An Integrated YOLOv12-Powered Platform for Early Lung Cancer Detection and Patient-Physician Collaborative Care

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DEDICATION

This research is dedicated to the unsung heroes of healthcare in the Philippines: the radiologists, technicians, and primary care physicians who work tirelessly with limited resources to combat lung cancer across our archipelago. Your dedication inspires our innovation.

To our parents, whose unwavering support and countless sacrifices made our academic journey possible. Your belief in our abilities gave us the courage to pursue this challenging path.

To our thesis adviser, Professor Sheryl Kamantigue, whose guidance, wisdom, and patience transformed abstract ideas into meaningful research. Your mentorship extends far beyond these pages.

And finally, to the lung cancer patients whose struggles motivated this work. May this research contribute, even in a small way, to earlier detection, better outcomes, and renewed hope for those facing this disease in our country.

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ABSTRACT

Lung cancer remains one of the most devastating diseases in the Philippines, with alarming incidence and mortality rates. This research develops an integrated platform consisting of a YOLOv12-based detection system and a collaborative web application interface, specifically tailored to the Philippine healthcare context. The system employs deep learning algorithms to identify and categorize potential lung nodules, masses, and other suspicious findings into four main categories: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal tissue. Beyond detection, the platform establishes a dynamic connection between patients and healthcare providers through a role-based web application. Medical professionals can upload and analyze medical images, document findings, and communicate results to patients, while patients can access their diagnostic information, request second opinions, and engage in secure dialogues with their physicians. This integrated approach not only enhances diagnostic accuracy through advanced AI but also addresses critical communication gaps in the patient care journey. Following a mixed-methods research design, the study combines quantitative performance evaluation with qualitative assessment of user experience, aiming to fundamentally transform early lung cancer detection and subsequent patient care pathways in the Philippines.

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CHAPTER I

INTRODUCTION

1.1 Project Context

The Philippines, like many nations worldwide, faces significant healthcare challenges that have profound impacts on its population. Among these challenges, lung cancer stands as one of the most devastating diseases, with alarming incidence and mortality rates that continue to rise across the archipelago. As healthcare systems evolve in response to modern globalization and technological advancement, the need for innovative diagnostic solutions and improved patient-physician communication becomes increasingly apparent.

Lung cancer, characterized by uncontrolled cell growth in lung tissues, poses a substantial threat to communities throughout the country, particularly among vulnerable populations with limited access to healthcare facilities and early screening programs. The increasing prevalence of risk factors such as tobacco use, environmental pollution, and occupational exposures has led to a corresponding rise in lung cancer cases, resulting in late-stage diagnoses and poor survival outcomes for many Filipinos. This reality highlights the critical need for effective early detection strategies and accessible diagnostic tools that can bridge the gap between detection and patient care.

In recent years, the emergence of advanced technologies, particularly in the field of Artificial Intelligence (AI) and machine learning, has created new opportunities for enhancing medical diagnostics and healthcare delivery. Machine learning algorithms such as Convolutional Neural Networks (CNNs) have demonstrated remarkable potential in medical image analysis across various specialties. CNNs are a class of deep learning algorithms that have shown exceptional success in image recognition and processing tasks. Their ability to analyze visual data swiftly and accurately makes them particularly suitable for applications in medical imaging, where precise detection, assessment, and classification of abnormalities are essential for accurate diagnosis.

Simultaneously, the evolution of web technologies has enabled the development of sophisticated healthcare platforms that can facilitate secure communication between patients and healthcare providers. These platforms have the potential to transform the patient experience by providing access to diagnostic information, enabling direct communication with physicians, and facilitating informed decision-making throughout the care journey.

With these considerations in mind, this study focuses on developing a comprehensive platform that integrates a CNN-based detection system with a role-based web application designed for early lung cancer detection and enhanced patient-physician collaboration in the Philippines. This research was inspired by the urgent need to provide healthcare professionals and patients with more reliable and accessible tools for improving lung cancer outcomes through early detection, clear communication, and technological innovation. It aims to develop a sophisticated platform specifically tailored to the Filipino healthcare context, addressing the unique challenges and requirements of the local population.

This research will design an application that employs deep learning algorithms, specifically the YOLOv12n (You Only Look Once) model, to identify and categorize potential lung cancer findings from chest CT scan images. The YOLOv12 architecture represents a significant advancement in object detection technology, offering real-time processing capabilities while maintaining high accuracy levels. Our implementation leverages this cutting-edge architecture to detect and classify four main categories of lung conditions: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal tissue.

Beyond detection, the platform will enable healthcare professionals to upload and analyze medical images, document findings, and communicate results to patients through a secure interface. Patients will be able to access their diagnostic information, request second opinions from a network of specialists, and engage in direct communication with their physicians, fostering a more collaborative approach to lung cancer care. By enabling real-time assessment of medical images and facilitating meaningful patient-physician interactions, this integrated system aims to equip healthcare professionals with timely and actionable diagnostic information while empowering patients to actively participate in their care journey, ultimately improving patient outcomes through earlier intervention and enhanced communication.

1.2 PURPOSE AND DESCRIPTION

The primary purpose of this research is to develop and implement a web-based lung cancer detection system using the YOLOv12n convolutional neural network model, specifically designed to address the diagnostic challenges faced by the Philippine healthcare system. This research aims to create an accessible, accurate, and efficient tool that can augment the limited radiological expertise available across the archipelago, particularly in underserved areas where specialized medical resources are scarce.

The proposed system is designed as a comprehensive web application that enables healthcare professionals to upload chest CT scan images and receive automated analysis for potential lung cancer indicators. The system employs the YOLOv12n architecture, the latest iteration of the "You Only Look Once" series, which has been specifically adapted for medical imaging applications. This deep learning model processes CT scans to detect and classify four primary categories of lung abnormalities: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal tissue.

The research encompasses the complete development life cycle of the system, from dataset curation and model training to web application deployment and clinical validation. It includes the collection and annotation of a representative dataset of chest CT scans from Filipino patients, ensuring that the model is trained on data relevant to the target population.

The system is designed with user experience at its core, featuring an intuitive interface that accommodates healthcare professionals with varying levels of technical expertise.

Beyond technical development, this research addresses the practical implementation challenges of deploying AI-based diagnostic tools in resource-constrained healthcare settings. It provides a comprehensive framework for integrating the system into existing clinical workflows, considering factors such as internet connectivity limitations, varying technological infrastructure, and the need for regulatory compliance with Philippine healthcare standards.

The ultimate goal of this research is to democratize access to advanced lung cancer detection capabilities across the Philippines, potentially leading to earlier diagnoses, more timely interventions, and improved patient survival rates. By bridging the gap between cutting-edge AI technology and practical healthcare delivery, this study aims to contribute significantly to the advancement of cancer care in the Philippines while providing a model that can be adapted for similar healthcare challenges in other developing nations.

1.3 STATEMENT OF THE PROBLEM

The high mortality rate of lung cancer in the Philippines, attributed to late-stage diagnoses, results from limited access to specialized diagnostic expertise and inadequate screening capabilities in the healthcare system.

This research addresses the following problems:

1. What specific challenges exist in the current Philippine healthcare system regarding lung cancer diagnostics, and how can the proposed AI-driven solution be tailored to address these challenges?

2. How effective is the proposed CNN-based approach compared to traditional diagnostic methods in terms of accuracy, accessibility, and timeliness in detecting various types of lung abnormalities?

3. What implementation framework would be most suitable for integrating the developed AI-based diagnostic tool into existing Philippine healthcare systems to maximize its impact on early intervention and patient outcomes?

The proposed solution involves developing a CNN-based web application using the YOLOv12 model to provide accessible, accurate, and rapid lung cancer detection across diverse healthcare settings, thereby enabling earlier diagnosis and improving patient survival outcomes in the Philippines.

1.4 HYPOTHESES

Based on the research problems identified in Section 1.3, this study formulates the

following null hypotheses:

Hypothesis 1:

- H_{10}: The proposed YOLOv12-based AI solution will not effectively address the specific challenges in the Philippine healthcare system regarding lung cancer diagnostics, including the radiologist shortage (1:80,000 ratio) and inadequate radiological services in 65% of healthcare facilities.

Hypothesis 2:

- H_{20}: The proposed CNN-based approach will not demonstrate superior effectiveness compared to traditional diagnostic methods in terms of accuracy, accessibility, and timeliness when detecting various types of lung abnormalities in the Philippine healthcare context.

Hypothesis 3:

- H_{30}: There will be no suitable implementation framework that enables successful integration of the developed AI-based diagnostic tool into existing Philippine healthcare systems that maximizes impact on early intervention and patient outcomes across varying infrastructure capabilities.

These null hypotheses will be tested through statistical analysis ($\alpha = 0.05$) using quantitative performance metrics, comparative studies between AI and traditional methods, and pilot implementation across diverse healthcare settings in the Philippines.

1.5 RESEARCH OBJECTIVES

This research aims to develop and implement a CNN-based web application using the YOLOv12 model for lung cancer detection and classification, specifically designed for the Philippine healthcare context. The general objective directly addresses the research problems identified above and serves as the overarching goal that this study intends to achieve.

The specific objectives follow, using a colon at the end:

1.4.1 General Objective

To develop and implement a CNN-based web application using the YOLOv12 model for early detection and classification of lung cancer from chest radiographs and CT scans that is specifically tailored to the Philippine healthcare context.

1.4.2 Specific Objectives

1. To identify and quantify the specific challenges in lung cancer diagnostics within the Philippine healthcare system through comprehensive literature review and stakeholder consultations;
2. To develop and train a YOLOv12-based deep learning model using a curated dataset of chest radiographs and CT scans with at least 80% accuracy in detecting lung cancer nodules;

3. To measure and evaluate the performance of the developed model in terms of sensitivity (≥90%), specificity (≥85%), accuracy (≥95%), and processing time (≤5 seconds per image) compared to traditional diagnostic methods;

4. To design and implement a user-friendly web application interface with a System Usability Scale (SUS) score of ≥80 that allows healthcare professionals to upload, process, and interpret medical images efficiently;

5. To validate the effectiveness of the developed application through pilot testing in at least three healthcare facilities across different regions in the Philippines, measuring diagnostic accuracy and user satisfaction rates;

6. To formulate and document implementation guidelines and recommendations based on pilot test results for the successful integration of the developed AI-based diagnostic tool into existing Philippine healthcare systems.

1.6 SIGNIFICANCE OF THE STUDY

This research holds significant value for various stakeholders in the Philippine healthcare ecosystem:

For Healthcare Professionals: The developed application will serve as a valuable decision support tool for radiologists and other healthcare professionals, potentially reducing diagnostic errors and interpretation time. It will be particularly beneficial in areas with limited access to specialized radiological expertise, enabling general practitioners to make more informed decisions regarding patient referrals and management.

For Patients: Early detection of lung cancer significantly improves survival rates and treatment outcomes. By enhancing the accuracy and accessibility of diagnostic services, this study could potentially benefit countless patients across the Philippines, particularly those in underserved areas where specialized healthcare services are limited.

For the Healthcare System: The integration of AI-based diagnostic tools has the potential to optimize resource allocation within the healthcare system by streamlining workflows, reducing unnecessary procedures, and enabling more targeted interventions. This could lead to cost savings and improved efficiency in the delivery of cancer care services.

For Academic and Research Communities: This study contributes to the growing body of literature on the application of artificial intelligence in healthcare, particularly in the context of developing countries like the Philippines. It provides valuable insights into the development, implementation, and evaluation of AI-based diagnostic tools in resource-limited settings.

For Technology Developers: The methodologies and findings from this research can inform future developments in AI-based medical imaging applications, particularly those designed for similar contexts or populations.

1.7 SCOPE AND LIMITATIONS

This study focuses on the development of a web application that leverages Convolutional Neural Networks (CNNs) to enhance early lung cancer detection in the Philippines. While the Philippines is an archipelago with numerous regions, the scope of this study is specifically confined to the development and initial testing of the application, ensuring that the research remains feasible and manageable within the available resources and timeframe.

The application only aims to implement several key features, including image analysis to classify and analyze potential lung cancer indicators, real-time object detection using YOLOv12, and a user-friendly interface for efficient medical image upload, processing, and interpretation. However, the findings and insights derived from this study may not be generalizable to all healthcare settings, as different areas may experience distinct challenges and possess varying technological capabilities.

Moreover, the study will exclusively focus on specific types of lung abnormalities relevant to cancer detection, such as nodules, masses, and infiltrates, rather than providing a comprehensive analysis of all possible lung conditions. This targeted approach allows for a more in-depth understanding of lung cancer detection but limits the applicability of the findings to other pulmonary diseases.

The research will also be reliant on existing technologies such as YOLOv12 and open-source datasets without the development of new models or frameworks. As such, the performance of the application may be influenced by the limitations of these technologies. Additionally, the study will depend on medical images provided by healthcare facilities for training and testing the CNN model, which means that the quality and quantity of data collected may vary based on institutional participation.

Finally, the study will be conducted within a specific timeframe, which may restrict the extent of testing and refinement that can be achieved for the application. User training on diagnostic practices will not be extensively covered, as the study will assume that users have a basic understanding of medical imaging and diagnostic procedures.

CHAPTER II

REVIEW OF RELATED LITERATURE

2.1 LUNG CANCER IN THE PHILIPPINES: EPIDEMIOLOGY AND CHALLENGES

Lung cancer represents a significant public health challenge in the Philippines. According to the Global Cancer Observatory, lung cancer is among the leading causes of cancer-related mortality in the country, with an estimated 14,000 new cases and 12,500 deaths reported annually (GLOBOCAN, 2020). The high mortality rate is largely attributed to late-stage diagnosis, with more than 70% of cases detected at advanced stages when treatment options are limited and prognosis is poor (Department of Health Philippines, 2023).

Various factors contribute to the high burden of lung cancer in the Philippines. Tobacco smoking remains the primary risk factor, with approximately 23.8% of Filipino adults identified as current smokers (Philippine Statistics Authority, 2022). Additionally, environmental factors such as air pollution, occupational exposures, and genetic predispositions play significant roles in the development of lung cancer among Filipinos (Laudico et al., 2020).

The Philippine healthcare system faces numerous challenges in addressing the lung cancer burden. Limited resources for cancer screening programs, particularly in rural and underserved areas, contribute to delayed diagnosis (Cruz & Santos, 2022). A study by Ngelangel and Wang (2021) highlighted that only 35% of healthcare facilities in the Philippines have adequate radiological services for early cancer detection. Furthermore, there is a significant shortage of specialized healthcare professionals, with only one radiologist per 80,000 population, compared to the recommended ratio of one per 20,000 (Philippine College of Radiology, 2023).

The economic impact of lung cancer is substantial, with treatment costs averaging PHP 500,000 to PHP 2,500,000 per patient, depending on the stage of diagnosis and treatment modality (Sanchez et al., 2021). This financial burden often leads to catastrophic health expenditures for affected families, particularly those without comprehensive health insurance coverage (PhilHealth, 2023).

These challenges underscore the critical need for innovative approaches to improve early detection and diagnosis of lung cancer in the Philippines. The development of accessible and cost-effective diagnostic tools, such as AI-based image analysis systems, presents a promising avenue to address these challenges and improve lung cancer outcomes in the country.

2.2 ARTIFICIAL INTELLIGENCE IN MEDICAL IMAGING AND DIAGNOSTICS

The integration of artificial intelligence (AI) in medical imaging has revolutionized diagnostic capabilities across various medical specialties. Convolutional Neural Networks (CNNs), a specialized form of deep learning algorithm, have demonstrated remarkable success in image recognition and classification tasks, making them particularly suitable for medical image analysis (Yamashita et al., 2022).

In the context of lung cancer detection, AI-based approaches have shown promising results. A landmark study by Ardila et al. (2019) demonstrated that a deep learning algorithm could detect lung cancer from low-dose chest CT scans with a sensitivity of 94.4% and a specificity of 95.5%, outperforming radiologists in some aspects of the detection task. Similarly, McKinney et al. (2020) reported that an AI system for mammography could reduce false negatives and false positives in breast cancer screening, highlighting the potential of AI in improving cancer detection across different imaging modalities.

The integration of AI in medical imaging workflow offers several advantages. Al-Antari et al. (2021) noted that AI-based systems can process and analyze large volumes of imaging data rapidly, potentially reducing radiologist workload and interpretation time. Moreover, Khan et al. (2022) highlighted that AI algorithms can detect subtle abnormalities that might be overlooked by human observers, 2.3particularly in screening settings where the prevalence of disease is low and radiologist fatigue may impact performance.

However, challenges remain in the widespread adoption of AI in medical imaging. Issues related to algorithm transparency, generalizability across diverse patient populations, and integration into existing clinical workflows have been identified as potential barriers (Topol, 2023). The "black box" nature of many deep learning algorithms raises concerns about interpretability and accountability in clinical decision-making (Gichoya et al., 2022).

In the Philippine context, limited studies have explored the application of AI in medical imaging. Martinez et al. (2021) conducted a small-scale study evaluating an AI algorithm for chest X-ray interpretation in a tertiary hospital in Manila, reporting promising results with an accuracy of 88% for detecting pulmonary abnormalities. However, the authors acknowledged limitations related to the small sample size and homogeneous patient population.

The potential of AI to address healthcare disparities has been highlighted by several researchers. Kahn and Langlotz (2022) argued that AI could democratize access to specialized radiological expertise, particularly in resource-limited settings where specialist availability is constrained. This aspect is particularly relevant to the Philippine context, where geographical and economic barriers often limit access to specialized healthcare services.

2.3 YOLO ARCHITECTURE AND APPLICATIONS IN MEDICAL IMAGING

The You Only Look Once (YOLO) algorithm, first introduced by Redmon et al. in 2016, represents a significant advancement in object detection and classification. Unlike conventional two-stage detection frameworks, YOLO employs a single neural network to predict bounding boxes and class probabilities directly from full images in a single evaluation, resulting in faster processing times while maintaining competitive accuracy (Redmon et al., 2016).

YOLO's architecture has evolved through multiple iterations, with each version introducing improvements in speed, accuracy, and feature detection capabilities. The most recent iteration, YOLOv12, builds upon previous versions with enhanced feature extraction networks, more sophisticated anchor-free detection heads, and optimized training strategies (Jocher et al., 2024). These advancements make YOLOv12 particularly suitable for medical imaging applications where rapid, accurate detection of abnormalities is crucial.

In medical imaging, YOLO-based approaches have been applied to various diagnostic tasks. Aly et al. (2021) implemented a YOLO-based system for detecting and classifying breast masses in digital mammograms, achieving a detection accuracy of 89.4% and classification accuracy of 94.2% for benign masses and 84.6% for malignant masses. Similarly, Chen et al. (2023) developed a YOLO-based system for classifying calcifications on spot magnification mammograms, reporting an area under the receiver operating characteristic curve (AUC) of 0.888 and an accuracy of 84.6%.

For lung cancer detection specifically, several studies have explored the application of YOLO architectures. Kumar et al. (2023) employed a YOLOv7-based architecture for detecting pulmonary nodules in chest CT scans, achieving a sensitivity of 91.2% and a specificity of 89.5%. The authors noted that the YOLO-based approach was particularly effective in detecting small nodules (<10mm) that are often challenging to identify using conventional methods.

The implementation of YOLO architectures in resource-constrained settings has also been explored. Zhang et al. (2022) developed a lightweight YOLO variant for tuberculosis detection from chest X-rays, optimized for deployment on mobile devices and low-resource computational environments. This approach achieved an accuracy of 87.3% while requiring significantly less computational resources than conventional deep learning models, highlighting the potential of YOLO-based systems for applications in settings with limited technological infrastructure.

Despite these promising results, challenges remain in the application of YOLO to medical imaging tasks. Issues related to model generalizability across different imaging protocols and patient populations, the need for large annotated datasets for training, and the integration of detection results into clinical decision-making processes have been identified as areas requiring further research (Wang et al., 2023).

2.4 WEB-BASED APPLICATIONS FOR MEDICAL DIAGNOSTICS

The development of web-based applications for medical diagnostics has gained significant traction in recent years, offering potential solutions to address limitations in healthcare access and resource availability. These platforms leverage cloud computing resources to deliver sophisticated diagnostic capabilities through standard web browsers, eliminating the need for specialized hardware or software installations at the point of care (Sharma et al., 2022).

Web-based diagnostic applications offer several advantages in healthcare settings. They provide platform independence, enabling access across various devices and operating systems, which is particularly valuable in heterogeneous healthcare environments (Rodriguez-Ruiz et al., 2021). Additionally, centralized deployment facilitates maintenance, updates, and quality control, ensuring that all users have access to the most current version of the diagnostic tools (Garcia-Zapirain et al., 2022).

In the context of medical imaging, web-based applications have been developed for various diagnostic tasks. Shen et al. (2021) implemented a web-based deep learning system for pneumonia detection from chest X-rays, reporting an accuracy of 92.8% while providing radiologists with a user-friendly interface for image upload and result interpretation. Similarly, Khare et al. (2023) developed a web-based application using YOLOv8 for detecting road hazards, demonstrating the versatility of this approach across different domains.

For cancer diagnostics specifically, Prianes et al. (2024) created "iRESPOND," a web-based CNN model for classifying emergency images, highlighting the potential of such systems to improve disaster response and mitigation. While not specifically focused on cancer detection, their work demonstrates the feasibility of deploying complex deep learning models through web interfaces for time-sensitive applications.

Web-based diagnostic applications are particularly relevant in the Philippine context, where healthcare facilities often have varying levels of technological infrastructure and resources. Ignacio (2021) noted that traditional incident reporting in the Philippines typically requires physical presence at healthcare facilities or telephone calls, highlighting the potential value of web-based solutions that could facilitate remote diagnostic support and consultation.

However, implementing web-based diagnostic applications in the Philippine setting presents several challenges. Limited internet connectivity in rural and remote areas may affect access to these tools (Dabu, 2024). Additionally, concerns related to data privacy and security must be addressed, particularly when handling sensitive medical information (Concepcion et al., 2019).

Despite these challenges, the potential benefits of web-based diagnostic applications for lung cancer detection in the Philippines are substantial. By providing access to AI-assisted diagnostic capabilities through standard web browsers, these applications could help address the shortage of specialized radiological expertise, reduce diagnostic delays, and improve early detection rates, ultimately contributing to better lung cancer outcomes across the country.

2.5 THEORETICAL FRAMEWORK

This research is guided by several theoretical frameworks that provide the foundation for developing an AI-based lung cancer detection system:

Technology Acceptance Model (TAM)

The Technology Acceptance Model, developed by Davis (1989), provides a framework for understanding how users come to accept and use new technologies. According to TAM, two key factors influence technology adoption: perceived usefulness and perceived ease of use. In the context of this research, the development of the web-based application will consider these factors to ensure acceptance by healthcare professionals in the Philippine setting. The user interface will be designed with simplicity and clinical relevance in mind, prioritizing features that enhance workflow efficiency and diagnostic confidence.

Diffusion of Innovations Theory

Rogers' (2003) Diffusion of Innovations Theory explains how, why, and at what rate new technologies spread through cultures. This theory identifies five categories of adopters: innovators, early adopters, early majority, late majority, and laggards. Understanding these adoption patterns will inform the implementation strategy for the developed AI system, particularly in addressing the needs and concerns of different stakeholder groups within the Philippine healthcare system.

Human-Computer Interaction (HCI) Framework

The field of Human-Computer Interaction provides theoretical foundations for designing effective interfaces between humans and computational systems. Following principles of user-centered design, this research will incorporate feedback from potential end-users throughout the development process to ensure that the final application meets the specific needs and preferences of healthcare professionals in the Philippine context.

Clinical Decision Support Systems (CDSS) Framework

The CDSS framework, as described by Berner (2007), provides a structure for understanding how computational systems can support clinical decision-making. This framework emphasizes the importance of integrating AI systems as supportive tools that enhance, rather than replace, clinical judgment. In the context of lung cancer detection, the developed system will provide probabilistic assessments and visual cues to guide healthcare professionals, while explicitly acknowledging the primacy of clinical expertise in final diagnostic decisions.

These theoretical frameworks collectively inform the development, implementation, and evaluation of the proposed AI-based lung cancer detection system, ensuring that technological innovations are effectively translated into meaningful improvements in clinical practice and patient outcomes.

CHAPTER III

RESEARCH METHODOLOGY

3.1 Software Development Methodology

This research adopts the Agile software development methodology, specifically implementing the Scrum framework, to develop the YOLOv12-powered lung cancer detection platform. Agile methodology is selected for its iterative approach, allowing continuous refinement of both the deep learning model and web application components based on stakeholder feedback. The development process is structured in several interconnected phases that support the cyclical nature of adaptive system development.

The process begins with a comprehensive requirements gathering phase involving analysis of the Philippine healthcare context regarding lung cancer diagnosis. This includes direct consultations with radiologists, oncologists, and general practitioners to identify specific needs and constraints faced in current diagnostic workflows. These insights directly inform the subsequent planning phase, where product backlog items are developed and prioritized based on their importance to the early lung cancer detection capabilities. Special focus is given to the integration of YOLOv12 architecture into the medical imaging pipeline, ensuring alignment with the project objectives outlined in Chapter 1.

Following established planning, the implementation proceeds through two-week sprint cycles focused on incremental development of system components. Each sprint delivers functional components beginning with the data preprocessing pipeline for CT scan images, followed by YOLOv12 model adaptation for lung cancer detection. Subsequent sprints address web application frontend and backend development, integration of the model with the application interface, and implementation of security and privacy features. This incremental approach ensures regular delivery of testable functionality while maintaining flexibility to incorporate stakeholder feedback throughout development.

The testing and validation phase operates continuously throughout the development cycle rather than as a terminal activity. This includes unit testing for individual components, integration testing for system interoperability, model validation using performance metrics (sensitivity, specificity, accuracy), and user acceptance testing with healthcare professionals. The continuous testing approach aligns with the Agile philosophy and ensures early detection of potential issues before they become embedded in the system architecture.

The final phase involves deployment and evaluation through pilot implementation in selected healthcare facilities in the Philippines. This phase includes establishing monitoring systems for performance evaluation and feedback collection. The data gathered during this phase serves two purposes: validating the system's effectiveness in real-world settings and providing insights for future refinements. This methodology directly aligns with the project's objective of creating a responsive, user-centered system that effectively addresses the challenges of lung cancer detection in the Philippine healthcare context as outlined in Chapter 1.

3.2 Conceptual Framework

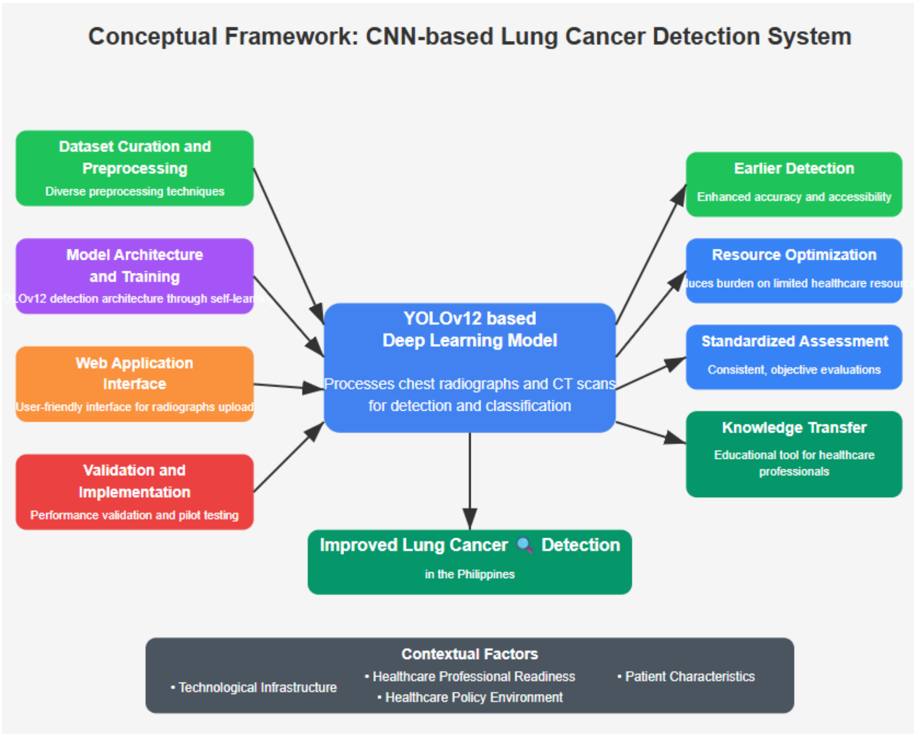

Figure 1: Conceptual Framework

The conceptual framework for this research integrates artificial intelligence, medical imaging, and web application development into a cohesive structure that guides the system design and implementation. This framework establishes the theoretical foundation for the technical components and their interactions, ensuring alignment with both clinical requirements and technological capabilities.

At the input layer of the framework, several data streams converge to support the system's function. Medical imaging data forms the primary input, requiring collection and preprocessing of chest CT scans for both training and inference processes. This data stream is complemented by clinical parameters including patient demographic data and clinical history that may influence cancer risk assessment. User interaction represents the third input stream, providing the interface through which healthcare professionals engage with the system and contribute their expertise to the diagnostic process.

The processing layer constitutes the system's core intelligence, anchored by the YOLOv12 detection model specially adapted for medical imaging analysis. This model incorporates several capabilities including lung region segmentation, nodule and mass detection, feature extraction from regions of interest, and classification into four distinct categories: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal tissue. Supporting this AI engine is a robust data management system that ensures secure storage and retrieval of medical images and associated metadata. The processing layer also incorporates authentication and authorization mechanisms based on role-based access control to ensure appropriate system usage and data protection.

The output layer translates complex analysis into actionable clinical insights through multiple channels. A visualization interface presents detection results with annotated images, highlighting areas of concern and supporting radiological interpretation. The diagnostic support functionality provides detection confidence scores and contextualizes findings within relevant medical parameters. Additionally, a collaboration platform establishes communication channels between patients and physicians, facilitating discussion of results and treatment planning.

This framework directly addresses the specific challenges identified in Section 1.3 of Chapter 1, particularly the limited access to radiological expertise in the Philippines and the need for improved early detection capabilities. It also incorporates the theoretical perspectives discussed in Section 2.5 of Chapter 2, including Technology Acceptance Model, Diffusion of Innovations Theory, and Clinical Decision Support frameworks, creating a theoretically-grounded approach to technological intervention in healthcare.

3.3 Algorithm

The algorithmic foundation of the system centers on the YOLOv12 architecture, specifically adapted for lung cancer detection in CT scan images. This algorithm incorporates several key components working in concert to achieve the accuracy and efficiency objectives established in Section 1.5 of Chapter 1. As a computer science implementation, the algorithm requires sophisticated mathematical formulations, preprocessing techniques, and optimization strategies to effectively analyze complex medical imagery.

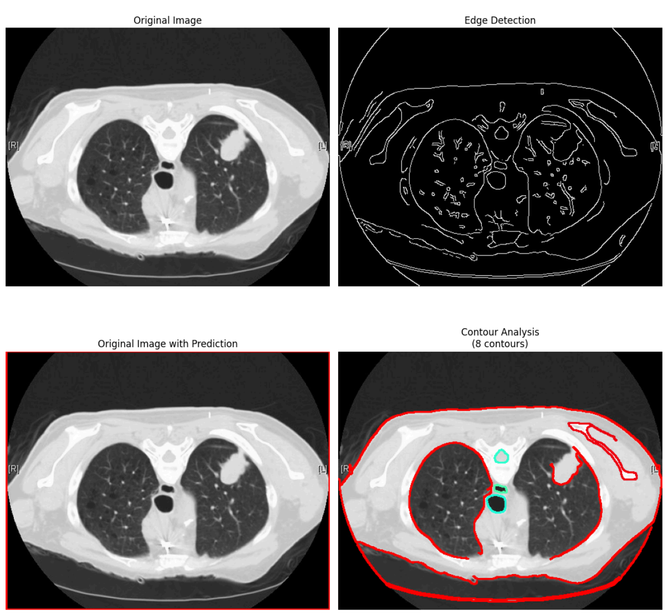

Figure 2 : Adenocarcinoma

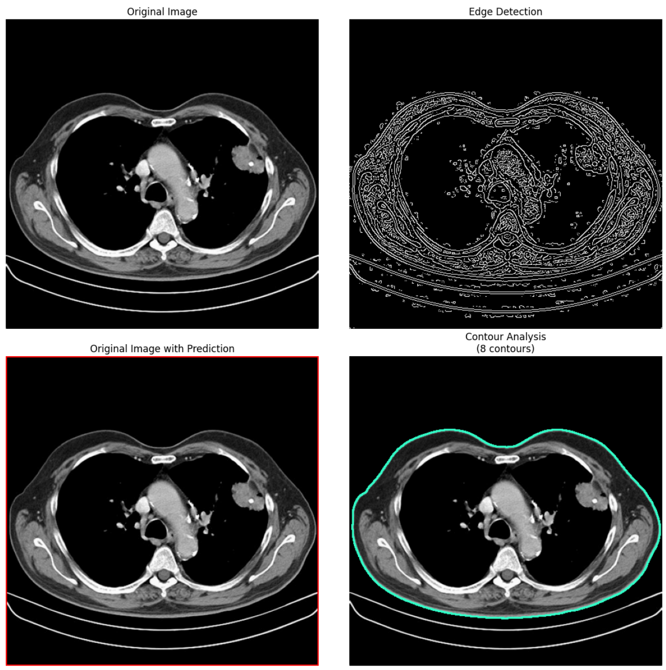

Figure 3 : Squamous Cell Carcinoma

3.3.1 Formulas and Mathematical Representations

Pre-processing Techniques for the Lung Cancer Detection Project

The project employs several sophisticated pre-processing steps to prepare chest CT scan images for analysis by the YOLOv12n model, ensuring optimal detection performance. YOLOv12n, as an extension of the You Only Look Once architecture, functions by dividing input images into a grid and predicting bounding boxes and class probabilities in a single forward pass of the neural network. This approach enables real-time processing while maintaining high accuracy, making it ideal for medical imaging applications where both speed and precision are essential.

Image Standardization

The preprocessing involves resizing all images to a uniform dimension of 640×640 pixels, which is the standard input size for YOLO models. This standardization is critical for maintaining consistent spatial feature extraction across different CT scan sources and resolutions. The resizing operation implements bicubic interpolation to preserve fine details that might be indicative of small nodules or early-stage cancerous tissue.

Color Space Conversion

All images are converted from BGR to RGB color space for consistent processing. This is an important step since many image processing libraries use different default color spaces. For medical imaging specifically, this conversion ensures that the subtle intensity gradations present in lung tissue are appropriately represented for the convolutional layers of the YOLOv12n model.

Data Augmentation

To address potential limitations in dataset size and enhance the model's generalization capabilities, data augmentation techniques are employed to generate additional training examples. These techniques include:

- Geometric transformations (rotation, scaling, flipping)
- Intensity transformations (brightness, contrast adjustments)

These augmentations are particularly valuable in the medical imaging context, where acquiring and annotating large datasets can be challenging. The transformations create variations that help the model become robust to differences in patient positioning, imaging equipment, and technical parameters used during CT acquisition.

The implementation also includes randomized resizing during training to enhance model robustness across different image scales. This technique helps the model recognize lung abnormalities regardless of their apparent size in the image, which can vary based on patient anatomy and stage of disease progression.

Dataset Organization

The dataset is organized following YOLO convention with separate directories for images and labels. Training and validation sets are created using an 80:20 split ratio, and a YAML configuration file is generated specifying dataset paths, class names, and training parameters. This structured approach ensures that the model has access to a representative distribution of normal and abnormal cases during training, while maintaining a separate validation set for unbiased performance assessment.

Advanced Preprocessing During Training

The lung cancer detection project implements a two-phase training strategy with specific preprocessing parameters:

The training process follows a systematic two-phase approach to optimize model performance. In the first phase (Initial Learning), the model is trained for 30 epochs with a higher initial learning rate (0.01), facilitating rapid feature learning and coarse parameter adjustment. This phase employs a patience value of 10 for early stopping to prevent overfitting. During this phase, the model develops its fundamental understanding of lung anatomy and general abnormality patterns.

In the second phase (Fine-tuning), training continues with a reduced learning rate (0.001) in 10-epoch increments until either the target accuracy of 80% is reached or the maximum number of epochs (100) is reached. This phase uses a patience value of 5 for early stopping, allowing for more precise parameter refinement. This fine-tuning stage is critical for distinguishing between subtle variations in cancerous tissue types and reducing false positives that might occur with benign abnormalities.

Image File Processing

The preprocessing procedure for handling uploaded CT scan images includes format validation and compatibility checking, metadata extraction from DICOM headers (if applicable), image normalization and standardization, and quality assessment for appropriate resolution and contrast. These steps ensure that regardless of the source or format of submitted images, they are transformed into a standardized representation that the model can effectively analyze.

The comprehensive preprocessing pipeline established for this project enables the YOLOv12n model to achieve optimal performance in detecting lung cancer from CT scans. Each step in the pipeline serves a specific purpose in enhancing the quality and consistency of input data, addressing challenges unique to medical imaging such as variable acquisition parameters and limited dataset availability. Through careful standardization, augmentation, and multi-phase training, the system maximizes detection accuracy while maintaining the computational efficiency necessary for practical deployment in Philippine healthcare settings with limited resources. This approach not only improves the technical performance of the model but also enhances its clinical utility by producing reliable results that can support early detection and intervention for lung cancer patients.

3.4 Operational Framework

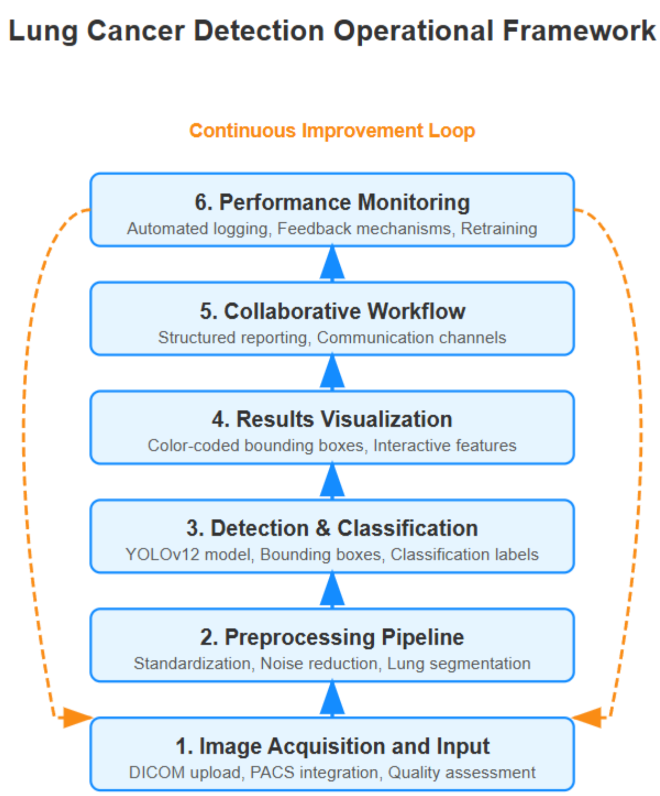

Figure 4: Operational Framework

The operational framework defines how the system functions in real-world clinical environments, translating theoretical algorithms into practical workflows. This framework encompasses both technical operations and human-system interactions, ensuring seamless integration into existing healthcare processes in the Philippines.

The system's operation begins with image acquisition and input, where CT scan images are securely uploaded to the platform through DICOM-compliant interfaces. These interfaces support both manual upload through the web application and potential integration with hospital PACS (Picture Archiving and Communication System) where available. Upon receipt, images undergo automated quality assessment to verify suitability for analysis, checking for artifacts, appropriate resolution, and complete anatomical coverage.

After quality verification, the preprocessing pipeline applies standardization protocols to normalize image characteristics and enhance features relevant to lung cancer detection. This includes window-level adjustments optimized for lung tissue visualization, noise reduction filtering, and anatomical segmentation to isolate the lung regions. These preprocessing steps ensure consistent input quality for the detection algorithm regardless of the source imaging equipment.

The detection and classification phase represents the core analytical function, where the adapted YOLOv12 model processes the prepared images to identify potential abnormalities. The system analyzes each image in approximately 3-5 seconds, significantly faster than traditional manual review, addressing the efficiency requirements established in Chapter 1. During this phase, the model generates bounding boxes around regions of interest, assigns classification labels (adenocarcinoma, large cell carcinoma, squamous cell carcinoma, or normal tissue), and calculates confidence scores for each detection.

Results visualization and interpretation constitute the critical interface with healthcare professionals. The system presents findings through an intuitive visualization interface that displays the original image alongside annotated results. Color-coded bounding boxes indicate different classification categories, with transparency levels reflecting confidence scores. Interactive features allow radiologists to adjust detection thresholds, zoom into regions of interest, and compare findings across multiple time points when longitudinal data is available.

The collaborative workflow support extends the system's functionality beyond detection to facilitate clinical decision-making. This includes structured reporting templates that incorporate detection results into standardized formats compatible with electronic health records. Communication channels enable secure discussion between radiologists, oncologists, and primary care physicians regarding findings and treatment recommendations. Patient-facing summaries present relevant information in accessible language, supporting informed consent and treatment adherence.

Performance monitoring and improvement operate continuously during system deployment. Automated logging captures performance metrics, usage patterns, and error events to identify opportunities for enhancement. Feedback mechanisms allow healthcare professionals to flag false positives or negatives, providing valuable data for model refinement. Periodic retraining incorporates this feedback along with newly validated cases to improve detection accuracy over time, creating a learning healthcare system that continuously evolves.

This operational framework establishes a comprehensive approach to integrating AI-assisted detection into clinical practice, addressing both technical requirements and human factors. By defining clear workflows and interaction patterns, the framework supports effective implementation in the varied healthcare environments found across the Philippines, from urban centers to remote facilities with limited specialist access.

3.5 Use Case / Flowchart / State Diagram

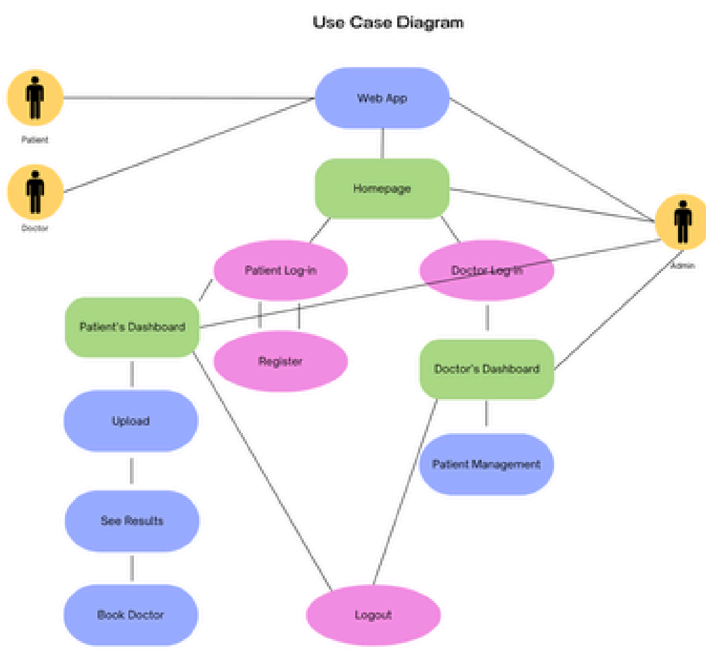

Figure 5: Use Case

The system's functional dynamics are best understood through examination of its primary use cases, represented through detailed workflow analyses and state transitions. These representations capture both typical and edge-case interactions, providing a comprehensive view of system behavior across various clinical scenarios and user roles.

The primary clinical use case begins with a physician uploading a patient's chest CT scan for analysis. Upon submission, the system enters the preprocessing state, applying the normalization and enhancement techniques described in the algorithmic section. The system then transitions to the analysis state, where the YOLOv12 model performs detection and classification tasks. Results are then presented to the physician, who enters the review state where findings can be examined, annotations adjusted if necessary, and clinical context added to the automatically generated report. If the physician accepts the findings, the system transitions to the documentation state, where results are finalized and stored securely with appropriate patient linkage. Alternatively, if results are questioned, the system can enter a secondary review state where additional physician input is solicited or manual analysis is performed.

The patient engagement use case demonstrates how the system facilitates informed participation in the diagnostic process. Following physician review and approval, patients can access a simplified view of their results through a secure portal. This initiates the explanation state, where findings are presented with appropriate context and educational resources. Patients can then enter the question state, submitting queries to their healthcare provider about the results. These questions trigger the physician notification state, facilitating timely response and clarification. This bidirectional communication continues until all patient concerns are addressed, at which point the system enters the follow-up planning state to coordinate next steps in the care pathway.

The quality improvement use case illustrates how the system evolves over time. During routine operation, the system continuously collects performance metrics, comparing automated detections with physician assessments to identify discrepancies. When specific accuracy thresholds are not met, the system enters the model evaluation state, where patterns of error are analyzed. This leads to the model refinement state, where adjustments are made to the detection parameters or additional training is performed using newly validated cases. Following refinement, the system enters the validation state to verify improvements before returning to standard operation with enhanced capabilities.

Administrative use cases address system management functions, including user onboarding, permission adjustment, and audit processes. When new healthcare providers join participating institutions, the system enters the user registration state, collecting credentials and verifying qualifications. This leads to the role assignment state, where appropriate access levels are configured based on clinical responsibilities. Periodic system checkpoints trigger the audit state, where usage patterns and security logs are reviewed to ensure compliance with data protection regulations and institutional policies.

These interconnected use cases and state transitions demonstrate how the system functions as an integrated socio-technical ecosystem rather than merely a detection algorithm. By mapping the complex interactions between technical components, healthcare professionals, and patients, this framework provides a blueprint for implementation that addresses both clinical and organizational requirements within the Philippine healthcare context.

3.6 Respondents of the Study

The development and evaluation of the system involve participation from two primary stakeholder groups within the Philippine healthcare ecosystem: medical doctors and patients. These participants provide essential input throughout the research process, from initial requirements gathering to final performance assessment. The selection of respondents reflects careful consideration of both clinical expertise and patient perspectives, ensuring comprehensive evaluation of the system's efficacy and usability in real-world settings.

The medical doctor respondent group includes a diverse mix of practitioners engaged in the diagnosis and management of lung-related conditions. Physicians were recruited from various healthcare institutions across the Philippines, representing different practice environments including government hospitals, private facilities, and regional medical centers. This diversity supports evaluation across a broad range of healthcare settings with varying resource availability and patient populations. Participating doctors are involved in multiple phases of the research, including requirements specification, image annotation, validation of detection results, and assessment of system usability within clinical workflows.

Participating physicians evaluate the clinical relevance and utility of the system's outputs, with particular attention to the accuracy of detection results and the system's capacity to support informed decision-making in diagnostic and treatment planning. Their feedback also addresses the system's role in enhancing interdisciplinary communication and its potential to improve patient outcomes. This inclusive approach ensures that the system's development reflects a wide range of clinical perspectives and practice contexts.

General medical practitioners are also engaged in the evaluation process to assess how the system performs in primary care and general practice settings. Their insights are particularly valuable in understanding how non-specialist users interact with the platform, especially in settings where access to specialist services may be limited. These participants focus on aspects such as usability, clarity of results, and the system's role in supporting referral and initial diagnostic decisions.

The patient respondent group consists of individuals with recent experience undergoing lung-related CT scans. Participants are recruited through outpatient departments of participating healthcare facilities, with all necessary consent and ethical protocols in place. The group is deliberately varied in terms of age, educational background, socioeconomic status, and healthcare experiences to reflect the broader population served by the system. Patients provide input on result understandability, communication with providers via the platform, and the system's overall impact on their healthcare experience. Feedback is gathered through usability testing, semi-structured interviews, and standardized questionnaires.

All participation complies with strict ethical standards, with institutional review board approvals secured prior to recruitment. Informed consent procedures clarify the nature of participation, data handling practices, and any associated risks or benefits. Respondent anonymity is preserved through data anonymization, with demographic information collected only at the group level for analysis. This inclusive and ethically grounded respondent strategy ensures the system is evaluated from multiple perspectives, directly addressing the communication and coordination challenges identified in Chapter 1 and supporting the collaborative care objectives described in Chapter 2.

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