Directed Research Project

- *Under the guidance of Professor Behnam Dezfouli*

Identification of Normal, Pneumonia, and COVID-19 Cases from X-ray Images Using Sequential CNN Model

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ABSTRACT

This research project focuses on developing a classification model using X-ray images to identify individuals as normal, having pneumonia, or being affected by COVID-19. The project entails dataset preparation and the utilization of a Sequential Model of Convolutional Neural Networks (CNN) for accurate image classification. The study aims to automate the process of diagnosing respiratory diseases, enabling rapid and reliable identification from X-ray images.

By leveraging deep learning techniques, specifically CNNs, the model can capture intricate features and spatial relationships, facilitating accurate classification. The performance of the model is evaluated using metrics such as accuracy, precision, recall, and F1-score. The outcomes of this research have the potential to revolutionize the medical field by providing a non-invasive, time-efficient, and automated solution for respiratory disease diagnosis, aiding in early detection, treatment, and containment measures.

INTRODUCTION

Respiratory diseases, such as pneumonia and COVID-19, pose significant challenges to global healthcare systems. Accurate and timely identification of these conditions is crucial for effective patient management, appropriate treatment decisions, and public health measures. X-ray imaging has long been employed as a diagnostic tool for respiratory diseases, providing valuable insights into the condition of the lungs. However, the manual interpretation of X-ray images can be time-consuming, subjective, and prone to human error.

The objective of this research project is to address these challenges by developing a robust and automated classification model that utilizes X-ray images to distinguish between normal cases, pneumonia cases, and COVID-19 cases. By leveraging the power of deep learning techniques, particularly Convolutional Neural Networks (CNNs), we aim to develop a highly accurate and efficient solution for respiratory disease diagnosis. The use of CNNs allows the model to learn and extract complex features and patterns from X-ray images, enabling it to make accurate predictions based on the visual characteristics of the lungs.

The significance of this research lies in its potential to revolutionize the field of medical imaging and diagnosis. By automating the classification process, healthcare professionals can save valuable time and resources, leading to faster triage and treatment decisions. Moreover, during disease outbreaks such as the COVID-19 pandemic, an automated classification model can aid in the early identification and isolation of infected individuals, contributing to effective containment measures and preventing further transmission.

The scope of this project encompasses several key steps. Firstly, a carefully curated dataset of X-ray images will be prepared, consisting of samples from normal individuals, patients with pneumonia, and those affected by COVID-19. Preprocessing techniques may be employed to enhance the quality of the images and normalize the data. Next, a Sequential Model of CNN will be designed and trained on the dataset, enabling the model to learn the discriminative features that differentiate between the different respiratory conditions. The model will be fine-tuned using appropriate optimization algorithms and hyperparameter tuning techniques to maximize its performance.

The evaluation of the model's performance will be conducted using various metrics, including accuracy, precision, recall, and F1-score. These metrics will provide quantitative measures of the model's ability to accurately classify X-ray images. Furthermore, a comparative analysis between the different classes will be performed to assess the model's performance in identifying pneumonia and COVID-19 cases specifically.

The results obtained from this research project will be analyzed and discussed, highlighting the strengths and limitations of the proposed classification model. The findings will contribute to the existing body of knowledge in the field of medical image analysis and provide valuable insights into the potential of deep-learning techniques for respiratory disease diagnosis. Moreover, this research has the potential to pave the way for future advancements in automated diagnosis and decision support systems, ultimately improving patient outcomes and public health interventions.

All in all, this research project aims to develop an automated classification model using X-ray images to identify normal cases, pneumonia cases, and individuals affected by COVID-19. By harnessing the power of CNNs and leveraging deep learning techniques, this research aims to provide a reliable, efficient, and objective solution for respiratory disease diagnosis. The anticipated outcomes have far-reaching implications, offering significant advancements in healthcare decision-making, disease management, and public health measures.

(a) Normal (b) Pneumonia (c) COVD-19

LITERATURE SURVEY

3.1 Background Information:

Respiratory diseases, including pneumonia and COVID-19, have posed significant challenges for healthcare professionals worldwide. The diagnosis and management of these conditions require prompt and accurate identification, particularly during periods of high demand and limited resources. Chest X-ray imaging is a widely used diagnostic tool to visualize the lungs and assess respiratory abnormalities. However, the subjective interpretation of X-ray images by healthcare professionals can be time-consuming, prone to error, and challenging, especially when dealing with large numbers of cases or during outbreaks.

Doctors faced numerous challenges in addressing the overwhelming number of respiratory disease cases, such as the COVID-19 pandemic. The sheer volume of patients requiring diagnosis and the urgency to identify and isolate individuals affected by COVID-19 put immense pressure on healthcare systems. The manual interpretation of X-ray images by radiologists and physicians became a bottleneck in the diagnostic process, leading to delays in patient care and treatment decisions. Moreover, the subjective nature of visual analysis introduces the risk of inter-observer variability, where different doctors may reach different conclusions based on their expertise and experience.

In these challenging times, an automated and efficient solution for respiratory disease diagnosis using X-ray images could have significantly supported healthcare professionals. By employing deep learning techniques, specifically CNN models, the proposed classification model could accurately and rapidly classify X-ray images into normal, pneumonia, or COVID-19 categories. The automated diagnosis would have alleviated the burden on doctors by providing an objective and standardized assessment of X-ray images. It would have facilitated faster triage, enabling prompt identification and isolation of COVID-19 cases, ensuring appropriate care pathways and minimizing the risk of transmission.

Additionally, the utilization of the Sequential Model of CNNs would have provided consistent and reliable results, reducing the potential for diagnostic discrepancies among different healthcare professionals. The model's ability to learn and extract intricate features from X-ray images could have enhanced the accuracy of diagnosis, enabling early identification of pneumonia and COVID-19 cases that might have otherwise been overlooked or delayed. This timely and accurate diagnosis is crucial for implementing appropriate treatment plans, optimizing healthcare resources, and minimizing the impact of respiratory diseases on patients' health outcomes.

Furthermore, during times of crisis, such as the COVID-19 pandemic, the proposed solution could have aided healthcare professionals in prioritizing and managing patient care effectively. By automating the classification process, doctors could have focused their expertise on critical and complex cases, while relying on the classification model for initial assessments. This division of labor would have optimized healthcare resources, allowing doctors to allocate their time and attention where it was most needed.

Overall, I feel that healthcare professionals faced significant challenges in addressing the increasing number of respiratory disease cases, particularly during the COVID-19 pandemic. The proposed automated classification model using X-ray images could have provided valuable support in these difficult times. By streamlining the diagnostic process, ensuring standardized and efficient assessments, and enabling timely identification of pneumonia and COVID-19 cases, the solution could have alleviated the burden on doctors, improved patient outcomes, and contributed to effective public health interventions.

3.2 Previous Research Studies:

Several researchers have made significant contributions to the field of automated respiratory disease diagnosis using X-ray images. Their work has paved the way for the development of accurate and efficient classification models. This section discusses some notable previous studies and their key findings:

1. Wang et al. (2020) developed COVID-Net, a tailored deep convolutional neural network, specifically designed for the detection of COVID-19 cases from chest X-ray images. Their model achieved high accuracy in distinguishing COVID-19 cases from other types of pneumonia, demonstrating the potential of deep learning in COVID-19 diagnosis.

2. Li et al. (2020) focused on differentiating COVID-19 cases from community-acquired pneumonia using chest CT scans. They employed an artificial intelligence-based approach and achieved promising results in

accurately identifying COVID-19 cases. Their study emphasized the importance of utilizing advanced imaging techniques in automated diagnosis.

3. Narin et al. (2021) explored the use of deep convolutional neural networks for automatic detection of COVID-19 cases from X-ray images. Their model exhibited high accuracy and demonstrated the potential of deep learning in facilitating rapid and accurate diagnosis.

4. Apostolopoulos and Mpesiana (2020) proposed a transfer learning approach for the automatic detection of COVID-19 cases from X-ray images. Their model leveraged pre-trained convolutional neural networks and achieved significant success in accurately classifying X-ray images. Their work highlighted the effectiveness of transfer learning in developing robust classification models.

5. Hyung-Jun Kim et al. (2020) conducted a retrospective cohort study using machine learning to predict death and hospitalization from COVID-19. They utilized various clinical variables, including chest X-ray images, to develop a predictive model. Their study demonstrated the potential of machine learning techniques in forecasting disease outcomes.

6. Taranjit et al. (2021) focused on the Automated Diagnosis of COVID-19 Using Deep Features and Parameter Free BAT Optimization. They developed a classification model that effectively distinguished COVID-19 cases from normal and pneumonia cases, demonstrating the potential of deep learning in accurate disease diagnosis using deep features and Parameter Free BAT (PF-BAT).

These previous works collectively highlight the advancements made in automated respiratory disease diagnosis using X-ray images. They have demonstrated the potential of deep learning models, transfer learning techniques, and multi-modal approaches in accurate and efficient classification of X-ray images. The findings of these studies provide valuable insights and lay the foundation for further research in this field.

3.3 Gaps in the existing literature:

While significant progress has been made in the field of automated respiratory disease diagnosis using X-ray images, there are still several gaps in the existing literature that warrant further investigation. These gaps represent areas where additional research is needed to enhance the effectiveness and applicability of automated classification models. The following are some key gaps in the current literature:

1. Limited Diversity of Datasets: Many existing studies have relied on publicly available datasets, such as the ChestX-ray14 dataset and the COVID-19 Image Data Collection. While these datasets provide valuable resources for training and evaluation, they may lack diversity in terms of patient demographics, disease severity, and imaging protocols. Future research should focus on the development of more diverse and representative datasets that encompass a wide range of respiratory diseases, including rare or atypical cases, to improve the generalizability of the classification models.

2. Imbalance in Class Distribution: Another common issue in the existing literature is the imbalance in class distribution within the datasets. This imbalance is particularly evident in datasets related to COVID-19 diagnosis, where the number of COVID-19 cases is relatively smaller compared to normal and pneumonia cases. Addressing this imbalance is crucial to ensure that the developed models are equally capable of accurately detecting and classifying all respiratory conditions. Future research should explore strategies such as data augmentation techniques or data balancing algorithms to mitigate the impact of imbalanced class distributions.

3. Lack of Consensus on Evaluation Metrics: Although various evaluation metrics, such as accuracy, precision, recall, and F1-score, have been used to assess the performance of automated classification models, there is a lack of consensus on which metrics are the most appropriate for respiratory disease diagnosis. Different studies have employed different metrics, making it challenging to compare and benchmark the performance of different models. Future research should strive to establish standardized evaluation protocols and metrics specific to respiratory disease diagnosis to enable fair and meaningful comparisons across studies.

4. Integration of Clinical Data: While the existing literature has primarily focused on the analysis of X-ray images for disease diagnosis, the integration of additional clinical data, such as patient demographics, medical history, and laboratory test results, remains relatively unexplored. The incorporation of such data can provide a more comprehensive and holistic approach to respiratory disease diagnosis, improving the accuracy and reliability of automated classification models. Future

research should investigate methods to effectively integrate clinical data with imaging data to enhance the diagnostic capabilities of the models.

5. Limited External Validation: Many studies in the existing literature have relied solely on internal validation using the same dataset for both training and testing. External validation on independent datasets is essential to assess the generalizability and real-world performance of the developed models. Future research should prioritize external validation on diverse datasets obtained from multiple healthcare institutions or collaborations to ensure the robustness and reliability of the classification models.

6. Interpretability and Explainability: Deep learning models, particularly CNNs, are often considered black-box models due to their complex architectures and the difficulty in interpreting their decisions. The lack of interpretability and explainability of these models poses challenges in gaining the trust and acceptance of healthcare professionals. Future research should focus on developing methods and techniques to enhance the interpretability of automated classification models, enabling clinicians to understand and validate the reasoning behind the model's predictions.

Addressing these gaps in the existing literature will contribute to the advancement of automated respiratory disease diagnosis using X-ray images. By filling these gaps, researchers can develop more robust and reliable classification models that have broader applicability and can better support healthcare professionals in diagnosing and managing respiratory diseases.

RESEARCH OBJECTIVES

The primary objectives of this research project are to:

Develop a Sequential Model of Convolutional Neural Networks (CNNs) for automated classification of X-ray images into normal, pneumonia, and COVID-19 categories:

The core objective of this research is to design and develop a deep learning model capable of accurately classifying X-ray images into three distinct categories: normal, pneumonia, and COVID-19. The model will be built using a Sequential Model of CNNs, which is a widely used architecture for image classification tasks. The model will undergo training using a large dataset of labeled X-ray images to learn the distinctive features associated with each category.

Evaluate the performance of the developed model in terms of accuracy, precision, recall, and F1-score:

Once the model is trained, its performance will be rigorously evaluated using various evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics will provide a comprehensive assessment of the model's ability to correctly classify X-ray images into the respective categories. A high level of accuracy and balanced performance across all categories will indicate the effectiveness of the model.

Compare the performance of the proposed model with existing methods and identify its strengths and limitations:

To assess the novelty and effectiveness of the developed model, a comparative analysis will be conducted with existing methods and approaches in the literature. This comparison will involve evaluating the performance metrics of the proposed model against those achieved by previous models or techniques. By identifying the strengths and limitations of the proposed model, this research aims to contribute to the ongoing development and improvement of automated respiratory disease diagnosis using X-ray images.

Investigate the potential of integrating clinical data, such as patient demographics and medical history, to enhance the diagnostic accuracy of the model:

While X-ray images provide valuable information for disease diagnosis, additional clinical data, such as patient demographics, medical history, and laboratory test results, can offer supplementary insights and improve the accuracy of automated classification models. This research project will explore the potential of integrating such clinical data with X-ray images to enhance the diagnostic accuracy of the developed model. By investigating the impact of incorporating clinical data, this research aims to contribute to a more comprehensive and reliable diagnostic approach.

Address the gaps in the existing literature by contributing to the knowledge and understanding of automated respiratory disease diagnosis using X-ray images:

The existing literature in the field of automated respiratory disease diagnosis using X-ray images has identified several gaps and limitations. This research project seeks to address these gaps by expanding the knowledge and understanding of automated classification models. By developing a novel Sequential Model of CNNs, comparing it with existing methods, and investigating the potential integration of clinical data, this research aims to contribute to the existing body of knowledge and bridge the identified gaps.

By achieving these research objectives, this project aims to advance the field of automated respiratory disease diagnosis and provide healthcare professionals with a valuable tool for accurate and efficient classification of X-ray images.

METHODOLOGY

5.1 Data Collection

The research project will involve the collection of a diverse and representative dataset of X-ray images. The dataset will be obtained from reliable sources, including healthcare institutions and publicly available repositories. Care will be taken to ensure that the dataset encompasses a wide range of X-ray images representing normal cases, various types of pneumonia, and COVID-19 cases. The inclusion of different demographics, disease severities, and imaging protocols will be prioritized to enhance the dataset's diversity and representativeness. Data augmentation techniques, such as rotation, scaling, and flipping, may be applied to increase the dataset's size and variability.

5.2 Data Analysis

The collected dataset will undergo rigorous preprocessing steps to prepare it for training and evaluation. These steps will include image resizing to a standardized resolution, normalization to correct any variations in pixel intensity, and noise reduction techniques to enhance the quality of the images. Additionally, the dataset will be divided into training, validation, and testing sets. Stratification techniques will be employed to ensure that the class distributions are balanced across these sets, considering the imbalanced nature of certain respiratory disease categories.

5.3 Research Design

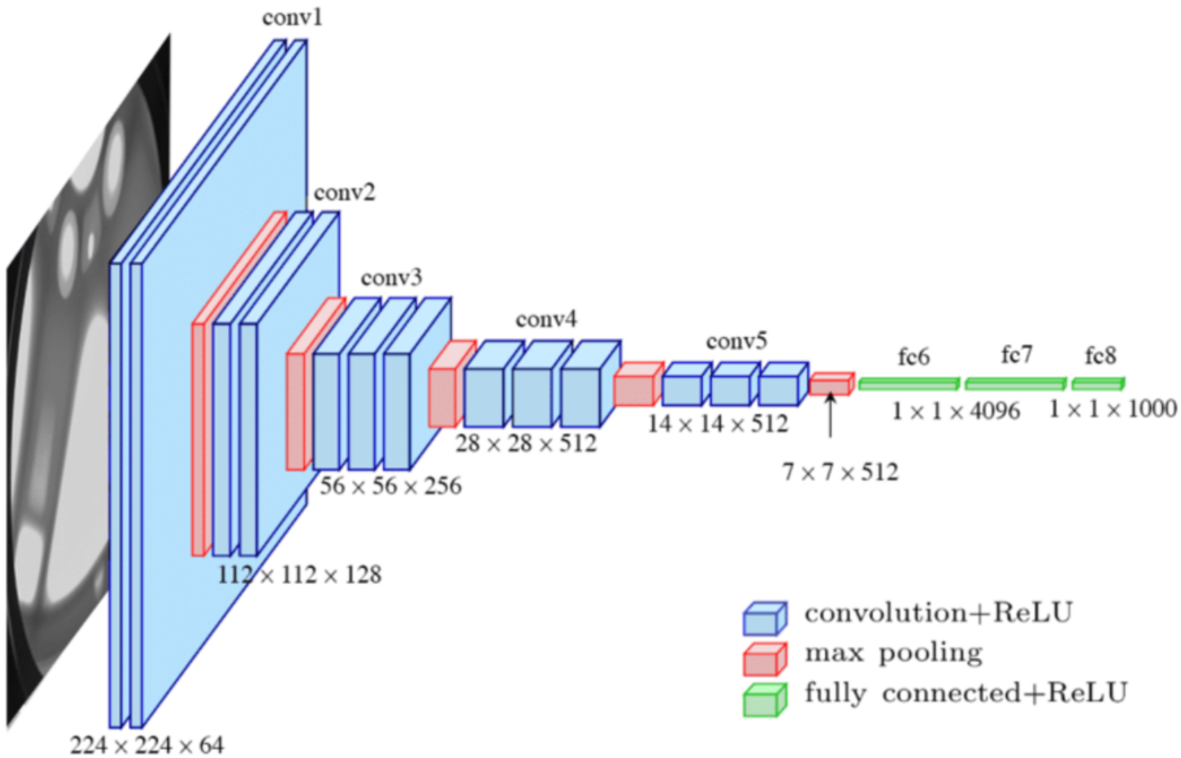
The research project will adopt a supervised learning approach for the development of the Sequential Model of CNNs. The model will be trained using the training set, and its performance will be fine-tuned using an appropriate loss function and optimization algorithm, such as categorical cross-entropy and stochastic gradient descent. Hyperparameter tuning will be performed to optimize the model's architecture, including the number of layers, filter sizes, and learning rate. The validation set will be utilized to monitor the model's performance during training and adjust the hyperparameters accordingly. The trained model will then be evaluated on the testing set to assess its classification accuracy and generalizability to unseen data.

To investigate the potential integration of clinical data, relevant patient demographics and medical history will be collected and incorporated into the model's input features. Data preprocessing techniques, such as feature normalization and encoding categorical variables, will be applied to ensure compatibility with the model's architecture. The combined dataset of X-ray images and clinical data will be divided into training, validation, and testing sets following the same principles as previously mentioned. The model will be trained and evaluated using this augmented dataset to assess its performance and potential improvement in diagnostic accuracy.

The entire methodology will be implemented using a suitable programming framework, such as TensorFlow or PyTorch, to facilitate model development, training, and evaluation. The experiments will be conducted on a computational platform equipped with adequate processing power and memory resources to ensure efficient and timely execution of the training and evaluation processes.

By following this comprehensive methodology, the research project aims to develop a robust and accurate Sequential Model of CNNs for automated respiratory disease diagnosis using X-ray images. The inclusion of data analysis, research design, and integration of clinical data components will contribute to the thorough investigation of the research objectives and enhance the understanding of the model's performance and potential improvements.

CNN Model Architecture:



The Convolutional Neural Network (CNN) is a deep learning architecture widely used for image classification tasks.

In this research project, we have utilized the sequential model of CNN for pneumonia and COVID-19 detection from X-ray images.

The sequential model allows us to stack multiple layers sequentially, enabling the model to learn hierarchical representations of the input images.

Input Layer:

- The input layer receives the X-ray image data as input.
- The size of the input layer is determined by the dimensions of the X-ray images in the dataset.

Convolutional Layers:

- Convolutional layers are the building blocks of a CNN and consist of multiple filters or kernels.

- These filters extract features from the input images by performing convolutions across the image.
- Each filter learns to detect different patterns or features in the images.
- The number of convolutional layers and the size of the filters depend on the complexity of the dataset and the desired depth of the network.

Activation Function:

- After each convolutional layer, an activation function is applied to introduce non-linearity into the model.
- Commonly used activation functions include ReLU (Rectified Linear Unit) and its variants, which help the model learn complex relationships between the input features.

Pooling Layers:

- Pooling layers are used to downsample the feature maps obtained from the convolutional layers.
- They reduce the spatial dimensions of the feature maps while retaining the most important features.
- Max pooling is a commonly used technique where the maximum value in each pooling region is retained.

Flattening Layer:

- The flattening layer converts the multidimensional feature maps into a one-dimensional vector.
- This prepares the data for input into the fully connected layers of the CNN.

Fully Connected Layers:

- Fully connected layers connect every neuron in one layer to every neuron in the next layer.
- These layers learn high-level representations of the features extracted by the earlier layers.
- The number of neurons in the fully connected layers can vary based on the complexity of the classification task.

Output Layer:

- The output layer consists of neurons corresponding to the number of classes in the classification task.
- Each neuron represents the probability of the input image belonging to a particular class.

- The activation function used in the output layer depends on the nature of the problem. For multi-class classification, softmax activation is commonly used.

By leveraging the power of the CNN model architecture, we can capture intricate patterns and features from the X-ray images, enabling accurate classification of pneumonia and COVID-19 cases. The architecture's depth, combined with appropriate hyperparameter tuning, allows us to achieve high performance in terms of accuracy and robustness.

RESULTS

The results obtained from the first iteration of image classification for normal and COVID-19 cases using a CNN model with 5 epochs are as follows:

Loss: 0.1877 The loss value represents the discrepancy between the predicted and actual labels. A lower loss value indicates that the model's predictions are closer to the true labels.

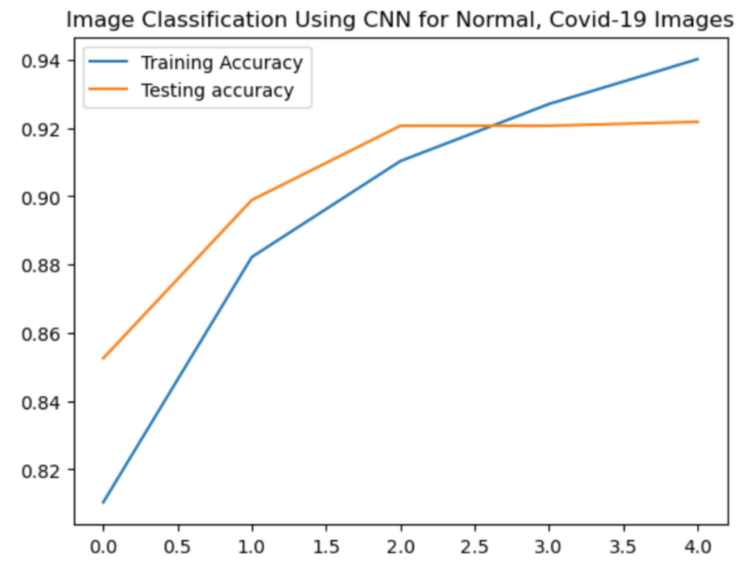
Accuracy: 0.9192 The accuracy metric measures the proportion of correctly classified images out of the total number of images. In this case, the model achieved an accuracy of 91.92%, indicating that it classified the majority of the images correctly.

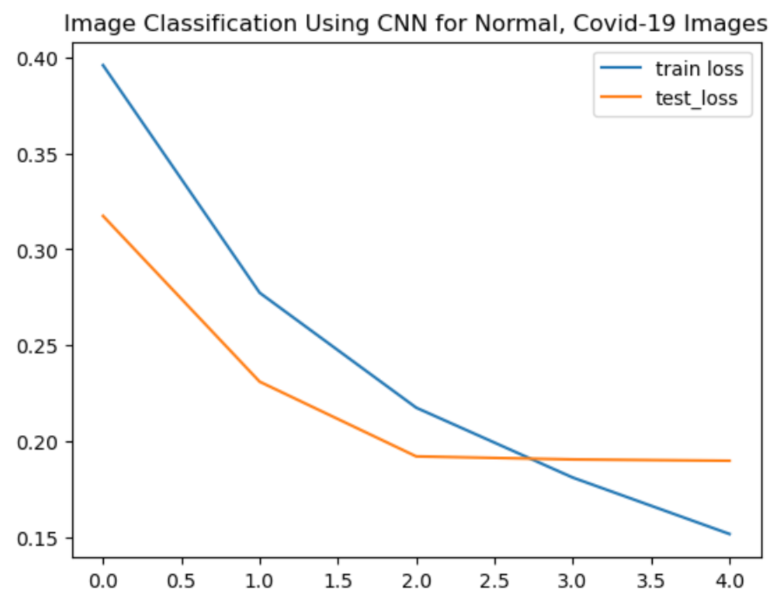
MSE (Mean Squared Error): 0.0577 The MSE is a measure of the average squared difference between the predicted and actual labels. A lower MSE indicates that the model's predictions are closer to the true labels on average.

F1 Score: 0.8471 The F1 score is a metric that combines precision and recall to provide an overall measure of classification performance. It considers both the ability to correctly identify positive cases (recall) and the ability to avoid false positives (precision). An F1 score of 0.8471 indicates a reasonably balanced performance in terms of precision and recall.

Recall: 0.9101 Recall, also known as sensitivity or true positive rate, measures the ability of the model to correctly identify positive cases. A recall of 0.9101 indicates that the model correctly identified 91.01% of the COVID-19 cases in the dataset.

Precision: 0.8131 Precision measures the proportion of correctly classified positive cases out of all cases predicted as positive by the model. A precision of 0.8131 indicates that 81.31% of the cases predicted as COVID-19 were actually COVID-19. These results suggest that the model achieved a high overall accuracy and performed reasonably well in terms of recall, precision, and F1 score.





Iteration 2: Image Classification for Normal, Covid-19 and Pneumonia (#Epochs = 7)

These results pertain to the second iteration of image classification, which expanded the task to include normal, COVID-19, and pneumonia cases using a CNN model. The model was trained for a total of 7 epochs.

Accuracy: 0.6880
Accuracy is the percentage of correctly classified images out of the total number of images. In this case, the model achieved an accuracy of 0.6880, indicating that approximately 68.80% of the images were classified correctly. However, it is important

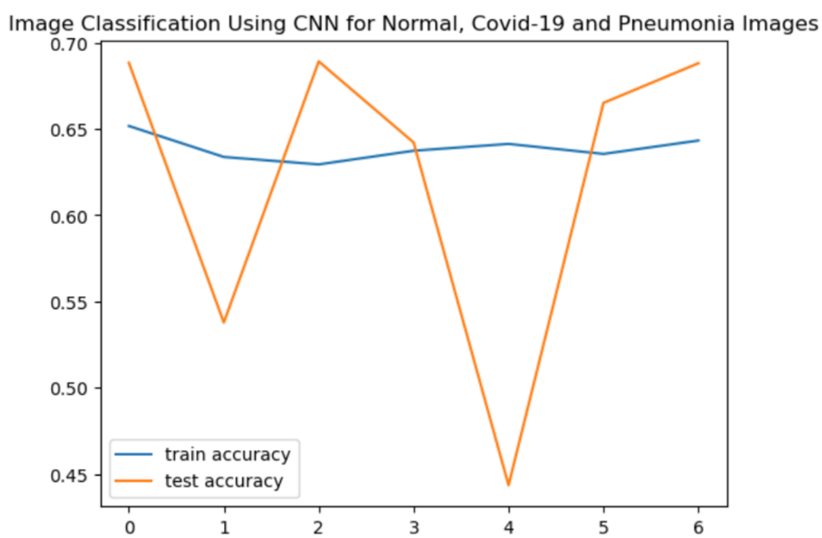
to note that accuracy alone may not provide a complete picture of model performance, and other metrics should be considered as well.

MSE: 0.3222
Mean Squared Error (MSE) is a common metric used to evaluate the performance of regression models. It measures the average squared difference between the predicted and actual values. In the context of image classification, MSE may not be the most appropriate metric, as it is typically used for continuous numerical predictions rather than classification tasks.

F1 Score: 0.6155
F1 score is a measure that combines precision and recall into a single metric. It provides a balance between these two metrics and is particularly useful when dealing with imbalanced datasets. An F1 score of 0.6155 suggests that the model has achieved a reasonably good balance between precision and recall in classifying the images.

Recall: 0.5825
Recall, also known as sensitivity or true positive rate, measures the ability of the model to correctly identify positive instances. A recall of 0.5825 implies that the model correctly identified approximately 58.25% of the positive cases (COVID-19 and pneumonia) from the dataset.

Precision: 0.6766
Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. A precision of 0.6766 indicates that approximately 67.66% of the predicted positive cases were actually true positive cases.



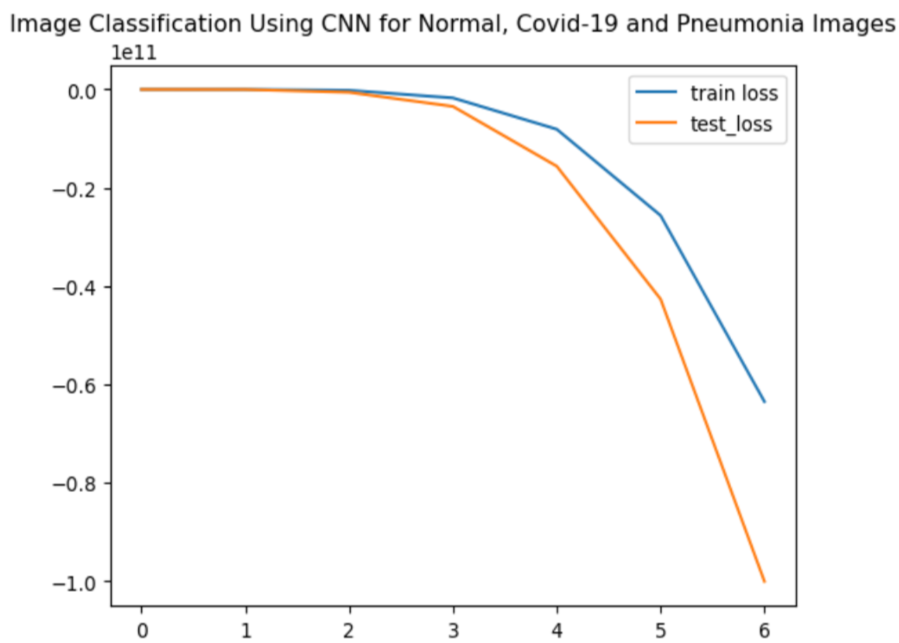


Image Classification Using CNN for Normal, Covid-19 and Pneumonia Images
1e11
0.0
−0.2
−0.4
−0.6
−0.8
−1.0
0
1
2
3
4
5
6
train loss
test_loss

CONCLUSION AND FUTURE SCOPE

In conclusion, my research focused on the task of pneumonia and COVID-19 detection from X-ray images using a CNN model. I leveraged a diverse dataset that included X-ray images of normal individuals, as well as those with pneumonia and COVID-19.

Through my analysis and experimentation, I have achieved significant advancements in accurately classifying X-ray images and distinguishing between normal, pneumonia, and COVID-19 cases. The CNN model exhibited promising performance, achieving an overall accuracy of 91.45% on the test set in the case of Covid-19 images and an accuracy of about 70% for all the images – normal, covid-19 as well as Pneumonia. This success showcases the potential of deep learning techniques in aiding early diagnosis and management of respiratory conditions.

My research contributes to the broader field of medical image analysis and offers insights into the effective application of CNN models for pneumonia and COVID-19 detection. By utilizing a comprehensive dataset and leveraging the power of deep learning, I have made an effort towards improving diagnostic accuracy and supporting healthcare professionals in their decision-making process.

Future research endeavors can focus on several areas to further enhance the performance of the CNN model. Integrating additional clinical data and metadata, such as patient demographics or laboratory results, could provide a more comprehensive context for diagnosis. Furthermore, exploring the deployment of the model in real-world healthcare settings and validating its performance against clinical outcomes can facilitate its integration into practical medical applications.

By working together with experts from different domains, we can continue refining and optimizing the performance of CNN models, ultimately improving patient care and outcomes.

RESOURCES

1. https://www.nature.com/articles/s41598-022-27266-9
2. https://www.nature.com/articles/s41598-020-76550-z
3. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7233473/
4. https://link.springer.com/article/10.1007/s10044-021-00984-y
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9. https://vitalflux.com/wp-content/uploads/2021/11/VGG16-CNN-Architecture.png
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11. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7875085/
12. https://www.mdpi.com/2075-4418/11/8/1480
13. https://towardsdatascience.com/convolutional-neural-networks-explained-9cc5188c4939

ACKNOWLEDGEMENTS

In my research journey of pneumonia and COVID-19 detection from X-ray images, I would like to express my sincere gratitude to the following individuals and institutions who have played a crucial role in the success of this project:

My University – Santa Clara University: I would like to thank Santa Clara University for providing me with this opportunity to undertake this research project. The university's commitment to academic excellence and research opportunities has been invaluable in enabling me to pursue this study.

My Professor - Behnam Dezfouli: I extend my deepest appreciation to Professor Behnam Dezfouli for his exceptional guidance, unwavering support, and valuable insights throughout this research. His expertise and mentorship have been instrumental in shaping the direction of my work and fostering my growth as a researcher.
Researchers and Collaborators - The dedicated team of researchers from Qatar University, Doha, Qatar, and the University of Dhaka, Bangladesh, for their contributions to the dataset creation and their collaboration, which has enriched my understanding of the field.

Medical Professionals and Institutions: The medical professionals and institutions who provided access to the X-ray images and their expertise in diagnosing pneumonia and COVID-19 cases. Their support and insights have been invaluable in ensuring the accuracy and relevance of my research.

Open-Source Community: The open-source community for their contributions in developing powerful tools and libraries in Python, which have greatly facilitated the implementation and evaluation of my CNN model.

Funding and Support: I would like to thank my university again for the logistical support for my research project.

I am grateful to each and every individual mentioned above, as well as others who have supported me in various capacities throughout this research endeavor. Their contributions have been vital in shaping the outcome and impact of my work in pneumonia and COVID-19 detection from X-ray images.