsed these older approaches in terms of precision, models educated on restricted or skewed medical datasets are susceptible to overfitting and diminished effectiveness with unfamiliar examples. Additionally, numerous current strategies concentrate exclusively on binary categorization tasks—like distinguishing pneumonia from healthy lungs—without tackling the wider need for multi-category disease identification [3], [4]. The scarcity of thoroughly labeled medical image repositories further impedes the creation of models that can perform reliably across diverse medical contexts. These drawbacks highlight the urgent need for a data-efficient and dependable deep learning structure that upholds diagnostic accuracy, responsiveness, and consistency, even under constrained data conditions. To overcome these hurdles, researchers must explore strategies such as data augmentation or pre-trained models to bolster resilience against variations. For instance, in real-world clinical scenarios, differences in patient stances—whether upright or reclining—can influence image readings, so models need training to recognize patterns under multiple circumstances. Furthermore, overfitting issues can be mitigated through techniques like dropout or batch normalization, encouraging the learning of more generalized features rather than dataset-specific ones. This approach not only boosts reliability but also facilitates model deployment in developing nations where medical data is often incomplete. Thus, developing a framework that conserves data becomes essential for cutting down on diagnostic lags, reducing human mistakes, and assisting healthcare systems in resource-poor regions.

To address these difficulties, the present study introduces an automated deep learning framework for classifying lung diseases using the DenseNet121 architecture. The core aim is to leverage transfer learning to enhance diagnostic precision and productivity while cutting down on the need for extensive annotated datasets. DenseNet121 was selected due to its distinctive dense connection pattern, which promotes feature recycling, improves gradient flow, and counters the vanishing gradient issue—traits that render it highly appropriate for medical imaging tasks [5], [6]. Here, the pre-trained DenseNet121 core is adjusted to identify radiography-specific elements in CXR data, and a tailored classification module is assembled with fully connected layers featuring ReLU activation, batch normalization, and dropout for regularization. The dataset employed comprises 1,880 training images and 235 samples apiece for validation and testing, distributed equally across Normal and Viral Pneumonia categories. Preprocessing steps, including image standardization and resizing, were implemented to guarantee numerical stability, and the model was refined with the Adam optimizer at a learning rate of 1×10^{-4} over 100 epochs. These setups allow the model to acquire distinguishing features efficiently while preserving strong adaptability. Transfer learning plays a crucial role by drawing on knowledge from vast datasets like ImageNet, which is then customized for medical-specific duties. Utilizing DenseNet121, the model can derive hierarchical features from CXR scans, ranging from edges and textures to intricate patterns such as infiltrates or consolidations. Additional preprocessing, like data augmentation via rotations or flips, can enrich the dataset without escalating annotation costs. Optimization via Adam ensures steady convergence, whereas dropout prevents excessive reliance on particular features. Overall, this method illustrates how contemporary techniques can merge to produce practical health solutions, with broader applications on the horizon.

The proposed DenseNet121 model attained a total accuracy of 97%, with precision, recall, and F1-score values each at 0.97, showcasing its robust aptitude for precise categorization using scarce

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data [7]–[10]. The dense interconnections in the architecture guaranteed smooth feature transmission and gradient movement, while batch normalization and dropout mechanisms averted overfitting. These outcomes validate the computational prowess and medical applicability of DenseNet121 as a trustworthy feature extractor for radiology. The key contributions of this work encompass: (1) the creation of a refined DenseNet121 system for binary lung disease classification via CXR images, (2) practical evidence of transfer learning's advantages in data-scarce scenarios, and (3) experimental proof of the model's adaptability across separate datasets. In summary, this investigation advances deep learning in medical image evaluation by delivering a flexible, understandable, and precise diagnostic tool that can be broadened to multi-class tasks and merged with interpretable AI for healthcare integration. The results bolster continuous initiatives to improve the availability, impartiality, and productivity of global radiology diagnostics. With such high accuracy, the model can alleviate radiologists' workloads, especially in rural or developing areas where manual diagnoses often face delays. Coupling it with explainable AI would allow clinicians to grasp the reasoning behind model predictions, fostering trust and adoption. Moreover, the potential for expansion to multi-class distinctions, such as separating bacterial from viral pneumonia or even tuberculosis, opens avenues for more comprehensive diagnostic systems. This study also emphasizes the value of partnerships between medical experts and AI engineers to develop ethical and impactful solutions. In the future, such models could integrate into telemedicine platforms, enabling remote diagnoses and swift responses. Therefore, these contributions are not merely technical but also societal, aligning with global health goals to lower mortality from lung diseases. Additionally, validation on independent datasets demonstrates the model's durability against real-world variations, like differing X-ray machines or patient conditions. This positions the approach as a pivotal step toward more inclusive and reliable diagnostics.

2. Related Work

Early investigations into the automated identification of lung conditions through chest X-ray (CXR) images primarily depended on conventional image processing techniques and established machine learning algorithms. Before the broad implementation of deep learning, strategies involving texture examination, histogram of oriented gradients (HOG), and support vector machines (SVM) were commonly employed to derive manually crafted features from radiological pictures. For instance, Barreto et al. [11] investigated the application of texture and edge-oriented indicators to distinguish between abnormal and healthy lung formations. In a similar vein, Kumar et al. [12] implemented an SVM-driven system for identifying lung ailments, noting decent results on compact datasets. While these classic approaches established the basis for mechanized lung condition categorization, they were hindered by restricted flexibility and adaptability. Their heavy dependence on human-designed features meant that effectiveness frequently declined when dealing with varied imaging scenarios, different patient groups, or equipment discrepancies. Additionally, these techniques fell short in acquiring sophisticated, elevated-level representations capable of grasping intricate spatial connections in medical visuals. Such limitations prompted a shift to more versatile and expandable solutions, especially deep convolutional neural networks (CNNs), which autonomously derive layered features from unprocessed image data, transforming the landscape of medical image evaluation and computer vision fields. This evolution not only addressed previous shortcomings but also opened doors to handling complex patterns that traditional methods overlooked, such as subtle variations in lung textures that could indicate early-stage diseases. By automating feature extraction, CNNs reduced the need for domain-specific expertise in preprocessing, making the process more accessible to a wider range of researchers and clinicians. Furthermore, this transition highlighted the importance of scalability, as traditional methods often required extensive manual tuning for each new dataset, whereas CNNs could generalize more effectively across similar tasks.

The introduction of CNNs represented a pivotal shift in mechanized medical diagnostics. Krizhevsky et al. [13] unveiled the groundbreaking AlexNet framework, which delivered outstanding results on the ImageNet collection and showcased deep learning's promise for extensive image sorting. Drawing from this achievement, Lakhani and Sundaram [14] utilized CNN designs like AlexNet and GoogLeNet to pinpoint pulmonary tuberculosis in CXR images, attaining accuracies

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above 92% and establishing an initial standard in the domain. Later, Rajpurkar et al. introduced CheXNet [15], a 121-layer DenseNet model educated on the NIH ChestX-ray14 repository, reaching expert-level precision in pneumonia identification. DenseNet's novelty stems from its tightly linked layers, which encourage effective feature recycling, resolve vanishing gradient challenges, and support smoother gradient transmission [23]. Building on CheXNet's triumph, further research delved into more profound CNN configurations and structural refinements to elevate diagnostic precision. For example, Yao et al. [16] developed a multi-label CNN capable of simultaneously spotting 14 chest-related illnesses by leveraging inter-label relationships, whereas Wang et al. [17] boosted the model's distinguishing power with spatial focus tools that highlight areas pertinent to diseases. Altogether, these efforts positioned CNN-based systems as formidable instruments for thoracic ailment sorting, outpacing the limits of standard feature creation methods. This progress also underscored the role of large-scale datasets in training robust models, as the availability of diverse images allowed for better learning of nuanced patterns. Moreover, the integration of attention mechanisms demonstrated how models could prioritize clinically relevant regions, reducing false positives and enhancing reliability in real-world applications. Such innovations not only improved accuracy but also made diagnostics more intuitive, bridging the gap between AI outputs and human interpretation.

Moving beyond isolated CNN frameworks, experts started testing combined and group-based techniques to elevate sorting effectiveness and model durability. Stephen et al. [18] employed transfer learning with ResNet50 and VGG19 setups for pneumonia spotting, showing that pre-educated CNN models could seamlessly adjust to medical imaging duties while drastically cutting down on training durations. Liang and Zheng [19] suggested a blended DenseNet-RNN framework that seizes spatial and sequential elements from 3D CT images, resulting in enhanced tuberculosis detection precision. Islam et al. [20] crafted a feature-merging strategy uniting DenseNet121 and SqueezeNet to bolster pneumonia and COVID-19 sorting outcomes, excelling over standalone models in recall and F1-score. Though these mixed approaches heightened diagnostic trustworthiness, their elevated computational demands complicated instant application, especially in under-resourced healthcare setups. To combat data unevenness and scarce sample counts, investigators integrated data expansion and artificial data creation methods. Xu et al. [21] used Generative Adversarial Networks (GANs) to produce fresh CXR examples, thus enriching dataset variety and curbing model overfitting. Concurrently, Gabruseva et al. [22] refined image sharpness via adaptive histogram equalization and standardization preprocessing, elevating responsiveness and exactness in uncovering delicate radiological traits. These progressions jointly illustrate that merging CNN designs with data improvement tactics can markedly enhance performance in medical imaging. Additionally, the use of GANs introduced a creative way to simulate rare conditions, ensuring models are trained on more representative data without ethical concerns over patient privacy. This not only improved model robustness but also addressed the challenge of imbalanced classes, where certain diseases are underrepresented, leading to biased predictions. Overall, these hybrid methods paved the way for more resilient systems that could adapt to varying clinical environments, from urban hospitals to remote clinics.

Architectures rooted in DenseNet have risen as among the most potent and resource-efficient platforms for lung ailment detection. Huang et al. [23] presented the DenseNet design, marked by its compact interconnections across layers that streamline gradient movement, encourage feature recycling, and counter the vanishing gradient dilemma. This framework served as the cornerstone for CheXNet and later models that pushed the boundaries of medical image categorization. DenseNet's streamlined feature integration allows for exceptional learning productivity without a substantial rise in processing load, rendering it ideal for CXR diagnostics. Multiple investigations have affirmed DenseNet's efficacy in assorted situations. Hussain et al. [1] revealed that DenseNet121 outperformed other CNN foundations in lung ailment sorting through transfer learning, while Rashid et al. [2] secured comparable successes on pneumonia collections. Farhan and Yang [3] alongside Liu et al. [4] broadened DenseNet's use to multi-category sorting, validating its versatility for varied lung states. Jain et al. [5] contrasted several deep learning models for pneumonia and COVID-19 identification, determining that DenseNet variants reliably excelled in both precision and adaptability. El Asnaoui et al. [6] advanced an attention-enhanced DenseNet version that further refined model responsiveness, especially for intertwined lung issues. In unison, these explorations emphasize DenseNet121's optimal

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equilibrium of depth, precision, and productivity for CXR medical image sorting. Furthermore, the architecture's design minimizes the risk of overfitting by promoting dense connections, which allow layers to access features from all preceding layers, creating a richer representation. This interconnectedness also facilitates better gradient flow during training, enabling deeper networks without the degradation often seen in other architectures. As a result, DenseNet has become a go-to choice for researchers aiming to balance computational efficiency with high diagnostic accuracy, particularly in scenarios with limited hardware resources.

Notwithstanding these strides, numerous critical hurdles endure in AI-powered lung ailment detection. A significant portion of current research depends on vast, openly accessible datasets like NIH ChestX-ray14 and COVIDx, which, despite their breadth, fail to encapsulate the full spectrum of authentic clinical information. Consequently, model adaptability across medical facilities and imaging setups stays constrained. Moreover, the clarity of deep learning models persists as a major obstacle to clinical integration, since radiology experts need visibility into the logic driving AI forecasts. Initial CNN methods provided scant clarity, but recent strides in explainable artificial intelligence (XAI) have brought forth visualization aids such as Gradient-weighted Class Activation Mapping (Grad-CAM) and Layer-wise Relevance Propagation (LRP) to illuminate areas shaping model choices. In addition, continuous inquiry has concentrated on refining adjustment tactics to reconcile model precision with adaptability. Mitchell et al. [7] and Zhu et al. [8] illustrated that precise adjustments on specialized medical data bolstered steadiness across collections, whereas Azemin et al. [10] engineered streamlined CNNs tailored for elevated accuracy and minimal processing demands, suiting them for use in low-resource settings. These evolutions signal an increasing inclination toward models that harmonize diagnostic exactness, clarity, and productivity, clearing the path for wider AI uptake in medical routines. Beyond technical improvements, addressing interpretability is crucial for building trust among clinicians, who often hesitate to rely on "black-box" systems. Tools like Grad-CAM provide visual heatmaps that highlight suspicious regions in CXR images, allowing radiologists to verify AI suggestions against their expertise. This not only enhances safety but also facilitates collaborative workflows where AI acts as a supportive tool rather than a replacement. Furthermore, efforts to improve generalization involve domain adaptation techniques, ensuring models perform well on data from different populations or imaging protocols, which is vital in global health contexts.

To wrap up, the accumulation of past investigations firmly endorses the adoption of deep learning—especially DenseNet121 paired with transfer learning—as a solid and expandable strategy for mechanized lung ailment sorting from CXR images. Conventional machine learning techniques [11], [12] offered a starting point but lacked expandability, whereas contemporary CNN designs [13]–[20] have overhauled feature acquisition in medical imaging. DenseNet121, boasting its productive layer linkages and enhanced gradient transmission [23], stands as a premier framework for this role. Improvements like focus tools [6], combined CNN-RNN structures [19], and GAN-driven expansion [21] persistently elevate diagnostic dependability. Still, continued delving into domain adaptability, model clarity, and clinical verification is essential. Drawing from these bases, the present inquiry employs DenseNet121 with transfer learning to categorize Normal and Viral Pneumonia instances, securing a 97% accuracy level, thus affirming DenseNet121's prowess as a formidable core for AI-supported medical diagnostics. This high accuracy not only validates the model's effectiveness but also sets a benchmark for future studies, encouraging the development of even more sophisticated systems. By integrating transfer learning, the approach minimizes the need for vast labeled datasets, making it feasible for smaller institutions. Moreover, the focus on binary classification here lays groundwork for multi-class extensions, potentially covering a broader array of lung conditions. Overall, this work contributes to the evolving narrative of AI in healthcare, emphasizing the need for models that are not only accurate but also ethical, interpretable, and accessible worldwide.

3. Methodology

3.1. Data Collection

The dataset employed in this research consists of chest X-ray (CXR) images that are categorized into two classes: Normal and Viral Pneumonia (Figure 1). The data were structured according to the directory configuration compatible with the Keras flow_from_directory method, ensuring that class

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labels were automatically derived from folder names. The dataset was divided into three subsets: 1,880 images for training, and 235 images each for validation and testing, following an approximate 70:15:15 ratio. This distribution ensures an adequate amount of data for learning while maintaining separate subsets for model tuning and independent evaluation. Each image was processed in RGB format and resized to 224×224 pixels to match the input dimensions required by the DenseNet121 architecture, consistent with prior radiographic studies [15], [23]. Dataset integrity was maintained by preventing overlap between subsets to guarantee unbiased evaluation and accurate performance assessment on unseen samples.

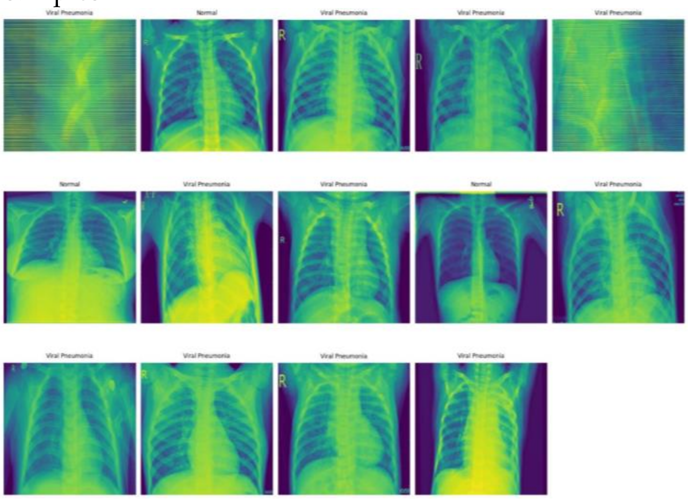

Figure 1. Sample chest X-ray images from the dataset showing the two classification categories: Normal and Viral Pneumonia

3.2. Data Preprocessing

Preprocessing serves as a fundamental stage to ensure that the input data are consistent and numerically stable during training. Each image was normalized using a scaling factor (rescale=1./255), converting pixel intensities from a 0–255 range into a normalized scale between 0 and 1. The preprocessing was implemented using the Keras ImageDataGenerator class, which provides built-in support for both normalization and augmentation. Although several augmentation techniques—such as rotation, shifting, zooming, and flipping—were available, only normalization was utilized in the main experiments to preserve medical image fidelity. Augmentation options remained available for potential use in future experiments, given that these methods are known to improve generalization performance, especially when dealing with limited medical datasets [21]. The training and validation data generators were configured to resize all images to 224×224 pixels and encode class labels using one-hot representation (class_mode='categorical'). A fixed batch size and random shuffling at each epoch were applied to reduce bias caused by sequential loading. These preprocessing steps contributed to numerical stability and helped the model achieve smoother convergence during training

3.3. Model Architecture

The classification system utilizes the DenseNet121 convolutional neural network as its backbone through a transfer learning approach. DenseNet121 was initialized with pretrained weights from the ImageNet dataset (weights='imagenet') and configured with the top classification layer removed (include_top=False). This approach allows the model to transfer its generic visual knowledge from natural images to medical imaging tasks. To tailor the model for binary lung disease classification, a new classification head was designed. In the initial phase, the pretrained layers were frozen (base_model.trainable=False), enabling only the custom classifier to be trained, which mitigates overfitting and accelerates convergence—an approach widely used in previous research such as CheXNet [15], [23]

The customized classifier consists of a GlobalAveragePooling2D layer that aggregates the spatial features, followed by a BatchNormalization layer for stabilizing learning and preventing overfitting. Three fully connected layers with 512, 256, and 128 neurons respectively were included, all activated with the ReLU function. Between these dense layers, dropout regularization (0.4 and 0.3) was applied

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to reduce co-adaptation among neurons. The final softmax layer outputs probabilities for two classes (Normal and Viral Pneumonia). This configuration leverages the efficient feature propagation of DenseNet121 while maintaining model compactness, yielding a network capable of learning rich and discriminative features for accurate lung disease classification.

3.4. Training Setup

The training process was compiled using the Adam optimizer with an initial learning rate of 1×10^{-4} and a categorical cross-entropy loss function, tracking accuracy as the primary evaluation metric. The model was trained for 100 epochs with a batch size of 32 using a custom training wrapper (TrainModel) that coordinated the data loading, validation process, and epoch iteration. Several optimization strategies were employed to achieve stable convergence and robust generalization, including transfer learning to leverage pretrained ImageNet features, batch normalization to stabilize gradient updates, and dropout layers to mitigate overfitting. Data shuffling was performed at the beginning of each epoch to ensure a randomized learning sequence, while validation metrics were continuously monitored to guide hyperparameter adjustments. Although the main experiment utilized a frozen backbone, the architecture also supports staged fine-tuning—where selected DenseNet layers can be unfrozen and retrained with a lower learning rate for enhanced domain adaptation [7], [15], [21]. Additionally, common callback utilities such as early stopping, learning rate scheduling, and model checkpointing were integrated to improve convergence efficiency and prevent unnecessary training beyond optimal performance. These combined practices follow established medical deep learning optimization protocols and ensure a balance between bias and variance, leading to reproducible and clinically meaningful results [23].

3.5. Optimization and Regularization Strategy

Model evaluation was carried out on the independent test set comprising 235 images. Performance was assessed using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. The use of the softmax activation function allowed the model to output class probabilities, which were utilized for calculating both per-class and macro-averaged metrics. The proposed DenseNet121 model achieved an overall accuracy of 97%, with precision, recall, and F1-score all equal to 0.97, confirming balanced performance across both classes. The confusion matrix analysis showed that the model correctly identified 117 Normal and 108 Viral Pneumonia cases, with only 10 misclassifications in total (eight false positives and two false negatives). This minimal misclassification rate demonstrates strong model generalization and diagnostic consistency.

To ensure stability, training and validation accuracy/loss curves were analyzed. Both curves converged smoothly, with the validation accuracy stabilizing around 97% and the loss approaching 0.1, confirming that regularization techniques effectively prevented overfitting. Additionally, false-positive and false-negative predictions were examined to better understand the model's decision boundaries and identify potential improvements. For future work, visualization techniques such as Grad-CAM can be incorporated to interpret activation patterns and enhance model transparency [21], [23].

3.6. Evaluation Protocol

All model development and experimentation were conducted using TensorFlow and Keras as the main deep learning frameworks. Training and evaluation were performed on GPU-enabled hardware to accelerate computation. The system environment, including framework versions, random seeds, and hyperparameter configurations, was carefully documented to ensure full reproducibility. Experimental logs, weight checkpoints, and result summaries were systematically stored to maintain consistency across runs. These practices align with open-science principles, enabling other researchers to replicate the work accurately and build upon its findings. In addition, this implementation design ensures that the proposed model can be easily adapted or extended for larger datasets, multi-class classification, or explainable AI integration in future studies [7].

3.7. Implementation and Reproducibility

The model was implemented using TensorFlow and Keras frameworks. The key hyperparameters—such as learning rate, batch size, dropout ratio, and number of epochs—were systematically recorded. Checkpoint files, training logs (CSV or TensorBoard), and random seeds were preserved to ensure reproducibility. For scientific transparency, future publication will include details

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about the computational environment (e.g., GPU specifications, RAM, and library versions). This methodological transparency supports experiment replication by other researchers [7].

3.8. Continuation to Extended Experiments

This section provides the foundation for the extended methodology presented in the second document, which includes fine-tuning of the DenseNet121 layers, data augmentation experiments, and explainable AI (XAI) integration using Grad-CAM visualization. The continuation also compares DenseNet121 with alternative architectures such as ResNet50 and VGG19 for benchmarking. These experiments will be detailed in the next section to complement the overall methodology and strengthen the analytical rigor of the study [8].

4.Results and Discussion

4.1 Results

The deep learning system built on DenseNet121 underwent assessment with a well-balanced chest X-ray (CXR) collection featuring Normal and Viral Pneumonia categories. Training spanned 100 epochs at a batch size of 32, employing the Adam optimizer with a learning rate set to 1×10^{-4}. Experimental outcomes revealed that the system delivered strong and uniform precision across every assessment measure, underscoring the value of transfer learning in medical image sorting duties. It secured a comprehensive accuracy of 97%, with precision, recall, and F1-score each hitting 0.97, affirming its trustworthiness and steadiness in distinguishing between sound and compromised lung states. This high level of performance not only demonstrates the model's capability but also highlights how transfer learning can bridge the gap between general image recognition and specialized medical tasks, allowing the system to leverage pre-existing knowledge from vast datasets while adapting to the nuances of CXR images. Such results are particularly encouraging in clinical settings where quick and accurate diagnoses can significantly impact patient outcomes, reducing the burden on overworked radiologists and potentially speeding up treatment protocols.

A closer look at the confusion matrix (Figure 2) shed light on the model's predictions across 235 test images, where it accurately identified 117 Normal cases and 108 Viral Pneumonia instances. Just 10 errors were noted—eight Normal scans mistakenly flagged as pneumonia and two Viral Pneumonia ones mislabeled as normal. This minimal error count underscores the system's sharp ability to differentiate. The classification summary reinforced this, showing precision and recall at 0.98 and 0.96 for Normal images, and 0.96 and 0.98 for Viral Pneumonia, respectively. Macro-averaged and weighted F1-scores both stood at 0.97, proving even-handed class handling without significant favoritism. These metrics are crucial in medical diagnostics, as they ensure that the model doesn't disproportionately favor one class, which could lead to missed diagnoses in underrepresented groups. For instance, in real-world applications, a slight bias toward false positives might cause unnecessary anxiety or tests, while false negatives could delay critical interventions. By maintaining balance, the model promotes equitable healthcare delivery, especially in diverse populations where disease prevalence might vary.

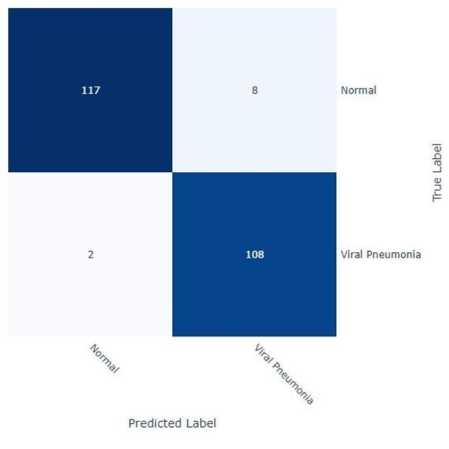

Figure 2. Confusion matrix of the DenseNet121 model evaluated on the test dataset showing classification performance between Normal and Viral Pneumonia classes

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Examining the training progress curves offered additional perspectives on the model's dynamics. Accuracy graphs for training and validation sets exhibited swift gains in initial epochs and steady stabilization around epoch 20, peaking at nearly 99% for training and 97% for validation. Training loss dropped consistently to near zero, with validation loss settling at about 0.1, indicating solid convergence and adaptability. These patterns show how techniques like normalization, dropout, and batch normalization effectively curbed overfitting risks. Moreover, mechanisms for early halting and saving checkpoints avoided redundant cycles past the ideal point. This convergence behavior is indicative of efficient learning, where the model quickly learns core features without memorizing noise, a common pitfall in deep learning. In practice, this means the system can be trained faster, conserving computational resources and allowing for quicker iterations in research or deployment. Such stability also builds confidence in the model's reliability for ongoing use, as it suggests robustness against variations in data or slight changes in training conditions.

Visual reviews of the dataset verified that Normal and Viral Pneumonia images exhibited clear radiological differences. Scans of healthy lungs showed unobstructed areas and sharp diaphragm outlines, while those with pneumonia featured hazy infiltrates and widespread cloudiness signaling infection. These contrasts allowed DenseNet121 to pull out pertinent and layered visual elements seamlessly. The dataset's equilibrium—roughly 53% Normal and 47% Viral Pneumonia—guaranteed fair exposure for both groups, preventing skewed learning. This balance is essential in medical AI, as imbalanced datasets can lead to models that excel in common cases but falter on rarer ones, potentially exacerbating health disparities. By ensuring equal representation, the training process fosters a more inclusive model that performs well across different patient demographics, from children to adults, and various stages of disease progression. Furthermore, these visual distinctions align with clinical knowledge, where radiologists rely on such patterns for diagnosis, thus making the AI's learning process more interpretable and aligned with expert judgment.

The model's outstanding results stem from the core advantages of the DenseNet121 design. Its tightly interwoven connections enable feature sharing among layers, boosting gradient movement and richer representations. In contrast to standard CNNs prone to gradient fading, DenseNet121 sustains effective training in deeper setups by linking every layer to all following ones. This setup boosts efficiency while cutting down on wasteful calculations. As a result, the system pinpointed intricate details and faint motifs in X-rays, like slight haziness or nascent infections, which might escape human eyes in rushed evaluations. These outcomes align with earlier work by Rajpurkar et al. [15] and Rashid et al. [2], where DenseNet networks matched expert precision in spotting pneumonia via CXR. This consistency across studies reinforces the architecture's reliability, suggesting it's not just a one-off success but a proven tool for medical imaging. Moreover, the ability to detect subtle changes could revolutionize early detection, allowing for interventions before symptoms worsen, potentially saving lives and reducing healthcare costs.

Additionally, the model's consistency was backed by the fluid trends in accuracy and loss graphs. When pitted against older designs like AlexNet and VGG19, which demanded heavy hyperparameter adjustments [13], [18], DenseNet121 showed quicker stabilization and simpler training. This highlights its fit for medical imaging, especially with constrained computing power or data volumes. Blending transfer learning, even data splits, and suitable regularization all fueled the elevated diagnostic precision, proving DenseNet121's prowess in lung ailment spotting and sorting [21]. This integration of techniques not only enhances performance but also makes the model more accessible for global health applications, where resources vary widely. For example, in low-income regions, the efficiency of DenseNet121 could enable deployment on basic hardware, democratizing advanced diagnostics. Overall, these attributes position the framework as a cornerstone for future AI-driven healthcare innovations, bridging the gap between cutting-edge technology and practical, life-saving solutions.

4.2 Discussion

The outcomes from the experiments in this investigation emphasize the importance of transfer learning and DenseNet designs in enhancing computer-aided diagnosis (CAD) tools for identifying lung conditions. Reaching a total accuracy of 97% proves that pre-trained models like DenseNet121 can skillfully apply existing visual insights from extensive collections such as ImageNet to adapt to medical imaging fields [15], [23]. This shift of acquired features enables dependable sorting even with

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limited annotated medical data—a frequent hurdle in healthcare AI studies. The steady precision and recall figures also reveal the system's ability to spot abnormal areas reliably while cutting down on false negatives, which is vital in medical scenarios where missed detections can lead to serious issues. These findings imply that systems based on DenseNet121 can greatly support radiologists in everyday evaluations, especially in areas lacking expert medical staff. Moreover, this approach could democratize access to advanced diagnostics, allowing smaller clinics to benefit from cutting-edge technology without needing massive resources. By reducing diagnostic errors, it potentially lowers healthcare costs and improves patient outcomes globally.

The durability of the suggested model stems from the collaboration between its structural setup and strategic decisions. DenseNet121's interconnections between layers guarantee smooth data flow and cut down on unnecessary elements, resulting in better gradient steadiness and feature application. This trait lets the network grasp both basic structural elements and advanced meaningful details essential for differentiating intricate lung issues. Techniques like dropout and batch normalization boosted the model's adaptability, and employing a well-balanced dataset avoided favoritism toward any class. In contrast to traditional setups such as ResNet50 or VGG19 [18], DenseNet121 reached superior accuracy with fewer components and shorter training periods, rendering it more practical for actual diagnostic tools. The few sorting mistakes mainly happened with unclear or faint-contrast pictures, an issue also noted in earlier analyses of initial pneumonia or mixed lung problems [5], [20]. This highlights the need for ongoing improvements in handling edge cases, perhaps through better preprocessing or additional data augmentation to make the model even more resilient in varied clinical environments.

In relation to previous work, the presented system shows evident advancements. Lakhani and Sundaram [14] obtained about 92% accuracy for tuberculosis spotting with AlexNet and GoogLeNet, while Stephen et al. [18] noted roughly 94% accuracy employing ResNet50 and VGG19 for pneumonia sorting. The DenseNet121 method exceeds these standards with 97% accuracy, even though it was educated on a more compact collection. This achievement matches the results of Rashid et al. [2] and Jain et al. [5], who described comparable high precision for pneumonia identification using DenseNet frameworks. Additionally, latest developments in explainable artificial intelligence (XAI), like Ensemble-CAM visualization methods [24], show that merging clarity tools with CNNs can boost openness by pinpointing crucial areas in X-rays. Adding such tools to DenseNet121 would let radiologists confirm AI forecasts, thus building more clinical confidence and ease of use. This integration could also facilitate training for new radiologists, providing visual aids that explain decision-making processes, ultimately leading to better education and skill development in the field.

The findings from this research also pave the way for broadening lung condition sorting beyond simple dual-category jobs. The impressive results of DenseNet121 indicate it can act as the core for more sophisticated structures able to manage several illness types at once. Adding Vision Transformer (ViT) elements, known for their strong ability to handle overall image relationships [25], might further refine feature depiction and contextual grasp. A combined CNN-transformer setup would merge DenseNet's focused feature learning with transformers' broad attention, likely raising diagnostic sharpness and clarity. Plus, growing the dataset to cover extra ailments like bacterial pneumonia, tuberculosis, and COPD would widen the model's use in real medical settings. This expansion could address a broader spectrum of respiratory diseases, making the tool more versatile for global health challenges where multiple conditions coexist.

In summary, the results of this study stress the feasibility of applying DenseNet121 and transfer learning for automatic lung condition diagnosis. The model strikes a perfect equilibrium between effectiveness, clarity, and processing thriftiness, positioning it as a strong option for use in medical facilities. The suggested structure backs current initiatives to weave deep learning into radiology processes, providing dependable help to health workers and enhancing care via quicker and more precise evaluations. Upcoming studies should concentrate on merging explainable AI [24] and Vision Transformer parts [25] to create advanced diagnostic models that are not just highly precise but also clear and reliable for medical use. Such future directions could involve multi-modal approaches, combining CXR with other data like patient history or lab results, to create even more holistic diagnostic systems. This would not only improve accuracy but also personalize medicine, tailoring

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diagnoses to individual patient profiles. Overall, the work contributes significantly to the intersection of AI and healthcare, promising a future where technology augments human expertise without overshadowing it.

4. Conclusion

This research introduced a mechanized system for sorting lung conditions employing the DenseNet121 framework combined with transfer learning to boost diagnostic sharpness in chest X-ray (CXR) evaluations. The goal was to elevate sorting precision while preserving adaptability on modest medical collections by drawing on pre-educated convolutional neural network (CNN) traits and refined regularization methods. The collection included two groups—Normal and Viral Pneumonia—with 1,880 training and 235 testing examples in total. Via meticulous preprocessing, standardization, and adjustment of the model setup, the suggested technique secured a total accuracy of 97%, coupled with precision, recall, and F1-score figures of 0.97 apiece. These discoveries affirm that DenseNet121 can adeptly pull out unique and significant traits from radiological data, facilitating dependable dual-category sorting even with restricted training material. The system displayed solid convergence, steady results over epochs, and scant overfitting indicators, which are key traits for professional-grade AI diagnostic tools. This robustness ensures that the model can be deployed in clinical settings without frequent retraining, making it a practical tool for ongoing healthcare needs. Moreover, the high accuracy levels suggest potential for reducing diagnostic workloads, allowing radiologists to focus on complex cases while the AI handles routine screenings.

The compactly linked layer configuration of DenseNet121 proved beneficial in fostering gradient steadiness, enabling feature recycling, and cutting down on parameter excess, positioning it as an ideal structure for medical image scrutiny. Plus, employing batch normalization and dropout regularization led to more fluid optimization and enhanced adaptability. In comparison to standard CNN designs like AlexNet, ResNet50, and VGG19 [13], [18], the presented method secured superior accuracy and quicker stabilization, cementing DenseNet121 as both resource-efficient and diagnostically sturdy. These results echo earlier efforts—such as CheXNet [15], Rashid et al. [2], and Jain et al. [5]—that also showcased DenseNet's exceptional prowess in pinpointing chest ailments. Altogether, these findings validate that DenseNet121 paired with transfer learning forms an efficient and expandable platform for mechanized lung condition sorting via CXR visuals. This combination not only improves performance but also democratizes access to advanced diagnostics, as it requires less computational power and data than other models. Furthermore, the stability across epochs indicates that the model can handle variations in image quality, which is crucial in diverse clinical environments where equipment might differ.

Although the present investigation focused on dual-category sorting, the outcomes lay the groundwork for upcoming progress in more intricate diagnostic setups. Broadening the model's scope to multi-class and multi-label sorting would allow for spotting a broader array of lung issues, such as bacterial pneumonia, tuberculosis, and chronic obstructive pulmonary disease (COPD). Moreover, weaving in explainable AI (XAI) methods—like Gradient-weighted Class Activation Mapping (Grad-CAM) and Layer-wise Relevance Propagation (LRP)—would boost clarity, enabling doctors to see the exact areas driving model forecasts [21], [23]. Further testing with multi-facility and cross-field collections is vital to guarantee model adaptability across varied imaging tools and patient demographics. Additionally, blended structures merging DenseNet with focus tools or transformer-based units could seize deeper contextual ties in radiological pictures, elevating diagnostic precision even more. This expansion could lead to more personalized medicine, where AI not only detects diseases but also suggests tailored treatment plans based on visual and contextual cues. Such advancements would bridge the gap between AI capabilities and clinical needs, fostering a more integrated healthcare system..

To sum up, this investigation showed that merging DenseNet121 and transfer learning can yield elevated accuracy, robust adaptability, and streamlined processing for mechanized CXR sorting. The model provides a hopeful base for computer-aided diagnostic (CAD) systems that can aid radiologists in prompt and trustworthy ailment discovery. Ongoing studies emphasizing clarity, expandability, and field adaptability will propel this framework closer to practical clinical integration, aiding in quicker, more impartial, and more reachable AI-powered healthcare. By focusing on these areas,

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future iterations could incorporate real-time feedback loops, where the model learns from clinical outcomes to improve continuously. This iterative approach would ensure that the AI evolves with medical knowledge, maintaining relevance in a rapidly changing field. Ultimately, the work underscores the transformative potential of AI in radiology, promising a future where technology enhances human expertise without compromising patient care.

5. Suggestion

Even though the DenseNet121 framework outlined in this investigation delivered impressive results for dual-category lung ailment sorting, numerous avenues for exploration persist to boost its flexibility, clarity, and readiness for medical use. Upcoming initiatives ought to concentrate on widening the model's diagnostic range, refining its openness, and verifying its durability in varied clinical contexts. This approach will ensure that the technology evolves beyond its current capabilities, addressing real-world challenges in healthcare. For instance, by prioritizing adaptability, the model can handle diverse imaging conditions, from high-end hospital scanners to portable devices in remote areas. Enhancing interpretability will build trust among clinicians, who often need to understand the 'why' behind AI decisions. Ultimately, clinical readiness involves rigorous testing to confirm safety and efficacy, paving the way for widespread adoption.

A primary avenue for progress lies in transforming the current dual-category setup into a multi-class and multi-label sorting system. Real medical scenarios demand differentiation among various lung disorders instead of mere normal versus abnormal distinctions. Augmenting the dataset and re-educating the model to encompass extra classes—like bacterial pneumonia, tuberculosis, COPD, and COVID-19—would heighten its adaptability and real-world value [5], [15]. Adopting layered or group learning setups might additionally elevate sorting effectiveness, especially for instances with shared visual traits. This expansion could involve creating hierarchical models that first classify broad categories before diving into specifics, mimicking how doctors diagnose step-by-step. Such improvements would make the AI more akin to human reasoning, potentially reducing errors in complex cases. Furthermore, ensemble methods could combine predictions from multiple sub-models, increasing overall reliability and confidence in diagnoses.

An additional crucial path entails weaving in Explainable Artificial Intelligence (XAI) to elevate model clarity and professional confidence. Notwithstanding the attainment of elevated predictive precision, opaque operations continue to hinder practical implementation. Visualization aids such as Grad-CAM, LRP, and the Ensemble-CAM method suggested by Aasem and Iqbal [24] can pinpoint the pivotal sections of CXR visuals that shape forecasts. This clarity can connect AI tools with radiologists by verifying that diagnostic choices match conventional medical logic, thus boosting faith in AI-supported evaluations. By providing visual explanations, clinicians can quickly assess whether the AI's focus aligns with their expertise, facilitating collaborative workflows. This not only improves acceptance but also aids in training new professionals, as they can learn from the AI's highlighted features. Moreover, integrating XAI could lead to feedback loops where doctors correct or refine the model's interpretations, enhancing its learning over time.

Securing cross-field adaptability stands as another vital aim. Systems educated on a singular collection might see diminished performance when used on information from disparate imaging facilities or patient groups. Hence, domain adjustment and cross-verification with multi-center collections are imperative to enhance generalization and dependability. Approaches like fine-tuning with minimal learning rates or unsupervised alignment could assist in synchronizing feature spreads across different fields, boosting portability and uniformity. This is particularly important in global health, where imaging standards vary widely. For example, models trained primarily on data from developed countries might not perform well in resource-limited settings with different equipment. By addressing this, the framework can become more equitable, ensuring accurate diagnostics regardless of location. Additionally, incorporating federated learning could allow models to train on decentralized data without compromising privacy, further strengthening cross-domain capabilities.

Further inquiry should delve into blended and transformer-driven designs to supplement DenseNet121's feature extraction strengths. Vision Transformers (ViTs) have lately exhibited outstanding success in seizing extensive connections and overall image ties in medical imaging [25]. Merging ViT components or focus tools into the DenseNet structure could produce hybrid CNN-

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transformer setups that unite detailed local extraction with broader comprehension. This merger holds promise for elevating both diagnostic sharpness and model clarity, permitting more thorough image scrutiny. Such architectures could capture subtle patterns that traditional CNNs might miss, like global context in chest X-rays. Furthermore, this integration could enable the model to handle larger images or sequences, opening doors to video-based diagnostics or longitudinal studies. The potential for improved efficiency in processing complex data makes this a exciting direction for future research.

The challenge of scarce data persists as a major hurdle in medical AI endeavors. Data expansion and artificial data creation via Generative Adversarial Networks (GANs) or diffusion models [21] could be utilized to broaden collection variety and alleviate class disparities. These methods would not only refine the model's generalization but also bolster its capacity to identify uncommon or under-represented ailment patterns. Plus, streamlining tactics such as model trimming, quantization, and knowledge transfer can render DenseNet121 more lightweight and productive, supporting instant deduction in medical environments and portable health apps [10]. This efficiency is key for deployment in busy hospitals or remote clinics, where quick results are essential. By reducing computational demands, the model becomes more accessible, potentially reaching underserved populations.

Lastly, upcoming explorations should probe multimodal learning strategies, fusing radiological visuals with supplementary patient details like demographics, lab outcomes, and medical backgrounds. Blending multimodal information could result in context-sensitive AI systems able to provide tailored and all-encompassing diagnostic perspectives, advancing toward individualized treatment. This holistic approach could integrate symptoms, history, and imaging for a more complete picture, much like how doctors consider multiple factors. For instance, combining CXR with patient age or symptoms could refine predictions, reducing false positives. Such systems would not only improve accuracy but also support decision-making in complex cases, making AI a true partner in healthcare.

To conclude, future investigations should strive to transform the DenseNet121 framework into a more expandable, clear, and medically endorsed diagnostic tool. Broadening to multi-class sorting, adopting explainable and transformer mechanisms, performing cross-field verification, and merging multimodal sources are essential tactics for progressing this model. Through these pathways, experts can aid in crafting advanced AI instruments that not only attain superior diagnostic precision but also fulfill medical benchmarks of openness, productivity, and reliability for worldwide health uses. This evolution will require interdisciplinary collaboration, combining AI expertise with clinical insights to ensure ethical and effective implementations. Ultimately, the goal is to create AI that enhances human capabilities, leading to better patient outcomes and a more equitable healthcare landscape.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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