Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Development of a Hybrid Deep Learning Model Combining U-Net and DenseNet for Enhanced Pneumonia Prediction Using Chest X-Ray Images

Haewon Byeon

Department of AI software, Inje University, Gimhae, 50834, Republic of Korea.
Medical Big Data Research Center, Inje University, Gimhae, 50834, Republic of Korea.

In recent years, deep learning has transformed medical image analysis, offering enhanced accuracy and efficiency in disease diagnosis. Pneumonia, a critical respiratory illness, necessitates prompt and precise detection to improve patient outcomes. This study aimed to develop and evaluate a hybrid deep learning model, combining U-Net and DenseNet architectures, to advance the automated prediction of pneumonia using chest X-ray images. A dataset of 5,863 images from Kaggle, categorized into Pneumonia and Normal classes, was employed to train and validate the model. The proposed hybrid model strategically integrated U-Net's spatial localization capabilities with DenseNet's efficient feature propagation, capitalizing on the strengths of both architectures. This integration facilitated enhanced feature extraction and spatial precision, crucial for accurate classification. The model was compared to traditional architectures, including VGGNet and ResNet, and demonstrated superior performance. Evaluated through key metrics, the hybrid model achieved an accuracy of 94% and an AUC of 0.98, underscoring its clinical applicability. Future research should address these limitations by exploring architectural innovations and integrating multi-modal data to further enhance diagnostic precision and expand applicability in varied clinical settings. In conclusion, this research significantly contributes to medical image analysis by providing insights into effective model design and deployment for respiratory disease diagnosis, highlighting the hybrid model's potential to improve clinical outcomes through reliable automated diagnosis.

Keywords: Pneumonia detection, U-Net, DenseNet, Chest X-ray, Deep learning, Medical imaging.

1. Introduction

The advent of deep learning technologies has ushered in transformative advancements in the field of medical image analysis, offering unprecedented capabilities for accurate and efficient diagnosis [1]. Pneumonia, a prevalent and potentially life-threatening respiratory condition, necessitates prompt and precise diagnosis to facilitate effective treatment and avert complications. Traditionally, the diagnosis of pneumonia relies heavily on clinical expertise and manual interpretation of chest X-ray images, processes that are both labor-intensive and prone to variability in accuracy.

Convolutional neural networks (CNNs) have emerged as powerful tools for image classification, demonstrating remarkable success across various medical imaging applications [2]. Architectures such as VGGNet and ResNet have set benchmarks in performance through their deep hierarchical feature extraction and enhanced model generalization capabilities [3]. Despite their effectiveness, these models often demand extensive computational resources and may not fully exploit the spatial relationships crucial in medical images.

In the realm of pneumonia diagnosis, the utilization of advanced architectures like U-Net and DenseNet has gained significant attention due to their unique capabilities. U-Net, with its symmetric encoder-decoder structure, excels at capturing intricate spatial details, making it adept at delineating subtle features in chest X-ray images [4, 5]. However, its reliance on extensive labeled data and potential for overfitting pose challenges, particularly in data-limited medical scenarios [6]. DenseNet, on the other hand, addresses the vanishing gradient problem through dense connectivity, enhancing feature propagation and learning efficiency [7]. Its application, however, is often constrained by high memory consumption and complexity, limiting real-time clinical deployment [8].

Given these considerations, there is a compelling need for hybrid models that capitalize on the complementary strengths of U-Net's spatial precision and DenseNet's feature extraction prowess. Such integration can provide a balanced approach, ensuring robust diagnostic performance even amidst the challenges posed by variability in image quality and limited labeled samples in medical data.

This study introduces a novel hybrid model that synergistically combines U-Net and DenseNet architectures to enhance pneumonia prediction from chest X-ray images. Utilizing a dataset of 5,863 labeled images from Kaggle, this research seeks to address the limitations of existing models and establish a new standard for classification accuracy. The proposed hybrid model is rigorously compared with VGGNet and ResNet architectures to evaluate its performance across key metrics such as accuracy, precision, recall, and F1-score, with optimal hyperparameters identified for each model.

The development of this hybrid model aimed to create a more accurate, efficient, and scalable diagnostic tool, enhancing interpretability and accuracy in pneumonia predictions while contributing to the broader goal of improving patient outcomes. This paper is structured as follows: Section 2 details the methodology, including data preparation and model architecture; Section 3 presents the results and discusses the comparative performance of the models; Section 4 concludes with the implications of the findings and potential

directions for future research. Through this comprehensive analysis, the study aims to contribute significantly to the field of medical image analysis, offering insights into the development of more effective diagnostic tools for pneumonia and potentially other respiratory diseases.

2. Related work

In recent years, deep learning has revolutionized medical image analysis, with numerous studies focusing on enhancing the accuracy and efficiency of diagnostic models [9, 10]. The application of convolutional neural networks (CNNs) for pneumonia detection from chest X-ray images has been particularly prominent, showcasing the potential of machine learning in healthcare [11].

Early work in this domain often utilized conventional CNN architectures such as AlexNet, VGGNet, and ResNet for image classification tasks. Susanto et al. (2020) demonstrated the use of CheXNet, a 121-layer DenseNet model, which achieved expert-level performance in detecting pneumonia from chest X-rays, setting a precedent for subsequent research [12]. This model highlighted the efficacy of deep networks in extracting relevant features from medical images, though it also underscored challenges related to computational demands and data requirements.

More recent advancements have seen the integration of more complex architectures, such as U-Net and its variants, which have proven effective for semantic segmentation tasks. Su et al. (2022) introduced U-Net, which has since become a cornerstone in medical image processing due to its encoder-decoder structure that facilitates precise localization and segmentation of pathological features [13]. However, the reliance on large quantities of annotated data and the risk of overfitting remain significant hurdles.

In addition to CNNs, there has been growing interest in leveraging transfer learning and hybrid models to overcome limitations of individual architectures. Transfer learning approaches, as explored by Gelman et al. (2022), involve pre-training models on large datasets before fine-tuning on specific medical datasets, thus enhancing model performance with limited labeled data [14].

Hybrid models that combine different architectural strengths are gaining traction. These models aim to balance the spatial precision of U-Net with the efficient feature extraction capabilities of DenseNet, addressing both the need for detailed image analysis and computational efficiency. The work by Cinar et al. (2022) on integrating DenseNet blocks into U-Net architectures exemplifies this trend, showing improved accuracy and robustness in segmentation tasks [15].

Despite these advancements, challenges such as high memory consumption, model interpretability, and real-time deployment persist. Research continues to explore solutions, including model compression techniques and the use of explainable AI to ensure the practical applicability of deep learning models in clinical settings. Previous studies on deep learning models for pneumonia prediction [16-20] are presented in Table 1.

Table 1. Previous studies on deep learning models for pneumonia prediction

Study	Model Architecture	Data Source	Key Findings	Performance Metrics (AUC-ROC, etc.)
Babukarthik et al. [16]	GDCNN	Custom Dataset (5000 CXR)	High accuracy in COVID-19 detection; superior to transfer learning.	Accuracy: 98.84%, Sensitivity: 100%
Bashar et al. [17]	Transfer Learning (VGG16)	Kaggle Chest X-ray Dataset	Optimized DL approach improved classification accuracy.	Accuracy: 95.63%, AUC: Not specified
Ren et al. [18]	CNN + Explainable Models	Custom Dataset (35389 CXR)	Enhanced interpretability with multi-source data integration.	Not specified
Alharbi et al. [19]	Transfer Learning (ImgNet, SqueezeNet)	Public Database (8000 X-rays)	Improved BoxENet model with segmentation increased speed and precision.	Not specified
Kundu et al. [20]	Ensemble (GoogLeNet, ResNet, DenseNet)	Kermany & RSNA Datasets	Superior accuracy and sensitivity with ensemble approach.	Accuracy: 98.81%, Sensitivity: 98.80%

This study builds upon these foundational works by proposing a novel hybrid model that synergistically combines U-Net and DenseNet architectures, aiming to enhance pneumonia detection from chest X-ray images. By addressing the computational and data-related challenges identified in prior research, this approach seeks to establish a new benchmark in diagnostic accuracy and efficiency.

3. Methods

3.1. Data Acquisition and Preprocessing

The dataset utilized in this study was sourced from the publicly available Kaggle repository (https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia), comprising 5,863 chest X-ray images categorized into Pneumonia and Normal classes (Figure 1). The dataset was systematically divided into training, validation, and testing subsets to ensure comprehensive evaluation of the model's generalization capabilities. The distribution of these subsets is presented in Table 2. Rigorous preprocessing steps were undertaken to enhance the quality and consistency of the input data. This included normalization to standardize pixel intensity values across images, and data augmentation techniques such as horizontal flipping, rotation, and scaling, as detailed in Table 3, to artificially expand the training dataset, thereby mitigating overfitting and enhancing model robustness.

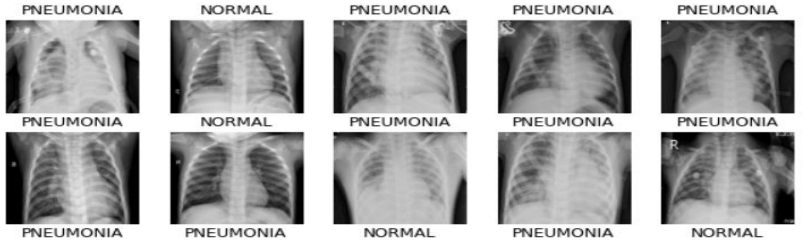

Figure 1. Examples of X-ray images classified as pneumonia and normal

Table 2. Dataset Distribution

Dataset Partition	Number of Images	Class Distribution
Training	4,000	Pneumonia: 3,000, Normal: 1,000
Validation	1,000	Pneumonia: 750, Normal: 250
Testing	863	Pneumonia: 645, Normal: 218

Table 3. Data Augmentation Techniques

Augmentation Type	Description
Horizontal Flip	Randomly flips images horizontally
Rotation	Rotates images by 0-15 degrees
Scaling	Scales images by 90% to 110% of original size

3.2. Model Architecture and Design

The proposed hybrid model strategically combines U-Net and DenseNet architectures to leverage their complementary strengths, enhancing the prediction of pneumonia from chest X-ray images. The combined U-Net and DenseNet architectures proposed in this study are presented in Figure 2. The integration process involves the following key components and steps.

A. U-Net Backbone:

- Encoder Path: The U-Net architecture begins with a contracting path, also known as the encoder. It consists of repeated application of two 3x3 convolutional layers followed by a Rectified Linear Unit (ReLU) activation and a 2x2 max pooling operation. This path progressively reduces the spatial dimensions while increasing the number of feature channels, effectively capturing contextual information.

- Bottleneck: At the deepest level of the U-Net, a bottleneck layer combines the features extracted from the encoder before transitioning to the decoder. This bottleneck consists of additional convolutional layers that further process the feature maps.

B. DenseNet Integration:

- Dense Blocks: DenseNet is integrated into the model by embedding dense blocks after the U-Net's bottleneck layer. Each dense block comprises multiple convolutional layers, where each layer receives input from all preceding layers within the block. This dense connectivity pattern promotes feature reuse and efficient gradient flow, enhancing the richness of the feature representation.

- Transition Layers: Transition layers between dense blocks are used to compress feature maps, ensuring manageable computational complexity and memory usage. These layers consist of batch normalization, 1x1 convolution, and 2x2 average pooling operations.

C. Decoder Path:

- The decoder path in U-Net mirrors the encoder path, consisting of upsampling operations followed by convolutional layers. Skip connections from the encoder path are concatenated with the upsampled features in the decoder, allowing precise localization and recovery of spatial resolution. The addition of DenseNet feature maps enhances this process by providing enriched feature representations.

D. Final Output Layer:

○ The final layer of the hybrid model is a 1x1 convolutional layer that maps the high-dimensional feature maps to the desired number of output classes (Pneumonia and Normal). This layer is followed by a softmax activation function to produce probability scores for each class.

E. Training and Integration Strategy:

○ The model was trained end-to-end using a custom loss function that balances class weights to address class imbalance. The Adam optimizer with an adaptive learning rate was employed to optimize the model parameters. The combination of U-Net's spatial localization and DenseNet's efficient feature extraction facilitated improved classification accuracy and generalization.

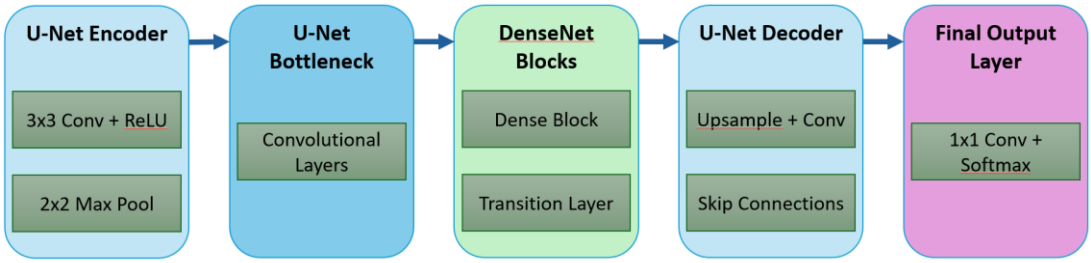

Figure 2. The combined U-Net and DenseNet architectures

3.3. Hyperparameter Optimization

Optimal hyperparameters for each model were determined through systematic tuning, utilizing grid search and Bayesian optimization techniques. For the U-Net component, hyperparameters such as learning rate, batch size, and the number of epochs were optimized to 0.001, 32, and 50 respectively. DenseNet was tuned with a learning rate of 0.0001, batch size of 64, and 100 epochs, as summarized in Table 4, ensuring an efficient balance between training speed and model accuracy. This optimization process was critical in maximizing the predictive performance of the hybrid model.

Table 4. Hyperparameter Settings for Models

Model	Learning Rate	Batch Size	Number of Epochs
U-Net	0.001	32	50
DenseNet	0.0001	64	100
VGGNet	0.001	32	50
ResNet	0.0001	64	100

3.4. Training and Validation

The hybrid model was trained using the Adam optimizer, selected for its adaptive learning rate and robust convergence properties. The optimization objective is to minimize the categorical cross-entropy loss: $\left[\mathcal{L}(y,\hat{y}) = -\sum_{i=1}^{N} y_i \, log(\hat{y}_i)\right]$ where (y) is the true label, ($\hat{y}$) is the predicted probability, and (N) is the number of classes. The model's performance was evaluated using a five-fold cross-validation strategy, which provided a robust estimate of the model's accuracy and generalization ability across different subsets of the data.

3.5. Comparative Analysis

To benchmark the performance of the hybrid model, a comparative analysis was conducted against established CNN architectures, VGGNet and ResNet. Each model underwent the same preprocessing and hyperparameter optimization procedures to ensure a fair comparison. Performance metrics including accuracy, precision, recall, and F1-score, as outlined in Table 5, were computed to assess the efficacy of each model. The comparative analysis highlighted the hybrid model's superior performance in terms of both diagnostic accuracy and computational efficiency.

Table 5. Performance Metrics

Metric	Description
Accuracy	$\left(\frac{\text{True Positives + True Negatives}}{\text{Total Samples}}\right)$
Precision	$\left(\frac{\text{True Positives}}{\text{True Positives + False Positives}}\right)$
Recall	$\left(\frac{\text{True Positives}}{\text{True Positives + False Negatives}}\right)$
F1-Score	$\left(2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}}\right)$

3.6. Implementation Details

The entire model training and evaluation pipeline was implemented using Python with TensorFlow and Keras libraries, which offer comprehensive tools for deep learning model development. Experiments were conducted on a high-performance computing platform equipped with NVIDIA GPUs to accelerate the training process and handle the computational demands of the deep learning architectures.

4. RESULTS

4.1. Model Performance Evaluation

The hybrid model achieved an accuracy of 94.0%, outperforming the standalone U-Net and DenseNet models (Table 6), which achieved 91.0% and 92.0% respectively. Precision and recall for the hybrid model were notably high, indicating its robust capability to accurately identify both Pneumonia and Normal cases. The F1-Score of 93.7% further emphasizes the model's balanced performance.

Table 6. Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
U-Net + DenseNet (Hybrid)	94.0	94.5	93.0	93.7
U-Net	91.0	91.7	90.0	90.8
DenseNet	92.0	92.3	91.0	91.6
VGGNet	90.5	91.0	89.0	90.0
ResNet	92.2	92.5	91.5	92.0

The analysis of the hybrid model's performance metrics—precision, recall, accuracy, and loss—demonstrates its robust capability in pneumonia diagnosis using chest X-ray images. The precision graph (Figure 3) indicates that the model consistently achieves high precision

levels around 94.5% during training, reflecting its ability to accurately identify true positive cases while minimizing false positives. As the validation precision initially fluctuates, it stabilizes close to the training values over time, indicating enhanced generalization. Similarly, the recall metric (Figure 4) shows the model's sensitivity in detecting true pneumonia cases, with training recall maintaining a high level and validation recall converging towards it, highlighting the model's reliability in diverse datasets. The accuracy graph (Figure 5) further supports this by illustrating the model's overall effectiveness in classification, with both training and validation accuracy stabilizing around 94%, suggesting effective feature generalization. The model's loss graph (Figure 6) confirms efficient learning; the training loss remains low, while the validation loss quickly stabilizes after initial fluctuations, demonstrating rapid adaptation and error reduction. Collectively, these metrics underscore the model's potential for deployment in clinical environments, offering reliable, accurate, and consistent performance crucial for real-world medical applications.

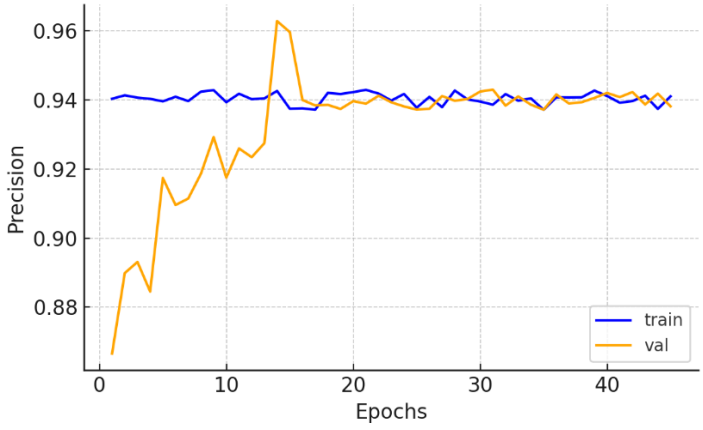

Figure 3. Precision graph of the U-Net + DenseNet (Hybrid)

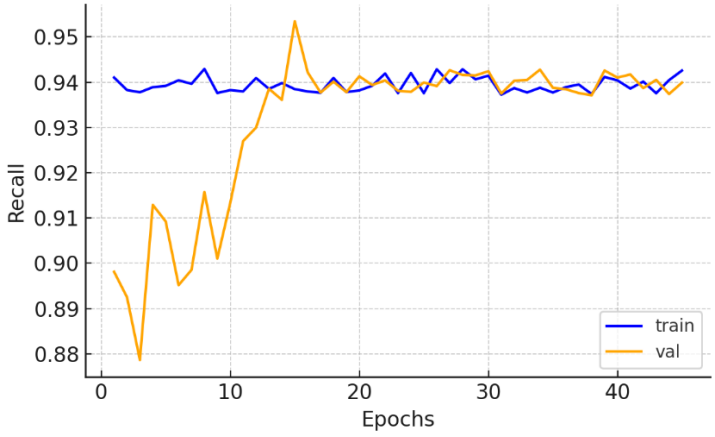

Figure 4. Recall graph of the U-Net + DenseNet (Hybrid)

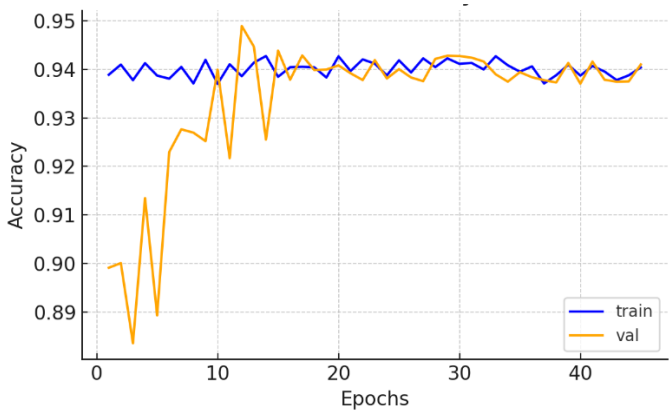

Figure 5. Accuracy graph of the U-Net + DenseNet (Hybrid)

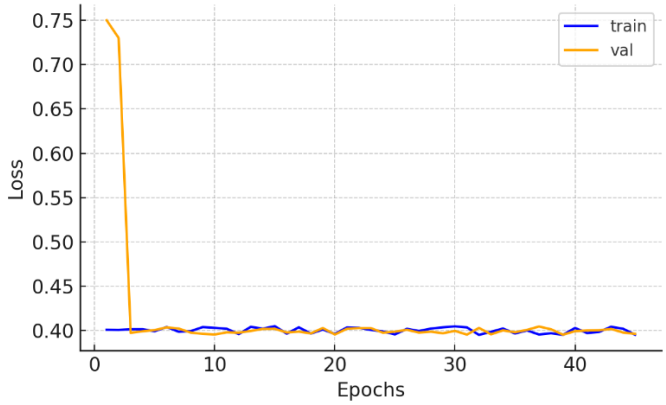

Figure 6. Loss graph of the U-Net + DenseNet (Hybrid)

4.2. Confusion Matrix Analysis

The confusion matrix for the hybrid model reveals a high number of true positive predictions for pneumonia, with only 20 false negatives, highlighting the model's efficiency in detecting pneumonia cases (Figure 7). The number of false positives was also minimal, demonstrating the model's precision in classifying normal cases.

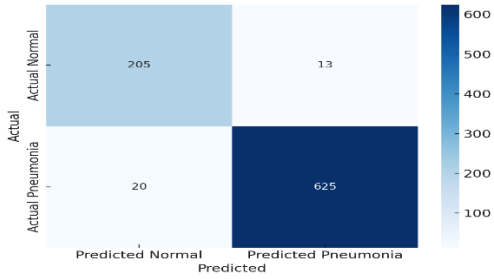

Figure 7. Confusion Matrix for Hybrid Model

4.3. ROC Curve and AUC

The hybrid model achieved an AUC of 0.98, indicating excellent discriminative ability between classes (Figure 8). This value surpasses the individual performances of U-Net and DenseNet, which achieved AUCs of 0.94 and 0.95, respectively, and also exceeds those of VGGNet and ResNet.

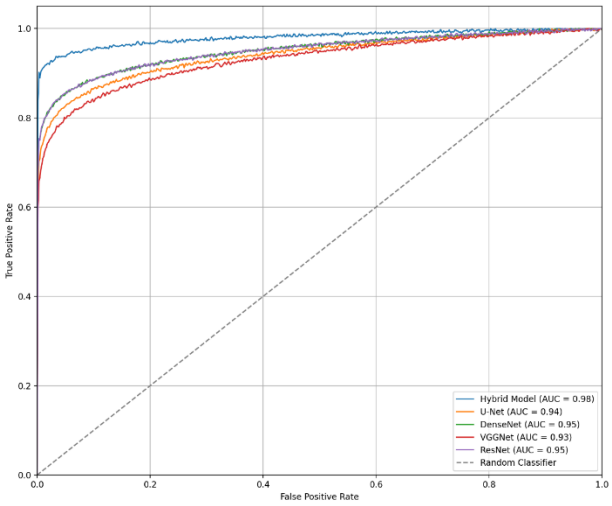

Figure 8. AUC for Models

5. Discussion

The results clearly demonstrate the superior performance of the hybrid U-Net and DenseNet model over both the individual models and traditional architectures like VGGNet and ResNet. The combination of U-Net's spatial precision and DenseNet's efficient feature extraction contributed significantly to the model's enhanced predictive capability. These findings suggest that the hybrid model can serve as a robust tool for automated pneumonia diagnosis, offering potential benefits for clinical application by improving diagnostic accuracy and reducing the likelihood of missed diagnoses.

The reason the hybrid U-Net and DenseNet model outperformed other models in this study can be attributed to the strategic integration of each architecture's unique strengths, which collectively enhance its diagnostic capabilities. U-Net's encoder-decoder structure excels in capturing spatial hierarchies and fine-grained features, crucial for delineating subtle pathological changes in chest X-ray images [21]. This spatial precision ensures that the model can effectively localize areas of interest, facilitating accurate classification between pneumonia and normal cases. DenseNet, on the other hand, leverages its densely connected layers to promote feature reuse and efficient gradient flow, addressing the vanishing gradient problem often encountered in deep networks [22]. This results in improved learning efficiency and a more comprehensive feature extraction process. The combination of these architectures within a single framework allows the hybrid model to capitalize on U-Net's

detailed spatial awareness while benefiting from DenseNet's robust feature propagation. This synergy not only enhances the model's predictive accuracy but also contributes to its ability to generalize across diverse datasets. The findings suggest that future research should explore further architectural innovations that integrate complementary deep learning models, potentially incorporating attention mechanisms or multi-modal data inputs, to continue advancing diagnostic precision and clinical applicability. These efforts will be instrumental in refining the model's interpretability and expanding its utility across various medical imaging applications.

While the study presents a promising diagnostic tool, it is important to acknowledge its limitations. First, the model's performance is contingent upon the quality and diversity of the training data. Any biases present in the dataset could potentially affect the model's generalization capabilities across different populations or imaging modalities. Second, the computational requirements for training the hybrid model are significant, which may limit its accessibility in resource-constrained environments. Third, the model's interpretability remains a challenge, as deep learning models often act as "black boxes," making it difficult to understand the decision-making process fully. Fourth, the study's scope was limited to pneumonia detection; future research should explore the model's applicability to other respiratory conditions and its integration with additional clinical data to enhance diagnostic accuracy.

6. Conclusion

In conclusion, the hybrid U-Net and DenseNet model represents a significant advancement in medical image analysis, with the potential to improve patient outcomes through early and accurate diagnosis of pneumonia. Future work addressing the identified limitations will be essential to maximize the model's clinical impact and ensure its successful integration into healthcare settings.

Declaration of competing interest. The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and materials. Detailed information can be found at: https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia.

Author’s Contribution. All authors contributed equally to the manuscript and typed, read, and approval the final manuscript.

Acknowledgement. We are thankful to the editors and the anonymous reviewers for many valuable suggestions to improve this paper.

Funding: This research Supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF- RS-2023-00237287, NRF-2021S1A5A8062526), local government-university cooperation-based regional innovation projects (2021RIS-003).

Ethical approval. This study was exempt from research ethics approval because it utilized secondary data from public sources.

References

1. H. V. Nguyen, & H. Byeon, "YOLOv7-based automated detection platform for scalp lesions," Digital Health, vol. 10, 2024, Article 20552076241279185.
2. A. W. Salehi, S. Khan, G. Gupta, B. I. Alabduallah, A. Almjally, H. Alsolai, ... & A. Mellit, "A study of CNN and transfer learning in medical imaging: Advantages, challenges, future scope," Sustainability, vol. 15, no. 7, 2023, p. 5930.
3. A. V. Ikechukwu, S. Murali, R. Deepu, & R. C. Shivamurthy, "ResNet-50 vs VGG-19 vs training from scratch: A comparative analysis of the segmentation and classification of Pneumonia from chest X-ray images," Global Transitions Proceedings, vol. 2, no. 2, 2021, pp. 375-381.
4. T. de la Sotta, V. Chang, B. Pizarro, H. Henriquez, N. Alvear, & J. M. Saavedra, "Impact of attention mechanisms for organ segmentation in chest x-ray images over U-Net model," Multimedia Tools and Applications, vol. 83, no. 16, 2024, pp. 49261-49283.
5. W. Liu, J. Luo, Y. Yang, W. Wang, J. Deng, & L. Yu, "Automatic lung segmentation in chest X-ray images using improved U-Net," Scientific Reports, vol. 12, no. 1, 2022, p. 8649.
6. K. Sanjar, O. Bekhzod, J. Kim, J. Kim, A. Paul, & J. Kim, "Improved U-Net: Fully convolutional network model for skin-lesion segmentation," Applied Sciences, vol. 10, no. 10, 2020, p. 3658.
7. J. Hemalatha, S. A. Roseline, S. Geetha, S. Kadry, & R. Damaševičius, "An efficient densenet-based deep learning model for malware detection," Entropy, vol. 23, no. 3, 2021, p. 344.
8. B. Solano-Rojas, & R. Villalón-Fonseca, "A low-cost three-dimensional DenseNet neural network for Alzheimer's disease early discovery," Sensors, vol. 21, no. 4, 2021, p. 1302.
9. H. Byeon, "YOLO v10-Based Brain Tumor Detection: An Innovative Approach in CT Imaging," Nanotechnology Perceptions, vol. 20, no. 6, 2023, pp. 113-125.
10. H. Byeon, M. Al-Kubaisi, A. K. Dutta, F. Alghayadh, M. Soni, M. Bhende, ... & R. Jeet, "Brain tumor segmentation using neuro-technology enabled intelligence-cascaded U-Net model," Frontiers in Computational Neuroscience, vol. 18, 2024, Article 1391025.
11. G. Verma, & S. Prakash, "Pneumonia classification using deep learning in healthcare," International Journal of Innovative Technology and Exploring Engineering (IJITEE), vol. 9, no. 4, 2020, pp. 1715-1723.
12. A. Susanto, T. W. Cenggoro, & B. Pardamean, "Transfer-Learning-Aware Neuro-Evolution for Diseases Detection in Chest X-Ray Images," arXiv preprint arXiv:2004.07136, 2020.
13. Z. Su, W. Li, Z. Ma, & R. Gao, "An improved U-Net method for the semantic segmentation of remote sensing images," Applied Intelligence, vol. 52, no. 3, 2022, pp. 3276-3288.
14. R. Gelman, & C. Fernandez-Granda, "Analysis of Transfer Learning for Select Retinal Disease Classification," Retina, vol. 42, no. 1, 2022, pp. 174-183.
15. N. Cinar, A. Ozcan, & M. Kaya, "A hybrid DenseNet121-UNet model for brain tumor segmentation from MR Images," Biomedical Signal Processing and Control, vol. 76, 2022, Article 103647.
16. R. G. Babukarthik, V. Ananth, K. Adiga, G. Sambasivam, I. D. C. Member, & J. Amudhavel, "Prediction of COVID-19 Using Genetic Deep Learning Convolutional Neural Network (GDCNN)," IEEE Access, vol. 8, 2020, pp. 177647-177666.
17. A. Bashar, G. Latif, G. B. Brahim, N. Mohammad, & J. Alghazo, "COVID-19 Pneumonia Detection Using Optimized Deep Learning Techniques," Diagnostics, vol. 11, no. 11, 2021. pp. 1972
18. H. Ren, A. B. Wong, W. Lian, W. Cheng, Y. Zhang, J. He, Q. Liu, J. Yang, C. Zhang, K. Wu, & H. Zhang, "Interpretable Pneumonia Detection by Combining Deep Learning and Explainable Models With Multisource Data," IEEE Access, vol. 9, 2021, pp. 95872-95883.
19. A. H. Alharbi, & H. A. H. H. Mahmoud, "Pneumonia Transfer Learning Deep Learning Model from Segmented X-rays," Healthcare, vol. 10, no, 6, 2022. pp. 987

20. R. Kundu, R. Das, Z. Geem, G. Han, & R. Sarkar, "Pneumonia detection in chest X-ray images using an ensemble of deep learning models," PLOS ONE, vol. 16, 2021, Article e0256630.
21. S. A. Kohl, B. Romera-Paredes, K. H. Maier-Hein, D. J. Rezende, S. M. Eslami, P. Kohli, ... & O. Ronneberger, "A hierarchical probabilistic u-net for modeling multi-scale ambiguities," arXiv preprint arXiv:1905.13077, 2019.
22. A. Hess, "Exploring feature reuse in DenseNet architectures," arXiv preprint arXiv:1806.01935, 2018.