Chapter 5

Conclusion & Future Work

The development and assessment of a pneumonia detection system employing cutting-edge machine learning methods were the main goals of this thesis. To precisely identify pneumonia patients in chest X-ray pictures, the suggested method included image processing, feature extraction, and classification techniques. The outcomes of the experimental evaluation showed the system's efficacy and promise for automating the diagnosis of pneumonia, assisting medical professionals in making precise and fast decisions.

The results of this study showed that the created pneumonia detection system classified pneumonia cases with a high degree of accuracy, sensitivity, and specificity. A vast dataset of annotated chest X-ray pictures and cutting-edge machine learning algorithms were combined to create a system that showed promise in identifying pneumonia from normal instances. According to the results, the proposed method may help radiologists and clinicians identify and diagnose pneumonia early, which would improve patient outcomes and lower healthcare expenditures.

9.1 Summary of Contributions

It is common knowledge that as a model gets more intricate, the number of parameters increases. The model becomes more adaptable as a result, and the training error is decreased. However, the generalisation error increases as a result of an excessive fit to the test data. In order to identify between normal and pneumonia, the model needs sufficient data. It takes medical experts with the required knowledge to distinguish between organs that are working regularly and symptoms that are abnormal. Therefore, large medical databases with precise answer tagging are expensive. To solve this problem, we used three pre-trained models from distinct sources (ImageNet, Chest X-ray14, Custom dataset). DenseNet121 was trained to recognise 14 anomalies, including pneumonia, on chest X-ray images.

Out of the pre-trained models stated above, it was determined that using the DenseNet121 model provided the highest accuracy. The domain of the test dataset is similar to that of the chest X-ray14 data set. The final model will display good performance when the models are integrated with an attention mechanism if the combined transfer learning model was pre-trained using data from a domain similar to the domain of the target task. To train models like ResNet and DenseNet, which require more than a million photographs, this study employed 5,856 photos as test data. With data preprocessing, our model can be trained with low-quality input photographs and perform well.

However, employing top-notch input photos can improve the performance of our model. There are limitations where it may not be possible to find a trained model using data from domains related to our desired task. In this case, it is expected that using pre-trained models that have been trained on many datasets or using additional models will improve performance. Future work on our subject will include a study on domain adaptation, which can achieve domain alterations while maintaining outstanding performance in the original domain. We also need to investigate the optimum number of trained models to use.

There are other methods for diagnosing pneumonia besides ours. Simply said, our approach is to analyse chest X-rays and categorise them as pneumonia or normal in the hopes that it would be helpful in making a diagnosis by a medical professional. Our methodology is also anticipated to give the pneumonia diagnosis more validity.

9.2 Limitations and Challenges

While the pneumonia detection thesis has made significant progress in developing an automated system, there are several limitations and challenges that need to be acknowledged:

Dataset Bias: The calibre and variety of the training dataset have a significant impact on how well the pneumonia detection system performs. The system's capacity to generalise to real-world scenarios or cases that differ from the training data may be impacted by biassed or unbalanced training data. In studies on pneumonia detection, addressing dataset bias and making sure that varied cases are included remain challenges.

Interpretability and Explainability: It is frequently difficult to interpret machine learning models, which makes it difficult to comprehend the underlying causes of their predictions. Gaining the faith of healthcare professionals can be difficult when it comes to the detection of pneumonia, thus it can be important to explain why a certain image is labelled as pneumonia or normal. A challenging undertaking in the discipline, developing methodologies for interpretability and explainability is a difficult one.

Limited Availability of Annotated Data: It can be difficult to get a sizable, carefully maintained collection of annotated chest X-ray pictures, despite the fact that annotated data is essential for training machine learning models. The efficacy and generalizability of the created approach may be constrained by the lack of annotated data, particularly for uncommon or unique kinds of pneumonia.

Ethical Considerations and Privacy: The use of automated pneumonia detection systems raises ethical questions about patient confidentiality, data security, and potential decision-making biases. Observing ethical standards, safeguarding patient information, and correcting systemic biases are significant difficulties that call for careful consideration.

Variability in Imaging Techniques: Chest X-ray images may be taken using a variety of imaging methods and protocols by various hospitals or medical facilities. When applied to photos from various sources, this variability can cause errors and have an impact on how well the pneumonia detection system performs. Robust algorithms that can cope with variations in imaging methods and standardisation protocols are needed to tackle this problem.

Limited Real-Time Implementation: Because of the computing needs and time restrictions, implementing a pneumonia detection system in real-time clinical situations can be difficult. For the system to be implemented practically, a significant problem that needs to be solved is achieving real-time performance while maintaining high accuracy and reliability.

Researchers, physicians, and politicians will need to work together to address these constraints and difficulties. To address these difficulties and create stable and trustworthy systems for the diagnosis of pneumonia, more research is required as well as improvements in the algorithms used to identify pneumonia, dataset curation techniques, interpretability techniques, and real-time implementation methods.

9.3 Future Directions

The resilience and generalizability associated with human learning are absent from current machine learning (ML) methods, which discover statistical regularities in complicated data sets and are often utilised across a variety of application fields. The results might have very broad scientific and societal implications if ML approaches could help computers learn from fewer instances, transfer information between tasks, and adapt to changing settings and surroundings. Larger, more capable learning models have been made possible by increased processing and memory capabilities, but it is becoming increasingly clear that even bigger computing resources would not be enough to produce algorithms that could learn from a small number of examples and generalise beyond initial training sets. Perspectives on feature selection, representation schemes and interpretability, transfer learning, continuous learning, and learning and adaptation in time-varying contexts and environments are presented in this study. These five core topics are crucial for developing ML skills. The benefits of emerging ML techniques that potentially solve these problems can be demonstrated through appropriate learning tasks that call for these abilities.

Multimodal Approach: At the moment, the majority of pneumonia detection systems concentrate on studying chest X-ray pictures. However, combining other imaging modalities, such as computed tomography (CT) scans or ultrasound images, may offer more details and boost the precision of pneumonia detection. A interesting path for future research may be exploring the fusion of various imaging modalities and creating multimodal algorithms.

Deep Learning Architectures: Medical image analysis offers significant promise for deep learning. The use of more sophisticated deep learning architectures, like convolutional neural networks (CNNs) or recurrent neural networks (RNNs), for the identification of pneumonia can be studied in the future. To improve the system's performance, new network topologies like attention mechanisms or graph convolutional networks can be investigated.

Explainable AI in Pneumonia Detection: Gaining the confidence and approval of medical experts requires improving the pneumonia detection system's interpretability and explainability. The development of techniques to offer understandable justifications for the system's predictions can be the topic of future study. To draw attention to the areas in the photos that affect the classification decision, techniques like attention maps, saliency maps, or feature visualisation might be used.

Integration of Clinical Data: Clinical information, such as patient demographics, medical history, and laboratory findings, can be used to help detect pneumonia. Future studies can look into how clinical and imaging data can be combined to provide a comprehensive and all-encompassing pneumonia diagnosis strategy. To increase the precision and dependability of the system, this could entail creating fusion models that incorporate both imaging and clinical features.

Real-Time Decision Support:A promising avenue is the creation of real-time decision support technologies that can help radiologists and physicians identify pneumonia. Chest X-ray pictures can be quickly and accurately analysed using real-time implementation of the pneumonia detection system, with effective algorithms and optimised hardware, assisting in rapid decision-making and patient care.

External Validation and Clinical Trials: It is crucial to test the pneumonia detection system's effectiveness and generalizability in actual clinical situations and on external datasets. Large-scale clinical studies should be conducted in future research with the goal of determining the system's efficacy, dependability, and effect on patient outcomes. Conducting such validation studies will require close cooperation with medical institutions and the participation of medical experts.

Deployment in Low-Resource Settings: In areas with limited resources, pneumonia is a substantial cause of mortality. Future studies should investigate the use of pneumonia detection systems in resource-constrained settings where access to specialised radiologists or cutting-edge imaging equipment may be restricted. The early detection and treatment of pneumonia can be greatly influenced by creating lightweight and affordable solutions that can be employed in these circumstances.

The science of pneumonia detection can develop by addressing these potential paths, resulting in systems for diagnosing and managing pneumonia those are more precise, effective, and available.

9.4 Conclusion

Each year, pneumonia claims the lives of hundreds of thousands of people and is the top cause of death in children and the elderly. Pneumonia risk factors include smoking, drinking, having surgery, having asthma, having a damaged immune system, and being over 65. The mortality rate of pneumonia may be lowered by early detection and timely treatment. Chest X-rays are frequently used to detect pneumonia by qualified specialists, however recently, treatment of pneumonia has become more challenging due to a shortage of medical professionals and a rise in pneumonia patients. This paper suggests a method for automatically detecting pneumonia utilising chest X-ray pictures and ensemble models that are based on deep learning.

By utilising the pre-trained models and merging them with a specially created CNN model, training time is cut down and accuracy is increased. The Inception-V3 ensemble outperformed the other models in terms of accuracy, scoring 99.29%, while also scoring 98.83%, 99.73%, and 99.28% for precision, recall, and F1. The VGG-16 ensemble came in second with an accuracy score of 98.06%, trailing only the ResNet50 ensemble with an accuracy score of 98.93%. The results suggest that when compared to their ensemble models, individual pre-trained models perform poorly.

In this study, we proposed stae-of-the-art VIYU model algorithm, a Deep CNN with transfer learning model for efficient pneumonia recognition in chest X-ray pictures. We employed numerous feature extractor models that had already undergone training across numerous domains. After joining feature vectors gathered from previously trained models, we employed the attention strategy to classify pneumonia and normal. While the results utilising the VIYU model by integrating all four models were 98.08% for the Guangzhou Women and Children's Medical Centre dataset, ResNet152, DenseNet121, ResNet18, and SE-attention all demonstrated 95.03%, 95.35%, 94.87%, and 96.63% accuracy for transfer learning using a single model.

To put it another way, by merging pre-trained models from other domains, using the techniques we've provided, we can create a model that can be applied to new tasks. This knowledge should be useful in a wide range of professions that require domain adaptability. This research’s findings may be used in studies or products that pinpoint possible pneumonia hotspots or produce annotations on the illness.