Pneumonia Detection from Chest X-ray Images using Convolutional Neural Networks (CNN)

A Project Report

Submitted by

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in partial fulfillment of the requirements for the award of the Degree of

Bachelor of Technology (B.Tech)

in

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Under the guidance of

Mrs. Parvathy Jyothi

CREATING TECHNOLOGY
LEADERS OF TOMORROW
ESTD 2002

Department of ARTIFICIAL INTELLIGENCE & DATA SCIENCE

Jyothi Engineering College

NAAC Accredited College with NBA Accredited Programmes*

Approved by AICTE & affiliated to APJ Abdul Kalam Technological University

A CENTRE OF EXCELLENCE IN SCIENCE & TECHNOLOGY BY THE CATHOLIC ARCHDIOCESE OF TRICHUR

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NBA accredited B.Tech Programmes in Computer Science & Engineering, Electronics & Communication Engineering, Electrical & Electronics Engineering and Mechanical Engineering valid for the academic years 2016-2022. NBA accredited B.Tech Programme in Civil Engineering valid for the academic years 2019-2022.

June 2023

DECLARATION

We hereby declare that the project report " PNEUMONIA DETECTION FROM CHEST X-RAY IMAGES USING CONVOLUTIONAL NEURAL NETWORKS (CNN) ", submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by us under supervision of MRS. PARVATHY JYOTHI. This submission represents the ideas in our own words and where ideas or words of others have been included, We have adequately and accurately cited and referenced the original sources. We also declare that we have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in this submission. We understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously used by anybody as a basis for the award of any degree, diploma or similar title of any other University.

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VISION OF THE INSTITUTE

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MISSION OF THE INSTITUTE

- To emerge as an institution par excellence of global standards by imparting quality Engineering and other professional programmes with state-of-the-art facilities.
- To equip the students with appropriate skills for a meaningful career in the global scenario.
- To inculcate ethical values among students and ignite their passion for holistic excellence through social initiatives.
- To participate in the development of society through technology incubation, entrepreneurship and industry interaction.

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Creating ethical leaders in the domain of Artificial intelligence and data Science through effectual teaching and learning process to develop emerging technology solutions for the benefits of industry and society with a focus on holistic learning and excellence.

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- Strengthening basic competencies in the domains of Artificial Intelligence and Data Science.
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PEO 2: To gain a broad grasp of computer science and engineering at many abstraction levels, including computer architecture and design, operating systems, database management, algorithms, and applications.

PEO 3: To provide students with a solid foundation in math and engineering foundations, which will enable them to examine and assess real-world engineering challenges connected to data science and artificial intelligence, as well as to further prepare them for further education and R&D.

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PEO 5: To inculcate in students an awareness of how to use their computer engineering and mathematical theory skills to address current and future computing challenges.

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The students upon completion of Programme, will be able: -

PSO 1: Understand and develop computer programs in the areas related to algorithms, system software, multimedia, web design, big data analytics and networking by identifying, demonstrating and analyzing the knowledge of engineering in efficient design of computer-based systems of varying complexity.

PSO 2: Applying algorithmic principles, innovative Computer science and engineering design and implementation skills to propose optimal solutions to complex problems by choosing a better platform for research in AI and data science.

PSO 3: Identify standard Software Engineering practices and strategies by applying software project development methods using open-source programming environment to design and evaluate a quality product for business success.

PSO 4: Demonstrate and examine basic understanding of engineering fundamentals, professional/social ethics and apply mathematical foundations to design and solve computational problems.

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1. **Engineering knowledge:** Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
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10. **Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
11. **Project management and finance:** Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
12. **Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

COURSE OUTCOMES

COs	Description
CO.1	Identify technically and economically feasible problems of social relevance.
CO.2	Identify and survey the relevant literature for getting exposed to related solutions.
CO.3	Perform requirement analysis and identify design methodologies and develop adaptable and reusable solutions of minimal complexity by using modern tools and advanced programming techniques.
CO.4	Prepare technical report and deliver presentation.
CO.5	Apply engineering and management principles to achieve the goal of the project.

CO MAPPING TO POs

	POs											
COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO.1	3	3	3	3	0	3	3	2	3	3	3	3
C0.2	2	1	3	2	2	2	0	2	2	2	2	2
C0.3	3	1	2	1	1	1	2	3	3	3	3	3
C0.4	2	2	2	2	2	0	0	1	2	1	2	2
C0.5	3	2	3	2	2	3	3	2	3	0	2	2
Average	2.6	1.8	2.6	2	1.4	1.8	1.6	2	2.6	1.8	2.4	2.4

CO MAPPING TO PSOs

	PSOs			
COs	PSO1	PSO2	PSO3	PSO4
CO.1	3	3	3	3
C0.2	3	3	2	3
CO.3	2	2	1	3
CO.4	3	2	3	1
CO.5	3	2	3	1
Average	2.8	2.4	2.4	2.2

ABSTRACT

Pneumonia is a life-threatening respiratory infection that affects millions of people worldwide. Early and accurate detection of pneumonia is crucial for effective treatment and improved patient outcomes. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNN), have shown great potential in medical imaging analysis. In this report, we present a pneumonia detection system that utilizes chest X-rays and employs a CNN-based approach for pneumonia diagnosis.

The proposed system consists of several stages, starting with preprocessing and augmentation of the chest X-ray images to enhance their quality and diversity. The preprocessed images are then fed into a CNN architecture specifically designed for pneumonia detection. The CNN model is trained on a large data set of labeled chest X-rays, allowing it to learn complex patterns and features indicative of pneumonia.

Our experimental results demonstrate the effectiveness of the proposed pneumonia detection system. The CNN-based approach achieves high accuracy in classifying chest X-ray images into Pneumonia, Normal, Tuberculosis, and COVID-19. Furthermore, the system exhibits excellent sensitivity and specificity, indicating its ability to accurately identify pneumonia cases while minimizing incorrect predictions. Overall, the developed system holds great promise for assisting healthcare professionals in the timely and accurate diagnosis of pneumonia, potentially leading to improved patient care and outcomes.

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CHAPTER 1

INTRODUCTION

1.1 Overview

This project focuses on the detection of Pneumonia and other lung conditions using Chest X-Ray(CXR) images, that can reveal specific patterns and abnormalities indicative of the disease. However, manual interpretation of these images is time-consuming and subjective, leading to potential errors and delays in diagnosis. Therefore, the development of automated systems for pneumonia detection using machine learning techniques holds significant promise in improving diagnostic accuracy and efficiency. Deep learning has revolutionised medical image analysis by leveraging the power of artificial neural networks with multiple layers to learn complex representations from large datasets. By training CNN models on a dataset of labelled chest X-ray images, we aimed to create a powerful tool for automatically detecting pneumonia and assisting healthcare professionals in making accurate diagnoses.

1.2 Objectives

The main objective of this project is to design and implement a convolutional neural network (CNN) model for the detection of lung diseases specifically Pneumonia, Tuberculosis, and Covid19 from chest X-ray images of different image quality, dimension, and colour. We aim to train the model using a dataset of labelled chest X-ray images, with a focus on achieving high accuracy and robust performance, to better assist patient outcomes and early detection of the disease.

1.3 Organization of the Project

The report is organised as follows:
Chapter 1: Introduction- Gives an introduction to ”Pneumonia Detection System”
Chapter 2: Literature Survey- Summarizes the various existing techniques that helped us in achieving the desired result.
Chapter 3: Methodology- Methods which are used in this project.
Chapter 4: Results and Discussion- The results of work and discussion
Chapter 5: Conclusion & Future Scope- The chapter gives a conclusion of the overall work along with the future scope of implementation.
Chapter 6: References- Includes the references for the project.

CHAPTER 2

LITERATURE SURVEY

2.1 Deep Reproductive Feature Generation FrameworkFor The Diagnosis Of COVID-19 And Viral PNneumonia Using Chest X-RAY Images [1]

Pneumonia is a lung infection that can range from mild to severe and affects a large number of individuals globally. Detecting and managing pneumonia cases relies heavily on imaging studies, with radiography currently being the preferred diagnostic method. However, accurately diagnosing pneumonia through chest X-rays can be challenging, as it requires skilled interpretation by experienced medical professionals. To address this issue, a study employed deep learning techniques to classify frontal-view chest X-ray images and identify signs of pneumonia in children. The effectiveness of the classifiers was assessed using a dataset of 5,856 labeled X-ray images from children. The results showed that the classifiers achieved an impressive accuracy of 96-97 percentage in distinguishing between the presence and absence of childhood pneumonia.

2.2 DenResCov-19: A deep transfer learning network for robust automatic classification of COVID-19, pneumonia, and tuberculosis from X-rays [2]

In this study, researchers introduced DenResCov-19, a new deep-learning network that demonstrated strong performance in classifying multi-class lung diseases. They evaluated the model using publicly available datasets comprising COVID-19 positive cases, pneumonia cases, tuberculosis cases, and healthy patients. Despite class imbalance in the DXR4 dataset due to limited COVID-19 positive images, DenResCov-19 outperformed state-of-the-art networks like ResNet-50, DenseNet-121, VGG-16, and Inception-V3, with improved accuracy, AUC-ROC, and F1 metrics. The network's heatmaps closely aligned with radiologists' identified points. The researchers aim to enhance the model's generalization by including a larger cohort of COVID-19 patients, expanding the number of classes, and evaluating it on different datasets for robustness in medical image classification tasks and the diagnosis of various lung diseases and medical conditions.

2.3 CDCNet: multi-classification convolutional neural network model for detection of COVID-19, pneumothorax, pneumonia, lung Cancer, and tuberculosis using chest X-rays [3]

The researchers introduced the CDCNet model for classifying COVID-19, pneumothorax, pneumonia, LC, and TB using chest x-rays. They compared its accuracy with three transfer learning models: Vgg-19, ResNet-50, and Inception-v3. The CDCNet model achieved an impressive accuracy rate of 99.39 percent in distinguishing COVID-19 from other chest-related disorders. This has the potential to revolutionize the diagnostic process for radiologic technologists and improve the identification of these diseases from chest X-rays. Future research aims to compare the additional diagnostic value of COVID-19 with standard morphological aspects using deep learning architecture and evaluate CNN-based algorithms for other chest-related cases. The integration of AI into radiology systems could provide valuable real-time guidance and enhance the global diagnosis of COVID-19 based on chest X-ray quality, usability, and cost.

2.4 CDCNet:Deep transfer learning for detecting Covid-19, Pneumonia and Tuberculosis using CXR images–A Review [4]

The reviewed research works demonstrate the efficacy of employing deep transfer learning approaches in the detection of lung diseases. Deep transfer learning models mostly used include ResNet-50, VGG-16, InceptionV3, ResNet-18 and DenseNet-121 among others. To improve the performance of models, the researchers have utilized techniques like transfer learning, data augmentation, and hyperparameter tuning. TL has been used as the base step to allow training of the pre-trained models on new datasets. Data augmentation techniques have been applied to generate new training samples by applying transformations to the existing data set .Hyperparameter tuning optimized the parameters that control the behavior of deep learning models, such as the learning rate or the number of layers. Despite the advancements of research in this field, there are still pre-existing gaps: The studies reviewed relatively use small data sets, for instance, most of the studies reviewed focus on detecting one lung disease, and in the experimental analysis of different deep and transfer learning approaches, data imbalance issue remains a key problem and this could result in biased results obtained in many researches.

2.5 Deep features to detect pulmonary abnormalities in chest X-rays due to infectious diseaseX: Covid-19, pneumonia, and tuberculosis [5]

In this research paper, the efficacy of a lightweight deep neural network (DNN) consisting of nine layers is demonstrated for the detection of pulmonary abnormalities in chest x-rays (CXRs) caused by infectious diseases, such as Covid-19, Pneumonia, and Tuberculosis

(TB). The experiments conducted in the study go beyond the simple classification of healthy versus non-healthy CXRs, encompassing the screening of multiple disease types. Comparative analysis of performance scores was carried out with existing models for Covid-19, Pneumonia, and TB, as well as popular DNNs used in previous studies with varying dataset sizes. The results show that the proposed DNN achieved an accuracy exceeding 99.50 percent, indicating its potential as a screening tool for infectious diseaseX detection. It is worth noting that such a tool could assist radiologists in making clinical decisions. The researchers are now motivated to explore cross-population train/test models within the scope of their activities, as well as investigate federated learning approaches.

2.6 Classification of COVID-19 from tuberculosis and pneumonia using deep learning techniques [6]

This study presented a model that addressed class imbalance using SMOTE and SVM-SMOTE, oversampling algorithms. They evaluated SMOTE's performance on two datasets, observing a significant accuracy improvement of 10 percent when using SMOTE compared to before. The researchers highlighted the potential of deep learning in disease detection using chest X-ray images, specifically for pneumonia, tuberculosis, and COVID-19 classification. They emphasized the model's ability to facilitate efficient mass screening for COVID-19, especially in resource-limited areas. Future research directions included exploring image data augmentation techniques, optimizing network parameters, and developing an online application for pneumonia diagnosis in underserved regions.

2.7 Diagnosis of Pneumonia from Chest X-Ray Images Using Deep Learning[7]

In this study, the researchers aimed to develop a computer-aided diagnosis system for pneumonia using chest X-ray images. They employed two popular convolutional neural network models, namely Xception and Vgg16, to train and evaluate their system. Transfer learning and fine-tuning techniques were applied during the training phase. The test results revealed that Vgg16 achieved a higher overall accuracy of 0.87 percentage compared to Xception with 0.82 percentage. However, when it came to detecting pneumonia cases specifically, Xception exhibited superior performance. This suggests that each network has its own distinct capabilities when applied to the same dataset.

2.8 Lung Disease Classification Using Deep Learning Models from Chest X-ray Images[8]

In this study, the researchers aimed to develop a computer-aided diagnosis system for pneumonia using chest X-ray images. They employed two popular convolutional neural network models, namely Xception and Vgg16, to train and evaluate their system. Transfer learning and fine-tuning techniques were applied during the training phase. The test results revealed that Vgg16 achieved a higher overall accuracy of 0.87 percentage compared to Xception with 0.82 percentage. However, when it came to detecting pneumonia cases specifically, Xception exhibited superior performance. This suggests that each network has its own distinct capabilities when applied to the same dataset.

2.9 A Lightweight CNN Architecture for Chest X-ray Images Analysis to Facilitate Early Stage Detection of Lung Diseases[9]

This paper proposes a lightweight CNN architecture for the analysis of chest x-ray images, specifically targeting pneumonia and Covid-19 detection in infants and children. The traditional method of manual interpretation by radiologists is time-consuming, emphasizing the need for automated systems. The proposed model offers a compact design with fewer parameters compared to pre-trained Imagenet models, reducing training time and improving the efficiency of the detection process. Experimental results on benchmark datasets demonstrate that the lightweight CNN model achieves comparable accuracy to state-of-the-art models, with an accuracy of 90.38 percentage on the kermany dataset and 96.90 percentage on the Covid-19 Radiography dataset. This research contributes to the advancement of early-stage lung abnormality detection, potentially reducing mortality rates among infants and children.

2.10 Visualization and Interpretation of Convolutional Neural Network Predictions in Detecting Pneumonia in Pediatric Chest Radiographs [10]

This study focused on evaluating, visualizing, and explaining the performance of customized convolutional neural networks (CNNs) in the detection and differentiation of pneumonia types in pediatric chest X-rays. The use of computer-aided diagnostic (CADx) tools aims to enhance decision-making in medical screening and diagnosis. However, the lack of interpretability in CNNs has been a significant limitation in clinical applications. The researchers addressed this issue by developing a novel visualization strategy to identify the relevant regions of interest (ROIs) for model predictions across various inputs. The customized VGG16 model achieved impressive results, with an accuracy of 96.2

CHAPTER 3

METHODOLOGY

3.1 Existing Systems

- While there are existing systems for identifying lung diseases like pneumonia, COVID-19, and tuberculosis, many suffer from certain drawbacks that limit their effectiveness. Some common shortcomings include the use of small data sets, low accuracy, and performance, and the restriction to binary classification. Addressing these limitations requires ongoing research and development efforts in the field of deep learning and medical imaging.

3.1.1 Disadvantages of existing systems

- Small data sets: One significant limitation in the existing systems is the reliance on small data sets for training and evaluation. Limited data can lead to overfitting, where the model becomes too specialized in the training data and fails to generalize well to unseen cases. To overcome this limitation, larger and more diverse data sets are needed to train the models effectively.

- Low accuracy and performance: Achieving high accuracy in disease detection is crucial for reliable diagnoses. However, some existing systems may fall short in terms of accuracy and performance. This could be due to various factors such as suboptimal model architectures, insufficient training, or limitations in the available computational resources. Enhancing the accuracy and performance of these systems requires advancements in model design, training techniques, and access to adequate computing power.

- Binary classification: Many existing systems are designed for binary classification, distinguishing between normal and abnormal cases. While this can be useful for initial screening purposes, it may not provide sufficient granularity for identifying specific lung diseases or their severity. Developing models that can handle multi-class classification, distinguishing between different lung diseases and their stages, would be more beneficial for accurate diagnosis and treatment planning.

- Class Imbalance: In pneumonia detection, the number of positive cases may be substantially lower than negative cases, leading to an imbalanced data set. Class imbalance can affect the model's ability to learn and generalize effectively, as the network may become biased towards the majority class. Proper techniques such as data augmentation, oversampling, or weighted loss functions can be employed to handle class imbalance and improve the system's performance.

3.2 Problem Statement

To develop and validate new diagnostic techniques capable of identifying patterns and bio markers associated with Pneumonia from X-ray images, and to improve patient outcomes by creating a system that enables mass identification with high accuracy.

3.3 Proposed System

The proposed pneumonia detection system utilizes deep learning algorithms, specifically Convolutional Neural Networks (CNNs), to analyze medical images and provide accurate diagnoses or probability scores indicating the likelihood of pneumonia,covid-19 and tuberculosis. Training the system involves providing a large dataset of labeled chest X-ray images, where each image is annotated into pneumonia-positive,pneumonia-negative, tuberculosis, or COVID-19. Once the CNN is trained, the system can process new chest X-ray images. The input image is fed into the trained network, and the CNN's convolutional and pooling layers analyze the image, progressively learning complex features. The fully connected layers combine these features to generate a prediction or probability score indicating the likelihood of pneumonia.

The proposed system aims to provide healthcare professionals with an efficient and accurate tool for pneumonia detection. By automating the analysis of medical images, the system can aid in early diagnosis, potentially leading to improved patient outcomes through timely interventions and treatment.

3.3.1 Data Collection and Compilation

The dataset consists of 4 classes - Pneumonia(P), Normal(N), Tuberculosis(T), Covid19(C). Multiple datasets were explored for each class. The datasets available have different combinations such as PN, PNC, NC, etc. One dataset included two kinds of Pneumonia - Bacterial and Fungal. Some datasets included images in certain classes where the images were of low quality. In the final dataset, the imagesets which have the highest quality and the highest image count, were included.

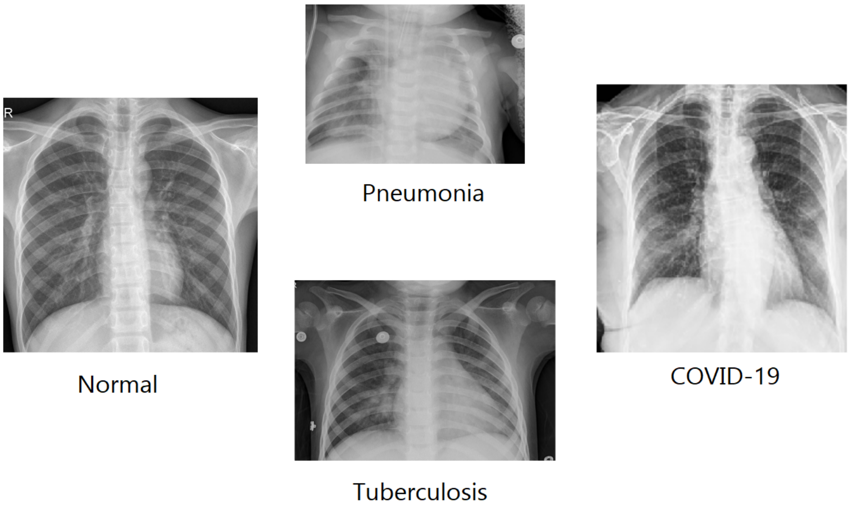

Figure 3.1: Images of each class

3.3.2 Data Preprocessing

The images are resized to 150x150. We perform grayscale normalization to reduce the effect of illumination's differences. One hot encoding is also performed on the class labels.

3.3.3 Model Architecture

The architecture of the CNN employed in the system consists of 20 layers. The layers work together to extract relevant features from the input images and make predictions based on the learned patterns. It consists of the following layer:

- Convolutional layers: These layers apply a set of (3x3) filters to the input images, extracting local features and identifying patterns related to pneumonia. By convolving these filters across the image, the CNN captures important spatial information.

- Pooling layers: After each convolutional layer, maxpooling layers downsample the feature maps, reducing the dimensionality and focusing on the most salient features. This process helps to make the CNN translationally invariant and reduces computational complexity.

- BatchNormalization layers: BatchNormalization layers help to improve the training and generalization of the model. Batch normalization normalizes the outputs of the previous layer by adjusting and scaling them. This technique reduces the internal covariate shift and accelerates the training process.

- Flatten Layer: The flatten layer transforms the multidimensional output of the previous layer into a one-dimensional vector, enabling the connection between convolutional or pooling layers and fully connected layers in the neural network architecture.
- Dense Layer: Dense layers, also known as fully connected layers, connect every neuron in the current layer to every neuron in the subsequent layer, performing computations with weighted inputs, biases, and activation functions, enabling complex non-linear transformations.
- Dropout layers: To prevent overfitting and enhance generalization, dropout layers are incorporated into the network. During training, these layers randomly deactivate a fraction of neurons, forcing the model to learn more robust and independent representations.

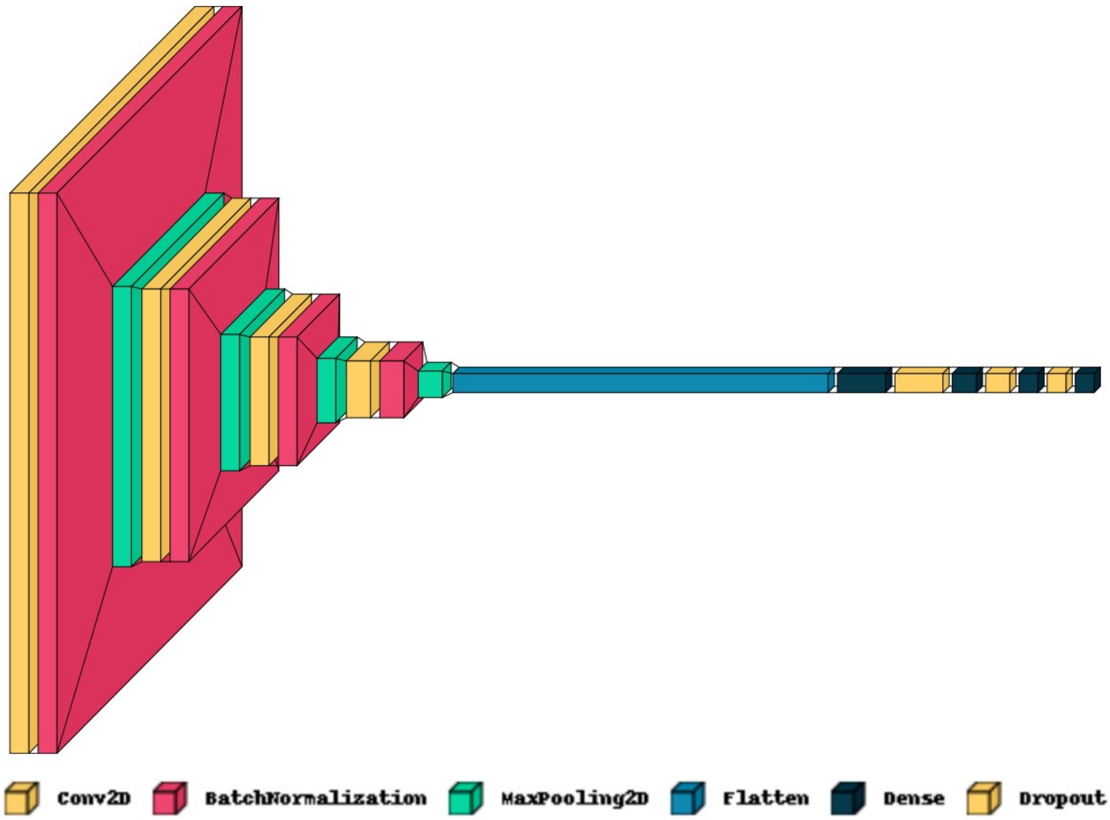

Figure 3.2: 3D Visulaization of the Model

The model starts with a 2D convolutional layer with 32 filters, using a (3, 3) kernel size and ReLU activation. The input shape is set to (150, 150, 1), indicating grayscale images of size 150x150. Batch normalization is applied after each convolutional layer to normalize the activations and improve training stability. Max pooling layers with a (2, 2) pool size are used to reduce the spatial dimensions of the feature maps. The convolutional and pooling layers are repeated with increasing filter sizes (64, 128, and 256) to capture higher-level features.

After the last pooling layer, a flatten layer is added to convert the 3D feature maps into a 1D vector. Dense layers are then introduced with 512, 256, 128 neurons and ReLU activation functions. Dropout layers with a dropout rate of 0.5 are added after each dense layer to prevent overfitting. The final dense layer has 4 neurons with softmax activation, suitable for multi-class classification tasks. The model is compiled with the Adam optimizer, categorical cross-entropy loss function, and accuracy as the evaluation metric.

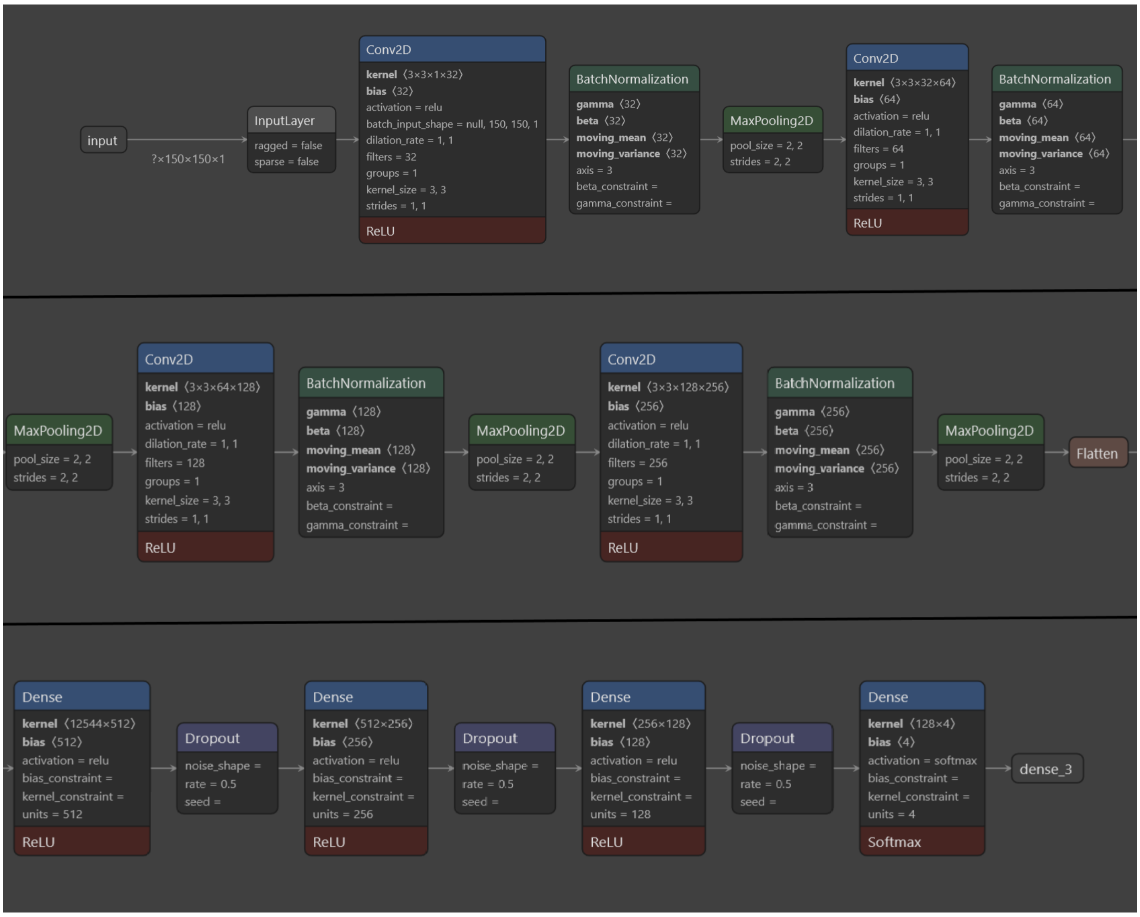

Figure 3.3: Architecure Details

3.3.4 Model training

The CNN model is trained using the following settings:

- Learning rate reduction: A learning rate reduction technique is employed to dynamically adjust the learning rate during training. The learning rate reduction variable represents an instance of the ReduceLROnPlateau callback. It monitors the validation accuracy and reduces the learning rate by a factor of 0.3 if no improvement is observed after two epochs (patience). The minimum learning rate is set to 0.000001 (min lr). This technique dynamically adjusts the learning rate based on the validation accuracy, potentially improving convergence and preventing the model from getting stuck in sub optimal solutions.

- Training data: The model is trained on the 9918 training images represented by xtrain (input images) and ytrain (corresponding labels).
- Batch size: The batch size is set to 16, indicating that the model is updated after processing 32 samples at a time. This parameter controls the number of samples processed before updating the model's weights.
- Epochs: The model is trained for 100 epochs, meaning the entire training dataset is passed through the network 100 times.
- Validation data: Validation data: The validation data is represented by 2144 images as xval (validation images) and yval (validation labels). During training, the model's performance is evaluated on this validation set to monitor its progress and prevent over-fitting.
- Callbacks: The learning rate reduction callback is included in the training process as a callback function to dynamically adjust the learning rate based on the validation accuracy
- Loss function: The loss function used during training is categorical cross entropy. This is a suitable loss function for multi-class classification tasks, measuring the dissimilarity between the predicted class probabilities and the true class labels.

  The training progress, including the loss and accuracy metrics for both the training and validation sets, is recorded in the history variable for later analysis and visualization.

3.3.5 Model Evaluation

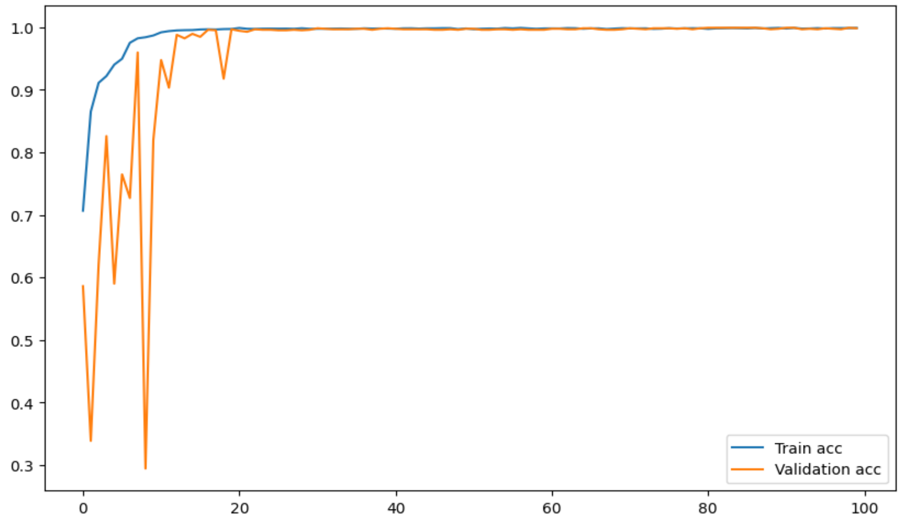

Figure 3.4: Accuracy Graph

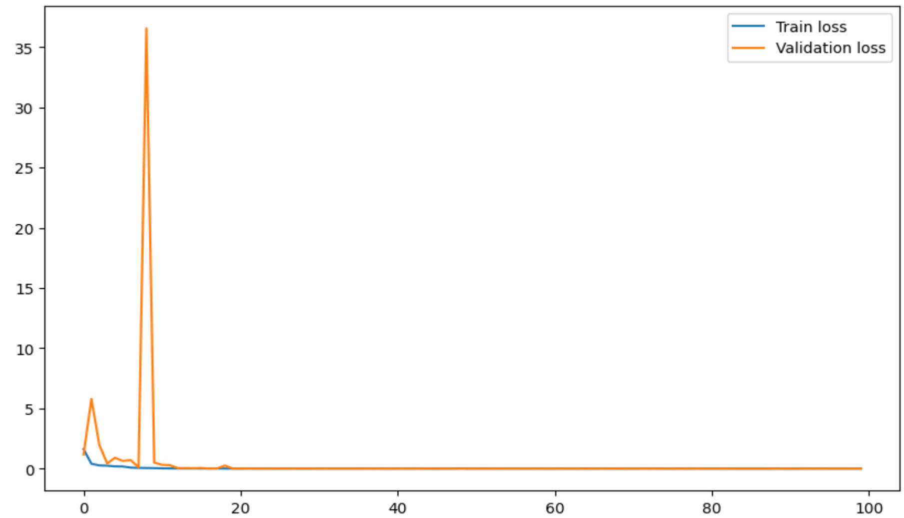

Figure 3.5: Loss Graph

After training the model for 100 epochs, the model achieved a training accuracy of 99.74 percentage. The validation accuracy of 99.68 percentage. The model achieved a training loss of 0.0083. The validation loss at the end of training was 0.0135. These metrics indicate that the model performed well during training, achieving high accuracy and relatively low loss on both the training and validation sets.

CHAPTER 4

RESULTS & DISCUSSION

4.1 Results

4.1.1 Accuracy & Loss

The model, evaluated on the test dataset, has a loss of 0.0241 and accuracy of 99.35 percentage. These metrics indicates that the model generalizes well to unseen data, as it maintains a high level of accuracy and reasonable loss on the test set.The model demonstrates strong performance in terms of accuracy, with a high level of accuracy achieved both during training and evaluation on the test dataset. The loss values indicate that the model effectively minimizes the dissimilarity between predicted and true class probabilities, further supporting its reliability for classification tasks.

4.1.2 Classification Report

The Classification Report is generated to show the following metrics

- Precision: Precision measures the proportion of correctly predicted positive instances (true positives) out of the total instances predicted as positive.
- Recall: Also known as sensitivity or true positive rate, measures the proportion of correctly predicted positive instances out of the total actual positive instances.
- F1 score: The F1 score is the harmonic mean of precision and recall and provides a balanced measure of the model's performance.
- Support: Support represents the number of instances in each class. It provides an understanding of the distribution of classes in the dataset.

Class	Precision	Recall	F1-Score	Support
Pneumonia	1.00	0.99	1.00	427
Normal	0.99	0.99	0.99	350
Tuberculosis	0.99	0.99	0.99	100
Covid19	0.99	1.00	0.99	367

Overall, the model demonstrates a high level of performance across the precision, recall, and F1 score metrics, indicating its effectiveness in classifying the different classes.

4.1.3 Confusion Matrix

The Confusion Matrix is generated to visualize the model's performance in classifying the test dataset.The test dataset is imbalanced, hence there are differences in the number of test images in each class.

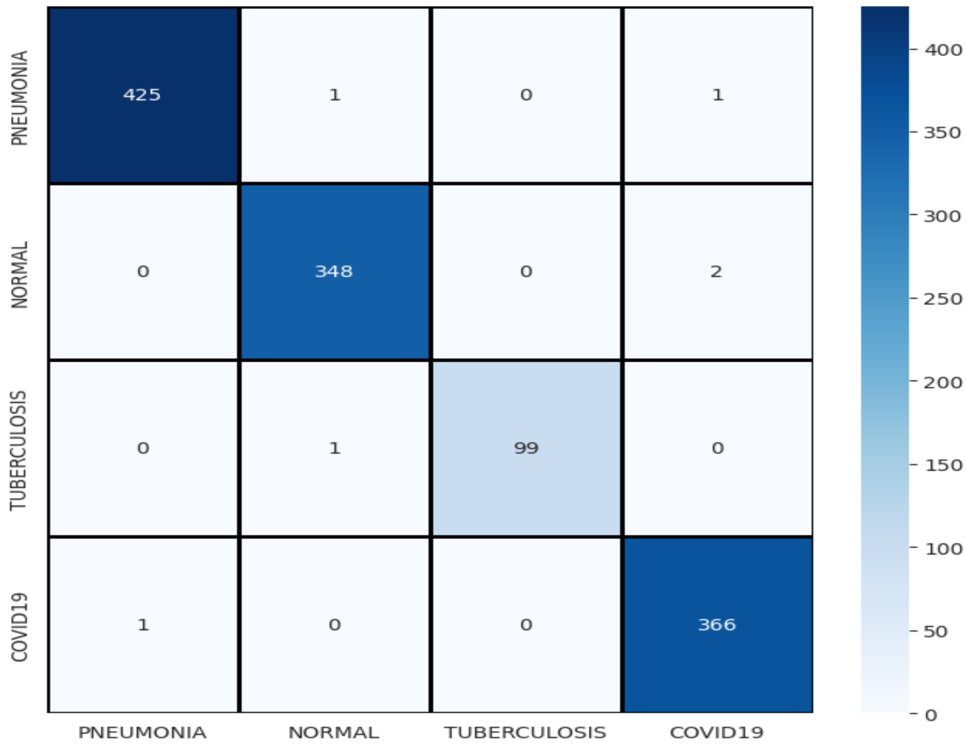

Figure 4.1: Confusion Matrix

4.2 Discussion

The results of our pneumonia detection model using X-ray images are promising and demonstrate its effectiveness in accurately classifying different types of lung conditions. We trained the model using a dataset consisting of four classes: Pneumonia, Normal, Tuberculosis, and COVID-19. The model architecture consisted of multiple convolutional layers with batch normalization and pooling operations, followed by fully connected layers and dropout regularization to prevent overfitting.

During training, we achieved a high accuracy above 99.53% on the test set, indicating that the model learned meaningful patterns and features from the X-ray images. The learning curve analysis showed a steady increase in both training and validation accuracy, suggesting that the model successfully generalized to unseen data. The loss curves demonstrated a consistent decrease over the epochs, indicating that the model effectively minimized the training loss and optimized its performance.

The evaluation of the model on the test set revealed an accuracy of 99.31, further confirming its robustness and generalization capabilities. The precision, recall, F1-score, and support metrics provided a comprehensive assessment of the model's performance for each class. We observed high precision and recall values for most classes, indicating a balanced classification performance.

The confusion matrix provided insights into the model's performance across different classes. The correct and incorrect image classifications showcased the model's ability to correctly identify distinct patterns in X-ray images, while also highlighting cases where misclassifications occurred.

Overall, our pneumonia detection model demonstrated reliable performance in classifying X-ray images and detecting lung abnormalities. It holds the potential for assisting medical professionals in the diagnosis of pneumonia and related conditions, enabling more accurate and timely treatment decisions. Future work could focus on expanding the dataset, to further improve the model's performance in identifying this specific condition. Additionally, the exploration of advanced techniques such as transfer learning or ensemble models could enhance the accuracy and robustness of the pneumonia detection system.

CHAPTER 5

CONCLUSIONS AND FUTURE SCOPE

5.1 Conclusion

Using machine learning techniques, the developed model achieved high accuracy in classifying chest X-ray images into different categories (Pneumonia, Normal, Tuberculosis, Covid). The used CNN architecture proved effective in extracting relevant features from the images and capturing patterns indicative of different chest conditions. The evaluation metrics, including accuracy, loss, precision, recall, and F1-score, provided insights into the model's performance and its ability to correctly classify the different chest conditions.

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5.1.1 Implications

Accurate classification of chest X-ray images can assist in the early detection and diagnosis of various chest conditions, leading to timely medical interventions and improved patient outcomes. The developed model can potentially support radiologists and healthcare professionals by providing an additional tool for preliminary screening and triage, especially in situations where resources are limited or time is critical. The project demonstrates the potential of machine learning and deep learning techniques in medical image analysis, showcasing the ability to automate the interpretation of medical images and aid in decision-making processes.

5.1.2 Limitations and Areas for Improvement:

The dataset used in the project has certain limitations, such as class imbalance and variations in image quality. Collecting a larger and more diverse dataset could improve the robustness and generalization of the model. The project utilized a custom-made CNN architecture. Exploring more advanced network architectures, such as residual networks (ResNet), dense networks (DenseNet), may further enhance the model's performance. While the model achieved a certain level of accuracy, it is essential to validate its performance on external datasets and compare it with human expert interpretations to ensure reliability and generalizability. The project focused on chest X-ray images. Expanding the analysis to other medical imaging modalities, such as computed tomography (CT) scans or magnetic resonance imaging (MRI), can broaden the scope and applicability of the model.

5.2 Significance and Potential Applications

- The system has the potential to assist healthcare professionals in analyzing and interpreting medical images, providing support in diagnosing lung conditions.

- Automated classification of chest X-ray images can aid in resource optimization by prioritizing urgent cases, reducing the burden on radiologists, and enabling faster diagnoses.

- The developed approach can be extended to other medical imaging tasks, such as detecting tumors, identifying abnormalities, or assisting in disease prognosis, contributing to the field of medical image analysis and enhancing healthcare delivery.

5.3 Future Scope

More data has to be collected in data related to some classes(Tuberculosis and Covid19). More preprocessing has to be applied to the current data to achieve better results. More advanced neural networks need to be experimented with In conclusion, the project highlights the potential of machine learning and deep learning techniques in medical image analysis, specifically in classifying chest X-ray images. While it demonstrates promising results, further research, and validation are necessary to ensure the reliability, scalability, and clinical applicability of the developed model.

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