Suez Canal Engineering Energy and Environmental Science Journal
Faculty of Engineering – Suez Canal University
2025, Volume 3, NO. 3, pages 89– 98

Detecting Pandemics by Using Artificial Intelligence

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DOI: 10.21608/sceee.2025.396033.1083,

Article Info:

Article History:
Received: 29\06\2025
Accepted: 19\17\2025
Published: 30\07\2025

DOI: 10.21608/sceee.2025.396033.1083,

Abstract

Timely detection of disease outbreaks is critical in public health. Artificial Intelligence (AI) can identify patterns in data that signal the onset of epidemics and pandemics. This schematic review examines the effectiveness of AI in epidemic and pandemic Early Warning Systems (EWS). To assess the capability of AI-based systems in predicting epidemics and pandemics and to identify challenges and strategies for improvement. A systematic review was conducted. The review included studies from the last 5 years, focusing on AI and machine learning applications in EWS. After screening 1087 articles, 33 were selected for thematic analysis. The review found that AI-based EWS have been effectively implemented in various contexts, using a range of algorithms. Key challenges identified include data quality, model explainability, bias, data volume, velocity, variety, availability, and granularity. Strategies for mitigating AI bias and improving system adaptability were also discussed. AI has shown promise in enhancing the speed and accuracy of epidemic detection. However, challenges related to data quality, bias, and model transparency must be addressed to enhance the reliability and generalizability of AI-based EWS. Continuous monitoring and improvement, as well as incorporating social and environmental data, are essential for future development.

Keywords: *Computer-aided diagnosis - Telemedicine - Deep learning - Infectious diseases.*

Suez Canal Engineering, Energy and Environmental Science Journal (2025), ***Vol. 3***, No. 3

1. Introduction

1.1. Background

A pandemic is characterized as an infectious disease that spreads rapidly across vast geographical areas with very high transmission rates. Artificial intelligence (AI) has revolutionized the management of infectious diseases by enhancing various aspects such as disease prediction, diagnosis, drug and vaccine discovery, and treatment. A major advancement in AI is deep learning (DL), an advanced form of machine learning. DL utilizes complex neural networks to analyze extensive datasets, recognize patterns, and make predictions. Building on the capabilities of deep learning, another sophisticated technique is reinforcement learning (RL). RL mimics human decision-making by leveraging continuously updated data to provide tailored recommendations. RL adapts to individual patient situations and makes dynamic, real-time decisions.

This Survey explores the applications and limitations of AI in the context of pandemics and infectious diseases, focusing on its role throughout all stages of an outbreak. AI has been instrumental in predicting, diagnosing, and treating infectious diseases, as well as aiding in the development of vaccines and drugs. By integrating large datasets and continuously evolving algorithms, AI technologies can process vast amounts of information, offering unparalleled accuracy and efficiency. Despite these advancements, the full potential of AI in medical practice is contingent on addressing the limitations and challenges that currently exist, including issues surrounding data privacy, model transparency, and evolving pathogen strains.

1.2. Problem Statement

Since the outbreak of the COVID-19 pandemic, there has been a growing interest in using AI to support medical diagnosis. One of the models that has been used is VGGNet, particularly the VGG16 architecture, which showed promising results in identifying diseases from chest X-ray images (Abueg M., Hinch R., Wu N., Liu L., Probert W., Wu A., et al. 2021).

In this survey, a dataset of 1206 chest X-ray images (from the Kaggle website) was used to classify four conditions: pulmonary tuberculosis, pneumonia, COVID-19, and normal lungs. The model was evaluated based on accuracy, specificity, and sensitivity, achieving scores of 0.97, 0.96, and 0.98, respectively. These results suggest that VGG16 was highly effective in distinguishing between different diseases in X-ray images.

Interestingly, the study found that VGG16 performed better than VGG19 in diagnosing epidemic-related diseases. This approach also helped in faster diagnosis, potentially increasing the chances of recovery. Overall, using chest X-rays with VGG16 was found to be more accurate, simpler, and less expensive than using CT scans (Figure 1).

Based on a review of several research studies, VGG-16 appears to be one of the most effective models for this task. This conclusion is consistently supported across multiple papers, which highlight its strong performance in comparison to other architectures.

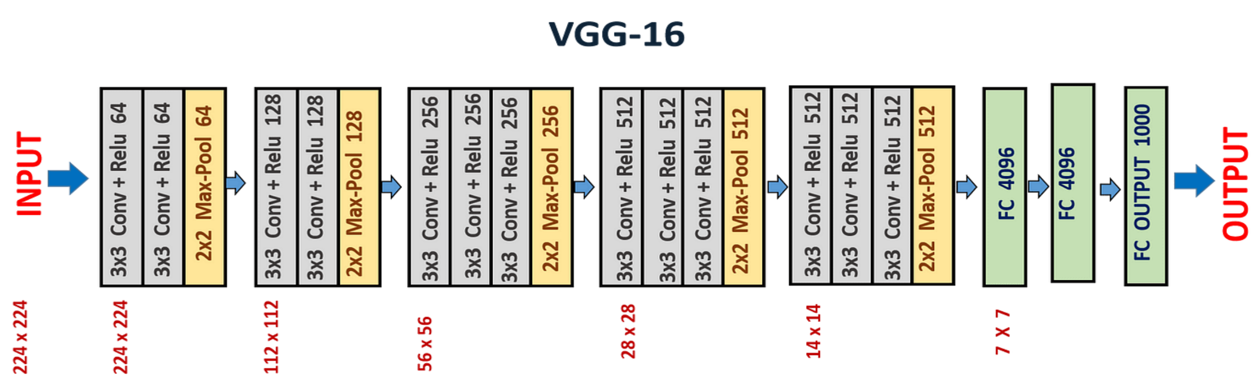

Figure 1: VGG16 Model (Abueg M., Hinch R., Wu N., Liu L., Probert W., Wu A., et al. 2021).

1.3. Objectives and methodology

Several machine learning methods are applied for the automated classification of digital medical images. Machine learning pattern recognition can determine visual features used for detection, diagnosis, or classification. The training types of machine learning algorithms are frequently classified: supervised, unsupervised, and reinforcement learning Adhikari, M., Ambigavathi M., Menon V. G., Hammoudeh M. 2021). Supervised learning entails accumulating experience with usable images and applying that knowledge to predict new images that have not been seen before (test data). A deep learning approach for pandemic identification has been proposed by researchers who used the Dense Net network with pandemics to predict which existing antivirals can benefit pandemic-affected patients.

Opacities in the correct space were discovered in a severe pandemic, according to Kong et al. Yoon et al also found that one out of three patients exhibited one nodular opacity in the left lower lung region. In both lungs, the opposing two exhibited four and five irregular opacities. In recent years, the Convolutional Neural Network (CNN) has become one of the most well-known methods in AI. MRI, X-ray, CT scans, Ultrasonography, and other medical image analyses have all shown success with CNN. In addition to linguistic communication processing, computer vision, audio recognition, and speech recognition, CNN has had much success (Ahmed S., Shrestha A., Yong J., 2021).

2. Related Works

Given the significant amount of research efforts on using mobile IoT devices for pandemic detection and prediction, in this paper, we conduct a survey of a subset of the pandemic-related work. Specifically, we categorize the related work into the following topics and accordingly present a survey of the current research efforts on using mobile IoT devices, AI, and telemedicine for pandemic detection and prediction.

1. Detection and Monitoring,
2. Contact Tracing,
3. Machine Learning Framework and Approaches,
4. Telemedicine,
5. Security.

2.1. Overview of papers reviewed in this survey

The current research is being conducted on the topic of using mobile devices for pandemic detection and prediction. We classify the related work and present the work in each category in the following subsections. Table 1 shows an overview of all methods and papers reviewed in this survey according to their categories or sub-categories. As we cited more than 150 papers in this survey, we picked 16 papers as an example to show the work in the area of pandemic detection and prediction using mobile devices, AI, and telemedicine. A summary of the selected studies is presented in Table 1.

Table 1: Summary of selected papers in this survey as illustration examples.

References	Country	Journal/conference	Method or focus	Functionality
Jeong et al. (2019)	South Korea	IEEE access	Magnetometer-based diagnostic test (Section 2.2.1)	Automatic contact tracing
Omboni (2020)	Italy	Telemedicine and e-Health	Case study (Section 2.4)	Create interconnection and multidisciplinary research
Seshadri et al. (2020)	USA	Front. Digit. Health	Survey (Section 2.1.2)	Digital health platforms
Vekaria et al. (2020)	USA	IEEE access	LSTM model (Section 2.1.1)	Health monitoring
Wang et al. (2020)	UK	IEEE access	Reinforcement learning (Section 2.3.4)	Risk-aware identification
Zhou et al. (2021)	China	Applied soft computing	CNN, Transfer learning (Section 2.3.3)	COVID detection and classification
Awal et al. (2021)	Bangladesh	IEEE Access	ML framework (Section 2.3.4)	Detection from inpatient data

Tahiliani et al. (2021)	India	IEEE Internet of Things Magazine	Blockchain (Section 2.4, Section 2.5)	Data security and user privacy
Elbasi et al. (2021)	Kuwait	Electronics	ML algorithms (Section 2.1)	Public space monitoring
Lo and Sim (2021)	USA	Annals of Internal Medicine	Survey (Section 2.1)	Framework for assessing contact tracing
Jiang et al. (2021)	USA	IEEE Reviews in Biomedical Engineering	AI and sensor fusion (Section 2.4)	Long-term monitoring for chronic diseases
Orlandic et al. (2021)	Switzerlan d	Scientific Data	Fleiss'Kappa scores (Section 2.3.3)	Cough detection and classification
Tan et al. (2021)	USA	Neural Computing and Applications	5G and LSTM (Section 2.1.2)	Real-time cardiovascular monitoring system
Tu et al. (2021)	China	IEEE Sensors Journal	CNN for PDR positioning trajectory (Section 2.2.2)	Contact tracing
Xu et al. (2022)	China	IEEE Transactions on Services Computing	ML and edge-cloud (Section 2.5)	Detection on X-ray images
Mir et al. (2022)	India	Journal of Healthcare Engineering	IoT-enabled framework (Section 2.3.2)	Detection and prediction of IoT data

2.2. Detection and monitoring

IoT devices can transmit data by connecting wirelessly to a network. Thus, wearable devices, such as head bands, chest bands, and wrist bands, have been used to collect real-time vital information from people to their smartphones for pandemic monitoring and detection. The focus of these technologies is on the health and well-being of occupants within a certain area (Alsarhan A., Almalkawi I. T., Kilani Y. 2021). The end goal is twofold: monitoring and detection before and after the pandemic's infection. Detection is for timely treatment in case a patient becomes symptomatic. Monitoring is used to further mitigate the spread of pandemics once a test is positive, by emphasizing the continuous monitoring of patients who test positive for pandemics.

Table 2: Summary of ML models, data modalities, and metrics of the papers reviewed in this survey

References	Journal/conference	Data	Data modality	ML	Metrics
Dang et al. (2019)	Journal of Medical Internet Research	Audio dataset	3	GRU	AUC: 79%, Sensitivity: 75%, Specificity 71%
Ardabili et al. (2020)	Algorithms	COVID dataset	2	MLP, ANFIS	N/A
Vekaria et al. (2020)	IEEE Internet of Things Journal	IoT and economic data	5	LSTM	MAPE: 1.27%, RMSE: 6308
Wang et al. (2020)	IEEE Access	Social Internet of	2	FL, GNN	N/A

		Things (SIoT) data			
Magesh et al. (2020)	International Journal of Pervasive Computing and Communications	Thermal, Acoustic	1-2	RNN, LSTM	N/A
Vedaei et al. (2020)	IEEE access	Health parameters	4	SVM, Decistion tree	Accuracy: 68.9–76.9%, F1-score: 69.7–77.3%
Alanazi et al. (2020)	Journal of Healthcare Engineering	PANDMICS data	3	Statistic analysis	N/A
Zhou et al. (2021)	Applied soft computing	CT images	2	CNN, Transfer learning, Ensemble learning	Accuracy: 97–99.05%
Shorfuzzaman (2021)	Computing	CT images	2	CNN	Accuracy: 96.58%, Precision & Specificity: 99.16%, AUC score: 96.6%
Orlandic et al. (2021)	Scientific Data	Audio dataset	7	XGB, CV	Precision: 95.4%, Sensitivity: 78.2%, Specificity: 95.3%, Balanced Accuracy: 86.7,% AUC: 96.4%
Xia et al. (2021)	NeurIPS	Audio dataset	6	SVM, CNN	AUC: 75% Sensitivity: 70%, Specificity: 70%
Singh and Kaur (2021)	World Journal of Engineering	Framework measurement	4	Fog computing	Classification: 81.2%, Kappa: 0.732, RMSE: 0.241
Muhammad et al. (2021)	IEEE Network	Cough sound, Chest X-ray	2	FL	Accuracy: 95%, Precision: 97%-99%
Purnomo et al. (2021)	Sensors	Breathing Movement	1	XGBoost, MFCC	Accuracy: 87.38%
Barnawi et al. (2021)	Future Generation Computer Systems	UAV Thermal image	2	CNN, DCNN	Accuracy: 98–99.4%, Precision: 100%, 96–99%
Alsarhan et al. (2021)	International Journal of Interactive Mobile Technologies	Contact tracing data	1	RL	Packet loss probability: 0.1–0.4, Arrival rates: 80–120
Almalki et al. (2022)	Computing	UAV Thermal image	1	CNN, MANN	Accuracy: 82.63%, F-1 score: 0.98

Karmore et al. (2022)	IEEE Sensors Journal	Humanoid modules	6	Decision tree, TCN	Sensitivity: 95.39%, Specificity: 97.60%, Precision: 95.47%, Accuracy: 97.95%
Fahad et al. (2022)	Biomedical Engineering: Applications, Basis, and Communications	CT images	2	AI-PSR model	N/A
Mir et al. (2022)	Journal of Healthcare Engineering	IoT Sensors	7	SVM, decision tree, NB, LR, NN	SVM Accuracy: 93.0%
Khelili et al. (2022)	Biomedical Signal Processing and Control	X-ray images	3	CNN	Classification: 97%, Precision: 100%

2.3. Machine learning on IoT devices

Widely-used smartphones, smart watches, and smart devices are promising in helping detect and predict using ML techniques. One method utilizes a patient's temperature data from an infrared thermometer (figure 2), a thermographic camera, and an acoustic device as inputs to a Mode and Mean Missing Data Imputation (MMM-DI) method to predict pandemic infections through a Recurrent Neural Network (RNN) with long-term short memory enacted (Figure 2). Another system utilizes smartphone apps and the patients'

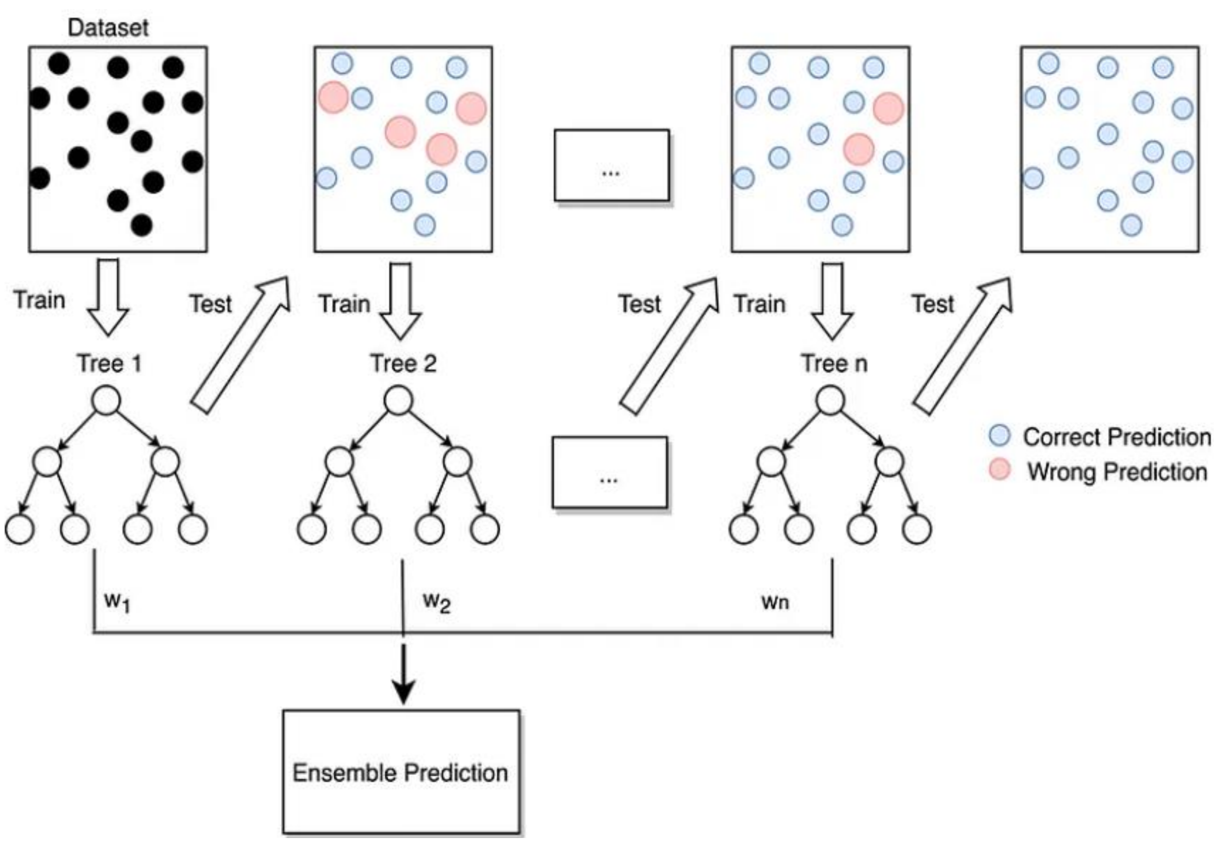

Figure 2 GBM Algorithm in ML (Dang T., Han J., Xia T., Spathis D., Bondareva E., Siegele-Brown C., et al. 2022)

IoT devices to track and send vital signs to an ML model in the cloud that predicts the risk of pandemic infection in real time in an area and then notifies the users. This approach is also utilized on a patient's breathing patterns for predicting pandemic detection through Xtreme Gradient Boosting (XGBoost), a Gradient Boosting Machine (GBM) algorithm, and classification ML models. Some ML-based approaches use smart devices for pandemic infection detection using their respiratory rate. Whoop is a wearable that has been validated by a third-party clinical trial to accurately measure respiratory rates to predict pandemic infections. Furthermore, there is a combination of AI and physiological sensor readings (AI-PSR) that helps the doctors predict and diagnose COVID-based respiratory failures (Dang T., Han J., Xia T., Spathis D., Bondareva E., Siegele-Brown C., et al. 2022).

One area of research focuses on integrating drones and Unmanned aerial vehicles (UAVs) into the wireless architecture along with AI systems to predict and combat pandemics. The approach uses thermal imaging cameras on the UAVs to evaluate body temperatures to help minimize the risk of spreading the infection through close contact. The drones are also equipped with a face mask recognition system to detect whether a person has a mask on their face or not. Another area of research focuses on studying the integration of AI systems with humanoid robots to detect pandemics in potential patients. The humanoid, through real-time monitoring by an AI system, can provide a patient with a complete pandemic diagnosis, which reduces the risk of spreading the virus and the medical system's workload.

2.4. Cloud and 5G platforms

A framework consisting of a data collection center, a data analytics center, a diagnostic system, and a cloud system. Through data collection and data analysis, the information would be stored in the cloud and be reused by healthcare professionals for further analysis. Also, the data will be used to update machine learning models for deriving more accurate results.

Research has also been conducted toward integrating AI systems with 5G networks and the cloud. The fifth-generation cellular technology assists medical services with 5G-cloud Robots that lessen the workload on mobile devices (Figure 3). The robot can be used for disinfection of surfaces, temperature testing, food delivery, and medicine delivery to infected people to mitigate pandemic virus spread (|Adhikari M., Ambigavathi M., Menon V. G., Hammoudeh M. 2021).

Some methods deploy AI and ML systems onto the cloud for pandemic prediction. Server or cloud-based AI screening services for pandemics, such as those in Buoy Health and others, have been developed. In these screening systems, the ML models running in the cloud receive data from users and send screening results back to the users. Some other works design fog-cloud-based systems for pandemic prediction using

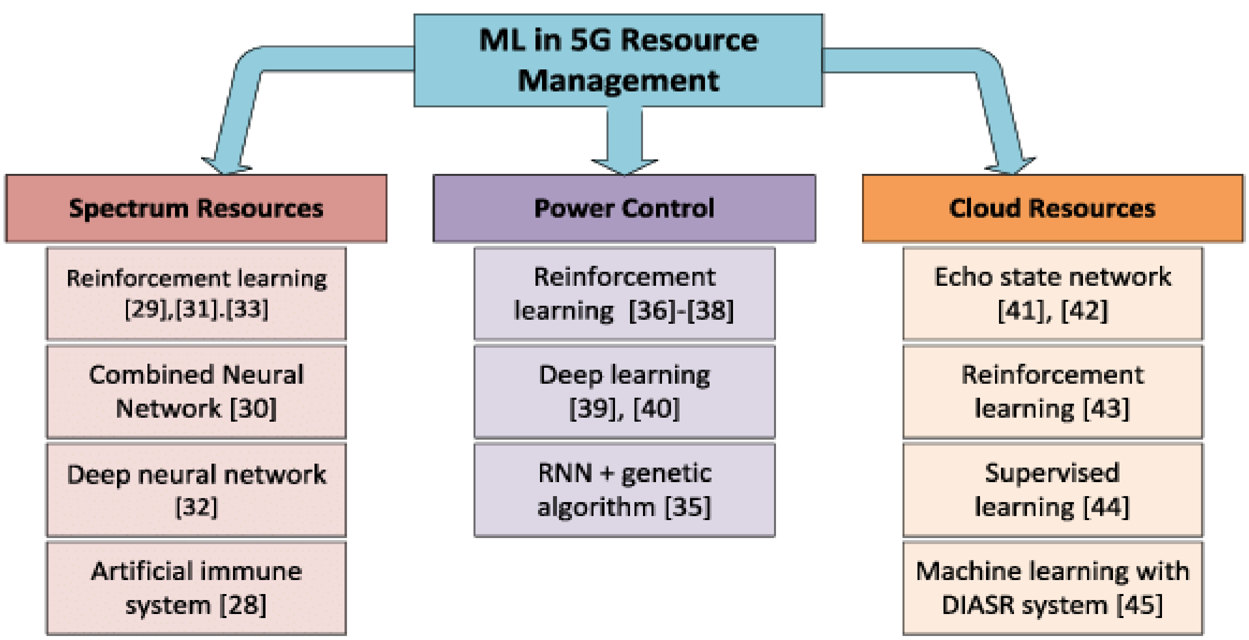

Figure 3 ML in 5G Resourse Management (|Adhikari M., Ambigavathi M., Menon V. G., Hammoudeh M. 2021)

IoT devices, where the fog computing cluster enables the processing of IoT tasks independently of the Cloud layer (Ardabili S. F., Mosavi A., Ghamisi P., Ferdinand F., Varkonyi-Koczy A. R., Reuter U., et al. 2020).

AI and ML models and systems have also been integrated with geo-location systems to predict and model the potential spread of pandemics. In a similar vein, ML models also have been used during the peak of the pandemic to forecast a long-term trajectory of the spread of the virus.

2.5. Multimodal datasets

As promising tools, ML and AI techniques are considered a key element in epidemic and transmission prediction, diagnosis and detection, and the development of new treatment options. These models utilize datasets that are based on patients' basic information, patients' health and medical data, and the pandemic test results. Three main types of datasets in pandemics have been gathered and used: textual data, medical data, and speech data. Textual data includes dashboards, mobility data, case reports, social media posts, and articles. Medical data is from the diagnosis and screening of pandemic patients, such as medical X-rays, CT scans, ultrasound, or MRI. Speech data includes cough sound, breathing rate, and stress detection techniques. It should be noted that missing value detection is necessary for pre-processing for all data that is used.

Chest X-ray images, CT images, mobile sensor data, pandemic symptoms, and previous medical data of the patients are used as input for an ML method to predict pandemics. AI and ML methods have a significant contribution in the areas of vaccine discovery (Dataset, 2022). Federated Learning), in which the development focuses on the prediction of potential epitopes by using a variety of methods, including artificial neural networks, gradient boosting decision trees, and deep neural networks. AI has been utilized in combating pandemics from various aspects, including pandemic detection and diagnosis, virology and pathogenesis, pandemic drug and vaccine development, and epidemic and transmission prediction (Dataset, 2022a). Apple Pandemic Screening Tool.

One example of research that has been conducted using medical data to predict pandemic infections utilizes patients' CT scan images. CT images can reflect clinical pandemic classification because of their high consistency and diagnostic ability (Figure 4). Proposed an IoT-enabled end-to-end integrated stacked deep learning method to precisely detect pandemic infections using CT images (Dataset, 2022d). Pandemics Self-Assessment Tool). It utilizes three different fine-tuned CNN models, achieving an accuracy of 96.58% in categorizing pandemics and non-COVID CT images, with a high specificity value. However, using chest CT images alone can lead to misdiagnosis of severe pandemic patients, which would bring potential infection risk; therefore, CT images were not recommended for an independent screening tool.

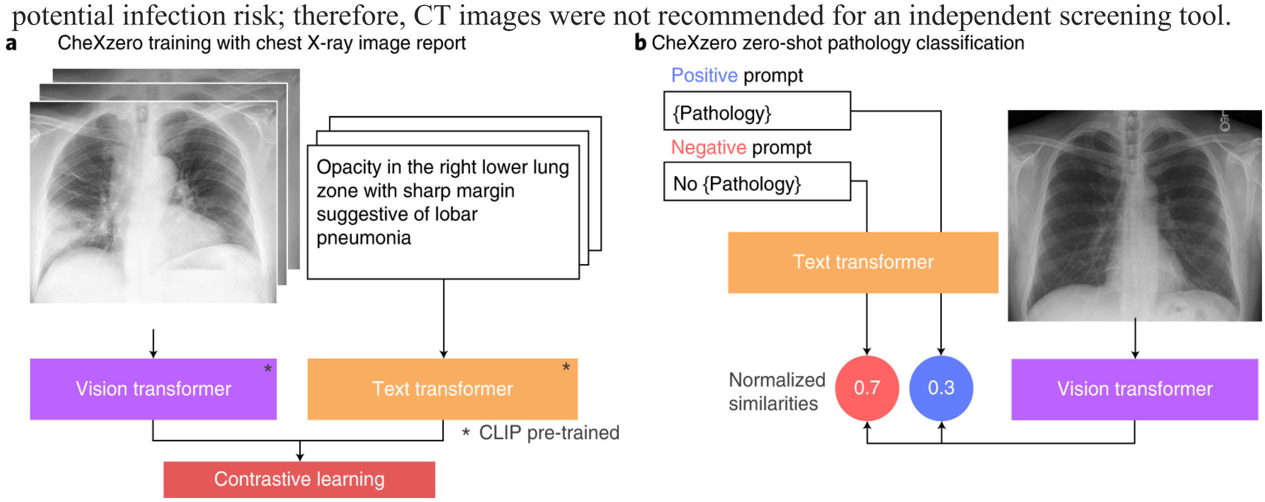

Figure 4 Chest X-ray Processing (|Adhikari M., Ambigavathi M., Menon V. G., Hammoudeh M. 2021)

2.6. Machine learning models

To reduce hospital admission pressure related to pandemics, AI-assisted edge computing systems use edge-centric e-healthcare models for monitoring patient symptoms to predict the risk levels according to the monitored symptoms. Also, a variety of pandemic prediction models have been proposed, ranging from decision trees, Naive Bayes classifier, adaptive network-based fuzzy inference system, Multi-Layer perceptron, and Support Vector Machines (Dataset, 2017). Federated Learning: Collaborative Machine Learning Without Centralized Training Data. These models have been designed to run on edge devices as well as on the cloud, with some models on the cloud utilizing stored data such as temperature data, audio data, and heart rate data to make pandemic diagnoses. Deep learning methods have also been utilized to predict pandemic infections using the data gathered from wireless devices. One example of this work is a learning pipeline that utilizes data from IoT devices to predict pandemic infections using a Long Short-Term Memory (LSTM). Furthermore, another approach uses reinforcement learning on COVID-19 infection data to build neural networks capable of predicting pandemics.

3. Conclusion

We present a survey of the current research work on the use of mobile IoT devices, AI, and Telemedicine for pandemic detection and prediction. In this survey, we first introduce monitoring and detection methods and their purposes, and then the contact tracing methods that can reduce the spread of the virus. We also present machine learning based approaches to aid in combating the pandemic. Next, we present the use of telemedicine as a new approach for pandemic diagnosis. Lastly. Pandemics are here to stay, and we must use all of the tools we can to effectively combat and mitigate their impact on our daily lives. Although there has been a great amount of research work done, there are still many challenges that lie ahead. Thus, we also illustrate the future work and challenges in using mobile IoT devices for combating pandemics.

In my opinion, we can make enhancements to prediction by using ML with 5G and integrate this model into a mobile application to facilitate its usage by people.

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