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Literature Review

Transformation Concept of Artificial Intelligencein the Early Identification of Tuberculosis Recovery Phase: A Systematic Literature Review

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ABSTRACT

Background: Another chronic problem in tuberculosis (TB) eradication programs amid the widespread use of artificial intelligence (AI) in the health world is that early identification of the healing phase has not been found using similar technology. The purpose is to find if the transformation concept of AI will be able to help identify symptoms of early recovery of TB.
Methods: This research used a document review with a descriptive design. Data was processed by PRISMA analysis. The keywords were Artificial Intelligence, convalescence phase, and tuberculosis. The data were filtered from Google Engine included from Google Scholar, ResearchGate, PubMed, and Semantic Scholar screened in the last 5 years (2018-2023), in English or Indonesian. The stages of document screening were adjusted to the PRISMA diagram, and were analyzed descriptively.
Results: The study shows that the majority of AI studies discussed diagnosis (n=9 or 69.2%), only 3 documents (23.1%) discussed on TB treatment, and 1 document (7.7%) on monitoring. In conclusion, early identification of the recovery phase of TB patients is supported by previous researchers and can be done in the form of an application.
Conclusions: Artificial intelligence in the TB eradication program has value especially if conducted integrated with other health programs.

Keywords: Artificial Intelligence, convalescence phase, tuberculosis.

INTRODUCTION

In the last two decades, the transition from the manual to the digital era in the world of health has been felt by the emergence of health education that is affiliated with and based on information technology(1). The peak occurred during the pandemic when there were limited face-to-face interactions throughout the world(2). All education providers are required to implement an online learning system(3,4). The impact is that not only educational institutions are improving, but administrative staff, lecturers, students, and society as a whole are forced to adapt to the existing transformation system(5). The impact on the field of health research is no less widespread(6,7). The discovery of sensor technology in the health sector in Japan, the United States, and Europe, for example, has been able to monitor the habits or activities of patients in healthcare centers(8,9). Those technological changes allow nurses to monitor patients remotely(10). The innovation is global concrete evidence that modern humans are starting to depend on artificial intelligence (AI)(11).

Concerning the tuberculosis eradication program, the detection of tuberculosis (TB), which was initially felt to be hampered, especially in remote areas due to a lack of experts in radiology who could read X-ray examination results, is also experiencing a transition(12). Lung X-ray examination is a form of early detection of TB(13). With the advent of AI technology, it is programmed to be able to read X-ray results of lung examinations(14). Researchers used the deep convolutional neural network (DCNN) method, to input data about how to read an x-ray photo, and what signs indicate TB symptoms(15). By using the two DCNN models, AlexNet and GoogLeNet, researchers managed to get TB-positive results with an accuracy rate of 96 percent(16). The application of AI in the field of lung health is something new(17). Previously no machine was capable of having a screening accuracy rate above 80 percent. With the existence of AI technology, TB eradication by finding the disease earlier can become a reality(18). That way, TB examinations in remote areas that do not have radiologists can run optimally(19). AI is a solution for reading radiographic results for suspected TB patients, especially in hard-to-reach areas(20).

Tuberculosis (TB) is a chronic infectious disease that requires a long duration of treatment, usually, someone who is infected with TB and must take medication needs to undergo a duration of treatment of 6 to 9 months(21). However, studies have shown that TB can be cured 100% provided TB patients get proper examination and treatment for a predetermined duration(22). The treatment regimen consists of an initial (intensive) phase of 2 months and a continuation phase of 4-6 months(23). During the intensive phase which usually consists of 4 drugs, it is expected that there will be a reduction in the number of germs accompanied by clinical improvement(23). In the initial stage (intensive phase), the drug is given every day for 2 months, namely in the form of a combination of isoniazid, rifampicin, pyrazinamide, and ethambutol(24). In the advanced stage, the drug is given every day for 4 months, namely in the form of isoniazid and rifampicin(25). Follow-up phase treatment is given within 7 months, especially for groups of patients with drug-resistant pulmonary TB, patients with sputum cultures who remain positive after 2 months of intensive phase treatment, and patients with HIV who do not receive antiretroviral drugs (ARV)(26). Patients on pulmonary TB therapy need to undergo periodic evaluations to assess the response to OAT therapy(27). Examination of acid-fast bacilli (AFB) sputum was carried out at the end of the intensive phase(28). Positive AFB sputum at the end of the intensive phase may indicate an inadequate dose of anti-TB drugs, poor adherence to medication, the presence of comorbidities, or the presence of resistance to first-line drugs. AFB sputum examination was carried out again at the end of TB treatment(29). If the sputum shows positive results, the treatment can be considered a failure, and testing for drug resistance needs to be done(30).

As a first step in the early detection of TB, evaluation while undergoing TB therapy is basically at a certain stage it is possible to do it using AI [31]. The stages are namely after smear sputum examination, poor adherence to taking medication, presence or absence of comorbidities, the occurrence of drug resistance, and status of decreased signs of TB signs and symptoms(16). However, this action needs to be proven through a study. Among them is whether or not it is necessary to involve TB patient companions, bearing in mind that not all TB patients can do this even with the help of information technology. Especially in remote areas in eastern Indonesia such as Papua and East Nusa Tenggara(32).

This research using the document review method seeks to discuss whether or not it is possible to identify the initial healing phase of TB patients using Artificial Intelligence (AI). The goal is to get an overview of identifying which stages of healing can be evaluated by using AI. The implications of this research in the future can be used as reference and provide input for research related to evaluating the healing phase of TB patients so that it can be distinguished between what can be done with AI or physically.

METHOD

This research was motivated by tuberculosis cases in Central Papua, Indonesia, which was conducted using the document review method with a descriptive design. The research was conducted in March 2023. The primary data was filtered through documents through Google Engine which was analyzed with PRISMA. Initial screening was carried out through keywords: Artificial Intelligence, tuberculosis, and the healing phase. The main documents are sourced from journals published and collected by Google Scholar, PubMed, Research Gate, and Semantic Scholar over the last five years (2018-2023). Other official documents are sourced from WHO, the Ministry of Health of the Republic of Indonesia, and other related official sources. The stages of data processing consist of the first stage of Identification, the second stage of Screening, and the third stage of Inclusion. In the first stage, all documents are identified from the database. Irrelevant, unimportant, or duplicate data are deleted. In the second stage, only documents that are focused on the topic are taken, while those that are out of focus and not appropriate are removed. At the Inclusion stage, all data was reviewed and selected both in English and Indonesian. The inclusion criteria for this study were Artificial Intelligence, tuberculosis, and the healing phase in English or Indonesian, published within the last 5 years. The inclusion criteria used in the analysis of the data contained in the document use the words AND and or OR associated with the keywords. The exclusion criteria are all tuberculosis cases outside the healing phase and not written in English or Indonesian, issued more than 5 years ago.

RESULTS

Prisma Analysis

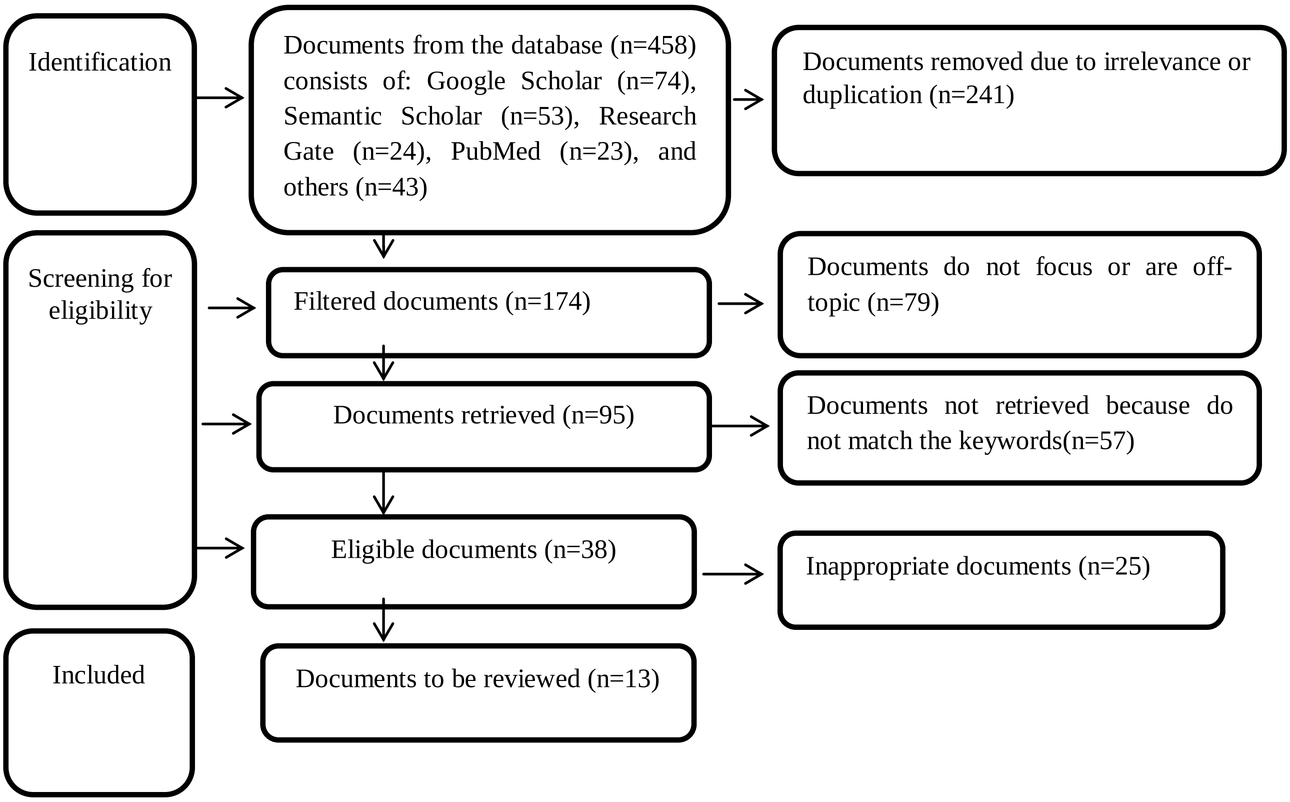

Diagram1: PRISMA Analysis Results

Reviewed Documents

The following are the detailed of 13 reviewed documents that consist of title, authors, year of publication, country of research, research methods, designs, populations, instruments and the results. Document number 1: Application of Machine Learning Clustering K-Means and Linear Regression in determination of the Risk Level of Pulmonary tuberculosis, by Ula et al., 2023, Indonesia. In quantitative, cluster-wise regression design, the instrument used was the K-Means algorithm, and the population was 400,000 residents of Beaureun-Aceh. The results show the clustering of areas prone to pulmonary tuberculosis are two areas belonging to cluster one, 6 regions belonging to cluster 2, and 9 regions belonging to cluster 3. They can be used as a reference for the health office in following up on lung disease(33).

Document number 2: A proposed artificial intelligence workflow to address application challenges leveraged on algorithm uncertainty, by Li et al., 2022, China. It was a quantitative, simulations, four scenarios with multi-center datasets. AI system consists of four main steps including CT slices segmentation and reconstruction. The results show artificial Intelligence was proven to be effective and improve practicability in clinical application. The human-machine convergence might improve the overall performance and gain more faith in AI algorithms in real-world settings(34).

Document number 3: Cough Sound Detection and Diagnosis Using Artificial Intelligence Techniques: Challenges and Opportunities, by Al Qudaihi et al., 2021, Saudi Arabia. It was a document review was used to search for articles on cough sound, diagnosis, artificial intelligence, machine learning, respiratory diseases, asthma diagnosis, pulmonary diagnosis, TB diagnosis, bronchitis diagnosis, pertussis diagnosis, and COVID-19 diagnosis. 93 papers were found, that proposed different AI-based solutions to classify and identify different respiratory diseases using cough sounds. The results show AI algorithms can be used to detect and diagnose different types of known diseases including pneumonia, pulmonary edema, asthma, tuberculosis (TB), COVID-19, pertussis, and other respiratory diseases(35).

Document number 4: COVID-19, Bacille Calmette-Guérin (BCG) and Tuberculosis: Cases and Recovery Previsions with Deep Learning Sequence Prediction, by Heni, 2020, Tunis. Document review and deep Learning sequence prediction models were used, for the continuous monitoring of the infection and recovery processes while considering the potential impacts of Bacille Calmette-Guérin (BCG) vaccination and tuberculosis (TB) infection rates in populations in 79 countries. The results show The model can evolve by continuously updating and enriching data and can help inform public health professionals, clinicians and decision-makers to take coordinative and collaborative efforts to control the epidemic(36).

Document number 5: Tuberculosis detection in chest radiograph using convolutional neural network architecture and explainable artificial intelligence, by Nafisah, and Muhammad, 2022, international. It was a quantitative, experimental design. The system used segmented lung CXR images and recent pre-trained CNN models. It is evaluated on multiple datasets and cross-dataset scenarios. The system includes several blocks. The results show using segmented lung CXR produces images with better performance than does use raw lung CXR images(37).

Document number 6: Ensemble deep learning for tuberculosis detection using chest X-Ray and canny edge detected images, by Hwa et al., 2019, Malaysia. It was a quantitative research. Deep learning for TB detection using chest x-ray and Canny edge detected images was used. To evaluate the proposed approach, two datasets were also publicly used. The results show that AI using different types of features extracted from different types of images can improve the detection rate(13).

Document number 7: Expert System Development For Diagnosis of TB Disease In Pandemic Time By Using The Forward Method Chaining At Medan Health Center, Johor, by Indra and Harahap, 2022, Indonesia. It was a quantitative and experimental design. The instrument used was computer technology of forward chaining to find signs and symptoms to help determine the TB diagnosis. The result of this study was the application of a system that can detect information on TB about the symptoms and diseases and seek advice and solutions for TB(38).

Document number 8: Database System for Storing Tuberculosis Sputum Sample Images as an AI Training Dataset, by Mulyo et al., 2022, Indonesia. It was a quantitative method, and experimental design. A database system for storing TB sputum sample images was used as the dataset to train an AI system for TB detection. The results show A database system for storing TB sputum sample images was presented. This allows health workers to manage them and be used to train AI systems to speed up the diagnostic process of TB(39).

Document number 9: Classification of TB using the Extreme Method Machine Learning, by Nurdiansyah, 2020, Indonesia. It was a Quantitative research with the ELM method. Using 2 classes namely class 1 is a positive class and class 2 is negative for TB disease. The dataset will be normalized, and at the training stage it will produce an output weight value, later this value will be used in the testing process to generate output layer values. The process of calculating the test using a confusion matrix with parameters sensitivity, specificity, and accuracy to calculate the system work in doing the classification process. The results show the ELM method for the classification of TB produces 99.33% accuracy, 0.99 sensitivity, and 1.00 specificity using optimal parameters on the test. The optimal number of hidden neurons is 20. The binary sigmoid activation function represents the optimal function in this study, and the optimal percentage of training data and testing data by 70%:30%(40).

Document number 10: The Digital Health Utilization to Improve Successful Treatment of Tuberculosis Patients in Developing Countries: Literature Review, by Farhana, 2022, Indonesia. It was a scoping review using the 5-step framework of Arksey and O'Malley. Inclusion criteria were research articles, published from 2016 to 2022, in full text, in English, and discussed the use of digital health applications to improve treatment success for tuberculosis patients. Digital health can be a solution in the treatment of tuberculosis patients. the type of application is used as an effort to increase the success of TB treatment namely short message service (SMS) and video observed therapy(VOTS)(41).

Document number 11: Application for Early diagnosis of tuberculosis By Using the Certainty Factor Method, by Alfianto and Benisius, 2018,Indonesia. It was a quantitative research followed by problem identification and literature study. The analysis and design of the application expert system include analysis of system requirements, flow design, database, and user interface. Then translated into an expert system application. The test validity of the output by the expert system is done before testing on the application. The results show The certainty factor method can be used to develop an expert system that can be used to diagnose pulmonary and gland tuberculosis with a low error rate(42).

Document number 12: Diagnosis of Pulmonary Tuberculosis Based on X-ray Image Using Convolutional Neural Network, by Bahri et al., 2021, Indonesia. It was a quantitative study. Machine learning based on x-ray image results using the CNN Algorithm was used, by classifying normal x-ray images and tuberculosis x-ray images. X-ray images of the lungs to detect lung disease caused by mycobacterium tuberculosis were discussed. The results show the classification results obtained by CNN after the model evaluation process show a fairly good value, namely for accuracy value within the range of 89%(43).

Document number 13: Early Diagnosis of Tuberculosis Using Deep Learning Approach for IOT Based Healthcare

Applications, by Margarat et al., 2022, India.n it was a Quantitative study with hybrid models. A dataset like Shenzhen China (SC) and Montgomery Country (MC) was used for the process. The image was resized and the noise was removed using the WF filter. The image was segmented using AFCM. GF, shape, texture, and HoG features were extracted. Finally, a DL model DBN-AMBO was used to classify the image as normal and TB. The results show 99% accuracy was achieved by the study while comparing it to other state-of-the-art approaches. CXR images can be used for TB-affected people who are affected by COVID-19 and pneumonia(44).

Analysis

Of the 13 documents above, 7 of them were made in Indonesia (53.8%). The rest is in Saudi Arabia, China, Tunisia, Malaysia, India, and mixed countries. The majority of the research methods used quantitative (n=10 or 76.9%) and the rest were document reviews (n=3 or 23.1%). Most of the research on AI discussed diagnosis (n=9 or 69.2%), 3 documents (23.1%) discussed TB monitoring, and 1 (7.7%). Although all documents (n = 13 or 100%) allude to the recovery phase, no research discusses the role of AI in identifying symptoms or signs during the TB healing phase, except for the medical treatment aspect. Table 2 below the projected documents analyzed in table 1. The keywords used in this analysis stage were based on keywords (Artificial Intelligence, tuberculosis, and recovery phase). Of the 13 documents that were filtered, 100% (n=13) fulfilled the two keywords namely 'Artificial Intelligence' and 'Tuberculosis', while 9 documents (n=9 or 69.2%) fulfilled the keywords 'Recovery', each document number 3, 5, 6, 7, 8, 9, 11, 12, 13). Meanwhile, the 3 advantages of AI discussed in the thirteen documents are: establishing diagnoses (n=9 or 69.2%), treatment (n=1 or 7.7%), and monitoring (n=3 or 23.1%).

DISCUSSION

This research has attempted to reveal the massive development of AI in the world of health, especially regarding tuberculosis. Three important issues are underlined by this study despite the rampant research on AI in treating TB (Table 1). Those problems are the majority of AI discussing the role of early detection of TB through X-Ray as a determinant of a definite diagnosis. Second, there has not been found the involvement of AI in early detection where patients have a role, for example in the form of downloadable applications that can be owned by patients, so that it benefits the public. Third, if the early symptoms/signs of tuberculosis can be identified, similar symptoms/signs should be carried out during the recovery phase.

The characteristics of cured TB disease can be seen from the absence of clinical symptoms in patients(45). Common symptoms such as coughing, chest pain, fatigue, or shortness of breath start to disappear. In some cases, symptoms such as coughing may still occur after being declared cured of TB(46). The disappearance of those symptoms should be based on the diagnosis. Usually, the doctor will carry out a series of examinations, from sputum examination to chest X-ray examination to compare and see the progress of treatment. If bacteria are still found, then pulmonary TB disease cannot be declared cured(47). Vice versa, if the pulmonary TB germs on the X-ray results are completely gone, it can be stated that treatment has been completed and a complete recovery(29).

Thus, there are two criteria used to determine the patient's recovery rate. Signs/physical symptoms of the patient and the results of laboratory tests and X-rays. The first criterion can be done by the patient which can be done through the application. Meanwhile, the second examination requires the intervention of a health worker as was done by the research in documents no. 3, 7, 10, and 11 (Table 1) for patients. As for health workers, according to research recommendations as discussed in documents number 5 and 12 (Table 1). Thus, the findings discussed in this study prove that the concept of using AI in the early identification of the recovery phase of TB patients can be implemented in the form of applications for both patients/clients and healthcare professionals.

Many studies discuss the advantages and disadvantages of using AI in medicine(13,48). The application of the use of AI in TB eradication programs, especially in remote areas or tribal areas, will be very helpful, especially due to the difficulty of reaching health facilities, as many are found in Papua, Indonesia(49,50). Nevertheless, one thing that needs to be taken into account is the availability of an adequate telecommunication network. Because without the internet, AI which depends a lot on it, the program will not work properly(51). On the one hand, AI in the TB eradication program has value especially if conducted integrated with other health programs (52), is effective and efficient. On the other hand, it requires large funds to implement it, especially in tribal areas (53). Therefore starting the program through a pilot project can be used as a solution so that an overview of the program can be obtained in the future.

The limitations of this study include the lack of relevant data that can answer all the research questions desired in the topic, for example, what can be done and contributed by Artificial Intelligence regarding the early identification of the recovery phase of tuberculosis, and what signs can be monitored (physical, laboratory, or lung X-Ray). The results of this study also did not mention that there was a study that discussed signs of recovery that could be identified during other healing periods except through chest X-Ray. The lack of research makes this study poor references according to the topic. Therefore, in the future, further research is needed in the form of direct research related to the role of AI during the recovery phase of TB patients.

CONCLUSION

One of the drawbacks of research with document reviews is that a concrete picture of research results cannot be obtained. Therefore, the solution is to do direct research. This article has attempted to reveal the possibility of realizing the use of AI in the early identification of the TB patient's recovery phase. The results of the analysis of previous studies show that the concept of using AI in the early identification of the healing phase of TB patients can be carried out in two stages. The first is in the form of an application for both patients/clients and healthcare professionals. The second is through the results of laboratory and X-Ray examinations whose results can also be uploaded in the application. So that patients do not have to meet directly with health workers to determine the stage of their recovery.

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