LiteCovidNet2.0: A lightweight deep neural network model for detection of COVID-19 using X-ray images

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Abstract This project involves the development of a Convolutional Neural Network (CNN) for the classification of chest X-ray images into three classes: 'COVID', 'NORMAL' and 'PNEUMONIA'.The workflow includes data preprocessing, model architecture design, training, and evaluation on a test set.The model is trained using a dataset organized into distinct classes and split into training, testing, and validation sets.The CNN architecture consists of convolutional and dense layers, with dropout regularization to enhance generalization.Early stopping is implemented to prevent overfitting during training.After training for 150 epochs, the model achieves 90.35 percent accuracy on the test set.The class distribution is visualized through a pie chart, providing insights into the distribution of true labels in the test dataset.This project contributes to the domain of medical image analysis, specifically in the context of chest X-ray image classification for pneumonia detection.The approach outlined in this work can be extended and adapted for similar image classification tasks in medical diagnostics

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1. Introduction

The project aims to create a Convolutional Neural Network (CNN) for the classification of chest X-ray images into three categories: 'COVID', 'NORMAL', and 'PNEUMONIA'.The pipeline involves data preprocessing, model architecture design, training, and evaluation on a test set.The evaluation includes metrics such as accuracy and a visualization of the class distribution.

The research aims to predict the patient who is tested COVID-19 positive.It also involves in predicting whether the patient is suffering from Pneumonia and if not it predicts as Normal.The model LiteCovidNet2.0 also exhibits value in public health surveillance by aiding in the rapid analysis and identification of potential COVID-19 cases through image-based screening.

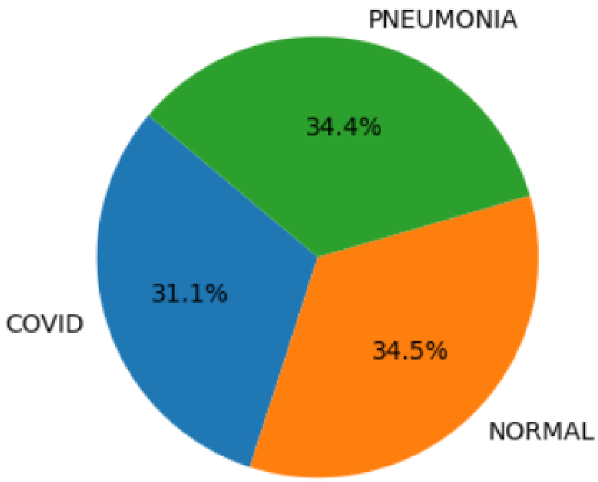

FIGURE 1. Class Distribution Pie Chart.

2. Data Acquisition and Preprocessing

The X-ray images which are taken from the dataset are not of equal sizes.For this, foremost all the images are resized and then converted to red, green, and blue (RGB) channel.The dataset is organized into folders for each class 'COVID', 'NORMAL', 'PNEUMONIA' within the reshaped data directory.The images are partitioned into training, testing, and validation sets using the train-test-split function from the scikit-learn library.The resulting datasets are stored in train data,test data and val data directories, respectively.The images undergo additional preprocessing using the ImageDataGenerator class from TensorFlow's Keras API to normalize pixel values.

3. Architecture

The CNN model is designed using the Sequential API of TensorFlow Keras.It consists of multiple convolutional layers with ReLU activation and max-pooling layers for feature extraction.The flattened output is followed by dense layers with dropout regularization to prevent overfitting.The output layer, with a softmax activation function, corresponds to the three classification categories ('COVID', 'NORMAL', 'PNEUMONIA').

4. Model Description

Convolutional Layers: Three sets of (3x3) convolutional layers with 32, 64, and 64 filters, respectively, followed by max-pooling layers.Dense Layers: Four dense layers with 512, 256, 128, and 64 neurons, respectively, and a dropout rate of 0.5.The model is compiled with the Adam optimizer, categorical crossentropy loss function, and accuracy as the evaluation metric.Early stopping is implemented with a patience of 15 epochs to prevent overfitting.

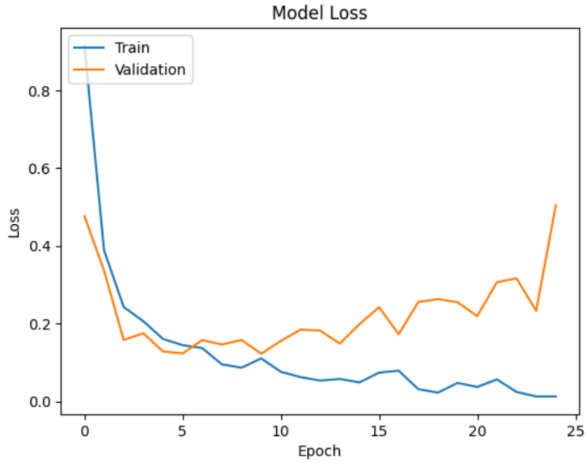

FIGURE 2. Graph Training Loss and Validation Loss vs Epochs.

5. Results

The model is trained for 150 epochs, and the training progress is visualized through accuracy and loss plots.The early stopping mechanism is employed to prevent overfitting, resulting in the best model weights being restored.On evaluating the model on the test set, an accuracy of 90.35 percent accuracy is achieved.A class distribution pie chart shows the distribution of true labels in the test set across the three classes.The project provides an end-to-end solution for image classification with a focus on chest X-ray images for pneumonia detection, contributing to the field of medical image analysis.

Figure 1 shows the class distribution pie chart visually summarizes the distribution of true labels ('COVID', 'NORMAL', 'PNEUMONIA') in the test set, providing insights into the model's performance across different classes.Figure 2 the model's training and validation loss progression is visualized using a line plot.The plot illustrates the convergence of the model over epochs, with the training and validation losses providing insights into the model's learning dynamics and generalization performance.

The Figure 3 .The confusion matrix, visualized through a heatmap,provides a detailed breakdown of predicted and true class labels, offering insights into the model's classification performance across different classes.The Figure 4 represents the results for the training accuracy and validation accuracy vs Epochs for the training data and validation data.

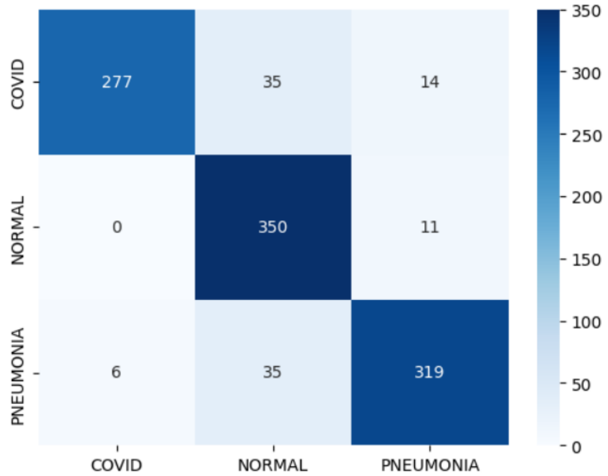

FIGURE 3. Confusion Matrix.

6. Conclusion

The model is trained for a total of 150 epochs, and the training progress is monitored through accuracy and loss plots.The early stopping function serves to prevent overfitting, ensuring the restoration of the best model weights.This iterative training approach enhances the model's generalization capabilities,leading to improved performance on unseen data.

Upon evaluation on the test set, the model demonstrates an accuracy of 90.35 percent, indicating its efficacy in classifying chest X-ray images for COVID detection.The class distribution pie chart visually conveys the balance or imbalance in true labels across the three classes, providing valuable insights into the model's performance on specific categories.The model's performance is comprehensively assessed using key metrics.Precision, recall, and F1 score are reported, demonstrating the model's ability to balance accuracy, sensitivity, and overall performance.

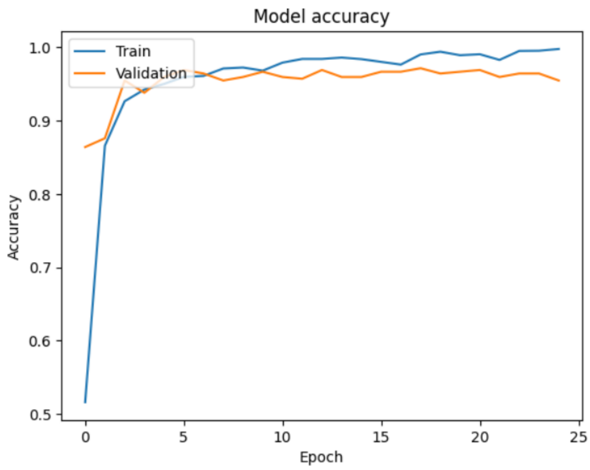

FIGURE 4. Graph for Training accuray and Validation accuracy vs Epochs.

7. Future Work

Assess the model's performance in real-world clinical settings, taking into account factors such as varying image qualities, diverse patient demographics, and potential integration with existing healthcare systems.Experiment with additional data augmentation techniques during training to increase the model's robustness.This could involve introducing variations in scale, rotation, and other transformations to enhance the model's ability to handle diverse input conditions.