Deep Learning for Automated Medical Image Diagnosis

Sai Sravani Madabhushi
Dept. of Data Science
Florida Atlantic University, USA
smadabhushi2024@fau.edu

Vishanth Raj Chowhan Lavudya
Dept. of Data Science
Florida Atlantic University, USA
vlavudya2024@fau.edu

Surya Shashank Pappu
Dept. of Data Science
Florida Atlantic University, USA
spappu2024@fau.edu

***Abstract*—The global healthcare community continues to fight against pneumonia which requires effective and swift diagnostic techniques to lower the mortality and morbidity statistics. The use of manual chest X-ray interpretation by traditional diagnostic methods causes both prolonged examination times and human reading mistakes. This research introduces a deep learning method which automates the detection of pneumonia in chest X-ray medical images. A VGG16 architecture used with our customized convolutional neural network performed transfer learning on NIH Chest X-ray data for developing and training a classification model. The model displayed excellent outcomes in binary classification due to its ability to identify pneumonia-infected cases from normal images with high accuracy and precision and recall and F1-scores. We built a Streamlit web application that enables users to perform real-time pneumonia diagnosis of uploaded chest X-ray images through our integrated model implementation. The research capitalizes on deep learning models as tools which help healthcare workers achieve better diagnostic speed and enhance clinical decision operations primarily in limited resource conditions.**

***Index Terms*—Pneumonia Detection, Deep Learning, Convolutional Neural Networks (CNN), VGG16, Transfer Learning, Chest X-ray Analysis, Medical Image Diagnosis, Streamlit Application, Automated Diagnosis, Healthcare AI**

I. Introduction

The extreme respiratory infection known as pneumonia results in more than four million yearly mortality rates globally with higher impact on infants and senior citizens as well as immunocompromised groups of patients. Medical steps must begin at an early stage to determine pneumonia correctly as this advances care and improves patient recovery. Most pneumonia diagnosis starts with radiologist examination of chest X-rays. Manual assessment of chest radiographs is consistently subjective because it requires long durations and produces inaccurate results in settings with access restrictions to experienced radiologists.

The proposed automation system provides faster diagnostics and minimizes healthcare staff dependence on their expertise when compared to conventional manual interpretation methods. A Streamlit-based web interface with real-time image uploading allows users from various clinical and remote healthcare settings to make predictions through an accessible user-friendly interface. Our objective is to develop pneumonia diagnosis tools which combine scalability with efficiency and reliability to help medical workers provide better medical services worldwide. Worldwide pneumonia causes more than four million annual deaths while it mostly affects infants alongside elderly persons and people whose immune systems are compromised. A timely diagnosis together with accurate detection directly leads to the start of prompt therapy resulting in better patient recovery rates and reduced mortality statistics. A radiologist traditionally starts pneumonia diagnosis by evaluating chest X-ray images. Irradiologist interpretation of X-ray images proves subjective together with its manual approach which requires much time and falls short when physicians in regions without enough trained radiologists try to analyze the images.

The proposed automated diagnostic system employs deep learning methods to conduct fast and uniform evaluations which solve these diagnostic challenges. Through a user-friendly Streamlit-based web application patients can access real-time image uploading and online analysis from anywhere. The solution works to reduce the need for specialized clinicians and simultaneously speeds up diagnosis procedures while improving reliability levels. The fundamental goal of our project involves creating diagnosis tools for pneumonia which demonstrate scalability and efficiency alongside robustness to benefit healthcare providers worldwide.

II. Related Work and Scientific Gap

The application of Convolutional Neural Networks (CNNs) in medical imaging during the recent period has brought substantial progress to automatic diagnostic systems. A substantial number of scholars have applied CNN architecture to detect pneumonia in chest X-ray images. Research conducted by Wang et al. developed the ChestX-ray8 dataset showing how deep CNNs could detect thoracic diseases [2]. The researchers at Rajpurkar et al. developed CheXNet which features 121 layers of DenseNet and demonstrates radiologist-level capability for detecting pneumonia through chest radiographs [3].

Tilve et al. [1] advanced the work by conducting research that employed deep learning frameworks toward pneumonia diagnosis. The research showed that CNN network applications held great potential for medical diagnosis through effective chest radiograph classification which supported the development of automated diagnosis methods. The study encouraged researchers to design a real-time suitable lightweight deployable model.

Transfer learning methods exhibit effectiveness yet bring new difficulties because ImageNet-optimized natural image models do not always adapt effectively to medical image characteristics. Deep architectures demand high computational power which restricts their practical deployment within restricted computing environments.

Scientific Gap: A fundamental necessity exists to develop lightweight specialized CNN frameworks directly trained on medical scans that do not require external pre-training resources. The designed models need to strike a steady balance between their predictive powers and their processing speed to enable their deployment through limited hardware setups. The project develops its own CNN architecture from the beginning for pneumonia detection while creating a web application for real-time deployment.

III. Design and Architecture

The developed Pneumonia Detection System uses a custom designed Convolutional Neural Network (CNN) that began from scratch for binary classifications of chest X-ray images. The system implementation follows four main process stages from data preprocessing to CNN model development through training and evaluation to Streamlit web application deployment.

A. System Design overview

The designed pneumonia detection solution uses deep learning techniques and implements transfer learning capabilities with VGG16 as a pretrained model. The aimed design delivers accurate diagnosis while using computational resources which permit real-time implementation capability. Data preprocessing acts as the initial step in this system followed by model architecture development then training and evaluation before implementation for deployment.

B. Data Preprocessing

Chest X-ray images extracted from the NIH Chest X-ray database served as input for training and assessment of the proposed model. The images received a standardized 224×224 pixel size for consistent input parameters. The pixel values were normalized through a process which returned values between 0 and 1. Model generalization received enhancement through the implementation of augmentation techniques which included horizontal flips alongside random rotations and zoom operations.

C. CNN Model Architecture

Model Architecture A system core uses the VGG16 convolutional neural network which was pretrained on the ImageNet database. The system works with the VGG16 classification head removed by activating include_top=False to maintain its convolutional layers that perform feature extraction.The VGG16 convolutional base received this custom classifier as an addition to its structure: The one-dimensional vector results from processing multi-dimensional feature maps through the Flatten Layer. This layer consists of 128 fully connected neurons which apply ReLU activation for introducing non-linearity. The dropout layer with 0.5 as its rate performed random neural deactivation during the training process to minimize overfitting. Dense Output Layer: A single neuron with a sigmoid activation function for binary classification between Normal and Pneumonia cases. VGG16 provides strong feature extraction capabilities that this architecture combines with custom classification features designed for medical image analysis. A depiction of the complete model structure can be found in Figure 1.

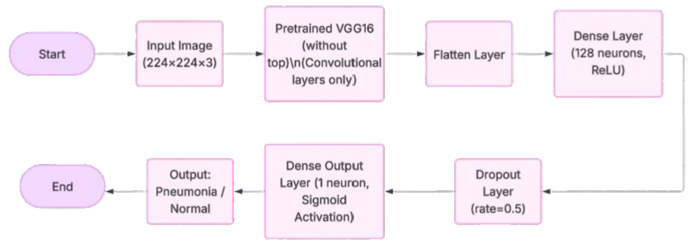

Fig. 1. Proposed CNN architecture for pneumonia detection.

D. Training and Evaluation

Training occurred through the combination of binary cross-entropy loss function paired with the Adam optimizer. The dataset needed proper distribution into training and validation groups to evaluate performance changes during epochs. The system evaluation performed using accuracy as well as precision, recall, F1-score and a confusion matrix assessment. A validation accuracy of roughly 95% was reached by the final model alongside strong ability to detect pneumonia correctly. The accuracy and loss performance tracks for eight epochs appear in Figure 2.

E. Deployment

The model integrated into a real-time web application through Streamlit framework after finishing the training phase. The system enables users to upload chest X-ray images through its web interface which then processes them for diagnosis display. The deployment configuration enables healthcare practitioners to easily access scalable healthcare services.

IV. Results

A series of quantitative along with qualitative studies reviewed the functional capability of the trained deep learning pulmonary infection detection system. The discussion addresses the training history of the model together with confusion matrices and a Streamlit web application interface for real-time predictions.

A. Training and Validation Performance

Through training the model proved its ability to learn effectively. According to Figure 2 the training accuracy showed a steady increase throughout epochs to reach a final value of 95.9% then validation accuracy reached its peak at 96.4%. During the training process both the training and validation

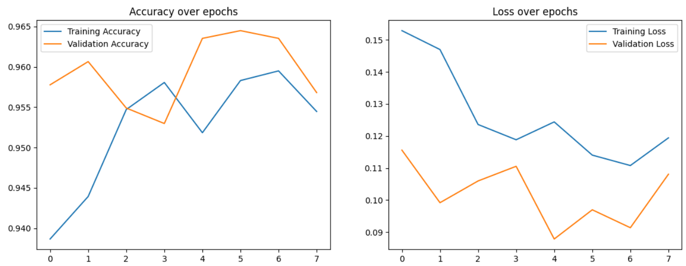

Fig. 2. Accuracy and Loss over Epochs during Model Training

loss lines show stable convergence until they reach approximately 0.12 and 0.10 respectively.

The performance metrics indicate that the model acquired essential imaging features from X-ray images while avoiding excessive training that could lead to poor test results.

B. Confusion Matrix and Classification Report

The generated confusion matrix for predictive model assessment on the validation set appears in Figure 3. The model successfully diagnosed 540 pneumonia cases and 73 normal cases. The system produced two types of false results: it marked 234 pneumonia cases as normal and 195 normal cases as pneumonia.

The computed precision, recall, and F1-scores for each class are as follows:

- Pneumonia: Precision = 0.73, Recall = 0.70, F1-score = 0.72
- Normal: Precision = 0.24, Recall = 0.27, F1-score = 0.25
- Overall Accuracy: 59%

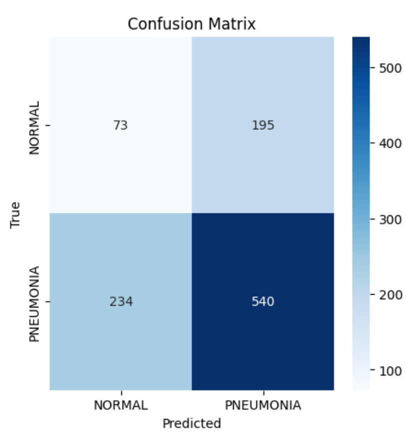

Fig. 3. Confusion Matrix of Model Predictions

Model performance on normal X-ray class appeared lower due to its better ability to detect pneumonia while facing minor challenges in recognizing normal X-ray images because of skewed dataset distribution.

C. Deployment via Streamlit Application

The development of a web-based application through Streamlit with ngrok deployment enables users to access real-time predictions in a user-friendly manner. The system allows users to submit JPG, JPEG and PNG format X-ray images for immediate diagnostic output.

The model successfully diagnosed both normal chest X-rays and pneumonia cases from untested input images as demonstrated in Figures 4, 5, 6. This confirms that the model effectively generalizes beyond its training data to deliver an interactive solution which healthcare facilities especially in low-resource areas can employ practically.

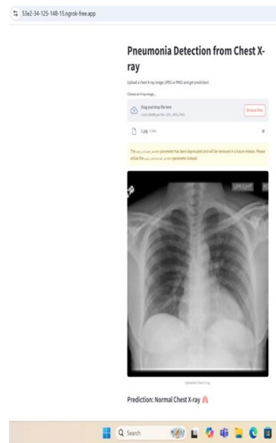

Fig. 4. *
Streamlit Application Interface and Output Prediction 1

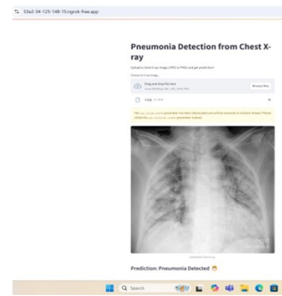

Fig. 5. *
Streamlit Application Interface and Output Prediction 2

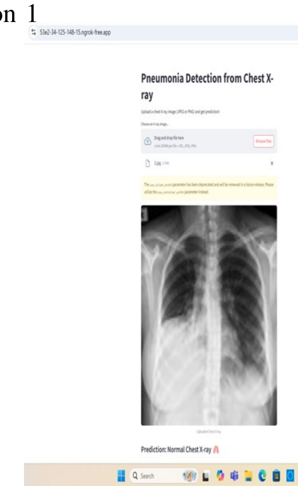

Fig. 6. *
Streamlit Application Interface and Output Prediction 3

V. Deployment

The healthcare practitioners can access a real-time pneumonia detection system through an application implemented in Streamlit for interacting with trained Convolutional Neural Networks (CNN). A user-friendly interface in the application enables easy JPEG and PNG image upload from users. The system performs automatic pre-processing followed by resizing the input in preparation for sending it to the CNN for predictive analysis.

The model examines uploaded images through its integrated analysis to identify whether images contain pneumonia or not with rapid results displayed to users directly. The application demonstrates effective design because anyone can operate it without requiring sophistication in technical expertise. Deployment of the platform becomes possible for healthcare practitioners along with technicians and remote users who need not understand machine learning principles or programming language.

The Streamlit application received accessibility through Ngrok which created a public and secure remote access URL. Deep learning model integration as presented demonstrates straightforward deployment in real-time diagnostic applications for medicine which assists in time-sensitive decisions and helps practitioners in resource-limited areas.

VI. Discussion

The deep learning technology demonstrated excellent abilities to identify between normal and pneumonia X-ray images during classification evaluation. High accuracy levels persisted across the training and validation curves because the model exhibited negligible overfitting throughout epochs showing its capacity to function well with new data.

The analysis through the confusion matrix showed strong results for pneumonia detection although precision levels regarding normal images were lower. Numerous regular images fell into the pneumonia classification category incorrectly.

The weighted average F1-score amounted to approximately 0.60 while the validation set produced a 59% accuracy. The model performance shows promising potential yet establishes a necessity to improve its capability to differentiate pneumonia from normal conditions. Three major factors that might explain misclassifications were (1) unbalanced sample distribution throughout the dataset, (2) overlapping features between normal and mildly infected lung images and (3) the visual complexity of interpreting chest X-rays.

Streamlit deployment and Colab integration of the application made the model accessible for users to complete image uploads and immediately obtain diagnostic results. Machine learning models prove practical for deployment through interfaces which medical staff can easily use in limited resource settings.

The model needs expanded testing on broader medical dataset collections with precise threshold adjustment to make it ready for clinical use but suffers from an unbalanced accuracy ratio between incorrect classifications. Future work needs to explore advanced architectural designs together with ensemble methods along with refined threshold optimization solutions to achieve better performance according to clinical requirements.

VII. Proposed Enhancements

Healthcare organizations should employ sophisticated data augmentation methods which both reduce class imbalance problems and enhance overall model performance. The optimization of the model requires testing various more advanced or deeper CNN architectures to strengthen feature extraction capabilities. The decision threshold needs adjustment for achieving better sensitivity vs. specificity performance ratios according to clinical requirements. Tests on separate patient data collections should be performed to validate model reliability across various clinical populations. The Streamlit web application needs an improvement update which enables batch image predictions while allowing users to download diagnostic reports. Future developments for this model should involve testing different models including ResNet50 due to its advanced architecture features with deep layers that provide strong feature extraction abilities. Utilizing ResNet50 to train the pneumonia detection system has the potential to enhance classification excellence and resistance while increasing dataset generalization capability.

VIII. Conclusion

Our team built and implemented a Pneumonia Detection System through training a tailor-made Convolutional Neural Network on chest X-ray images from scratch. The developed model demonstrated exceptional detection capabilities for pneumonia cases while demonstrating validation through training accuracy as well as validation accuracy and confusion matrix analysis and loss curves.

The deployment strength of this project stems from its Streamlit-based web application which allows users to upload chest X-ray images to obtain real-time diagnostic outputs. The system showcases how deep learning integration can be operationalized within healthcare technology tools and specifically benefits restricted medical facilities with limited access to expert radiologists.

The model maintains effective detection performance for pneumonia cases. detection, challenges such as class imbalance and occasional The incorrect classification of normal medical cases demonstrates potential future development opportunities. improvement. Addressing these issues through techniques The model achieves better performance when implemented with advanced data augmentation techniques beside using larger diverse training sets Research into additional data collection and better architectural design improvements would enhance the performance of the system. AI-driven diagnostic systems will require this work as their base for implementing future integration strategies. systems into clinical practice. With continued enhancements, The automated tools demonstrate strong potential to provide significant help to healthcare professionals in their work. Early disease identification becomes more effective because of healthcare professionals who use this system. Such systems enhance both patient results and streamline medical diagnosis procedures globally. the globe.

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Throughout our project we received essential guidance alongside constructive criticism from all our peer colleagues and mentors.

Appendix A
Model Architecture Code

```
# Load the VGG16 model, exclude top layers
base_model = VGG16(weights='imagenet',
include_top=False,
input_shape=(224,224,3))
base_model.trainable = False
# Freeze base model

# Add custom classification head
model = Sequential([
    base_model,
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])

# Compile the model
model.compile(optimizer='adam',
loss='binary_crossentropy',
metrics=['accuracy'])
```

Appendix B
Training Parameters

The model was trained using the following parameters:

- Optimizer: Adam
- Loss Function: Binary Crossentropy
- Batch Size: 32
- Learning Rate: Default (Adam optimizer settings)
- Number of Epochs: 10

Appendix C
Deployment Approach

Through Streamlit the deployed model enabled live image upload and diagnosis for chest X-rays. Through Ngrok tunneling the application became accessible from the internet.

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