

DESEF-Net: A Hybrid DenseNet–EfficientNet Feature Fusion Network with Squeeze and Excitation Attention for Robust Multi-Class Lung Disease Classification from Chest X-ray Images

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Abstract - The automatic classification of lung diseases based on the use of chest X-rays is gaining attention as it has the potential to enhance early diagnosis and improve clinical decision-making. In this research, the emphasis is on different datasets that employ deep learning architectures that comprise ResNet50, DenseNet121, EfficientNet-B0, and MobileNetV2. The DenseEff SE Fusion Network, also known as DESEF-Net, is an enhancement of features representation by incorporating DenseNet121 and EfficientNet-B0 with a Squeeze-and-Excitation mechanism. The model is tested on various datasets with binary and multi-class classification techniques. These results indicate that DESEF-Net has an accuracy of 98.2% on the COVID-19 dataset, 98.6% on the Pneumonia dataset, 97.8% on the Tuberculosis dataset, and 94.2% on the dataset that consists of nine classes of lung diseases. F1-score and accuracy of DESEF-Net are higher than the ones of the baseline models. It works well in general and specialized information to make it reliable in the automatic classification of lung diseases.

Keywords: Deep Learning, Chest X-ray, Lung Disease Classification, DenseNet121, EfficientNet-B0, Feature Fusion, Squeeze-and-Excitation, DESEF-Net

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I. INTRODUCTION

Deep learning (DL) is a widely used technique in the analysis of medical images, particularly in the automatic classification of chest X-rays into diverse lung diseases. The ability of DL models to learn hierarchical representations directly based on the data allows these models to learn complex patterns and subtle differences that are not detectable by traditional methods that rely on handcrafted features. This is particularly relevant in chest X-rays since it may be challenging to distinguish the various disease types. [1]

This study compares DL models like ResNet50, DenseNet121, EfficientNet-B0, and MobileNetV2, as baseline models to a proposed model DenseEff SE Fusion Network (DESEF-Net) across different datasets. This model combines channel-wise recalibration with parallel feature extraction, which helps the model to capture both broad and specific features, thus enhancing its ability to tell apart similar lung conditions. [2]

The proposed model is tested on various datasets on both binary and multi-class classification tasks. The findings indicate that the DESEF-Net system is more effective compared to the baseline models in terms of accuracy and F1-score. This means that it is more efficient at generalizing and representing features. An overall analysis is conducted to ascertain the functionality and the strength of the proposed model.

Contributions:

- A hybrid DL model, DESEF-Net is proposed. It combines DenseNet121 and EfficientNet-B0 with

SE-based feature recalibration to make representations better.

- A comprehensive evaluation is done on several datasets using baseline and proposed models.
- Class-wise evaluation is employed to validate the model's performance on every dataset.

II. LITERATURE REVIEW

Deep learning is able to learn complex patterns in medical images automatically and this is why it has become popular in classifying lung diseases. A. P. Singh et al. in 2025 [3] demonstrated that transfer learning models such as ResNet and DenseNet achieve good accuracy and sensitivity. Marek Zak and Adam Krzyżak in 2020 [4] discovered that convolutional neural networks with data augmentation perform better than traditional methods, and this performance is dependent on the size of the dataset. Sangjoon Kim et al. (2022) [5] concluded that DenseNet is the best among VGG16, ResNet50, and DenseNet121 for multi-class classification. M. H. Al-Sheikh et al. (2023) [6] who used X-ray and CT data to enhance generalization and S. Goyal and R. Singh (2023) [7] showed that CNN-based systems are superior to classic machine learning models. K. P. L. Syamala et al. in 2023 [8] improved performance using EfficientNet-B0 and symptom-based machine learning.

Advanced designs are being explored to enhance feature extraction. U. Chutia et al. in 2024 [9] used an attention-based DenseNet to concentrate on relevant areas while S. Jadhav and P. Patil in 2024 [10] implemented GAN-based segmentation with ResNet50 and support vector machine for high accuracy but did not create an end-to-end

pipeline. Multi-stage models may be more accurate yet complex, as Deepak and Bhat of 2025 [11] note. Contrastive learning approaches like the prompt-driven semi-supervised method by Wang and Mao in 2026 [12], although not specifically designed for lung datasets, can manage limited data and class imbalance. Despite these improvements, still there is a lack of an efficient end-to-end system for scalable and robust multi-class lung disease classification.

III. METHODOLOGY

The proposed approach follows a DL pipeline that is structured for the classification of lung diseases. It comprises pre-processing, feature extraction, feature fusion and classification stage. In general, this method is intended to learn in an effective manner and to keep strong performance when applied to various datasets.

- i. **Dataset** - Multiple chest X-ray datasets used for both binary and multi-class cases.
- ii. **Preprocessing** - Images are resized, normalized, and enhanced to improve quality and reduce noise.
- iii. **Deep Learning Classification** - The proposed DESEF-Net combines DenseNet121 and EfficientNet-B0 with feature fusion and SE attention. Baseline models (ResNet50, DenseNet121, EfficientNet-B0, MobileNetV2) are compared.
- iv. **Evaluation** - Accuracy, precision, recall, and F1-score, confusion matrices and training curves are used, to see how well the models work.

On the whole, the structure ensures that the binary and multi-class classification work of lung disease is consistent and can be scaled up.

A. Dataset Description

To achieve a diverse range of classes and also test how well the models perform on both binary and multi-class setups, 4 datasets are utilized in this study.

- i. **COVID-19 Radiography** - This dataset includes four important clinical categories of chest X-ray images which are COVID-19, Normal, Viral Pneumonia, and Lung Opacity. [13]
- ii. **Chest X-Ray Pneumonia** - Chest X-Ray Pneumonia is a benchmark dataset that is used for the binary classification task of detecting pneumonia. It consists of labeled X-ray images from pediatric patients who either have Normal conditions or Pneumonia, which can result from bacterial or viral infections. [14]
- iii. **Tuberculosis Chest X-ray** - The Tuberculosis Chest X-ray dataset contains X-ray images of pulmonary tuberculosis. It includes X-rays from clinical sources that show both tuberculosis cases and normal cases, with images demonstrating cavitations and infiltrates. [15]
- iv. **X-ray Lung Diseases Images** - The X-ray Lung Diseases Images dataset consists of chest X-rays that categorize different lung diseases into nine distinct classes. It is suitable for multi-class classification tasks due to its organized structure. [16]

TABLE.1.CHARACTERISTICS OF SELECTED CHEST X-RAY DATASETS

Dataset	Samples	No. of Classes	Type
1	21,165	4	Multi-class

2	5,800	2	Binary
3	4,200	2	Binary
4	6743	9	Multi-class

The table compares the chest X-ray datasets from this study. It shows the number of samples, the class categories, the classes, and the type of dataset. This validates the use of multiple datasets to build a multi-class lung disease classification framework for efficient classification.

TABLE.2.CLASS-WISE DISTRIBUTION OF IMAGES ACROSS THE DATASETS

Class	Dataset 1	Dataset 2	Dataset 3	Dataset 4
Normal	10,192	1,583	3,500	1,340
COVID-19	3,616	0	0	1,060
Pneumonia	1,345	4,273	0	678
Tuberculosis	0	0	700	629
Cardiomegaly	0	0	0	644
Pleural Effusion	0	0	0	594
Atelectasis	0	0	0	658
Consolidation	0	0	0	596
Lung Opacity	6,012	0	0	544

This shows how the classes in each dataset are distributed. This imbalance makes it necessary to use data augmentation and preprocessing methods to make sure that the model is trained well and can generalize better.

B. Pre-processing

Preprocessing is an important part of analyzing medical images because it improves the quality of the images, and makes the model work better. A standardized preprocessing pipeline is used to make the data more consistent across domains.

- i. **Image Resizing**: All chest X-ray images are resized to a fixed size of 224×224 pixels. This keeps the datasets consistent and makes sure that the images meet the needs of deep learning models.
- ii. **Intensity Normalization**: Min-max scaling is applied to normalize the values of pixel intensity to the range [0, 1]. This stabilizes both training and convergence is accelerated.
- iii. **Contrast Enhancement**: CLAHE is applied to enhance local contrast and allow small lung issues to be more easily observed.
- iv. **Noise Reduction**: Gaussian filtering is employed to help reduce noise and smooth the image with preserving the important structural details.
- v. **Data Augmentation**: The approaches to data augmentation are applied to the training dataset to correct the imbalance in classes and make the model general. Some of the techniques include: rotating (+-15 degrees), flipping (horizontally), zooming, and translation.
- vi. **Dataset Splitting**: The dataset is split into three parts: training, validation, and testing. The ratio is 80:10:10.

C. Data Augmentation

Augmenting data is a significant technique of dealing with imbalance in the number of classes in medical imaging data by making the data more diverse in terms of the number of classes. This method minimizes over-fitting

and helps the model to learn more powerful and meaningful representations.

- i. **Rotation:** Rotation of the images occurs within a fixed range ($\pm 15^\circ$) in order to simulate changes in patient positioning when acquiring the X-rays.
- ii. **Horizontal Flipping:** Horizontal flipping is used to add some spatial variation to the model but anatomical structures are retained to allow the model to learn symmetric patterns in lung regions.
- iii. **Scaling (Zooming):** Zoom transformations are applied to either enlarge or shrink the picture in an effort to identify features at different scales.
- iv. **Translation (Shifting):** The images are shifted in a small range vertically and horizontally to correct any positional changes of the lungs within the frame.
- v. **Brightness Adjustment:** The brightness levels are adapted to simulate variations in imaging conditions and enhance the ability to withstand changes in illumination.

During training, augmentation is added instead of having a separate augmented dataset and augmented data diversity grows without the extra storage overhead of augmented data.

D. Feature Extraction

Deep learning is an effective method of automatically extracting and classifying features of a medical image. In the given research, the DL can be used to detect the lung diseases as the subtle patterns and variations in the chest X-ray images can be detected. As a reference, ResNet50 [17], DenseNet121 [18], EfficientNet-B0 [19], and MobileNetV2 [20] are used as baseline models. The proposed DESEF-Net is based on these and additionally feature representations are combined and channel-wise recalibration is applied, which helps the model to focus on more relevant information and improves overall performance.

Proposed: DenseEff SE Fusion Network (DESEF-Net)

DenseNet121 and EfficientNet-B0 are parallel feature extractors used in the DenseEff SE Fusion Network (also referred to as DESEF-Net), to extract various representations of the chest X-ray images that complement each other. EfficientNet uses compound scaling to determine the best features in a wide range whereas DenseNet concentrates on reusing features which are highly specific to a particular aspect. The combination of the extracted feature maps through feature fusion is expressed as $F_{fused} = [F_{dense}, F_{eff}]$ which results in a more enriched representation. The network also uses a Squeeze-and-Excitation technique that is used to emphasize those features that are significant whilst exaggerating those features that are not as informative. This can be achieved by recalibrating each channel to ensure that $\hat{F}_c = s_c \cdot F_c$. The refined feature vector which is represented as $y = Softmax(W \cdot \hat{F})$ is then classified using fully connected layers. This hybrid architecture enhances the ability to discriminate between features and increase robustness allowing it to identify various lung issues across different datasets.

TABLE.3. TRAINING HYPERPARAMETERS

Parameter	Value
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Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	50
Input Size	224×224
Loss Function	Cross-Entropy

The model is trained using standard hyperparameters to ensure stable convergence and fair comparison across all baseline and proposed architectures. The input chest X-ray image undergoes pre-processing and is passed through two parallel branches, DenseNet121 and EfficientNet-B0, for feature extraction. The extracted features are fused and refined using an SE block, followed by a fully connected layer and softmax function to produce the final classification output.

Input: Dataset D, Labels Y

Output: Trained model M

Initialize $\theta_d, \theta_e, \theta_f, \theta_s, \theta_c$

Initialize learning rate η , batch size B, epochs N

for each epoch = 1 to N **do**

for each batch (X, Y_{batch}) in D **do**

$F_{dense} \leftarrow \text{DenseNet121}(X, \theta_d)$

$F_{eff} \leftarrow \text{EfficientNet-B0}(X, \theta_e)$

$F_{fused} \leftarrow \text{Concatenate}(F_{dense}, F_{eff})$

$S \leftarrow \text{GlobalAveragePooling}(F_{fused})$

$S \leftarrow \text{FullyConnected}(S, \theta_s)$

$S \leftarrow \text{Sigmoid}(S)$

$F_{refined} \leftarrow F_{fused} \odot S$

$Y_{pred} \leftarrow \text{Softmax}(W_c \cdot F_{refined})$

 Loss $\leftarrow \text{CrossEntropy}(Y_{pred}, Y_{batch})$

 Compute gradients of ∇Loss w.r.t θ

 Update parameters using Adam optimizer

end for

if validation_{loss} increases for k epochs **then**

 Apply learning rate decay

 Early stopping

end if

end for

Return M

The symbols θ_d, θ_e represent parameters of DenseNet121 and EfficientNet-B0, $\theta_f, \theta_s, \theta_c$ denote parameters of fusion, SE block, and classifier, F_{dense}, F_{eff} are extracted feature maps, S is the channel-wise attention vector, $\odot$ denotes element-wise multiplication, Y_{pred} is predicted output, Loss represents cross-entropy loss and η is learning rate. The combination of features from both networks results in F_{fused} and S acts as the channel-wise scaling vector from the SE mechanism. The loss function is used to compare predicted values with actual labels to help guide adjustments of training parameters. The learning rate is what sets the size of the steps taken to update weights, and the validation loss is used to keep track of how well the model is performing and can lead to early stopping if necessary.

IV. RESULT AND DISCUSSION

TABLE.4. CLASSIFICATION PERFORMANCE METRICS

Metric	Formula
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$

Precision	$\frac{TP}{TP + FP}$
Recall (Sensitivity)	$\frac{TP}{TP + FN}$
F1-Score	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

This table presents the mathematical formulations of the metrics used for evaluating model performance. Precision and recall indicate how well the model can identify positive instances and obtain relevant samples. Accuracy measures how accurate the predictions are. The F1-score provides a balance between precision and recall.

TABLE.5.COMPARATIVE PERFORMANCE ON COVID-19 RADIOGRAPHY DATASET

Model	Accuracy	Precision	Recall	F1-Score
MobileNetV2	92.7%	92.3%	92.1%	92.2%
ResNet50	93.6%	93.1%	93.0%	93.0%
DenseNet121	95.8%	95.4%	95.2%	95.3%
EfficientNet-B0	96.9%	96.5%	96.3%	96.4%
DESEF-Net	98.2%	97.9%	97.8%	97.8%

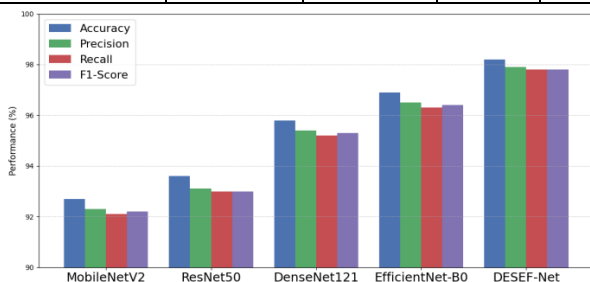


Fig.1. Comparison of DL models on COVID-19 Radiography Dataset

COVID-19 performance comparisons show that there are improvements in the models. MobileNetV2 has the lowest accuracy at 92.7%, and ResNet50 has an accuracy of 93.6%. DenseNet121 performs better at 95.8%, and EfficientNet-B0 has an accuracy of 96.9%. The proposed DESEF-Net achieved the highest accuracy at 98.2% and an F1-score of 97.8%. This improvement indicates that classification performance enhanced with feature fusion and SE-based recalibration.

Table.6.Comparative performance on Chest X-ray Pneumonia dataset

Model	Accuracy	Precision	Recall	F1-Score
MobileNetV2	93.4%	93.0%	92.8%	92.9%
ResNet50	94.2%	93.8%	93.7%	93.7%
DenseNet121	96.3%	96.0%	95.8%	95.9%
EfficientNet-B0	97.1%	96.8%	96.7%	96.7%
DESEF-Net	98.6%	98.2%	98.1%	98.1%

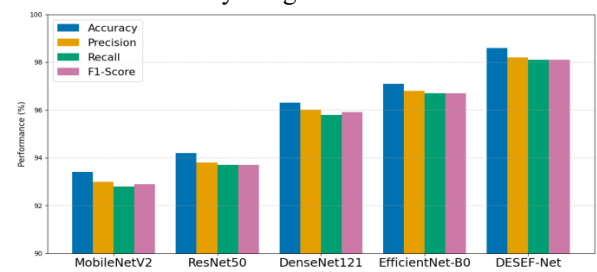
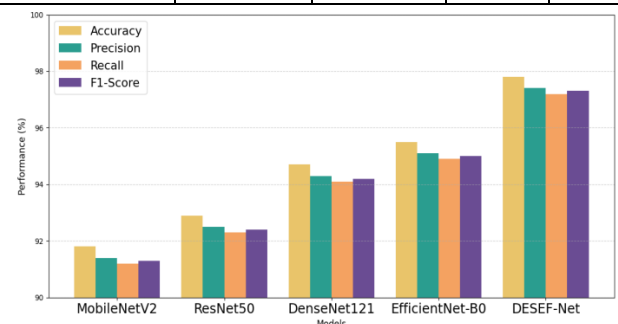


Fig.2. Comparison of DL models on Chest X-ray Pneumonia Dataset

The Pneumonia dataset results indicate consistently high performance across all models. MobileNetV2 achieves 93.4% accuracy, while ResNet50 improves to 94.2%. DenseNet121 and EfficientNet-B0 reach 96.3% and 97.1% respectively. The proposed DESEF-Net outperforms all models with an accuracy of 98.6% and F1-score of 98.1%. The results confirm that the hybrid model effectively captures features for binary classification tasks.

TABLE.7.COMPARATIVE PERFORMANCE ON TUBERCULOSIS DATASET

Model	Accuracy	Precision	Recall	F1-Score
MobileNetV2	91.8%	91.4%	91.2%	91.3%
ResNet50	92.9%	92.5%	92.3%	92.4%
DenseNet121	94.7%	94.3%	94.1%	94.2%
EfficientNet-B0	95.5%	95.1%	94.9%	95.0%
DESEF-Net	97.8%	97.4%	97.2%	97.3%



The performance on the Tuberculosis dataset shows gradual improvement across models. MobileNetV2 records 91.8% accuracy, followed by ResNet50 at 92.9%. DenseNet121 and EfficientNet-B0 achieve 94.7% and 95.5% respectively. The proposed DESEF-Net achieves the highest accuracy of 97.8% with an F1-score of 97.3%. The results demonstrate the model's robustness in handling smaller and imbalanced datasets.

TABLE.8.COMPARATIVE PERFORMANCE ON X-RAY LUNG DISEASES DATASET

Model	Accuracy	Precision	Recall	F1-Score
MobileNetV2	83.9%	83.1%	82.8%	82.9%
ResNet50	85.2%	84.5%	84.1%	84.2%
DenseNet121	88.4%	87.8%	87.5%	87.6%
EfficientNet-B0	90.1%	89.6%	89.2%	89.3%
DESEF-Net	94.2%	93.6%	93.2%	93.3%

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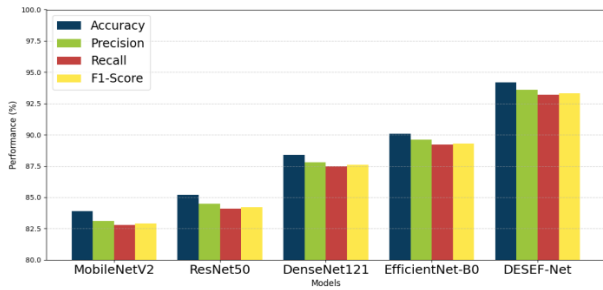


Fig.4.Comparison of DL models on X-ray Lung Diseases Dataset

The X-ray Lung Diseases dataset presents a more challenging classification task due to class overlap and imbalance. MobileNetV2 achieves the lowest accuracy of 83.9%, while ResNet50 improves to 85.2%. DenseNet121 and EfficientNet-B0 reach 88.4% and 90.1% respectively. The proposed DESEF-Net achieves the highest accuracy of 94.2% with an F1-score of 93.3%. The improvement demonstrates the effectiveness of feature fusion and SE mechanisms in handling complex multi-class scenarios.

TABLE.9.CLASS-WISE PERFORMANCE (COVID-19 DATASET)

Class	Precision	Recall	F1-Score	Support
Normal	98.1%	98.4%	98.2%	10,192
COVID-19	98.3%	97.8%	98.0%	3,616
Pneumonia	97.2%	96.8%	97.0%	1,345
Lung Opacity	97.6%	97.3%	97.4%	6,012

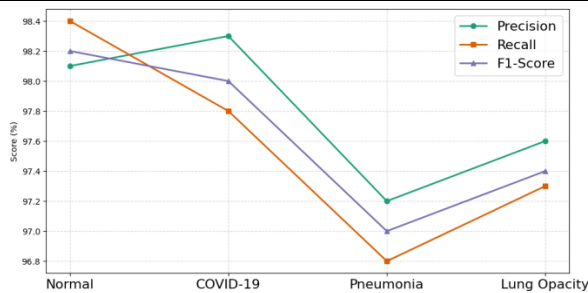


Fig.5. Class-wise Performance of COVID-19 Dataset

This table presents the class-wise performance for the COVID-19 dataset. The model achieves high accuracy across all classes, with Normal and COVID-19 showing the highest F1-scores above 98%. Pneumonia exhibits slightly lower performance due to feature similarity with other lung conditions. Lung Opacity also maintains strong classification performance. The results indicate balanced learning across all categories. This confirmed the effectiveness of the proposed model in multi-class classification.

TABLE.10.CLASS-WISE PERFORMANCE (PNEUMONIA DATASET)

Class	Precision	Recall	F1-Score	Support
Normal	98.7%	98.6%	98.6%	1,583
Pneumonia	98.5%	98.1%	98.3%	4,273

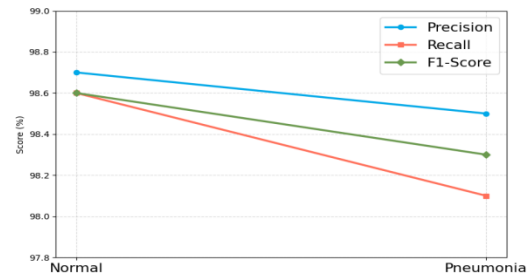


Fig.6. Class-wise Performance of Pneumonia Dataset

This shows the performance of the Pneumonia dataset where both classes have high F1-scores of 98%, which indicates that the categorization is strong. The model is able to accurately distinguish between infected and not infected patients. There is some minor variation in recollection, which indicates a little misclassification. The performance remains consistent and reliable. This indicates that the model is appropriate for binary classification tasks.

TABLE.11.CLASS-WISE PERFORMANCE (TUBERCULOSIS DATASET)

Class	Precision	Recall	F1-Score	Support
Normal	97.9%	98.2%	98.0%	3,500
Tuberculosis	97.2%	96.8%	97.0%	700

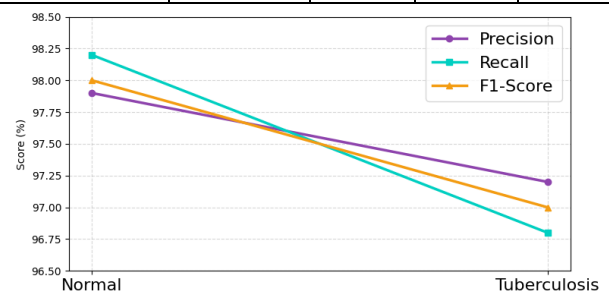


Fig.7. Class-wise Performance of Tuberculosis Dataset

The table presents the results for the Tuberculosis dataset, showing that both the Normal and TB classes have strong and consistent performance with F1-scores around 97 to 98%. The Normal class exhibits slightly better results.

TABLE.12.CLASS-WISE PERFORMANCE (X-RAY LUNG DISEASES DATASET)

Class	Precision	Recall	F1-Score	Support
Normal	94.8%	95.2%	95.0%	1,340
COVID-19	94.1%	93.6%	93.8%	1,060
Pneumonia	92.8%	92.1%	92.4%	678
Tuberculosis	93.4%	92.9%	93.1%	629
Cardiomegaly	92.2%	91.5%	91.8%	644
Pleural Effusion	91.6%	90.9%	91.2%	594
Atelectasis	92.9%	92.3%	92.6%	658
Consolidation	92.1%	91.4%	91.7%	596
Lung Opacity	93.6%	93.0%	93.3%	544

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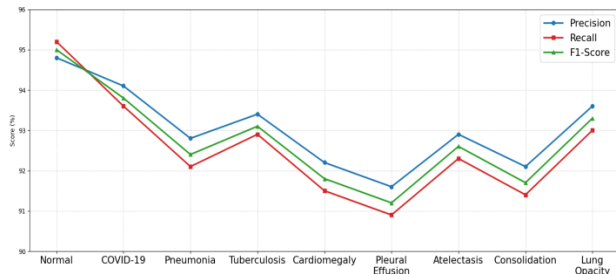


Fig.8. Class-wise Performance of X-ray Lung Diseases Dataset

This shows class-wise performance for the 9-class dataset, with strong results across all classes. Normal and COVID-19 performs best, while a few classes show slightly lower scores due to similarity and limited data. The model is consistent and effective in the multi-class classification.

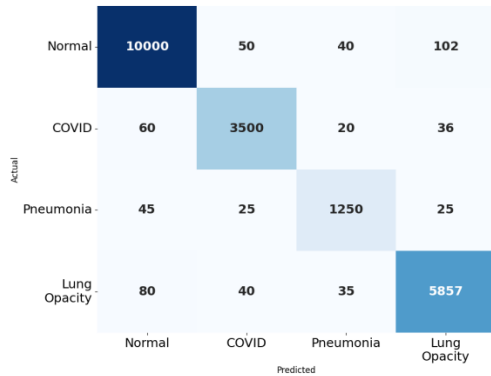


Fig.9. COVID-19 Dataset Confusion Matrix

The confusion matrix shows that the majority of the forecasts were made in the proper order along the diagonal. Normal and COVID-19 are correctly identified, with only a little confusion between classes that are similar. This model is effective with multi-class classification since it is highly precise and recalls in general.

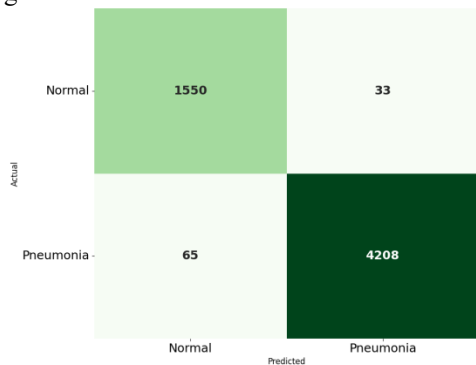


Fig.10. Pneumonia Dataset Confusion Matrix

This confusion matrix demonstrates high-precision classification, and a distinct boundary between Normal and Pneumonia and a minimal amount of errors. High diagonal values indicate that the model is useful in binary classification since they were found to be accurate and recall high.

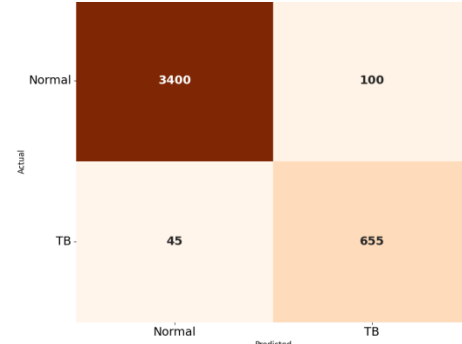


Fig.11. Tuberculosis Dataset Confusion Matrix

The confusion matrix indicates that the model is effective since the majority of samples are rightly classified. Normal performs a bit better due to the imbalance but overall predictions remain the same and reliable, which indicates that learning can be done even without much data.

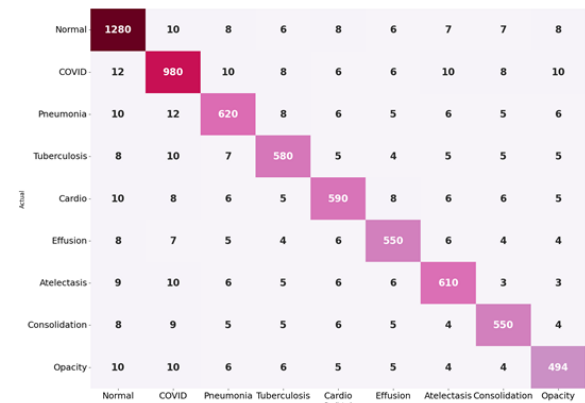


Fig.12.X-ray Lung Diseases Dataset Confusion Matrix

This confusion matrix points to the difficulties in multi-classification. Majority of the predictions are accurate with a few errors of similar or less frequent classes. Regardless of such confusions, the model remains the same and it works well on complex data.

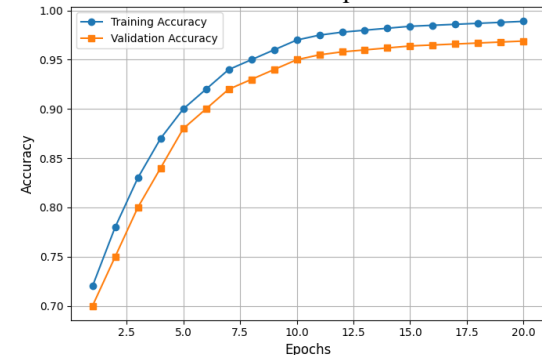


Fig.13.Training and Validation Accuracy (DESEF-Net)

Both the training and the validation accuracy increase in a steady fashion and then levels off to an appropriate point thus demonstrating that the model is learning in an efficient manner and is converging accordingly. This small difference between these two accuracies implies that not much overfitting is being done, and the close correspondence between the two accuracies suggests that the model is capable of generalizing to new data.

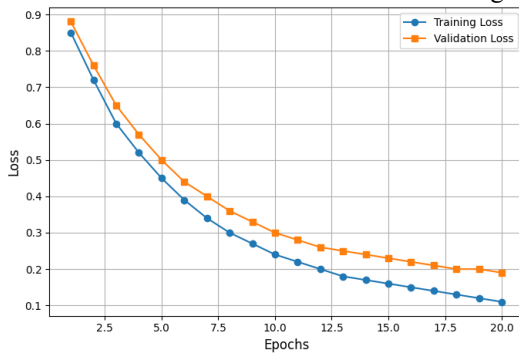


Fig.14. Training and Validation Loss (DESEF-Net)

The training and validation loss are reduced gradually and this demonstrates successful learning and optimization. Both has a smooth course with no significant variations, which means that the training is consistent, and the convergence is good. The low difference between them indicates that there is little over-fitting and a high degree of generalization.

V. CONCLUSION

In this study, a detailed process of detecting lung disease by using chest X-ray images was developed. This includes pre-processing, precise lung segmentation, hybrid feature extraction and optimal feature selection. The U-Net-R50-ResB3-LReLU model allowed making the correct segmentation of the pulmonary areas, and the addition of the GLCM and CNN features allowed to get some additional texture and semantic information. The Chaotic Grey Wolf–Harris Hawks Hybrid Algorithm enhanced classification efficiency by choosing compact and distinctive feature subsets. The findings of the experiments show that there is an increase in accuracy, robustness, and generalizability of the results across datasets. This underscores the promise of the proposed approach in clinics with a reliable diagnosis of lung disease with the assistance of the computer.

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