**Synthesized Methodology:**

A unified methodology for diagnosing pulmonary diseases from chest X-ray (CXR) images using artificial intelligence involves a multi-stage pipeline that begins with data collection and progresses through advanced preprocessing, sophisticated modeling, and rigorous evaluation.

**Dataset Curation and Preparation**

The initial step involves creating a comprehensive dataset, often by aggregating images from multiple public sources like Kaggle, NLM, Belarus, and RSNA. These datasets are structured for various classification tasks, including binary classification (e.g., Tuberculosis vs. Normal) , multi-class classification (e.g., COVID-19, Pneumonia, Tuberculosis, and Normal) , or a generalized "normal vs. abnormal" distinction. For robust generalization testing, some studies intentionally exclude specific diseases like TB and COVID-19 from the training set to evaluate the model's performance on truly unseen conditions.

**Image Preprocessing and Enhancement**

Before model training, all images undergo a series of preprocessing steps to ensure consistency and improve quality.

* **Standardization**: Images are resized to a uniform dimension, such as 224×224 or 300×300 pixels, and pixel values are normalized.
* **Data Augmentation**: Techniques like rotation and translation are applied to increase the size and diversity of the training data, which helps in balancing classes and preventing overfitting.
* **Advanced Enhancement**: More sophisticated methods are used to tackle specific data challenges:
  + **Lung Segmentation**: A dedicated U-Net model is first trained to automatically segment the lung regions. The main classification model is then trained on these segmented images, forcing it to focus only on the relevant anatomical areas. \*

**Super-Resolution**: For low-quality CXRs, an **Enhanced Fast Super-Resolution CNN (EFSRCNN)** is used to reconstruct high-resolution images, enhancing texture details and removing noise before classification.

**Model Architecture and Training**

The core of the methodology lies in the selection and design of the deep learning model. The approaches range from using established architectures to developing novel, hybrid systems.

* **CNN-Based Models**: A common approach is to compare several pre-trained CNN architectures (like MobileNetV2, ResNet, DenseNet) or to design a custom CNN tailored to the specific classification task.
* **Hybrid Systems**: An advanced pipeline uses a pre-trained **Vision Transformer (ViT)** as a powerful feature extractor to capture complex patterns from the CXR images. The resulting high-dimensional feature vectors are then reduced using

**Principal Component Analysis (PCA)**. Finally, traditional machine learning classifiers like

**Random Forest (RF), XGBoost, or SVM** are used on the reduced feature set for the final diagnosis.

* **Novel Architectures**: Some research proposes unique models like a **Siamese wavelet multi-resolution CNN**, which uses wavelet transforms to capture both spectral and spatial information at different scales for more robust feature extraction.

**Evaluation and Validation**

The final step is a thorough evaluation of the model's performance and reliability.

* **Quantitative Metrics**: Performance is measured using a comprehensive set of standard metrics, including **accuracy, precision, recall, F1-score, sensitivity, specificity, and Area Under the Curve (AUC)**.
* **Qualitative Analysis**: The **Score-CAM** visualization technique is used to generate heatmaps that show which regions of the CXR the model focused on, ensuring that its decisions are based on clinically relevant features.
* **Reliability and Impact**: The model's robustness is confirmed using cross-validation and statistical tests. Additionally, simulations are run to assess the AI's potential impact on clinical workflows, such as its ability to prioritize abnormal cases and reduce turnaround time for radiologists.

1. *COVID-19 Detection Using Deep Learning Algorithm on Chest X-ray Images* (Biology, 2021) :

Methodology:

**Dataset Preparation:** 13,808 X-rays (COVID-19 + healthy), augmented to 52,000.

**Preprocessing:** Histogram equalization, normalization (NCLAHE), grayscale variations.

**Models:** Compared 11 CNN architectures; MobileNetV2 chosen for modification.

**Training:** RMSprop optimizer, balanced dataset, data augmentation to prevent overfitting.

**Evaluation:** Confusion matrix, statistical validation (Wilcoxon signed-rank test)

1. *Deep learning for distinguishing normal versus abnormal chest radiographs and generalization to two unseen diseases: tuberculosis and COVID-19* (Scientific Reports, 2021):

Methodology:

**Training:** 250,066 CXRs (213,889 patients) from Indian hospitals.

**No TB or COVID cases included** in training → ensures true generalization testing.

**Evaluation:** 6 datasets (11,576 CXRs) including 2 TB and 2 COVID-19 datasets.

**Metrics:** AUC, sensitivity, specificity, predictive values; comparison with radiologists.

**Simulation:** AI system prioritizing abnormal cases to test clinical workflow impact.

1. *COVID-19 Diagnosis from Chest X-ray Images Using a Robust Multi-Resolution Analysis Siamese Neural Network with Super-Resolution Convolutional Neural Network* (Diagnostics, 2022):

Methodology:

**Datasets Used:**

* + COVID-19 radiography database: 3,616 COVID-19 CXR scans.
  + Kaggle RSNA Pneumonia Challenge: 3,029 bacterial pneumonia, 2,983 viral pneumonia, 8,851 healthy cases.
  + NIH CXR dataset: 74,999 pneumonia-related cases.

**Data Preprocessing:**

* + Super-resolution reconstruction of low-quality CXRs using **EFSRCNN** to generate high-resolution images.
  + Noise removal and enhancement of texture details.

**Proposed Model – COVID-SRWCNN:**

* + Combines **super-resolution** (for image clarity) + **Siamese wavelet multi-resolution CNN** (for robust feature extraction).
  + Wavelet transforms capture spectral and spatial information at multiple resolutions.

**Training & Evaluation:**

* + Evaluated against pre-trained models (ResNet, DenseNet, Inception, etc.).
  + Metrics: accuracy, AUC, sensitivity, precision, specificity.
  + Cross-validation performed for reliability.

1. Reliable Tuberculosis Detection using Chest X-ray with Deep Learning, Segmentation and Visualization:

Methodology:

The methodology involved a multi-stage process to classify TB from chest X-rays.

**Dataset Creation:** A dataset for TB classification was created by combining images from three public databases: **NLM (Montgomery and Shenzhen), Belarus, and RSNA**, totaling 700 TB and 3,500 normal images. A separate Kaggle dataset of 704 images with corresponding lung masks was used to train the segmentation models.

**Image Preprocessing & Augmentation:** All images were resized to fit the input requirements of the CNN models (224×224 or 227×227 pixels) and normalized using Z-score. To address the class imbalance, the TB-infected training images were augmented four-fold using

**rotation and translation** techniques.

**Lung Segmentation:** Two U-Net models (original and modified) were trained on the Kaggle dataset to segment the lung regions from the chest X-rays. The better-performing

**original U-Net model** was then used to segment the entire classification dataset.

**TB Classification:** Nine pre-trained CNN models (e.g., ResNet18, ResNet50, ChexNet, DenseNet201) were trained and tested in two separate experiments:

* 1. Classification using the **original, non-segmented** chest X-ray images.
  2. Classification using the **segmented lung images**.

**Visualization:** The **Score-CAM** technique was used to generate heatmaps, visually confirming which regions of the X-ray the models used for making their classification decisions.

1. Joint Diagnosis of Pneumonia, COVID-19, and Tuberculosis from Chest X-ray Images: A Deep Learning Approach:

Methodology:

The study's methodology was structured into three main steps: image preprocessing, model building, and evaluation.

Dataset: The study combined three publicly available datasets from Kaggle to create a comprehensive database for a four-class classification problem. The final dataset consisted of:

* + COVID-19: 3,616 images
  + Pneumonia: 4,273 images
  + Tuberculosis: 3,500 images
  + No-Findings (Normal): 10,192 images

Image Preprocessing: All images from the different sources were standardized to ensure uniformity. This involved resizing every image to

300×300 pixels and normalizing the pixel values by dividing them by 255.

Proposed Model Architecture: A custom Convolutional Neural Network (CNN) was designed for the multiclass classification task. The model architecture consists of five sequential convolutional blocks. The number of channels increases with each block (16, 32, 64, 128, and finally 256), and each convolutional layer is followed by a max-pooling layer to reduce dimensionality. The final layers are dense layers that output the probability for each of the four classes.

Evaluation: The model's performance was evaluated using standard metrics, including accuracy, precision, recall, and F1-score, and visualized with a confusion matrix. The model was also tested on 100 unseen images (25 from each class) during an inference stage to validate its real-world performance.

1. A Robust Tuberculosis Diagnosis Using Chest X-Rays Based on a Hybrid Vision Transformer and Principal Component Analysis:

Methodology:

The proposed CAD system for TB diagnosis follows a multi-phase hybrid methodology.

**Dataset:** The study utilized the **TB Chest X-ray dataset**, which contains 700 TB images and 3500 normal images compiled from the NLM, Belarus, and RSNA databases. This dataset was split into

**80% for training and 20% for testing**.

**Image Preprocessing:** To prepare the data for the models, all CXR images underwent several preprocessing steps: resizing to 224×224 pixels, scaling pixel values, and applying noise removal techniques.

**Hybrid Feature Extraction and Classification:** The core of the methodology is a hybrid pipeline:

* 1. **Deep Feature Extraction:** A pre-trained **Vision Transformer (ViT)** model (pre-trained on ImageNet) was used as a base feature extractor to capture complex patterns from the CXR images. For comparison, other deep learning models like DenseNet121 and ResNet101V2 were also used as feature extractors.
  2. **Dimensionality Reduction:** **PCA** was applied to the high-dimensional feature vectors extracted by the ViT. This step reduced the number of features to 41, retaining the most critical information while removing redundancy.
  3. **Machine Learning Classification:** The reduced feature set from PCA was then used to train and test several traditional ML classifiers, including **Random Forest (RF), XGBoost (XGB), Decision Tree (DT), Support Vector Machine (SVM), and Adaptive Boosting (AdaBoost)**.

**Evaluation:** The performance of each combination of feature extractor and ML classifier was assessed using a comprehensive set of metrics: accuracy, precision, recall, F1-score, specificity, False Negative Rate (FNR), and Negative Predictive Value (NPV).