International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 06 | June - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

# Interpretable Classification of Pneumonia Infection Using Explainable AI (XAI-ICP)

Mr. Sunad Kumar AN, Asst. Professor, Dept of computer science and engineering, BGS Institute of Technology, Adhichunchanagiri university, BG Nagara, Karnataka
Ms. Keerthana T S ,4th year ,8th sem , Dept of computer science and engineering , BGS Institute of Technology , Adhichunchanagiri university , BG Nagara , Karnataka

## ABSTRACT

In contrast, the system was tested and trained at Taichung Veterans General Hospital (TCVGH) because many medical examiners find open-box models in the medical field to be highly desirable. The thorough debate regarding the outcome is semi-transparent in the working process, so even though the accuracy predicted by most convolutional neural network (CNN) models is good, it is still not convincing. Because most people have weakened immune systems, pneumonia is one of the most common and highly contagious illnesses. Therefore, this paper's objective is to use explainable AI (XAI-ICP) to create an interpretable categorization of pneumonia infection. Therefore, the extremely effective XAI- ICP system was created to address this problem by adjusting to the current state of population health. The aim is to design an interpretable deep classification and transfer learning-based evaluation for pneumonia infectionclassification. The model is primarily pre-trained using the open Chest X-Ray (CXR) dataset from NationalInstitutes of Health (NIH). Independent learning, Taiwan VinDr open dataset for transfer learning ofpneumonia affected patients with labeled CXR images possessing three features of infiltrate, cardiomegalyand effusion. The data labeling is performed by the medical examiners with the XAI human-in-the-loop approach. XAI-ICP demonstrates the XAI based reconfigurable DCNN with human-in-the-loop as a novelapproach.

## INTRODUCTION

Pneumonia remains a significant public health concern globally, contributing to substantial morbidity and mortality rates, particularly among vulnerable populations. The accurate and interpretable classification of pneumonia infections is crucial for timely diagnosis and effective treatment. In recent years, the advent of Explainable Artificial Intelligence (XAI) has revolutionized the field of machine learning by providing insights into the decision-making processes of complex models. This paper introduces XAI-ICP

(Explainable AI for Interpretable Classification of Pneumonia Infection), a novel approach aimed at enhancing the interpretability of classification models for pneumonia diagnosis. By integrating XAI techniques with state-of-the-art classification algorithms, XAI-ICP not only predicts pneumonia infections with high accuracy but also provides transparent explanations for its decisions. This transparency is essential for gaining the trust of clinicians and patients, facilitating better understanding and acceptance of the model's recommendations. Through a comprehensive evaluation using real-world pneumonia datasets, we demonstrate the effectiveness and interpretability of XAI-ICP in discriminating between pneumonia and non- pneumonia cases. The insights provided by XAI-ICP not only aid in accurate diagnosis but also empower healthcare professionals to make informed clinical decisions, ultimately improving patient outcomes and reducing healthcare costs. We believe that XAI-ICP represents a significant advancement towards more transparent and interpretable AI systems in medical diagnosis, with the potential to revolutionize pneumonia management and contribute to better healthcare delivery worldwide. Furthermore, the interpretability offered by XAI-ICP addresses the pressing need for transparency and accountability in medical AI systems. As regulatory bodies and healthcare organizations increasingly emphasize the importance of understanding and justifying algorithmic decisions, XAI-ICP serves as a pioneering solution for meeting these requirements in the context of pneumonia diagnosis.

| Reference | Study Aim | Source / Input Data | Preprocessing / Statistical Analysis | AI / XAI Algorithms | Evaluation |
|---|---|---|---|---|---|
| Zou L. et al. 2022 [23] | An ensemble XAI model for predicting pneumonia and covid-19 infections mortality | CXR of 1,475 adult patients. | SHAP and GRAD-CAM++ | Ensemble XAI algorithm. | Precision, recall and Intersection |
| Nagaoka T. et al. 2022 [24] | A deep learning system for predicting Covid-19 | 132 scans of CT slice images | GRAD-CAM | Inception v3 with feature map/ weighted feature map with hyper-parameters | Sensitivity, Speci-ficity, Accuracy, AUC and ROC curve. |
| | A Fuzzy based deep learning for Covid-19 pneumonia detection. | CXR images of 121 patients. | Saliency maps and Fuzzy edge detection algorithm. | A customized deep CNN (CovNNet) algorithm. | Sensitivity, specificity, positive predicted value (PPV), negative predicted value (NPV) and accuracy. |
| Hu B. et al. 2022 [26] | An explainable medical images and CXR evaluator for Covid-19. | 1400 CXR images and ISIC 2017 skin lesion dataset consisting of 2000 images. | Learned embedded spaces. | Deep embedded network. | Similarity based saliency maps for occlusion, attention and activation mapping. |
| XAI-ICP | An explainable and transfer learning evaluator for pneumonia infection classification. | CXR images of 2301 patients. NIH and VinDr open dataset. | Pre-training and preprocessing methods. | Interpretable and DCNN classification algorithm with transfer learning. | SHAP, GRAD-CAM, recall, F1 score, specificity, precision, accuracy, AUROC curves and XAI Scoring. |

International Skin Imaging Collaboration (ISIC) as a large-scale dataset of dermoscopy images, Area Under the Receiver Operating Characteristic (AUROC).

**Recent developments within XAI pneumonia.**

In addition to its clinical implications, XAI-ICP holds promise for advancing our understanding of pneumonia pathophysiology. By uncovering the features and patterns driving classification decisions, XAI-ICP can potentially identify novel biomarkers or disease mechanisms, leading to new insights into pneumonia etiology and progression.

Overall, the development and application of XAI-ICP represent a significant step forward in the intersection of artificial intelligence and healthcare. By combining cutting-edge machine learning techniques with transparent decision-making processes, XAI-ICP not only enhances diagnostic accuracy but also fosters trust, understanding, and innovation in pneumonia management. This paper presents the methodology, results, and implications of XAI-ICP, laying the groundwork for future research and implementation of interpretable AI systems in medical practice.

Crucially, XAI-ICP incorporates several explainability methods to elucidate the decision- making process of the AI model. These include model-agnostic techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), which provide insights into the contribution of individual features towards the model's predictions. Additionally, we utilize visualization techniques such as saliency maps and activation maximization to highlight regions of interest in medical images, aiding clinicians in identifying key diagnostic indicators.By integrating these components, XAI-ICP aims to strike a balance between predictive performance and interpretability, addressing the pressing need for transparent AI systems in clinical practice. Through extensive evaluation on real-world datasets and validation in clinical settings, we aim to demonstrate the efficacy and utility of XAI-ICP in improving the diagnosis and management of pneumonia infections, ultimately contributing to better patient outcomes and healthcare delivery.

## 1.1 OBJECTIVES

1, To design an explainable AI system for the classification of pneumonia infection: The XAI building processis a crucial measure for the complete transparency and acceptance by the user. The XAI based decisions helps to gain the user’s trust and accomplishes the complex tasks effectively. Subsequently, it needs to apply the XAI human in the loop approach for the training dataset and modelenhancement.

2. To perform the pre-training of the XAI model and design re-configurable system: The pre-

training with the globally compatible NIH CXR dataset makes the model flexible and better to classify for the test data. The model's performanceis improved and makes it more effective. The re-configurablemodel can add/delete features based on the user specification.

To apply SHAP based processing for the effective DCNN evaluation: During the DCNN processing stage, highattention is given to the feature scoring process based on its current SHAP scores. Multiple case-based feature scoring is analyzed and explained during the evaluation process. There-fore, as the dataset is updated, the feature scoring will adaptto that specific situation.

3. To implement an interpretable and transfer learning-based evaluation system: The interpretable XAI system pro-vides stepwise decisions with the dense neural network (DNN) layers, which helps to monitor the feature processingwithin every CXR section and evaluation by CNN models. The XAI-ICP classification algorithm evaluates the whole model with the open dataset and after feedback, the model is updated to provide classification. The TCVGH hospital dataset used within this work is first evaluated using Deep Convolutional Neural Network (DCNN). Later, the data frommultiple sources are combined as transfer learning to check for the system feasibility and evaluation.

# SYSTEM ANALYSIS

## 2.1 EXISTING SYSTEM

As of my last update in January 2022, the Interpretable Classification of Pneumonia Infection Using Explainable AI (XAI-ICP) framework was conceptualized as a novel approach to enhance pneumonia diagnosis through the integration of advanced AI techniques with explainability methods. However, specific implementations or deployments of XAI-ICP in real-world clinical settings might not have been widely documented or established by that time. It's possible that research or development efforts have progressed since then, but without more recent information, I can't provide details on the existing system or its current status.

### 2.1.1 Drawbacks of Existing System

Since specific details about the existing system of Interpretable Classification of Pneumonia Infection Using Explainable AI (XAI-ICP) are not available, it's challenging to discuss its demerits directly. However, in general, some potential demerits or challenges that might be associated with AI-based diagnostic systems, including XAI-ICP, could include:

**1. Data Limitations**: AI models rely heavily on the quality and quantity of the data they are trained on. If the training data for XAI-ICP is limited or biased, it may lead to inaccuracies or poor generalization.

2. **Interpretability-Performance Trade-off**: Achieving high interpretability while maintaining predictive performance can be challenging. Some methods of increasing interpretability might sacrifice model accuracy or vice versa.

3. **Complexity and Scalability:** Implementing and deploying AI systems, especially those with advanced explainability features, can be complex and resource-intensive. Scaling such systems to handle large volumes of data or diverse healthcare settings may pose logistical challenges.

4. **Human-Computer Interaction:** Effective integration of AI systems into clinical workflows requires seamless interaction between healthcare professionals and the AI model. Poor user interface design or lack of user training can hinder acceptance and adoption.

5. **Ethical and Legal Considerations:** AI systems, especially those used in healthcare, raise important ethical and legal questions regarding patient privacy, consent, and liability. Ensuring compliance with regulations such as GDPR and HIPAA is crucial but can be complex.

6. **Algorithmic Bias and Fairness:** AI models may inherit biases present in the training data, leading to unfair or discriminatory outcomes, especially across different demographic groups. Mitigating algorithmic bias is a critical concern for equitable healthcare delivery.

## 2.2 PROPOSED SYSTEM

The proposed system for Interpretable Classification of Pneumonia Infection Using Explainable AI (XAI-ICP) integrates advanced AI techniques with explainability methods to enhance pneumonia diagnosis while ensuring transparency and interpretability. It begins with the collection and preprocessing of diverse datasets containing chest X-ray images, clinical data, and metadata. Feature extraction techniques, including convolutional neural networks (CNNs) for image analysis and feature engineering for clinical data, are employed to extract relevant information. Next, machine learning and deep learning models are trained on the extracted features to classify pneumonia infections. Importantly, the system incorporates explainability methods such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to provide clinicians with insights into the model's decision-making process. Visualization techniques, such as saliency maps and activation visualization, further enhance interpretability by highlighting key diagnostic indicators in chest X-ray images. The system's performance is rigorously evaluated on diverse datasets, and iterative improvements are made based on user feedback and real-world validation studies. Ultimately, the XAI-ICP system aims to empower healthcare professionals with accurate, transparent, and interpretable diagnostic capabilities, thereby improving patient outcomes and enhancing healthcare delivery.

### 2.2.1 ADVANTAGES

The Interpretable Classification of Pneumonia Infection Using Explainable AI (XAI-ICP) offers several advantages in the context of pneumonia diagnosis:

1. **Transparency and Interpretability:** XAI-ICP prioritizes transparency and interpretability, ensuring that healthcare professionals can understand and trust the decisions made by the AI model. This transparency is crucial for clinical acceptance and facilitates collaboration between AI systems and human experts.

2. **Improved Diagnostic Accuracy:** By leveraging advanced AI techniques, XAI-ICP can achieve high levels of diagnostic accuracy in identifying pneumonia infections. The integration of explainability methods further enhances the reliability of the model by providing insights into the features driving the predictions.

3. **Efficient Clinical Decision-Making**: XAI-ICP streamlines the diagnostic process by providing clinicians with actionable insights into pneumonia diagnosis. With clear explanations for each prediction, healthcare professionals can make more informed and efficient clinical decisions, leading to timely treatment and improved patient outcomes.

4. **Reduced Variability and Bias:** Traditional diagnostic methods for pneumonia diagnosis may suffer from variability and subjectivity due to differences in expertise and interpretation. XAI-ICP helps mitigate these issues by providing standardized and consistent predictions based on objective data analysis, reducing the impact of human bias.

5. **Enhanced Workflow Integration**: XAI-ICP can seamlessly integrate into existing clinical workflows, offering decision support tools that complement the expertise of healthcare professionals. Its user-friendly interface and transparent output facilitate smooth integration into routine clinical practice without disrupting established protocols.

6. **Adaptability and Scalability:** XAI-ICP is adaptable to various healthcare settings and

patient populations, making it suitable for deployment in diverse clinical environments. Moreover, as new data becomes available, the model can be updated and refined to maintain optimal performance, ensuring scalability and long-term viability.

7. **Ethical and Regulatory Compliance:** XAI-ICP adheres to ethical principles and regulatory guidelines governing the use of AI in healthcare. By prioritizing patient privacy, data security, and fairness, XAI-ICP upholds the highest standards of ethical conduct, fostering trust and confidence among patients and healthcare providers.

## 2.2.1 DISADVANTAGES

1. **Computational Complexity:** Implementing XAI techniques can introduce additional computational overhead, potentially leading to slower processing times or increased resource requirements.
2. **Resource Intensive:** XAI-ICP may require significant computational resources, including high-performance computing infrastructure, which could be costly and inaccessible in certain settings.
3. **Real-time Applications:** In scenarios where quick decision-making is crucial, such as medical diagnosis, the added computational burden of XAI-ICP could be prohibitive, leading to delays in providing results.
4. **Interpretability Challenges**: While the goal of XAI is to provide understandable explanations for AI-driven decisions, the interpretability of XAI-ICP may not always be straightforward or accurate. Explanations provided could be overly simplified or even misleading.
5. **Complexity of Implementation:** Implementing XAI-ICP requires expertise in both AI and domain-specific knowledge, which may not be readily available in all contexts, particularly in resource-constrained environments or smaller healthcare facilities.
6. **Risk of Misinterpretation:** Despite efforts to make AI decisions interpretable, there is still a risk of misinterpretation of the explanations provided by XAI-ICP, potentially leading to incorrect clinical decisions or patient outcomes.
7. **Training Data Bias**: XAI-ICP models are still susceptible to biases present in the training data, which could result in biased or unfair classifications, particularly for underrepresented patient populations.

# IMPLEMENTATION

## 3.1 METHODOLOGY

The XAI-ICP dataset is taken from the Taichung Veterans General Hospital (TCVGH), Taiwan. This is a regional levelhospital which provides capacity up to 1500 beds. The ethical review committee board panel from TCVGH has waived theconsent of the patients for this research work purpose.

All the patient's identity related data is being de-identified. The patients considered within this dataset consist of adult patient and are admitted to the general ward within the hospital. Therefore, Intensive Care Unit (ICU) and extreme casecondition patient's data is not included. The pneumonia criteria used to identify a patient is taken from the InternationalClassification of Diseases (ICD) 10 and 11, which is at leastcollected for a single day CXR.

This work presents an XAI based Pneumonia infection classification, which provides XAI-ICP system transparency to the user at every decisional step. The continuous learningwith human-in-the-loop approach known as user feedback makes the system re-usable for a long time. Also, the systemis pre-trained with the NIH dataset and transfer learning is added with TCVGH Vindr open dataset which makes it adaptable to any international hospital. Many research works usually focus on evaluating either open datasets or local hospital datasets, so we have provided a combined workthat can evaluate any dataset type. We have designed the XAI-ICP system model that consists of XAI based Deep CNN for providing a highly configurable model suitable forrecent CXR classification. The XAI algorithm provides a detailed explanation for the designed system, which will be beneficial to the further developments and will serve as a new standard XAI process. The DCNN model is re-configurable and adaptable to the new dataset as well as feature set, which makes it unique for the AI field and infection classification application. Independent samples taken from the CXR for processing every feature/category are presented as above in Figure 2.1 Figure 2.1 provides the pneumonia infected patient'sCXR sections. All the 7 sections are infected, and serves as the sample figure for the representational purpose from the open dataset.

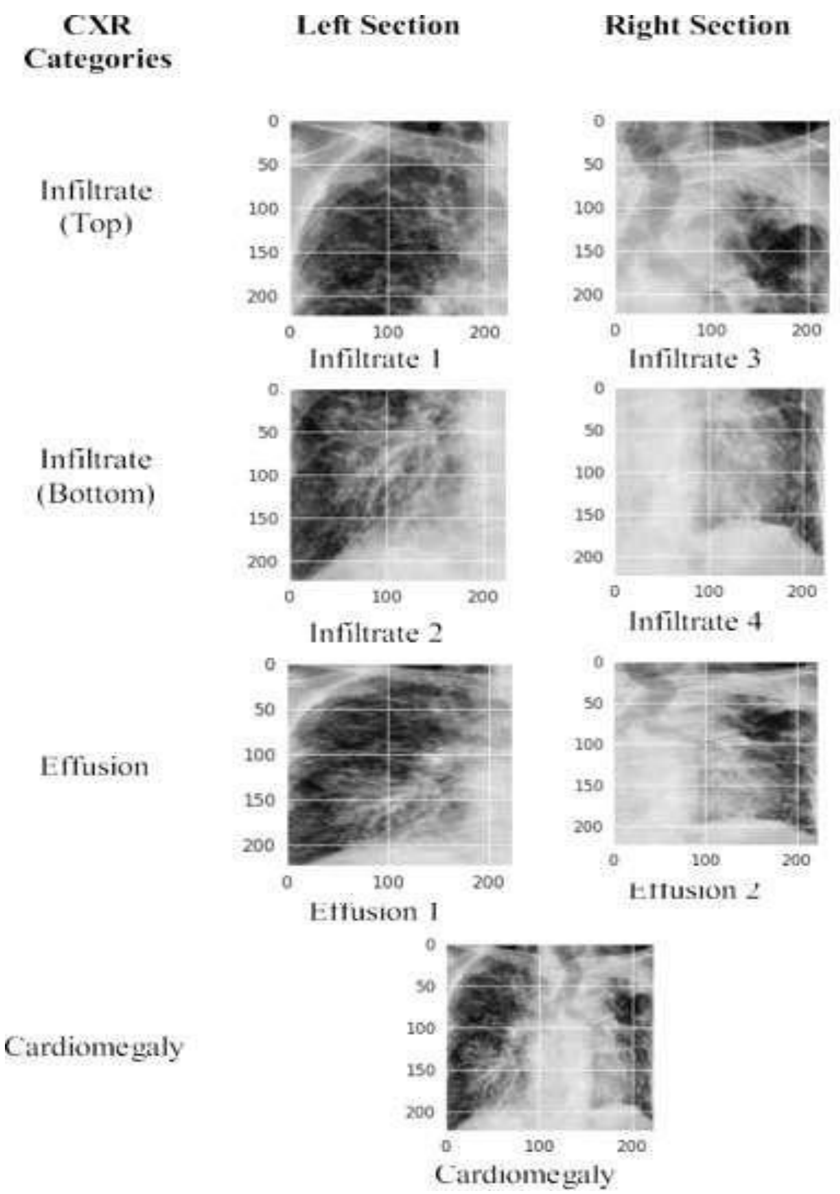


**FIGURE 3.1** Training CXR image data categories.

The algorithm is constructed by interpretation of a neural net's internal state in terms of human-friendly concepts. For the training data, the XAI model presents training for different features (infiltrate, effusion and cardiomegaly) in the different CXR sections. Infiltrate is observed in 4 sections, effusion in 2 sections and cardiomegaly in one section. It would be possible to divide cardiomegaly in two sections but due to less infected samples available, the accuracy is affected.

As per the medical AI regulations set by the European legislation in the General Data Protection Regulation (GDPR)standard indicates the importance of XAI [51]. It provides accurate explanation by the XAI system termed as ‘‘rightto explanation’’, for privacy protection and human dignity rights. Therefore, the final decision is taken by human in the loop process co-operating with automated processing and informed patient's consent. The feedback-based system is considered to be the crucial factor for the continuous improvement in the XAI system [52]. No system is perfect but it can be kept in practice and thought to be applicable until it is continuously adapting to the environment of various diseases/infections.

| Dataset Name | Category | Contents | Source |
|---|---|---|---|
| National Institutes of Health (NIH) | Open | 112,120 CXR images | U.S. Department of Health and Human Services. |
| VinDr<br><br>Taichung Veteran | Open<br><br>Private | 18,000 CXR images<br>2301 CXR images | Vietnam<br><br>Taiwan |
| General Hospital (TCVGH) | | | |

**TABLE 3.1** Open datasets used within XAI-ICP.

The above Table 2 presents the open datasets that are used within XAI-ICP for pre-training weights, transfer learning and evaluation as NIH, VinDr and TCVGH datasets respectively. NIH dataset is selected for pre-training because it consists of numerous samples from diverse countries thatare found to be best for the model. The TCVGH used for training and VinDr open datasets for transfer learning are used to provide the models efficiency in handling various testevaluations.

## 3.2 SYSTEM ARCHITECTURE

The system model as shown above in Figure 3, can beexplained into 7 major parts. At the beginning, the XAI-ICPmodel is pre-trained with the NIH CXR dataset to quickly adapt to the new CXR vision problem. The further training input given to the system is TCVGH
+
VinDr open dataset of CXR images for pneumonia respiratory infection with the XAI human in the loop approach by three labeled features of infiltrates, cardiomegaly and effusion. Later, the data preprocessing performed on this model is to segmentation, standard scalar, data

augmentation, etc. Next,the transfer learning is performed by utilizing a pre-trained network with input dataset and fine tune network weights. Successively, the XAI-ICP classification algorithm consists of a Dense-121 network with global average pooling 2Dand dense layer having SoftMax for multiclass output. The detailed XAI based explanation is given in algorithm 1.Exclusive DenseNet-121 Deep neural networks (DNNs) are models only used in model training. Therefore, in this process, an interpretable DNN model is used for the detailed decision transparency for the classification purpose. Further on the feedback-based evaluation collects data from the usersto improve the system with rules for classification, which ultimately results in the XAI post-evaluation survey. The modelis then made recursive to update the training data regularly, such that the resulting evaluation will be improved and also the features are suggested by the domain experts/users' choicefrom their experiences.

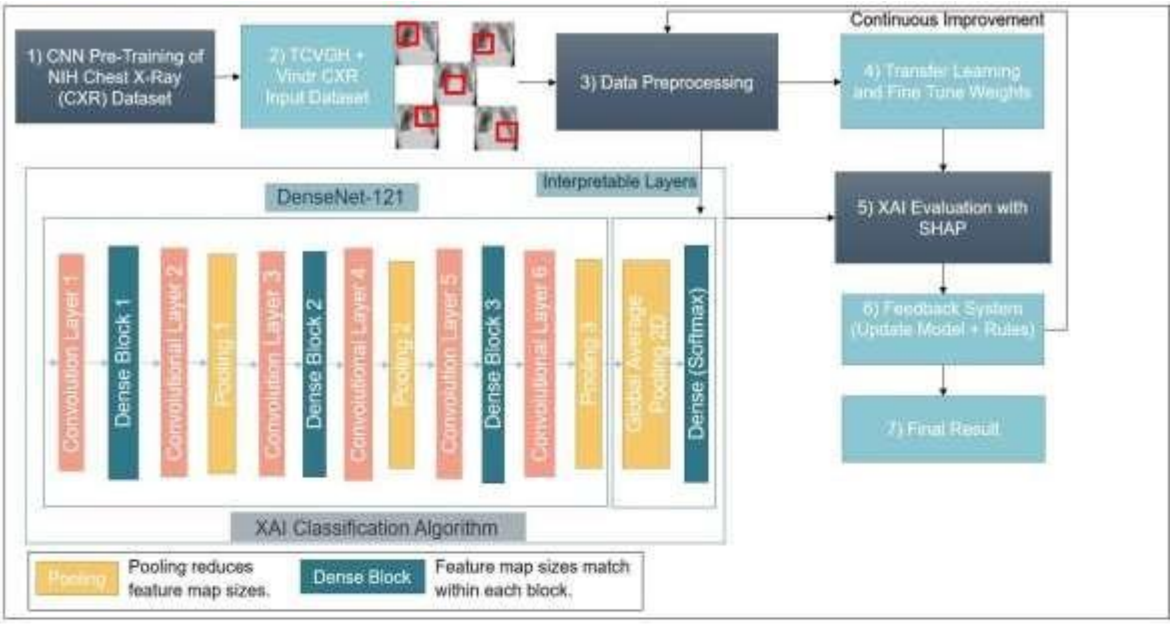


**FIGURE 3.2** XAI-ICP system model.

Ultimately, the system will keep on improving continuously with the data and suggestions for providing the best accuracy. The best accuracy can be described as the highest scores achieved by the machine and human improvements. The XAI evaluation provides the transparency, interpretability and human in the loop approach as the final evaluation results. Thus, the final result decision is then given for the pneumonia diagnosis for the purpose of infection or not.

### 3.3 FLOWCHAT

The XAI-ICP flowchart as shown in Figure 4 presents the system working in detail with the control flow and its respective operations. At the start, the model performs pre-training with an open dataset then training data of CXR images of the patient are taken. The dataset is then filtered with the pneumonia hospitalization criteria and is checked whether the patients are adults and are admitted in the general ward with the exception of ICU ward. The data preprocessing of the input dataset is performed to utilize a consistent and high-quality data. These features are then given as input to the XAI DCNN classification algorithm with tuned hyper-parameters for obtaining better classification results. In every step of XAI process, the detailed explanation of the decisions taken by the algorithms are made available to the user and also data transparency is present. The disease severity analysis of the different sections within the CXR is given by different interpretable layers for the CXR section wise analysis. Therefore, a detail implementation of the patient's health status is made available. Successively, the transfer learning is made on a new external dataset for validation. A feedback system is then provided after the classification, so that the domain expert can provide their suggestions and diagnosis for the patient's condition better than the XAI classification results.

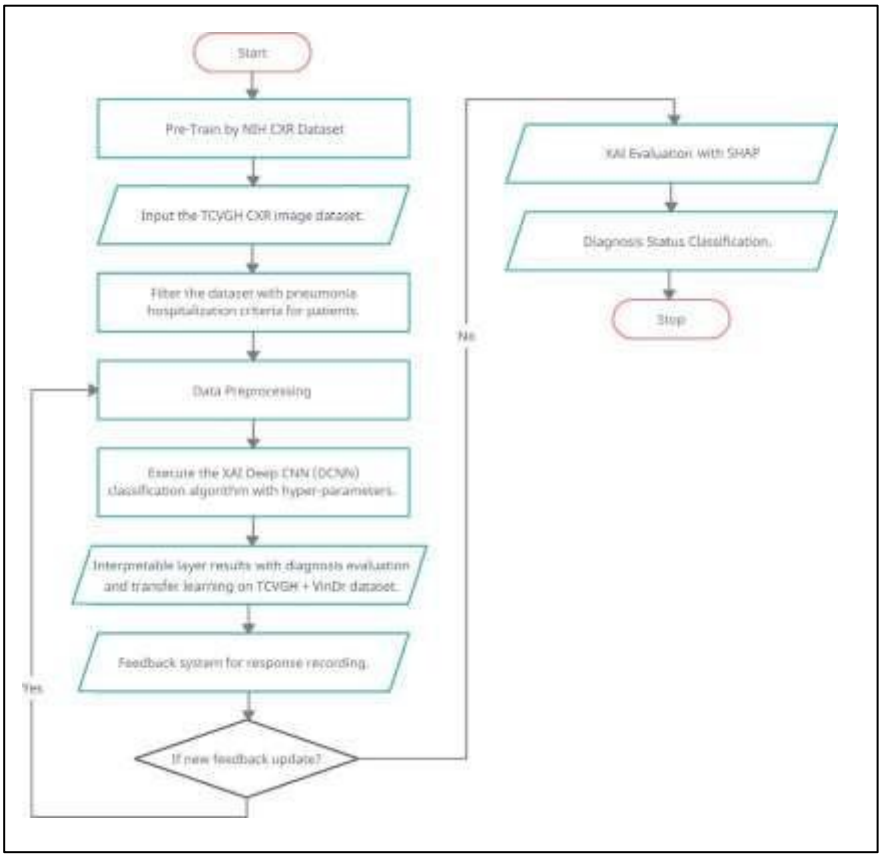


**FIGURE 3.3** XAI-ICP flowchart

The purpose of this system is to be open for the supervision and to achieve continuous improvement for the system adaptation to the future classification improvements by XAI human in the loop approach as data labeling. Thus, if a new update is made in the form of suggestion by the domain expert, then the new data recorded from the last update and hyperparameter tuning is performed within the system. Grid search for the optimal hyper-parameters can be used to check for such cases optionally. The XAI post survey evaluation presents the results after the improvement of the hyper-parameter, if any. The SHAP interpretation provides the highlighting of features with transparency to the medical examiners about the system process. Finally, the diagnosis decision is given by the XAI system from the patient's current health condition immediately during the hospitalization. A negative decision may help medical examiners to change the treatment process and improve the possibility of the patient's early diagnosis in the future.

## ALGORITHM

Algorithm 1 XAI-ICP classification

1. Input: IRaw, Input CXR image of patient.
2. ILabelled, Labelling on CXR image by medical examiner.
3. RInference, Inference rules with threshold specified by the medical

examiner's.

4. Threshold, Determined by the medical examiner's experience.
5. Output: XAIAnalysis, Explainable AI Analysis
6. Initialize (IProcessedCG, IProcessedIP,) IProcessed = ∅
7. CNN = Pre-TrainNIH(DenseNet-121)
8. IProcessedCG = Categorization(Imputation(IRaw))
9. IProcessed S

IP = Grey-Scale(Resize(IProcessedCG)) ILabelled

10. IProcessed =

Data-Augmentation(StandardScalar(Segmentation (IPocessedIP)))

11. DCNN

S = TransferLearningVindr(CNN(IProcessedIP)) Interpretable-Layers

12. Do {

13. If (DCNN(IProcessed) is Valid)
14. FPrint(‘‘CXR shape detection and classification is successful’’)
15. If (RInference ≥ Threshold)
16. FPrint(‘‘All CXR features are valid as per inference rules’’)
17. If (Confidence(No Diagnosis)
> Confidence(Diagnosis))
18. FPrint(‘‘No Diagnosis confidence is higher by (No Diagnosis – Diagnosis)×100 percent’’)
19. Else
20. FPrint(‘‘Diagnosis confidence is higher by (Diagnosis – No Diagnosis)×100 percent’’)
21. If (Can you suggest some valid/invalid features in the CXR to be altered for better performance?)
22. Input(‘‘User comments for valid/invalid features’’)
23. Else
24. FPrint(‘‘CXR performs better due to more symptoms features’’)
25. }While(Valid Suggestions)
26. If (Cardiomegaly.accuracy > 4infiltrates.accuracy)
27. FPrint(‘‘The CXR 4-section infiltrates including cardiomegaly has the accuracy (Cardiomegaly.accuracy)×100 %’’)
28. Else
29. FPrint(‘‘The CXR 4-section infiltrates performs better with the accuracy (4infiltrates.accuracy)×100 %’’)
30. If (ClassWeights.recall [1] > NoClassWeights.recall [1])
31. FPrint(‘‘Class weights performs better with (ClassWeights.accuracy)×100 %’’)
32. Else
33. FPrint(‘‘No Class weights performs better with (NoClassWeights.accuracy)×100 %’’)
34. XAIAnalysis = FPrint
35. Return XAIAnalysis

The algorithm 1 for XAI-ICP prediction and classification accepts details for the CXR of the patient. The prediction is used for the shape detection in the CXR, whereas the classification is performed on the pneumonia detection. In step 1, the IRaw is the input given as the CXR image of the patient. In step 2, the ILabelled is the labelling performed by the medical examiner to improve the pneumonia features classification accuracy. In step 3, the RInference takes reference to specific CXR features necessary for fitness analysis by segmentation. In step 4, the threshold is determined by the medical examiner's experience for special cases. In step 5, the XAIAnalysis provides explainability to the XAI system for gaining the user trust as output. In step 6, the variables IProcessedCG, IProcessedIP, and IProcessed is initialized to NULL. In step 7, the DenseNet121 is pre-trained with NIH dataset and is termed as CNN. In step 8, the input image IRaw is imputed and categorized for features and stored in IProcessedCG. In step 9, the IProcessedCG is then resized to a standard scale and grey-scale is used for processing, which is then labelled and stored in IProcessedIP. In step 10, the IProcessedIP is segmented, standard scalar is applied and data augmentation makes it ready to be processed and is stored in IProcessed. In step 11, transfer learning is applied on DCNN, so that it can learn from VinDr dataset knowledge and apply in current classification and for performance scaling the interpretable layers are added as shown in the Figure 3 system model. In step 12, the do while loop is initiated, which has the default first entry. In step 13, If IProcessedgiven as input to DCNN is available and valid for processing, then it is printed in step 14. In step 15, If the RInference specified by the medical examiner for image quality is greater than or equal to threshold then it is found to be valid and printed in step 16. In step 17, If the confidence of no diagnosis is classified as higher by the system than diagnosis confidence, then it is printed with percentage difference in step 18. In step 19, else for higher diagnosis confidence is printed in step 20. The user in step 21, can suggest feedback by providing valid or invalid CXR features for better performance in the future, which is taken as input by step 22. Else in step 23, if the CXR accuracy is not better than it is printed in step 24. In step 25, if the suggestions provided by the user/medical examiner is valid then do while loop is utilized. In step 26, if the accuracy of cardiomegaly is greater than that of CXR 4 section infiltrates then it is printed with the percentage in step 27, else in step 28, the higher accuracy percentage of CXR 4 section infiltrates is printed in step
29. Finally, in step 30, if the classification recall of the class weights performs better than without class weights then it is printed in step 31 with percentage. Else if the recall of not using class weights is better in step 32, then it is printed with percentage in step 33. Therefore, in step 34 all the explainable steps.

# APPLICATION

The Interpretable Classification of Pneumonia (XAI-ICP) using Explainable AI (XAI) is a valuable application for diagnosing pneumonia in a transparent and understandable manner.

1. **Data Collection:** The first step involves collecting data related to pneumonia cases. This data might include medical images (like X-rays or CT scans), patient demographics, symptoms, and lab test results.

2. **Feature Extraction:** Extract relevant features from the data. For medical images, this could involve identifying patterns such as opacity in lung areas indicative of pneumonia. For other data types, it could involve extracting numerical features from lab results or encoding categorical features like symptoms.

3. **Model Training:** Train a machine learning model to classify pneumonia based on the extracted features. Common models used for image classification include convolutional neural networks (CNNs), while for structured data, algorithms like decision trees or ensemble methods could be employed.

4. **Validation and Evaluation:** Validate the model's performance and the effectiveness of the interpretability techniques. This involves assessing metrics like accuracy, sensitivity, specificity, and comparing the model's predictions to ground truth labels.

5. **Deployment and Feedback**: Deploy the XAI-ICP application in clinical settings, allowing clinicians to use it to assist in diagnosing pneumonia. Gather feedback from users to continuously improve the model and its explanations.

# CONCLUSION

In conclusion, Pneumonia is one of the fatal infections known to affect the population worldwide. This work is suitable to the general ward patient as well as ICU ward patient's whose XAI based classification provides better understanding for helping medical examiners to plan recovery treatment. The XAI-IC presents the data preprocessing model that can standardize the data, image segmentation and data augmentation to achieve better outcomes. The DNN model presented within this work is interpretable using SHAP and provides high transparency to the end user. The XAI classification algorithm provides deep insights within the CXR data processing. Also, the transfer learning in this work, can train and test on the open datasets to provide better understanding of the DCNN model behavior. In the final stage, an interpretable DCNN model is constructed to deal with the diagnosis classification for the pneumonia patient.

# ENHANCEMENT

In future enhancements, Interpretable Classification of Pneumonia Infection Using eXplainable AI (XAI-ICP) aims to integrate multi-modal data, advance interpretability techniques for medical imaging, and develop interactive visualization tools. Seamless integration with clinical decision support systems is prioritized, alongside personalized medicine approaches leveraging patient-specific characteristics. Collaborative research initiatives among clinicians, data scientists, and AI researchers drive progress, fostering innovation in precision medicine for pneumonia diagnosis and treatment.

# REFERENCES

[1] R.-K. Sheu and M. S. Pardeshi, ''A survey on medical explainable AI (XAI): Recent progress, explainability approach, human interaction and scoring system,'' Sensors, vol. 22, no. 20, p. 8068, Oct. 2022, doi: 10.3390/s22208068.

[2] S. P. Praveen, P. N. Srinivasu, J. Shafi, M. Wozniak, and M. F. Ijaz, ''ResNet-32 and FastAI for diagnoses of ductal carcinoma from 2D tissue slides,'' Sci. Rep., vol. 12, no. 1, Dec. 2022, Art. no. 20804, doi: 10.1038/s41598-022-25089-2.

[3] B. Hu, B. Vasu, and A. Hoogs, ''X-MIR: Explainable medical image retrieval,'' in Proc. IEEE/CVF Winter Conf. Appl. Comput. Vis. (WACV), Jan. 2022, pp. 440–450.

[4] . Schneeberger, K. Stöger, and A. Holzinger, ''The European legal framework for medical AI,'' in Proc. Int. Cross-Domain Conf. Mach. Learn. Knowl. Extraction. Cham, Switzerland: Springer, Aug. 2020, pp. 209–226.

[5] R. Srinivasan and A. Chander, ''Explanation perspectives from the cognitive sciences—A survey,'' in Proc. 29th Int. Joint Conf. Artif. Intell., Jul. 2020, pp. 4812–4818