Classifying Pneumonia and COVID X-Rays Using Deep Learning

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Introduction

There is a global shortage of radiologists with demand rising faster than supply [27]. Radiologists must now work more efficiently than ever to ensure timely diagnoses without compromising patient outcomes. Since 2020, COVID-19 has killed 7 million people, and pneumonia claims 2.5 million lives annually. These deaths often occur in areas where access to affordable and timely medical care is limited. Although CT scans are the gold standard for diagnosing respiratory disease [8], they are expensive and less accessible in remote communities. This project explores how deep learning can classify x-ray images as COVID-19, pneumonia, or normal, enabling radiologists to reduce diagnosis time while maintaining accuracy. This approach has the potential to improve productivity, lower costs, and extend healthcare to underserved areas using portable x-ray machines [22].

Problem Definition

The COVID-19 era has underscored the need for tools that empower medical practitioners to diagnose respiratory illnesses quickly and accurately. As of 2022, only 12 deep learning-based tools are FDA-approved for Computer-Aided Diagnosis, and none address COVID-19 [11]. A CNN classification model (trained on chest x-ray images) may help medical practitioners distinguish between COVID and pneumonia when testing is not available, lowering costs and improving patient outcomes [8, 13], with applications to future pandemics.

Literature Survey

Deep learning in medical imaging: General overview: Convolutional Neural Networks (CNNs), have shown promise in medical imaging. Technological challenges include access to high quality training data, overfitting, and the "black box" aspect of deep learning.

AI in medical imaging informatics: Current challenges and future directions: Deep-dive on segmentation, feature extraction, and classification methodologies like CNNs and transfer learning. Based on the success of Transfer Learning in this paper, we will explore using it in our project.

A comprehensive survey on the progress, process, and challenges of lung cancer detection and classification: A large meta-analysis of AI techniques used in medical imaging. Our project will address the lack of high quality data, which was highlighted as a key issue.

A machine learning-based framework for diagnosis of COVID-19 from chest X-ray images: Like our project, this paper uses both logistic regression and CNNs to detect COVID from chest x-rays.

Enhancing lung cancer diagnosis with data fusion and mobile edge computing using DenseNet and CNN: We will leverage this paper's combination of DenseNet and CNN algorithms to improve lung cancer detection from medical images.

Lung cancer detection from X-ray images using hybrid deep learning technique: Researchers combined CNN with Support Vector Machines (SVM) to improve lung cancer detection.

Generalization of deep neural networks for chest pathology classification in X-rays using generative adversarial networks: A Generative Adversarial Network (GAN) augmented images for model training. We will leverage data augmentation in our own model – using Augly.

Contrast Enhancement based CNN model for Lung Cancer Classification and Prediction using Chest X-ray Images: By correcting image gamma, deep learning models showed improved performance compared to uncorrected images. We will explore using gamma correction.

Pre-processing methods in chest X-ray image classification: Extensive preprocessing of image data significantly enhanced performance of deep learning models. We will apply similar preprocessing.

Interpretation and Visualization Techniques for Deep Learning Models in Medical Imaging: Perturbation and gradient-based methods, such as Class Activation Maps (CAM), were used to successfully visualize the importance of identified features in chest x-ray images.

Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead: AI often uses "black box" models that cannot easily be interpreted. The author argues data scientists have an ethical responsibility to opt for interpretable models.

On evaluation metrics for medical applications of artificial intelligence: An overview of evaluation metrics used in gastroenterology classifiers, recommending confusion matrices to interpret results.

Chest pathology detection using deep learning with non-medical training: A CNN pre-trained on non-medical (ImageNet) data, then medical data, outperformed CNNs trained only on medical data.

Lung cancer detection using CT scan images: The paper combines watershed segmentation & SVMs to detect lung cancer nodules in CT scans. Our project will explore this combination of techniques.

Recent advances and clinical applications of deep learning in medical image analysis: The paper discusses current advancements and challenges. The primary challenge is the lack of labeled data.

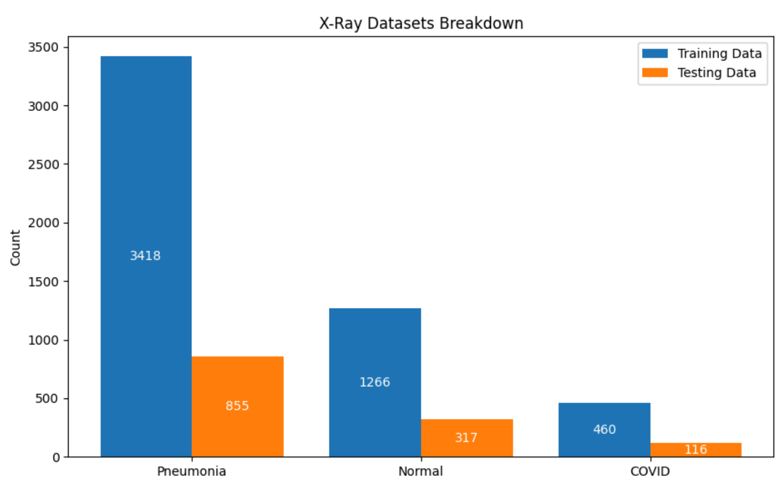
Machine learning for medical imaging: methodological failures and recommendations for the future: This paper discusses the limitations and best practices when using machine learning on image datasets. For our project, we will follow the best practices, and ensure that our model remains unbiased.

How Artificial Intelligence Is Shaping Medical Imaging Technology: A Survey of Innovations and Applications: This paper highlights the valuable insights Deep Learning has produced in the medical domain. Combining classifiers and improving the training dataset improved model results.

Preparing Medical Imaging Data for Machine Learning: A large, curated, representative dataset is important for deep learning training. We will properly clean and preprocess data for our project.

Methods

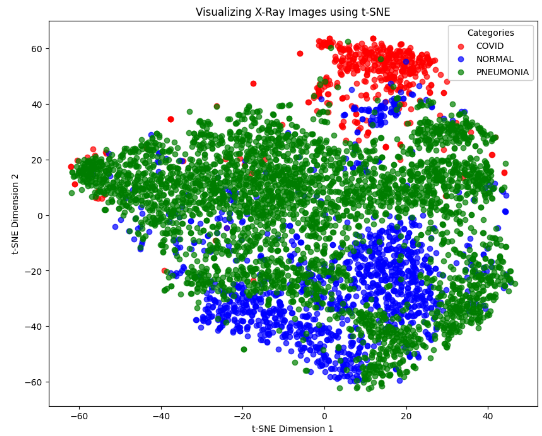
Medical imaging techniques in radiology face challenges of workforce shortages, high workload (leading to potential for diagnostic errors), limitations in visualizing specific tissue, and complex image interpretation due to large volume. Our approaches and methods (optimizing for accuracy, usability, and speed) cut out inefficiencies caused by physical testing and offer more reliable quality results.



The training dataset includes 5144 chest x-rays: 460 COVID-19, 3418 pneumonia, and 1266 “normal.” Images were resized, normalized, and converted to grayscale. A baseline model predicted classes proportional to their frequencies (e.g., pneumonia at 66.44%). This random chance baseline achieved a balanced accuracy and F1 score of 33%, setting the minimum benchmark for subsequent experiments to surpass.

Experiments

Several computational experiments were performed. The first was a simple CNN model with two convolutional layers, a pooling layer, and two fully connected linear layers. To evaluate, images in the reserved test dataset (1288 images) were classified as either COVID-19, pneumonia, or normal (i.e., "No diagnosis") and then compared to known labels.



The second experiment explored parameter tuning of the baseline CNN model. Stride, padding, and kernel hyperparameters were tuned to optimize the CNN model's balanced accuracy. Additional layers were explored to capture more complex features within our images to improve our Pneumonia and Covid detection rates.

The third experiment incorporated Contrast Limited Adaptive Histogram Equalization (CLAHE) for better contrast adjustment in our data preprocessing pipeline. CLAHE helps enhance local contrast, which can be particularly beneficial in x-ray images where subtle features need to be highlighted [6].

The fourth experiment made use of transfer learning and extended our training dataset to include MobileNetV2 and ResNet18. Transfer learning – training models on datasets not directly relevant to the primary task – can improve models' performance by taking advantage of learning from previous tasks.

Finally, data augmentation was added to the prediction API, creating a voting ensemble. When prediction tasks are performed, the submitted chest x-ray image undergoes several transformations, generating a set of new test images - all slightly altered versions of the original image [3]. Our model then attempts to classify each modified image and aggregates the subsequent predictions into one final label.

Visualization

The current iteration of our visualization allows a user to select a sample x-ray (with a known label) in the left column. The middle column shows the various augmented versions of the chosen x-ray. When the user shows prediction results, green represents a correctly predicted label; red is incorrect. The intensity of the label's color indicates the probability the model calculated for that prediction (darker color representing higher confidence). The user may view x-rays from the training set the model recommends as similar to the current sample. The right column shows interactive model analytics describing the training data, model creation, and model evaluation metrics.

A caveat: we made a strategic decision to implement Similar X-rays vs implementing real time connection to the API in the background. The model code for Similar X-rays has been drafted, however it is bogged down in excessively long runtimes and is not producing recommendations. Thus, Similar Xrays works on dummy data. Other data was produced from the API/model on the CLI, then hard coded.

Accessibility and Infrastructure

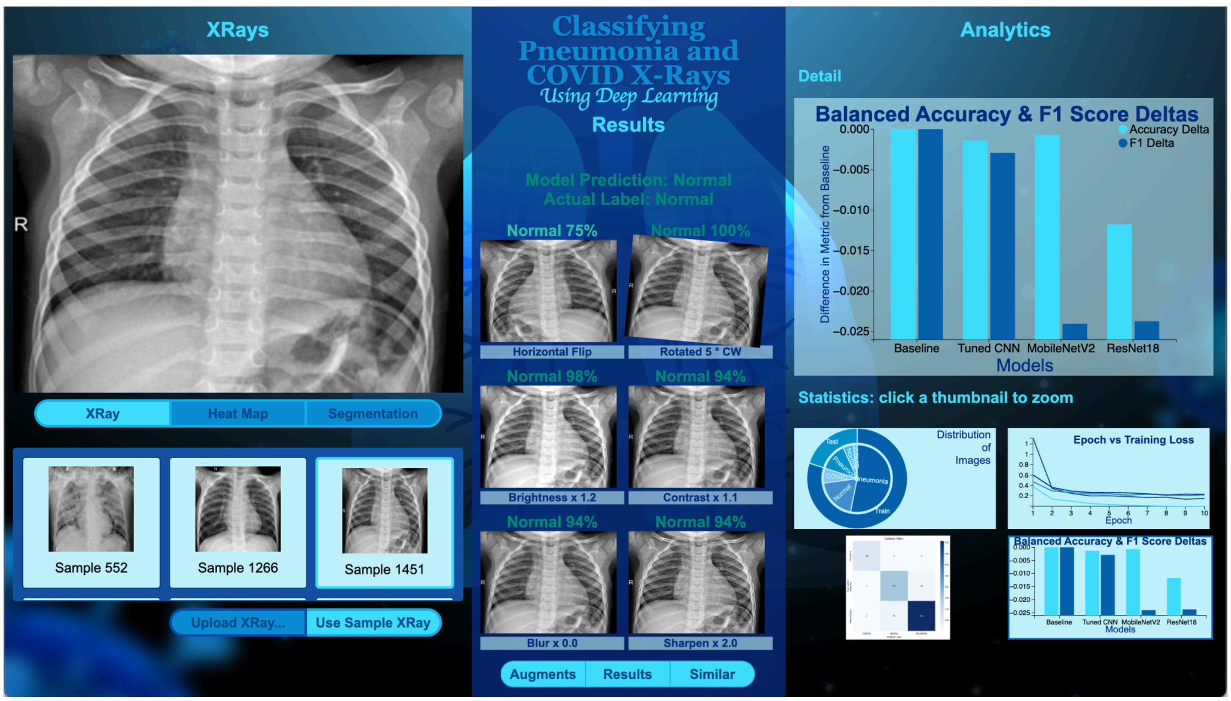
Where practicable, the visualization is responsive to window size (although the design works best on the 15" MacBook Air). Future versions would improve the responsiveness. The color scheme was vetted for appropriateness for color deficient users. In cases where we selected inaccessible colors (red for incorrect predictions and green for correct ones), we also provided text based cues. Size and contrast were considered when selecting fonts, to accommodate low-vision and mature users. Due to the heavy reliance on x-rays, the visualization is less accessible to users with low vision. In future iterations, attempts might be made to mitigate this, perhaps by integrating a light-weight medical LLM, which could create alt-text for x-rays on the fly.

The visualization was designed to be extremely light-weight. Except for the uploaded x-ray, no images are sent over the network. This increases security, reliability, and speed of execution. With the exception of the API and the model itself, all calculation is done in JavaScript and D3 by the browser which elides any need for heavy, back end infrastructure.

Real World Applications

In the real world, a user would upload an unlabeled chest x-ray where the actual diagnosis is not known. Within seconds, detailed results would be displayed in the left and middle columns. The Similar X-rays feature provides radiologists useful clues to interpret inconclusive (or possibly erroneous) results.

The right column contains model analytics that can be used to identify anomalies or shortcomings in the model. A product application might contain different information more appropriate to the real practice of medicine. While the current implementation exists as a web interface, a slightly condensed version could be packaged for use on portable x-ray machines to assist in remote or rural healthcare.



Evaluations

Our final model and visualization has been evaluated on three principles: accuracy, usability, and speed. Since accuracy scores on their own can be misleading when dealing with imbalanced datasets, we have opted to use a balanced accuracy (average of recall scores per class) and F1 score to measure success. In all cases, full confusion matrices have been reported in the Appendix to encourage transparency and reproducibility [4]. To measure usability, we have surveyed friends and family with medical background, especially those working in rural or remote healthcare. Finally, the amount of time taken to submit an x-ray image and receive a prediction through our model must not exceed the average manual diagnosis time. According to Forsberg, Rosipko, and Sunshine, the median time to review a chest x-ray is 71 seconds [21], so this is our baseline.

Accuracy

Although our first experiment was relatively simple in implementation (simple CNN model), it achieved a balanced accuracy of 94.45% and a weighted F1 score of 92.10%. The model was the most precise when diagnosing COVID-19, while occasionally confusing "normal" and pneumonia x-ray images; in particular, the model incorrectly diagnosed patients who actually had pneumonia as having no diagnosis in about 7% of cases.

Our second experiment explored tuning the parameters and layers of our simple CNN model. The best combination was found to be four convolutional layers (kernel size = 3, stride = 1, padding =1), a pooling layer (kernel size = 2, stride = 2, padding = 0), a dropout layer, and three fully connected layers. This model achieved a balanced accuracy of 93.96% and an F1 score of 94.61%. While the balanced accuracy is slightly less than our simple CNN model, we believe this tuned model to be more useful since it is significantly less likely to misdiagnose a patient who is experiencing respiratory disease as "normal" (7.2% in the simple CNN model to 3.3% in the tuned CNN model).

Our third experiment (improving local contrast of training image using CLAHE) did have a significant positive impact on our balanced accuracy and F1 score (95.81% and 94.14% respectively). Notably, this x-ray preprocessing continues to decrease the number of erroneous "normal" diagnoses when respiratory disease is present (3.3% in the tuned model to 2.0% when CLAHE is applied).

In our fourth experiment, the tuned model was retrained using two different libraries: ResNet18 and MobileNetV2 to explore the potential benefits of incorporating transfer learning. Initial runs did not show significantly different results than our baseline or tuned models; however, training times when including these additional datasets were substantial. It's possible if more time was available, the models could have been tuned to outperform earlier experiments.

Finally, Experiment 5 included adding data augmentation and a "voting ensemble" into our API endpoint for prediction. All chest x-rays submitted for classification underwent 6 image transformations: a 5 degree rotation, horizontal flip, increased brightness, increased contrast, increased sharpness, and increased blur. This results in 7 total images (6 transformations in addition to the original image) fed into our model, returning 7 predicted labels. The majority label is selected and returned to the user. When comparing the results of each data augmentation against the true labels for our test dataset, the (simple) accuracies to the right were calculated.

Original image	94.55	Increase sharpness	94.55%
5 degree rotation	79.22%	Increase contrast	94.86%
Horizontal flip	90.35%	Increase brightness	92.53%
Increase blur	94.71%	**Aggregate Results**	**94.63%**

This experiment demonstrated that our data augmentation did not produce significantly different results from our tuned CNN model with CLAHE preprocessing; however, deeper analysis revealed possible improvements for future iterations. For instance, although the "5 degree rotation" augmentation was only 79.22% accurate overall, it was 99.13% accurate when classifying just COVID-19 x-rays and 97.78% accurate when classifying just "normal" x-ray images. Overall, the data augmentations for increasing blur, increasing sharpness, and increasing contrast were the most consistently helpful across all labels.

Ultimately, we have opted to use the tuned CNN model (experiment 2), applying CLAHE preprocessing (experiment 3), and predicting with the data augmentation and voting ensemble (experiment 4) for our final solution which produced a balanced accuracy of 94.6% and an F1 Score of 94.68%.

Usability

When surveying medical practitioners on the usefulness of this technology, the response was overwhelmingly positive. A nursing student, Lauren Burrows of Western Carolina University, shared her recent experience providing medical care following a natural disaster: “After Hurricane Helene, I [saw] the need for pop-up medical shelters and emergency response clinics. I think this software could be extremely useful in these disaster relief settings.” She went on to discuss the need for such technology in underserved or remote communities: “It could also be extremely helpful in low-income medical clinics with less access to proper imaging technology. One population I immediately think of [is the] historical mining communities within the Appalachian mountains that often have not had the financial means or medical resources to check their respiratory health and receive proper diagnosis.”

Another commented on the speed of diagnosis: “In understaffed areas, obtaining an official x-ray read from a radiologist can sometimes take many hours to days, ultimately delaying the patient’s diagnosis and treatment.” Shannon Kelly, P.A., said. “ By increasing the speed and accuracy of respiratory diagnoses, this has the ability to increase the quality of healthcare and improve outcomes for those in underserved communities.”

Speed

The API, on average, takes about 1.81s to perform a prediction task. Incorporating CLAHE transformations increases the prediction time to about 4s. Both of these prediction times are significantly shorter than the 71s baseline it takes, on average, for a radiologist to manually analyze an x-ray.

Conclusions and Discussion

While radiologists already achieve high levels of accuracy in their work, computer-aided technology can drastically reduce cycle times while maintaining the same level of accuracy. Our preliminary CNN model performed very well, surpassing our goal of “better than chance.” We were able to further improve our model using data preprocessing, parameter tuning, and leveraging data augmentation when classifying new x-ray images.

Although COVID-19 antigen tests are now largely available, there are still several benefits to computer-aided x-ray diagnosis. Diagnosis by antigen test can involve several tests with varying accuracy, availability, and distribution networks [28]. Our service requires only a single x-ray image. Using x-rays means personnel would not be required to manage or predict inventory needs for physical tests. Additionally, as new respiratory diseases emerge, our model can be retrained with new labeled x-ray images; this would almost certainly outpace the development of new antigen tests. Although our solution met all of our goals for accuracy, usability, and speed, the following gaps remain:

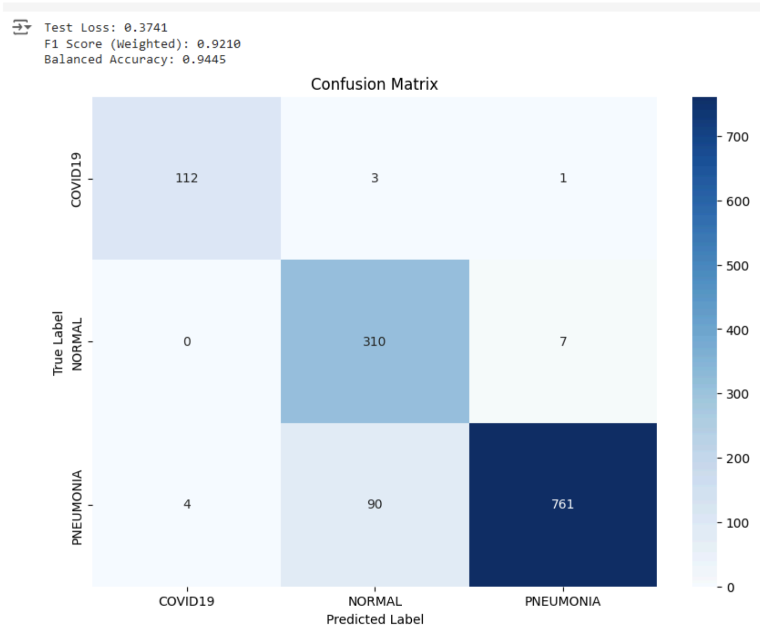
- **Usability Assessment:** The solution requires a more comprehensive usability assessment surveying accredited radiologists.
- **API:** The data augmentation + voting ensemble could be better architected, potentially exploring new image transformations, introducing weighting (i.e., giving consistently accurate augmentations higher priority) or incorporating probability calculations.
- **New Visualizations:** Image heatmaps or segmentation would allow users to see which sections or features of x-ray input were most influential in classification. These visualizations would be helpful when the model produces unclear or incorrect output.
- **Similar X-rays:** The feature is rudimentary and only works within the visualization. The model requires additional debugging and rework.
- **Background Connections:** Only a local API is offered. Similarly, the visualization is a local web page; it is not hosted in the cloud, and does not connect to the API. In future revisions, the visualization, API, and model would be hosted online and exchange data in real time.
- **Accessibility:** There is potential for further design improvement centering accessibility, responsiveness, and portability/performance of required infrastructure–a mobile version is a must.

⭐All team members met reasonable standards for participation in the project.⭐

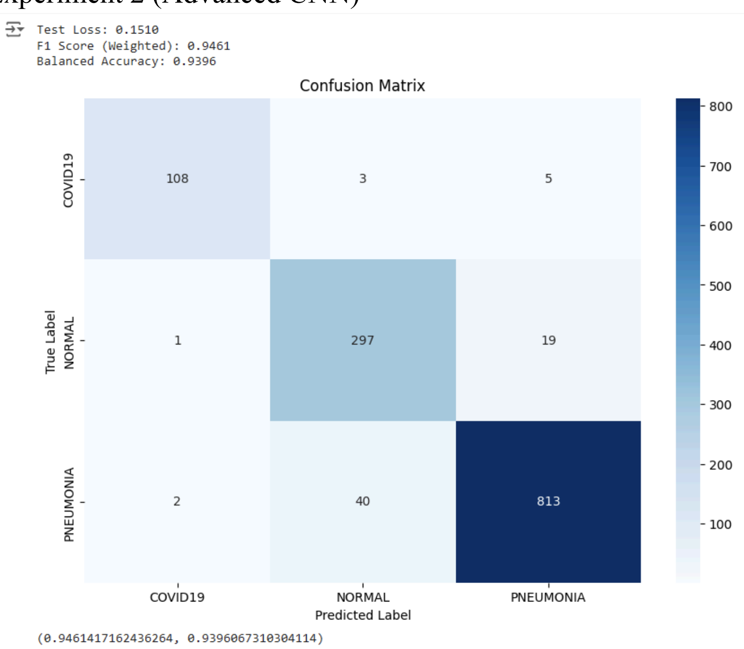
Appendix

Confusion Matrices

Experiment 1 (Simple CNN)

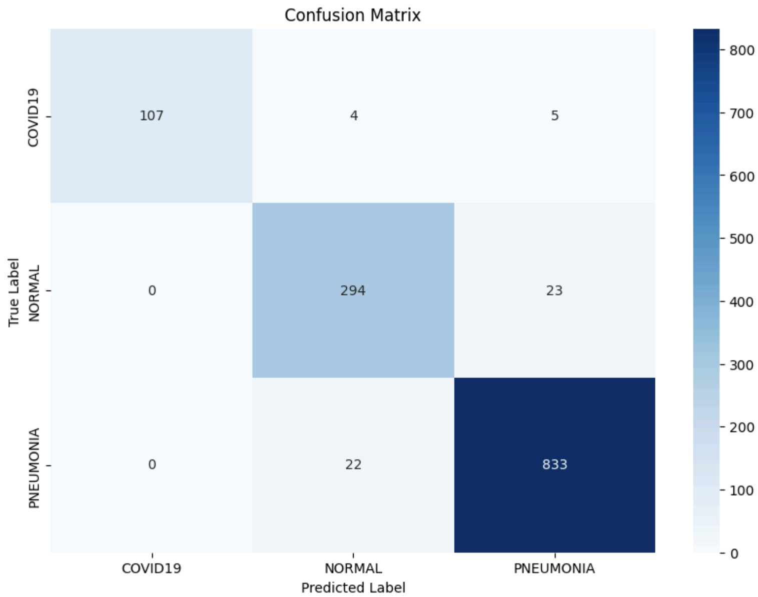


Experiment 2 (Advanced CNN)



Experiment 3 (CLAHE Preprocessing)

```
Test Loss: 0.1337
F1 Score (Weighted): 0.9581
Balanced Accuracy: 0.9414
```

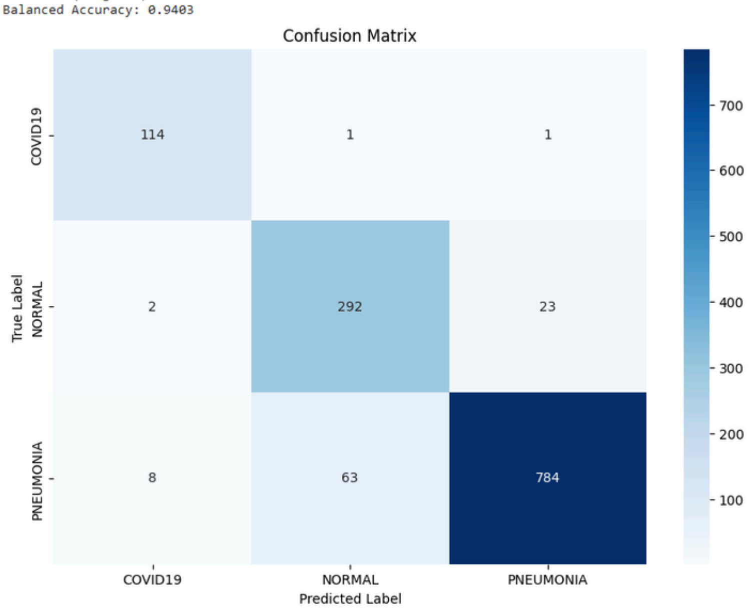



```
(0.9580909804759483, 0.9413758646346944)
```

Experiment 4 (Transfer Learning)

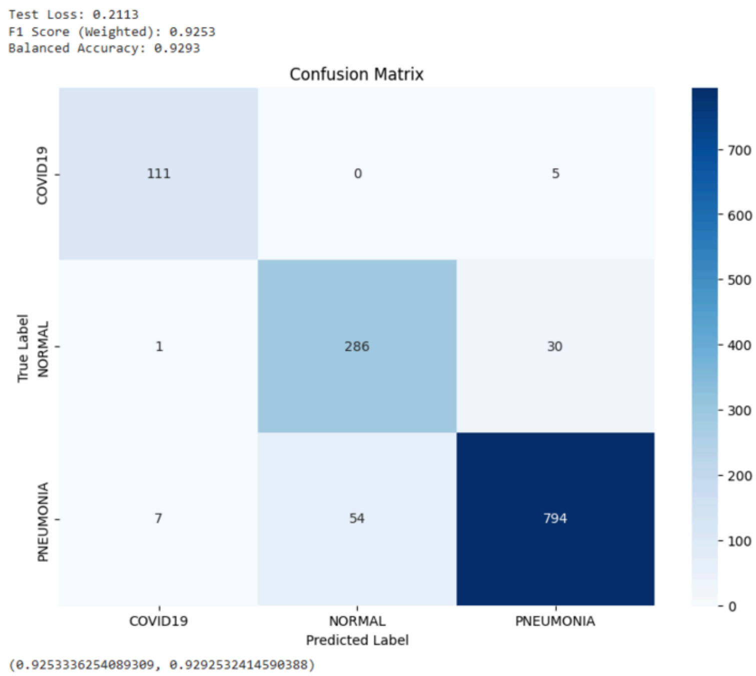
MobileNetV2

```
Test Loss: 0.2082
F1 Score (Weighted): 0.9250
Balanced Accuracy: 0.9403
```

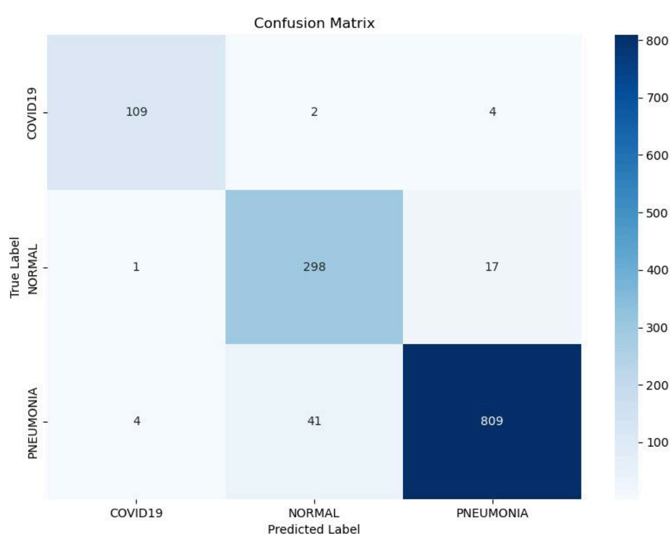



```
(0.9250281820340688, 0.9402844439016126)
```

ResNet18



Experiment 5 (Data Augmentation and Voting Ensemble)



Full "Usability" Quotes

"I haven't seen any software like this in the wild; however, I haven't had a lot of experience in radiology/respiratory specialities within the clinical setting. However, I do think this would be extremely useful in remote settings in rural clinics. After Hurricane Helene devastated so much of Western North Carolina, I did see the need for pop-up medical shelters and emergency response clinics. I think this software could be extremely useful in these disaster relief settings. I'm sure it could also be extremely helpful in low-income medical clinics with less access to proper imaging technology outside of larger, equipped regional hospitals. One population I immediately think of benefitting from this type of software would be historical mining communities within the Appalachian mountains that often have not had the financial means or medical resources to check their respiratory health and receive proper diagnosis." - Lauren Burrows, Nursing Student (Western Carolina University).

"I haven't had the opportunity to see software like this in my personal practice yet, but I think this could be incredibly helpful, especially in remote/rural communities. In understaffed areas, obtaining an official x-ray read from a radiologist can sometimes take many hours to days, ultimately delaying the patient's diagnosis and treatment. By increasing the speed and accuracy of respiratory diagnoses, I think this technology has the ability to increase the quality of healthcare and improve outcomes for those in underserved communities. It would be interesting to see this technology continue to expand in x-ray diagnostics in other specialities such as orthopedics." - Shannon Kelly, Physician Assistant.

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