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Development of an Internet of Things-based Smart Health Monitoring System for COVID-19

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ABSTRACT

The application of machine learning (ML) -based Internet of Things (IoT)- in healthcare during COVID-19 has proven effective in preventing disease spread. This paper proposed an IoT system to remotely detect and monitor suspected COVID-19 cases at home. To develop the system, IoT sensors, a mobile application, and ML algorithms were used for data analysis. The IoT node tracked health parameters, including body temperature, heart rate, blood oxygen saturation level, and blood pressure, as well as age and gender information, then used a user interface to display health status updates and sent them to a cloud server. The decision-making module based on ML algorithms was placed on the server side. The system's efficiency was evaluated using accuracy, precision, recall, and F1 score metrics. Doctors could view and track users' health status through an interface, and Pearson's correlation coefficient was used to determine the correlation between sensor measurements and vital sign devices. The proposed system achieved 99.05% accuracy, 98.66% precision, 99.32% recall, and 98.99% F-measure using the random forest algorithm. The Pearson correlation coefficient also showed a strong correlation in evaluating the sensors. The system could aid in diagnosing and monitoring suspected COVID-19 cases.

Keywords: Internet of Things, Artificial Intelligence, Machine Learning, Mobile Health, COVID-19

INTRODUCTION

The Coronavirus disease 2019 (COVID-19), also known as the acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has placed an unprecedented burden on the healthcare system (1, 2). In 2020, the WHO declared the outbreak of COVID-19 as a pandemic (3, 4).

Serious symptoms in COVID-19 patients include high fever, low oxygen saturation, and abnormal pulse rates (5). Hypoxemia and hypoxia are caused by low levels of oxygen saturation and shortness of breath, respectively. Patients with these conditions have a lower chance of survival. Sometimes, patients are unaware of their hypoxemia and elevated pulse rate, which can ultimately lead to their demise without receiving the necessary treatment (6). Given the increased risk of outbreaks, especially among asymptomatic COVID-19 patients, early diagnosis is crucial for timely intervention and to prevent hospital admission (1, 7, 8).

The combined use of IoT and ML has significant potential to provide deeper insights into healthcare data and facilitate accessible personalized care (9). Specifically, IoT refers to a system of physical devices that autonomously collect, digitally record, and exchange information wirelessly without requiring human intervention (10, 11). When combined with Artificial Intelligence (AI), this technology provides valuable insights into healthcare data and enables personalized care through wearable sensors, leading to effective and affordable solutions (9, 12). ML is a subset of AI that empowers systems to make decisions by utilizing trained data models (13). The development of intelligent diagnostic systems aids healthcare professionals in making more informed decisions regarding patients' health (14). A smart IoT system offers an in-home telehealth monitoring tool that facilitates health assessment and aids in diagnosing illness conditions during the COVID-19 pandemic (1, 15).

The main objective of this research is to develop a system equipped with IoT to detect and monitor persons suspected of having COVID-19 remotely at home.

Research studies have been carried out in the field of developing COVID-19 detection systems based on the IoT and ML, all of which confirmed the high efficiency of the combination of these two technologies in the early diagnosis of this disease (16-18). Hossein Miro et al (16). proposed an IoT-based ML framework for predicting COVID-19 suspects, utilizing various sensors and a decision tree algorithm with 0.98 accuracy for decision support. Bilandi et al. (18). developed an energy-efficient Wireless Body Area Network (WBAN) model for diagnosing and monitoring COVID-19 patients, using biosensors and random forest classification with 88.6% accuracy as the decision-making module. Sreehari et al. (17). proposed an IoT-based ML framework for early COVID-19 detection, utilizing health parameters sensors and a random forest model that achieved 94.4% accuracy as the decision module.

Despite the practical similarities between the present study and these studies, operational use of them in Iran is not possible due to access and permission issues. Therefore, this study results in a national sample of an IoT-enabled system developed to detect and monitor COVID-19 suspects remotely at home, which is being implemented for the first time in Iran.

METHODS

This study received ethical approvals from the Ethics Research Committee of Shiraz University of Medical Sciences (IR.SUMS.NUMIMG.REC.1401.023)

Proposed System

Based on the hardware and software requirements, body temperature sensors, blood oxygen saturation levels, and heart rate sensors, as well as the boards, were prepared, programmed, and assembled. Arduino was chosen as the platform. Arduino is an open-source platform that consists of both software and hardware components. It utilizes the Java programming language as its primary language and the Atmel microcontroller as its main hardware component (19).

User interfaces for the patient-doctor interaction were developed using the Android Studio environment. The system architecture consists of three layers: the data collection layer, the data transfer layer, and the data processing/storage layer. The data collection layer is responsible for gathering symptoms from the suspect through various sensors such as the temperature sensor, heart rate sensor, and blood oxygen level sensor. On the user side, the data is recorded through the companion application, which is connected to the sensor board via a wireless network, along with the age, gender, and blood pressure data. Here, both manual and non-manual login are built into the app. In the data transfer layer, registered patient data is sent to the cloud server through the Internet. The data processing/storage layer is responsible for analyzing the received data. The decision assistant module was implemented on the server to process real-time data sent by the user. An ML model is deployed in this layer to get better insights from data. Once stored in the individual's file, the analysis of the individual's health status can be viewed and monitored by the doctor through a dashboard. If an individual is evaluated as positive for COVID-19, the doctor will be notified.

Development of a diagnosis model

A) Dataset

In this research, we used the freely available data set from http://www.c19data.info/index.php/admin/patients. The data was collected from a wearable device used by individuals in quarantine, including both healthy and unhealthy patients. The data sets were divided into two categories: infected with COVID-19 and healthy. The dataset contains 1084 records (945 positive and 139 negative) with eight features (Table 1).

TABLE I. THE DATASET FEATURES

#	Attribute	Data type	Non-Null count
0	Id	Int 64	1084 non-null
1	gender	Object	901 non-null
2	Age	Float 64	842 non-null
3	Heart_ rate	Int 64	1084 non-null
4	Temperature	Float64	1084 non-null
5	SPO 2 _saturation	Float64	1084 non-null
6	Bpm	Int 64	1084 non-null
7	Health_ status	Object	1084 non-null

B) Data Pre-processing

To improve the quality of ML models, various data preprocessing techniques were utilized. Since hyperparameters are used by ML models to manage model training, the only way to determine these is through multiple experiments (20). ML models were consecutively trained with different hyperparameter sets, and the hyperparameters were adjusted in a way that had a significant impact on the accuracy and overall capability of the model. During the initial phase of data cleaning, heuristic methods were used to identify and address any instances of noise and outliers. The hyperparameters used for outlier removal with a distance-based exploratory method include 17 outlier points in the dataset based on the distance to the four nearest neighbors. Estimates of missing cases were utilized to account for any missing values. The K-Nearest Neighbor (K-NN) algorithm was used for estimation, with a hyperparameter of k=5. After cleaning the data set, the next challenge was dealing with data discretization. In this stage, the variables of age, body temperature, blood oxygen saturation level, heart rate, and blood pressure were discretized based on a determined threshold. Since the classes were not equally classified, the dataset was imbalanced, with more samples belonging to the infected class (945 cases) and a smaller number of samples in the healthy class (139 cases). Consequently, the developed models often provided results biased towards the dominant class, and ML models were more likely to classify new observations into the majority class. The issue of class imbalance was solved by re-sampling the dataset using the Synthetic Minority over-sampling Technique (SMOTE). During the training of the classifiers, 70% of the total data was used for training purposes, and the remaining 30% was used to evaluate the performance of the classifiers.

C) Supervised Classification Methods

Various supervised classification methods, such as decision tree, random forest, gradient boosted trees, decision stump, random tree, and ID3, were implemented in RapidMiner software version 9.10 for COVID-19 detection.

D) Classifier Evaluation Metrics

Various evaluation metrics were employed to evaluate the performance of the ML algorithms, including accuracy, precision, recall, and f-measure. These evaluation criteria were compared to determine the most effective algorithm for detecting COVID-19. The performance metrics of the confusion matrix are shown in Table 2.

TABLE III. THE PERFORMANCE EVALUATION METRICS

Measure	Formula	Intuitive meaning
Accuracy (A)	(TP + TN)/(TP + TN + FP + FN)	The percentage of predictions that are correct.
Precision (P)	TP/(TP + FP)	The percentage of positive predictions that are correct.
Recall	TP/(TP + FN)	The percentage of positive labeled instances that were predicted as positive.
F-measure	2* PR/(P + R)	The weighted harmonic means of Precision and Recall.

System evaluation

In the context of comparing the devices, Pearson's correlation coefficient can be used to determine the closeness of the measurements taken by the devices. In this study, to assess the accuracy of the sensors used in the proposed system, these sensors were compared with conventional medical devices that measure heart rate, body temperature, and blood oxygen levels. This test was continued until a significant correlation was established.

RESULTS

Development of a diagnosis model

Table 3 displays the metric performance scores of the ML classifier in predicting COVID-19 and indicates that Random Forest and Decision Tree classifiers perform the best. By training multiple trees on subsets of data and features and then averaging their predictions, random forest achieves better prediction accuracy overall (21). Therefore, for this research, the random forest model has been used as the decision module. The random forest classifier outperforms with an accuracy of 99.05%, precision of 98.66%, recall of 99.32% and f-measure of 98.99%. This demonstrates its superior capability in diagnosing COVID-19.

TABLE IIIII. THE PERFORMANCE OF EACH ML CLASSIFIER

#	Predictive ML models	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
1	**Decision tree**	99.05	98.66	99.32	98.99
2	**Random forest**	99.05	98.66	99.32	98.99
3	**Gradient boosted trees**	97.47	99.30	95.27	97.24
4	**ID3**	98.10	97.97	97.97	97.97
5	**Decision stump**	95.25	100	89.86	94.66
6	**Random tree**	60.44	63.22	37.16	46.81

System development

The architecture of the proposed system is shown in Figure 1.

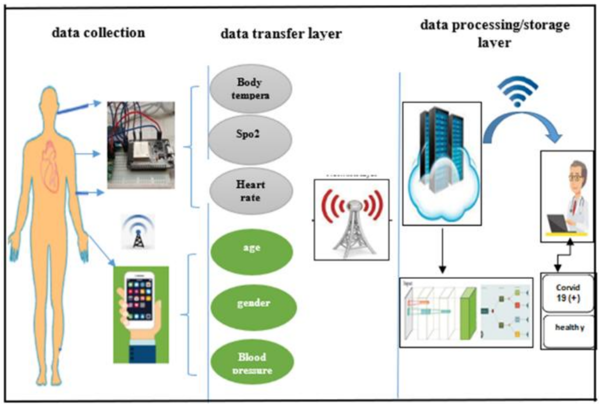

FIGURE I. THE ARCHITECTURE OF THE PROPOSED MODEL

It is assumed that user registration is completed through the family doctor. By inputting relevant information, the user can record their health status. The user utilizes sensors to measure symptoms, such as blood oxygen level, body temperature, and heart rate, in order to determine their COVID-19 infection status. This data, along with manually entered information, including the user's gender, age, and current blood pressure, is integrated into the accompanying application. The symptoms measured by the sensors, as well as the manually measured symptoms, age, and gender, are combined to form a request. Once the user confirms the information by pressing the health check button, the request is sent online to the cloud server. The decision-maker module on the server determines the user's final state. In the decision assistant module, the random forest model is used to detect the final state. If the user's condition is assessed as positive for COVID-19, the doctor is notified. The doctor can then monitor the health status of their patients through the dashboard. Figure 2 shows a view of the final test of the assembled board.

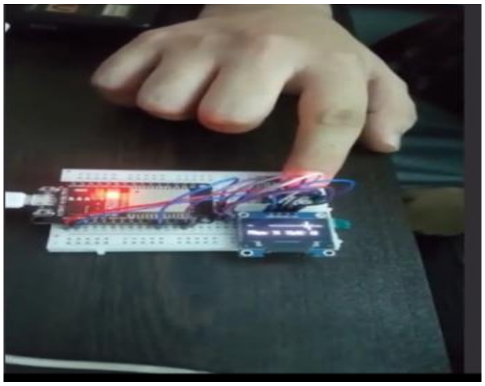

FIGURE II. THE FINAL TEST OF THE ASSEMBLED BOARD

System evaluation

The Pearson correlation coefficient indicated a strong correlation in evaluating body temperature sensors, blood oxygen saturation levels, and heart rate sensors. A strong positive correlation was observed between the designed board and standard commercial devices in the evaluation of blood oxygen level measurements ($r = 0.995$, $p < 0.0001$), heart rate ($p < 0.0001$), and body temperature measurements ($r = 0.989$, $p < 0.0001$). These results demonstrate the reliability of the designed infrastructure for monitoring this category of vital signs.

DISCUSSION

In this study, an IoT-enabled system was developed to detect and monitor suspected COVID-19 persons remotely at home. The decision-making data included vital signs such as body temperature, blood oxygen saturation level, heart rate, and blood pressure, along with age and sex. The random forest model was also proposed to classify suspected COVID-19 persons. The evaluation results showed that the combination of IoT and ML technologies can be effective in managing the COVID-19 pandemic.

Introducing and selecting the appropriate platform for system development is one of the critical steps in IoT-based projects. The Arduino platform has been chosen as the ideal platform for system development. The Arduino microcontroller can provide a quick tool for developing small projects that involve sensors and is easy to learn and program (22). Saranya et al. designed a system to monitor and diagnose the severity of coronavirus in patients. They used various unobtrusive sensors to measure disease-specific vital parameters such as heart rate, temperature, oxygen level, and pulse rate. The system utilized Arduino to collect information from these sensors and transfer it to the web server. This approach resulted in a low-cost, scalable, accurate, and efficient solution (23).

This study lacks a decision assistant module. However, the present study incorporates a decision assistant module that uses the ML technique.

Increasing emphasis on ML techniques in medicine can provide a suitable ground for revolution and progress. The studies (24, 25) can be mentioned among the studies conducted using the same data sets as the present research. In the study (24), Asif Hossein et al. predicted and evaluated the risk of COVID-19 disease progression through simulation using a random forest classification algorithm. They achieved an accuracy of 99.26%. In the present study, the random forest model achieved an accuracy of 99.05%, precision of 98.66%, recall of 99.32%, and f-measure of 98.99%.

While Study (24) reported a higher accuracy than the current research, the present study demonstrates significant strength through a superior recall rate. Given that the cost of false negatives is critical in diagnosing infectious diseases, a higher recall indicates that the classifier is more effective in accurately identifying true positive cases. This capability is crucial for minimizing the risk associated with undetected infections and highlights the robustness of the model in practical applications for COVID-19 detection.

In a study (25), Vila Para introduced an integrated portable medical assistant that could collect biomedical data to help infer the diagnosis of COVID-19 through ML algorithms. This research utilized cough and speech from the Cambridge Sound Database, as well as body temperature, heart rate, and blood oxygen saturation level data from the dataset collected in (24). A decision tree was used to measure heart rate, body temperature, and blood oxygen saturation level. The accuracy rate for the decision tree algorithm was obtained at 98.62%. The accuracy of the decision tree algorithm in this research was lower than in the current research.

Considering that the sensors of the developed system are not user-friendly, to commercialize this system and align it with the goals of monitoring vital signs, the development of a user-friendly interface in the form of a wearable gadget is necessary.

CONCLUSION

This study shows that an intelligent diagnosis system based on IoT, with high accuracy, can provide a significant improvement in detecting and monitoring persons suspected of COVID-19 remotely at home. It also facilitates rapid notification to physicians through the integration of sensor data and ML. The proposed system can benefit COVID-19 patients as well as those suffering from other diseases, such as chronic obstructive pulmonary disease (COPD) and asthma because these patients need to closely monitor their vital signs, and this system can help better manage their health status. In addition, this system remains an effective and usable telemedicine tool even after COVID-19 because it can facilitate remote monitoring of vital signs.

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CONTRIBUTORSHIP STATEMENT

AY contributed to the conceptualization, formal analysis, funding acquisition, investigation, methodology, resources, supervision, validation, visualization, writing the original draft, responding to reviewers, and editing. SF was responsible for data curation, formal analysis, resources, software, validation, visualization, and writing the original draft. All authors reviewed and commented on the manuscript, and all are responsible for its content.

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DECLARATION OF CONFLICTING INTERESTS

The authors declared no conflicts of interest regarding the research, authorship, and publication of this article. Additionally, they confirmed that this manuscript provides an honest, accurate, and transparent account of the reported study. They stated that no significant aspects of the study have been left out and that any deviations from the original study plan (and, if applicable, the registered protocol) have been clearly explained.

DATA AVAILABILITY STATEMENTS

The data utilized in this study is publicly accessible from the http://www.c19data.info/index.php/admin/patients.

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