

22-03-2024

DEEP LEARNING FOR PNEUMONIA DETECTION



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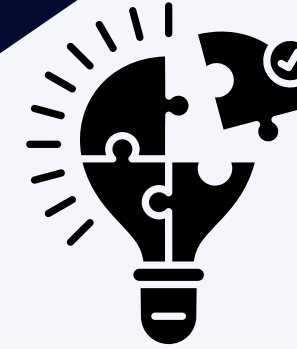
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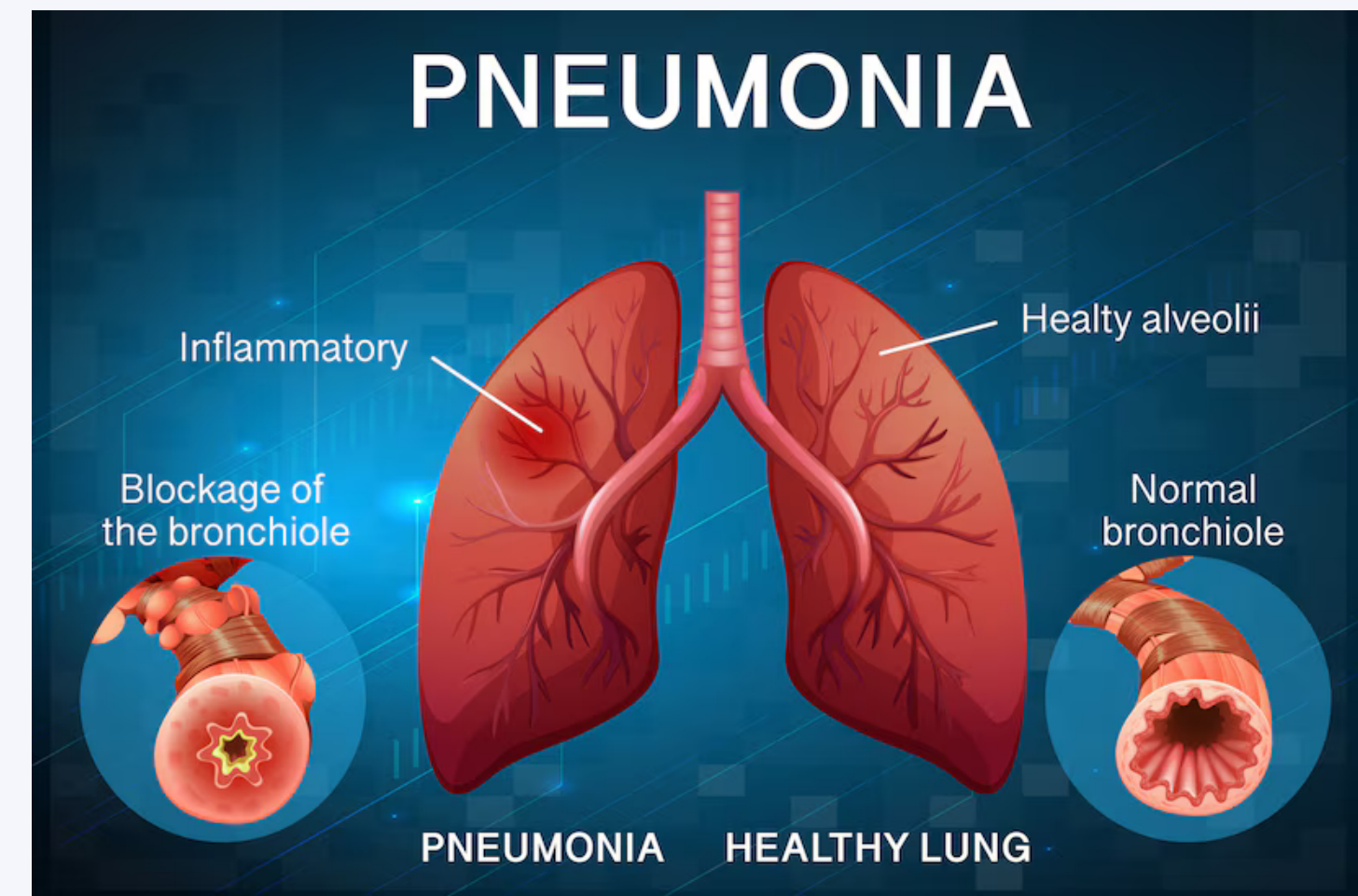


PROBLEM STATEMENT



RESULTS EVALUATION

- Pneumonia is a serious respiratory illness, especially affecting vulnerable groups.
- Current diagnosis methods have limitations:
 - Time delays
 - Subjectivity
 - Dependence on specialized expertise
- Urgent need for faster, objective, and accessible diagnostic tools.
- The Research questions are as follows:
 - Best deep learning model for pneumonia detection accuracy?
 - Transfer learning's effect on pneumonia detection?
 - Model vs. radiologist performance: clinical relevance?



OBJECTIVES

- 01** Develop an automated system for pneumonia identification using deep learning techniques.
- 02** Train the system to detect pneumonia from chest X-ray images.
- 03** Validate the system's performance against current diagnostic methods.



THE PROCESS

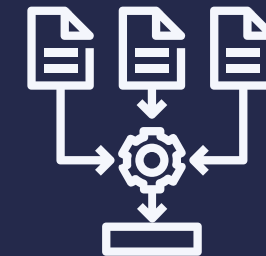
- The research process was generally divided into 3 sections:
 - Exploratory Data Analysis & Preprocessing
 - Modeling
 - Results Evaluation

EDA & DATA PREPROCESSING



Initial analysis to understand data distribution and classes as well as to prepare it for modeling

MODELING



Developed and trained various Deep Learning algorithms to detect pneumonia cases from chest x-rays

RESULTS EVALUATION



Compared model performance using metrics such as accuracy and loss on test results

MODELING

RESULTS EVALUATION

- In the modeling phase, various deep learning models were developed and trained using the preprocessed data.

MODELING

Compared model performance using metrics such as accuracy, precision, recall, and loss on test results

01

Baseline CNN Model

DATA
PROCESSING

02

Tuned Baseline CNN Model

Used various deep learning algorithms to detect pneumonia cases from chest x-rays

03

Different Architecture CNN

Analysis to find data and class labels to prepare for modeling

04

ResNET50V2 Model



MODEL RESULTS

- **Accuracy:**

- Baseline Model: **38%**
- Tuned Baseline Model: **42%**
- Different Architecture Model: **63%**
- ResNet50v2 Model: **92%**

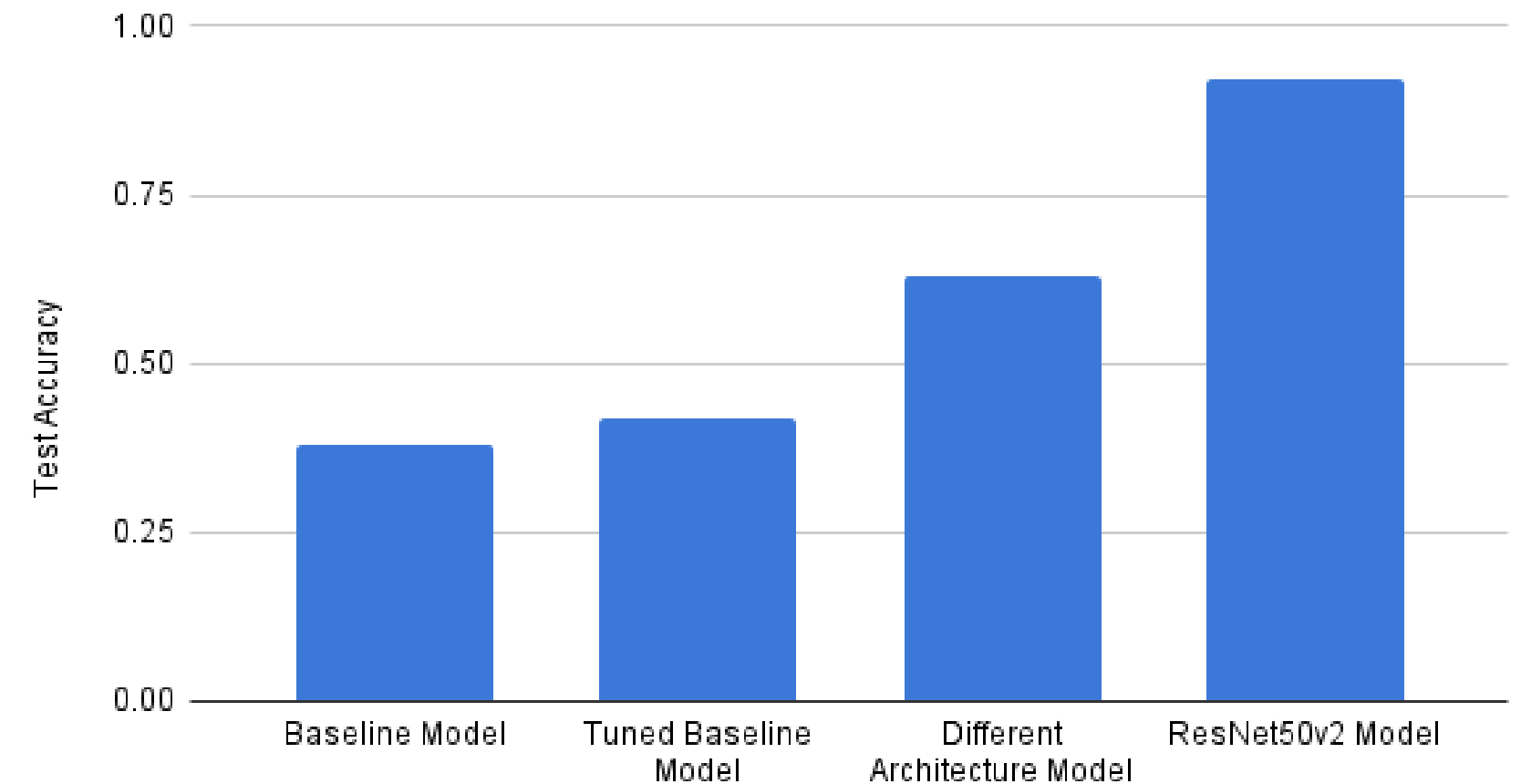
- **Training Times:**

- Baseline Model: **48.40 mins**
- Tuned Baseline Model: **26.45 mins**
- Different Architecture Model: **10.25 mins**
- ResNet50v2 Model: **48 mins**

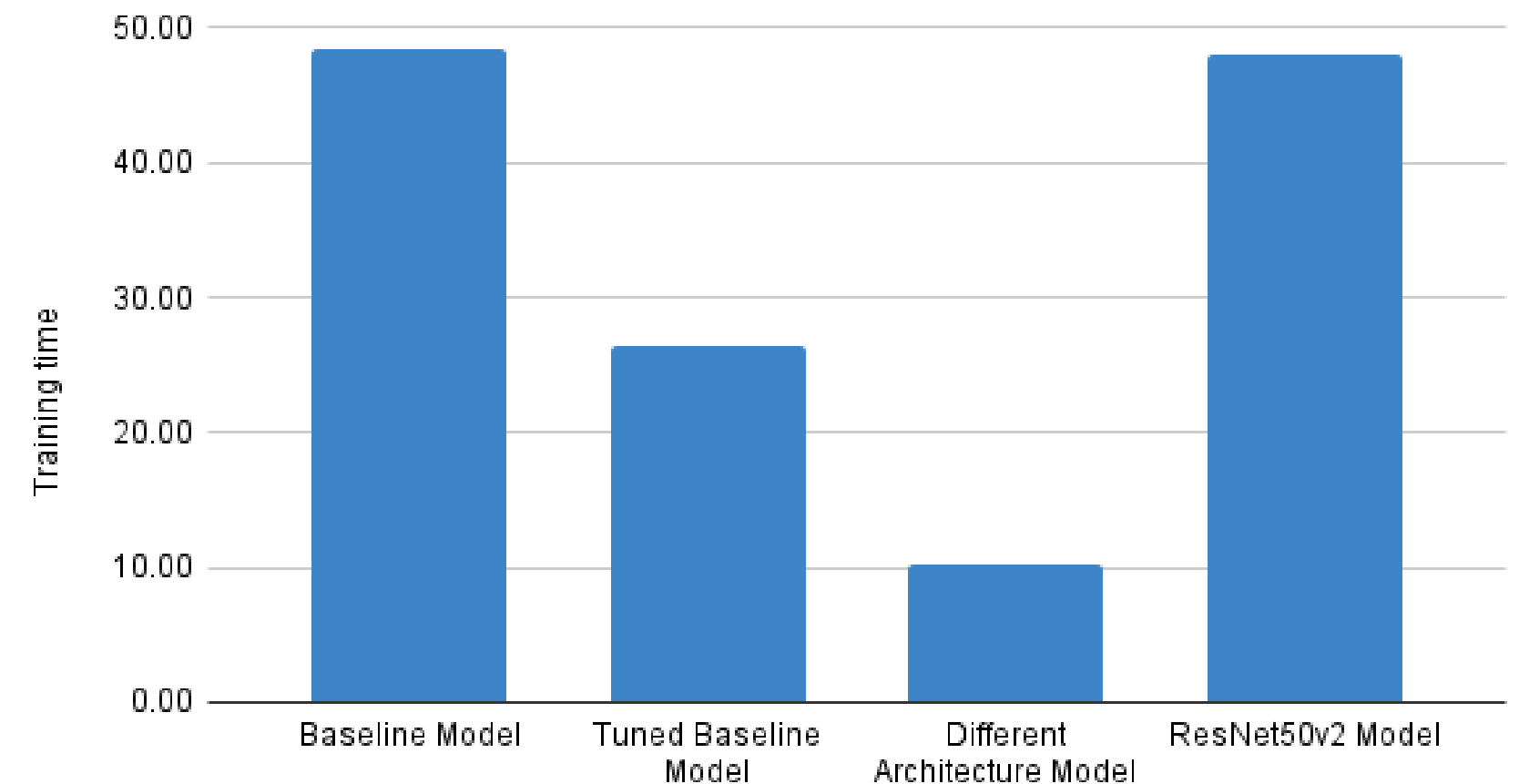
60%

Average Human
Radiologist
Accuracy

Test Accuracy vs. Model



Training Time Vs. Model



COMPARATIVE ANALYSIS



SN.NO	Model Name	Model Architecture	Hyperparameters	Training Time	Validation Accuracy	Test Accuracy	Test Loss
1	Baseline Model	CNN with original architecture	Adam optimizer, lr=0.001	48.40 mins	0.50	0.38	172.32
2	Tuned Baseline Model	CNN with original architecture	Adam optimizer, lr=0.001, early stopping	26.45 mins	0.56	0.42	40.07
3	Different Architecture Model	CNN with modified architecture	Adam optimizer, lr=0.001, early stopping	10.25 mins	0.45	0.63	19.45
4	ResNET50v2 Model	Pretrained ResNet50v2	Adam optimizer, lr=0.0001	48 mins	0.88	0.92	0.23



RECOMMENDATIONS



While the results from the models are promising, there can be further improvements to get the most accurate diagnoses using deep learning:

- Validation: Validating the developed model through clinical trials is needed to ensure its reliability for diagnoses.
- Deployment: Focus on creating a system that functions effectively with limited computational resources.
- Accuracy: Further optimization of hyperparameters such as dropout rate and batch size to enhance model performance.





THANK YOU!

PRESENTED BY: JOYLEEN CHERONO
ALLAN ESHITERA
JOHNMARK KIBUI
ANDREW MAINA
COLINS WANJAO