Evaluating Machine Learning Tools as Clinical Decision Support in Chest X-ray

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Abstract

Chest X-rays are one of the most frequent imaging modalities and are consistently in demand within the field of radiology. With the rise of innovation in AI, this study evaluated the machine learning tool's performance as a clinical decision support tool to help reduce the radiologists' workload and improve clinical workflow. The machine learning focused on diagnosing the diseases cardiomegaly, pneumonia, and mass. A total of 56 chest X-ray radiographs were analyzed by the machine learning tool and were compared with those diagnoses made by a radiologist as the diagnostic gold standard. Additionally, the acceptability of the tool was evaluated using a Likert scale focusing on its functionality, reliability, usability, efficiency, and security. The results showed that the MLT demonstrated a good performance in detecting pneumonia, but had poor accuracy in detecting cardiomegaly and mass cases. Additionally, the acceptability survey tool showed an overall neutral rating from the radiologist. While the machine learning tool shows potential as a support, it is still unreliable and inaccurate for clinical use. This suggests the need for further improvement of the MLT in its algorithm design and training process to enhance its diagnostic accuracy and reliability.

Keywords: *Machine Learning Tool, chest x-ray, clinical decision support tool*

1. Introduction

Looking at the pace of innovation in modern healthcare, it is impossible to ignore how quickly technology is reshaping the healthcare system. In radiology, chest X-rays are one of the machines that have long been a cornerstone of medical imaging (Rayan et al., 2025). The idea that a machine can analyze images and potentially flag life-threatening conditions is necessary, especially where radiologists are overworked or scarce.

To this day, chest X-ray is still one of the most commonly used imaging modalities in modern medicine (Abbott, 2025). It's in constant demand across hospitals, especially in Intensive Care Units (ICUs) results in an overwhelming number of procedures performed daily (Gale & Singh, 2025). However, this surge in workload has brought a pressing Challenge: which is the growing lack of radiologic manpower.

As hospitals face workloads and overburdened staff, the very backbone of diagnostic imaging is being stretched thin. This imbalance raises a critical question—how can we sustain accuracy and efficiency in one of the most performed imaging procedures when manpower can no longer meet demand? This cycle not only weakens diagnostic accuracy but also endangers the efficiency and reliability of the entire healthcare system.

Globally, approximately 3.6 billion chest X-rays are performed annually, accounting for nearly 40% of all radiologic tests (WHO, 2023). Despite their widespread use, over 50% of respiratory diagnostic delays result from backlogs in radiology departments. Chest X-rays are performed at a rate of about 785 per 1,000 people each year (Kragsterman, 2024).

However, many hospitals struggle with the large chest X-rays workload due to a radiologist shortage. This leads to missed disease signs and poor readings (Ayasrah et al., 2025). Low-income countries have fewer than one radiologist per 100,000 people, limiting diagnosis. The global lack of radiographers delays imaging services (Konstantinidis, 2024), leading to backlogs that slow treatment and harm outcomes.

In the Philippines, chest X-ray imaging remains widely performed with 15-20 million exams annually (Alberto et al,2022). However, because Luzon has a lot more X-ray facilities per population than Mindanao, access to imaging resources is uneven (Nolan & Lapira, 2024). Given the limited availability of CT and MRI in provincial areas, chest X-rays continue to serve as an essential first-line diagnostic tool.

In La Union, chest X-rays remain essential for detecting tuberculosis. The Department of Health launched a ₱8 million mobile X-ray van in December 2023 (Trinidad, 2023). Tuberculosis cases rose from 17,349 in 2022 to 18,512 by the end of 2023 (Trinidad, 2023b). These figures highlight the need for machine learning chest X-rays to improve detection in rural areas.

Furthermore, by 2024, over 4,000 tuberculosis cases were reported, showing that this disease is still a serious problem in the province (Austria, 2025). The provincial government promotes awareness of tuberculosis and its social, health, and economic impacts (Flores, 2025). New technology enables faster, more accurate care in remote areas, strengthening the local health system.

In manual diagnosis, variability and delay in chest X-ray interpretation can lead to missed or inconsistent diagnoses of conditions such as pneumonia, pneumothorax, pleural effusion, and lung nodules (Ahmad et al., 2023). The accuracy and limited availability of radiologists can further delay patient treatment.

To address these challenges, machine learning tools automate chest X-ray analysis, quickly detecting diseases from large imaging data (Akter et al., 2023). To extract valuable information from images and movies, machine learning image processing integrates computer vision and artificial intelligence (Kumar, 2025). Machine learning tools these days are capable of identifying objects and understanding complex images.

Machine Learning Tools (MLT) in healthcare use AI algorithms to analyze patient data such as records, images, and genomics for pattern detection and clinical support. Types include supervised, unsupervised and deep learning for imaging. Systems like federated learning protect data privacy, while on-device machine learning enables real-time alerts from wearables (Struk, 2025).

Machine learning tools in interpreting chest X-rays can be tested for various conditions, such as Pneumonia, Bronchitis, etc. Machine learning models are given human intelligence through pattern recognition (Great Learning, 2024). By learning the patterns and making predictions, these methods aid in resolving complicated issues with high accuracy without explicit programming by recognizing complex patterns.

A chest X-ray is considered normal when lungs are clear with no opacities, central trachea, symmetrical hila, and sharp costophrenic angles (Scriven, 2025). Tuberculosis appears as upper zone consolidation or calcified Ghon foci, often with ipsilateral hilar enlargement. Bronchitis typically presents with bronchial wall thickening and peribronchial markings but lacks focal parenchymal abnormalities like those in TB.

Machine learning techniques have become more popular throughout the years and have been widely used all over the world to detect and classify diseases. It has displayed high performance, shown in multiple studies, and was used to classify a lot of medical conditions of the chest, such as tuberculosis, pneumonia, cardiomegaly, and even COVID-19 (Ait Nasser & Akhloufi, 2023).

Having put much effort into solving the issues, machine learning tools offer significant support in radiologic technology by helping in the diagnosis of medical conditions in the chest. Due to the challenges of hospitals, whether private or public, one of these outcomes is the number of chest X-rays performed daily several outcomes may arise that affect both the performance and well-being.

Therefore, machine learning tools can act as a support to the hospitals that face challenges. Moreover, machine learning tools have been widely used in radiology to assist chest X-ray interpretation for diseases like pneumonia, tuberculosis, and cardiomegaly (Mello-Thoms & Mello, 2023). By optimizing machine learning tools, it can potentially strengthen the workflow of hospitals.

However, integrating these tools into healthcare systems presents challenges, including data accessibility, standardization, data quality, algorithm fairness, and regulatory oversight (Radwan Qasrawi et al., 2025). While these issues are solvable, they require coordinated efforts from healthcare institutions, developers, and researchers.

Thus, this study aims to compare chest X-ray interpretations from machine learning tools and radiologists to assess diagnostic accuracy and disease detection. It examines the reliability and consistency of the tool in identifying chest conditions. The goal is to determine how effectively machine learning can support routine radiology practice.

Furthermore, aligning machine-generated and radiologist interpretations will guide safe clinical use. Machine learning tools may provide faster and more consistent readings while ensuring patient safety (Guo et al., 2024). Ultimately, the study seeks to confirm if these tools can deliver reliable results and help reduce radiologists' workload.

In fact, the workloads that radiology professionals face can cause stress and burnout, negatively impacting diagnostic accuracy and well-being. Machine learning tools help by automating routine image assessments and triaging, reducing mental fatigue, and supporting workforce sustainability. This approach improves both efficiency and radiologists' well-being (Liu et al., 2024).

Moreover, machine learning tools enhance clinical decision-making by improving diagnostic accuracy and consistency. This boosts diagnostic confidence, enabling personalized treatments and timely interventions, leading to better patient outcomes (Parreira et al., 2024). These tools also adapt to new medical knowledge, supporting more precise and responsive healthcare tailored to individual needs.

Finally, this study explores optimizing machine learning tool integration, highlighting that these tools complement human expertise. Building a collaborative relationship between radiologists and artificial intelligence is key for successful adoption and trust (Lawrence et al., 2025). This partnership ensures improved efficiency in diagnosing medical conditions in the chest without disrupting diagnostic processes.

Overall, this study evaluates machine learning tools for improving medical diagnosis by boosting efficiency, accuracy, and reducing workload. The Machine learning tool supports radiologists and technologists in image analysis and decision-making, minimizing errors and streamlining workflow. It promotes innovation and enhances healthcare efficiency while ensuring timely, reliable diagnoses.

2. Objectives

This study aims to evaluate the machine learning tool as a clinical decision support in diagnosing chest x-rays.

3. Materials and Methods

The study used a quantitative comparative-descriptive research design to collect and study numerical data. According to Sreekumar (2023), quantitative research systematically gathers and analyses numerical data to describe, predict, or control certain factors in the study. In addition, comparative research, as stated by Appinio Research (2023), compares two or more groups or methods to find their similarities and differences. Moreover, according to Sirsilla (2023), descriptive research design is a method that gathers detailed information about a group or phenomenon to provide an accurate understanding that can guide future studies.This combined design helped the researchers identify strengths, weaknesses, and performance patterns that support clear and evidence-based results.

This study was conducted in San Fernando City, La Union, involving hospitals and clinical facilities equipped with chest X-ray services. These hospitals were LORMA Medical Center, La Union Medical Diagnostic Center (LUMED), Bethany Hospital and Ilocos Training and Regional Medical Center. Since all healthcare facilities in San Fernando City, La Union were included, total enumeration was used to involve all licensed radiologists, where a total of 9 radiologists were working in these institutions, of which 5 of them participated in our study. For this study, the inclusion criteria for radiologist respondents are as follows: They must be fully registered radiologists with an active Professional Regulation Commission (PRC) license, currently practicing and employed in a healthcare facility with at least six months of clinical experience interpreting chest X-rays in a hospital or clinic within San Fernando City, La Union, where their expertise in interpreting chest radiographs is used in daily clinical practice.

The primary tools for data collection in this are the Machine Learning Tool, matrix and likert scale. The Machine Learning Tool (MLT) that was used in the study was provided by the College of Computer Studies and Engineering (CCSE). The tool is specifically designed to analyze chest x-ray radiographs and generate automated findings that may assist in identifying abnormalities. It was solely used for only scanning radiographs for gathering data. Next, the matrix was used and it was designed to record and compare the diagnostic interpretations produced by the machine learning tool and those made by licensed radiologists. The researchers also administered an acceptability survey tool patterned after the ISO/IEC 25010 survey to the radiologist, after the tool was introduced and given sufficient time to review and use it. The acceptability survey tool assessed the level of acceptability of the machine learning tools, which has five parts: functionality, reliability, usability, efficiency, maintainability, and security, each with three questions.

After approval, the researchers undergo training under the supervision of the College of Computer Studies and Engineering (CCSE) on the proper use of the Machine Learning Tool (MLT), including data input, system functions, and interpretation of outputs. The CCSE organized seminars for the researchers. The training focused on the proper operation of the MLT and the standardized procedure in scanning radiographs.

The CCSE also guided the researchers on the safe and correct use of the MLT to ensure accurate image capture and maintain data quality. This preparatory training ensures technical competence and minimizes procedural errors during data collection. The trained researchers were the only ones using the machine learning tool, while the radiologists who voluntarily participated only observed how well the machine learning tool can perform in evaluating chest x-rays.

Informed consent was then obtained from the participating radiologists. Once consent is secured, the researchers coordinate with the hospital administration to set the schedule for the testing procedures using anonymized chest X-ray radiographs. In the scheduled session, the researchers provided radiographs, obtained from the National Institute of Health Chest X-ray Dataset, which was then scanned by the MLT.

The scanning process was conducted in the Radiology Department together with the radiologists, who then provided their own diagnosis for the radiograph. The diagnostic outputs of the radiologist and the MLT were then recorded in the matrix.

Lastly, the researchers gathered the feedback of each radiologist using the acceptability survey tool to determine whether the machine learning tool is acceptable as a clinical decision support in chest X-ray radiographs. The MLT results, radiographs interpretation, and the rating scale answered by the radiologists were collected as primary data for evaluating the tool’s accuracy and usability.

4. Results

The results of the study provided an understanding of the Machine Learning Tool's diagnostic performance and its capability as a clinical decision support system in chest radiography. The researchers identified similarities and differences between the diagnoses generated by the Machine Learning Tool and the interpretations made by the radiologist, which led to the evaluation of its diagnostic accuracy, sensitivity, specificity, and acceptability level.

The findings of the study were organized into the following areas: (Table 1) Diagnosis for the Chest X-ray Radiograph Using Machine Learning Tool, (Table 2) Diagnosis of Radiologists for the Chest X-ray Radiograph, (Table 3) Difference Between the Diagnosis of the Chest X-ray Radiograph Using a Machine Learning Tool from the Diagnosis of Radiologists Based on Accuracy, Sensitivity, and Specificity, and (Table 4) Acceptability Level of the Machine Learning Tool from the Evaluation of Radiologists. These sections provide insights into the performance, reliability, and clinical applicability of the Machine Learning Tool in chest radiography.

Table 1
Diagnosis for the Chest X-ray Radiograph Using a Machine Learning Tool

Diseases	Frequency	No. of Correct Diagnosis
Cardiomegaly	9	8
Pneumonia	31	19
Mass	16	0
Total	**56**	**27**

Table 2
Diagnosis of a Radiologist to the Chest X-ray Radiograph

Diseases	Frequency	No. of Correct Diagnosis
Cardiomegaly	27	27
Pneumonia	26	26
Mass	3	3
Total	**56**	**56**

Table 3
Descriptive Analysis of the Results of Machine Learning Tool and Diagnosis of Radiologists in Chest X-rays

Diseases	MLT	Radiologist	Similar Diagnosis	SN	SP	A
Cardiomegaly	9	27	8	29.62%	96.55%	64.28%
Pneumonia	31	26	19	73.07%	60%	66.07%
Mass	16	3	0	0%	69.81%	66.07%
Total	56	56	27	_	_	_

Legend: MLT= Machine Learning Tool; **A** = Accuracy; **SN**=Sensitivity; **SP**= Specificity

Table 4
Statistical Analysis of the Acceptability Level of the Machine Learning Tool

Respondents	WM	DE
1. Functionality		
1.1. The software provides all the required functions necessary to perform its intended task.	2.4	D
1.2. The software accurately processes user inputs and executes commands correctly.	2.8	N
1.3. Error messages and system feedback are clear, informative, and helpful.	2.8	N
2. Reliability		
2.1. The software operates reliably with minimal crashes or system failures.	2.8	N
2.2. The software maintains data integrity and consistency during operation.	2.8	N
2.3. The software is capable of recovering smoothly from errors or system failures.	2.8	N
3. Usability		
3.1. The software is easy to learn and operate without extensive training.	3.6	A

3.2. The software interface is intuitive, clear, and user-friendly.	3.6	A
3.3. Navigation within the software is straightforward and well structured.	3.4	N
4. Efficiency		
4.1. The software responds promptly to user inputs.	3.6	A
4.2. The software utilizes system resources efficiently.	3	N
4.3. The software utilizes system resources efficiently.	3	N
5. Security		
5.1. The software protects data against unauthorized access.	3	N
5.2. The software enforces appropriate access control for authorized users.	3	N
5.3. The software ensures secure storage and transmission of sensitive information.	2.6	D
6. Overall Acceptability	2.4	D
AWM	**2.975**	**N**

Legend: **WM**= Weighted Mean; **DE**= Descriptive Equivalent; **AWM** = Average Weighted Mean; **D** = Disagree; **N** = Neutral; **A** = Agree

5. Discussion

The machine learning tool (MLT) showed varying diagnostic performance in interpreting chest x-ray images across the three conditions as shown in **Table 1**. Out of 56 total cases, the MLT correctly diagnosed only 27 cases. It demonstrated the strongest performance in detecting pneumonia, correctly identifying 19 out of 31 cases, suggesting that the MLT has better recognition pneumonia due to its more common and visually distinct radiographic patterns. For cardiomegaly, the tool correctly diagnosed 8 out of 9 cases, indicating good performance but based on a limited number of cases. In contrast, the MLT failed to correctly identify any of the mass cases, with all 16 cases misdiagnosed, highlighting its significant limitations in detecting it due to its subtle appearance or overlapping features with other diseases. These findings suggest that the MLT's diagnostic capability differs depending on the chest condition being analyzed.

The findings shown in **Table 2** that among the diseases diagnosed by the radiologists, the majority of the radiographs are cardiomegaly and pneumonia, with 27 cases in cardiomegaly and 26 cases in pneumonia, indicating that these conditions are commonly observed or easily recognized due to their clearer radiographic features. In contrast, only a small number of cases was identified as mass (3 cases), suggesting either a lower incidence or difficulty in detection because of less distinct appearances.

In **Table 3**, using the radiologists' diagnoses as the gold standard, the machine learning tool (MLT) was evaluated based on how closely its interpretations matched the radiologists in diagnosing chest x-ray findings. For cardiomegaly, radiologists identified 27 cases, while the MLT identified only 9 cases, with 8 cases in agreement. This resulted in low sensitivity (29.62%) but high specificity (96.55%), suggesting that although the MLT was effective at ruling out cardiomegaly, it failed to detect many true positive cases that radiologists identified. For pneumonia, radiologists diagnosed 26 cases, while the MLT identified 31 cases, with 19 matching diagnoses. This condition showed the highest agreement between the two, reflected in the MLT's higher sensitivity (73.07%). However, its lower specificity (60%) suggests that the MLT tended to overdiagnose pneumonia, producing more false positives compared to radiologists. In mass detection, radiologists identified 3 cases, while the MLT classified 16 cases as mass, yet none matched the radiologists' diagnoses, resulting in 0% sensitivity and no agreement. This demonstrates a major limitation of the MLT in recognizing and accurately distinguishing more subtle or complex abnormalities.

Lastly, the results in **Table 4** indicate that the machine learning tool has an overall neutral acceptability among radiologists (AWM = 2.975), showing hesitation in fully integrating it in clinical settings. In terms of functionality, the tool received ratings of 2.4 (Disagree) and 2.8 (Neutral), indicating concerns about whether the system provides sufficient and dependable features needed for accurate diagnostic support. For reliability, the consistent weighted mean of 2.8 (Neutral) suggests uncertainty regarding the tool's consistency and dependability in producing accurate results. Furthermore, the highest ratings were observed in usability, with weighted means of 3.6 (Agree) and 3.4 (Neutral), showing that radiologists generally found the tool easy to learn, understand, and operate. Similarly, efficiency received ratings of 3.6 (Agree) and 3.0 (Neutral), indicating that the tool may help improve workflow and reduce the time needed for certain tasks. However, security received lower ratings of 3.0 (Neutral) and 2.6 (Disagree), suggesting concerns about the protection of sensitive patient data and the overall safety of integrating the tool into clinical systems. Overall, while the MLT demonstrates strengths in usability and efficiency, limitations in functionality, reliability, and security significantly affect radiologists' confidence and willingness to adopt it.

6. Conclusion

The results of this study indicate that the machine learning tool (MLT) has the potential to be a clinical decision support tool in chest x-ray diagnoses, especially in detecting conditions like pneumonia and cardiomegaly, which are also the most frequently identified findings by radiologists. However, its effectiveness is still uneven across various disease types, particularly in mass detection, where it demonstrated its notable shortcomings. Although the MLT demonstrated average performance in detecting diseases, its low sensitivity and failure to effectively recognize more complex abnormalities hinder its dependability as a standalone diagnostic tool.

In contrast, radiologists exhibited greater consistency and reliability in diagnosing chest x-rays, especially in identifying prevalent and clinically evident abnormalities like cardiomegaly and pneumonia. The notable differences seen between the MLT and radiologists regarding sensitivity, specificity, and accuracy indicate that the machine learning tool is not yet on par with the diagnostic skills and clinical judgment of an experienced radiologists. These results emphasize the need to uphold radiologists as the definitive experts in chest X-ray diagnosis, with the machine learning tool acting mainly as a support tool instead of a substitute.

Additionally, the evaluation made by the radiologists to the MLT indicated that while the tool is typically easy to use and effective, potentially enhancing clinical workflow, its general clinical acceptance remains average. Worries about the tool's functionality, reliability, and security diminish its trust in practical use and hinder its complete integration into clinical settings.

Overall, the machine learning tool shows promise as a clinical decision-support system that can assist radiologists in chest X-ray diagnosis and potentially improve efficiency in healthcare settings. However, further improvements in training data quality, algorithm refinement, diagnostic performance, and system reliability are necessary before it can be more widely accepted and integrated into clinical practice. Until these limitations are addressed, the MLT should be used only alongside radiologist evaluation to ensure accurate diagnosis and patient safety.

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9. Appendices

APPENDIX A
Approval Sheet from the Research Ethics Committee

LORMA COLLEGES

LC-REC Form #024
APPROVAL LETTER

REC Reference #: 2026-022

March 9, 2026

To: **Heron Troy Abenoja, Ella Mae Etrata, Princess Galang, Juneah Baby Hidalgo, Lean Mecos and Kyna Xandrey Taclawan**
LORMA Colleges, College of Radiologic Technology

Subject: Approval of the Research Study – "EVALUATING MACHINE LEARNING TOOLS AS CLINICAL DECISION SUPPORT IN CHEST X-RAY DIAGNOSIS" – by the Research Ethics Committee (REC).

Dear Researcher/s,

The Research Ethics Committee (REC) has reviewed your application to conduct the above-mentioned research study in the District Hospitals and Clinics in the City of San Fernando, La Union with you as the Principal Investigators within a duration of March 9, 2026 to March 9, 2027.

The Following documents have been reviewed and approved:

1. Endorsement of the Research Coordinator
2. Title and Statement of the Problem/Objective
3. Literature Review
4. Methods and Procedures
5. Population and Locale
6. Exclusion/Inclusion Criteria
7. Data Analysis
8. Ethical Considerations

We approve the study to be conducted in the presented form provided the following are integrated in the final research protocol:

1. Write the Informed Consent Form in the second person point of view. Write the entries for Risks, Benefits, and Reimbursements in sentences. In addition, move the certificate of consent to a separate page.

The institutional REC expects to be informed about the progress of the study, any revision in the protocol before implementation and participants'/respondents' information/informed consent. Likewise, you are required to provide the Board a copy of the final report.

Yours Sincerely,

JEROME P. VERA, LPT
Chairman, LC-REC

10. Author(s) Biodata

Heron Troy M. Abenoja, Ella Mae G. Etrata, Princes V. Galang, Juneah Baby M. Hidalgo, Lean P. Mecos, and Kyna Xandrey P. Taclawan are Bachelor of Science in Radiologic Technology students from Lorma Colleges, together with their research adviser Ms. Gryn T. Salagma, MPH, RRT. The researchers conducted the study entitled "Evaluating Machine Learning Tools as Clinical Decision Support in Chest X-ray" as partial fulfillment of the requirements for the degree of Bachelor of Science in Radiologic Technology. By evaluating the potential of machine learning tools to become a precise and reliable clinical decision support tool, they hope to contribute to society by expanding the knowledge on the field of artificial intelligence in medical imaging.