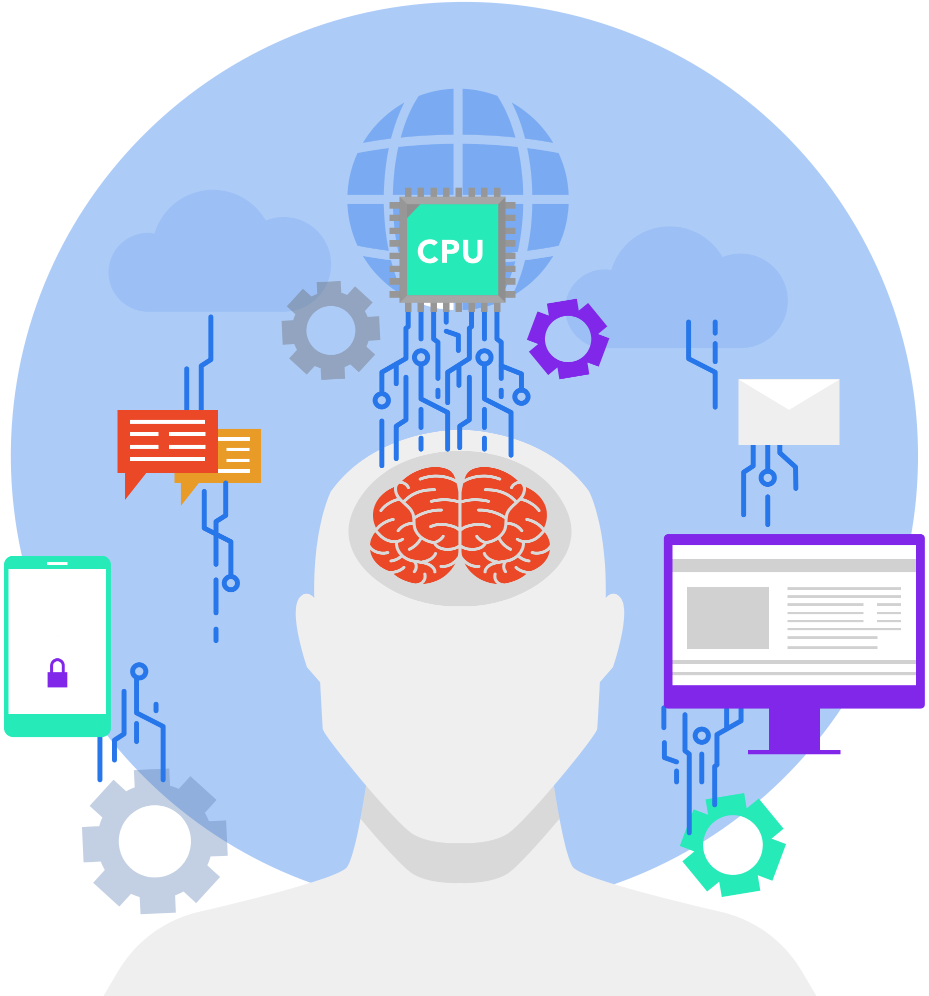

Group P

Pneumonia Detection

from Chest X-Rays using CNN

Team Details:
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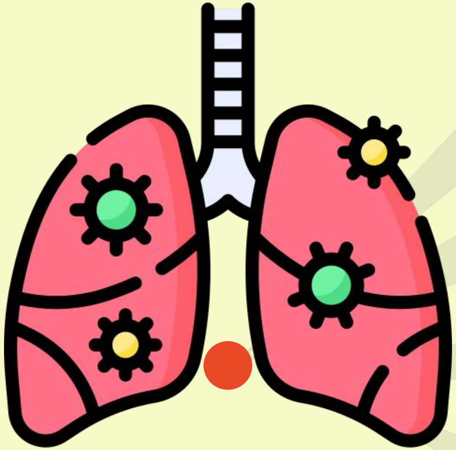
Pneumonia Detection as a Problem and its Importance



Serious Respiratory Infection

Leading cause of morbidity and mortality worldwide.

Complex Diagnosis

Diagnosis can be difficult due to shared symptoms.

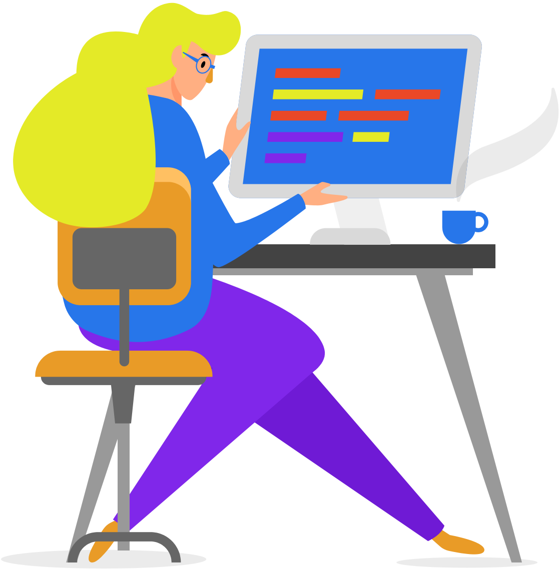
Shortage of Professionals

Dependent on expert interpretation and medical access.

Potential AI solutions

AI adoption challenges: dataset diversity, model interpretability, and generalizability.

Goals of the Project



01 Create an AI system for pneumonia detection using CNNs on chest X-rays.

02 Address the challenge of accurate pneumonia diagnosis, especially in resource-constrained healthcare settings.

03 Assess CNN performance (ResNet18, DenseNet121, InceptionV3) across diverse datasets using multiple metrics.

04 Enhance healthcare and patient outcomes with improved pneumonia detection through AI.

Methodology: Used Datasets

	Details of Each Datasets of the Project	
01	Dataset 1	• Categories: Pneumonia and Normal • Resolution: 1120 x 800 pixels • Training: 3,514 images • Validation: 878 images • Testing: 1,464 images
02	Dataset 2	• Categories: Bacterial, Covid-19, Lung Opacity, Normal, Viral • Resolution: 1780 x 1800 pixels • Training: 2,020 images • Validation: 500 images • Testing: 1,035 images
03	Dataset 3	• Categories: 14 lung disease classes including pneumonia • Resolution: 1024 x 1024 pixels • Training: 67,272 images • Validation: 16,818 images • Testing: 28,030 images

Methodology: CNN Models

ResNet18

- Addresses vanishing gradient issue
- 18 layers Architecture
- Parameters: ~11.7M
- Input image size: 224x224 pixels
- FLOPS: Approximately 1.8 billion

Vs

Inception-V3

- Utilizes filters with multiple sizes for wider networks
- Approximately 23.8 million parameters
- Input image size: 299x299 pixels
- FLOPS: Approximately 5.7 billion

Vs

DenseNet121

- Chosen for dense connectivity promoting reuse
- 121 layers Architecture
- Parameters: ~7.0M
- Input image size: 224x224 pixels
- FLOPS: Approximately 2.9 billion

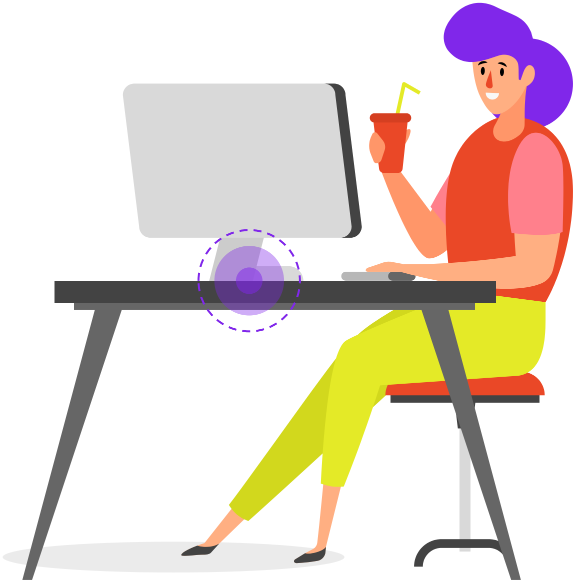
Methodology: Optimization Algorithm

01 Utilized Stochastic Gradient Descent (SGD) optimization algorithm

02 SGD updates parameters by subtracting a fraction of loss gradient.

03 Momentum value of 0.9 set for accelerated convergence

04 Learning rate of 0.001 varied to optimize model convergence



05 Loss function: Cross entropy loss

06 Evaluation metrics: Accuracy, Precision, Recall, F1-score

07 Utilized t-SNE for visual comparison of feature distributions in lower-dimensional space

08 Model hyperparameters:

Optimizer: SGD

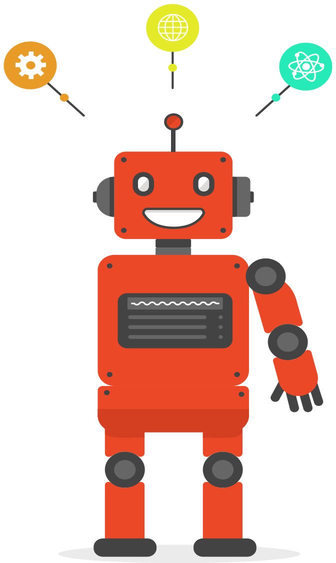
Learning rate: 0.001

Batch size: 30

Loss function: Cross entropy loss

Number of epochs: 30

Experimental Setup



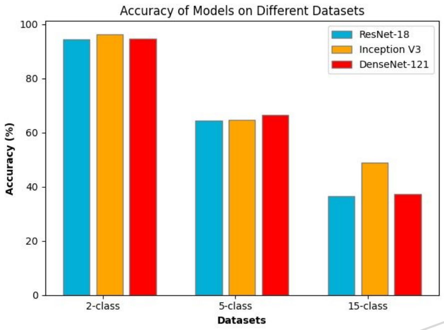
01 Data from three Kaggle sources was preprocessed: cleaned, resized, and converted to PIL Image format and torch.float32.

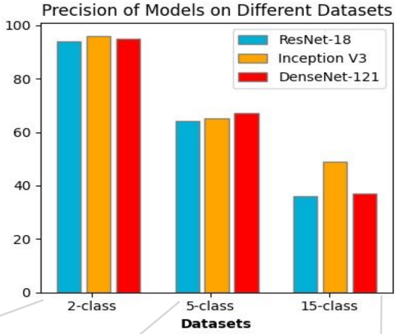
02 Dataset split into 60:15:25 ratios for training, validation, and testing.

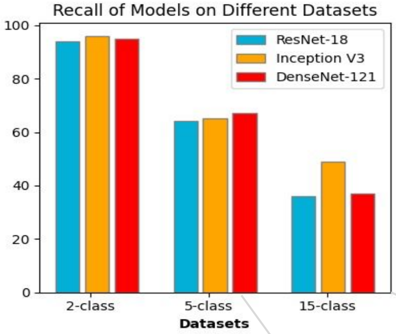
03 Data augmentation techniques, including normalization, were applied during training.

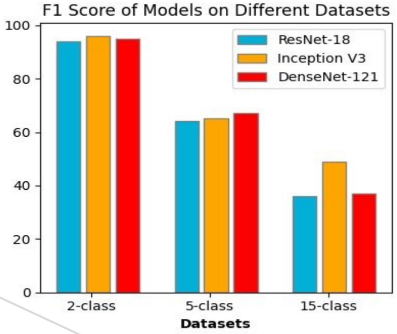
04 Utilized SGD, ReLU, and optimized hyperparameters; evaluated using accuracy, loss, and confusion matrices on validation/test data.

Main Results









01

Inception v3 consistently outperforms ResNet-18 and DenseNet-121 across all datasets

02

Accuracies of 96.39%, 64.63%, and 49.02% for Inception v3, and 94.35%, 64.44%, and 36.43% for ResNet-18 and DenseNet-121.

03

Performance declines as the number of classes in the dataset increases.

04

Inception v3 demonstrates the highest accuracy across datasets, while ResNet-18 tends to overfit.

05

DenseNet-121 exhibits consistent learning and stronger generalization.

Hyper Parameter Tuning and Ablative Study

01 Hyperparameter Tuning

- Learning rate adjustment crucial for model convergence.
- Optimal learning rate for ResNet-18 on a 5-class dataset was 0.001, with limited computational resources preventing further hyperparameter fine-tuning.

02 Transfer Learning

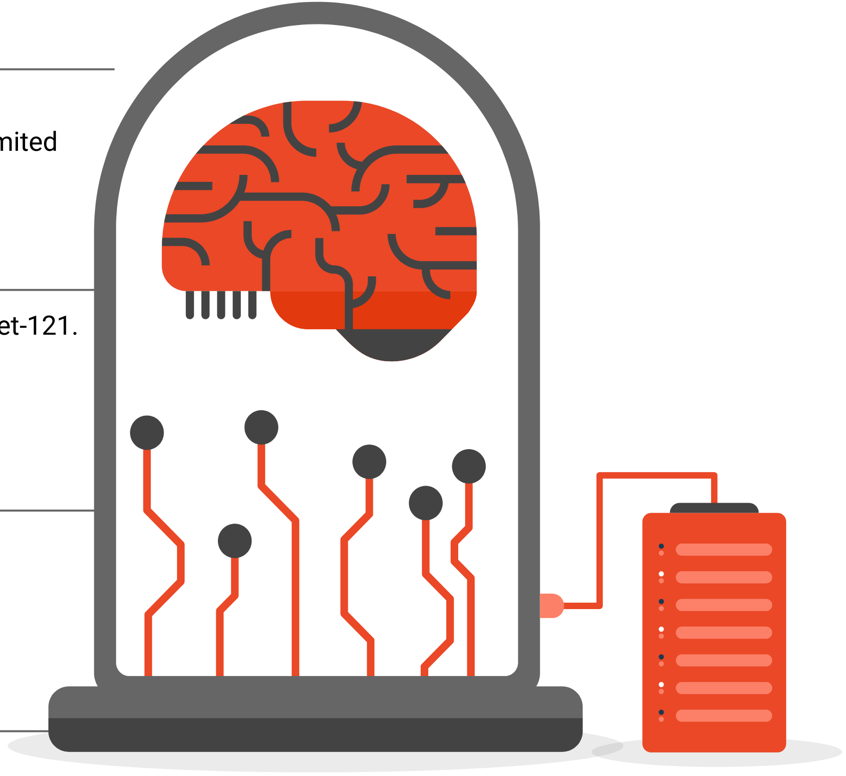
- Pretrained weights from IMAGENET1K V1 used for ResNet-18 and DenseNet-121.
- Pretrained models improve initial accuracy and convergence speed, while overfitting is countered with regularization and data augmentation.

03 Feature Understanding using t-SNE

- t-SNE visualization reveals class clusters and overlap.
- Pretrained weights lead to more generalized but less distinct feature representations.

04 Ablative Study

- Learning Rate Finder tool identifies optimal learning rate of 0.001.
- Performance metrics inversely correlate with the number of classes in the dataset.



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THANK YOU