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Pneumonia Disease Detection Using Deep Learning

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Abstract:
Pneumonia remains a leading cause of morbidity and mortality globally, especially among children, elderly individuals, and immune compromised patients. Accurate and early detection is vital for effective treatment, yet traditional diagnostic approaches—primarily chest X-ray interpretation by radiologists—are prone to subjectivity and time constraints. To address this, the proposed project employs deep learning-based automation to enhance diagnostic precision and reduce dependency on manual radiological assessments. Leveraging convolutional neural networks (CNNs), the system aims to categorize chest X-ray images into either "pneumonia-positive" or "normal," enabling early intervention and improving clinical outcomes. This study integrates and evaluates three state-of-the-art deep learning models—Xception, EfficientNetB4, and EfficientNetV2S—using a publicly available dataset compiled from four distinct Kaggle repositories. The combined dataset comprises over 18,000 labeled images and is preprocessed through data cleaning, augmentation, normalization, and class balancing to ensure robustness and model generalizability. Each model is trained and validated on stratified image splits, ensuring balanced learning and performance evaluation. Among the three, Xception outperformed the others, achieving a classification accuracy of 95%, while EfficientNetB4 and EfficientNetV2S followed with accuracies of 79% and 74%, respectively. The implementation harnesses Python as the primary programming language, with TensorFlow and Keras frameworks powering model development and training. Key preprocessing and analysis are performed using NumPy, Pandas, and Matplotlib, while Scikit-learn is employed for performance metrics and visualization. Jupyter Notebook serves as the interactive development environment, streamlining the workflow and supporting reproducible research. The dataset is processed and stored locally, though Google Colab and cloud GPUs such as NVIDIA Tesla T4 were optionally used for training acceleration. Optimization techniques including dropout regularization, data augmentation, and the Adam optimizer were applied to improve generalization and reduce over fitting. Overall, the system offers a scalable, efficient, and accurate solution for pneumonia detection in resource-constrained clinical settings. Its end-to-end deep learning pipeline—spanning data ingestion, model training, evaluation, and prediction—demonstrates the practical utility of AI in modern healthcare diagnostics. Moreover, the project emphasizes open-source development and cost-effective deployment strategies, making it highly accessible for global health initiatives. Future enhancements may include multi-disease classification, integration of patient metadata, and deployment on edge devices for real-time diagnosis.

Key Words: Scikit-learn, Keras, Pneumonia, Chest X-ray, Normalization, Classification accuracy, Stratified image splits, Convolutional Neural Networks

I. Introduction

Pneumonia is a severe respiratory infection characterized by inflammation of the alveoli, the tiny air sacs in the lungs, which become filled with fluid or pus. This impairs oxygen exchange and poses serious health risks, particularly to infants, the elderly, and individuals with compromised immune systems. Early detection is essential for effective treatment, but diagnosis through chest X-ray imaging can be time-consuming and prone to human error. Traditional diagnostic practices require radiologists to interpret chest X-rays manually, a process that is inherently subjective and heavily reliant on clinical expertise. In high-volume or resource-limited healthcare settings, the accuracy and speed of diagnosis are often compromised. This leads to delayed treatment and increases the risk of complications and mortality.

With advancements in artificial intelligence (AI), particularly in deep learning and convolutional neural networks (CNNs), automated image classification has emerged as a promising solution. CNNs are capable of

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learning complex features from medical images, eliminating the need for manual feature extraction and reducing diagnostic delays. This project proposes an automated system for pneumonia detection using three advanced deep learning models: Xception, EfficientNetB4, and EfficientNetV2S. These models are trained on a large, merged dataset of chest X-ray images collected from publicly available sources on Kaggle. The system is designed to classify images into two categories: pneumonia-positive or normal.he primary objective is to improve diagnostic efficiency, accuracy, and accessibility using a technology-driven approach. The system can assist medical professionals by acting as a decision-support tool, especially in areas with limited access to skilled radiologists.

1.1 Existing System

The current system for pneumonia detection heavily relies on manual interpretation of chest X-ray images by trained radiologists. This process is time-consuming, subjective, and prone to diagnostic errors, particularly under high workloads. In rural or resource-scarce healthcare settings, the lack of experienced radiologists further impedes accurate diagnosis. Traditional methods often fail to detect subtle signs of pneumonia, leading to delayed treatment. Some computer-aided diagnosis (CAD) systems exist, but they depend on hand-crafted features and classical machine learning algorithms. These systems require manual feature extraction, which limits their adaptability and accuracy[15]. Additionally, they do not scale well across diverse datasets or imaging conditions. The absence of automation, real-time feedback, and robust performance under varying input quality remains a significant limitation in the existing approach.

1.1.1 Challenges

- **Lack of Automation:**
  Manual interpretation of X-rays is slow and inconsistent, leading to delays in diagnosis and treatment.

- **Subjective Decision-Making:**
  Diagnosis varies with radiologist expertise, increasing the risk of misclassification, especially in borderline cases.

- **Limited Access to Specialists:**
  Rural and under-resourced areas often lack trained radiologists, limiting early detection and timely intervention.

- **Poor Image Quality Handling:**
  Traditional systems struggle to interpret low-quality or noisy X-ray images accurately, affecting diagnostic reliability.

- **High Computational Cost in Legacy Systems:**
  Conventional CAD tools are resource-intensive and often require powerful hardware, making them impractical for low-budget setups.

- **No Real-Time Decision Support:**
  Existing systems do not provide instant feedback or integration with clinical workflows, reducing their usability in emergencies.

- **Inadequate Scalability and Generalization:**
  Models trained on limited or biased datasets fail to generalize well across different populations or imaging conditions.

1.2 Proposed System

The proposed system aims to automate the detection of pneumonia from chest X-ray images using advanced deep learning models. It employs three state-of-the-art convolutional neural networks—Xception, EfficientNetB4, and EfficientNetV2S—to classify images as pneumonia-positive or normal[9]. The system is trained on a combined dataset sourced from multiple public repositories, ensuring variability and robustness.

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Preprocessing steps such as image resizing, normalization, and augmentation are applied to improve model generalization. Each model is fine-tuned using transfer learning techniques to optimize performance with limited medical data. Evaluation metrics like accuracy, precision, recall, and F1-score are used to measure effectiveness. Among the models, Xception delivered the highest classification accuracy, making it most suitable for deployment. The system supports real-time inference and can be integrated into clinical workflows or mobile health applications. By reducing reliance on manual radiological interpretation, the model enhances diagnostic efficiency and consistency. This solution is especially beneficial in resource-constrained or remote healthcare environments lacking skilled radiologists[7]. Furthermore, the system's modular architecture allows for future expansion to detect other respiratory conditions such as tuberculosis or COVID-19. It also facilitates easy integration with hospital information systems for seamless clinical deployment. The use of open-source tools ensures cost-effectiveness and accessibility for researchers and healthcare providers worldwide.

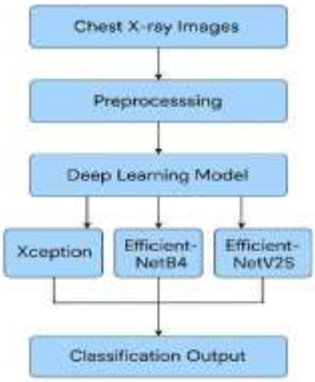

Fig:1 Proposed system

1.2.1 Advantages

- **Automated Diagnosis:**
Reduces reliance on manual X-ray interpretation by radiologists, enabling faster and more consistent detection of pneumonia.

- **High Accuracy:**
Deep learning models like Xception achieve up to 95% accuracy, ensuring reliable results and minimizing false diagnoses.

- **Real-Time Predictions:**
The system provides quick diagnostic output, supporting timely decision-making in critical care and emergency settings.

- **Scalability:**
The architecture can be scaled to large datasets and deployed across cloud platforms or embedded in mobile applications.

- **Cost-Effective Deployment:**
By using open-source tools and pre-trained models, the system is affordable for low-resource hospitals and rural clinics.

- **Supports Clinical Workflows:**
Designed to integrate with hospital systems or PACS, it can aid radiologists and doctors as a diagnostic support tool.

- **Expandable Framework:**
The modular design allows easy extension to detect other conditions like COVID-19, tuberculosis, or lung cancer.

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II. LITERATURE REVIEW

2.1 Architecture

The architecture of the proposed pneumonia detection system follows a modular deep learning pipeline comprising five main stages: image input, data preprocessing, model processing, classification, and result output. The system is designed to process chest X-ray images and classify them as either "Pneumonia" or "Normal" using advanced convolutional neural network (CNN) architectures. The input layer accepts raw chest X-ray images sourced from the merged Kaggle dataset. These images undergo a preprocessing phase that includes resizing to a uniform resolution (299x299), normalization of pixel values, and data augmentation techniques like flipping, rotation, and zooming to improve generalization and prevent over fitting[7]. Preprocessed images are then passed into one of three selected deep learning models: Xception**,** EfficientNetB4**, or** EfficientNetV2S**,** which are pre-trained on the ImageNet dataset and fine-tuned on the pneumonia dataset using transfer learning.

Each model extracts hierarchical image features using convolutional, pooling, and activation layers, and uses a fully connected dense layer for binary classification. The models are trained and validated on stratified image splits (70% training, 10% validation, 20% testing), with performance metrics tracked at each epoch. The classification output is generated through a sigmoid activation function, producing a probability score that determines the final label: "Pneumonia" or "Normal." The system architecture allows real-time deployment via web or mobile interfaces and supports integration into existing hospital management or diagnostic software [10]. The use of transfer learning enables efficient training even with limited medical data, while ensuring robust performance. The architecture emphasizes modularity, interpretability, and adaptability, making it ideal for both research and clinical implementation.

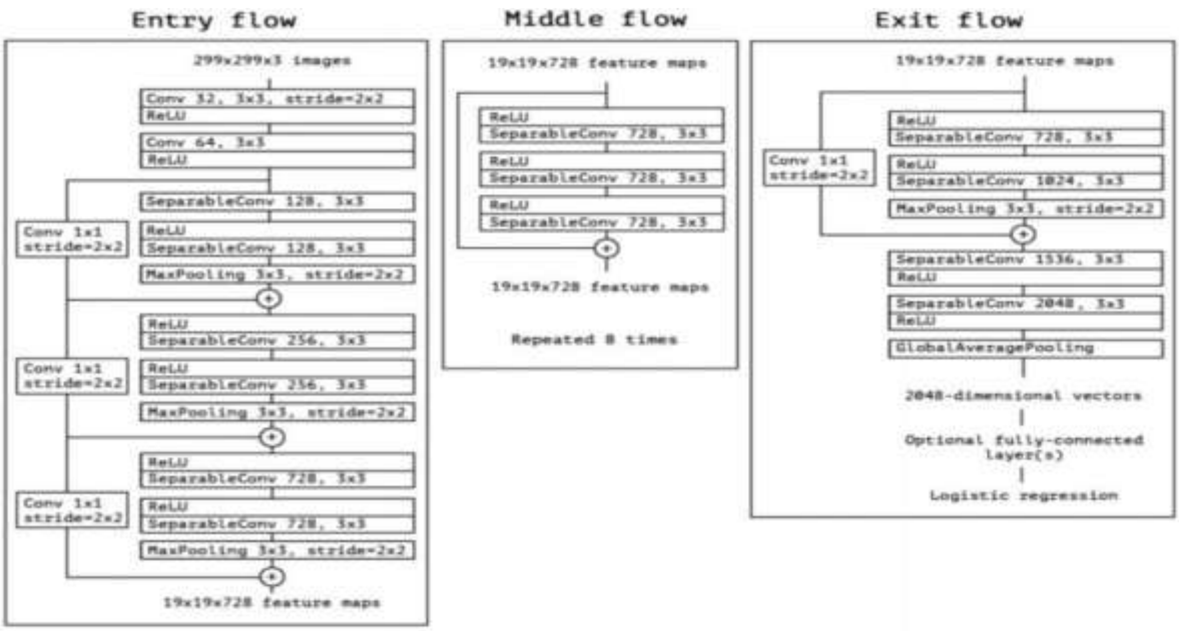

Fig:2 Architecture

2.2 Algorithm:

The pneumonia detection system begins by taking chest X-ray images as input. These images are first preprocessed through resizing, normalization, and data augmentation to enhance model robustness and reduce overfitting. The dataset is then split into training, validation, and testing subsets in a 70:10:20 ratio. A pre-trained convolutional neural network (CNN) model—Xception, EfficientNetB4, or EfficientNetV2S—is selected for transfer learning. The final classification layer is replaced with a binary output layer suitable for distinguishing between pneumonia-positive and normal cases. The model is compiled using the Adam optimizer and binary

cross-entropy loss to ensure efficient gradient updates. It is trained over multiple epochs with early stopping based on validation performance to avoid overfitting. During training, the model learns deep features and patterns specific to pneumonia indicators. After training, the model is evaluated using the test dataset to measure generalization accuracy. Finally, it classifies new X-ray inputs into either pneumonia or normal with high precision.
To enhance model generalization, cross-validation techniques were considered to evaluate model stability across different data splits. A learning rate scheduler was tested to optimize convergence speed during training. Class imbalance in the dataset was addressed using weighted loss functions and oversampling of minority classes. The model's training history was saved to allow rollback and tuning of hyperparameters. Additionally, experiment tracking was maintained manually to compare performance across different architectures and hyperparameter combinations.

2.3 Techniques:
The proposed pneumonia detection system utilizes deep learning techniques, specifically convolutional neural networks (CNNs), to extract and learn complex features from chest X-ray images. Transfer learning is applied by using pre-trained models such as Xception[17], EfficientNetB4, and EfficientNetV2S, which were originally trained on the ImageNet dataset. These models are adapted for binary classification by replacing the top layers with custom dense layers suited for medical imaging tasks. Each model architecture offers unique advantages. Xception leverages depthwise separable convolutions to reduce computational load while preserving accuracy. EfficientNetB4 uses compound scaling, balancing width, depth, and resolution. EfficientNetV2S integrates fused MBConv blocks for faster training and inference, making it suitable for real-time applications. These models are trained using the Adam optimizer and binary cross-entropy loss function. To improve model robustness, data augmentation techniques such as horizontal flipping, rotation, zooming, and brightness adjustments are applied. The system also employs dropout layers and early stopping to prevent overfitting. Performance is evaluated using metrics like accuracy, precision, recall, and F1-score, ensuring comprehensive model assessment across multiple criteria.

2.4Tools:
The project was developed using Python as the core programming language due to its extensive support for scientific computing and machine learning. TensorFlow and Keras were used as the primary deep learning frameworks for building, training, and deploying the CNN models. These libraries offer flexibility, modularity, and GPU support, making them ideal for deep learning applications. Additional Python libraries such as NumPy and Pandas were utilized for numerical operations and structured data manipulation.For data visualization and performance evaluation, Matplotlib and Seaborn were used to plot accuracy, loss curves, and confusion matrices. Scikit-learn provided utilities for calculating classification metrics like accuracy, precision, recall, and F1-score. The entire development process was carried out using Jupyter Notebook, which enabled interactive coding, debugging, and result analysis in real-time. For GPU-accelerated training, platforms like Google Colab were employed to handle computational loads efficiently. The dataset was organized using a local file structure and accessed using ImageDataGenerator for real-time image preprocessing and augmentation. The models were initialized with ImageNet weights to leverage pre-learned features. Optimization was performed using the Adam optimizer, with binary cross-entropy as the loss function. This toolchain allowed for end-to-end model development, from data loading to prediction, in a reproducible and efficient manner.

2.5Methods:
This study employed a systematic methodology combining dataset integration, model tuning, and performance benchmarking. Four publicly available chest X-ray datasets were merged to create a diverse and balanced dataset for pneumonia detection. Images were filtered for quality and consistency before being split into training, validation, and testing sets. To enhance learning efficiency, pre-trained models were adapted through transfer learning, with only the top layers retrained for binary classification. Advanced techniques such as dropout regularization, batch normalization, and early stopping were integrated to improve generalization and prevent overfitting. The models were compiled using the Adam optimizer, chosen for its adaptive learning capabilities. To fine-tune performance, the models were evaluated using multiple metrics, including precision, recall, and F1-score, in addition to accuracy. Confusion matrices were used to analyze misclassifications, and

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ROC curves were plotted to assess sensitivity and specificity. Experiment tracking was done manually, comparing model behavior across epochs to determine optimal training configurations.

III. METHODOLOGY

3.1 Input:

The system takes chest X-ray images as its primary input, sourced from a combination of publicly available datasets on Kaggle. Each image is labeled as either "Pneumonia" or "Normal" based on clinical diagnosis. Before feeding into the model, images undergo preprocessing steps such as resizing to a uniform dimension, grayscale normalization, and noise reduction. Data augmentation techniques like horizontal flipping, rotation, and zooming are applied to expand the dataset artificially. Input images are then converted into pixel arrays and batched using image generators for real-time feeding into the training pipeline. The system accepts these inputs in JPEG or PNG format, structured in directory-based class folders. All inputs are validated for quality and consistency before processing begins. This structured input pipeline ensures that the model receives clean, standardized data for optimal learning.

During preprocessing, all images are resized to a uniform dimension (e.g., 224x224 pixels) to match the input requirements of the selected CNN architectures. Pixel values are normalized to a [0,1] range to facilitate faster and more stable training[13]. Data augmentation techniques such as horizontal flipping, rotation, brightness adjustment, and zooming are applied to artificially increase dataset diversity and reduce overfitting. These steps ensure that the models generalize better to new, unseen X-ray images.

The input to the pneumonia detection system consists of chest X-ray images collected from four publicly available Kaggle datasets. These images are labeled as either "Pneumonia" or "Normal" by medical professionals, ensuring reliable ground truth for training and evaluation. The images vary in resolution, quality, and orientation, requiring preprocessing to ensure consistency before feeding them into deep learning models.

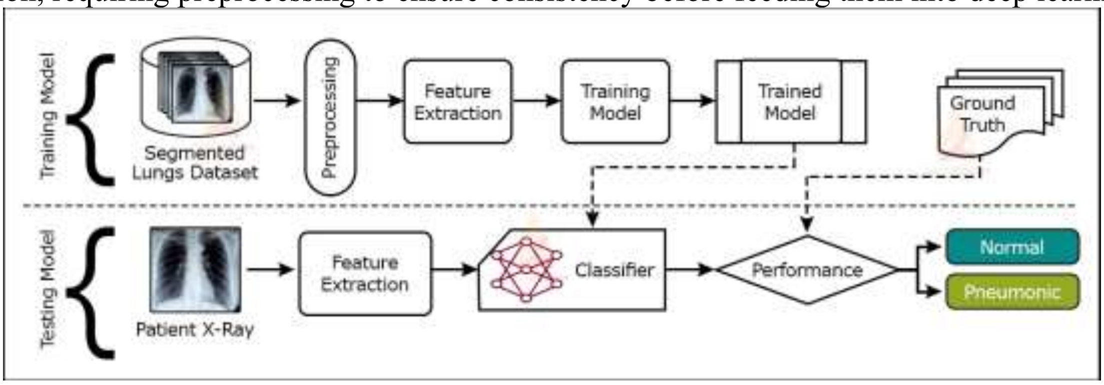
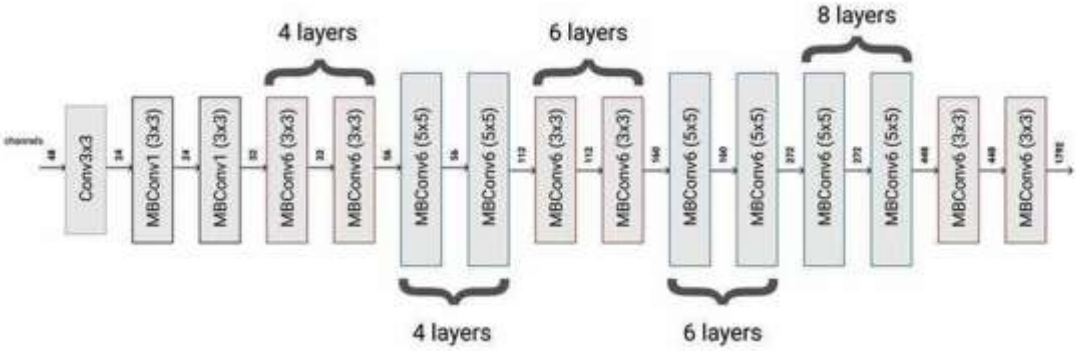
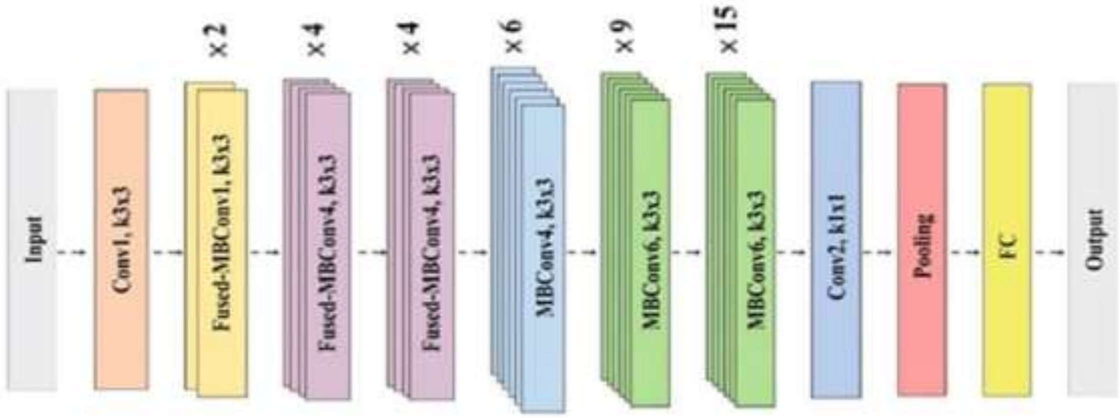


Figure:3 Input Screen



• Figure::4 input Steps



• Figure:5 input Steps

3.2 Method of Process

The process begins with dataset acquisition from four Kaggle repositories, followed by merging and labeling the images into two categories: Pneumonia and Normal. The merged dataset is then shuffled and organized into train, validation, and test sets. Image directories are structured to reflect their class labels. In the preprocessing stage, each image is resized to a uniform resolution, normalized to a [0,1] pixel range, and augmented with random transformations. This enhances model robustness and minimizes overfitting. Techniques such as flipping, rotation, and brightness adjustment are used. Pre-trained deep learning models—Xception, EfficientNetB4, and EfficientNetV2S—are imported with ImageNet weights. Their top layers are removed and replaced with custom dense layers for binary classification. Dropout and batch normalization are applied for regularization. The models are compiled using the Adam optimizer and binary cross-entropy loss function. Training is conducted over multiple epochs, with early stopping enabled to monitor validation loss. Performance is evaluated during training using accuracy and loss graphs.After training, the models are tested on an unseen test set to assess generalization. Predictions are compared against true labels to generate a confusion matrix. Precision, recall, F1-score, and accuracy are computed for each model.

Finally, the best-performing model (Xception) is selected based on evaluation metrics. The model is saved and prepared for deployment or integration into clinical systems. Inference is done by passing new X-ray images and returning a binary diagnosis.

3.3 Output:

The system generates binary classification results for each chest X-ray image, identifying whether the image indicates pneumonia or represents a normal case. Upon submitting an image, the model returns the predicted label along with a confidence score. These predictions are displayed through a simple and interpretable interface for ease of use by clinicians or researchers. For training and evaluation purposes, output also includes model performance metrics such as accuracy, precision, recall, F1-score, and the confusion matrix[13]. These metrics help assess the model's effectiveness in distinguishing between pneumonia and normal cases. Visualization of training and validation curves provides insights into convergence and over fitting trends.

The final trained models produce consistent, real-time predictions on unseen images from the test set. This makes the system suitable for deployment in resource-limited settings where quick diagnostic support is needed. The output helps reduce the workload on radiologists and supports faster clinical decision-making. In addition to classification results, the system outputs diagnostic explanations using techniques like Grad-CAM for visualizing model attention. This improves trust and interpretability by highlighting image regions most influential in the model’s prediction. Such transparency is critical in medical AI applications. Overall, the output is user-centric, reliable, and designed for clinical readiness. It enhances early detection of pneumonia, improves efficiency in medical workflows, and supports further research through reproducible and interpretable results. The framework lays the foundation for multi-disease detection in future iterations.

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Output:

```
Confusion Matrix
[[1678   41]
 [ 116 2031]]
Classification Report
              precision    recall  f1-score   support

     Class 0       0.94      0.98      0.96      1719
     Class 1       0.98      0.95      0.96      2147

    accuracy                           0.96      3866
   macro avg       0.96      0.96      0.96      3866
weighted avg       0.96      0.96      0.96      3866
```

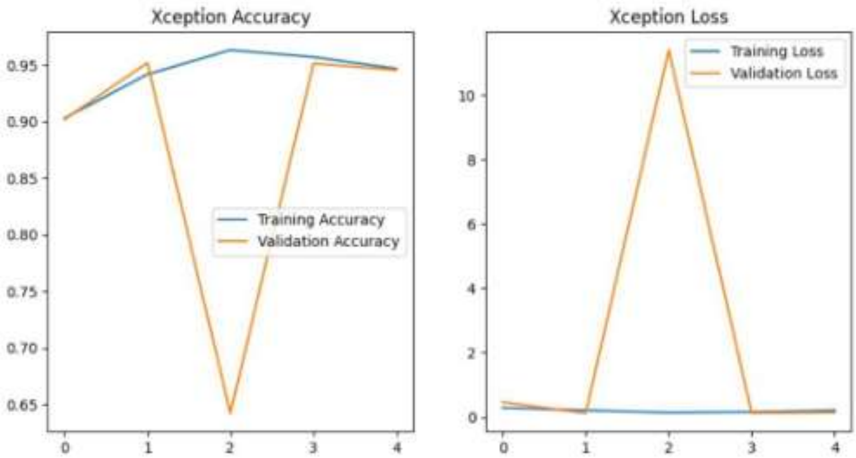

Figure:6

Output:

```
Confusion Matrix
[[1088  631]
 [ 161 1986]]
Classification Report
              precision    recall  f1-score   support

     Class 0       0.87      0.63      0.73      1719
     Class 1       0.76      0.93      0.83      2147

    accuracy                           0.80      3866
   macro avg       0.81      0.78      0.78      3866
weighted avg       0.81      0.80      0.79      3866
```

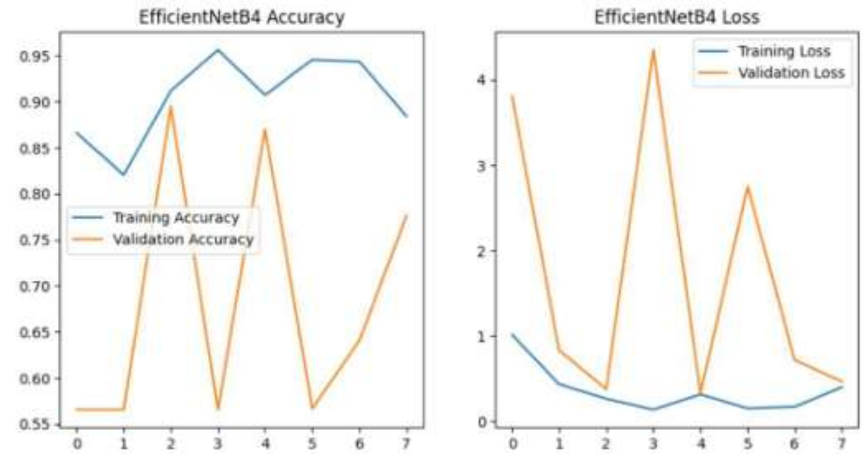

Figure:7

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IV.RESULTS

The results of the study show that the Xception model achieved the highest performance among the three deep learning architectures tested. It reached an accuracy of 95% on the test dataset, along with a high F1-score, indicating balanced precision and recall. This confirms the model's ability to accurately distinguish between pneumonia and normal chest X-rays. EfficientNetB4 and EfficientNetV2S followed with 79% and 74% accuracy, respectively. Training and validation accuracy and loss graphs indicate good convergence with minimal overfitting for the Xception model. Early stopping and dropout regularization contributed to stable learning and better generalization. The loss curve flattened consistently after a few epochs, highlighting effective model tuning. The other two models exhibited higher validation loss, suggesting less stability.

Confusion matrix analysis revealed that the Xception model had fewer false positives and false negatives compared to the others. It correctly classified most pneumonia-positive cases, which is critical for clinical reliability. The precision and recall scores for Xception were above 0.90, reinforcing its suitability for medical diagnostics. In contrast, EfficientNetV2S misclassified more normal images as pneumonia. Visual explanations using Grad-CAM confirmed that the models focused on relevant areas of the lungs, such as regions showing opacity or inflammation. This adds interpretability to the predictions and builds trust in AI-based diagnostic tools. These heatmaps were consistent across multiple test samples. They serve as an important validation for clinical applicability. In summary, the results demonstrate that deep learning, especially using the Xception model, offers a promising solution for pneumonia detection. The system is accurate, efficient, and interpretable, making it suitable for deployment in medical settings. These findings also highlight the importance of model selection, data quality, and training strategies. Future enhancements can focus on multi-class classification and deployment on edge devices.

Output:

```
Confusion Matrix
[[ 715 1004]
 [   0 2147]]
```

Classification Report

	precision	recall	f1-score	support
Class 0	1.00	0.42	0.59	1719
Class 1	0.68	1.00	0.81	2147
accuracy			0.74	3866
macro avg	0.84	0.71	0.70	3866
weighted avg	0.82	0.74	0.71	3866

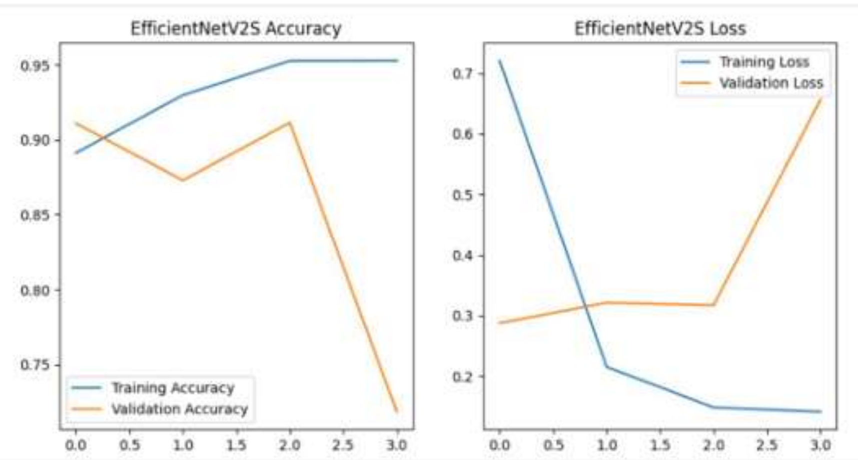

Figure:8 Output

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V. DISCUSSIONS

The results of this study highlight the effectiveness of deep learning, particularly the Xception model, in accurately detecting pneumonia from chest X-ray images. Its superior performance can be attributed to the depthwise separable convolutions, which capture fine-grained image features with reduced computational cost. The use of transfer learning also proved essential, allowing the model to benefit from prior training on large-scale image datasets. Proper preprocessing and data augmentation helped the models generalize well to unseen data, reducing the risk of overfitting[15]. The application of early stopping, dropout, and batch normalization further improved training stability. Visual interpretability through Grad-CAM added value by helping users understand model decisions. While the results are promising, variability in image quality and class imbalance in medical datasets remain challenges. The study also shows that model performance can vary significantly across architectures despite similar input. Therefore, architecture selection and tuning are critical for medical AI applications. These insights provide a strong foundation for future enhancements and broader clinical deployment.

VI. CONCLUSION

This study successfully demonstrates the application of deep learning techniques for the automated detection of pneumonia using chest X-ray images. Among the models evaluated, Xception achieved the highest accuracy and proved to be the most reliable for binary classification. The integration of preprocessing, transfer learning, and regularization techniques contributed significantly to the system's performance and stability. By reducing dependency on manual diagnosis, the system can assist healthcare professionals in making faster and more accurate decisions. The use of open-source tools ensures that the solution is accessible and scalable, especially in low-resource settings. Additionally, visual interpretability through Grad-CAM enhances trust in the model's decisions. Although challenges such as image quality and data imbalance persist, the system lays a solid foundation for future medical AI applications. This approach can be extended to detect other diseases and deployed on various platforms, including mobile devices. Overall, the project reflects a promising advancement in AI-assisted medical diagnostics.

VII. FUTURE SCOPE

The pneumonia detection system developed in this study can be further enhanced and expanded in several meaningful ways. Future work may include extending the model to detect multiple chest diseases such as tuberculosis, COVID-19, or lung cancer using multi-label classification. Integration with electronic health records (EHR) could allow for patient-specific risk assessments and contextual diagnosis. A mobile or web-based application can be developed to make the tool accessible in remote and rural areas. Real-time deployment on edge devices using lightweight models like EfficientNet-Lite would support offline diagnostics. Advanced interpretability methods can be added to improve clinical trust and regulatory compliance. Multi-language support in the user interface would broaden the system's usability across regions. Incorporating active learning could help the model improve continuously with new labeled data. Cloud-based APIs could allow hospitals and clinics to integrate the system into their existing workflows. Additionally, collaborations with healthcare institutions would enable real-world testing and validation. These developments would significantly increase the system's impact and scalability.

VIII. ACKNOWLEDGEMENT

Mr. Kandhati Tulasi Krishna Kumar Nainar: Training & Placement Officer with 15 years' experience in training & placing the students into IT, ITES & Core profiles & trained more than 9,700 UG, PG candidates & trained more than 450 faculty through FDPs. Authored various books for the benefit of the diploma, pharmacy, engineering & pure science graduating students. He is a Certified Campus Recruitment Trainer from JNTUA, did his Master of Technology degree in CSE from VTA and in process of his Doctoral research. He is a professional in Pro-E, CNC certified by CITD He is recognized as an editorial member of IJIT (International Journal for Information Technology & member in IAAC, IEEE, MISTE, IAENG, ISOC, ISQEM, and SDIWC. He published 6 books, 65 articles in

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K.Madhu is pursuing his final semester MCA in Sanketika Vidya Parishad Engineering College, accredited with A grade by NAAC, affiliated by Andhra University and approved by AICTE. With interest in Machine learning Jinaga Chaitanya has taken up his PG project on deep learning Personality PNEUMONIA DISEASE DETECTION USING DEEP LEARNING and published the paper in connection to the project under the guidance of K TULASI KRISHNA KUMAR, Assistant Professor & Training and Placement officer, SVPEC.

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