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Medical Image Analysis: Deep Learning Models for Pneumonia Detection

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***Abstract*— Pneumonia is one of the most common causes of death globally, especially for individuals over 65 and children under five. Even with improvements in medical technology, diagnosing pneumonia from chest X-rays is still difficult and frequently calls for qualified radiologists. This paper offers a thorough deep learning-based framework for the identification of pneumonia from chest X-ray images in order to overcome these difficulties. A Convolutional Neural Network (CNN), Transfer Learning models (EfficientNet, VGG19, and ResNet), and Machine Learning classifiers like Support Vector Machine (SVM) are among the models included in the suggested framework. model was 94.2%, but the accuracies of the Transfer Learning models, ResNet, VGG19, and EfficientNet, were 80.4%, 89.6%, and 79.6%, respectively. Furthermore, the resilience of the SVM classifier using a Radial Basis Function (RBF) kernel was demonstrated by its 92.4% performance. To improve diagnostic accuracy even more, this approach incorporates an ensemble of classifiers. The system offers a dependable, effective, and scalable approach to early pneumonia detection by utilizing these models. The findings show how the suggested approach might help radiologists by prioritizing cases and expediting the diagnosis process, which would eventually improve patient outcomes and save lives.**

Index Terms*— Pneumonia detection, CNN, transfer learning, EfficientNet, VGG19, ResNet, SVM, CAD systems, ensemble models, medical imaging, early diagnosis, healthcare AI.

I. INTRODUCTION

A serious respiratory infection, pneumonia is a major global source of morbidity and mortality, particularly in young children under five and the elderly over 65. Millions of people die from pneumonia every year, with developing nations bearing the heaviest burden, according to international health reports. For prompt treatment and better patient outcomes, pneumonia must be diagnosed early and accurately. One of the main diagnostic methods for diagnosing pneumonia is a chest X-ray (CXR). However, because their features often overlap with those of other lung disorders, their interpretation can be difficult and frequently calls for qualified radiologists. This emphasizes how important automated and trustworthy diagnostic tools are.

Medical imaging has been transformed in recent years by deep learning and machine learning techniques, which provide excellent accuracy and efficiency in identifying complicated disorders. In particular, transfer learning models and convolutional neural networks (CNNs) have shown promise in image-based diagnostics. This paper uses a variety of deep learning architectures, such as CNNs, EfficientNet, VGG19, ResNet, and Support Vector Machine (SVM) classifiers, to present a multi-model framework for detecting pneumonia from chest X-rays. Robust performance and increased diagnostic accuracy are made possible by the combination of several models and ensemble approaches.

The dataset used in this study comprises labeled chest X-ray images, with data augmentation applied to improve model generalization. Each model was evaluated for its accuracy, with CNN achieving 93.6%, EfficientNet 77.77%, VGG19 89.4%, ResNet 80.6%, and SVM with RBF kernel achieving 96.5%. The ensemble approach further enhances the reliability of the diagnostic process, paving the way for a scalable computer-aided diagnosis (CAD) system that can support radiologists in prioritizing cases and improving diagnostic efficiency.

This paper discusses the implementation and performance of the proposed models, emphasizing their potential to reduce diagnostic errors and assist healthcare professionals in combating pneumonia effectively.

A. Structure of the paper

The introduction explains pneumonia detection using chest X-rays, the role of deep learning models (CNN, ResNet, VGG19, SVM, EfficientNet), and the importance of automated diagnosis.The methodology describes the dataset, preprocessing steps, and model implementation, detailing how each algorithm was applied for classification.The results section presents model performance comparisons based on accuracy, precision, recall, and F1-score, highlighting the best-performing models.The discussion interprets the findings, analyzing strengths, limitations, and real-world applications of the models.The conclusion summarizes key insights and suggests future improvements, such as federated learning for enhanced privacy and generalization.

B. Objectives

- To investigate deep learning models for the identification of pneumonia.
- To create models that can correctly categorize X-ray pictures of the chest.

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- To evaluate the accuracy, precision, and recall of the model.
- To assess how well various picture preparation methods work.
- To ascertain whether the model can accurately categorize cases of pneumonia.
- To examine how dataset quality affects model performance.

II. RELATED WORK

Chest EfficientNet achieved the highest accuracy among 20 CNN architectures, while hybrid models CNN-SVM and CNN-KNN improved classification robustness using feature fusion techniques [1]. VGG19, EfficientNet-B7, and DenseNet-201 demonstrated high classification performance, with SVM classifiers enhancing feature-based prediction, though challenges remained in distinguishing pneumonia from COVID-19 [2]. Pre-trained models VGG16, VGG19, and ResNet-50 combined with SVM classification showed that EfficientNet outperformed other models due to optimized scaling techniques [3]. A modified EfficientNet model (EfficientCovNet) outperformed VGG and ResNet models in pneumonia and COVID-19 detection, leveraging advanced feature extraction capabilities [4]. In multi-class lung disease classification, ResNet-50 and EfficientNet demonstrated the highest accuracy, while SVM and random forest enhanced post-classification refining [5]. A DenseNet-based method for pneumonia identification that combines CNN layers and Global Average Pooling (GAP) was presented in Chest X-Ray Pneumonia identification by Dense-Net. The study highlighted the significance of overlapping pooling layers to lessen overfitting and attained 90% accuracy [7]. Five models—a custom CNN, VGG16, VGG19, Inception-V3, and ResNet152V2—were used in the classification of chest X-ray images to detect pneumonia using CNN and Transfer Learning. VGG16 had the highest accuracy (92.78%). The study also highlighted data augmentation techniques to improve model performance [8]. Pneumonia Detection with U-EfficientNet introduced a hybrid U-Net and EfficientNet model, leveraging IoU, precision, and recall metrics for evaluation. The study demonstrated improved efficiency and accuracy in pneumonia detection compared to conventional CNN architectures [9]. Pneumonia Detection using Deep Learning compared CNN and Multi-Layer Perceptron (MLP) models, revealing that CNN outperformed MLP with an accuracy of 92.63%. A graphical user interface (GUI) was also developed to assist with real-time predictions [10]. A Federated Learning Approach to Pneumonia Detection proposed a privacy-preserving pneumonia detection model using Federated Learning (FL). The study trained local models in hospitals and aggregated them into a global model, achieving an accuracy of around 90%, while maintaining patient data privacy [11].

III. METHODOLOGY

The study starts by pointing out the drawbacks of conventional pneumonia detection techniques and then uses deep learning to increase accuracy. To improve model robustness, a chest X-ray dataset is gathered and preprocessed using data augmentation, normalization, and scaling. The preprocessed dataset is used to choose, train, and optimize various deep learning models. Following training, the models' accuracy, precision, recall, and F1-score are compared using a different validation dataset. Each model's advantages and disadvantages are examined in order to assess how well it classifies pneumonia.

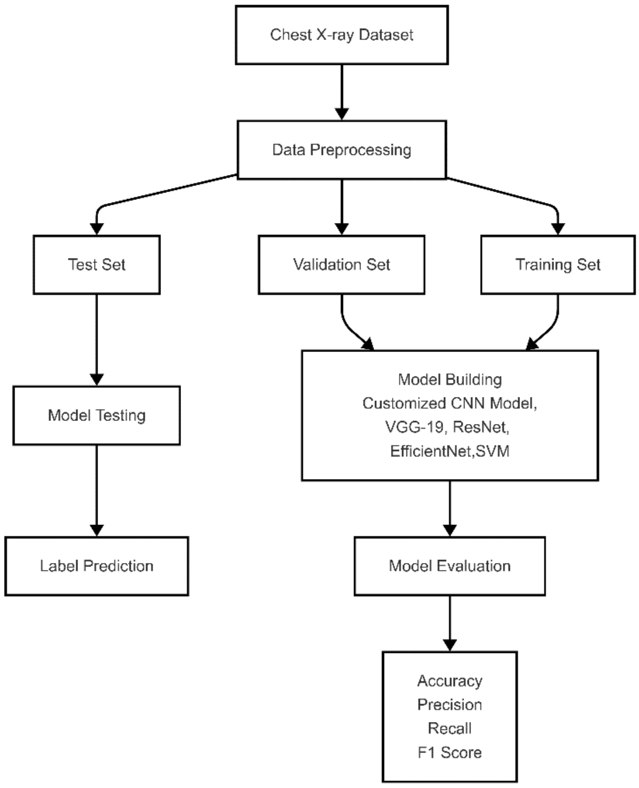

Fig. 1. Flow of the work

A. Convolution Neural Network

An initial convolution layer (Conv2D) using 15 filters and a subsequent convolution layer with 64 filters comprise the architecture of the Convolutional Neural Network (CNN) utilized in this study. Max-pooling is used in conjunction with the Conv2D layers to lower computational complexity and down-sample the feature maps. Two more convolution layers, each with 64 filters, are added after the original convolution layers, and then there is another max-pooling layer. A final max-pooling layer is then added, after which two further convolution layers with 128 filters each are added. Three dense, fully connected layers—512, 256, and 16 units, respectively—complete the network. In order to

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diagnose pneumonia, binary classification is made possible by the sigmoid activation design of the final output layer. The CNN architecture, illustrated in Fig. 2, effectively extracts hierarchical features from chest X-ray images, making it suitable for real-life applications in pneumonia classification.

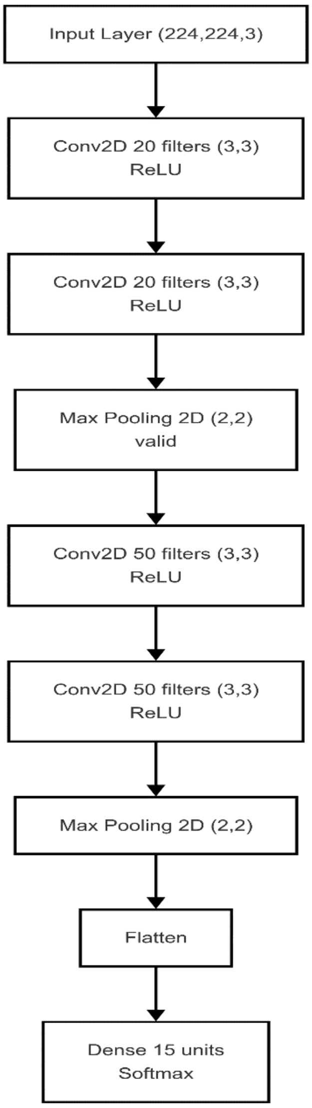

Fig. 2. CNN Architecture

The layer configurations and parameters for the CNN model are presented in Table I, outlining the convolutional layers, pooling layers, and dense layers used in the implementation.

Table I: Layers in CNN Model

Layer	Output shape	Parameters
conv2d 4	(None, 222, 222, 20)	560
conv2d_5	(None, 220, 220, 20)	3620
max_pooling2d_2	(None, 110, 110, 20)	0
conv2d_6	(None, 108, 108, 50)	9050
conv2d_7	(None, 106, 106, 50)	22550
max_pooling2d_3	(None, 53, 53, 50)	0
flatten_1	(None, 140450)	0
dense_1	(None, 15)	2106765

B. VGG 19

Three fully connected layers and sixteen convolutional layers make up the 19 layers of the VGG19 model, a deep CNN architecture. Its compact 3x3 convolution filters, which effectively extract spatial hierarchies from medical images, are its defining feature. The model's input dimensions are (224, 224, 3), and same-padding convolutions are used to ensure a constant spatial resolution across the layers. A max-pooling layer (2×2, stride 2) comes after two convolutional layers (64 filters, 3×3 kernel size) at the beginning of the architecture. In later blocks, this pattern is maintained with rising filter sizes of 128, 256, and 512 filters, each divided by max-pooling layers. After that, the feature maps are compressed into a vector of size 25088 and run through three fully connected layers that have ReLU on. Finally, the last layer applies softmax activation for classification. The architecture of VGG19, represented in Fig. 4, provides robust feature extraction for pneumonia classification.

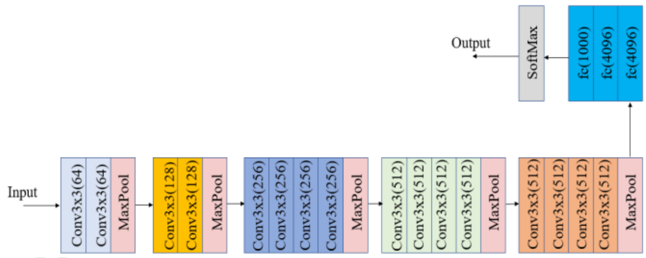

Fig. 3. VGG 19 Architecture

C. ResNet-50

ResNet-50 is a deep residual neural network that enhances feature learning by utilizing residual connections to overcome the vanishing gradient problem. The architecture begins with an initial convolutional layer using 64 filters and a kernel size of 7×7, followed by a max-pooling layer (3×3 kernel, stride 2) to reduce the spatial dimensions. The network is then structured into four residual blocks, each consisting of multiple convolutional layers with bottleneck layers (1×1 convolutions) to reduce the number of parameters. ResNet-50 has 50 layers, including convolutional, batch normalization, ReLU activation, and shortcut connections that facilitate efficient gradient flow. The final layers include a global average pooling layer followed by fully connected layers, with a softmax activation function for classification. The ResNet-50 model, depicted in Fig. 3, allows deeper representations of pneumonia features while maintaining computational efficiency.

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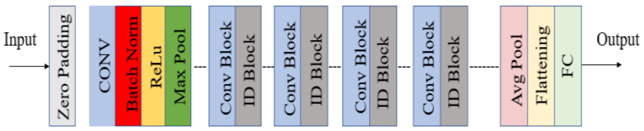

Fig. 4. ResNet-50 Architecture

D. EfficientNet-B0

Using compound scaling to balance network depth, width, and resolution, EfficientNet-B0 is a lightweight, highly optimized deep learning model that increases accuracy while preserving computing economy. Mobile Inverted Bottleneck Convolution (MBConv) blocks, which are depthwise separable convolutions that drastically reduce parameter count, come after the initial convolutional layer (32 filters, 3×3 kernel size) in the model. Each of the five MBConv block stages that make up EfficientNet has a squeeze-and-excitation (SE) layer that improves feature extraction by channel-wise recalibration. With a softmax activation for pneumonia classification, the last layers consist of fully connected layers and a global average pooling layer. The improved architecture of EfficientNet-B0, shown in Fig. 5, has shown better performance than VGG19, ResNet-50, and conventional CNNs.

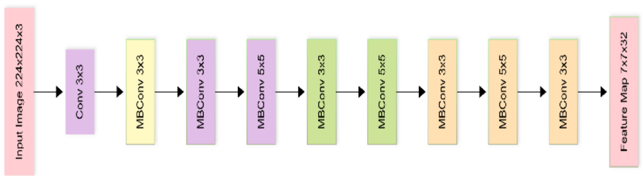

Fig. 5. EfficientNet Architecture

E. Support Vector Machine (SVM)

Support Vector Machines (SVM) serve as a hybrid classification approach, where deep features extracted from CNN, VGG19, and ResNet-50 are used as input for the SVM classifier. Instead of directly classifying chest X-ray images, SVM processes high-dimensional feature representations obtained from convolutional layers. The SVM model utilizes a Radial Basis Function (RBF) kernel to maximize the decision boundary between pneumonia-positive and normal images. The classification pipeline includes feature extraction, dimensionality reduction (using PCA), and final classification through SVM. The implementation of CNN-SVM hybrid models has shown improved generalization, reducing misclassification in pneumonia detection. The workflow for the SVM-based approach is shown in Fig. 6.

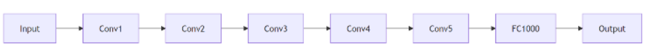

Fig. 6. SVM Architecture

IV. RESULTS AND INTERPRETATION

In order to predict pneumonia disease from X-ray pictures, we used a variety of deep learning and machine learning algorithms in this study. Numerous deep learning models, such as CNN, VGG 19, ResNet-50, and EfficientNet, were constructed. Finding out if models can accurately forecast pneumonia disease is our aim.

A. Dataset Description

The 5,866 X-ray pictures in the Pneumonia Detection Dataset are divided into two classes: PNEUMONIA (lungs with pneumonia) and NORMAL (lungs in good condition). Training, testing, and validation sets make up the dataset. There are 4693 photos in the training set, 586 images in the testing set, and 585 images in the validation set. Deep learning models for the identification of pneumonia can be developed and assessed using each image, which depicts a chest X-ray. This dataset is frequently used in medical image analysis to enhance automated pneumonia diagnosis, especially when CNN-based architectures are used.

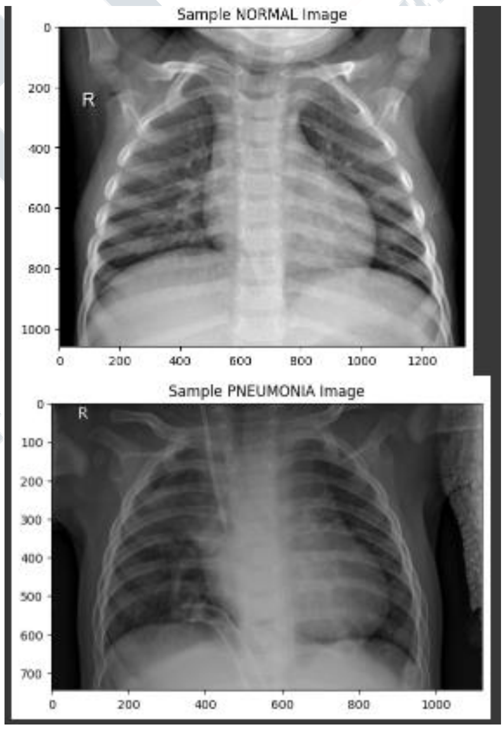

Fig. 7. Class Labels of dataset.

The chest X-Ray images dataset consists of 5866 images with 2 different class labels, such as Normal and Pneumonia Fig.8 shows bar graph representation of 2 different class labels.

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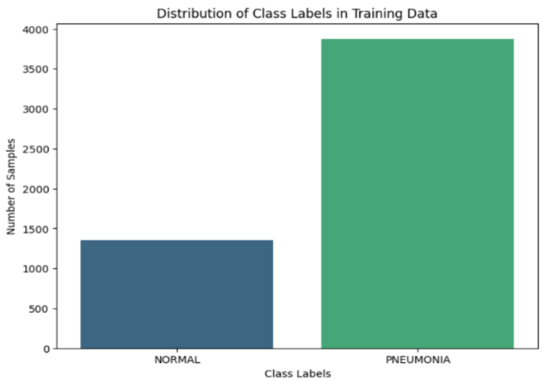

Fig. 8. Class Labels Representation

Table II represents splitting percentage is 80% for training and 10% for validation and 10% for testing.

Table II: Train and Test Split

Class Name	Training	Testing	Validation
Images	4693	586	585

The following bar graph represents training, testing and validation splits in chest X-ray dataset.

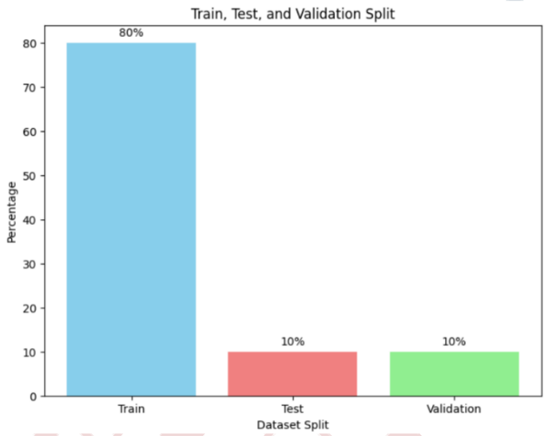

Fig. 9. Train,Test and Validation Splits of dataset

B. Model Performance

Fig.10 shows the model loss over epochs for CNN Model. Model loss is based on train and test sets. Test loss is more compared to train loss.

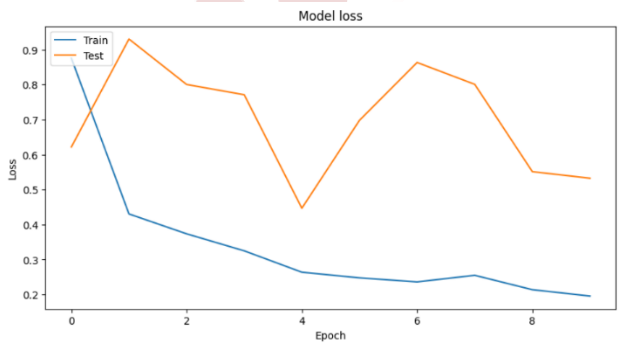

Fig. 10. Model Loss over Epochs

Fig.11 shows the Model Accuracy over Epochs for the CNN model. Model Accuracy between training and tests sets. Train accuracy is more than test accuracy.

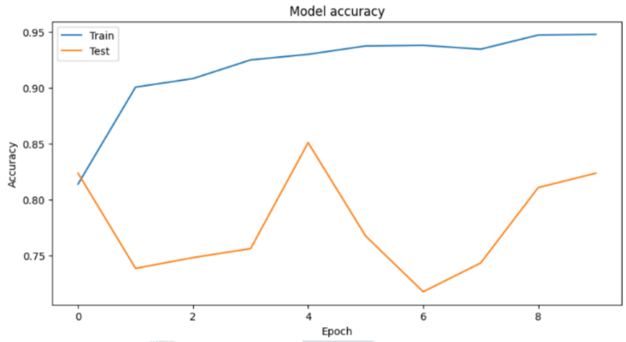

Fig. 11. Model Accuracy over Epochs

Fig.12 shows the model loss over epochs for VGG-19 Model. Model loss is based on train and validation sets. Training loss is more compared to validation loss.

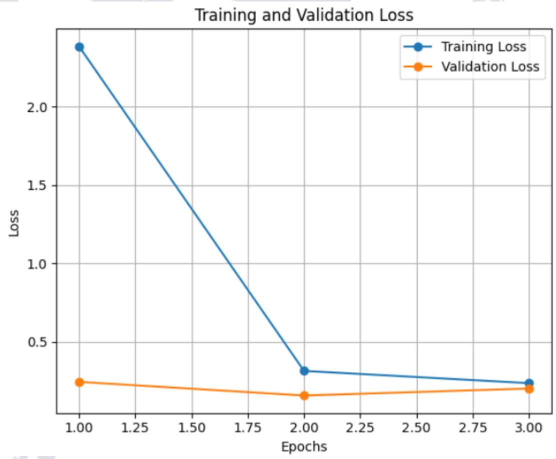

Fig. 12. Model Loss over Epochs

Fig.13 shows the Model Accuracy over Epochs for the VGG-19 model. Model Accuracy between train and validation sets. Validation accuracy is more than train accuracy.

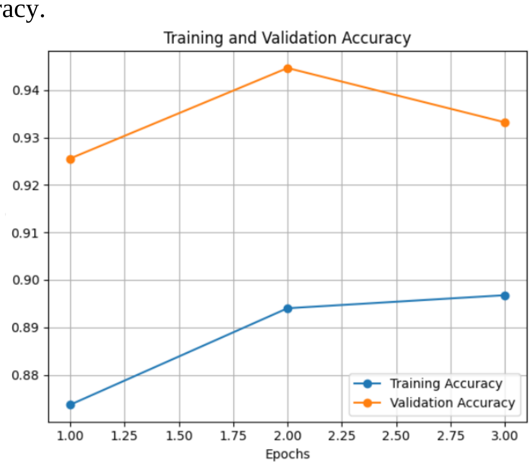

Fig. 13. Model Accuracy over Epochs

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Fig.14 shows the model loss over epochs for EfficientNet Model. Model loss is based on train and validation sets. Training loss is more compared to validation loss.

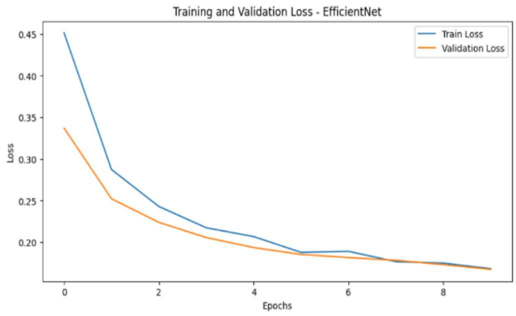

Fig. 14. Model Loss over Epochs

Fig.15 shows the Model Accuracy over Epochs for the EfficientNet model. Model Accuracy between train and validation sets. Train accuracy is more than Validation accuracy.

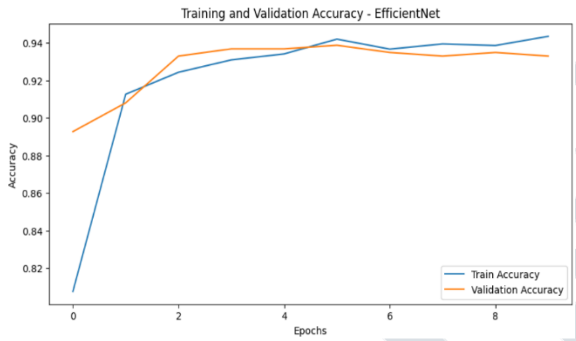

Fig. 15. Model Accuracy over Epochs

The confusion matrix is used to evaluate a model's performance by displaying the percentage of accurate and inaccurate instances based on the model prediction. Prediction results are provided by this confusion matrix. Both anticipated and true class labels are provided by this matrix. Four elements make up the confusion matrix: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

Fig.16 shows the confusion matrix for the CNN model with 2 different class labels as true and predicted.

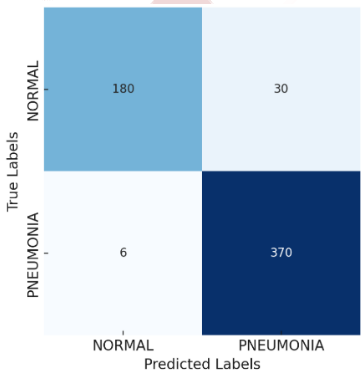

Fig. 16. Confusion Matrix of true and predicted labels

Table III shows the various performance metrics for CNN model. Performance metrics such as accuracy, precision, recall and f1-score.

Table III: CNN Performance Metrics

Accuracy	Precision	Recall	F1-Score
94.23	86	93	89

Fig.17 shows bar graph which represents different performance metrics for CNN model.

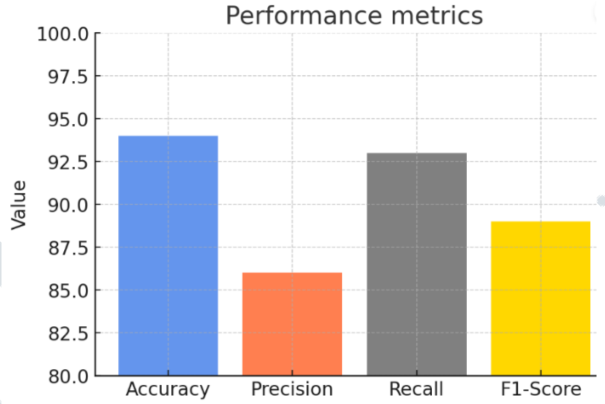

Fig. 17. CNN Performance Metrics

Table IV shows the various performance metrics for the VGG-19 model.

Table IV: VGG-19 PERFORMANCE METRICS

Accuracy	Precision	Recall	F1-Score
89.4	89	77	83

Fig.18 shows bar graph which represents performance metrics of VGG-19 model. Metrics are accuracy, precision, recall and f1-score.

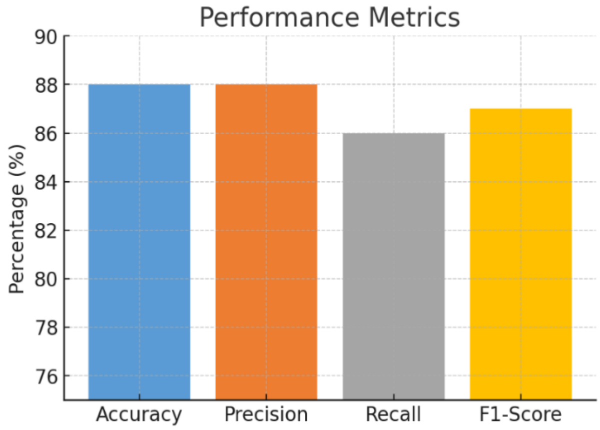

Fig. 18. VGG-19 Performance Metrics

Table V shows the various performance metrics for the ResNet model.

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Table V: ResNet Performance Metrics

Accuracy	Precision	Recall	F1-Score
80.6	76	99	86

Fig.19 shows bar graph which represents performance metrics of ResNet model. Metrics are accuracy, precision, recall and f1-score.

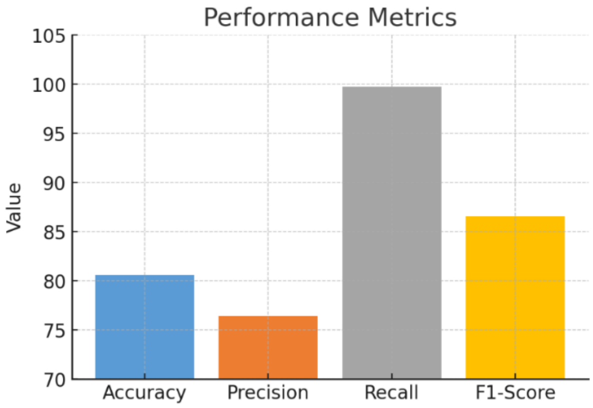

Fig. 19. ResNet Performance Metrics

Table VI shows the various performance metrics for the EfficientNet model.

Table VI: EfficientNet Performance Metrics

Accuracy	Precision	Recall	F1-Score
79.6	83	74	76

Fig.20 shows bar graph which represents performance metrics of EfficientNet model. Metrics are accuracy, precision, recall and f1-score.

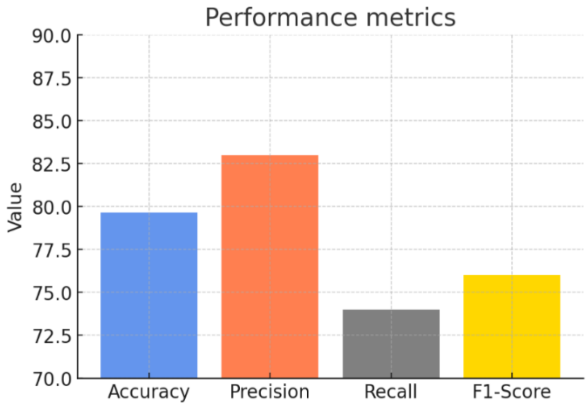

Fig. 20. EfficientNet Performance Metrics

Table VII shows the various performance metrics for the SVM model.

Table VII: SVM Performance Metrics

Accuracy	Precision	Recall	F1-Score
92.4	86	75	83

Fig.21 shows bar graph which represents performance metrics of SVM model. Metrics are accuracy, precision, recall and f1-score.

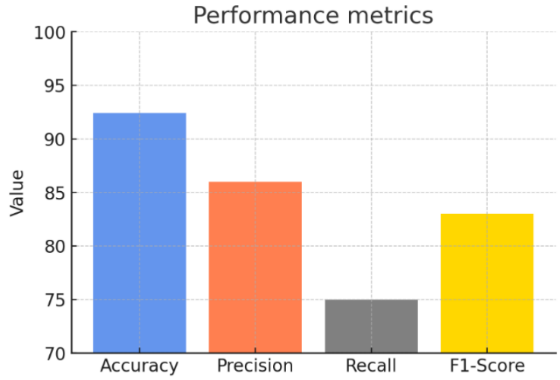

Fig. 21. SVM Performance Metrics

Table VIII displays the total accuracy of the models. The values were obtained by deploying various deep-learning models on the dataset.

Table VIII: Accuracy of the Various Models

Model	Accuracy
CNN	94.23
VGG-19	89.4
ResNet	80.6
EfficientNet	79.6
SVM	92.4

Fig.22 shows graph which represents overall accuracy of five different models such as CNN, VGG-19, ResNet, EfficientNet and SVM models.

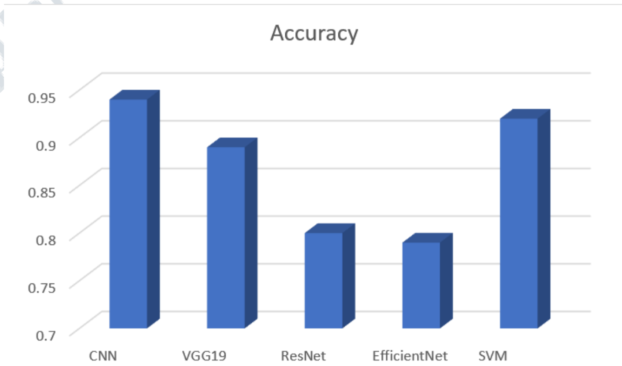

Fig. 22. Accuracy of Various Models

The CNN model achieves an accuracy of 94%. Finally, the results show that CNN achieved the highest accuracy on the dataset, attaining 94%, while other models performed as follows VGG19 with 89% accuracy, ResNet with 80%, EfficientNet with 79%, and SVM with 92% accuracy. Based on these findings, CNN emerges as the most suitable model for recognizing images in this dataset.

V. CONCLUSION

Automated diagnostic methods based on deep learning have the potential to transform the detection of pneumonia by providing quick, accurate, and dependable evaluations of chest X-ray images. In order to assess the efficacy of several deep learning models in detecting pneumonia cases, this study looked at CNN, VGG19, ResNet, EfficientNet, and SVM. According to the results, the CNN model was the most dependable choice for automated pneumonia identification, with the greatest accuracy of 94.23%. By lowering reliance on qualified radiologists and increasing early detection rates, the incorporation of ensemble models further improves diagnostic precision. These developments in AI-powered medical imaging have the potential to greatly improve clinical judgment, expedite procedures, and eventually better patient outcomes. Future research can focus on enhancing model robustness by incorporating larger and more diverse datasets, leveraging federated learning for privacy-preserving training, and integrating real-time deployment in healthcare settings. These improvements can pave the way for scalable, AI-assisted diagnostic solutions in radiology.

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