Classifying Tuberculosis (TB) and Normal Chest X-ray Images

Group 3

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I. Executive Summary

Tuberculosis (TB) is a contagious illness caused by Mycobacterium tuberculosis bacteria, and it stands as the primary cause of death from a single infectious agent. Fortunately, TB can be effectively treated with antimicrobial medications. Early diagnosis, followed by appropriate treatment, is crucial for curing this potentially deadly disease [1]. In clinical practice, experienced physicians examine chest radiographs to detect TB, but this process is time-consuming and subjective. Consequently, there are inherent inconsistencies in disease diagnosis through radiographs, and TB images may be mistaken for other diseases with similar radiological patterns [2]. Such misclassifications can result in incorrect treatment, worsening patient health. Moreover, there's a shortage of trained radiologists in low-resource countries, particularly in rural areas. In light of the study, it is also worth noting that the healthcare industry is extremely different from other industries as it is a high priority industry where customers are willing to pay a higher price for higher quality.

To address these challenges, computer-aided diagnosis (CAD) systems offer a promising solution for mass TB screening by analyzing chest X-ray images. Among the various deep learning techniques, convolutional neural networks (CNNs), along with the accessibility of large-scale labeled datasets have emerged as a powerful tool for image classification and are widely embraced by the research community [3].

The dataset utilized in this study includes 3,500 normal chest X-ray images and 700 tuberculosis-positive images sourced from the National Library of Medicine and the National Institute of Allergy and Infectious Diseases. This dataset has been used in a paper published in IEEE Access [4].

In this experimental study, we explored multiple approaches to develop models for image classification. We constructed deep neural network (DNN) models with varying numbers of hidden layers, ranging from DNN1 to DNN4, and convolutional neural network (CNN) models with different architectures, including a basic CNN model and another with dropout regularization. Additionally, we incorporated transfer learning by utilizing a pre-trained model, specifically InceptionV3 and DenseNet201. Through thorough experimentation and evaluation, we identified the best-performing model as the CNN model with one Dropout layer before output, achieving a high validation accuracy of 0.996. This result shows the effectiveness of using the model for image classification tasks, demonstrating the ability to capture complex patterns and features in the data.

II. Different Approaches

A. Deep Neural Networks (DNN)

Deep Neural Networks is a complex computational model inspired by the structure and function of the human brain's neural networks. DNNs are capable of learning intricate patterns and representations from data. Defining the DNN model we constructed, we have implemented a default dropout rate of 0.5 and tested it with 1,2,3 and 4 hidden layers. The ReLU activation function and the final Dense layer with a single unit and a sigmoid activation function is used as it is suitable for binary classification tasks. Then, the function compiled the model using the Adam optimizer, binary cross-entropy as the loss function, and accuracy as the evaluation metric.

Before fitting the model, we obtained the summary of the architecture of the DNN model, which includes information about the layers in the model, the number of parameters in each layer, and the total number of parameters in the model. We have found that as the number of layers increases, the total number of parameters and trainable parameters have increased as well. Through training the model, we have used 50 epochs, a batch size of 64, and validation split of 0.2. Using the ModelCheckpoint callback, the best-performing models are saved by looking at the validation accuracy. After training the models, we obtained an accuracy of 0.9583 on the validation set for all the DNN models indicating a good fit.

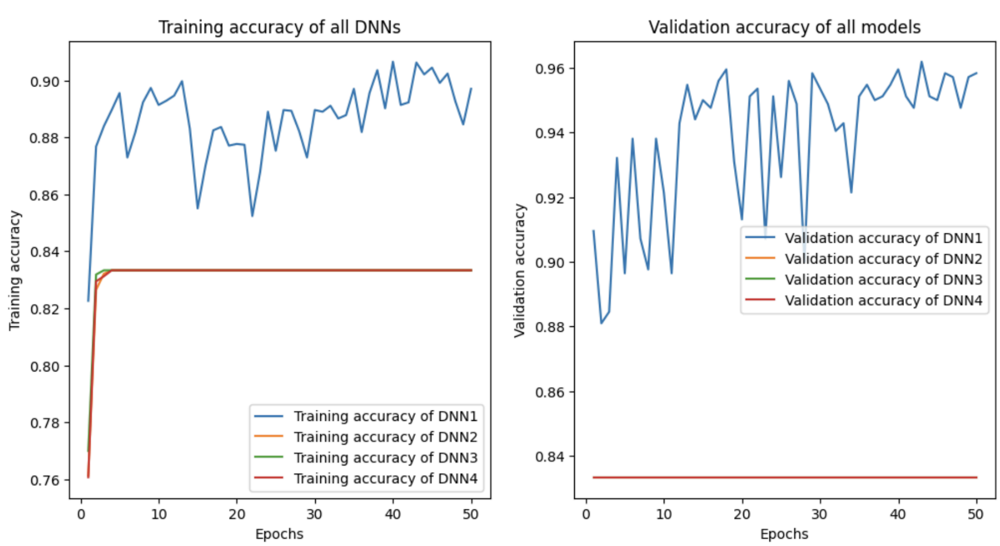

Figure 1: Training Accuracy and Validation Accuracy for DNN models

B. CNN with Pre-Trained Models: Inception V3 and DenseNet201

We utilized transfer learning by leveraging two powerful architectures: Inception V3 and DenseNet201, both pre-trained on the ImageNet dataset, to tackle our image classification task. These pre-trained models provided a strong foundation with learned representations of diverse visual features, enhancing our model's ability to detect complex patterns in images.

To tailor the pre-trained architectures to our specific classification task, we augmented them with additional layers. For the Inception V3 model, we appended a series of layers, including a Flatten layer, a Dropout layer for regularization, and a Dense layer with a sigmoid activation function. Similarly, for the DenseNet201 model, we added a GlobalAveragePooling2D layer, a Dropout layer, a BatchNormalization layer, and a final Dense layer with a sigmoid activation function. These architectures enabled our models to effectively learn and classify features relevant to our task.

Furthermore, we fine-tuned the training process by freezing the weights of the pre-trained layers and optimizing the models using the Adam optimizer and binary cross-entropy loss function. Throughout the training, we monitored the models' performance on the validation dataset, training them for 50 epochs with a batch size of 64. Leveraging the ModelCheckpoint callback, we saved the best-performing models based on validation accuracy.

In the end, we got high validation accuracy scores of 0.994 for InceptionV3 and 0.995 for DenseNet201, showcasing the effectiveness of using transfer learning models in deep learning for real-world applications.

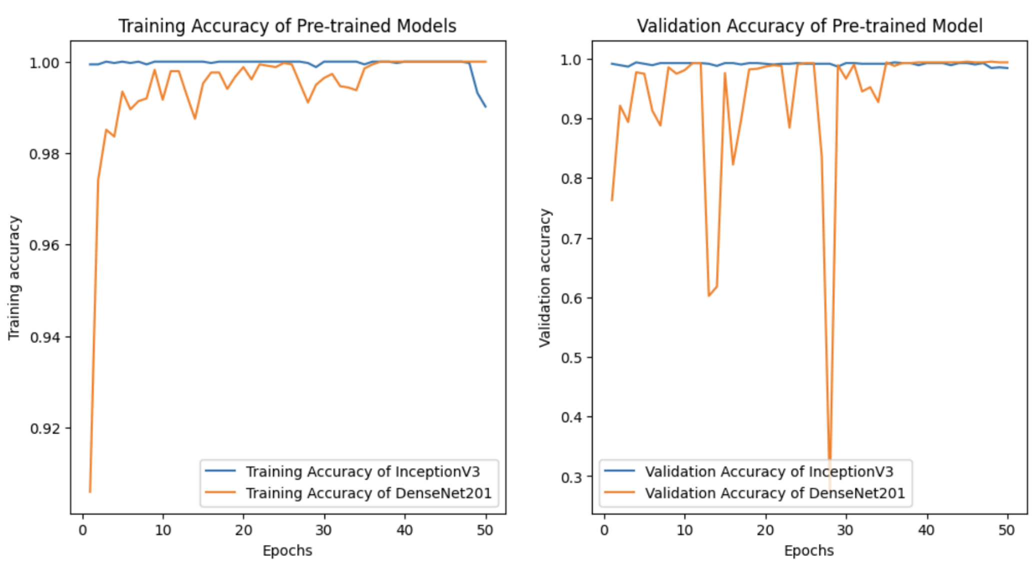

Figure 2: Training Accuracy and Validation Accuracy for Pre-trained Models

C. CNN with or without a Dropout layer

We developed two distinct convolutional neural network architectures for image classification. The first architecture is characterized by a sequence of three convolutional layers, each followed by a max-pooling layer. This design is intended to extract key features from the input images through convolutional operations, followed by downsampling the feature maps to capture the most important information via max-pooling. In contrast, for the second architecture, we added a Dropout layer before the output layer to prevent overfitting by randomly deactivating a proportion of neurons during training.

In both models, we compiled them using Adam optimizer and binary cross-entropy loss function. These steps are essential for guiding the model's learning process, optimizing parameters and quantifying the difference between predicted and actual outcomes. Furthermore, accuracy is utilized as the primary evaluation metric, providing insights into the model's classification performance.

During the training phase, we used a validation split of 20% to monitor and validate the models' performance. By including a ModelCheckpoint callback, it enables us to save the best-performing model based on validation accuracy. As a result, the CNN model achieves an outstanding validation accuracy of 0.991, while the CNN model with a Dropout layer demonstrates an even higher validation accuracy of 0.996, further signifying its ability to accurately classify previously unseen instances.

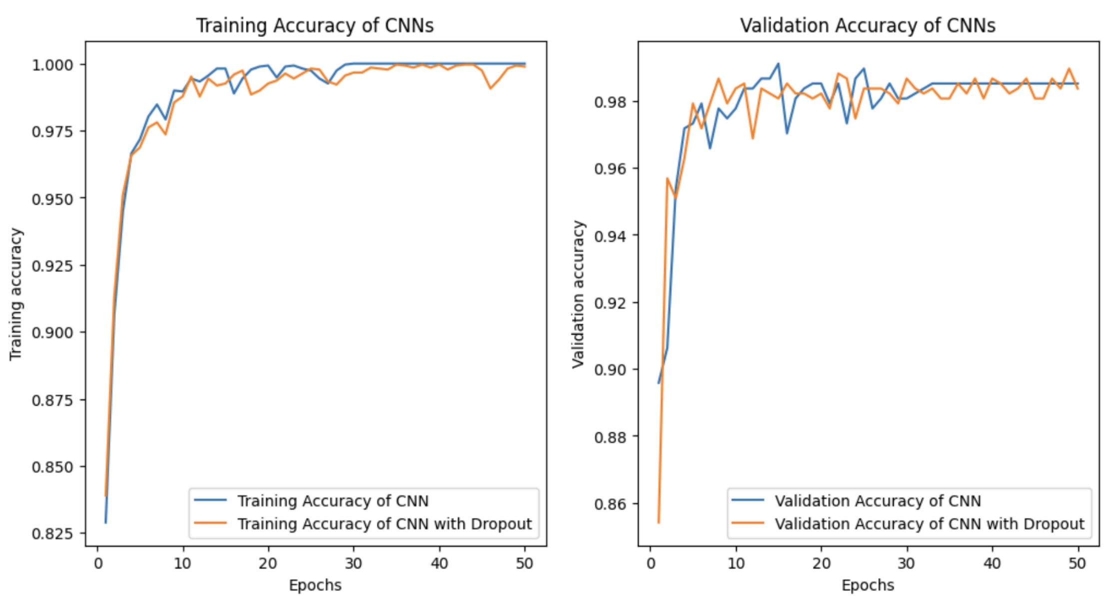

Figure 3: Training Accuracy and Validation Accuracy for CNN models

III. Best Model - CNN with a Dropout Layer

After a thorough evaluation, our analysis shows that the CNN model with a Dropout layer stands out as the top-performing model. This model has a remarkable result, achieving the highest validation accuracy of 0.996. This outcome signifies the importance of integrating Dropout layers, showcasing their pivotal role in building models to increase the accuracy of image classification tasks.

	Best_training_accuracy	Best_validation_accuracy
CNN_with_dropout	0.999107	0.996429
DenseNet201	1.000000	0.995238
InceptionV3	1.000000	0.994048
CNN	1.000000	0.991667
DNN1	0.906548	0.961905
DNN4	0.833333	0.833333
DNN2	0.833333	0.833333
DNN3	0.833333	0.833333

Table 1: Comparison of Training and Validation Accuracies of Different Models

IV. Conclusion

In conclusion, after we have tested DNN model, CNN with pre-trained models *(Inception V3 and DenseNet201),* and CNN model with and without a dropout layer, we have found out that CNN with a dropout layer is the best for classifying Tuberculosis (TB) and Normal Chest X-ray images. This would be extremely beneficial for chest X-ray processing, especially in hospitals where there might not be enough radiologists on site. This would also help mitigate the misclassification of results, hence resulting in incorrect treatment, which worsens the patient's health.

As an extension of our project, we can move on to multi-class classification, finding a wider dataset of chest X-ray images and performing classification on chest X-rays with diseases other than TB, such as pneumonia, lung cancer, etc., enhancing our model's ability to distinguish between these various conditions. This expansion will not only increase the diagnostic capabilities of our tool but also make it a more versatile asset in clinical settings, aiding in quicker and more accurate disease identification.

References

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