Policy Recommendations for the Strategic Implementation of Public Health Policy to Mitigate PM 2.5 Pollution through Artificial Intelligence: A Case Study on AI-Driven Lung Cancer Diagnosis

Techatach Khlaisokk[*]
Janita Boriboon[**]
Jutamas Moolkamsri[***]
Pongphon Chamat[****]
Rangsiman Songklod[*****]
Thanakon Sangkhaloke[******]
Saowalak Klamsakun[*******]

Abstract

This study investigates the application of big data and artificial intelligence (AI) to support the formulation of evidence-based public health policy recommendations, with an emphasis on mitigating lung cancer risks linked to PM2.5 air pollution. Using 15,000 social media images, an AI model was trained via a convolutional neural network using Google's Teachable Machine. The model achieved high performance with an accuracy of 100 percent and test accuracy of 99.5 percent, and low prediction error with loss of 0.01 percent and test loss of 1.67 percent. Key factors influencing policy implementation include policy resources, organizational capacity, and teamwork. The resulting AI model was deployed as a web application using the Python Flask framework, enabling real-time lung cancer

[*] Department of Social Sciences, Faculty of Liberal Arts and Management Science, Kasetsart University, Campus Sakon Nakhon Email: techatach.k@ku.th
[**] Department of Social Sciences, Faculty of Liberal Arts and Management Science, Kasetsart University, Campus Sakon Nakhon
[***] Department of Social Sciences, Faculty of Liberal Arts and Management Science, Kasetsart University, Campus Sakon Nakhon
[****] Department of Social Sciences, Faculty of Liberal Arts and Management Science, Kasetsart University, Campus Sakon Nakhon
[*****] Department of Social Sciences, Faculty of Liberal Arts and Management Science, Kasetsart University, Campus Sakon Nakhon
[******] Department of Social Sciences, Faculty of Liberal Arts and Management Science, Kasetsart University, Campus Sakon Nakhon
[*******] Department of Social Sciences, Faculty of Liberal Arts and Management Science, Kasetsart University, Campus Sakon Nakhon

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diagnosis and rapid treatment responses. The study's contributions include the design of a policy framework for the National Health Environment Data Center (NHEDC), the development of an AI-driven platform for real-time risk prediction, and the integration of proactive public health surveillance policy in high-risk PM2.5 areas.

Keywords: Public Health Policy Development, AI-Driven Governance, Big Data-Based Policymaking

Introduction

Thailand's 20-year national strategic plan for public health (2017–2036) provides a long-term roadmap for systemic health reform with the overarching goals of promoting better population health, ensuring healthcare worker well-being, and achieving a sustainable health system. This strategic framework is explicitly aligned with the Thailand 4.0 policy, the 12th national economic and social development plan, and the United Nations Sustainable Development Goals (SDGs). The strategy addresses critical challenges such as population aging, the rising burden of non-communicable diseases (NCDs), environmental pollution, and the rapid evolution of digital technology (Strategy and Planning Division, 2018). From a top-down policy perspective, the Ministry of Public Health (MOPH) drives national strategic direction through four key pillars: promotion, prevention and protection excellence, service excellence, people excellence, and governance excellence. Within this structure, particular emphasis is placed on governance and the development of health informatics and innovation systems. These form a foundation for incorporating artificial intelligence (AI) into clinical decision-making, especially in diagnosing conditions linked to air pollution, such as lung cancer. Environmental strategies like the "green & clean hospitals" initiative also support AI-driven approaches by integrating health and environmental data to enhance system-level decision-making (Strategy and Planning Division, 2018). Simultaneously, a bottom-up implementation model empowers local engagement through structures such as district health boards (DHBs) and primary care clusters (PCCs). These community-level platforms enable context-specific deployment of AI, including tools for analyzing lung cancer trends in high-risk PM2.5 areas, integrating radiographic images with local air quality datasets, and training local health workers in AI-assisted screening techniques. Such grassroots engagement reflects a decentralized innovation ecosystem that aligns with global recommendations for digital health integration in low and middle income countries (Hsu, Verma, Mauri, Nourbakhsh, & Bozzon, 2022; World Health Organization, 2021b).

Integrating AI into public health policy to mitigate PM2.5 pollution and associated lung cancer risk thus requires a synergistic approach combining centralized policy direction, resource allocation, and infrastructure investment (top-down) with localized implementation, data generation, and capacity building (bottom-up). This dual-level model not only reflects the core principles of the 20-year strategy but also supports global best practices in precision public health and environmental epidemiology (Adefemi, Ukpoju, Adekoya, Abatan, & Adegbite, 2023; Topol, 2019). The advancement of public health policy aimed at mitigating and reducing the impacts of PM 2.5 necessitates the utilization of effective technological tools, particularly artificial intelligence, which is capable of processing big data to support efficient policy planning, analysis, and monitoring processes (Meskó, Hetényi, & Győrffy, 2018; Reddy, Fox, & Purohit, 2019). AI technology has garnered significant attention in the medical field, especially in accurate disease diagnosis. One of the most critical diseases in which AI plays a vital supporting role is lung cancer, a leading cause of death globally (Ardila et al., 2019; Lynch et al., 2018). Consequently, healthcare policy must integrate AI technology into public health service systems to enable timely and accurate diagnosis and treatment.

Thailand is currently facing a severe air pollution crisis, particularly regarding fine particulate matter (PM2.5), which has had significant adverse health effects across multiple regions, especially among vulnerable populations such as children, the elderly, and individuals with chronic respiratory diseases (Rujirawat, 2024). Although government agencies have implemented surveillance and public warning measures regarding particulate levels, there remains a lack of proactive policy frameworks and diagnostic systems capable of assessing health impacts at the individual level with clarity. In contrast, AI technology, particularly the application of deep learning to chest radiographic imaging, has demonstrated the ability to enhance the accuracy and speed of lung cancer diagnoses associated with long-term exposure to airborne particulates (Javed et al., 2024; Setio et al., 2017). Therefore, it is imperative that the state adopts big data and AI technology as strategic tools to support health policy proposals aimed at the effective prevention and treatment of diseases linked to PM2.5 exposure.

According to statistics on lung cancer patients in Thailand, lung cancer ranks as the second most common type after liver and bile duct cancer, with 17,222 new cases reported, averaging 48 new patients per day and 40 deaths per day. The primary causes include prolonged exposure to pollution and PM2.5 particles, smoking or e-cigarette use, secondhand smoke, occupational exposure to carcinogens, and genetic predisposition (Department of Medical Services, 2024). This public health issue has prompted the government to allocate policy resources, enhance organizational capacity, and promote teamwork to support the prevention, control, and treatment of cancer (Chantarasorn, 2005). Traditionally, cancer diagnosis relies on X-ray imaging for interpretation; however, artificial intelligence technology is now being used to assist in interpreting patients' X-ray films to improve the speed and accuracy of diagnosis (Bangkok Cancer Hospital, 2018; Ruangsapdech, 2022). Consequently, the application of technology and innovation in both public and private sectors aims to advance the country's development under the Thailand 4.0 initiative. This strategic direction seeks to drive public policy forward and foster national prosperity, security, and sustainability (Kanluem, Jantharote, Worasiriwatthananon, Janthachot, & Bodeerat, 2023).

Currently, Thailand has adopted policies to expand healthcare services at both the primary level, which focuses on basic treatment and general health promotion, and the tertiary level, which provides treatment for complex diseases using advanced medical technology. However, cancer care services remain fragmented, particularly in the application of artificial intelligence technology for effective diagnosis. As a result, lung cancer screening continues to face limitations, especially in remote areas where there is a shortage of radiologists, leading to delayed diagnoses and high medical costs. Integrating AI to assist in the analysis of medical imaging offers a promising approach to enhance diagnostic speed and accuracy, alleviate the workload of healthcare personnel, and reduce long-term costs for patients. Moreover, it represents a policy alternative with strong potential to improve the efficiency and sustainability of the healthcare system in the long term (Munpolsri, Sarakarn, & Munpolsri, 2021; Srikam & Joralee, 2025).

Within the context of proactive policy and the challenges faced by medical personnel in patient care during the digital era, this study identifies three critical factors that contribute to the successful adoption of innovations such as artificial intelligence in the diagnosis of lung cancer. The first factor is policy-related resources, which include access to appropriate technology, sufficient funding, and supportive infrastructure for the effective utilization of AI, as well as the presence of personnel with technological expertise (Jain, Bhardwaj, Saxena, & Elumalai, 2020). The second factor is organizational capacity, referring to an organization's ability to manage, transition, and adapt to digital technology. Organizations with an innovation-oriented culture and openness to adopting new technology are more likely to achieve success (Koschmann, Myers, Feltovich, & Barrows, 1994; Martínez-Cerdá, Torrent-Sellens, Martínez-Cerdá, Torrent-Sellens, & González-González, 2018). The final factor is teamwork. The integration of expertise from various fields such as medicine, software engineering, and data science plays a crucial role in enhancing the capacity of AI in disease diagnosis. Effective collaboration within teams is a key variable driving the practical application of such technology (Barak, Maymon, Harel, & Education, 1999; Soboleva & Karavaev, 2020). Therefore, the synergy of appropriate resources, strong organizational capacity, and effective teamwork supported by both public and private sectors serves as a fundamental mechanism in advancing AI policy implementation for accurate and sustainable cancer diagnosis (Pawar, Kharat, Pardeshi, & Pathak, 2020; Rahane, Dalvi, Magar, Kalane, & Jondhale, 2018).

However, despite existing studies highlighting the benefits of driving public health policy through artificial intelligence technology, certain research gaps remain. First, human resource development in the AI era, particularly in relation to the development of AI technology for cancer diagnosis, has overlooked the importance of upskilling medical personnel who are required to utilize emerging technology. There is a lack of research on how physicians, nurses, and public health officers should be trained to acquire the necessary skills to effectively adopt AI in diagnostic processes and adapt to long-term changes in their work practices (Vrontis et al., 2023). Second, the integration of AI technology with public policy implementation in health systems has not yet been examined in depth, particularly in terms of leveraging AI to modernize and promote equity in healthcare systems. This research gap must be addressed through studies that link AI technology with effective public health policymaking, in order to ensure that policy development becomes more explicit, actionable, and applicable within governmental organizations (Ghanem, Moraleja, Gravesande, & Rooney, 2025; Ramezani et al., 2023).

This study is expected to yield findings on policy system design for establishing the National Health Environment Data Center (NHEDC), the development of public policy, and the advancement of an artificial intelligence platform for real-time prediction of lung cancer risks. Additionally, it aims to formulate an integrated policy for proactive health surveillance in areas at risk from PM2.5 dust pollution. Therefore, this research focuses on examining the processes of applying big data in the development of evidence-based public health policy, along with the use of artificial intelligence to support the practical implementation of such policy, which currently represents a significant gap in public policy. This research will lead to policy recommendations for integrating AI technology into health surveillance efforts aimed at mitigating lung cancer risks associated with PM2.5 exposure. These findings will serve as a foundation for proactive measures and support decision-making by policymakers at both local and national levels, in alignment with the concept of “smart health policy,” which emphasizes evidence-based decision-making (Evidence-Based Policy) alongside good governance in technology management (Tantivess, Yothasamut, & Saengsri, 2019; World Health Organization, 2021a), with the ultimate goal of promoting health equity and sustainability for the Thai population in the future.

Research Objectives

1. To examine the process of applying big data in the development of effective and evidence-based public health policy.

2. To develop and apply artificial intelligence to support the practical implementation of public health policy.
3. To formulate policy recommendations for integrating AI technology in monitoring public health risks related to lung cancer caused by PM2.5.

Scope of Research

This policy proposal aims to advance public health policy by leveraging artificial intelligence technology to mitigate the PM2.5 particulate matter issue. The case study focuses on the application of AI in diagnosing lung cancer, using artificial intelligence to drive public policy. The study will collect data from the social data platform kaggle.com, which is an open-access repository where AI developers share code and utilize big data to train and test machine and deep learning models. The dataset used in this study consists of 15,000 photomicrographic images of lung tissues, categorized into three groups: 5,000 images of lung adenocarcinomas (lung_aca), 5,000 images of benign lung tissues (lung_bnt), and 5,000 images of lung squamous cell carcinomas (lung_scc). These images will be used to train the AI model using convolutional neural network (CNN) architecture.

Research Limitations

The use of research data to drive public health policy through artificial intelligence technology, utilizing social media databases that gather images of lung cancer patients from around the world, presents some limitations. Most of the data comprises images of international patients and does not directly include lung cancer images from Thai patients. Therefore, this model serves as a case study and cannot yet be applied directly to Thai patients.

However, if direct data on lung cancer patients from Thailand were used to train the AI, and the model achieved high accuracy, it could then be applied for diagnosing lung cancer in Thai patients. Nevertheless, this would require the model to be used in conjunction with expert radiologists interpreting photomicrographic images of lung cancer patients in several cases, until it is confirmed that the model has negligible or no errors. Only then could it be used independently.

Although the AI model is not yet ready for practical use, this research represents an interdisciplinary paradigm shift among public administration, AI technology, and digital technology. It offers a policy proposal for driving public health policy using artificial intelligence and enhances public administration research by developing tangible innovations. Furthermore, it supports the transformation of public sector organizations into digital entities in the era of technological disruption.

Expected Benefits

First, support for the development of policy proposals aimed at advancing the public health system through the integration of artificial intelligence technology is essential to enhance the efficiency and accuracy of lung cancer diagnosis, particularly in relation to PM2.5 exposure. The application of AI in the analysis of photomicrographic images enables medical professionals to detect lung cancer at earlier stages with greater precision, facilitating faster diagnoses and more timely treatments. This, in turn, contributes to reduced mortality rates and fosters proactive health surveillance strategies to mitigate the risks posed by air pollution.

Second, establishing a solid academic foundation for policy proposals is crucial for advancing public health management at the organizational level through AI technology. The findings of this study will provide valuable insights to medical professionals and healthcare administrators on how AI can be effectively integrated into service delivery systems. Such integration is expected to support continuous improvements within healthcare organizations and promote evidence-based decision-making, ultimately enhancing the quality of healthcare services provided to the public.

Third, policy recommendations aimed at reducing the workload of healthcare personnel using AI in managing health risks associated with PM2.5 are essential for improving efficiency in healthcare settings. AI can perform diagnostic tasks with a level of precision comparable to that of expert radiologists, thereby alleviating the burden on medical staff, especially in regions experiencing shortages of healthcare professionals. This can contribute to more equitable access to quality healthcare services, particularly in underserved or rural areas.

Finally, this research advocates for the promotion of an integrated paradigm that aligns public administration with emerging technology through AI-driven policy proposals focused on preventive public health. It is anticipated that the research will contribute to the establishment of a new framework for incorporating AI technology into public administration practices. This will lay the foundation for developing preventive public health policy that leverages AI as a strategic tool for monitoring, assessing, and managing health risks associated with air pollution at both local and national levels.

Literature Review

Policy Resources

Policy resources represent a crucial component within the inter-organizational model, which functions as a systemic mechanism pivotal to the effective implementation of public policy. Among these resources, artificial intelligence plays an increasingly vital role in enhancing the efficiency and responsiveness of public services across all sectors. AI serves not only as a tool for improving service delivery to the public but also as a strategic driver for key policy domains, including budget allocation, human resource development, and the deployment of technological infrastructure that supports effective policy development (Chantarasorn, 2005). Reddy et al. (2019) emphasized that AI-driven healthcare delivery systems can be categorized into four main functions: patient management, clinical decision support, patient monitoring, and healthcare interventions. Their study underscores the importance of AI in streamlining care processes and enhancing the accuracy of medical decisions. In the context of cancer care, Sila (2023) explored the use of digital technology in managing chemotherapy patients, highlighting how telemedicine and mobile health devices help in the continuous monitoring of side effects, thereby reducing hospital congestion and minimizing the risk of infectious disease transmission. These digital interventions have also been shown to reduce the frequency of hospital visits, contributing to both patient well-being and system-wide resource optimization. Moreover, Dank, Salwen, and Iticovici (2021) investigated the advances of AI in lung cancer diagnostics, noting that the integration of deep learning algorithms with radiological imaging systems significantly improves diagnostic accuracy, reduces the workload of medical personnel, and enhances the cost-effectiveness of cancer care.

AI plays a pivotal role in mobilizing resources for health policy development. Fei et al. (2017) reviewed applications of AI in healthcare and reported its strong potential in optimizing diagnostic procedures, predicting patient outcomes, and reducing operational inefficiencies. Similarly, Kelly, Karthikesalingam, Suleyman, Corrado, and King (2019) found that integrating AI into clinical pathways contributes to improved resource allocation, enhanced staff performance, and more informed policy design. A study by Obermeyer and Emanuel (2016) highlighted the importance of addressing bias in AI-driven healthcare systems to ensure the equitable distribution of health resources. In addition, Amann, Blasimme, Vayena, Frey, and Madai (2020) emphasized the critical role of explainable AI in fostering trust and accountability, particularly when deploying AI-based diagnostic tools within public health systems. Collectively, these findings indicate that when leveraged appropriately, AI technology can transform policy resources to support evidence-based and proactive public health policy, especially in managing high-risk health conditions such as lung cancer linked to PM2.5 exposure.

Organizational Capacity

Organizational capacity is a fundamental component in organizational theory, emphasizing the responsibility of translating policy into actionable strategies and adapting them to align with specific tasks, as well as planning and managing resources to ensure smooth operations. This includes the development of digital skills to effectively leverage technology in management processes. Such a model examines methods to overcome obstacles in policy implementation by adjusting organizational structures. Additionally, it necessitates planning for the readiness of materials, equipment, budget, and the expertise of personnel (Sridacha, Chamruspanth, & Piyanantisak, 2024; Khamphui, Khantahate, & Phetchsudhi, 2021).

In the context of public health policy driven by artificial intelligence, organizational competency encompasses digital skill development, which is vital for effectively utilizing emerging technology to enhance management processes. This model focuses on addressing the challenges of policy implementation by adjusting internal organizational systems, including infrastructure, equipment, budget allocation, and the professional expertise of personnel (Brynjolfsson & McAfee, 2024).

Furthermore, Chaiyapan (2021) explored the use of digital technology in cardiothoracic patient care and found that healthcare professionals, especially nurses, are required to engage with advanced tools such as telecommunication, telemedicine, AI, internet-based systems, wearable devices, robotics, and drones. Therefore, medical personnel must develop digital competencies that encompass knowledge, skills, and professional attributes. Institutional support is also essential in promoting the adoption of such technology to ensure that patient care is efficient, high-quality, and safe (Oyekunle, Matthew, Preston, & Boohene, 2024; Wahl, Cossy-Gantner, Germann, & Schwalbe, 2018).

Additionally, Chaiyapan (2021) examined the relationship between practitioner competency and service quality in both public and private organizations and found that clinical competency, cost-efficiency, and governmental support were crucial to organizational success. The study indicated that technology acts as a primary factor in enhancing workforce competency and improving service quality. He et al. (2019) emphasized that AI applications in medicine improve clinical decision-making and operational efficiency. Similarly, Reddy et al. (2019) argued that AI integration enhances healthcare delivery through automation and predictive analytics. In addition, Chen et al. (2017) highlighted the role of wearable and cloud-integrated technology in developing a more responsive and data-driven workforce. Integrating AI into public health systems, particularly for monitoring lung cancer risks associated with PM2.5 exposure, will therefore require a high level of organizational competency to ensure that the implementation is effective, and evidence based. According to Rajkomar, Dean, and Kohane (2019), the successful deployment of AI in health contexts depends on structured data systems and competent personnel capable of interpreting machine learning outputs. Furthermore, Obermeyer and Emanuel (2016) noted that while AI offers promising capabilities in disease detection, its impact relies heavily on institutional readiness and workforce digital literacy.

Teamwork

Teamwork, in conjunction with the integration of digital technology, constitutes a critical element of organizational development, particularly in the context of public health policy innovation. It enhances engagement and mutual recognition among stakeholders through the utilization of online platforms and participatory mechanisms, thus contributing to more efficient public service delivery. Effective leadership and the appropriate exercise of authority help to foster team cohesion and shared understanding, which are essential for implementing AI-driven public health interventions. In advancing public policy aimed at mitigating health risks associated with PM2.5 through AI applications in lung cancer diagnostics, both frontline health workers and the public must adapt to digital systems and develop positive user experiences. The success of such policy interventions depends largely on inclusive participation and the direct involvement of practitioners, making the synergy between teamwork and digital technology indispensable for institutional transformation in the digital age (Maneerat & Tharakorn, 2022).

In addition, Khanthaniyom (2019) observed that the use of collaborative technology in educational settings positively influences team performance by supporting infrastructure and strategic implementation, suggesting broader applicability in public health governance. Similarly, Lei (2024) found that AI-powered image processing significantly enhances the accuracy of early-stage lung cancer diagnosis, underscoring the potential of AI technology to elevate healthcare delivery. This view is supported by several international studies: Javed et al. (2024) and Topol (2019) emphasized that AI, when used collaboratively with clinical teams, augments diagnostic accuracy and patient engagement; Sharma et al. (2018) highlighted that interdisciplinary AI-supported teams can reduce diagnostic errors and expedite decision-making in low-resource environments; Esteva et al. (2017) demonstrated AI's diagnostic capability in dermatology as comparable to expert physicians, signaling its potential for broader medical applications; Rajpurkar et al. (2017) reported that AI models outperformed radiologists in pneumonia detection via chest X-rays, showcasing AI's value in radiological teamwork; and Mulshine et al. (2025) found that team-based AI integration in hospitals improved early detection of high-risk lung cancer and facilitated localized health policy implementation. Collectively, these findings reinforce the view that digital teamwork, when strategically aligned with AI technology, plays a vital role in shaping evidence-based, participatory public health policy, particularly in addressing complex environmental health challenges such as lung cancer arising from PM2.5 exposure.

Convolutional Neural Network (CNN)

The integration of big data for training AI models using convolutional neural network (CNN) has been widely applied in image recognition, image classification, and object detection. The CNN process aims to enhance performance through data augmentation techniques and comparative accuracy evaluations (Bhavnagri, 2019; Sriwiboon, 2021; Promboonruang, Boonrod, Radasai, & Suphaphan, 2023). In this study, a large dataset comprising 15,000 medical images was utilized, categorized into three classes: (1) 5,000 images of lung adenocarcinoma (lung_aca), typically originating in the mucus-producing glands or alveoli; (2) 5,000 images of non-cancerous lung tissue (lung_bnt); and (3) 5,000 images of squamous cell carcinoma of the lung (lung_scc). The distribution of these classes is illustrated in Figure 1.

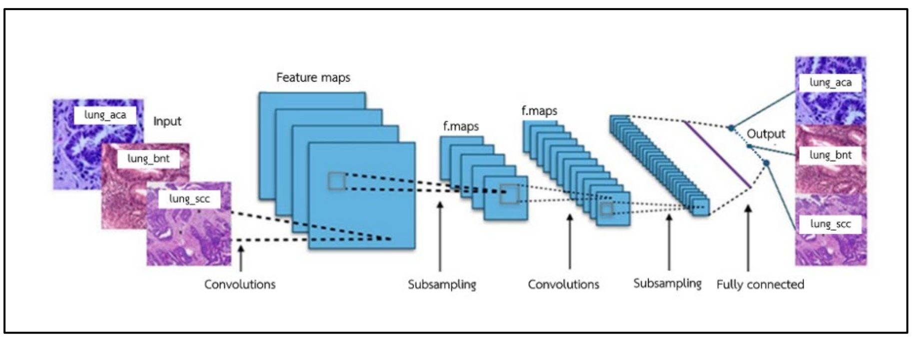

Figure 1. Convolutional Neural Network (CNN)
Source: Adapted from Bhavnagri (2019).

Conceptual Framework of the Study

This study constructs its conceptual framework based on established theoretical concepts, a comprehensive review of related literature, and prior research findings. It aims to propose a public policy framework that leverages artificial intelligence technology to mitigate PM 2.5 pollution in the field of public health. As a case study, the research focuses on the application of AI in the diagnosis of lung cancer, which serves as a practical model for policy innovation. Within this framework, the independent variables comprise key factors influencing policy implementation, including policy resources, organizational capacity, and teamwork, while the dependent variables represent the outcomes of policy implementation, specifically the development of policy recommendations and the creation of a web-based application for lung cancer diagnosis. The overall conceptual framework of the study is presented in Figure 2 as follows.

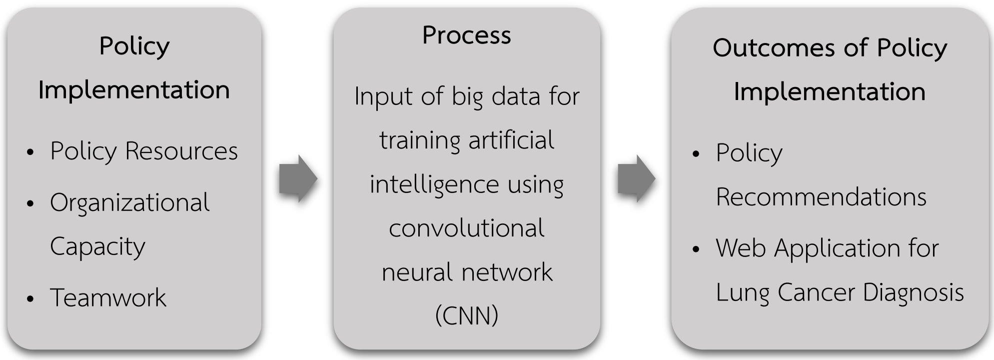

Figure 2. Conceptual Framework of the Study

Research Methodology

Research Design

The study titled “policy recommendations to advance public health policy through artificial intelligence technology for mitigating PM2.5 pollution: a case study of ai application in lung cancer diagnosis” adopts a mixed-methods research design, combining both qualitative and quantitative approaches. The qualitative component involves the collection and analysis of relevant literature and previous research from both domestic and international sources. The quantitative component focuses on the collection of big data from social media databases, which is then analyzed using convolutional neural network (CNN). This process is aimed at training artificial intelligence to learn and evolve into a diagnostic AI model for lung cancer.

Sample Used in the Study

The sample used in this study was obtained from the social media-based platform kaggle.com, which serves as a collaborative community for AI developers to share code and datasets for machine learning, deep learning and artificial intelligence development. The dataset used pertains to lung cancer and comprises 15,000 photomicrographic images, categorized into three distinct groups: 5,000 images of pulmonary adenocarcinoma (originating from mucous glands or alveolar structures), 5,000 images of normal (non-cancerous) lung tissue, and 5,000 images of pulmonary squamous cell carcinoma.

Research Instruments

The research employed data collection instruments to gather photomicrographic images from social media databases. For data analysis, the study utilized Google's Teachable Machine platform to train the AI using convolutional neural network (CNN) until a high level of accuracy was achieved. Subsequently, the trained AI model was developed into a web application using the Python Flask framework to perform lung cancer diagnosis.

Data Analysis

The study used Google's Teachable Machine to analyze big data for the purpose of developing the AI model. The training process involved feeding a total of 15,000 photomicrographic images into convolutional neural network, categorized into 5000 images of lung adenocarcinomas (lung_aca), 5000 images of benign lung tissues (lung_bnt), and 5000 images of lung squamous cell carcinomas (lung_scc). After the AI model was trained to a satisfactory level of performance, it was developed into a web application using the Python Flask framework. This application is intended to support public health policy implementation in the digital era.

Research Results

The Application of Big Data in the Development of Public Health Policy

This policy proposal aims to promote the systematic integration of artificial intelligence (AI) technology to enhance public health strategy aimed at mitigating the adverse health effects of fine particulate matter (PM2.5) pollution. A case study is employed to demonstrate the practical application of AI in the diagnostic process of lung cancer, utilizing big data as the foundation for developing a highly accurate and reliable predictive model. The dataset used in this study comprises 15,000 photomicrographic images of lung tissues, which were processed through a deep learning architecture using convolutional neural network (CNN). The entire dataset of 15,000 images was divided into two subsets: 85 percent (12,750 images) for training the AI model and 15 percent (2,250 images) for evaluating the model's performance. The data were evenly distributed into three diagnostic categories: 5,000 images of lung adenocarcinoma, 5,000 images of normal lung tissue, and 5,000 images of squamous cell carcinoma.

Each image category namely, lung adenocarcinoma (lung_aca), normal lung tissue (lung_bnt), and squamous cell carcinoma (lung_scc) comprised precisely 5,000 labeled samples. The lung_aca class represents malignancies originating from mucus-secreting glands or alveolar structures, while lung_scc comprises neoplastic tissues derived from the bronchial epithelium. The AI model was trained with key hyperparameters including 50 training epochs, a batch size of 16, and a learning rate set at 0.001. The training methodology, as illustrated in Figure 3, was designed to optimize both feature extraction and classification accuracy, ensuring the model's capacity to distinguish between histological subtypes with high precision.

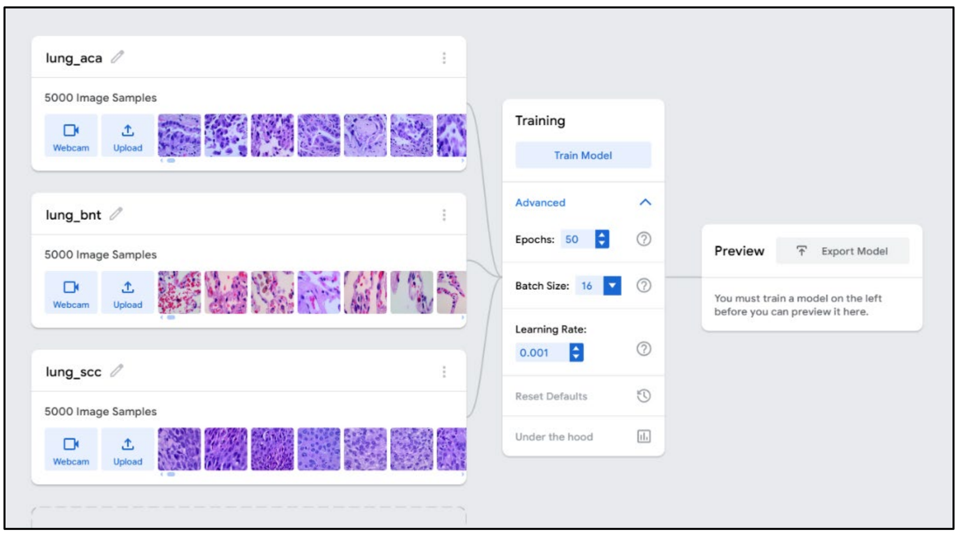

Figure 3. The process of training an AI model using big data through a convolutional neural network architecture

The AI model was trained using a dataset of 15,000 images, of which 85 percent were divided for model training and 15 percent for testing and performance evaluation. A comprehensive assessment of the model’s reliability was conducted by evenly distributing the test dataset across the three diagnostic categories, allocating 750 images to each class, as illustrated in Figure 4. The model achieved 99 percent accuracy in classifying lung_aca images and 100% accuracy in classifying both lung_bnt and lung_scc images. Further verification using the confusion matrix, presented in Figure 5, confirmed the model’s high classification performance. Specifically, the model correctly classified 742 out of 750 lung_aca images, with 8 images misclassified as lung_scc. All normal lung tissue (lung_bnt) images were classified with perfect accuracy. For the lung_scc category, 748 out of 750 images were correctly identified, with only 2 images misclassified as lung_aca. These overall results demonstrate the model’s strong ability to distinguish between malignant and non-malignant lung tissues with high precision, supporting its potential for application in clinical diagnostics and early-stage cancer screening.

Figures 6 and 7 illustrate the training process of the AI model using big data comprising 15,000 photomicrographic images. Of these, 85 percent (12,750 images) were allocated for training, and the remaining 15 percent (2,250 images) were reserved for model testing. The model was developed using convolutional neural network (CNN) architecture, trained over 50 epochs with a batch size of 16. The learning rate was fixed at 0.001. Based on this training configuration, the AI model achieved a perfect training accuracy of 100 percent and a high-test accuracy of 99.5 percent on previously unseen data. In terms of error metrics, the model exhibited a minimal training loss of 0.01 percent and a test loss of 1.67 percent, indicating a low rate of prediction error in both phases. These results highlight the model’s ability to accurately and reliably predict lung cancer, with strong generalizability across different data samples. Moreover, the model demonstrated an optimal fit to the data, avoiding both overfittings characterized by excellent performance on training data but poor generalization and underfitting, which occurs when a model fails to capture essential patterns due to limitations in training data, network complexity, or insufficient learning iterations. The successful training and evaluation process culminated in the creation of the final model file, “keras_model.h5,” which demonstrates robust and precise diagnostic capability for lung cancer classification.

An evaluation of the model’s generalizability and robustness was subsequently performed through a 5-fold cross-validation on the entire dataset of 15,000 photomicrographic images. Each fold preserved the original class distribution to ensure balanced representation across categories. The resulting accuracy scores were 0.94, 0.96, 0.94, 0.96, and 0.93, yielding a mean classification accuracy of 94 percent, as presented in Table 1. These cross-validation results demonstrate consistent and reliable performance across different data partitions, underscoring the model's capacity to generalize effectively to unseen data. The absence of significant performance variation across folds further supports the model’s potential for clinical deployment without substantial risk of overfitting.

Accuracy per class

CLASS	ACCURACY	# SAMPLES
lung_aca	0.99	750
lung_bnt	1.00	750
lung_scc	1.00	750

Figure 4. Classification of lung cancer types, model accuracy, and the sample groups used for testing

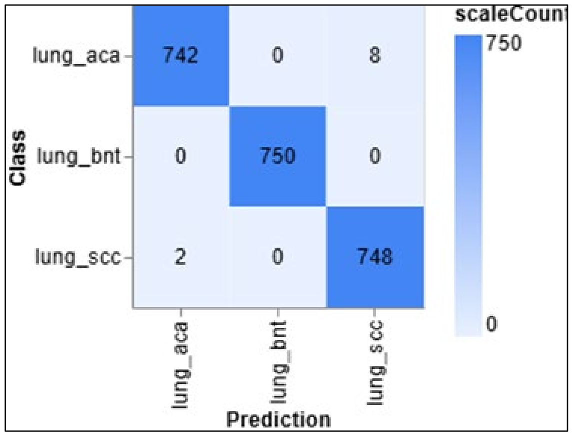

Figure 5. Model evaluation using the confusion matrix

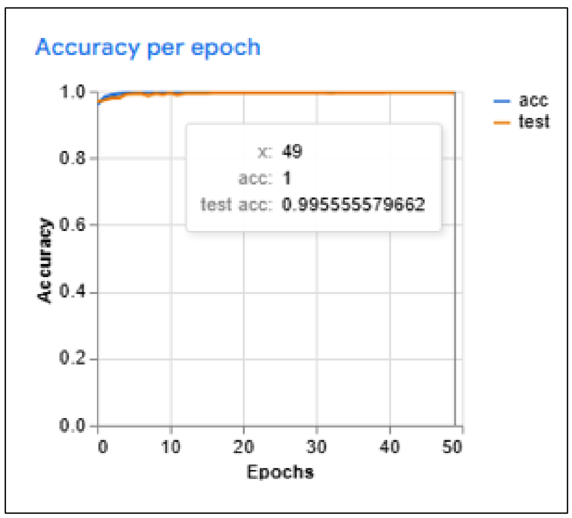

Figure 6. Model accuracy values

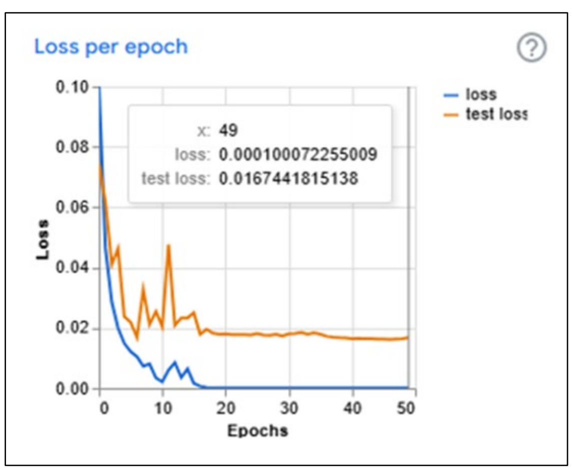

Figure 7. Model error values

Table 1. Evaluation of model performance using 5-fold cross-validation

Evaluation of model performance	Averages
Fold 1 Accuracy	0.94
Fold 2 Accuracy	0.96
Fold 3 Accuracy	0.94
Fold 4 Accuracy	0.96
Fold 5 Accuracy	0.93
Total	**0.94**

The development and application of AI support the implementation of public health policy

The artificial intelligence (AI) model utilized for lung cancer diagnosis is directly aligned with public policy objectives aimed at mitigating the health effects of fine particulate matter (PM2.5), a known contributor to respiratory diseases and lung cancer, particularly in regions with elevated air pollution. In this context, AI functions not only as a diagnostic tool but also as a mechanism for proactive health surveillance and evidence-based decision-making. Its capacity to analyze photomicrographic images with high speed, precision, and consistency significantly enhances the likelihood of early detection, reduces the diagnostic workload for physicians, and improves the efficiency of screening at-risk populations in PM2.5 affected areas.

Although the AI model discussed in this study primarily serves to support clinical diagnostics of lung cancer, its relevance to public policy concerning PM2.5 lies in its potential role as a downstream intervention within a broader environmental health surveillance system. PM2.5 exposure has been epidemiologically linked to increased incidence and mortality of lung cancer, particularly in urban and industrialized areas. By enabling early detection and classification of PM2.5-related pulmonary malignancies, this AI model aligns with the preventive and diagnostic strategies promoted in public health policy frameworks addressing air pollution. Thus, while the model does not directly mitigate PM2.5 pollution, it operationalizes health system responsiveness to its adverse effects, bridging environmental monitoring and clinical response. In addition, although current applications primarily emphasize hospital-based use by medical professionals, the proposed research expands the role of AI beyond the clinical setting to strengthen public health systems at both local and national levels. A key component of this policy framework is the integration of AI model with the NHEDC. When real-time data from the pollution control department indicates that PM2.5 concentrations have exceeded safety thresholds, the system can automatically trigger the deployment of mobile health units to conduct screening in affected communities. Radiographic images collected in the field are then analyzed by the AI model, with diagnostic outcomes recorded and disseminated through the NHEDC dashboard, thereby enabling data-informed and timely decision-making by policymakers across multiple sectors and administrative levels.

In terms of cost and implementation, the development of artificial intelligence (AI) models particularly convolutional neural network (CNN) for medical diagnostics requires considerable resources in the initial phase. This is especially true for the collection, preprocessing, and annotation of large-scale medical image datasets, as demonstrated in this study which utilized 15,000 photomicrographic images. Furthermore, high-performance computing infrastructure is essential during the training phase to ensure model convergence and accuracy. However, once the model achieves a satisfactory level of diagnostic precision, its operational deployment becomes economically feasible. Model inference in clinical settings can be performed using standard GPU-equipped workstations, significantly reducing long-term computational costs. Integration into existing hospital infrastructures, such as picture archiving and communication systems (PACS) and hospital information systems (HIS), further enhances its practical viability. Additionally, the model is compatible with widely used open-source platforms like Keras and TensorFlow, facilitating flexible implementation across institutions. From a usability perspective, the system can be designed with user-friendly interfaces and offers a high degree of automation, enabling frontline healthcare professionals to utilize the model effectively without requiring advanced technical knowledge. As such, it functions as a cost-effective, scalable, and accessible clinical decision-support tool that aligns well with digital pathology workflows and public health system requirements.

The artificial intelligence (AI) model proposed in this study is not merely an innovation for diagnosing lung cancer but also plays a strategic role in developing a data-driven public health management ecosystem. This model can be linked to the NHEDC, as outlined in the policy recommendations, serving as a centralized cloud-based platform accessible to medical personnel in all public hospitals. The platform will enable the utilization of the AI model for diagnostic purposes while also functioning as a centralized repository for big data on health, air quality, and environmental conditions from various regions. Moreover, this platform will support diagnostic decision-making and facilitate the management of big data to advance medical AI development. It will allow healthcare professionals to efficiently apply the model for lung cancer screening, support real-time disease surveillance, and foster long-term epidemiological research. The AI model is also designed to be applicable within diagnostic workflows in secondary and tertiary healthcare facilities, enabling medical personnel to analyze radiographic images rapidly and accurately with AI assistance. The resulting data can be transmitted into an integrated epidemiological surveillance system through a continuous feedback loop, effectively linking clinical findings, environmental data, and public health policymaking. In the future, if the model is further developed to achieve higher accuracy and stability, it holds strong potential for integration into existing government digital platforms such as Paotang, Mor Prom, or Tangrath as part of the national e-Government framework. This would facilitate broader access to preventive healthcare services for both healthcare providers and the general population. In summary, this AI model is not a standalone technology; rather, it is a critical mechanism that bridges clinical data, environmental monitoring, and public health policy, aiming to establish an efficient and sustainable healthcare system capable of addressing escalating health risks associated with environmental factors.

Despite these benefits, the integration of AI into government healthcare systems faces several challenges. These include inadequate technological infrastructure in rural or resource-limited areas, difficulties in integrating data across multiple agencies, and a general lack of digital literacy among certain healthcare workers. Nevertheless, AI provides distinct advantages over traditional approaches that rely solely on human resources, particularly in terms of speed, accuracy, and scalability. Its adoption has the potential to significantly enhance public health responses, especially in managing persistent environmental hazards such as PM2.5, which require prompt and effective interventions.

Potential barriers to the implementation of the AI model include concerns regarding data privacy, the need for standardization of image data formats, and resistance from healthcare practitioners unfamiliar with AI-assisted diagnostic tools; furthermore, variability in data quality across different healthcare institutions may present challenges to achieving the generalizability and robustness of the model at the national level. Despite these obstacles, the AI model offers substantial advantages over the current standard of care, such as faster diagnostic turnaround times, reduced rates of diagnostic errors, and enhanced consistency in image interpretation. Moreover, when integrated with complementary policy instruments, including health surveillance systems and the NHEDC dashboard, the model significantly improves the capacity of public health authorities to monitor disease trends associated with environmental exposures, thereby enabling more proactive policymaking and efficient allocation of healthcare resources.

To support these goals, the AI model was developed as a web-based application designed to assist medical personnel in diagnosing lung cancer through photomicrographic images. The application operates via two primary methods. The first method involves predicting lung cancer by uploading a photomicrographic image into the system. Once the image is obtained, the user selects the "Choose

File" option and uploads the image. The user then clicks the "Predict" button, prompting the system to analyze the image and generate a diagnostic result. The outcome is categorized into one of three classifications: (1) lung_aca, indicating lung adenocarcinoma a cancer originating from mucous-secreting glands or alveolar tissue in Figure 8; (2) lung_bnt, indicating a normal lung condition without signs of cancer in Figure 9; and (3) lung_scc, referring to squamous cell carcinoma, a type of lung cancer that arises from the epithelial lining of the bronchi in Figure 10. The second method enables the prediction of lung cancer from photomicrographic images using a webcam. Once the lung tissue sample has been prepared and its photomicrographic image is available, the image is placed in front of a webcam. The user then clicks the "Start" button in Figure 11, activating real-time image capture and analysis. The system processes the image and displays a predictive result. For example, a prediction of lung_aca: 1.00 indicates lung adenocarcinoma in Figure 12; lung_bnt: 1.00 confirms normal tissue in Figure 13; and lung_scc: 1.00 indicates squamous cell carcinoma of the bronchial epithelium in Figure 14. This method provides greater flexibility in both clinical settings and remote health screening scenarios.

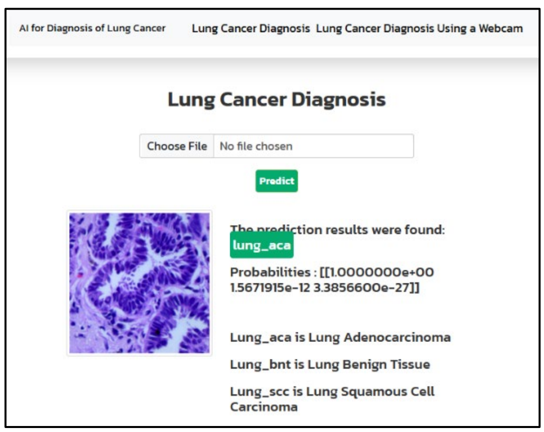

Figure 8. shows the prediction of lung_aca, indicating lung adenocarcinoma, a type of cancer originating from the mucous glands or alveoli of the lung

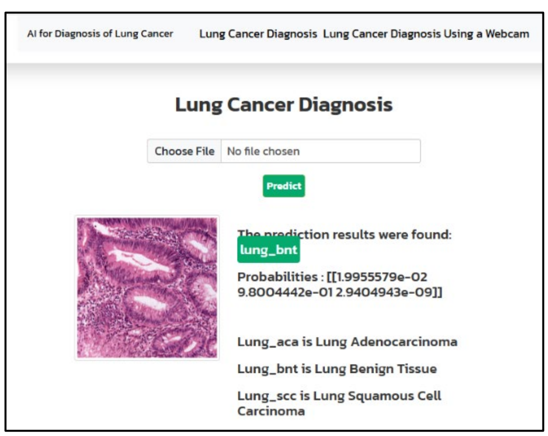

Figure 9. shows the prediction of lung_bnt, indicating a normal lung with no signs of lung cancer

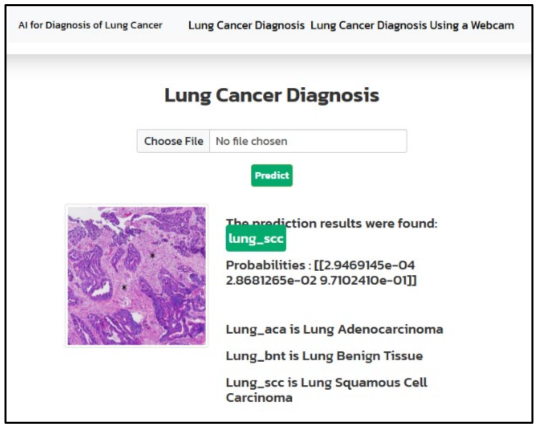

Figure 10. shows the prediction of lung_scc, indicating squamous cell carcinoma of the bronchial epithelium

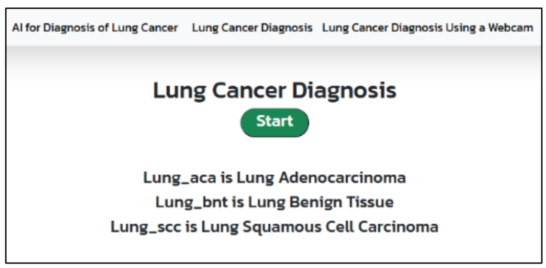

Figure 11. shows the diagnosis of lung cancer using a webcam

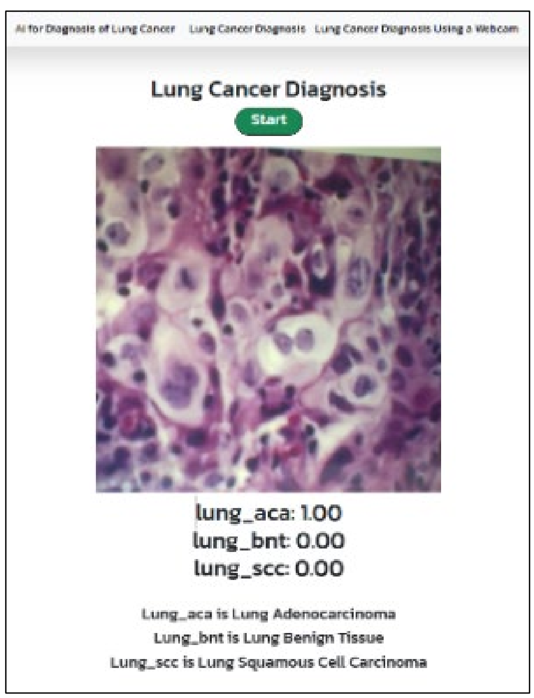

Figure 12. lung_aca: 1.00 shows a prediction of lung adenocarcinoma with a prediction probability of 100 percent

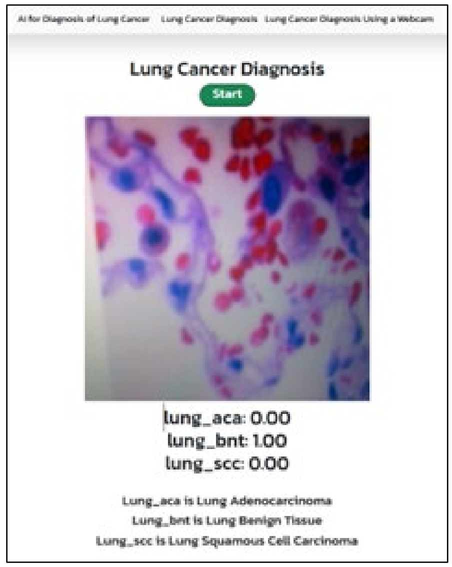

Figure 13. shows the prediction lung_bnt: 1.00, indicating normal lungs with no lung cancer with a prediction probability of 100 percent

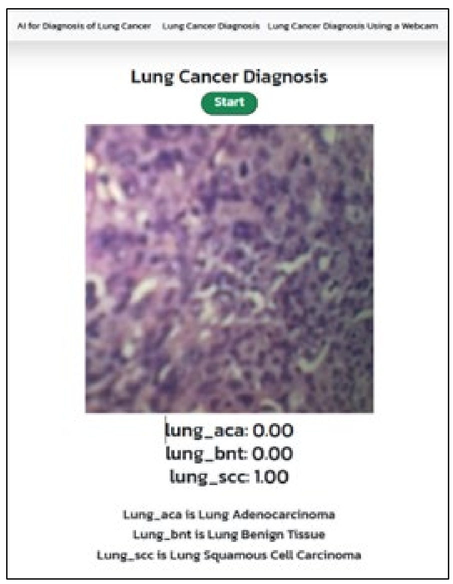

Figure 14. shows the prediction lung_scc: 1.00, indicating squamous cell carcinoma of the bronchial epithelium with a prediction probability of 100 percent

This study presents the development of an artificial intelligence (AI) model for the diagnosis of lung cancer through the analysis of photomicrographic images, with the goal of supporting public health systems in effectively responding to the health impacts of fine particulate matter (PM2.5). Although the model remains at the proof-of-concept stage, preliminary results demonstrate promising accuracy and diagnostic speed. This suggests potential for future development into a clinical decision support system, particularly in areas with high levels of PM 2.5 pollution, which have been associated with increased lung cancer incidence.

The clinical applications of the AI model include assisting pathologists in accelerating photomicrographic image analysis, reducing workload, and improving diagnostic accuracy. The model can be deployed via both image upload and real-time analysis using a microscope connected to a webcam. From a public health systems perspective, when linked with the NHEDC platform, the model could function as an early warning tool in high-risk areas by proactively prompting lung cancer screening. At the policy level, the model could serve as a data bridge between real-time environmental data and health data, enabling governments to formulate context-sensitive prevention strategies and allocate healthcare resources more efficiently.

Regarding the development process, although the model is still at the proof-of-concept stage, this study outlines a systematic pipeline for its advancement. Data preparation involved the selection and labeling of histopathological images from publicly available datasets and the application of data augmentation techniques to enhance training diversity. The model was designed using convolutional neural network (CNN) architecture implemented with TensorFlow/Keras, optimized for high-resolution image input. Relevant hyperparameters such as loss function, learning rate, and number of epochs were carefully configured. Training and validation employed k-fold cross-validation to prevent overfitting and assess model generalizability, with performance metrics including accuracy and confusion matrix systematically reported. For prototype deployment, a web-based application was developed to allow diagnostic testing using either image uploads or webcam-connected microscopes, with the classification outcomes displayed alongside model confidence scores to support clinical decision-making.

For future improvements, several directions are proposed. First, data quality control should be enhanced by expanding the dataset to include images from domestic healthcare facilities, thereby improving contextual accuracy for the Thai population. Second, clinical validation should be conducted by comparing AI-generated diagnoses with those of physicians under real-world conditions. Third, integration with national health information systems (HIS) and picture archiving and communication systems (PACS) is recommended to enable large-scale implementation. Finally, cost-effectiveness analysis should be undertaken to evaluate the economic and operational efficiency of the AI model compared to traditional diagnostic approaches.

Discussion

A study on the application of big data in the development of evidence-based and efficient public health policy

The successful implementation of public health policy aimed at mitigating PM2.5 pollution through artificial intelligence technology necessitates several key factors. Firstly, policy resources and governmental support play a crucial role in delivering quality medical services to the public. The integration of smart medical technology enhances service accessibility, reduces treatment costs, and enables efficient disease outbreak predictions. AI technology can analyze medical and public health data to expedite disease diagnosis. Specifically, employing AI in diagnosing lung cancer reduces diagnostic time and increases the likelihood of appropriate treatment, thereby standardizing healthcare services and improving the quality of life equitably. This approach also addresses the shortage of radiology specialists and facilitates efficient management of medical resources. Phon-eg-phan (2019) found that the demand for medical devices in Thailand is growing in three areas: disease prevention tools, home healthcare equipment, and personalized patient technology. The primary driving force behind these developments is technological advancement, which must align with social needs and the actual healthcare budget. International studies corroborate these findings. For instance, Ghose, Guo, Li, and Dang (2021) demonstrated that mobile health platforms significantly improve health behaviors and reduce medical expenses among chronic disease patients. Linkous, Zohrabi, and Abdelwahed (2019) highlighted the potential of IoT in smart homes for health monitoring, emphasizing the need for integration with conventional healthcare. Baucas, Spachos, and Gregori (2021) discussed the applications and challenges of IoT devices in healthcare, underscoring their role in alleviating healthcare system burdens. Kittiamornkul (2019) emphasized the importance of digital technology, including AI and big data, in transforming Thailand's healthcare system. Furthermore, Leelahavarong et al. (2019) reviewed the institutionalization of health technology assessment in Thailand, illustrating its contribution to informed healthcare decision-making.

Secondly, organizational capacity refers to the ability to provide efficient and reliable medical services, encompassing knowledge, skills, capabilities, equipment, facilities, and adequate budgets to enable personnel to work effectively. Organizations must be responsible and understand the correct application of smart medical technology in implementing public health policy, fostering an environment that promotes the use of such technology. The development and application of smart medical technology enhances service efficiency and improves patient quality of life. Efficient management of medical resources creates opportunities for personnel to learn and develop flexible skills to adapt to changes in healthcare services, particularly in areas with limited access. Chaiyapan (2021) found that core competencies of personnel affecting service quality include medical expertise, cost reduction, and government support, all of which are crucial for Thailand's potential in the global medical industry. International research supports these insights. For example, Kruachottikul et al. (2024) proposed a comprehensive MedTech product innovation development framework tailored for university research commercialization within emerging markets, emphasizing the importance of aligning innovations with clinical needs and market strategies. Shaik et al. (2023) reviewed AI-enabled remote patient monitoring systems, highlighting their role in transforming healthcare monitoring applications. Pichetworakoon, Kooptarnond, and Ngamchuensuwan (2021) analyzed the economic and legal aspects of deploying medical and healthcare robotics, comparing the European Union, South Africa, and Thailand, and discussing the potential and challenges of medical robots. Kingkaew and Teerawattananon (2014) reviewed the development of health technology assessment in Thailand, noting the influence of economic status and health financing reforms on the demand for HTA information. Mohara et al. (2012) discussed the use of health technology assessment in informing coverage decisions in Thailand, emphasizing its role in policy decision-making.

Thirdly, teamwork is essential in developing AI models for lung cancer diagnosis through web applications, enhancing diagnostic accuracy and timely treatment. This supports national development in the Thailand 4.0 era. Success stems from collaboration between medical professionals and technology experts, leading to innovative treatments. Clear division of roles and responsibilities fosters the development of appropriate systems and technology, promoting organizational adaptation to the digital era. Data processing and medical application development improve work efficiency and responsiveness to user needs. Teamwork accelerates problem-solving and the development of suitable services, reducing unnecessary steps and enabling rapid and widespread access to services, thereby conserving resources. This aligns with the findings of Wisetsena (2022), who noted that healthcare innovation in the Thailand 4.0 era can streamline processes, enhance accessibility, and increase user satisfaction. International studies further substantiate these points. Mahakunajirakul (2022) investigated factors influencing the adoption of healthcare wearable devices in Thailand, emphasizing the role of performance expectancy and social influence. Patel et al. (2024) highlighted the role of AI-integrated remote patient monitoring in refining chronic disease management strategies by offering more personalized and effective treatments. Nigar (2025) explored the integration of AI in remote patient monitoring, emphasizing enhancements in monitoring accuracy, predictive analytics, and personalized treatment plans. De Filippo et al. (2025) presented the PrediHealth project, which integrates telemedicine and predictive algorithms for the care and prevention of patients with chronic heart failure, showcasing the benefits of AI-enhanced remote monitoring in improving patient outcomes and reducing healthcare costs.

Development and Application of AI in Supporting the Practical Implementation of Public Health Policy

The application of artificial intelligence in analyzing photomicrographic images has significantly improved the early detection of lung cancer, particularly in resource-limited settings where radiologists are scarce. AI tools such as qXR by Qure.ai have demonstrated diagnostic performance comparable to expert radiologists in identifying thoracic abnormalities (Ardila et al., 2019; AstraZeneca, 2025; Hwang et al., 2019; Rajpurkar et al., 2017). This innovation not only accelerates diagnosis but also increases the chances for timely treatment, which is crucial in managing lung cancer risks influenced by PM2.5 exposure. AI also plays a vital role in processing big data to explore the intricate relationships between PM 2.5 air pollution and lung cancer risks. Studies have shown that machine learning techniques can accurately predict the health impact of PM**2.5** by correlating environmental data with health records, hospitalization rates, and mortality (Kelly & Fussell, 2015; Lary, Lary, & Sattler, 2015; Xing et al., 2020). These insights enable policymakers to design proactive health interventions based on empirical evidence.

The development of Explainable AI (XAI) marks a critical advancement in enhancing the transparency and trustworthiness of AI systems, particularly in clinical settings. XAI allows healthcare professionals to understand the rationale behind AI-generated recommendations or diagnostic outputs, thereby facilitating its integration into life-critical decisions (Barredo Arrieta et al., 2020; Ghassemi, Oakden-Rayner, & Beam, 2021; Holzinger, Langs, Denk, Zatloukal, & Müller, 2019; Tjoa & Guan, 2020). Such models establish a robust foundation for AI adoption in health systems, ensuring both ethical and practical usability. In terms of public health policy, AI enables data-driven decision-making by predicting disease risks, assessing PM2.5 impact on communities, and suggesting actionable interventions. These capabilities support targeted policy responses, enhance risk communication, and promote community participation in environmental health governance (Hwang et al., 2019; Obermeyer & Emanuel, 2016; Rajkomar et al., 2019; Wong, 2022). Ultimately, AI fosters the integration of scientific evidence into sustainable and equitable policy design.

Conclusion

This study highlights the crucial role of artificial intelligence and big data in enhancing evidence-based public health policy, particularly in addressing the health impacts of PM2.5-related lung cancer in Thailand. The integration of AI in smart medical technology significantly improves diagnostic accuracy, especially in resource-limited settings. The application of AI, such as analyzing photomicrographic images, reduces diagnostic time, facilitates timely treatment, and enables predictive modeling for disease surveillance. These capabilities support health equity by improving access to healthcare and optimizing the allocation of medical resources.

Organizational capacity and inter-professional collaboration are essential for the successful implementation of AI-based public health interventions. Medical institutions must invest in infrastructure, personnel training, and the ethical application of AI tools. The study confirms that effective teamwork among healthcare professionals, technology developers, and policymakers enhances innovation, fosters system adaptability, and improves healthcare service delivery. These efforts are aligned with the goals of Thailand 4.0 in promoting digital transformation within the health sector.

To advance the practical implementation of AI-driven health policy, the study proposes comprehensive policy recommendations. These include establishing centralized health and environmental data systems, developing real-time AI risk analysis platforms, deploying proactive health surveillance, and integrating AI into diagnostic workflows. Moreover, policy frameworks must address ethical governance, data security, and citizen rights, while also encouraging public engagement and capacity-building through education and local partnerships. Collectively, these recommendations aim to support sustainable, data-informed health governance and strengthen national resilience to air pollution–related health threats.

Research Contributions

A policy framework has been proposed to drive public health policy aimed at mitigating $PM_{2.5}$ pollution through the application of artificial intelligence, as illustrated by a case study on AI-based lung cancer diagnosis. This study yields the following key contributions: First, the design of a policy system for the establishment of the NHEDC is proposed, and the center is envisioned as a centralized structural mechanism that integrates health, air quality, and environmental data from government agencies at all levels. This approach emphasizes the application of information technology and artificial intelligence, and it aims to enhance data analysis efficiency while supporting systematic and evidence-based policy decision-making.

Second, the development of public policy and the advancement of an AI-driven platform for real-time prediction of lung cancer risk are emphasized, and this includes supporting the creation of AI platforms that can analyze epidemiological and environmental data to forecast lung cancer risks in real time. The initiative is grounded in the concepts of strategic public management and anticipatory governance, and it enables both central and local agencies to utilize analytical results to inform their decision-making processes more effectively.

Third, the formulation of an integrated policy for proactive health surveillance in PM2.5 risk areas is advocated, and this involves promoting policy integration among government sectors, academic, and healthcare service units to implement proactive health screening measures for populations in high-risk areas. AI systems are employed to process health data in conjunction with air quality data, and this integration supports both preventive planning and the timely, appropriate allocation of public health resources.

Policy Recommendations for AI Integration in Public Health Surveillance of PM2.5 Related Lung Cancer

This study presents nine policy recommendations aimed at guiding the development of a systematic and integrated framework for the application of artificial intelligence in monitoring and mitigating public health risks related to PM2.5 induced lung cancer. The first recommendation is the establishment of the NHEDC, which would serve as a central repository for big data on health, air quality, and environmental conditions from across the country. This initiative would require collaborative efforts among the Ministry of Public Health, the Pollution Control Department, and various research institutions. It also involves the development of a secure national cloud-based big data infrastructure that aggregates hospital health data nationwide, to be used as training datasets for the development of AI diagnostic models. Additionally, it includes the nationwide installation of PM2.5 sensors that are connected to hospital networks.

Second, the development of a real-time AI-based risk analysis platform for lung cancer is essential. This platform would utilize historical data from hospitals and meteorological departments to create machine learning models that predict health risks by location and time, with pilot implementations in high-risk provinces such as Bangkok and Chiang Mai.

Third, proactive health surveillance measures should be implemented in PM2.5-affected areas by deploying mobile medical units and photomicrographic images screening services and collecting health data for AI-driven analysis.

Fourth, AI-assisted medical image analysis should be promoted to enhance diagnostic accuracy and reduce the workload of medical personnel. This includes training programs for physicians, provision of AI-enabled software, and integration with electronic medical records (EMR) systems.

Fifth, public health AI governance policy must be established to ensure data security and citizen rights protection. This includes drafting regulations or laws to govern AI use, defining ethical guidelines (AI ethics) for medical personnel, and forming algorithm audit and transparency committees.

Sixth, strengthening public-private-academic collaboration is crucial for developing context-appropriate AI solutions. This can be achieved through joint academic conferences, cross-institutional research funding, and intersectoral data sharing initiatives.

Seventh, support for provincial-level pilot projects is vital for testing feasibility before national scale-up. Targeted provinces such as Bangkok, Chiang Mai, and Pathum Thani would serve as prototypes for AI surveillance and reporting systems, with evaluations to inform broader implementation.

Eighth, local health data analyst networks should be developed to build local capacity. This includes offering AI and data analytics training in collaboration with local governments and universities and establishing provincial data centers.

Ninth, public education and communication campaigns are necessary to promote understanding and engagement with AI in health care. These would include mobile applications for self-assessment and air quality alerts, local media campaigns, and awareness programs encouraging proactive health screening. Collectively, these integrated policy proposals aim to strengthen public health resilience, promote evidence-based policymaking, and leverage AI technology to mitigate the adverse health impacts of PM2.5 air pollution in Thailand.

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