Grenze International Journal of Engineering and Technology, June Issue

Optimizing Pneumonia and Tuberculosis Detection using GAN and CNN

Mrs. Pappula Madhavi[1], Amarana Varshini[2], Jillela Prem Praneeth Kumar[3] and Muthi Janitha Sri Raj[4]
[1-4]Lakireddy Bali Reddy College of Engineering, Mylavaram, India
Email: pappulamadhavi06@gmail.com, varshiniamarana15@gmail.com, prempraneethkumar7@gmail.com, janithasriraj10@gmail.com

***Abstract*—Pneumonia and tuberculosis (TB) are serious respiratory diseases that continue to pose significant global health challenges, leading to high rates of illness and death, particularly in low- and middle-income countries. Our project focuses on developing a prediction model specifically designed to detect pneumonia, tuberculosis, or both. Using deep learning algorithms like GANs and CNN, this model enhances healthcare by enabling quicker diagnosis and proactive intervention. It offers a cost-effective solution for remotely screening patients, helping to improve access to timely care and reduce the burden on healthcare systems.**

***Index Terms*— Tuberculosis, Pneumonia, Generative Adversarial Network (GAN), Convolutional Neural Network (CNN)s.**

I. Introduction

Early detection of pneumonia and TB is crucial in today's world due to their significant impact on global health, especially in regions with limited healthcare resources. Countries like India, Indonesia, China, the Philippines, Pakistan, and Nigeria account for nearly two-thirds of the global TB burden. This prediction system facilitates the early and efficient detection of these diseases. Since both pneumonia (in some bacterial and viral cases) and TB are infectious, timely detection and isolation are essential to curb their spread, particularly in densely populated or resource-constrained areas. By enabling early outpatient treatment, predictive systems play a key role in reducing hospitalizations, lowering medical costs, and minimizing disease complications. Although many prediction systems exist for detecting these diseases, they still face challenges in accurately predicting outcomes and often misclassify cases when using chest X-ray images. Current prediction systems have advanced with the integration of new technologies like deep learning architectures or neural network models. Nevertheless, these models still face challenges in achieving reliable and accurate pneumonia detection, struggling with generalizability to different populations or settings. Additionally, they often require a large amount of labeled data, which can be a limiting factor. Previous research has made strides in predicting these diseases, but several limitations persist. Firstly, many traditional methods have focused on predicting pneumonia or tuberculosis individually, rather than detecting both simultaneously. Secondly, these approaches still struggle with achieving reliable and accurate detection of pneumonia, lack generalizability across diverse populations. Finally, these models need a lot of labeled data and some have been trained on only limited datasets, which poses a significant challenge. Our contribution is to develop and deploy an optimized prediction system that improves the accuracy of detecting pneumonia, tuberculosis, or normal cases. We propose an architecture that integrates deep learning techniques, leveraging CNN for accurate feature extraction and GAN for enhanced data augmentation. This

Grenze ID: 01.GIJET.11.2.569

approach enables the model to effectively analyze chest X-ray images and identify signs of pneumonia, tuberculosis, or their co-occurrence. By utilizing these technologies, the system supports healthcare professionals, especially in resource-limited settings, serving as a dependable tool for early diagnosis, informed clinical decisions, and better disease management. Our paper is organized as follows: The second section presents a literature review of our relevant work. The third section describes the intended technique and project approach. The fourth section contains a full overview of the techniques used. The fifth section examines the dataset used in the study. Finally, the sixth section concludes the study with a complete list of sources cited.

A. Related Work

In the year 2020, Sivaramakrishnan and Sameer utilized convolutional neural networks (CNNs) combined with ensemble learning to detect tuberculosis in chest radiographs. Their ensemble model outperformed individual models in terms of AUC, accuracy, and other performance metrics. However, the study's reliance on a small dataset introduced a risk of overfitting, which could hinder the model's effectiveness in real-world applications. The paper by Subrat Kumar Kabi et al (2023), introduces a multiscale eigendomain gradient boosting (MEGB) approach, achieving high accuracy and efficiency. However, this method depends heavily on feature selection and does not incorporate image segmentation.

B. Problem Statement

The proposed system in the document focuses on optimizing pneumonia and tuberculosis (TB) detection using deep learning techniques, specifically Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN). This hybrid approach enhances medical image analysis by leveraging CNN for accurate feature extraction and GAN for data augmentation, ensuring a more robust and reliable model. The system processes chest X-ray images, identifies disease patterns, and classifies cases as pneumonia, TB, both, or normal. By integrating deep learning, the model provides a cost-effective and efficient diagnostic tool, particularly beneficial in resource-limited healthcare settings. The model also features a user-friendly graphical interface for accessibility.

II. METHODOLOGY AND SOLUTION APPROACH

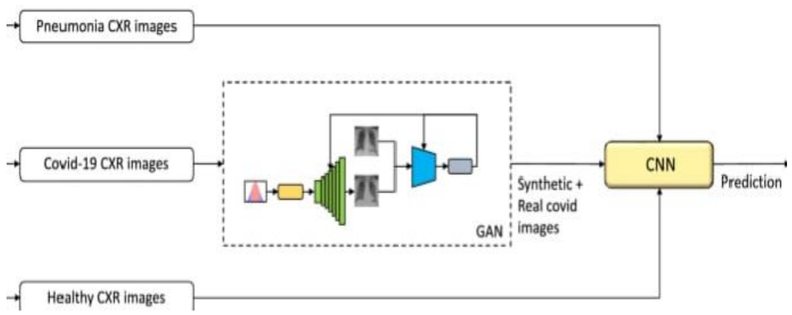

Figure 1. Flow Chart on Methodology

In the pneumonia and tuberculosis detection model, CNN and GAN work together in a hybrid architecture to ensure accurate identification and diagnosis using chest X-ray scans. CNN is used for feature extraction, where it processes the X-ray images through its deep convolutional layers to capture fine-grained features that are crucial for identifying signs of pneumonia, tuberculosis, or their co-occurrence. These extracted features are then passed through the network for classification. GAN, on the other hand, plays a key role in augmenting the dataset, addressing challenges such as limited data availability. It generates additional, synthetic X-ray images that help the model generalize better and improve its performance by exposing it to more varied data. By integrating CNN's feature extraction skills with GAN's data augmentation capacity, the model can diagnose illnesses with high accuracy, especially in resource-constrained environments. This hybrid method assures that the model can accurately recognize and categorize pneumonia and TB, allowing for trustworthy early diagnosis and decision-making. The combination of CNN and GAN improves both the quality and amount of data, resulting in better model performance and more dependable clinical outcomes.

A. Analyzing X-ray Images

The first step in our pneumonia and tuberculosis detection project involves processing chest X-ray scans as the input to the model. Each image is resized and normalized to meet the input requirements of CNN, ensuring consistency and accuracy in feature extraction.

Feature Extraction

The X-ray images are passed through the CNN model, which analyzes the chest region to extract key features related to different diseases, such as pneumonia or tuberculosis

Pattern Recognition

These extracted features are then processed to identify distinctive patterns indicative of the diseases, enabling the model to learn the visual characteristics of each condition.

B. Model Development

The model is developed through multiple epochs, with each iteration fine-tuning the CNN layers to improve accuracy. During training, backpropagation adjusts the weights in each layer based on the loss calculated using categorical cross-entropy., optimizing the model to classify the X-rays accurately. Dropout and batch normalization are applied to maintain generalization and prevent overfitting, ensuring reliable performance.

Convolutional Neural Network (CNN)

CNN is a deep convolutional neural network architecture made up of 19 layers: 16 convolutional layers and three fully connected levels. It is recognized for its basic and consistent structure, which employs tiny 3x3 convolutional kernels across the network. This approach enables CNN to extract fine-grained characteristics and details from pictures while being computationally efficient. It is widely employed in a variety of image identification applications, including medical imaging, where its ability to extract exact characteristics from complicated datasets like chest X rays makes it very useful. CNN is also useful for transfer learning and feature extraction because of its simple and versatile design.

Generative Adversarial Networks (GANs)

GAN's are machine learning models that incorporate two neural networks, a generator and a discriminator. The generator creates synthetic data, such as images, while the discriminator assesses the authenticity of the generated data by distinguishing it from true data. These two networks are trained in a competitive way, with the generator striving to improve its ability to generate realistic data and the discriminator attempting to distinguish between genuine and fraudulent data. GANs have received a lot of interest for a variety of applications, including picture production, data augmentation, and enhancing medical image quality. In the domain of medical imaging, GANs are especially beneficial for supplementing datasets, allowing the development of extra training data from limited resources, which can increase model performance for tasks like illness identification.

C. Data Exploration

Exploratory Data Analysis (EDA) is performed to understand data distribution, identify correlations, and visualize trends in energy generation.

Statistical Analysis

Mean, median, and standard deviation values are computed for key features to understand their distributions. Correlation matrices are used to identify relationships between input variables (e.g., wind speed vs. energy output).

Data Visualization

Several visualizations are created to interpret data trends effectively:

Heatmaps: Display correlations between different meteorological factors and energy generation. Scatter Plots: Show relationships between solar radiation and energy output. Histograms: Provide distributions of numerical variables such as temperature and wind speed.

Time Series Analysis

Seasonality Analysis: Energy production is evaluated across different months to detect seasonal patterns.

Trend Analysis: Moving averages are used to observe long-term energy production trends.

D. Predictive Model Training and Evaluation

Once the data is explored and generated the synthetic images by GAN model, the CNN model is trained and evaluated.

Model Training

The dataset is split into training, validation, and test sets (typically 70% training, 15% validation, 15% testing). The model is trained on Google Colab with GPU acceleration to improve efficiency. The Adam optimizer updates weights iteratively to minimize the MSE loss function.

Model Evaluation Metrics

Mean Squared Error (MSE): Measures the average squared difference between actual and predicted values. Mean Absolute Error (MAE): Calculates the average magnitude of errors without considering direction. R^2

Score: Determines how well the model explains variations in energy generation.

Model Testing and Deployment:
After training, the model is tested on unseen data to validate its ability to generalize well. The final ResNet model is deployed in a real-world energy management system for continuous forecasting of solar and wind energy production.

E. Flask Framework

Flask application is a web-based image classification system that takes an image as input, processes it, and predicts whether it falls into one of the three categories: Normal, Pneumonia, or Tuberculosis.
Prediction flow using Flask:
1. User uploads an image via the web interface.
2. Flask saves and preprocesses the image (resize, normalize, expand dimensions).
3. Pre-trained deep learning model predicts the class.
4. Flask extracts the prediction and maps it to a human-readable label.
5. Result is displayed on the web page.

F. Model Evaluation

Classification Report:
The pneumonia and TB detection model performs well, especially in distinguishing normal and tuberculosis patients. With a high accuracy of 0.94 for "Normal" cases, the model provides solidpredictions, while its recall of 0.80 shows that some normal examples are missed. This is counterbalanced by its high F1-score of 0.87, which indicates an efficient capacity to distinguish between normal and abnormal chest X-rays. Similarly, the model performs admirably in "Tuberculosis" detection, with a fantastic accuracy of 0.99,ensuring that practically all predictions for this class are true, and a high recall of 0.94, demonstrating its ability to properly identify the majority of TB cases. The F1-score of 0.96 demonstrates the model's accuracy in identifying TB. The model is also good at detecting "Pneumonia" instances, with an impressive recall of 0.96, indicating that it captures nearly all real pneumonia cases. However, its accuracy of 0.77 indicates a tendency to categorize some non-pneumonia patients as pneumonia, which has a modest influence on its total performance in
this area. Despite this, the model's F1-score of 0.85 demonstrates a good combination of precision and recall, making it a trustworthy diagnostic tool for pneumonia patients.

Confusion Matrix:
The confusion matrix gives further insights into its performance, highlighting its strengths in discriminating between the three categories while also showing opportunities for development, such as minimizing misunderstanding between "Normal" and "Pneumonia" instances. These findings demonstrate the model's potential as a significant diagnostic tool for healthcare practitioners, notably in reliably recognizing Normal and Tuberculosis illnesses, with opportunity for improvement in diagnosing Pneumonia.

ROC Curve:
The ROC curve below evaluates the performance of a binary classification model by plotting the True Positive Rate (Recall) against the False Positive Rate. The curve’s proximity to the top-left corner indicates strong discriminatory power, and the Area Under the Curve (AUC) score of 0.99 confirms exceptional model performance. This high AUC value suggests the model is highly effective at distinguishing between positive and negative classes, making it suitable for tasks like medical diagnostics, fraud detection, or spam filtering where accurate classification is critical.

TABLE I: CLASSIFICATION REPORT

	precision	recall	f1-score	support
Normal	0.94	0.80	0.87	101
Pneumonia	0.77	0.96	0.85	73
Tuberculosis	0.99	0.94	0.96	71
Accuracy			0.94	245
Macro Avg	0.90	0.90	0.94	245
Weighted avg	0.90	0.89	0.90	245

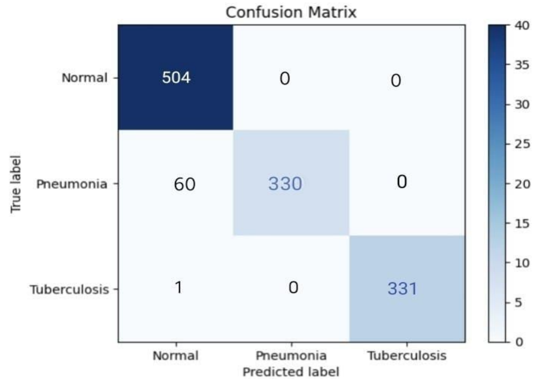

Figure 2. Confusion Matrix

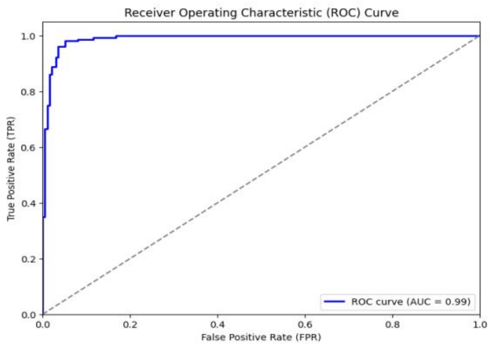

Figure 3: Receiver Operating Characteristic

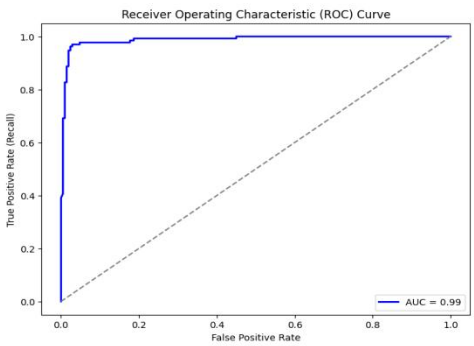

Figure 4: Receiver Operating Characteristic (ROC) Curve for Tuberculosis(ROC) Curve for Pneumonia

III. CONCLUSIONS

This paper presents a robust hybrid model aiming to improve pneumonia and TB diagnosis utilizing AI approaches, especially CNN and GAN models. By combining these two basic components—CNN for feature extraction and GAN for data augmentation—this model overcomes the constraints of existing approaches that frequently struggle with tiny or unbalanced datasets in medical imaging. The algorithm outperforms in recognizing pneumonia and TB from chest X-ray pictures, as measured by accuracy metrics and performance tests. With an excellent accuracy of 93.75%, the model can provide trustworthy diagnoses even in resource-constrained environments. The initiative also features an easy-to-use user interface that allows healthcare practitioners to input X-ray pictures and get real-time predictions on whether they exhibit indications of pneumonia, TB, or both. This user-friendly interface improves the model's accessibility, making it suitable for usage in clinical settings. The combination of high diagnostic accuracy with an easy-to-use interface demonstrates the system's potential as a vital tool in medical diagnostics, aiding early illness diagnosis and improving patient outcomes. This study highlights the transformational influence of deep learning technology in medical imaging, taking a step further in the incorporation of AI-powered technologies into everyday healthcare operations.

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