**Himel Script**

**Slide Title: Related Works**

"Let’s take a look at the related works in this field.

1. **L. Silva and L. Araujo** used the InceptionResNetV2 model with X-ray images of children. Their model demonstrated high recall and precision in detecting pneumonia. However, the study lacked a comparative analysis with other models and didn’t mention Grad-CAM for visualization.
2. **Yogesh H.** employed a Deep CNN Network on radiology X-ray images for COVID-19, pneumonia, and normal cases. This model achieved a high classification accuracy of 92%. However, similar to the previous study, it didn’t provide a comparative analysis of models or mention Grad-CAM.
3. **V Asha et al.** implemented ResNet101 on a COVID-19 dataset. They enhanced the ResNet-101 model for effective classification of COVID-19. Despite this, it had high computational costs and offered limited classification options.
4. **No Adiwiijava et al.** used a CNN Network with chest X-ray images. Their study focused on detecting infectious lung diseases using Kaggle data. While the method was effective, it was constrained by dataset limitations and lacked explainability in the results.

**Slide Title: Methodology**

"Our methodology follows a structured process to ensure accurate and reliable results.

1. **Data Collection**: We begin by gathering the necessary data for our analysis.
2. **Preprocessing**: The data is then preprocessed using techniques like image sharpening, zoom, and CLAHE to enhance the quality of input images.
3. **Model Selection**: We explore several models for testing, including:
   * Custom CNN
   * VGG19
   * Vision Transformer (ViT)
   * ResNet50
4. **Model Testing**: Each selected model is tested to ensure optimal performance.
5. **Model Evaluation**: The models are evaluated based on metrics such as:
   * Accuracy
   * F1 Score
   * Recall
   * Precision
6. **Output**: Finally, the best-performing model is selected to generate the desired output.

**Slide Title: Result and Analysis**

"Let’s discuss the results and analysis of the models:

1. **VGG19**:
   * Achieved a **test accuracy** of 94%.
   * Precision, recall, and F1 score are all 0.94, with an AUC of 0.99.
   * Loss value is 0.15.
2. **CustomCNN**:
   * This model performed the best, with a **test accuracy** of 97%.
   * Precision is 0.92, recall is 0.99, and F1 score is 0.92, with an AUC of 0.99.
   * Loss value is slightly higher at 0.20.
3. **ResNet50**:
   * Achieved a **test accuracy** of 93%.
   * Precision and F1 score are 0.93, recall is 0.93, and AUC is 0.99.
   * Loss value is 0.22.
4. **Vision Transformer (ViT)**:
   * Performed the least effectively, with a **test accuracy** of 78%.
   * Precision is 0.81, recall is 0.76, and F1 score is 0.78, with an AUC of 0.95.
   * Loss value is significantly higher at 0.66.

In summary, the **CustomCNN** model outperformed the others, showing the highest accuracy and strong performance metrics, while the ViT model had the lowest performance in this analysis."

**VGG19 Confusion Matrix:**

Here’s a simplified summary:

The confusion matrix in Figure 4.4 confirms our earlier observations from the data analysis. The model struggled to distinguish between **lung opacity** and **normal images** because their pixel intensity distributions overlap.

* The model performed well overall, as seen from the correct predictions on the diagonal of the confusion matrix.
* The most significant misclassifications were:
  + **126 normal controls** misclassified as lung opacity.
  + **84 lung opacity cases** misclassified as normal.

Additionally, some **COVID-19 cases** were misclassified as **Viral Pneumonia** or **Tuberculosis**, though the numbers were smaller compared to lung opacity and normal misclassifications.

**ResNet50 Confusion Matrix:**

**Lung Opacity vs. Normal:** The largest number of misclassifications for the model were between 'Lung Opacity' and 'Normal', with 147 and 54 instances, respectively. This agrees with our previous EDA findings where these two classes presented analogous pixel intensity distributions. More likely than not, such statistical similarity confuses the model, leading to mistakes that could prove clinically meaningful.

**CustomCNN Confusion Matrix:**

The CustomCNN model demonstrated classification patterns similar to those observed in the VGG19 and ResNet50 models, particularly in the task of distinguishing between the ‘Lung Opacity’ and ‘Normal’ classes.

**Grad Cam Slide:**

This technique uses **Grad CAM** to show which parts of an image activate deeper model layers. However, it often highlighted irrelevant areas instead of clinically important ones, possibly because zooming wasn’t applied during preprocessing.

**Guided Grad CAM** improves this by combining Grad CAM with backpropagation to provide clearer visuals of feature importance across the network.

While the deeper layers focused more on noise (like edges), analyzing earlier layers can help detect patterns related to important clinical features.

In short, Guided Grad CAM offers better resolution and helps focus on relevant clinical areas.