Deep Neural Network Approaches for Pneumonia Identification in Chest X-Rays

Prof. Nirmala Ganiger
Department of Computer Science
KLS Vishwanathrao Deshpande
Institute of Technology Haliyal, India
ng@klsvdit.edu.in

Prof. Bhagat Inamdar
Department of Computer Science
KLS Vishwanathrao Deshpande
Institute of Technology Haliyal, India
bgi@klsvdit.edu.in

Mr. Aditya G Hegde
Department of Computer Science
KLS Vishwanathrao Deshpande
Institute of Technology Haliyal, India
adityaghegde123@gmail.com

Ms. Pallavi Haribhattanavar
Department of Computer Science KLS
Vishwanathrao Deshpande Institute of
Technology Haliyal, India
pallaviharibhattanavar046@gmail.com

Mr. Abhijit U Naik
Department of Computer Science KLS
Vishwanathrao Deshpande
Institute of Technology Haliyal, India
naikabhi081004@gmail.com

Abstract- Pneumonia is a type of infection that affects the lungs and in some cases may be life-threatening. The images of chest x-ray can give useful [1]information for diagnosis and cure plans of pneumonia. So, training and building a model that can label a given chest x-ray image can prove to be of great use in the medical field. The current research is focused at enhancing the accuracy of the pneumonia analysis using CNN. We will also test other various architectures such as RESnet, Googlenet, VGGnet, and Alexnet. We do so by examining their effectiveness in feature extraction and image analysis to offer improvements in accuracy. We will go ahead and implement ensemble learning methods in building our classification model. To optimize the model, we make use of hyperparameter fine-tuning. In this work, we shall also look at the subtle impact of the learning rates, batch sizes, and other critical parameters to observe what effect it would have on the perfection of the classification model, thereby contributing to a wider understanding of CNNs in medical analysis.

I. INTRODUCTION

The demand for accurate and efficient classification of pneu-monia in Chest X-ray images underscores the significance of advancements in machine learning techniques. The Convolutional Neural Networks (CNNs) have proven to be instrumental in image classification tasks, prompting a thorough examination of their efficacy in the specific context of pneumonia detection. This research meticulously evaluates four prominent CNN ar-chitectures—ResNet, GoogLeNet, VGGNet, and AlexNet—to identify the most effective model for pneumonia classification. Going beyond individual model evaluations, we introduce a stacking ensemble approach, which amalgamates diverse strengths to achieve a collective improvement in accuracy. The subsequent hyperparameter fine-tuning endeavors to tailor each model's configuration, optimizing the ensemble's overall performance. In addition, our study explores into the nuanced exploration of learning rates, batch sizes, and other critical parameters to discern their impact on the accuracy of the pneumonia classification model. By addressing these intricacies,our research contributes to the evolving landscape of medical image.

II. LITERATURE SURVEY

The following is a literature review of some of the landmark works in the area of medical image analysis for the detection of pneumonia. Ligueran et al. [1] conducted research on 2-dimensional lung X-ray images with the deployment of computer vision, reaching an accuracy of 91.2% in assisted medical diagnosis. Other significant deployment have been recorded in studies dealing with datasets of chest X-rays, namely, CNNs based approach [2] and deep learning with particular attention to class imbalance problems [3]; in these applications, the accuracy ranges from 89% to 99.4%.Besides, research on ResNet models on large-scale hospital X-ray datasets reports an accuracy of 86.6% [4]. Finally, the stack of deep learning models on real clinical chest X-rays has produced an accuracy of 86.85% [5].All these studies combined have presented different techniques, which include applied computer vision, CNNs, deep learning without class balance handling, and ensemble methods to improve pneumonia detection in the area of medical image analysis. In the current work, a real clinical dataset has been used instead of public datasets like Kaggle or NIH to improve the model's reliability, authenticity, and clinical relevance.

III. METHODOLOGY

As CNNs with more depth have attained better accuracy for large and complex datasets, many researchers have accepted them as the de facto standard in medical image analysis. The utilization of transfer learning, where the models are pre-trained on huge datasets like ImageNet, with already optimized parameters, further improved their performance. In this work, we describe experiments and methodologies that have been performed to validate the result of our proposed model using real clinical CXR datasets gathered from the records of various hospitals. The present CNN model was implemented and trained using the open-source Python libraries Keras and TensorFlow to extract and classify features for the exact identification of pneumonia from chest X-ray images.

A. Dataset description

Here In present research paper, we analyze a real clinical pneumonia dataset obtained through hospital record collection that contains 5216 chest X-ray images in the training set. It includes 4273 images showing pneumonia and 1583 normal images. Its testing set includes 624 images, while the validation set includes 16 images. The current study aims to explore and contribute to the classification and detection of pneumonia using this diverse and clinically sourced dataset.

Fig 1: The chest X-ray images of (a) a patient with pneumonia (b) normal patient

B. Preprocessing

Preprocessing of the real clinical X-ray dataset for analysis followed a number of steps aimed at making these images more suitable for our study. First, the images were converted to grayscale, reducing them to a single color channel while preserving essential intensity information. This not only simplified data but also reduced computational complexity. Then, a Gaussian blur was applied to smooth these images and minimize noise, improving overall image clarity. We also put in place Fourier transform analysis in order to look into the frequency content of the X-rays, enabling us to identify significant patterns of pixels and regions that were particularly useful in determining pneumonia.

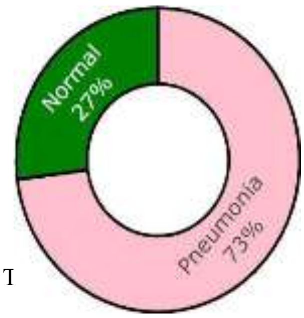


Fig. 2: T images.

Besides, erosion and dilation enhanced the refinement of image structure, improving key features for better recognition by the deep learning model. Generally, the preprocessing steps, while applied to a real dataset, have been important in minimizing noise, enhancing the quality of the images, and hence letting the model extract more accurate and meaningful features, which strengthened the performance of our pneumonia detection system.

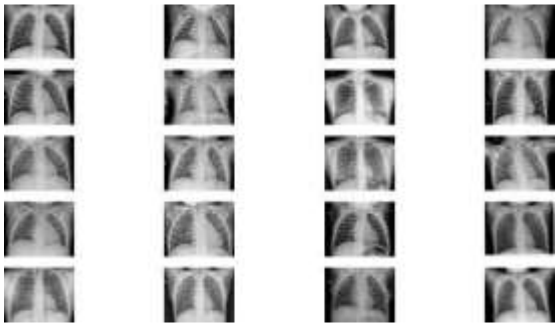


Fig. 3: Viewing the images in X-ray.

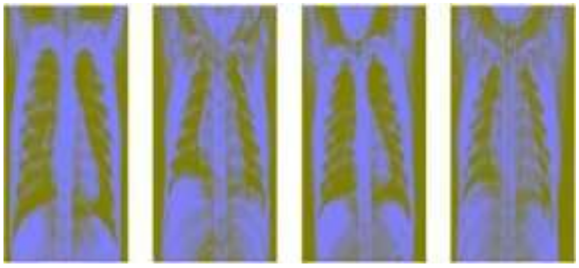


Fig. 4: Grey Scaled images and applied Gaussian blur to them.

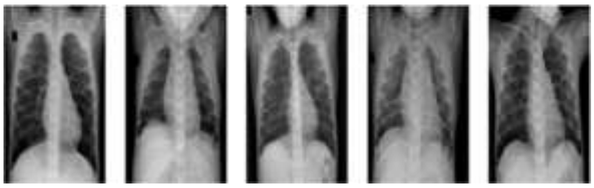


Fig. 5: Image erosion.

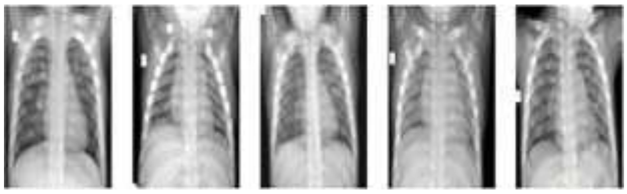


Fig. 6: Dilation of images.

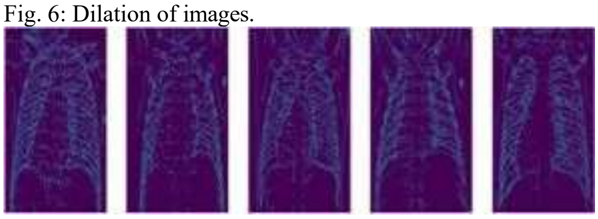


Fig. 7: Final Preprocessed images.

C. Googlenet

GoogLeNet represents a sophisticated CNN architecture for image classification. It employs Inception modules, a parallel stack of convolutional pathways to extract features at multiple scales. It starts by taking 3-channel input images that are 224×224 pixels, followed by initial layers of convolution and pooling to capture low-level spatial features.Later layers use deeper convolution and pooling to find more complex features. The inception modules take in information at various filter sizes (1×1, 3×3, and 5×5), capturing both fine and coarse details at the same time. Auxiliary classifiers have been introduced along the depth of the network to improve training by reducing the vanishing gradient problem and aiding better convergence.It culminates into a model that combines a series of fully connected dense layers and a SoftMax classifier to provide the final prediction. The real clinical dataset used in this work, instead of public ones like Kaggle or NIH, will increase the model's reliability, authenticity, and its application to the clinic.

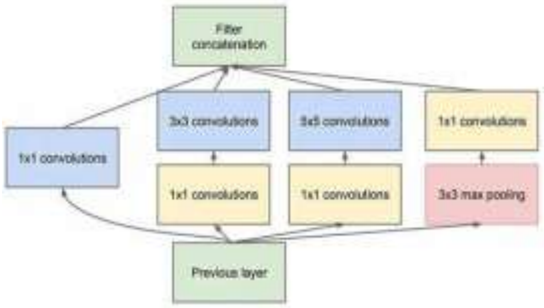


Fig. 8: Inception box

D. Alexnet

AlexNet, one of the pioneering CNN architectures, takes an input three-channel image of size 224 × 224 pixels and extracts hierarchical spatial features by passing it through a stack of convolutional and pooling layers. Segmentation using SLIC is utilized for enhancing region-based feature representation for classification.The pre-processing step for the images includes the following: resizing, normalization, and encoding the input images using one- hot encoding. The data is augmented to prevent overfitting and improve generalization. This involves rotation, flipping, and scaling. Optimization using the Adam optimizer resulted in a loss value as low as 0.3617 with an accuracy of 85.74%.AlexNet with its robust multi-layer architecture along with effective feature extraction capability, performs well on medical image classification tasks. In the present work, the real clinical dataset has been used instead of publicly available datasets such as Kaggle or NIH. This enhances the authenticity, reliability, and clinical applicability of the model, especially regarding the detection of pneumonia in chest X-ray images, so resulting the great potential for addressing some of the challenging aspects related to medical image analysis.

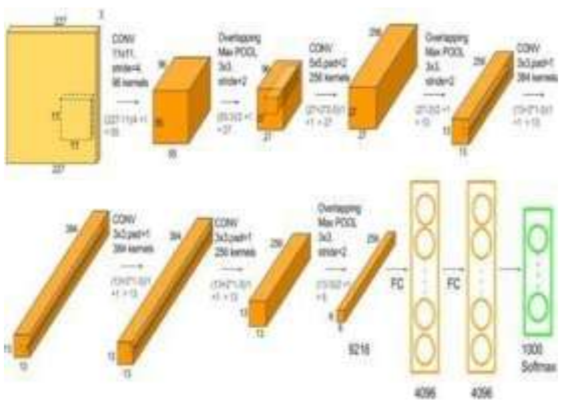


Fig.9:Architecture of Alexnet

E. Resnet

The ResNet model utilizes the ResNet50 architecture of the deep convolutional neural network that is pre-trained on ImageNet, performing a binary classification for detecting pneumonia by using chest X-ray images. The network architecture is configured with a flattening layer continued by a dense layer utilizing sigmoid activation, applicable for binary output prediction.This model is optimized by the Adam optimizer having a low learning rate of 0.00001 and trained with binary cross-entropy loss for up to 50 epochs with each batch size of 64. This ensures stable convergence and effectively updates weights at each step of training. It reaches an accuracy of 1.0000 on the training set and an impressive 0.9764 on the validation set, demonstrating great generalization and learning capabilities.Leveraging transfer learning from the pre- trained ResNet50 backbone enhances the model's feature extraction ability to capture deep hierarchical representations that are of central importance for medical image analysis. This article has used a real clinical dataset to ensure improved authenticity, reliability, and clinical relevance in pneumonia detection and analysis from chest X-ray images.

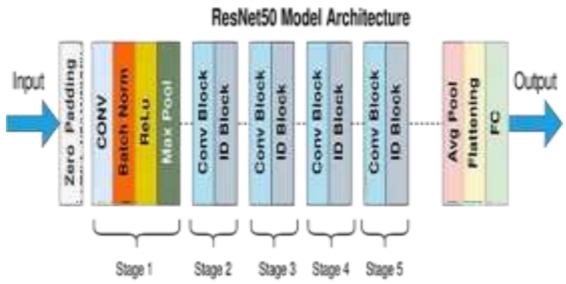


Fig.10: architecture of ResNet-50

F. Vgg16

A VGG16-based CNN was implemented in performing pneumonia detection using chest X-ray images. This work employed a dataset with equal classes of normal and pneumonia cases to ensure unbiased learning of the model. The pre-trained VGG16 convolutional base remains intact; however, additional layers have been added to enable the model to capture high-level image features.Training was carried out with the Adam optimizer and binary cross-entropy loss for stable and efficient convergence. The model reached an accuracy of 98.27% on the training set and 87.5% on the validation set, indicating a robust generalization capability.A real clinical dataset was used in the present study to strengthen the reliability, authenticity, and diagnostic relevance of the proposed model in pneumonia detection from chest X-ray images.

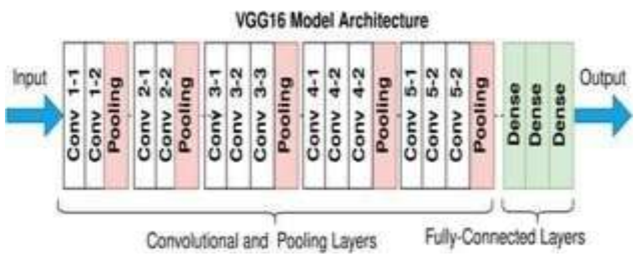
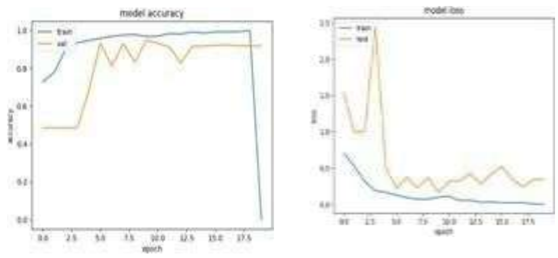


Fig. 11:Architecture of VGG16

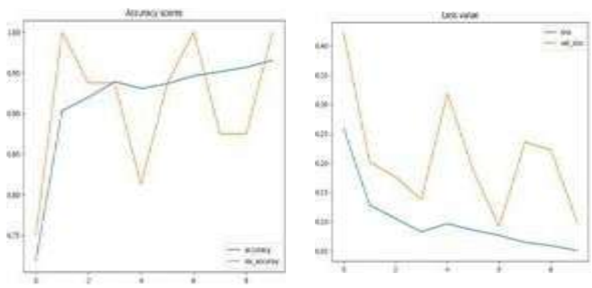
G. Vgg16+Vgg19

This paper proposes a hybrid VGG16-VGG19 network for pneumonia detection from chest X-ray images, a design that combines the complementary feature extraction strengths of both models. In particular, this architecture adapts VGG16 to grayscale medical images and adds attention mechanisms to improve focusing on clinically relevant regions of interest.This model was optimized by training it with an Adam optimizer and a learning rate of 5×10^{-5}, minimizing the loss using binary cross-entropy to optimize classification performance. The model produced a very strong validation accuracy of 95.96% and test accuracy of 88.78%, proving that it generalizes well between data partitions. Preprocessing and data augmentation were done in a very comprehensive way, including balanced class partitioning, rotation, and scaling to make the model robust. Extensive evaluation with standard performance metrics and using a confusion matrix proved that the model was highly effective in distinguishing between Normal and Pneumonia cases. In this current study, an actual clinical dataset was employed to provide more authenticity, reliability, and diagnostic value in pneumonia detection from chest X-ray images.



(a) (b)

Fig.12:The image of variation of (a) Accuracy score (b) Loss value for GoogleNet



(a) (b)

Fig.13:The images of variation of (a) Accuracy score(b)loss value for AlexNet

(a) (b)

Fig.14: (a) Correctly (b) Incorrectly classified images

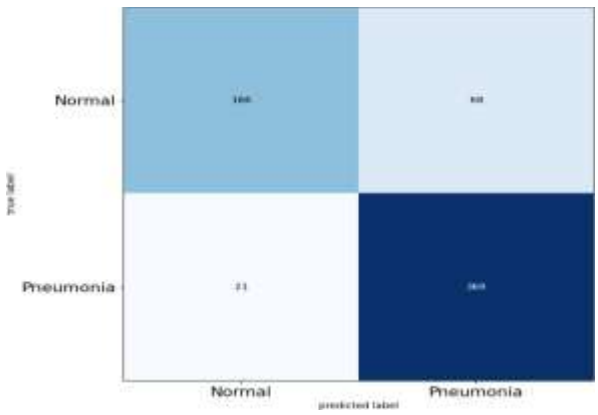
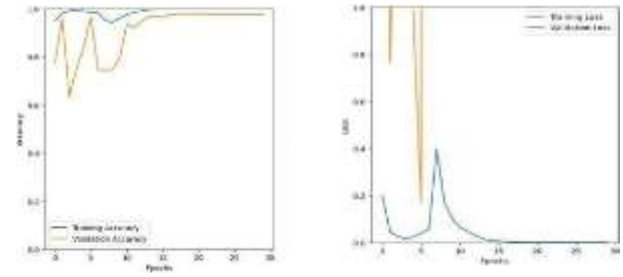
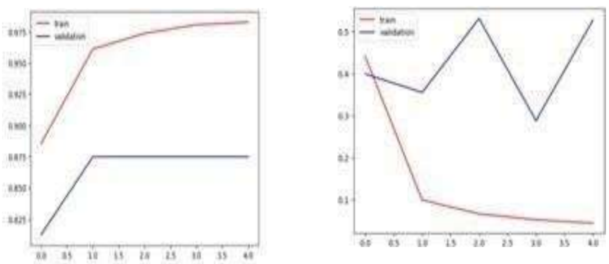


Fig.15: Confusion matrix



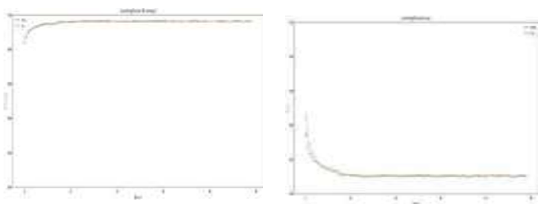
(a) (b)

Fig.16:The images of variation of (a) accuracy score (b)loss value for ResNet



(a) (b)

Fig.17:The images of variation of (a) accuracy score (b) loss value for VGG16



(a) (b)

Fig.18:The images of variation (a)accuracy score (b) loss value for VGG16+VGG19

II. Experimental Results & Discussion

In this study, various deep learning architectures were implemented and analyzed to determine their effectiveness in classifying pneumonia from chest X-ray images. The result of every model was examined using metrics such as training perfection, validation accuracy, test accuracy, and total loss value. A comparison of the performance outcomes is summarized in Table 1.

Table 1: Performance Comparison of Different CNN Models

Model	Trainin g Accurac y	Validation Accuracy	Test Accuracy	Loss Valu e
GoogLeNet	94.23%	86.78%	85.12%	0.42
AlexNet	89.56%	85.74%	82.44%	0.36
ResNet50	100%	97.64%	94.92%	0.06
VGG16	98.27%	87.50%	84.00%	0.21
VGG16 + VGG19 Hybrid	97.92%	95.96%	88.78%	0.17

The ResNet50 architecture recorded the highest accuracy due to the use of residual skip-connections, which effectively solve the vanishing gradient problem and enable deeper feature extraction. Meanwhile, VGG16 demonstrated high training accuracy but significantly lower validation accuracy, indicating mild overfitting because of its deeper architecture and large parameter count.

The hybrid VGG16-VGG19 model produced a strong balance between training and validation performance, demonstrating the advantage of combining complementary feature extraction layers. The results clearly indicate that ensemble and hybrid learning approaches outperform standalone CNN architectures. Overall, the gothrough confirms that deep learning is majorly effective in assisting medical professionals with reliable pneumonia analysis from chest X-ray images.

III. SYSTEM IMPLEMENTATION & RESULTS

To validate the proposed AI-based pneumonia detection system in a real-world environment, a fully functional and interactive web application named **PneumoScan AI** was developed. The platform integrates deep learning–based classification with a user-friendly graphical interface designed for hospitals, radiologists, and medical researchers.

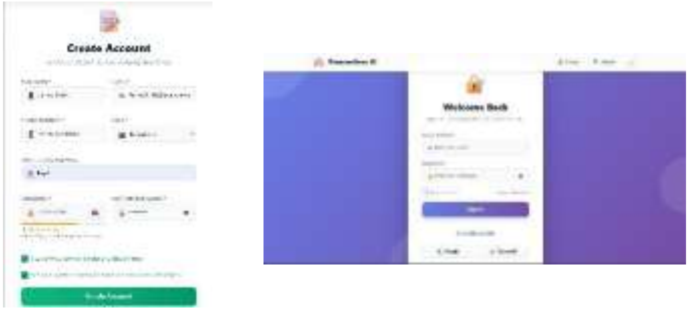
A. System Overview

The web system consists of multiple modules including, home Page and User Authentication, secure Login and Registration System, role-based Dashboard (Admin, Doctor, Radiologist, Student), X-ray Upload and AI- powered Detection Page, real-time Report Generation, Grad-CAM heatmap visualization, analysis history tracking

The platform ensures data security, restricted access, and personalized medical workflow support.

B. User Registration and Authentication Interface

Users such as doctors, radiologists, patients and others can securely register and log in through a multi-level authentication system. During registration, details including complete name, email id, phone number, role, and institution are collected to verify user identity and ensure regulated access.fig.19(b) shows The login portal, which prevents unauthorized access and protects sensitive medical image data.



(a) (b)

Fig.19 The images of Register and Login page

C. Admin Dashboard

A dedicated admin dashboard enables system monitoring and management of registered users. The dashboard displays, total number of registered users,breakdown by roles (Doctors, Radiologists, Students, Researchers), live account status and registration date and search, filter, view, delete and export (CSV) functionality.

This allows secure oversight of system usage in medical environments.

Fig.20 Image of Admin Dashboard

D. AI Detection and Analysis Page

The detection module allows authorized users to upload chest X-ray images and input patient information including, name, age, gender, X-ray date and symptoms (fever, cough, chest pain, fatigue, difficulty breathing)

Users can choose the preferred deep learning model (VGG16, ResNet, GoogLeNet, etc.). Upon submission, the system processes the image and generates classification results.The output includes:

Classification Result: Pneumonia / Normal, **probability Score (%)**, **confidence Level**, m**edical Recommendations** and **option to Download Report**

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 12 | Dec - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

(a)

(b)

(c) (d)

Fig.21 The image of AI Detection and Analysis Page

E. Grad-CAM Heatmap Visualization

To improve clinical interpretability, a **Grad-CAM visualization heatmap** highlights the lung regions contributing to the prediction. The heatmap reveals infected areas with color emphasis (red/yellow indicating high risk regions). This visual explanation increases trust and supports doctors in decision-making.

(a) (b)

(a) (b)

Fig.22 Image of Real and Grad-cam x-ray

F. Detection Results and History Dashboard

After analysis, the system stores records in the **Analysis History** section, showing, date and time of diagnostic test along with the monthly analysis total session logins, patient details, final prediction result, confidence level, view/Delete options, monthly and weekly statistics

This feature ensures traceability and continuous monitoring of pneumonia detection trends.

Fig.23 Detection Results and History web interface

MediBot AI Health Chatbot

The PneumoScan AI system integrates an intelligent conversational assistant called **MediBot**, designed to support users with real-time medical guidance and platform navigation. MediBot provides interactive assistance by answering common health-related queries, offering information about pneumonia symptoms, prevention measures, treatment recommendations, and guidance on when to seek medical care. Integrated directly into the dashboard interface, the chatbot delivers a personalized experience by greeting users by name and offering quick-access options such as Symptoms, Prevention, Healthy Foods, Dashboard Help, and AI Accuracy details. It enhances user engagement through a clean and intuitive chat window that enables instant communication and eliminates confusion during the diagnostic workflow. Although MediBot is not a replacement for professional medical consultation, it plays a valuable role in improving accessibility, offering immediate preliminary support after AI-based diagnosis, and assisting users in understanding system features and next steps, thereby strengthening the overall usability and clinical practicality of the PneumoScan AI platform.

Fig.24 MediBot Assistant

IV. FUTURE SCOPE

Future developments can further enhance the clinical applicability and scalability of the proposed system. Additional research may include integrating more advanced neural architectures such as EfficientNet, DenseNet, and Inception-ResNet to improve accuracy while reducing computational cost. Expanding the system for multi-class classification (Normal, Viral Pneumonia, Bacterial Pneumonia, and COVID-19) will increase diagnostic capability. Implementing federated learning would enable privacy-preserved training using multi- hospital data. The deployment of the model into a crossplatform mobile application will enable remote rural screening, emergency triage, and telemedicine support. Improvements such as real-time IoT-enabled digital X-ray connectivity, electronic health record (EHR) integration, and enhanced explainability methods beyond Grad-CAM would further support clinical trust and regulatory adoption. With continued development, PneumoScan AI can evolve into a comprehensive automated radiology assistant for respiratory disease monitoring and hospital decision-support systems.

V. CONCLUSION

In this research, most deep learning architectures, including GoogLeNet, AlexNet, ResNet50, VGG16, and a hybrid VGG16-VGG19 model, were implemented and evaluated for the automatic finding of pneumonia using chest X-ray images. Among all models, ResNet50 achieved the top validation accuracy of 97.64%, demonstrating superior learning capability through residual skip connections, while the hybrid VGG16- VGG19 also performed competitively with 95.96% validation accuracy. Furthermore, a complete web-based diagnostic interface, PneumoScan AI, was developed to integrate real-time AI classification with clinical usability, featuring secure login, patient data entry, Grad-CAM visualization, automated report generation, and analysis history. The system significantly improves diagnostic efficiency and supports medical professionals in early decision-making by providing clear probability-based outcomes and visual interpretability. In total, this research proves that combining deep learning with an interactive web platform offers a reliable, scalable, and practical solution for early pneumonia identification and medical workflow enhancement.

REFERENCES

[1] Ligueran, R.J.S., Santos, M.L.C., Tinio, D.R.S. and Valencia, E.H., 2022. Applied Computer Vision on 2- Dimensional Lung X-Ray Images for Assisted Medical Diagnosis of Pneumonia. arXiv preprint arXiv:2207.13295.

[2] Ali, W., Qureshi, E., Farooqi, O.A. and Khan, R.A., 2023. Pneumonia Detection in Chest X-Ray Images: Handling Class Imbalance. arXiv preprint arXiv:2301.08479.

[3] Nishio, M., Kobayashi, D., Nishioka, E., Matsuo, H., Urase, Y., Onoue, K., Ishikura, R., Kitamura, Y., Sakai, E., Tomita, M. and Hamanaka, A., 2022. Deep learning model for the automatic classification of COVID-19 pneumonia, non-COVID-19 pneumonia, and the healthy: A multi-center retrospective study. Scientific Reports, 12(1), p.8214.

[4] Kundu, Rohit , Das, Ritacheta , Geem, Zong Woo , Han, Gi-Tae , Sarkar, Ram. (2021). Pneumonia detection in chest X-ray images using an ensemble of deep learning models. PLOS ONE. 16. e0256630. 10.1371/journal.pone.0256630.

[5] Kundu, R., Das, R., Geem, Z.W., Han, G.T. and Sarkar, R., 2021. Pneumonia detection in chest X-ray images using an ensemble of deep learning models. PloS one, 16(9), p.e0256630.

[6] Ghanadi Ladani, F. and Semnani, S.H., 2023. Optimized Deep Feature Selection for Pneumonia Detection: A Novel RegNet and XOR-Based PSO Approach. arXiv e-prints, pp.arXiv-2309.

[7] Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K. and Lungren, M.P., 2017. Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225.

[8] Szepesi, P. and Szil´agyi, L., 2022. Detection of pneumonia using convolutional neural networks and deep learning. Biocybernetics and Biomedical Engineering, 42(3), pp.1012-1022.

[9] Kermany, D.S., Goldbaum, M., Cai, W., Valentim, C.C., Liang, H., Baxter, S.L., McKeown, A., Yang, G., Wu, X., Yan, F. and Dong, J., 2018. Identifying medical diagnoses and treatable diseases by imagebased deep learning. cell, 172(5), pp.1122- 1131.

[10] Singh, A., Van de Ven, P., Eising, C. and Denny, P., 2023. Connecting the Dots: Graph Neural Network Powered Ensemble and Classification of Medical Images. arXiv preprint arXiv:2311.07321.

[11] Verma, P., 2023. Neural Architectures Learning Fourier Transforms, Signal Processing and Much More arXiv preprint arXiv:2308.10388.

[12] S. Mehta, C. Paunwala and B. Vaidya, ″CNN based Traffic Sign Classification using Adam Optimizer,″ 2019 International Conference on Intelligent Computing and Control Systems (ICCS), Madurai, India, 2019, pp. 1293-1298, doi: 10.1109/ICCS45141.2019.9065537.

[13] Nwankpa, C., Ijomah, W., Gachagan, A. and Marshall, S., 2018. Activation functions: Comparison of trends in practice and research for deep learning. arXiv preprint arXiv:1811.03378.

[14] S. Yanan, Z. Hui, L. Li and Z. Hang, ″Rail Surface Defect Detection Method Based on YOLOv3 Deep Learning Networks,″ 2018 Chinese Automation Congress (CAC), Xi′an, China, 2018, pp. 1563- 1568, doi: 10.1109/CAC.2018.8623082.

[15] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. and Rabinovich, A., 2015. Going deeper with convolutions. Published in the IEEE Conference on Computer Vision and Pattern Recognition proceedings (pp. 1-9).

[16] Sirma, Kerem and Erdogmus, Pakize. (2021). GENDER ESTIMATION WITH CONVOLUTIONAL NEURAL NETWORKS USING FINGERTIP IMAGES.

[17] Gorla Praveen(2021)'ResNet50 Model Architecture'. Photograph, Wikimedia Commons. Available at: https://commons.wikimedia.org/wiki/File:ResNet50. png

[18] Gorla Praveen(2021)'VGG16 Model Architecture'. Photograph,Wikimedia Commons. Available at:

[19] https://commons.wikimedia.org/wiki/File:VGG16.p ng