Project Report

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

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Abstract

Pneumonia is a prevalent respiratory condition that requires early detection and prompt intervention to prevent complications. This project presents an innovative approach that utilises deep learning techniques to automatically detect pneumonia using chest X-ray images as the dataset. By leveraging convolutional neural network models, the proposed method achieves impressive performance metrics without the need for manual or automated measurements, feature extraction, or complex image processing.

The research workflow involves several crucial steps in designing and customising models to efficiently classify X-ray images into 4 classes. Through extensive experimentation and fine-tuning, the deep learning architecture's performance is optimised, resulting in accurate and reliable predictions. Importantly, the absence of elaborate image processing or modelling simplifies the process while maintaining robust classification capabilities.

The developed system demonstrates promising results in accurately identifying pneumonia cases, potentially enabling timely intervention and improving patient outcomes. By automating the classification process, healthcare professionals can benefit from a time-efficient and accurate tool for pneumonia detection, facilitating early diagnosis and treatment. This research highlights the potential of deep learning algorithms in revolutionising medical image analysis, specifically in the context of pneumonia detection using chest X-ray images.

1. Introduction

Pneumonia, a common respiratory infection, is a serious health concern that requires early detection for timely intervention and effective treatment. Chest X-ray images play a crucial role in diagnosing pneumonia, as they 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, a subfield of machine learning, has revolutionised medical image analysis by leveraging the power of artificial neural networks with multiple layers to learn complex representations from large datasets. Convolutional neural networks (CNNs), a type of deep learning architecture, have demonstrated exceptional performance in image classification tasks. By training CNN models on a dataset of labelled chest X-ray images, we can create a powerful tool for automatically detecting pneumonia and assisting healthcare professionals in making accurate diagnoses.

The objective of this research paper is to explore the application of deep learning techniques for pneumonia detection from chest X-ray images. We aim to develop a robust CNN model that can analyse X-ray images and accurately identify the presence or absence of pneumonia. Additionally, we will evaluate the model's performance using various evaluation metrics to assess its effectiveness in pneumonia detection.

The proposed deep learning-based approach offers several advantages over traditional manual interpretation. It can significantly reduce the time required for pneumonia diagnosis, allowing for faster initiation of appropriate treatment. Moreover, by eliminating subjectivity and variability associated with human interpretation, the deep learning model can provide more objective and consistent results, improving the reliability of diagnoses.

In this paper, we will describe the methodology employed to develop the deep learning model for pneumonia detection. This includes acquiring and preprocessing the dataset of chest X-ray images, designing the CNN architecture, and training the model using suitable optimization algorithms. We will present the experimental results, evaluating the performance of the proposed approach on a comprehensive dataset of pneumonia cases.

Furthermore, we will discuss the limitations of the approach, potential areas for improvement, and the significance of this research in the field of medical image analysis.

Overall, this project aims to contribute to the advancement of automated pneumonia detection using deep learning techniques, with the ultimate goal of improving patient care and outcomes by enabling faster and more accurate diagnoses.Also the system also detects Covid19 and Tuberculosis

1.1 Problem Statement

The accurate and timely detection of pneumonia is crucial for effective medical intervention and treatment. Chest X-ray images play a vital role in diagnosing pneumonia, as they can reveal abnormalities in the lungs that indicate the presence of the disease. However, manual interpretation of these images is time-consuming and subject to human error. Therefore, the development of an automated system for pneumonia detection using machine learning techniques is of great importance. To develop and validate new diagnostic techniques capable of identifying patterns and biomarkers associated with Pneumonia from X-ray images, and to improve patient outcomes by creating a system that enables mass identification with high accuracy is the problem statement.

1.2 Motivation

The motivation behind this project stems from the need to improve the efficiency and accuracy of pneumonia diagnosis. By leveraging the power of machine learning and computer vision, we aim to develop a model capable of accurately detecting pneumonia from chest X-ray images. Such a system has the potential to assist healthcare professionals in making faster and more reliable diagnoses, leading to timely treatment and improved patient outcomes.

1.3 Objectives

The main objectives of this project are as follows:

1. 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.
2. To train the model using a dataset of labelled chest X-ray images, with a focus on achieving high accuracy and robust performance.
3. To evaluate the performance of the developed model by measuring various metrics, such as accuracy, precision, recall, and F1 score.

1.4 Significance of the Project

The significance of this project lies in its potential to revolutionise pneumonia diagnosis by automating the process of analysing chest X-ray images. An accurate and efficient automated system can help healthcare professionals make more informed decisions, reduce the time required for diagnosis, and improve patient care. Furthermore, this project contributes to the field of medical image analysis and demonstrates the capabilities of machine learning in addressing real-world healthcare challenges.

1.5 Application

The primary application of this project is in the field of radiology and healthcare. The developed pneumonia detection system can be integrated into existing medical imaging systems, aiding radiologists in the detection and diagnosis of pneumonia from chest X-ray images. The system has the potential to be utilised in hospitals, clinics, and healthcare facilities worldwide, facilitating faster and more accurate diagnosis.

In summary the applications of this system are,

- Medical diagnosis
- Screening in clinical trials
- Screening in a high-risk population
- Public Health Surveillance

- Tele-medication

1.6 Overview of the Report

- Conducting a comprehensive literature review on pneumonia detection from chest X-ray images, highlighting relevant research and existing approaches.
- Searching for the public datasets that can be used in this project, including its characteristics, preprocessing steps, and data splitting strategies.
- Researching the different methodologies to be employed, focusing on the design and implementation of the convolutional neural network (CNN) model for pneumonia detection.
- Evaluating the results obtained from the experiments conducted, evaluating the performance of the developed model, and comparing it with the previous results.
- Summarising the main findings of the project and its limitations, and suggest potential areas for future improvement.

2. Literature Review

2.1 Papers Published

Some papers published in the domain of Pneumonia detection from X-Ray images are listed with their details.

2.1.1 Detecting Pneumonia in chest radiographs using convolutional neural networks

Paper type: Conference
Name of Publisher: SPIE Digital Library
Year: 2020
Authors: Jennifer Ureta, Oya Aran, Joanna Pauline Rivera

2.1.2 Pneumonia Detection in Chest X-ray images using an Ensemble of deep learning models

Paper type: Journal
Name of Publisher: PLOS ONE
Year: 2021
Authors: Rohit Kundu, Ritacheta Das, Zong Woo Geem, Gi-Tae Han, Ram Sarkar.

2.1.3 Pneumonia Detection on Chest X-Ray Using Machine Learning Paradigm

Paper type: Conference
Name of Publisher: Springer
Year: 2022
Authors: Tej Bahadur, Chandra, Kesar Verma

2.2 Review

Inferences derived from the papers are described below

2.2.1 Detecting Pneumonia in chest radiographs using convolutional neural networks

The use of deep learning algorithms for the multi-class classification of frontal-view chest X-ray images is a promising approach for the detection of lung diseases. The study showed that the classifiers were able to accurately identify the presence or absence of pneumonia with an accuracy between 96-97%.

2.2.2 Pneumonia Detection in Chest X-ray images using an Ensemble of deep learning models

The system developed in this study using deep transfer learning-based classification and an ensemble framework has demonstrated high accuracy, sensitivity, precision, and f1-score rates in classifying chest X-ray images into pneumonia and normal classes.

2.2.3 Pneumonia Detection on Chest X-Ray Using Machine Learning Paradigm

The paper presents a machine-learning method for the automatic detection of pneumonia in segmented lungs, achieving high accuracy of 95.63% using the Logistic Regression classifier and 95.39% using the Multilayer Perceptron classifier. The proposed method can potentially aid radiologists in the early detection and diagnosis of pneumonia, leading to better patient outcomes.

2.3 Gaps Identified

Since all of the above mentioned papers use binary classification (Normal and Pneumonia) they are not able for the determination of other lung diseases. In [2.1.1] in some instances the ensemble framework failed to produce correct predictions. In [2.1.3] the dataset only consists of a total of 412 chest X-ray images containing 206 normal and 206 pneumonic cases from the ChestX-ray14 dataset are used in experiments, which is smaller as compared to the others.

3. Dataset

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.

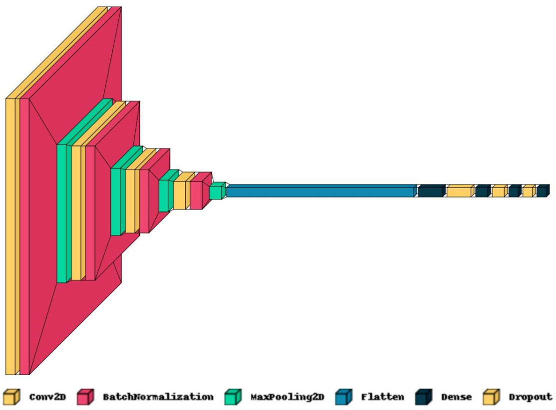
4. Methodology

4.1 Data Preprocessing

We use basic preprocessing such as normalizationa and resizing. The images are greyscale normalized after which they are resized to 150x150.

4.2 Architecture Design

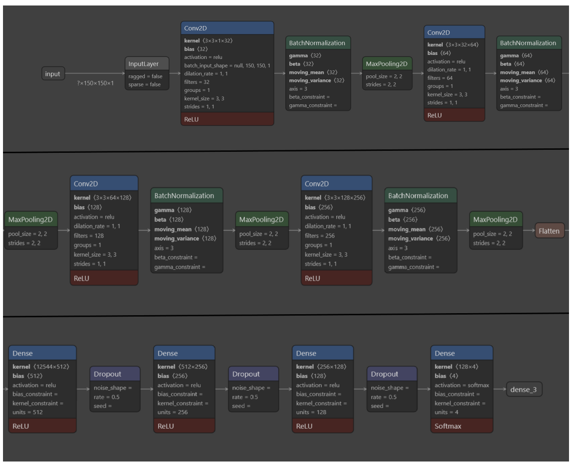
Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for image classification tasks. CNNs are inspired by the visual processing mechanisms in the human brain, where neurons respond to specific local regions in the visual field. The fundamental building blocks of CNNs are convolutional layers, which perform localised feature extraction through the application of convolutional filters. These filters learn to detect low-level features such as edges, corners, and textures. As the network progresses deeper, higher-level features and semantic representations are learned by combining and abstracting the low-level features. This hierarchical feature extraction enables CNNs to capture complex patterns and structures in images.



Additionally, CNNs incorporate pooling layers, which reduce the spatial dimensions and provide translational invariance, making the models robust to slight spatial variations. The final layers of a CNN typically consist of fully connected layers, which perform classification based on the learned features. The combination of convolutional, pooling, and fully connected layers allows CNNs to effectively learn and classify image features, making them well-suited for image classification tasks.

This is an overview of the architecture. The model starts with a Sequential container, indicating a linear stack of layers.

1. Conv2D layer: The first layer is a Convolutional layer with 32 filters, each having a size of 3x3. The activation function used is ReLU (Rectified Linear Unit), which introduces non-linearity to the model. The input shape for this layer is set to (150, 150, 1), indicating a grayscale image of size 150x150.
2. BatchNormalization layer: This layer normalizes the outputs from the previous layer, helping in faster and more stable training.
3. MaxPool2D layer: A Max Pooling layer with a pool size of 2x2 is applied to reduce the spatial dimensions of the feature maps by selecting the maximum value in each 2x2 region.



The above three layers are repeated three more times, gradually increasing the number of filters to capture more complex features and applying batch normalization and max pooling to downsample the feature maps.

4. Flatten layer: This layer flattens the 3D feature maps into a 1D vector, preparing them to be passed to the fully connected layers.
5. Dense layers: Three dense (fully connected) layers follow the flatten layer. The first dense layer has 512 neurons with a ReLU activation function. Dropout regularization with a rate of 0.5 is applied after this layer to prevent overfitting. The subsequent dense layers have 256 and 128 neurons, respectively, with ReLU activation and dropout applied after each.
6. Dense output layer: The final dense layer has 4 neurons, corresponding to the number of classes in the classification task. The activation function used is softmax, which provides a probability distribution over the classes.
7. Compilation: The model is compiled using the Adam optimizer, which is an adaptive learning rate optimization algorithm. The loss function is set to categorical_crossentropy, suitable for multi-class classification. The metric chosen to evaluate the model's performance is accuracy.

The ReLU activation function introduces non-linearity, and batch normalization helps stabilize training. Dropout regularization is applied to prevent overfitting. The model is optimized using the Adam optimizer, and the categorical cross-entropy loss function is used for multi-class classification tasks.

4.3 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).

- Training data: The model is trained on the training data represented by x_train (input images) and y_train (corresponding labels).
- Batch size: The batch size is set to 32, 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 20 epochs, meaning the entire training dataset is passed through the network 20 times. Each epoch consists of forward and backward propagation, weight updates, and evaluation.
- Validation data: The validation data is represented by x_val (validation images) and y_val (validation labels). During training, the model's performance is evaluated on this validation set to monitor its progress and prevent overfitting.
- 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_crossentropy. This is a suitable loss function for multi-class classification tasks, measuring the dissimilarity between the predicted class probabilities and the true class labels.
- Evaluation metrics: The model's performance is evaluated using the validation data. The metrics used for evaluation are typically the same as those specified during the model compilation. In this case, the model's accuracy is evaluated to assess how well it classifies the validation images.

The learning rate reduction technique dynamically adjusts the learning rate based on the validation accuracy, potentially improving convergence and preventing the model from getting stuck in suboptimal solutions. 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.

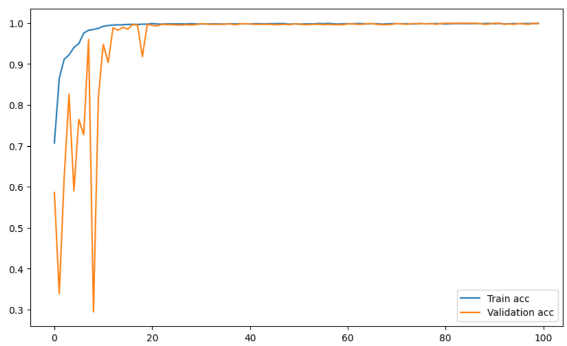
5. Results

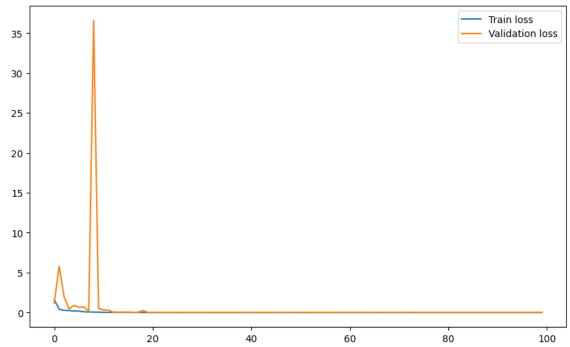
Presenting the results of the experiments. The performance metrics used are,

- Accuracy and Loss
- Precision, Recall, F1 score, Support
- Confusion Matrix

5.1 Accuracy and Loss

The model, evaluated on the test dataset, has a loss of 0.0241 and accuracy of 99.35%. 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. After evaluating the model on the test dataset, it achieved a test loss of 0.1788 and a test accuracy of 95.49%. This indicates that the model generalizes well to unseen data, as it maintains a high level of accuracy and reasonable loss on the test set.





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5.2 Precision, Recall, F1 score, Support

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.

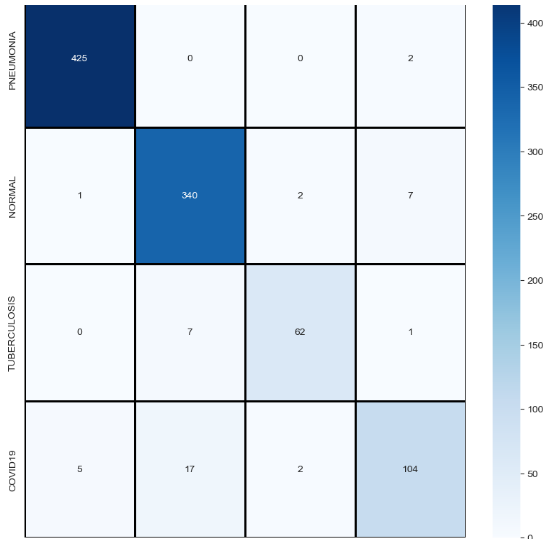
• F1 score: The F1 score is the harmonic mean of precision and recall and provides a

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.

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.

5.3 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

6. Conclusion

6.1 Main Findings:

1. The developed model achieved a certain level of accuracy in classifying chest X-ray images into different categories (Pneumonia, Normal, Tuberculosis, Covid) using machine learning techniques.
2. The use of convolutional neural networks (CNNs) proved effective in extracting relevant features from the images and capturing patterns indicative of different chest conditions.
3. 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.

6.2 Implications:

1. 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.
2. 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.
3. 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.

6.3 Limitations and Areas for Improvement:

1. The dataset used in the project may have certain limitations, such as class imbalance, limited sample size, or variations in image quality. Collecting a larger and more diverse dataset could improve the robustness and generalisation of the model.
2. The project utilised a traditional CNN architecture. Exploring more advanced network architectures, such as residual networks (ResNet), dense networks (DenseNet), or attention mechanisms, may further enhance the model's performance.
3. 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.
4. 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.

6.4 Significance and Potential Applications:

1. The project's significance lies in its potential to assist healthcare professionals in the analysis and interpretation of medical images, providing support in diagnosing and triaging chest conditions.
2. Automated classification of chest X-ray images can aid in resource optimization by prioritising urgent cases, reducing the burden on radiologists, and enabling faster diagnoses.
3. The developed approach can be extended to other medical imaging tasks, such as detecting tumours, identifying abnormalities, or assisting in disease prognosis, contributing to the field of medical image analysis and enhancing healthcare delivery.

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.

7. Future Work

- 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 Dense Neural Networks need to be exprerminted with

8. References

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