Proposing a Mobile Application for Educational Institutions' Support during Epidemic Crises

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Abstract

This study proposes an intelligent system designed to detect and manage epidemic outbreaks within institutional settings by leveraging a fusion of advanced AI technologies. The system operates through five key stages: symptom-based diagnostic testing, AI-powered cough detection, analysis of X-ray and CT scan images using Convolutional Neural Networks (CNN), evaluation of vital signs, and the geolocation of COVID-19 patients using GPS. Cough detection is enhanced by integrating Short-Time Fourier Transform (STFT) and Mel-Frequency Cepstral Coefficients (MFCC). Trained on an extensive dataset comprising over 5,856 CT scans, 7135 X-ray images, and over 30,000 crowdsourced cough recordings, the system demonstrates a high accuracy rate of 95% in identifying potential epidemic cases. This fusion of techniques offers a robust solution for early detection and rapid intervention, significantly mitigating the risk of widespread transmission within high-density environments.

Keywords: Institutions; Epidemics, CNN; MF-STFT; Crisis; CT, X-Ray

1. Introduction

In recent decades, several new diseases have emerged in different geographical areas, with pathogens including the Ebola virus, Zika virus, Nipah virus, and coronaviruses (CoVs) [1]. An epidemic is "the occurrence in a community or region of cases of an illness, clearly over normal expectancy" [2]. Controlling an epidemic necessitates extensive surveillance, data exchange, and patient monitoring. Effective healthcare, from local hospitals to the World Health Organization (WHO), requires support tools that ensure promptness and simplicity in communication to prevent the spread of diseases [3].

Disasters and crises are situations that people may face throughout their lives. These scenarios often have severe consequences, including death and property loss. The importance of crisis management has grown significantly, as calamities such as terrorism, floods, earthquakes, fires, traffic accidents, workplace accidents, and others can have a detrimental impact on all or significant portions of society [4]. Events that cause severe emotional and social distress can occur at any time and without warning. These occurrences are often called traumatic incidents, crises, critical incidents, catastrophes, and emergencies [5].

A crisis is an unanticipated event that can threaten an organization's employees, property, stakeholders, reputation, and future assets. This may include school bus accidents, suicides, multiple injuries or deaths, and natural disasters, which can quickly escalate into widespread destruction if not addressed promptly and effectively [6]. A crisis is an unexpected challenge, a complex phase of an event, a difficult situation to overcome, a sudden escalation, or a critical moment that can lead to further deterioration [7]. Crisis management is more than a single mouse click or a series of steps to address a Crisis; it also involves coordinating efforts to avoid or stop a crisis. It also involves a proactive strategy for managing potential crises. Previously, this was known as emergency management, which might include responding to accidents and incidents [6].

DOI: https://doi.org/10.54216/FPA.170118
Received: November 29, 2023 Revised: March 20, 2024 Accepted: July 25, 2024

Artificial intelligence (AI) is an emerging field of technology and science. It affects numerous human activities across various societal levels, including individuals, social groups, organizations, and governments. AI rapidly expands globally in nearly every industrial, economic, and societal sector, from information technology to commerce, manufacturing, space exploration, remote sensing, security and defence, transportation, and vehicles. Since the beginning of the twenty-first century, AI has also made significant inroads into medicine and healthcare [8].

Deep learning is an artificial intelligence function that mimics how the human brain processes data and creates patterns for decision-making. It is a subset of machine learning within artificial intelligence (AI) that enables networks to learn from unstructured or unlabelled data, often unsupervised. This approach is called deep neural learning or networks [9]. Smartphones and mobile devices can offer fantastic support for healthcare, but their full potential and optimal applications have yet to be realized. To do this, a thorough list of the healthcare requirements for mobile devices should be evaluated and updated [10].

This paper introduces a proposed mobile application to help institutions face epidemic crises. The structure of this paper is organized as follows: Section 2 discusses the related works in the area of the impact and detection of Covid on institutions, Section 3 describes the contributions of the proposed system, Section 4 introduces system development, and Section 5 presents an implementation for the proposed system, the last section discusses the results achieved using various combinations.

2. Related work

Govardhan Jain et al. (2020) developed a deep-learning method for detecting the COVID-19 coronavirus using X-ray pictures. The proposed technique was implemented in four stages: data augmentation, pre-processing, Stage-I, and Stage-II deep network model building. They employed web resources containing 1,215 photos and enhanced them with data augmentation techniques to improve model generalization and prevent overfitting by increasing the dataset's overall size to 1,832 images. In the case of COVID-19 detection, the high classification accuracy of 97.77%, recall of 97.14%, and precision of 97.14% indicate the effectiveness of the proposed technique within the existing time constraints [11].

Mohamed Bader et al. (2020) provided research on the similarity of COVID-19 sounds using MFCC correlation analysis. They developed, evaluated, and investigated the assessment of MFCC acoustic characteristics, as well as the correlation analysis of these features obtained from infected patients and healthy individuals, to determine whether there was a link. Using Pearson's correlation coefficients, they demonstrated the significance of speech signal processing in defining the relationship between the Mel-Frequency Cepstral Coefficients (MFCCs) of COVID-19 and non-COVID-19 samples. Their findings showed considerable consistency in MFCCs between various COVID-19 cough and breathing sounds. However, the MFCCs of voice samples were more robust in distinguishing between COVID-19 and non-COVID-19 cases [12].

Seyed Mosayeb Eftekhari et al. (2021) conducted a study titled "The Approach of a New Model of Earthquake Crisis Management in the Classification of Vital Arteries." The study examined the impact of earthquakes on critical infrastructure in Iran, a country frequently affected by strong earthquakes. The researchers aimed to develop a new approach to managing earthquake crises by classifying vital arteries. They employed a descriptive applied methodology with a sample of 265 technicians and specialists from Isfahan Province, using questionnaires and analyzing the data with the Pearson correlation coefficient in SPSS software. The findings revealed a significant correlation between the new classification of arteries and effective crisis management, highlighting the importance of passive defence. The model introduced a revised classification system for critical arteries and enhanced disaster management across various stages. Additionally, the study recommended establishing a Social Crisis Management Headquarters to implement and train on effective strategies [13].

Agata Gieczyk et al. (2022) introduced pre-processing methods for categorizing chest X-ray images. They suggested a machine learning-based approach. They also investigated certain pre-processing techniques, including thresholding, blurring, and histogram equalization. They discovered that the F1-score outcomes improved to 97%, 96%, and 99% for the 3 investigated classes: healthy, COVID-19, and pneumonia [14].

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Daniel G. Costa et al. (2022) conducted a study titled "A Survey of Emergencies Management Systems in Smart Cities". The study examined the challenges of increasing urbanization and the need for effective public services in densely populated areas. It focused on smart city emergency management systems, emphasizing detection, alerting, and mitigation. The research reviewed contemporary smart city solutions and categorized emergency management systems based on technology and services. It highlighted IoT, AI, and Big Data advancements and discussed future research challenges and directions. The study stressed the importance of integrated solutions for urban emergencies, viewing cities as interconnected systems. Key focus areas included detection, alerting, mitigation, networking, security, and energy efficiency. The study concluded that innovative and integrated technological solutions are essential for improving urban emergency management [15].

Mahmoud Khalifa et al. (2022) examined the impact of applying artificial intelligence (AI) on human resources crisis management, specifically focusing on the effects of the COVID-19 crisis on Human Resource Management (HRM) in the industrial sector. The study analysed how AI can address the challenges faced during the COVID-19 crisis. It provided several recommendations for mitigating its effects and preparing an integrated research agenda to tackle these challenges. The research highlighted that AI has become crucial for managing human resources during crises like COVID-19. The study identified several critical impacts of the pandemic on the industrial sector, including decreased production, investments, and profits, contributing to rising unemployment rates. The significant economic consequences included increased poverty rates, shortages in essential production materials imported from abroad, rising raw material prices (particularly in medical industries), and reduced industrial commercial exchange between countries. The pandemic decreased Egypt's economic growth rate to 6.3% in 2020 from 6.5% in the previous year. However, Egypt was noted as the only emerging economy that achieved growth during this period [16].

Malaka Parker et al. (2022) conducted a study titled "education during the covid-19 pandemic". The COVID-19 pandemic has reshaped the educational landscape to the extent that its consequences (along with the insights gained from managing the crisis) need to be considered in educational planning for both recovery and the fulfilment of Sustainable Development Goal SDG 4. This goal is dedicated to ensuring inclusive and equitable quality education for all [17].

Shamik Tiwari et al. (2022) demonstrated a lightweight capsule network architecture for COVID-19 identification in lung computed tomography (CT) data. Combining a capsule network with several convolution neural network variations suggested a deep learning architecture. Using lung CT images, DenseNet, ResNet, VGGNet, and MobileNet collaborated with CapsNet to discover COVID-19 patients. It was found that all four models performed adequately, with the VGGCapsNet, DenseCapsNet, and MobileCapsNet models achieving the greatest accuracy of 99%. Android-based software used The MobileCapsNet model to detect COVID-19 because it was lightweight and most suited for portable devices like cell phones [18].

Xiaole Fan and colleagues (2022) presented a COVID-19 computed tomography (CT) image identification technique based on a transformer and CNN. They built a deep learning network to extract medical characteristics from CT scans. They presented a parallel two-branch model (through CNN) based on the adapters and convolutional neural network modules. They used the convolutional neural network's local feature extraction ability and the adapters' global feature extraction capability. The classification accuracy on the COVIDx-CT dataset is 96.7%, which is greater than the classification accuracy of a conventional CNN network (ResNet-152) (95.2%) and a Transformer network (Deit-B) (75.8%). These findings show that accuracy has improved [19].

Paulina Bravo et al. (2023) conducted a study titled "What is needed to Effectively Communicate Risk during a Health Crisis? A Qualitative Study with International Experts Based on the COVID-19 Pandemic". The study aimed to develop a framework for risk communication during health crises, using the COVID-19 pandemic as a case study. It explored the perspectives of experts from various countries, each employing different strategies to manage the first year of the pandemic. The study identified three essential best practices for risk communication in health emergencies. Experts from diverse cultural and academic backgrounds provided insights into effective communication strategies. The study included four men and six women, with participants from Europe (three),

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Latin America (two), North America (two), Asia (one), and Oceania (two). The analysis revealed three main themes: institutionalizing the communication strategy, defining the problem clearly, and developing a practical communication approach [20].

Sara Raimondi et al. (2023) conducted a study titled "European Cohorts of Patients and Schools to Advance Response to Epidemics (EuCARE): a cluster randomized interventional and observational study protocol to investigate the relationship between schools and SARS-CoV-2 infection". They compared LM-based surveillance with the standard public health department approach. The study involved 440 classes, approximately 8,800 students, teachers, and staff from two countries, randomly assigned to LM or standard surveillance. They collected and tested samples using PCR and gathered data through questionnaires. The study also examined the prevalence of SARS-CoV-2 in schools, cluster sizes, and the psychological effects of pandemic measures on students and teachers. Overall, they aimed to assess the effectiveness of LM and the impact of preventive measures [21].

Yujia Xu Yujia Xu et al. (2023) proposed learning parameter-efficient representation to improve the COVID-19 computed tomography (CT) classification of convolutional neural networks (CNNs). They developed incremental-level augmentation techniques and applied them to the most significant open-access benchmark dataset, COVIDx CT-2A. In this paper, similarity regularization (SR) generated from contrastive learning was suggested to enable CNNs to acquire more parameter-efficient representations, hence improving CNN accuracy and sensitivity. The COVID-19 pneumonia category attained accuracy, sensitivity, and specificity of 98.40%, 99.59%, and 99.50%, respectively [22].

Furriel BCRS et al. (2024) conducted a systematic review titled "Artificial Intelligence for Skin Cancer Detection and Classification in Clinical Environments." This review evaluated research on detecting, classifying, and assessing skin cancer images in clinical settings. A comprehensive literature search was conducted across PubMed, Scopus, Embase, and Web of Science for studies published up to April 4, 2023. Two independent reviewers performed the study selection, data extraction, and critical appraisal, presenting results through a narrative synthesis. Out of 760 studies identified, 18 were selected based on their focus on developing, implementing, and validating systems for detecting, diagnosing, and classifying skin cancer in clinical settings. The review includes descriptive analysis, data scenarios, processing techniques, study outcomes, and aspects of physician diversity, accessibility, and engagement [23].

Experimental results show that the system performs better than the corresponding unimodal systems. Most studies proposed multimodal systems using X-rays, CT scans, or coughs to detect COVID-19, while the proposed system integrates all of the detection methods.

3. Proposed System

The proposed system generally includes interacting and interdependent elements and components. Scientifically, there are several alternatives to explain the new system. A better alternative is to present the details of the developed system in separate sub-sections within a simplified form, such as the following:

3.1 System Overview

Several epidemics, such as skin disorders, respiratory ailments, and others, may afflict students within the educational institution. COVID-19 was recognized as one of the latest diseases that expanded and became a pandemic, widespread throughout a nation or the world. Therefore, the proposed system focuses on controlling the epidemic inside educational institutions by detecting the disease through symptoms; using the questionnaire, examining the cough, and using an X-ray and CT scan.

This paper offers, via a smartphone application, an Android-based COVID-19 management system for educational institutions. An Android system is installed on the smartphone. The system allows users to register their information. The diagram of privilege for users is shown in Figure 1:

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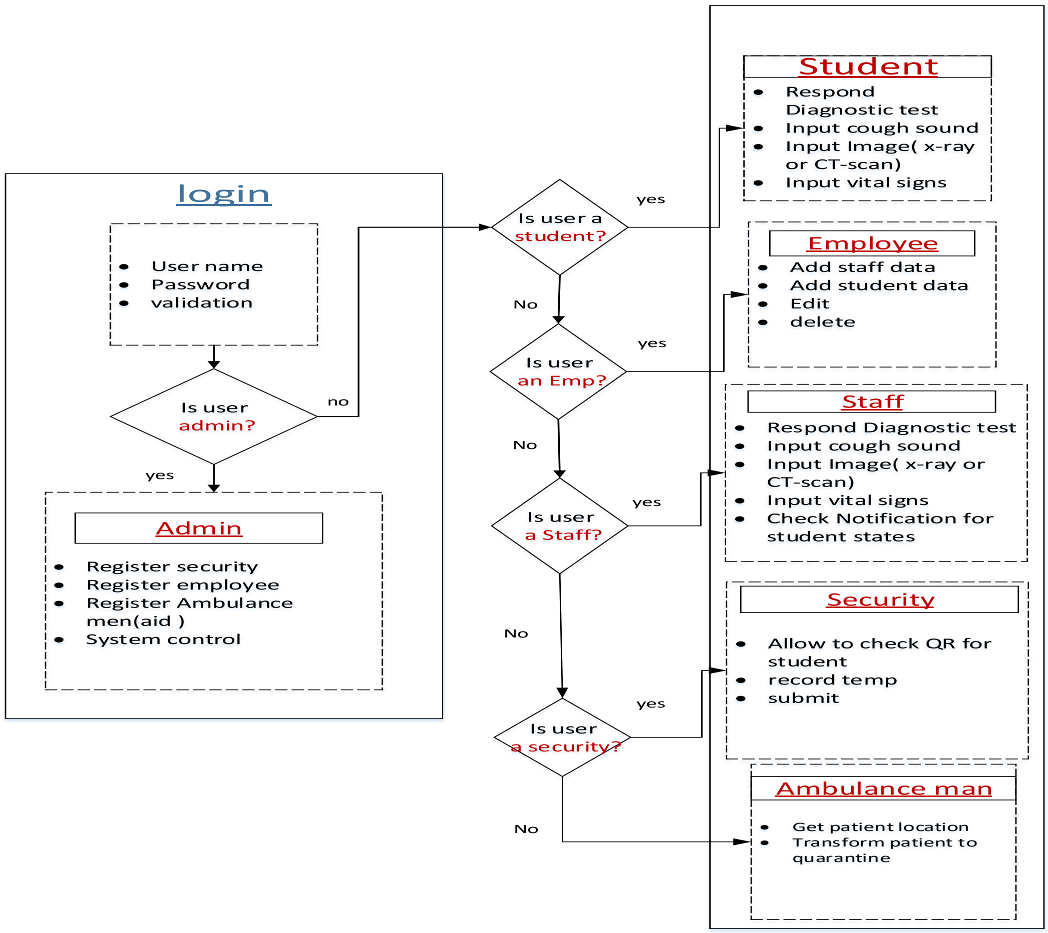

Figure 1. Diagram of privilege for users

Privileges are granted to users of the system according to their respective jobs, as follows:

1. The Admin/System Administrator: The administrator supervises and monitors the system. Additionally, he supervises the data registration of system users, including staff members, employees, security personnel, and ambulance personnel.
2. The Student/the core of system management: After checking in, the Student can complete diagnostic questions to discover whether he or she is afflicted. If he is suspected to have an infection, he proceeds to the following phase: entering the sound of the cough, followed by an X-ray or CT scan if an infection is detected.
3. The Staff: Staff may log in and follow the same procedures as students and get information about the health status of suspected or afflicted students.
4. The Employee: The employee can register staff and student information so that they can access the system. He can also log in and follow the same procedures for detecting COVID-19.`
5. The Security man: The security guard monitors students' admittance to the institution. He examines the Student's quick-response (QR) code to determine whether the Student belongs to the educational institution. Next, with the nurse's assistance, he determines this Student's temperature and whether he can enter. He submits it so that the Student is permitted to enter.
6. The Ambulance man: If it is determined that the Student has COVID-19, then the Student enters the Vital Signs, which have standard rates; when these rates differ from the average rate, the Student's location is determined, and a notification of the location is sent to the ambulance man to go to the nearest place for the students' quarantine.
The steps of the proposed system are displayed, as shown in the figure.2:

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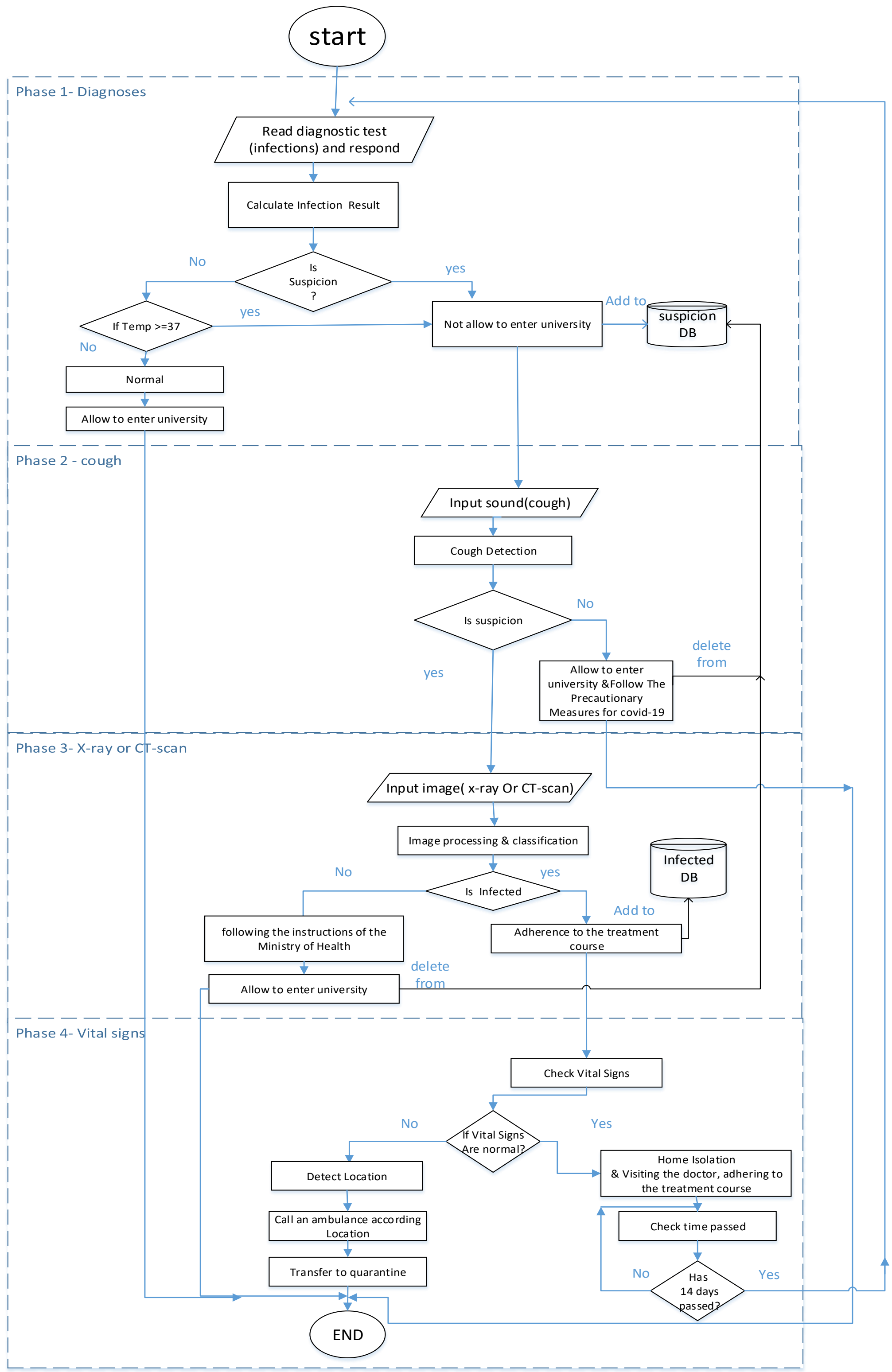

Figure 2. flowchart indicates the steps of the proposed system

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3.2 System Procedures

The system consists of a set of procedures, as follows:
1. Diagnostic questionnaire/symptoms.
2. Cough recognition.
3. X-ray or Computerized Tomography detection.
4. Check vital signs.
5. Detect the location.
In the following, each of these parts will be presented in detail:

3.2.1 Diagnostic Questionnaire/Symptoms:

The questions are designed in the Android software and called from the Firebase database, which contains several questions with choices that the student answers. Symptoms were evaluated based on whether they were common, occasional, or rare. Symptoms range from mild to severe [24]. The process for evaluating a patient based on symptoms and rules for detecting COVID-19:

1. Collect Symptoms:

- Gather common symptoms of COVID-19, such as fever, dry cough, fatigue, shortness of breath, and loss of taste or smell.
- Less common symptoms might include muscle aches, headache, sore throat, nasal congestion, and nausea or vomiting.

2. Categorize Symptoms:

- Classify symptoms such as Severe, Moderate, and Mild.

3. Determine Symptom Weights

4. Develop Evaluation Criteria:

- Symptom Classification Rules:
  - Severe Symptoms: such as difficulty breathing and chest pain.
  - Moderate Symptoms: such as fever and dry cough.
  - Mild Symptoms: such as sore throat and nasal congestion.

Rule-Based Symptom Model:
1. Do you have a fever? (Yes = 2 points, No = 0 points)
2. Do you have a dry cough? (Yes = 2 points, No = 0 points)
3. Do you have difficulty breathing? (Yes = 3 points, No = 0 points)
4. Have you lost your sense of taste or smell? (Yes = 2 points, No = 0 points)

Total Points:
- 0-3 points: Mild symptoms may not be related to COVID-19.
- 4-6 points: Moderate symptoms, recommend COVID-19 testing.
- 7 points or more: Recommend immediate COVID-19 testing and seek medical care for severe symptoms.

After completing this stage, a healthy student can enter the institution after analyzing the data with the security guard present and examining the temperature to ensure it does not exceed 37 °C with the nurse's assistance. Suppose the outcome of this test contains some suspicion. In that case, the algorithm advances to the next level: evaluating the sound of coughing, and this student is added to the database of suspected COVID-19 instances.

3.2.2 Sound Processing:

The main objective of this stage is to diagnose COVID-19 through sound processing. The proposed framework for a cough processing stage is displayed in Figure 3.

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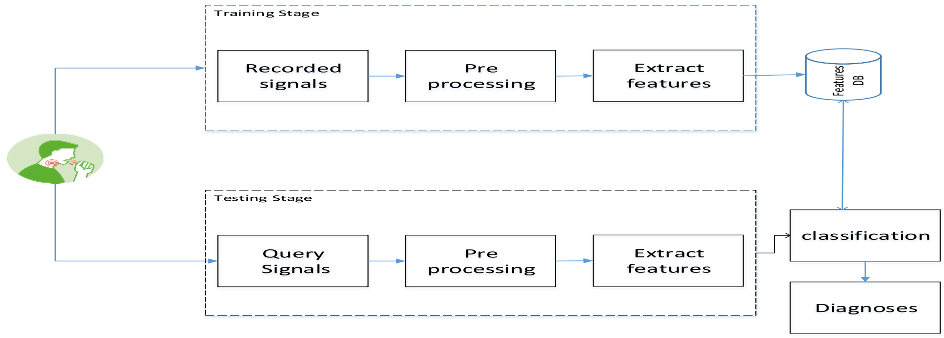

Figure 3. Sound processing frameworks

a) Training phase:

The training phase of the fusion model MF-STFT (STFT and MFCC), the steps for the sound classification Algorithm are displayed, as shown in figure.4:

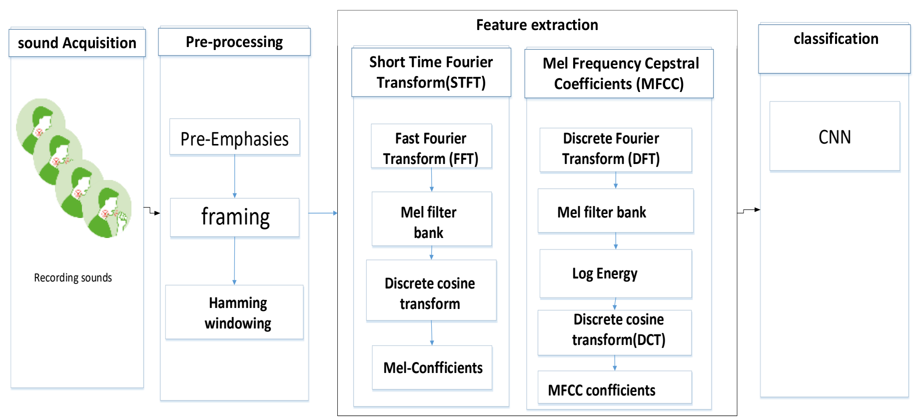

Figure 4. Training phase steps for proposed fusion model (STFT and MFCC) for sound classification

b) Testing phase:

In the testing phase of the fusion model MF-STFT (MFCC and STFT); the steps for the sound classification Algorithm are displayed, as shown in Figure 5:

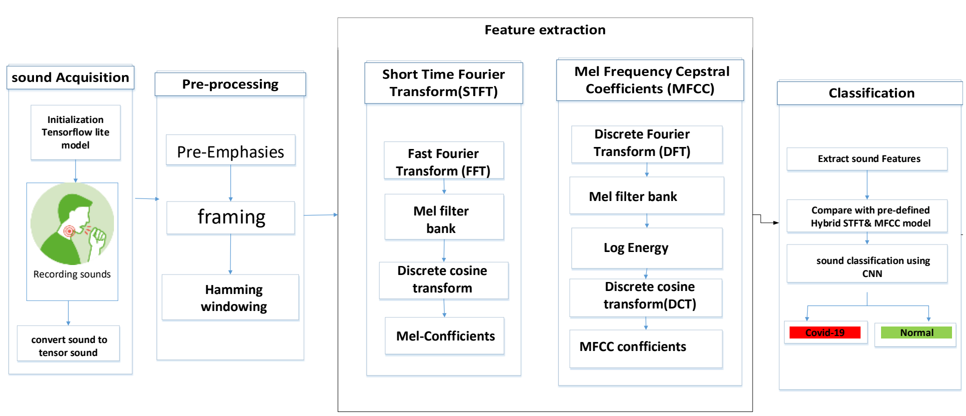

Figure 5. Testing phase steps for proposed fusion model (STFT and MFCC) for sound classification

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According to the previous figures, we will discuss the sound processing steps:
1. Sound acquisition:
The dataset, which is used in the proposed system, is on https://www.kaggle.com/ , which is available to everyone, as shown in (Table 1)

Table 1: Datasets name and link

Dataset name	link
COUGHVID-3	https://www.kaggle.com/datasets/dineshcr7/coughvid-3

2. Pre-processing
3. Feature extraction
4. Classification using CNN [25]

After completing this stage, the cured student can enter the institution and be removed from the patient or suspected infection data set. As for the student who was confirmed to be suspected of being infected, the algorithm advances to the next level, which evaluates image processing using an X-ray or CT scan, and the student remains in the database of suspected COVID-19 cases.

3.2.3 Image Processing:

The main objective of this stage is to use students' smartphones to examine their X-rays and CT scan images to identify whether the patient has COVID-19. The image classification process is divided into two main stages:

1) Training phase:

CNN is used to classify x-ray and ct-scan images [26]; the steps for proposed c-19 using the CNN algorithm are displayed, as shown in the figure 6:

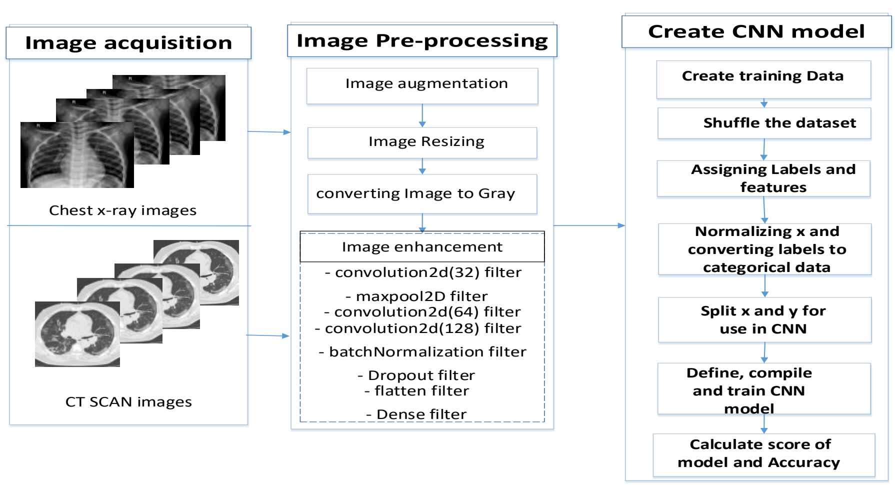

Figure 6. Training steps for image classification using cnn

2) Testing phase:

In this section, we review the diagram that illustrates the stages of the procedure of the testing phase for an X-ray or CT scan, as shown in Figure 7:

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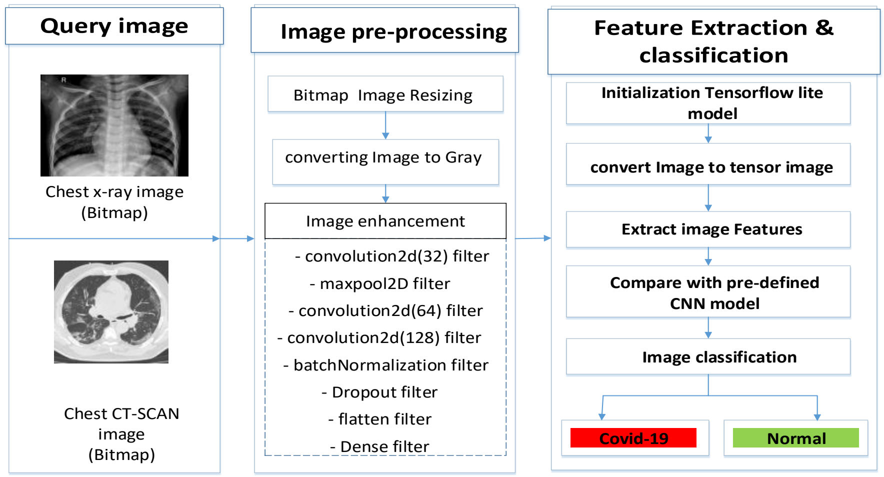

Figure 7. Testing steps for image processing with cnn

According to the previous figures, we will discuss the image processing steps:
Step 1: Choose a dataset or image acquisition

The dataset, which is used in the proposed system, is on https://www.kaggle.com/, which is available to everyone, as shown in (Table 2)

Table 2: Datasets name and link

Dataset name	link
Chest X-Ray	https://www.kaggle.com/datasets/jtiptj/chest-xray-pneumoniacovid19tuberculosis
COVIDx CT	https://www.kaggle.com/datasets/hgunraj/covidxct

Step 2: Prepare Dataset for Training/ Image pre-processing
Preparing our dataset for training will involve assigning paths and creating categories (labels), Image augmentation, and resizing images.

a) Image augmentation is shown in the figure.8

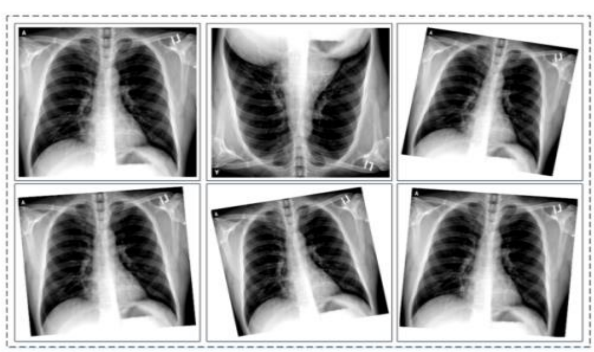

Figure 8. Images augmentation

b) Resizing images into 150 X 150
c) Converting image to gray
d) Image enhancement using these training layers:

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Convolution layer
Rectified Linear Unit (ReLU) layer
Maxpooling layer
Batch normalization
Flatten
Dropout layer
Dense layer
Step 3: Create Training Data
Training is an array that will contain image pixel values and the index at which the image in the categories list.
Step 4: Shuffle the Dataset
Step 5: Assigning Labels and Features.
Step 6: Normalizing X and converting labels to categorical data
Step 7: Split X and Y for use in CNN
Step 8: Define, compile and train the CNN Model
Step 9: Accuracy and Score of model

3.2.4 Vital Signs

Modern clinical care of patients in hospitals and at home heavily relies on the monitoring of human vital signs, such as respiratory rate (RR), blood oxygen saturation (SpO2), heart rate (HR), heart rate variability (HRV), and blood pressure (BP) [27].

In the proposed system, the aforementioned percentages were utilized in the proposed system in order to analyze the Covid patient's vital signs and determine whether these percentages are abnormal. If the specific signs exceed the normal values, a signal or alert is sent to the ambulance man, including the patient's location so that the patient's location is determined and the ambulance is easily directed to his place to transfer him to the quarantine.

3.2.5 Detect the Location

The Global Positioning System (GPS) is a space-based satellite navigation system that offers location and timing data in climate conditions, anywhere on or near the Earth when there is an unhindered line of sight to four or more GPS satellites [28, 29].
In the proposed system, GPS technology was used to determine the location of the sick person in case of a rise in the vital rates mentioned in the previous stage, and thus a notification of the location that was determined is sent to the ambulance man to move to the location of this patient and transfer him to the quarantine to receive full care.

3.3 System Development

To develop the prototype of the proposal, named Cov-19, we used the Android development environment due to its useful features for rapid development. During the development phase of Cov-19, we utilized an Android smartphone device (HUAWEI Y10). However, any other smartphone device can be used during the development and implementation phases of Cov-19, provided it meets the following criteria:

- Android Version: 4.4 (KitKat) or Higher
- Internet Enabled
- GPS Enabled

4. Results

The confusion matrix is a machine-learning tool for predictive analysis. The confusion matrix is used to evaluate the effectiveness of a classification-based machine-learning model, and it can be calculated according to the following equations [30, 31]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Misclassification = \frac{FP+FN}{TP+TN+FP+FN}$$

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$Precision = \frac{TP}{TP+TN}$

$Recall = \frac{TP}{TP+FN}$

$FPR = \frac{FP}{TN+FP}$

4.1 For coughs:

Proposed system was applied on 525 cough sounds, 311 of which were positive cough sounds and 214 negative cough sounds, as shown in (Table.4)

Table 3: Results for cough model

	True	False
positive	TP True positive 300	FP false positive 11
negative	TN true negative 200	FN False negative 14

$Accuracy = = \frac{300+200}{300+14+11+200} = \frac{500}{525} = .95$

$Misclassification = = \frac{14+11}{525} = .047$

$Precision = = \frac{300}{300+200} = .6$

$Recall == \frac{300}{300+14} = .96$

$FPR == \frac{11}{200+11} = .052$

4.2 For CT-scan:

Proposed system was applied on 1437 CT scan images, 707 of which were positive images and 730 negative images, as shown in (Table 4)

Table 4: Results for CT-Scan model

	True	False
positive	TP True positive 682	FP false positive 25
negative	TN true negative 695	FN False negative 35

$Accuracy = \frac{682+695}{682+35+25+695} = \frac{1377}{1437} = .958$

$Misclassification = = \frac{25+35}{1437} = .041$

$Precision = = \frac{682}{682+695} = .49$

$Recall == \frac{682}{682+35} = .95$

$FPR == \frac{25}{695+25} = .034$

4.3 For x-ray:

Proposed system was applied on 1367 x-ray images, 696 of which were positive images and 642 negative images, as shown in (Table 5)

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Table 5: Results x-ray model

	True	False
positive	TP True positive 640	FP false positive 56
negative	TN true negative 660	FN False negative 11

$Accuracy = \frac{640+660}{640+56+11+660} = \frac{1300}{1367} = .946$

$Misclassification = = \frac{56+11}{1367} = .049$

$Precision = =\frac{640}{640+660} = .49$

$Recall == \frac{640}{640+11} = .98$

$FPR == \frac{56}{660+56} =.078$

Table 6: Results for CT-Scan x-ray and cough models

	cough	CT-scan	x-ray
Accuracy	.95	.958	.95
Misclassification	.047	.041	.049
Precision	.6	.49	.49
Recall	.96	.95	.98
FPR	.052	.034	.078

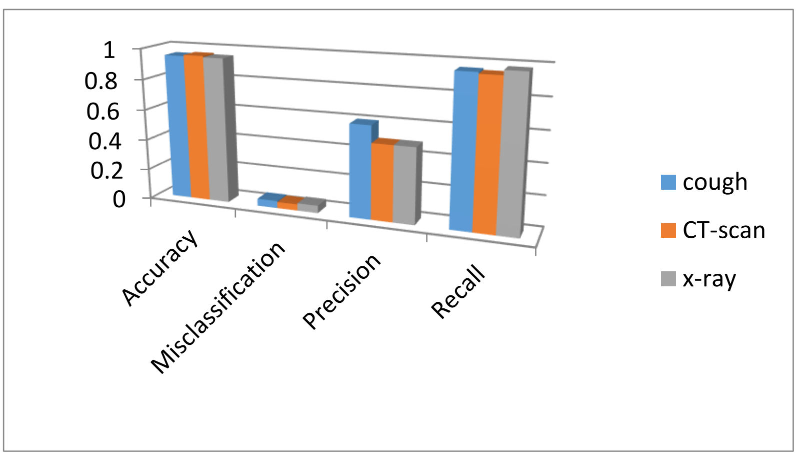

Figure 9. Results for CT-Scan x-ray and cough models

5. Conclusion

Crises within educational institutions constitute critical junctures in their operational history. Effective management of pandemic-related crises in such settings necessitates prompt and accurate responses to infections. This study aimed to develop an advanced system for epidemic detection within educational institutions during the COVID-19 pandemic. To achieve this objective, the researchers utilized sophisticated sound and image processing

DOI: https://doi.org/10.54216/FPA.170118
Received: November 29, 2023 Revised: March 20, 2024 Accepted: July 25, 2024

methodologies, including Convolutional Neural Networks (CNN), Mel-Frequency Cepstral Coefficients (MFCC), and Short-Time Fourier Transform (STFT) algorithms, to detect COVID-19 symptoms, analyze cough acoustics, and evaluate X-ray and CT imaging. The system demonstrated high efficacy, achieving 95% accuracy across CT scans, sound analysis, and X-ray evaluations.

6. Future work

1. Develop a real-time monitoring system that continuously collects and analyzes data from various sources within educational institutions to detect early signs of potential epidemics.
2. Implement predictive analytics models to forecast potential outbreaks based on historical data and current trends, enabling proactive measures to be taken.
3. Explore the integration of Internet of Things (IoT) devices and wearable technology to gather real-time health data from students and staff, enabling early detection of symptoms and rapid response to potential outbreaks.

7. Data availability

1. COUGHVID-3 at: https://www.kaggle.com/datasets/dineshcr7/coughvid-3
2. Chest X-Ray at: https://www.kaggle.com/datasets/jtiptj/chest-xray-pneumoniacovid19tuberculosis
3. COVIDx CT at: https://www.kaggle.com/datasets/hgunraj/covidxct

Funding: “This research received no external funding”.

Conflicts of Interest: “The authors declare no conflict of interest.”
“I will pay the APC in case of final acceptance of my paper”.

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