Pneumonia Detection in Radiological Images:

Using A.I and Deep Learning.

Introduction:

In this study, we use deep learning to detect pneumonia in children through chest X-ray images. We've meticulously selected and validated our dataset from a children's medical center. Using TensorFlow, we've crafted and refined models for both accuracy and computational efficiency, crucial for practical medical applications. This research represents the intersection of advanced technology and pediatric healthcare, offering the potential to elevate patient care and diagnostic efficiency. We advocate for further exploration of deep learning in healthcare, particularly in pediatrics, as it holds promise for enhancing healthcare outcomes.

Report Overview :

1. Business Understanding
2. Data Assembly And Preparation
3. Modelling
4. Model Refinement and Evaluation
5. Summary.
6. Recommendations.

Business Understanding :

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Intended audience:

St. Mary's Hospital (Hospital): St. Mary's utilizes the models in radiology to enhance early pneumonia detection, particularly in critical cases. This approach improves patient care and optimizes resource allocation, aligning with St. Mary's commitment to high-quality healthcare.

MediTech Research Corporation (Medical Drug Research Company): MediTech incorporates these models into medical trials to monitor disease progression more effectively. The insights derived from this research bolster MediTech's clinical trials and support the development of innovative disease-monitoring methods.

Problem Statement :

In pediatric healthcare, accurately diagnosing pneumonia is a pressing challenge. Traditional methods relying on manual chest X-ray interpretation are prone to errors, causing delays and resource strain. This affects patient care and healthcare efficiency.

The current diagnostic process lacks consistency, especially where expert radiologists are scarce. There's a crucial need for a reliable, efficient diagnostic tool for pediatric pneumonia. It should speed up diagnosis, reduce subjectivity, and optimize resource use while maintaining or enhancing accuracy.

Solving this challenge is vital to improve pediatric healthcare and healthcare system efficiency. Developing and implementing an advanced diagnostic solution using deep learning on chest X-ray images has the potential to transform pediatric pneumonia diagnosis, leading to better treatment outcomes and resource management.

Objectives :

1. Develop Deep Learning Models: Create precise deep learning models for pediatric chest X-ray analysis, optimizing for pneumonia detection and computational efficiency.

2. **Enhance Diagnostic Accuracy:** Validate models with diverse pediatric chest X-rays, measuring diagnostic accuracy and comparing to conventional methods.

3. **Enable Early Diagnosis:** Develop algorithms for early pneumonia detection and implement an automated severity scoring system.

4. **Optimize Resource Allocation:** Build a triage system to categorize cases by severity, aiding resource allocation and improving healthcare efficiency.

Metrics Used for Model Evaluation :

1. **Accuracy:** Measures overall correctness.
2. **Sensitivity (Recall):** Ability to detect positive cases.
3. **Specificity:** Precision in identifying negatives.
4. **Precision:** Accuracy of positive predictions.
5. **F1 Score:** Balance between precision and recall.
6. **AUC-ROC:** Discrimination ability.
7. **Loss Function:** Measures prediction disparity.

These metrics provide a comprehensive assessment of our deep learning models for pediatric pneumonia detection, from basic correctness to disease detection and prediction accuracy.

Our project will be considered a success if it achieves:

1. **High Accuracy:** Indicates model proficiency.
2. **High Sensitivity (Recall):** Ensures early disease detection.
3. **High Specificity:** Minimizes false alarms.
4. **Balanced F1 Score:** Addresses imbalanced data.
5. **High AUC-ROC Score:** Effective class distinction.
6. **Low Loss Function:** Better model convergence.

Meeting these success metrics demonstrates our models' real-world impact in improving pediatric pneumonia diagnosis, enhancing patient care and healthcare resource optimization.

Dataset Overview:

- **Source:** Guangzhou Women and Children's Medical Center, China.

- **Patient Age:** One to five years old.

- **Classes:** "Pneumonia" and "Normal."

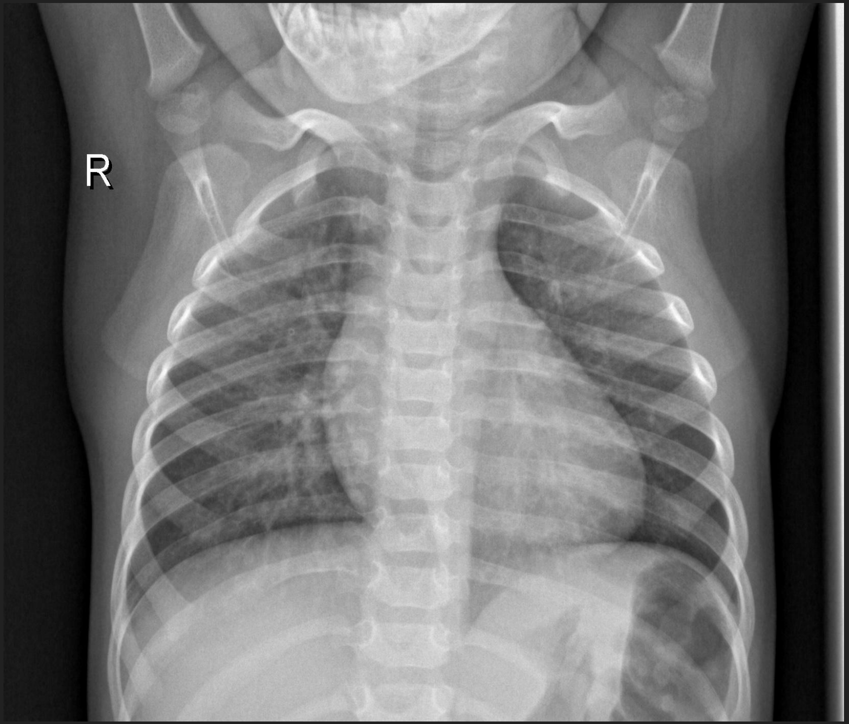
- **Size:** 5,863 X-ray images in JPEG format.

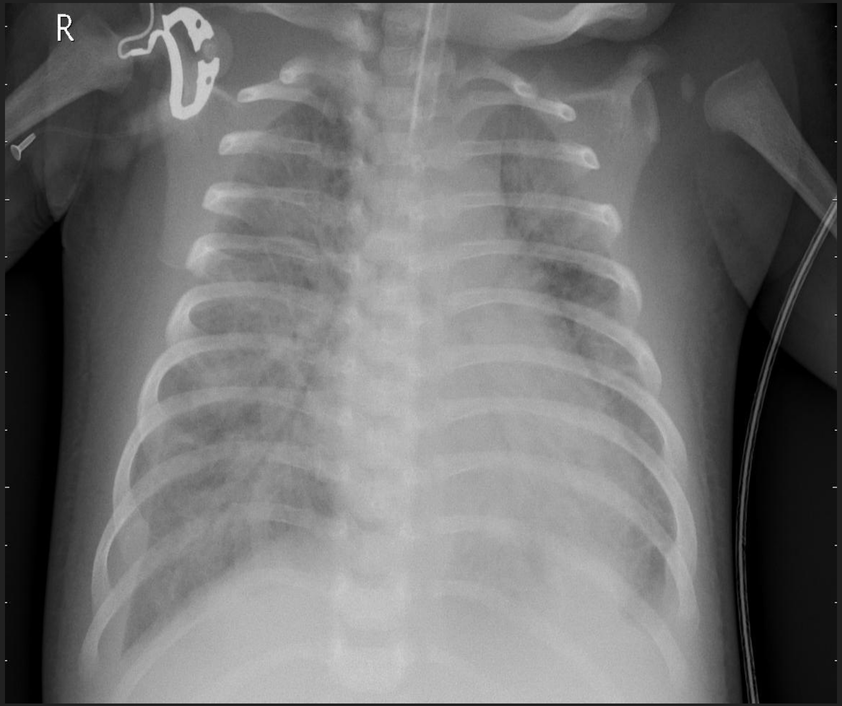
- **License:** CC BY 4.0.

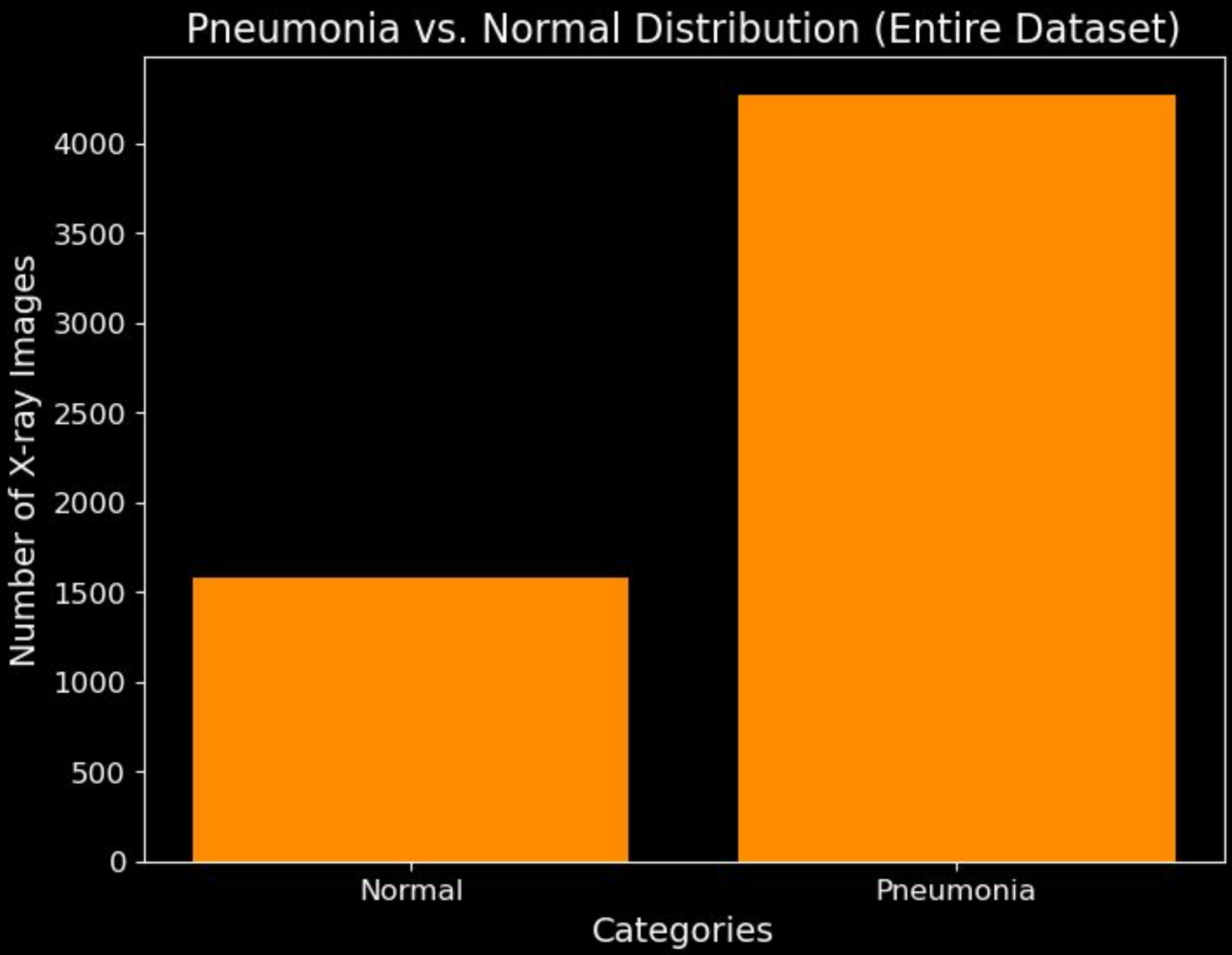
- **Publication:** [Mendeley Dataset](Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification - Mendeley Data)

- **Citation:** [Cell Publication](Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning: Cell)

Our classes preview: Left (normal), Right(pneumonia)






Pneumonia vs. Normal Distribution (Entire Dataset)
Number of X-ray Images
0
500
1000
1500
2000
2500
3000
3500
4000
Normal
Pneumonia
Categories

Modelling :

Modelling Methodology

we developed and fine-tuned five models. Each model represents a step towards enhanced feature extraction and better accuracy. Given limited computing resources, we initially trained all five models for a constrained 10 iterations each to evaluate their performance. After careful evaluation, we identified the best-performing model, which showed the most promise for accurate pneumonia detection.

Baseline Model:

- **Architecture:** A single Fully Connected (Dense) layer followed by a Flatten layer.

- **Optimization:** Adam optimizer, binary cross-entropy loss function, accuracy metric.

- **Training:** Trained on the training data with validation on a separate validation set.

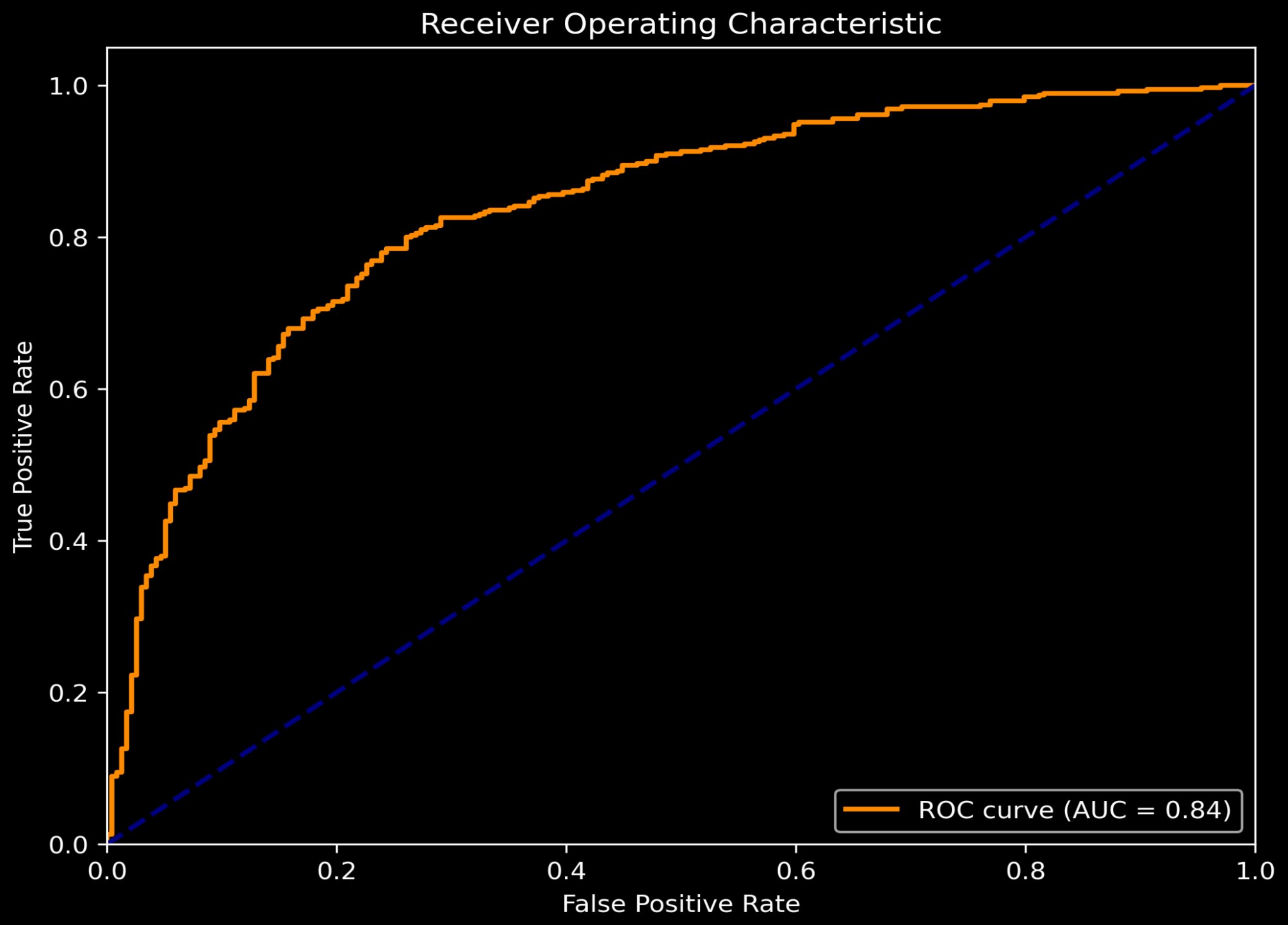
- **Evaluation:** Assessed on the test data, using data augmentation.

- **Purpose:** Establishes a performance baseline for more complex models aimed at enhancing pneumonia detection accuracy in X-ray images.

Baseline Model Evaluation:

- **Test Accuracy**: Achieved 75.80% accuracy on the test dataset.
- **Validation Accuracy:** Reached 73.28% during training.
- **Training Accuracy**: Attained 86.26% on the training dataset.
- **Precision:** Scored 75.26%, indicating the model's ability to identify pneumonia cases.
- **Recall:** Achieved 91.28%, showcasing the model's capability to detect actual pneumonia cases.
- **F1 Score:** Obtained an F1 score of 82.50% as a balanced measure of precision and recall.
- **AUC-ROC:** Registered an AUC-ROC of 83.51% for distinguishing between classes.

Baseline Model ROC-AUC Curve :



Confusion Matrix Analysis

- **True Positives (TP)**: The model correctly predicted 356 pneumonia cases.

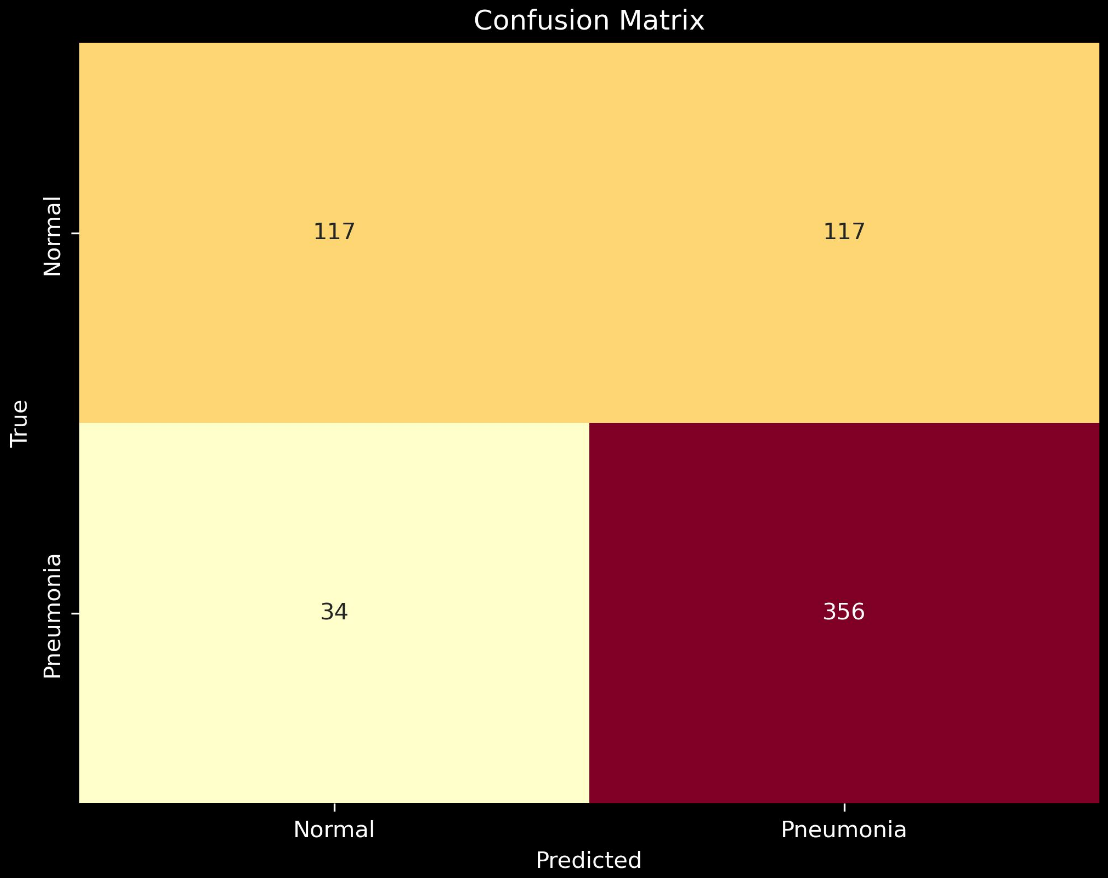
- **True Negatives (TN)**: The model correctly identified 117 normal cases.

- **False Positives (FP)**: It incorrectly classified 117 normal cases as pneumonia.

- **False Negatives (FN)**: It missed 34 actual pneumonia cases.

These results provide a comprehensive view of the model's performance in terms of correct and incorrect classifications, which is essential for evaluating its effectiveness in diagnosing pneumonia from X-ray images.

Baseline Model Confusion Matrix:



Model 1:

Model 1 (Simple CNN):

- **Input Shape:** Grayscale images (224x224 pixels).

- **Architecture:** One convolutional layer (32 filters, ReLU activation) followed by max-pooling, a flattening layer, one hidden layer (128 neurons, ReLU activation), and an output layer (1 neuron, sigmoid activation) for binary classification.

- **Purpose:** Detects patterns in X-ray images to classify them as normal or pneumonia cases.

Model 1 Evaluation:

- **Test Accuracy**: The model achieved an accuracy of approximately 72.12% on the test dataset.

- Validation Accuracy: The validation accuracy was approximately 82.76%.

- **Training Accuracy:** During training, the model reached a high training accuracy of approximately 92.79%.

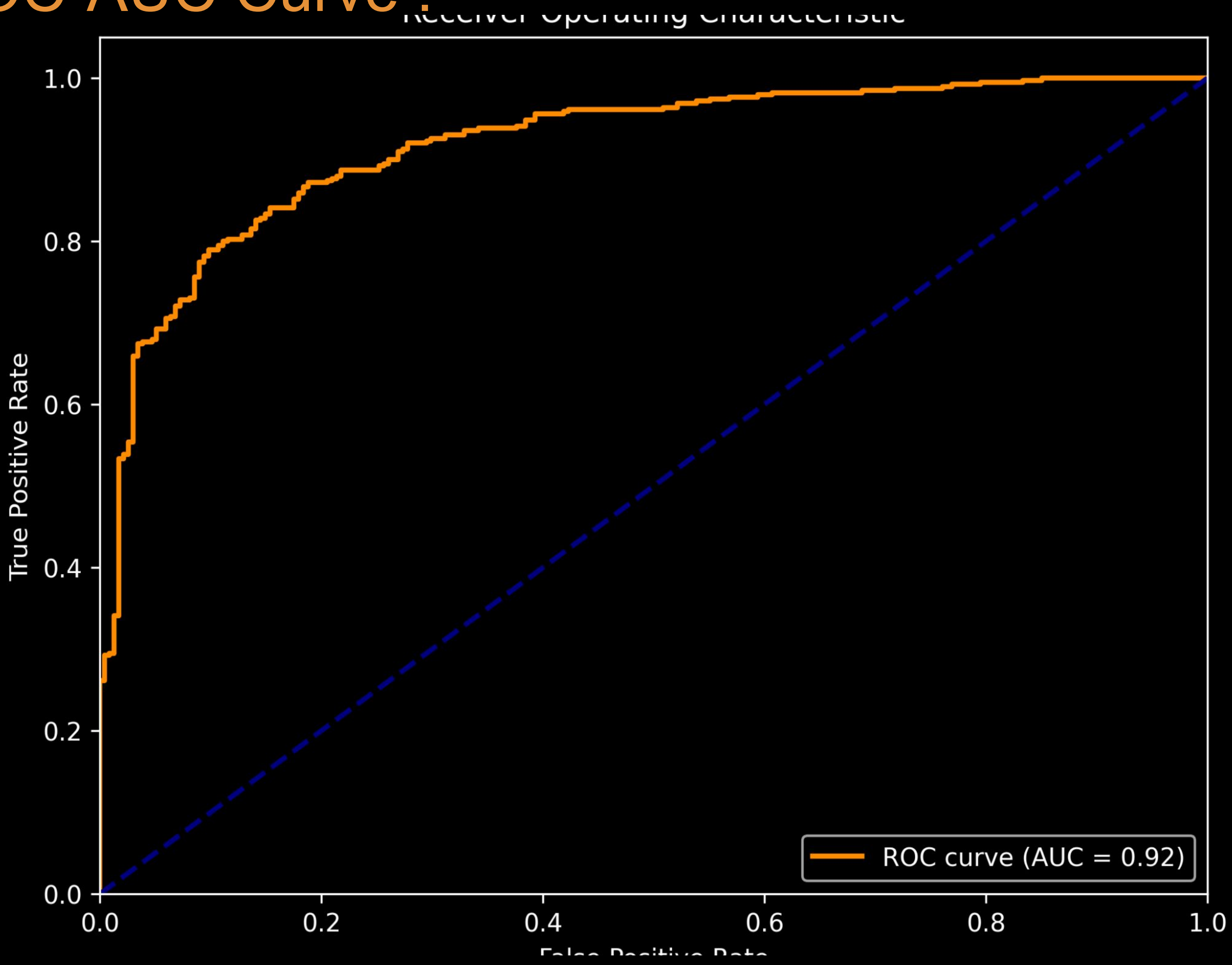
- **Precision:** The precision score, which measures the model's ability to correctly classify positive cases, was approximately 69.57%.

- **Recall:** The recall score, indicating the model's ability to correctly identify all relevant instances, was approximately 98.46%.

- **F1 Score:** The F1 score, which balances precision and recall, was approximately 81.53%.

- **AUC-ROC:** The area under the ROC curve (AUC-ROC) was approximately 91.85%, showcasing the model's overall discriminative ability

Model1 ROC-AUC Curve :



Confusion Matrix Analysis

- True Positives (TP): 384 cases correctly predicted as pneumonia.

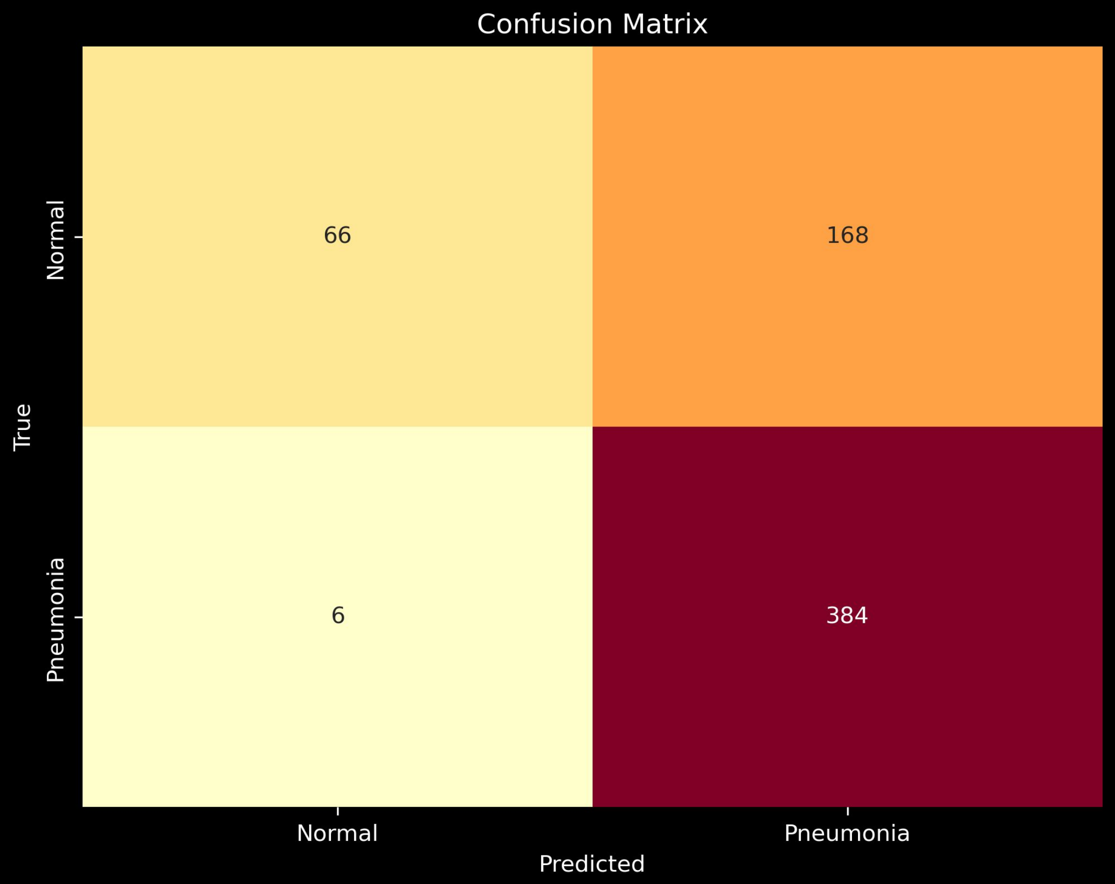
- True Negatives (TN): 66 normal cases correctly identified.

- False Positives (FP): 168 normal cases incorrectly classified as pneumonia.

- False Negatives (FN): 6 actual pneumonia cases missed by the model.

These results provide insights into the performance of Model 5 in pneumonia detection, highlighting its high recall and overall effectiveness.

Model 1 Confusion Matrix:



Model 2:

(Deeper CNN)

- **Input Shape:** Grayscale images (224x224 pixels).

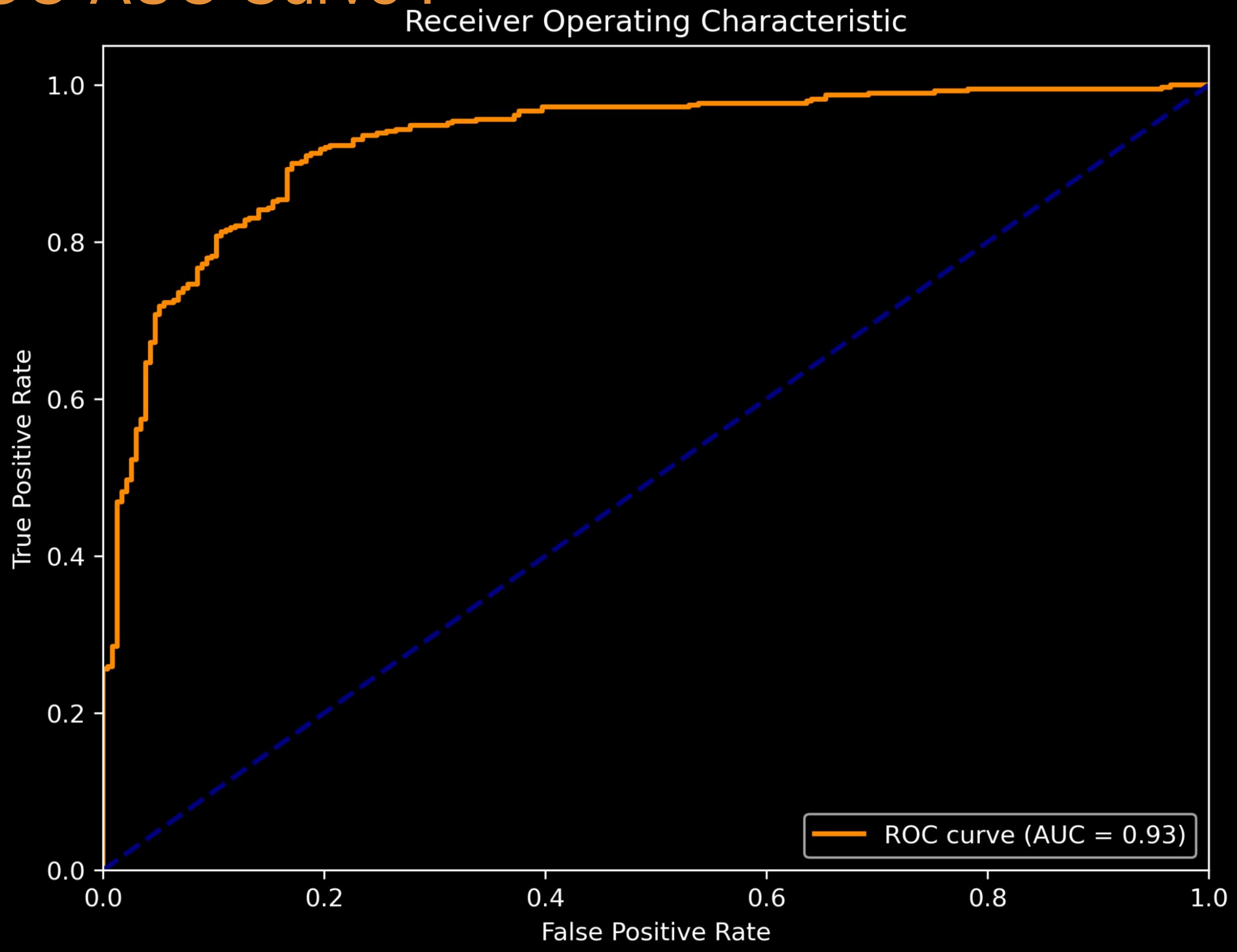
- **Architecture:** This model includes two convolutional layers. The first convolutional layer consists of 32 filters with ReLU activation, followed by a max-pooling layer. The second convolutional layer has 64 filters with ReLU activation, followed again by max-pooling. The architecture also includes a flattening layer, one hidden layer with 128 neurons and ReLU activation, and an output layer with 1 neuron and sigmoid activation for binary classification.

- **Purpose:** Model 2 aims to capture more complex patterns and features in X-ray images by introducing additional convolutional layers, potentially improving its ability to distinguish between normal and pneumonia cases.

Model 2 Evaluation:

1. **Test Accuracy:** 75.80%- Indicates the proportion of correctly classified test samples.
2. **Validation Accuracy:** 73.28%- Represents the model's performance on a validation dataset used during training.
3. **Training Accuracy:** 86.26%- Reflects how well the model learned from the training dataset.
4. **Precision:** 75.26% - Measures the accuracy of positive predictions made by the model.
5. **Recall (Sensitivity):** 91.28% - Evaluates the model's ability to correctly identify positive cases.
6. **F1 Score:** 82.50% - The harmonic mean of precision and recall, providing overall performance.
7. **AUC-ROC:** 83.51%- Indicates the model's ability to distinguish between classes.

Model2 ROC-AUC Curve :



Confusion Matrix Analysis

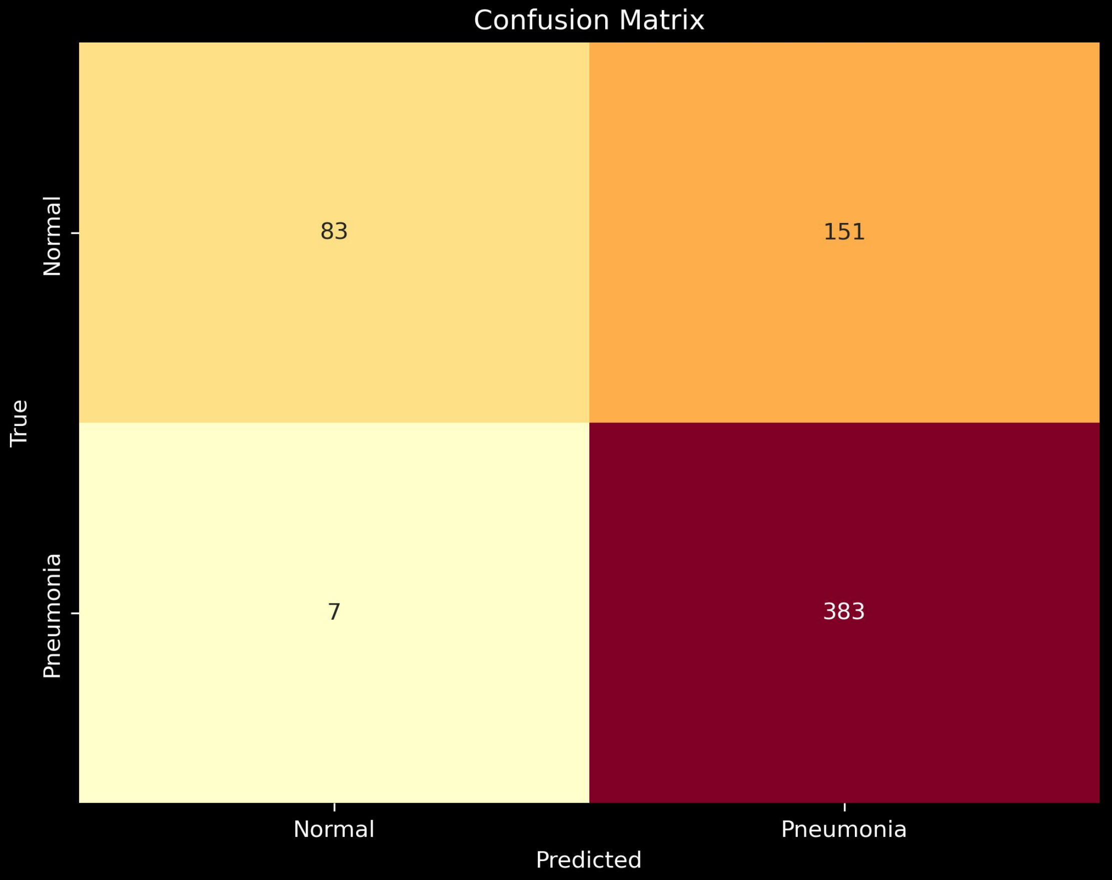
- True Positives (TP): The model correctly predicted 383 cases as pneumonia.

- True Negatives (TN): It accurately identified 83 normal cases.

- False Positives (FP): There were 151 normal cases that the model incorrectly classified as pneumonia.

- False Negatives (FN): The model missed 7 actual pneumonia cases.

Model 2 Confusion Matrix:



Model 3:

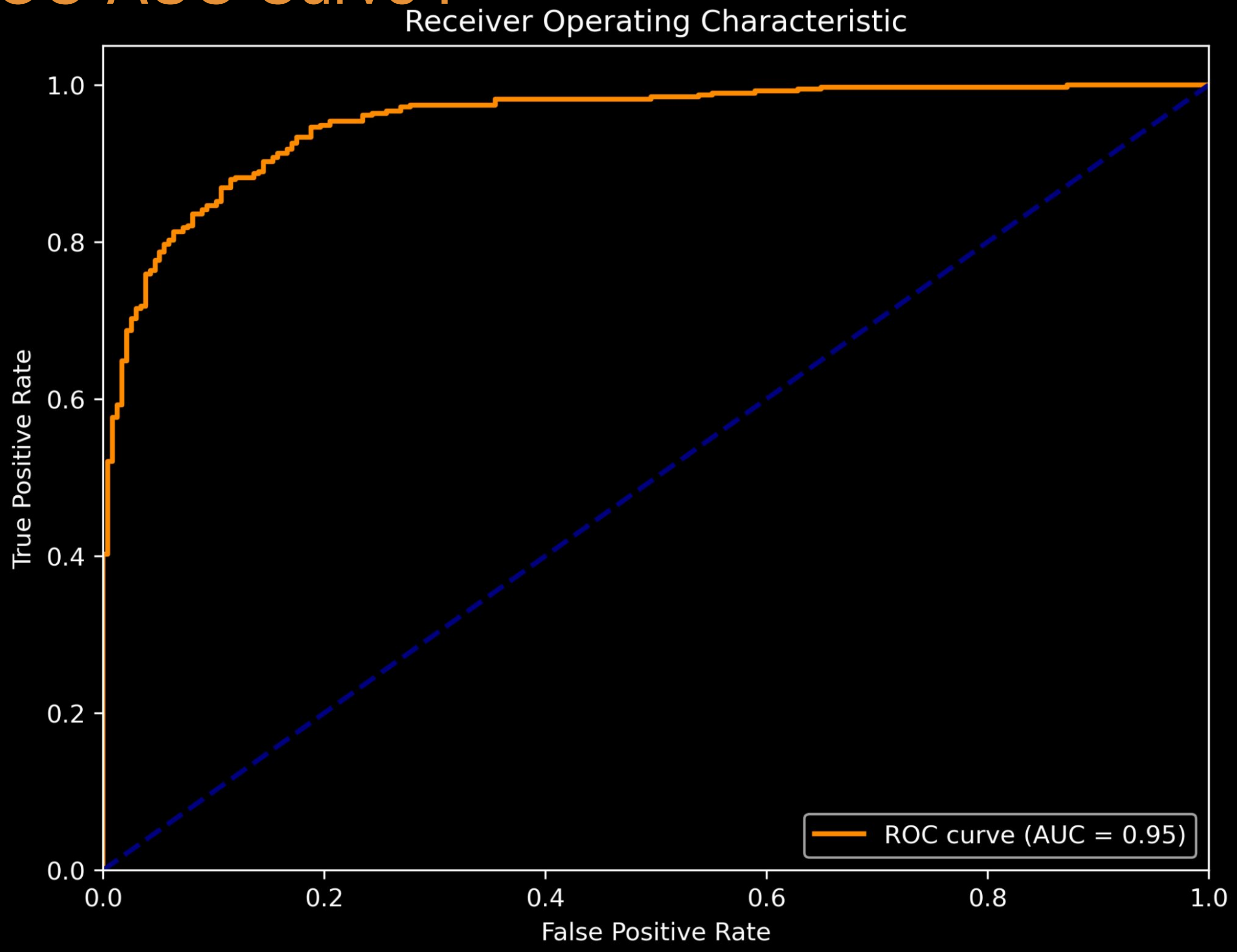
Model 3, a Convolutional Neural Network (CNN), is tailored for pneumonia detection from 224x224 grayscale X-ray images. It boasts two convolutional layers with 32 and 64 filters, both employing ReLU activation functions, followed by two max-pooling layers for spatial dimension reduction. Afterward, a flattening layer transforms the 2D feature maps into a 1D vector, feeding into a dense layer with 128 neurons using ReLU activation.

To curb overfitting and enhance generalization, a dropout layer with a 0.5 dropout rate is inserted. Finally, an output layer with sigmoid activation yields binary classification predictions, where values close to 0 indicate normal cases and values near 1 signify pneumonia. This intricate architecture empowers Model 3 to excel in pneumonia detection tasks while resisting overfitting.

Model 3 Evaluation:

1. **Test Accuracy:** 76.76% - Proportion of correctly classified test samples.
2. **Validation Accuracy:** 79.31% - Model's performance on a validation dataset during training.
3. **Training Accuracy:** 93.28% - Reflects how well the model learned from the training dataset.
4. **Precision:** 73.16% - Accuracy of positive predictions.
5. **Recall (Sensitivity):** 99.23% - Model's ability to identify positive cases.
6. **F1 Score:** 84.22% - Harmonic mean of precision and recall, providing overall performance.
7. **AUC-ROC:** 95.40% - Model's ability to distinguish between classes.

Model 3 ROC-AUC Curve :



Confusion Matrix Analysis

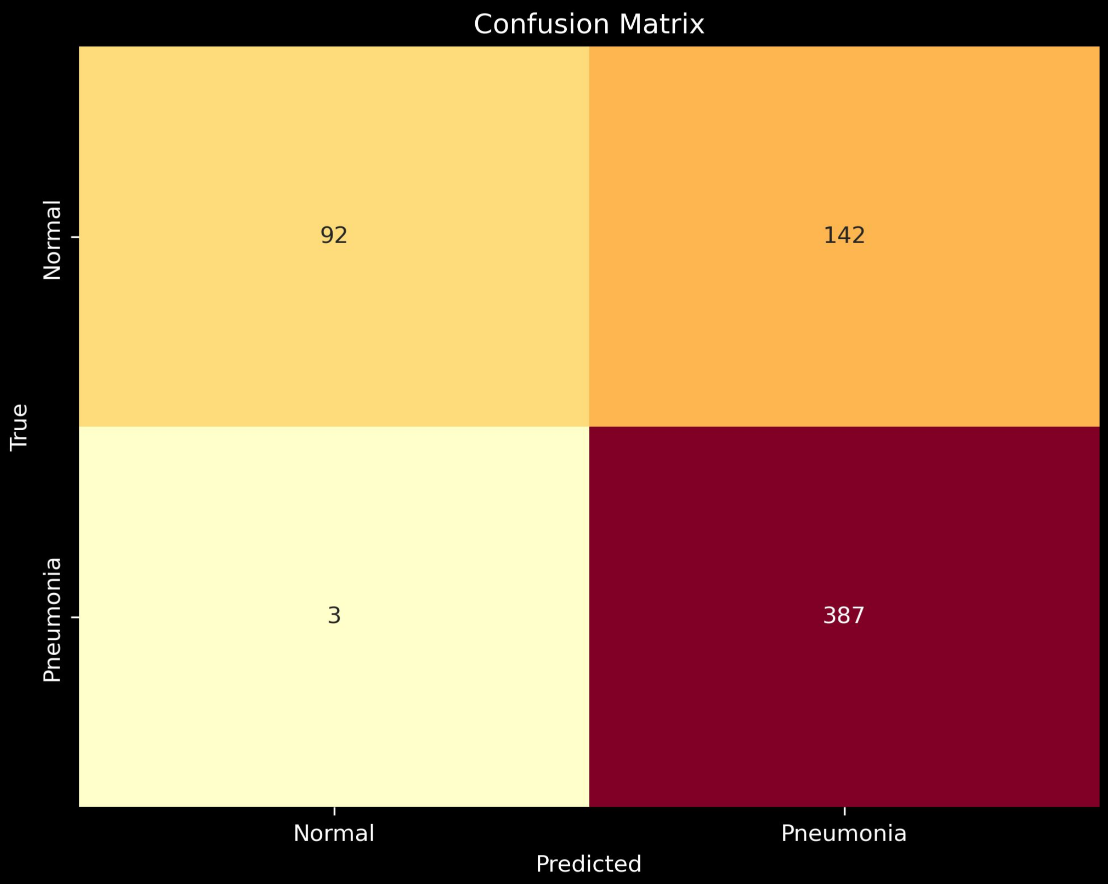
- There are 92 true negatives, indicating that the model correctly identified 92 healthy cases.

- There are 142 false positives, signifying cases where the model incorrectly predicted the condition when it was absent.

- There are 3 false negatives, representing cases that the model missed.

- There are 387 true positives, meaning the model accurately identified 387 positive cases.

Model 3 Confusion Matrix:



Model 4 :

Model 4 (Deeper CNN with Batch Normalization) is a deep convolutional neural network designed to classify grayscale X-ray images (224x224 pixels) for pneumonia detection. It includes convolutional layers with 32, 64, and 128 filters, each followed by batch normalization and max-pooling layers. These architectural elements enhance feature extraction and training stability. A fully connected layer with 256 neurons and ReLU activation learns high-level features, while a dropout layer with a 0.5 dropout rate prevents overfitting. The final output layer, with sigmoid activation, facilitates binary classification. This model aims to improve accuracy and stability in pneumonia detection.

Model 4 Evaluation:

1. Test Accuracy: 83.97% - Indicates the proportion of correctly classified test samples.

2. Validation Accuracy: 85.34% - Represents the model's performance on a validation dataset during training.

3. Training Accuracy: 88.31% - Reflects how well the model learned from the training dataset.

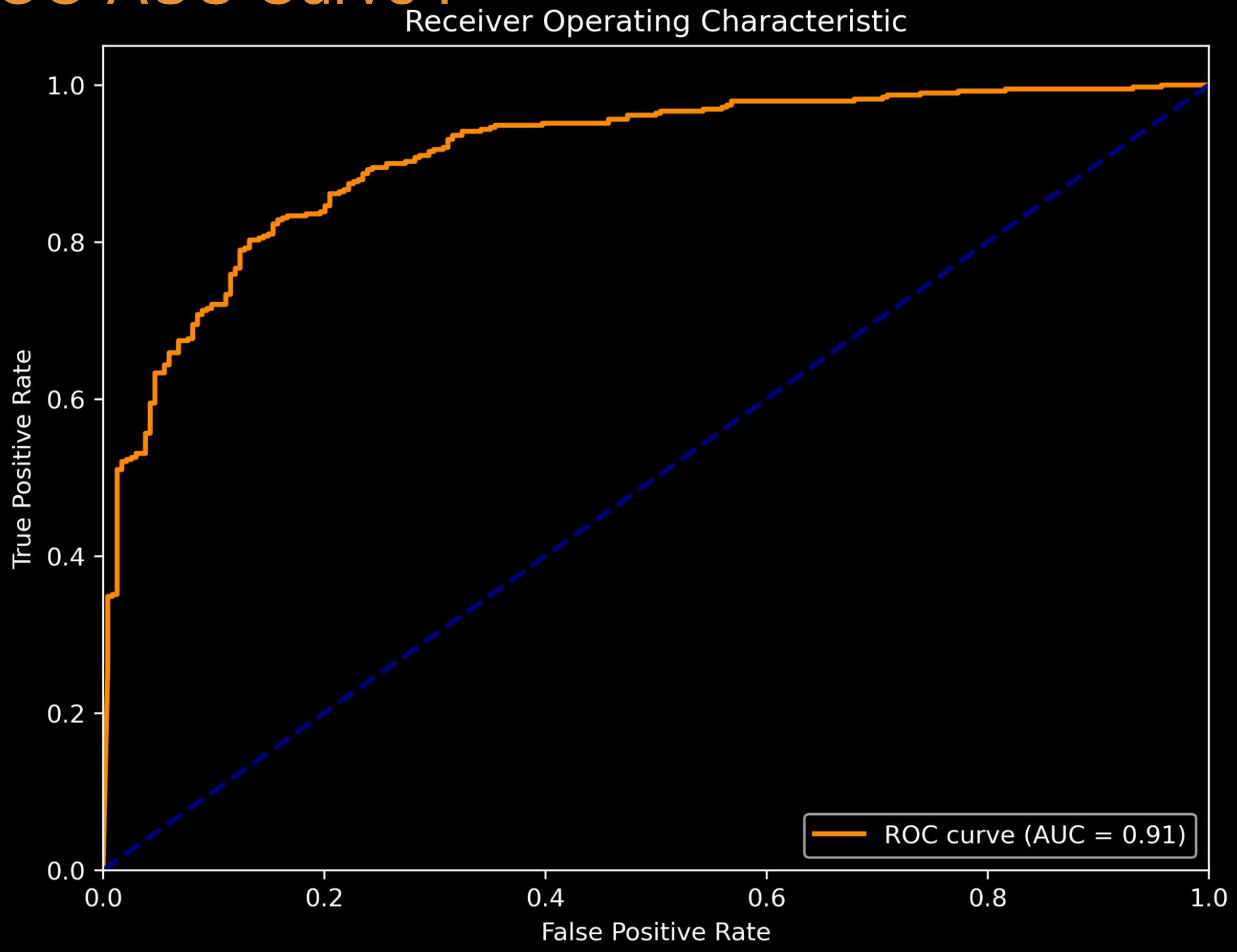
4. Precision: 85.19% - Measures the accuracy of positive predictions.

5. Recall (Sensitivity): 90.00% - Evaluates the model's ability to identify positive cases.

6. F1 Score: 87.53% - The harmonic mean of precision and recall, providing overall performance.

7. AUC-ROC: 90.95% - Indicates the model's ability to distinguish between classes.

Model 4 ROC-AUC Curve :



Confusion Matrix Analysis

In the confusion matrix:

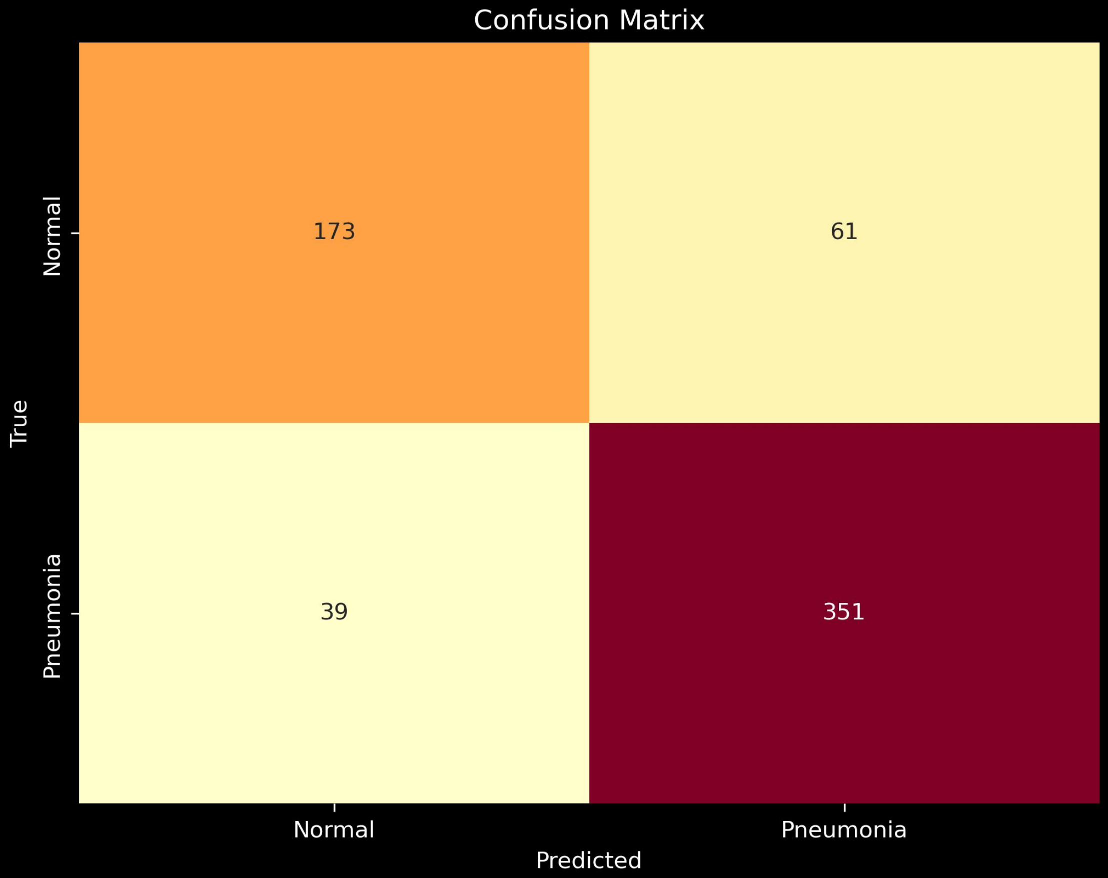
- True Positives (TP): 351 - The model correctly identified 351 pneumonia cases.

- True Negatives (TN): 173 - The model correctly identified 173 normal cases.

- False Positives (FP): 61 - The model incorrectly classified 61 normal cases as pneumonia.

- False Negatives (FN): 39 - The model incorrectly classified 39 pneumonia cases as normal.

Model 4 Confusion Matrix:



Model 5 :

Model 5 (CNN with Regularization):

- **Architecture:** This model utilizes a deep convolutional neural network (CNN) with multiple layers for feature extraction, including convolutional and pooling layers. It also includes a global average pooling layer for spatial dimension reduction and a fully connected layer for high-level feature learning. Dropout regularization with a rate of 0.5 is applied to prevent overfitting.

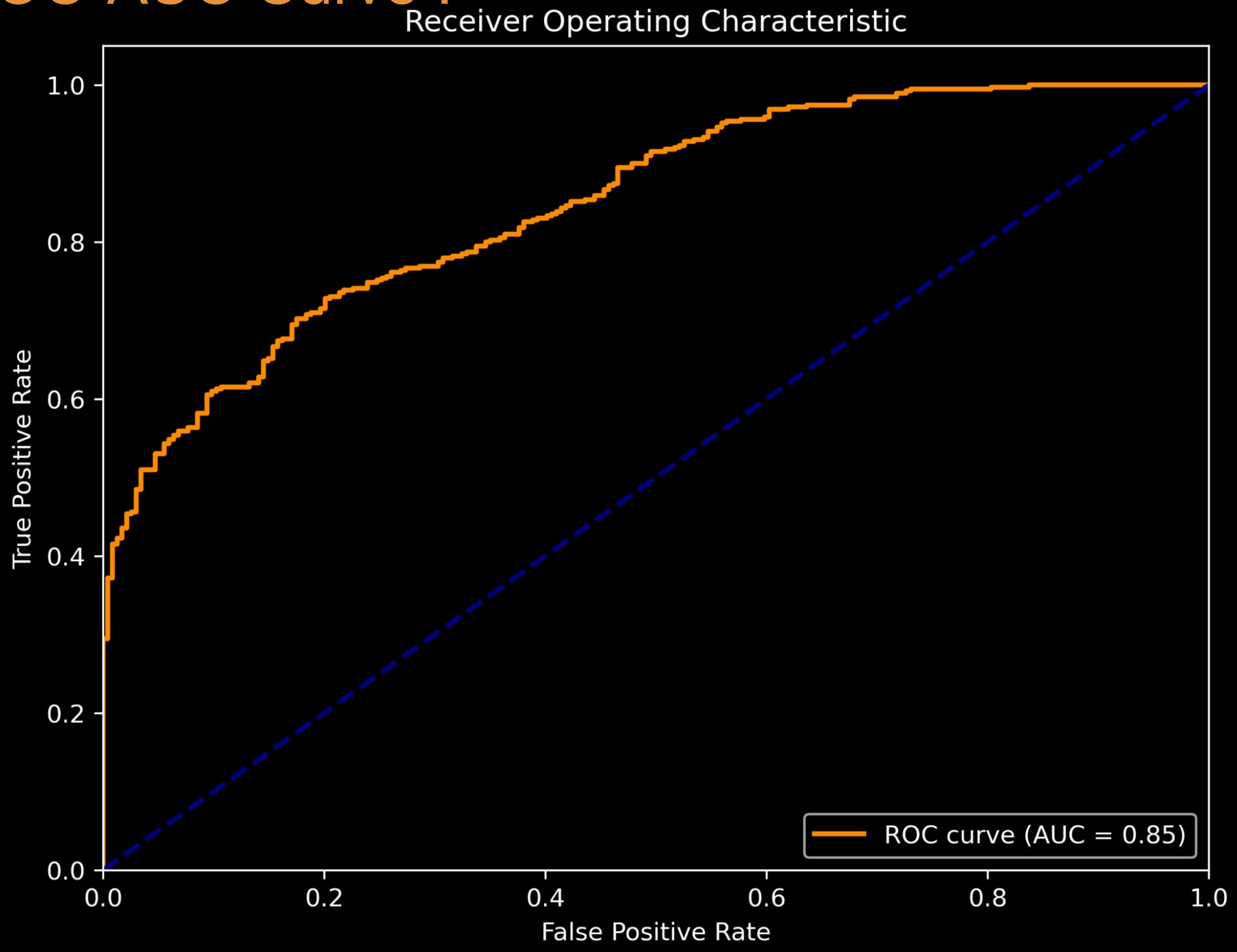
- **Regularization:** Dropout with a rate of 0.5 is employed to prevent overfitting by randomly deactivating 50% of neurons during training. And l2 regularization of 0.01

- **Purpose:** Model 5 aims to enhance generalization and mitigate overfitting while efficiently classifying X-ray images for pneumonia detection, thanks to the inclusion of dropout regularization and global average pooling.

Model 5 Evaluation:

1. **Test Accuracy:** 74.84% - Proportion of correctly classified test samples.
2. **Validation Accuracy:** 80.17% - Model's performance on a validation dataset during training.
3. **Training Accuracy:** 87.71% - Reflects how well the model learned from the training dataset.
4. **Precision:** 75.95% - Accuracy of positive predictions.
5. **Recall (Sensitivity):** 87.44% - Model's ability to identify positive cases.
6. **F1 Score:** 81.29% - Harmonic mean of precision and recall, providing overall performance.
7. **AUC-ROC:** 84.87% - Model's ability to distinguish between classes.

Model 5 ROC-AUC Curve :



Confusion Matrix Analysis

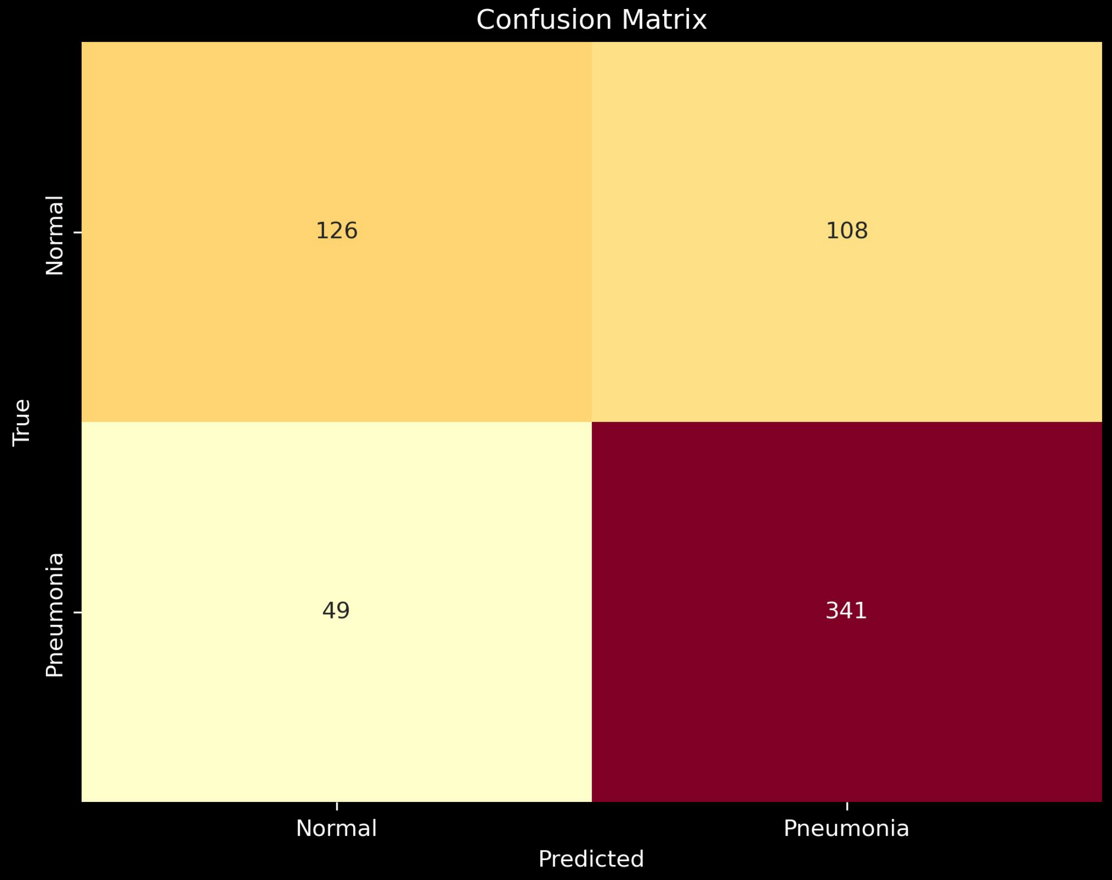
-True Positives (126): The number of pneumonia cases correctly predicted.

- True Negatives (341): The number of normal cases correctly predicted.

- False Positives (108): The number of normal cases incorrectly predicted as pneumonia.

- False Negatives (49): The number of pneumonia cases incorrectly predicted as normal.

Model 5 Confusion Matrix:



Final model:

We selected Model 4 as our final model due to its superior performance compared to other models. It achieved the highest test accuracy, precision, recall, F1 score, and AUC-ROC value, making it the most effective in classifying X-ray images as normal or pneumonia. Model 4 also struck a balance between high recall for detecting pneumonia cases and high precision for minimizing false positives. Despite limited training epochs, it demonstrated promising results, with potential for further improvement through extended training. In summary, Model 4's exceptional accuracy and balanced performance make it the preferred choice for pneumonia detection in X-ray images.

Summary:

This project focused on developing and implementing an AI-powered pneumonia detection model using X-ray images. The model, integrated into St. Mary's Hospital's radiology department, facilitates early detection of pneumonia, particularly critical cases. Additionally, MediTech Research Corporation utilizes the model in clinical trials to monitor disease progression effectively. Key outcomes include improved patient care, optimized resource allocation, and enhanced clinical trial quality. To further benefit from this technology, recommendations encompass integration into routine workflows, training and education, data security, and collaboration between St. Mary's Hospital and MediTech Research Corporation. These efforts promise to elevate healthcare quality and accelerate medical research.

Conclusion:

In conclusion, our AI-driven pneumonia detection model presents a significant advancement in healthcare and medical research. Its deployment at St. Mary's Hospital enhances patient care, streamlines radiology operations, and supports critical case identification. For MediTech Research Corporation, the model contributes valuable insights for disease progression tracking and clinical trials.

However, successful implementation requires careful consideration of integration into existing workflows, comprehensive training, robust data security measures, and fostering strong collaboration between healthcare providers and research organizations. By adhering to these recommendations, we can fully harness the potential of this technology to improve healthcare and accelerate medical research.

Recommendations to St. Mary’s Hospital :

1. **Integration into Routine Workflow:** Continue integrating the developed pneumonia detection model into the radiology department routine workflow. Ensure that it becomes a standard tool for early detection.

2. **Training and Education:** Invest in training radiologists and medical staff in effectively using AI-assisted diagnostic tools. This includes providing ongoing workshops and resources to keep them updated on the latest advancements.

3. Data Security and Privacy: Prioritize data security and privacy to safeguard patient information. Regularly update and strengthen security protocols to comply with healthcare regulations.

4. **Performance Monitoring:** Implement a system for continuous performance monitoring of the AI model. Regularly assess its accuracy and efficiency in identifying critical cases.

5. **Resource Allocation:** Optimize resource allocation based on the model's predictions. Identify critical cases early to allocate resources effectively and improve patient care

Recommendations for MediTech Research Corporation

1. **Incorporate in Clinical Trials:** Integrate the developed pneumonia detection model into clinical trials related to respiratory diseases. Utilize its capabilities to track disease progression accurately.

2. **Research Enhancement:** Leverage insights gained from AI-assisted disease monitoring to enhance the quality and efficiency of clinical trials. Utilize the model's predictions to identify relevant patient cohorts.

3. **Collaboration:** Explore opportunities for collaboration with St. Mary's Hospital and other healthcare institutions that have implemented the AI model. Share knowledge and contribute to ongoing research efforts.

4. **Regulatory Compliance:** Ensure that the use of AI in clinical trials complies with regulatory standards. Maintain transparency in data handling and reporting.

5. **Data Collection:** Continue collecting high-quality medical imaging data for training and validation purposes. Consider expanding datasets to enhance model generalization.

6. **Publication and Communication:** Publish research findings related to the use of AI in clinical trials. Communicate the benefits and insights gained from AI-assisted disease monitoring.