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AI Multi Disease Diagnosis

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Abstract — In the modern era, the healthcare sector has started to adopt smart monitoring systems that include AI, IoT, and embedded technologies. This paper discusses the design and development of a real-time medical monitoring system that includes AI to identify medical conditions in ECG signals and lung sounds. The proposed medical monitoring system includes a set of physiological sensors, an ESP32 microcontroller, machine learning algorithms, and a web-based platform to identify medical conditions. In the proposed medical monitoring system, we have used an ECG sensor to identify heart signals and a MAX4466 microphone to identify lung sounds. The ESP32 microcontroller collects physiological data from the sensors and sends the data to a computer for further processing. In the proposed medical monitoring system, a Convolutional Neural Network (CNN) algorithm is used to identify irregular heart patterns, i.e., arrhythmia. In the proposed medical monitoring system, the Mel Frequency Cepstral Coefficient (MFCC) feature is used to identify features in the lung sounds. In the proposed medical monitoring system, deep learning algorithms are used to classify the lung sounds.

On the frontend side, we have developed a dashboard based on the Flask framework, HTML, CSS, JavaScript, and Chart.js, which shows the real-time visualization of the ECG signals and lung signals, as well as the predictions of the diagnosis. Our system has two different modes: one is for real-time monitoring, while the other is for testing the data in the lab. The results of the experiment show that our system is capable of detecting heart and lung problems at a low cost and portability. This system has huge scope in telemedicine as well as disease diagnosis.

Keywords — IoT, ECG Monitoring, Lung Sound Analysis, Machine Learning, CNN, Healthcare Monitoring., ESP32.

I. INTRODUCTION

With the advent of healthcare technology, the requirement of smart and automated systems of patient monitoring is quite high [1], [4]. Cardiovascular diseases and respiratory diseases are two of the primary causes of death worldwide. This necessitates the early detection of diseases to ensure better health outcomes and lower mortality rates [3]. Electrocardiography is a popular method of monitoring the electrical activities of the heart and diagnosing diseases such as arrhythmia, tachycardia, and bradycardia [5]. Lung sounds also play a significant role in the diagnosis of respiratory diseases. Unusual sounds such as crackles and wheezing can be indicative of diseases such as pneumonia, asthma, bronchitis, and COPD [6], [11], [24].

The conventional healthcare monitoring system utilizes expensive medical devices as well as continuous monitoring by professional health workers [7]. Most of the time, these tests are performed in hospital settings or specific laboratories. As a result, it becomes difficult to perform these operations in remote areas where there are limited medical facilities [8]. Sometimes, it takes a lot of time to analyze the results obtained from the electrocardiogram as well as lung sounds, and it could also lead to human errors, especially while working with huge volumes of physiological data [9]. This shows the need for developing smart monitoring systems that could analyze the results as well as assist medical practitioners in the early detection of diseases [10].

In recent times, Artificial Intelligence (AI), Internet of Things (IoT), as well as machine learning, offer opportunities for developing an intelligent healthcare monitoring system [2], [12], [22]. IoT helps medical devices continuously gather physiological data from patients and transmit it to computer systems for further analysis [13]. Recently, machine learning techniques such as Convolutional Neural Networks (CNN) have demonstrated impressive capabilities in recognizing complex patterns of data in biomedical signals, e.g., analyzing an electrocardiogram as well as classifying lung sounds [14], [17], [26].

These technologies can automatically detect abnormal patterns which may not be easily recognized through manual analysis.
Various research studies have been done on the classification of ECG signals using deep learning algorithms for precise identification of abnormal heart rhythms [15]. Various audio signal processing techniques, such as Mel Frequency Cepstral Coefficients (MFCC), have been used for the analysis of lung sounds and the identification of respiratory diseases [16], [30]. Most of the modern technologies have been focused on cardiovascular or respiratory analysis individually. Only a few technologies have been focused on the analysis of both heart and lung conditions simultaneously [18].

II. EXISTING WORK

Healthcare monitoring systems based on physiological signals have been extensively researched over the last few decades. Several research works have been conducted to improve the accuracy of disease detection, facilitate remote monitoring, and reduce costs. Among the various physiological signals, ECG signal processing and classification of respiratory sounds have been extensively researched, especially because they play an important role in the diagnosis of cardiovascular and respiratory diseases [1], [5]. The traditional monitoring systems operate independently for each physiological signal. This does not provide a comprehensive overview.

A. ECG Based Detection Based Systems:

For a long time now, the interpretation of electrocardiograms has been considered a primary way to diagnose heart-related problems. There have been a number of automated electrocardiogram classification systems proposed using machine learning as well as deep learning algorithms [9], [15]. The systems make use of the electrocardiogram signals obtained using wearables or devices and then make the necessary analysis using different techniques.

It has been seen that deep learning algorithms like Convolutional Neural Networks have been quite successful in determining heart-related problems using the electrocardiogram signals. This is because they have the capability to detect complex waveforms as well as abnormal heart rhythms [2], [14], [23]. For example, it has been seen that the systems using CNN have been able to achieve the same level of accuracy as a cardiologist in determining arrhythmia. This has been seen especially if the system is trained on a large dataset like the MIT-BIH Arrhythmia Database [15].

Although there are a number of advantages, most ECG-based monitoring systems have been focusing on heart-related information.

B. Lung Sound Analysis System:

Respiratory Sound Analysis is another area of research that is being carried out as a means of identifying diseases of the lungs. Digital stethoscopes or microphone sensors are commonly used as a means of detecting the sounds of the lungs, which are then fed into computers for analysis [6]. Next, audio signal processing techniques are used as a means of extracting useful information from the sounds of the lungs.

The Mel Frequency Cepstral Coefficients (MFCC) method is one of the most popular methods of analyzing the sounds of the lungs. This method is able to pick up important features of the sounds of breathing [16]. These features are then used as a means of teaching machine learning models how to classify the sounds of the lungs into various categories, including normal sounds, crackles, wheezes, or a combination of crackles and wheezes [17].

Though these systems are able to provide important information regarding respiratory health, they are commonly developed as standalone systems without being integrated into cardiovascular systems.

C. IoT - Based Healthcare Monitoring Systems:

However, with the evolution of the IoT technology, there has been a rise in the use of smart healthcare monitoring systems, which allow us to remotely monitor patients [12]. These technologies utilize devices, sensors, and other wireless technologies to collect physiological information from patients, which can be sent over to a remote server or a local computer for analysis.

Some of the popular microcontrollers like Arduino, Raspberry Pi, and ESP32 have been extensively used to develop IoT-based healthcare technologies. The primary reason is their cost-effectiveness and the fact that they can be wirelessly connected to other devices. These devices can be utilized to monitor the health statistics of patients over a given period of time. Moreover, they can be easily used to visualize the information as well.

However, a majority of the IoT-based healthcare technologies do not utilize the enhanced features of the technology, which can be used to detect diseases through machine learning algorithms.

D. Gap Analysis:

As indicated by the literature study, the majority of the healthcare monitoring systems appear to be designed to monitor a single health-related signal or parameter, such as the analysis of the ECG signal or the classification of the lung sounds [5], [17]. Although such systems have certainly helped to increase the accuracy of disease detection, they seem to miss the point when it comes to the integration of different types of health monitoring systems.

For example, ECG-based health monitoring systems can provide detailed information about the functioning of the heart, but they do not indicate any problems with the respiratory system. Similarly, the analysis of the lung sounds can indicate any problems with the respiratory system, but they do not indicate any problems with the heart or the functioning of the heart. Moreover, such systems have mostly focused on the transmission of the data or visualization of the data, as opposed to the intelligent detection of the diseases [10], [18].

However, as can be easily seen, the requirement is to design a system that can integrate the analysis of the ECG signal as well as the analysis of the lung sounds together using the machine learning approach so that the diseases can be detected early on by the healthcare professionals. This research aims to fill the gap by proposing an AI-based real-time health monitoring system that can integrate the analysis of the ECG signal, the analysis of the lung sounds, the IoT data collection, as well as the visualization of the data using the web interface.

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III. PROPOSED METHODOLOGY

The newly proposed healthcare monitoring system is smart and cost-effective, enabling the real-time detection of problems related to the heart and lungs. Unlike the traditional systems, which generally monitor only a single type of signal, the newly proposed system integrates ECG monitoring and lung sound analysis. This enables the detection of diseases automatically through IoT technology, signal processing, and machine learning. The overall system architecture of the proposed system is depicted in Fig. 1. Some of the important components of the proposed system include sensor modules, ESP32 microcontrollers, algorithms, machine learning models, and a dashboard.

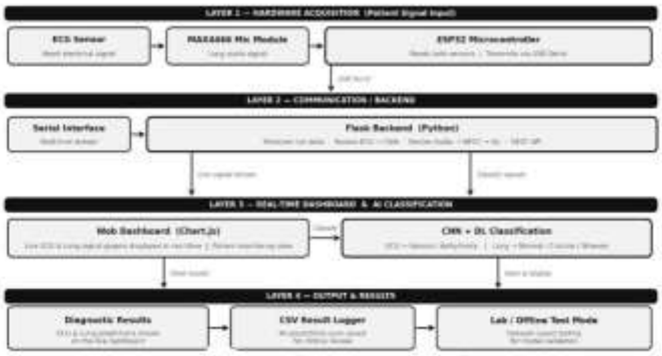

Fig. 1. Block diagram of the proposed AI-Based ECG and Lung disease monitoring system.

A. Physiological Signal Acquisition:

The first part of this system is all about picking up these physiological signals with the correct kind of biomedical sensors. For example, we are making use of the ECG sensor to pick up the electrical signals sent by the heart and the MAX4466 microphone module to pick up the sounds of breathing.

The way this ECG sensor works is that it picks up the electrical signals sent with each heartbeat. This kind of sensor picks up these electrical signals and converts them to analog voltage signals. This signal indicates the rhythm of the heartbeat. This signal can also be used to pick up any problems with the heartbeat, like arrhythmia.

The MAX4466 microphone module picks up the sounds of breathing when a person inhales and exhales. This indicates some of the most important sounds and could also be an indicator of problems with breathing, like wheezing and crackling sounds.

After these signals are picked up, they are sent to the microcontroller

B. ESP32 Microcontroller and Data Communication:

ESP32 microcontroller is the central component that regulates all the data acquisition operations. The ESP32 microcontroller collects the analog data from the ECG sensor and the microphone module by using the analog input provided by the ESP32 microcontroller.

After collecting the physiological data, the ESP32 microcontroller sends the data to the computer in the form of digital data by serial communication. The reason for choosing the ESP32 microcontroller is that it has a lot to offer in terms of processing, wireless communication, and power consumption, especially in the field of healthcare in IoT [12], [13].

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C. Signal Processing and Feature Extraction:

However, prior to being able to classify the physiological signals that we have obtained, it is important that we be able to process the signals obtained in order to eliminate any noise that may be present in the signals. This is possible if we are able to utilize various signal processing techniques in order to improve the quality of the signals obtained [28].

In the case of ECG signals, it is important that we be able to utilize filtering techniques in order to eliminate any noise that may be present in the signals obtained. Once we have been able to eliminate any noise from the ECG signals, it is important that we be able to normalize the signals obtained prior to being able to feed the signals into the machine learning model.

In the case of lung sound signals, it is important that we be able to utilize various audio signal processing techniques in order to obtain the important features of the signals obtained. In this regard, the most important technique that may be used is Mel Frequency Cepstral Coefficients (MFCC), as it is able to perform really well in classifying the signals obtained.

D. ML - Based Disease Classification:

We apply machine learning algorithms to analyze these processed signals and identify any abnormal patterns. In our system, we apply different models to classify ECG signals and lung sounds.

For ECG signals, we apply a Convolutional Neural Network model and train it with the MIT-BIH Arrhythmia Dataset. This model detects complex patterns in ECG signals and helps classify heartbeats according to their types.

When it comes to lung sound classification, we apply MFCC features of respiratory audio signals to a deep learning model for classification. This model classifies lung sounds into four types:

- Normal
- Crackle
- Wheeze
- Crackle and Wheeze

Deep learning methods have proven to be effective in classifying biomedical signals as they have the ability to learn complex features directly from the data [14].

E. Web Based Monitoring and Visualization Dashboard:

We have also used a web dashboard using the Flask library for web development, along with other front-end tools like HTML, CSS, JavaScript, and Chart.js, to keep an eye on things in real time. This web dashboard is a friendly interface where all the physiological signals and predictions will be shown.

On the back end, we have a server that processes the data being sent from the ESP32 device using Python algorithms. Once the signals have been processed, they will be sent to the front end, and the signals will be shown.

You will see real-time graphs for ECG signals, lung sounds, and the diagnosis signals.

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F. Flowchart of System Operation:

The system's operation sequence is shown in Fig. 2.

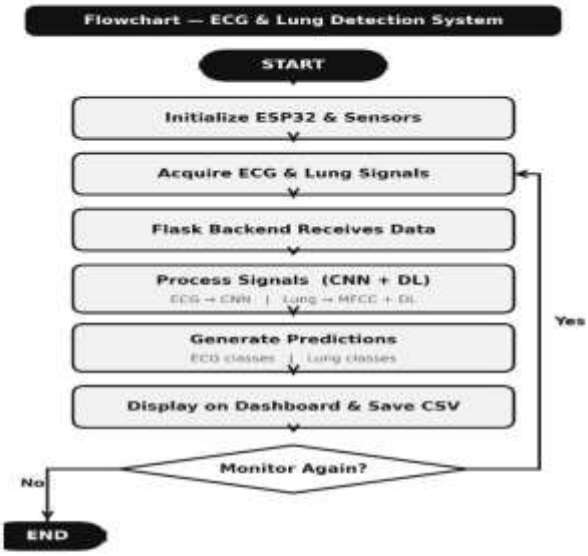

Fig. 2. Signal processing workflow for ECG signal filtering and lung sound feature extraction.

Step-by-Step Process:

• Initialisation: The micro controller, communication modules, and sensors are initialized.

• Signal Acquisition: The ECG sensor and microphone module are used to acquire lung sound and ECG signal

• Data Transmission: The ESP32 uses a serial communication method to transmit the signal collected to the computer.

• Signal Processing: The signal is processed using methods for feature extraction and filtering [31].

• Machine Learning Analysis: The signal is classified, and abnormalities are detected.
• Visualization: The web interface displays the signal and forecast.

• Storage of Results: The results obtained from the diagnosis process are stored as a CSV file for later analysis.

IV. RESULTS AND ANALYSIS

We put the proposed AI healthcare monitoring system into action and tested it with real-time sensor data along with publicly available biomedical datasets. This system combines ECG signal monitoring with lung sound classification through machine learning algorithms, and it offers a web-based dashboard for real-time visualization.

The experimental results show that the system is effective in spotting abnormalities in both cardiovascular and respiratory signals. We got results that include waveform visualizations, outputs from the machine learning classifications, and an evaluation of how well the monitoring platform performs.

A. Real - Time Signal Monitoring:

In the first phase of testing, we focused on checking how well we could gather and display physiological signals in real time. The ECG sensor did a great job picking up the heart's electrical activity, showing continuous waveform patterns that reflect the cardiac cycles. At the same time, the microphone module was able to capture the sounds of breathing during both inhalation and exhalation.

The signals we collected were sent from the ESP32 microcontroller to a computer system, where they were processed and shown on a web dashboard live. This dashboard gives a graphical view of the ECG waveforms and lung sounds through dynamic charts.

With this visualization interface, users can keep an eye on the signal patterns constantly and track changes in physiological data over time. This real-time monitoring is crucial for spotting sudden issues and aiding remote healthcare efforts [18].

Fig. 3. Real-Time ECG waveform displayed on the monitoring dashboard.

B. ECG Signal Classification Results:

We trained the ECG classification model using the MIT-BIH Arrhythmia Dataset, which includes labeled ECG signals that capture various heart rhythms. The Convolutional Neural Network (CNN) we developed looks at these ECG waveform patterns and determines if a heartbeat is normal or not.

When we put the system to the test, it effectively recognized abnormal ECG patterns, like arrhythmias, by examining the signals coming from the ECG sensor [14], [15]. The prediction outcomes are shown on a web dashboard along with the waveform visuals.

Thanks to deep learning models, the accuracy of classifying ECG signals has seen a considerable boost compared to older feature-based techniques. This model can automatically pick out key waveform features that indicate unusual heart activity.

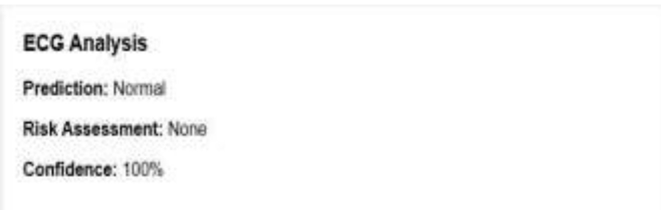

Fig. 4. ECG classification output showing predicted heartbeat category.

C. Lung Sound Classification Results:

We analyzed lung sounds by recording respiratory audio using the MAX4466 microphone module. To make sense of those recordings, we applied Mel Frequency Cepstral Coefficient (MFCC) techniques to pull out key spectral features [16].

These features were then fed into a machine learning model that categorizes lung sounds into four main types [29].

- Normal breathing
- Crackle
- Wheeze
- Crackle and Wheeze

The system did a good job of spotting abnormal sounds that could suggest lung issues. We displayed the classification results on a dashboard, along with visualizations of the signals, to help with diagnosis.

Fig. 5. Lung sound signal visualization captured from the sensor.

Fig. 6. Lung sound analysis output identifying abnormal crackle sound.

D. System Performance Evaluation:

We examined the efficiency of the proposed system, especially in terms of its ability to "accurately monitor signals, diseases, and data visualization in real time." The integration of IoT data collection and machine learning allows the system to "intelligently" analyze physiological signals.

When stacked against traditional healthcare monitoring systems, the new setup has a bunch of cool benefits:

- It allows for real-time monitoring of ECG and lung signals.
- It automatically detects diseases using machine learning models.
- The hardware is portable and cost-effective.

Plus, it offers web-based visualization for remote monitoring.

This makes it a good choice for applications such as remote healthcare monitoring, telemedicine, or disease detection. Overall, the results demonstrate that combining AI and IoT technologies can be a powerful way to increase the efficiency of biomedical signal monitoring.

V. CONCLUSION

In this paper, we have introduced a healthcare monitoring system that uses AI to analyze ECG signals as well as lung sounds. The objective was to use this system for the early detection of heart and lung problems. The system combines a number of components, which include physiological sensors, an ESP32 microcontroller, signal processing techniques, as well as machine learning algorithms. The system provides a much more comprehensive overview of a patient's health, as it not only uses ECG signals but also lung sounds. The usual healthcare monitoring systems only use a single type of signal.

The experimental results obtained from this system have shown that it can successfully pick up physiological signals, process them using feature extraction techniques, and then use deep learning algorithms to identify possible abnormalities. Moreover, we have also added a web-based interface, which can provide a much more effective overview of the patient's health, as users can view the ECG signal as well as lung sounds. The use of IoT components makes this system affordable and portable.

All in all, the system demonstrates the potential of the integration of Artificial Intelligence and the Internet of Things to aid the detection of diseases as well as the monitoring of health conditions. These intelligent health monitoring systems can help healthcare professionals make decisions quickly and patients monitor their health better.

VI. FUTURE SCOPE

The system proposed here seems to have a few good prospects for tracking heart and lung signals; however, there are definitely a few areas where we can further improve this system to make it more viable for real-world healthcare purposes.

In further development of this system, we could explore adding more sensors to this system, like sensors that track blood oxygen levels, body temperature, and blood pressure. This will enable us to create a more comprehensive health monitoring system. Additionally, this will allow us to integrate wearable technology to enable continuous patient monitoring during their daily lives.

We could also improve this system further by employing more data to improve the accuracy and reliability of this system. We could explore more advanced deep learning techniques to improve feature extraction and disease prediction.

Furthermore, we could also explore incorporating this system with cloud technology and a mobile app to enable healthcare providers to monitor their patients' health and track any unusual changes to their health. This will enable us to further improve this system and make it more viable for remote healthcare and telemedicine purposes.

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