DEVELOPMENT OF AIOT-BASED HEALTH KIOSKS FOR PATIENT CLASSIFICATION IN E-HEALTH

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Abstract: This study aimed to develop health kiosks that collect demographic data, body indices, and vital signs of patients. Additionally, this paper proposed the integration of Artificial Intelligence (AI) to predict and classify patients based on various respiratory infectious diseases, using the data collected by the device. Furthermore, the paper discussed formatting the device's output packages according to HL-7 standards to facilitate seamless integration with hospital management system (HMS). It also proposed a solution for deploying these devices on e-Health platforms utilizing Internet of Things (IoT). During routine operations, the kiosks collect demographic data, body indices, and vital signs from patients for medical examination and treatment. In the event of an epidemic, these kiosks can be utilized to detect and manage positive cases, thereby contributing to the reduction of the spread of infectious respiratory diseases.

Key words: Artificial Intelligence of Things, e-Health, Health kiosk, HL-7.

1. INTRODUCTION

The Health Kiosk is a recent technological achievement. These devices help people easily access to healthcare services. Their advantages include improved productivity, lower expenses, less time needed by staff and patients, and the capacity to provide specific medical services in case of emergencies [1]. Leading companies in this field include Higi in the United States, Pulse Active Stations Network in India, Well.me in the United Kingdom, and Sonka in China. However, the current functionality of these devices is primarily limited to measuring body height and weight, calculating Body Mass Index (BMI), Body Surface Area (BSA), and measuring vital signs, including body temperature, blood pressure, heart rate, and oxygen saturation (SpO2).

This paper presents a method for developing health kiosks, designed to measure vital signs, body height and weight, collect demographic data, reason and time of the visit (month, respiratory, fever, etc). The data will be utilized to classify patients according to the types of respiratory diseases using a machine learning model. The output packets from the device are formatted in accordance with the HL7 standard [2]. Furthermore, IoT technology will be applied to integrate these devices into HMS, remote medical examination platforms, electronic medical records, and other e-Health systems. The objective of developing this health kiosk is to enhance the efficiency of medical examinations and improve the prevention of infectious respiratory diseases.

2. RELATED WORKS

Health kiosks are a promising research topic, according to recent studies. Chavis Srichan et al. developed and implemented a telemedicine health kiosk system equipped with non-invasive biosensors and time-series predictors to improve non-communicable disease (NCD) indicators. The results support telemedicine kiosks as an effective tool for NCD management, significantly improving major NCD indicators, average blood glucose, and blood pressure [3]. Kiran Kumar et al. developed a solar-powered kiosk with a face-mask detector. The kiosk system equipped with a camera detects the facial mask of the person entering, using Machine Learning Algorithms (MLA). Those without masks are denied entry by the system, which also alerts people whose masks are below their noses and prevents them from entering through the kiosk [4]. In addition, recent studies indicate the potential of integrating new technologies into the healthcare kiosk platform. For example, Harsh Taru et al. proposed the application of AI, natural language processing (NLP), and computer vision to telemedicine kiosks. Their results showed significant improvements in kiosk performance, as well as decrease in misdiagnoses and waiting times. They concluded that AI-integrated system efficiently processes patient data, facilitates diagnoses more accurately and enhances communication between patients and healthcare professionals [5].

3. DESIGN METHODS

This device consists of two primary components: the first is a health kiosk that collects demographic data and measures vital signs and body indices; the second is an Artificial Intelligence Unit (AIU) designed to develop predictive models for patient classification. The device is characterized by specific technical parameters, presented in Table 1.

Table 1. The device's specifications

No.	***Specifications***	***Value***
1	Touch screen	10.1 inch.
2	Output standards	HL7/RS-232, RESTful.
3	Main functions	Collect reason and time of the visit, demographic data, including name, birthday, and identifier, using QR codes or barcodes.
		Measure vital signs, including blood pressure, heart rate, temperature, respiratory rate and oxygen saturation (SpO2).
		Measure body weight and height, and calculate BMI, BSA.
		Based on the patient's demographic data, BMI, BSA and vital signs, classify patients into specific types of respiratory diseases using machine learning model.
		Utilize IoT technology to integrate devices into e-Health systems. Print and export the output data.

3.1. Hardware model

In this paper, the health kiosk will be named as AIoTM-1, an AIoT-based health kiosk. Fadi Al-Turjman et al. detail this AIoT platform in [6]. The AIoTM-1 device is designed to collect demographic data, reason and time to visit, BMI, BSA and vital signs from patients, subsequently export this information to the AIU. This unit is tasked with utilizing a machine learning model to predict types of infectious respiratory diseases based on the data obtained from the AIoTM-1 device. Furthermore, the AIoTM-1 can communicate with HMS following HL7 standards and with e-Health systems via API RESTful. The device connection diagram is presented in Figure 1a.

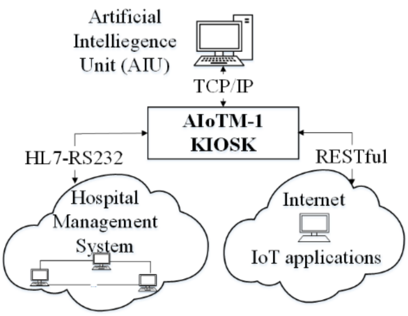

Figure 1a. Device connection diagram

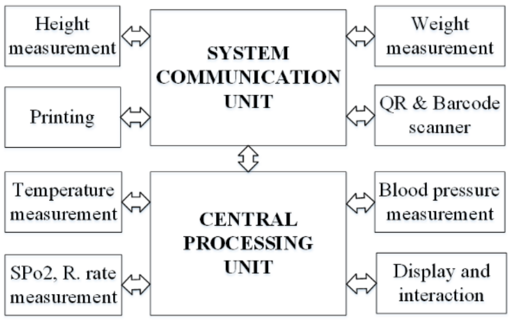

Figure 1b. Hardware block diagram

Figure 1b illustrates the hardware block diagram of the AIoTM-1 device. Specifically, the device comprises a Raspberry Pi 5 embedded computer, serving as the Central Processing Unit (CPU), which acts as the processing core of the system.

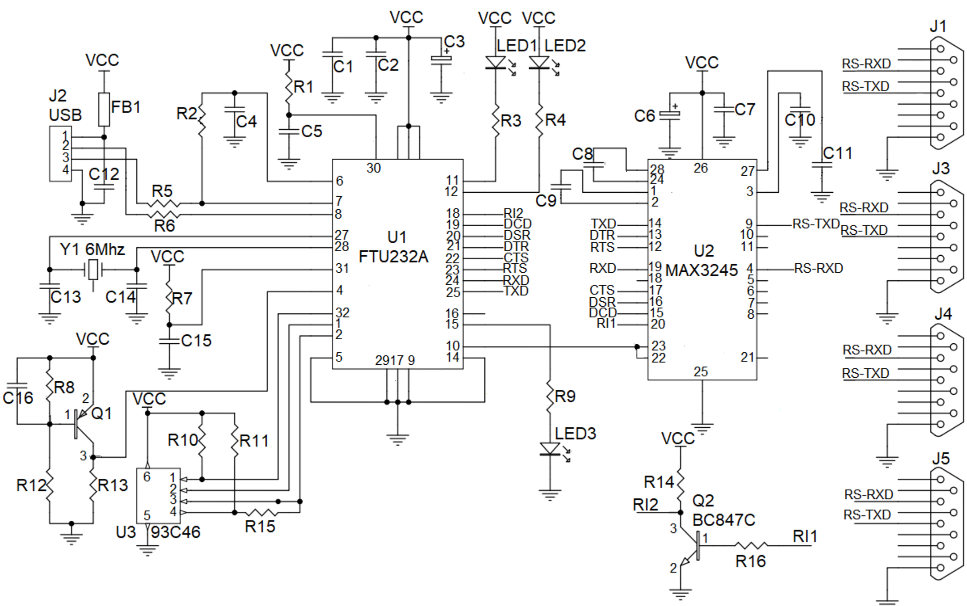

Figure 2. Principle diagram of SCU

The CPU processes user interactions and controls other units to measure vital signs and BMI, BSA, and displays the resulting data on the touchscreen. The System Communication Unit (SCU) serves as the intermediary between the CPU and the other units. It employs the RS-232 standard for data exchange. The principle diagram of this unit is shown in Figure 2.

The Beurer PM58 Blood Pressure Monitor is utilized to measure the patient's heart rate, diastolic and systolic blood pressure, transmitting the collected data to the CPU via the USB-HID protocol. The Microlife Infrared Thermometer facilitates non-contact temperature measurement using infrared technology, with the resulting data also transmitted to the CPU via Bluetooth connectivity. The Honeywell barcode scanner is capable of reading various common code types, encompassing both one-dimensional (1D) and two-dimensional (2D) formats. This scanner is responsible for gathering patient's information from health insurance card codes and identification codes, subsequently transmitting the data to the CPU in accordance with the RS-232 standard. A MightySat Fingertip Pulse Oximeter device is utilized to measure SpO2 levels and respiration rate. In addition, a load cell with a measurement range of 0 to 150 kg is employed to assess the patient's weight, while an ultrasound sensor is used to measure the patient's height. The Epson TM-T52 thermal printer is utilized to print results on K80-sized thermal paper. A touchscreen with a resolution of 1920x1080 is used for displaying information and capturing user input.

3.2. Software model

The algorithmic model of the software for the AIoTM-1 device is illustrated in Figure 3.

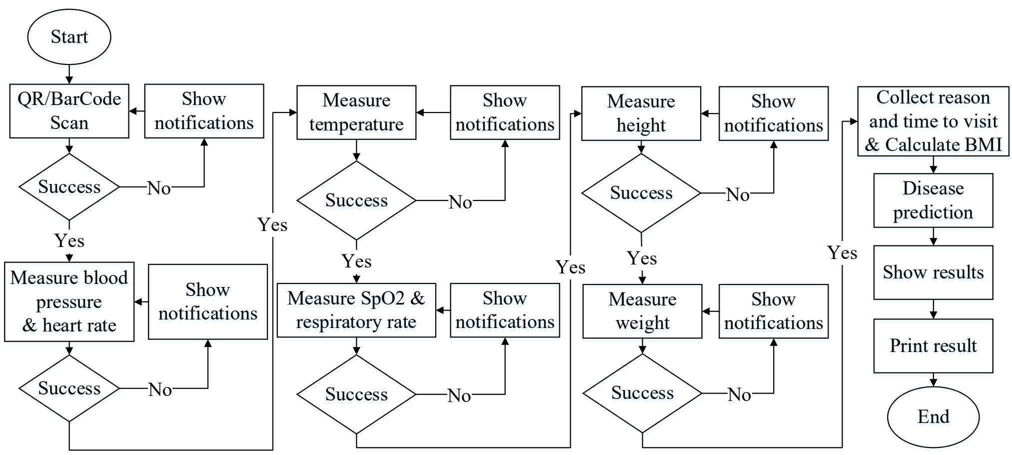

Figure 3. The algorithm flow diagram of the AIoTM-1 device

Initially, the device retrieves patient information by scanning a QR code or barcode on the health insurance card or the patient identification card. It then proceeds to collect data such as heart rate, blood pressure, temperature, oxygen saturation (SpO2), respiratory rate, height, weight, reason and time to visit. If a measurement is conducted successfully, the device will perform subsequent measurements. Conversely, if a measurement fails, the device will warn and ask the user to remeasure. Following the data collection process, the information is updated in the database. The AI model subsequently predicts potential types of infectious respiratory diseases and displays prediction results on the touchscreen. Finally, the device outputs the results via a thermal printer and exports the data to external systems, such as hospital management or e-Health systems, utilizing either RS-232 or REStful interface.

3.3. Integration of the device within e-Health systems

The device must possess compatibility with other medical systems. A review of relevant legal documents revealed that the HL7 standard can be used to format output data of the device. HL7 serves as an international standard, providing a uniform protocol for the management, exchange, and integration of medical data across health information systems. To ensure seamless integration of the device into HMS and medical platforms, output data will be formatted according to the HL7 standard and exported via RS-232 protocol. For this output RS-232 packages, data will be transmitted in serial communication format, following the default parameters: a baud rate of 9600, no parity, eight data bits, and one stop bit. The device is also designed with the APIs listed in Table 2. These APIs are used to integrate the device into e-Health systems through the RESTful interface.

Table 2. API table for the device in e-Health systems

Request	***Meaning***	***Response***
GET /data	Retrieve all data stored in the device	All data stored in the device
GET /data/{n}	Retrieve the data at the n-th position. If n=0, the operation returns the most recent data.	Data at the n-th position. If n=0, the operation returns the most recent data.
PUT /data/{n}	Update the results for the data at the n-th position	Success/Failure
DELETE /data	Delete all data	Success/Failure

3.4. Utilizing AI for patient classification

The device uses machine learning model to predict and classify patients based on various respiratory infectious diseases, including: Influenza (Class 0), SARS-CoV-2 (Class 1), and Other diseases (Class 2), using the data collected by the device. Research conducted by Naveena Yanamala et al at West Virginia University [7] involved a cohort of 3883 patients with a mean age of 52 ± 24 years. Among these patients, 1223 (31.5%) were diagnosed with Class 0, 747 (19.2%) were tested positive for Class 1, and 1913 (49.3%) were diagnosed with Class 2. The TriNetX external validation cohort included 3125 patients, of whom 2068 were Class 0, 1057 were Class 1. This paper utilized the data and XGBoost model of [7] to classify patients based on demographic data, reason and time to visit, BMI, BSA and vital signs. This approach's objective is to employ machine learning models to automatically identify and isolate positive cases of infectious respiratory diseases. This solution serves as a potential alternative to traditional testing methods. In addition, to evaluate the capacity of this approach in classifying respiratory infectious disease, the paper used three other models for comparison, including the: Houman's model [8], Chi's model [9] and Li's model [10].

4. RESULTS AND DISCUSSION

4.1. Results of development of the AIoTM-1 Health Kiosk

Figure 4a illustrates the AIoTM-1 device, and figure 4b illustrates the user interface of the AIoTM-1 device.

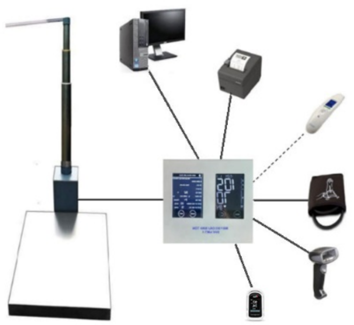

Figure 4a. The AIoTM-1 device

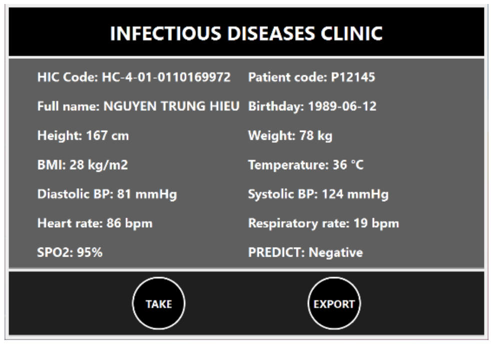

Figure 4b. User Interface of the AIoTM-1 device

The operating principle of the device is as follows: Initially, the user employs a barcode or QR code scanner to extract the patient's demographic data from the health insurance card, which includes such information as name, age, gender, and other data. The data are then presented on the device's touchscreen interface. Following this, the user utilizes the device to measure body indices and vital signs, including weight, height, systolic blood pressure, diastolic blood pressure, heart rate, oxygen saturation (SpO2), respiratory rate, and body temperature. All collected data, in conjunction with the previously gathered demographic information, reason and time to visit, are recorded and updated in the database. Simultaneously, AI predictive models process these data for patient classification according to the types of infectious respiratory diseases. The predictive outcomes generated by the AIU are subsequently displayed on the touchscreen or conveyed audibly through the device's speaker, provided that the installation of the device makes it possible.

4.2. Experimental results of the predictive model for patient classification

To evaluate the performance of the model, this paper computes and analyzes specific metrics, as detailed below:

Confusion Matrix: In the field of machine learning and specifically statistical classification, Confusion Matrix is a specific table layout that allows visualization of an algorithm performance. Each row of the matrix represents the instances in an actual class while each column represents the instances in a predicted class, or vice versa.

Table 3. Confusion Matrix.

	Predicted Class		
Actual Class		Yes	No
	Yes	TP(a)	FN(b)
	No	FP(c)	TN(d)

Where:

a: TP (true positive) – This occurs when both the actual class and the predicted class of the data point are True.

b: FN (false negative) – This occurs when the actual class of the data point is True, but the predicted class is False (for example, when a pregnancy test indicates that a woman is not pregnant, but she actually is).

c: FP (false positive) – This occurs when the actual class of the data point is False, but the predicted class is True (for example, when a pregnancy test indicates that a woman is pregnant while she is not).

d: TN (true negative) – This occurs when both the actual class and the predicted class of the data point are False.

Accuracy: Accuracy in classification is the most common evaluation metric. It is defined as the ratio of the number of correct predictions made by the model to the total number of predictions.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} = \frac{a+d}{a+b+c+d} \quad (1)$$

Error Rate: The Error Rate of the model is calculated as follows:

$$ErrorRate = 1 - Accuracy \quad (2)$$

Precision: Precision is defined as the number of true positives divided by the sum of true positives and false positives. It indicates the proportion of positive predictions that are actual positives, in relation to the total number of predicted positives.

$$Precision = \frac{TP}{TP+FP} = \frac{a}{a+c} \quad (3)$$

Recall/Sensitivity: is defined as the number of true positives divided by the sum of true positives and false negatives. It indicates the proportion of positive predictions that areactual positives, relative to the total number of positives in the original dataset.

$$Recall = \frac{TP}{TP+FN} = \frac{a}{a+b} \quad (4)$$

F1 Score: The F1 score combines precision and recall for a specific positive class. It reflects the balance between precision and recall, particularly in cases of uneven class distribution. The F1 score achieves its highest value of 1 and its lowest value of 0.

$$F1Score = \frac{2*Recall*Precision}{Recall+Precision} = \frac{2a}{2a+b+c} \quad (5)$$

Table 4 presents the outcomes of the aforementioned values as derived from the model application, according to types of infectious respiratory diseases.

Table 4. Results of the prediction model.

	Precision	***Recall***	***F1-score***	***Support***
Class 0	0,95	0,95	0,95	19
Class 1	1,00	0,80	0,89	5
Class 2	0,93	0,96	0,94	26
Accuracy			0,94	50
Macro avg	0,96	0,90	0,93	50
Weighted avg	0,94	0,94	0,94	50

The model demonstrates robust performance in detecting Class 0 cases, with high precision and recall, exhibiting a good balance between the two. Additionally, the accuracy level in detecting Class 1 cases is higher, but the recall rate for this class is lower, indicating that some actual cases are not being detected. This results in a higher false negative rate compared to the other two classes. Furthermore, the model performs well in predicting Class 2, effectively identifying true Class 2 cases while minimizing the occurrence of false positives. The confusion matrix of the model is presented in Figure 5a.

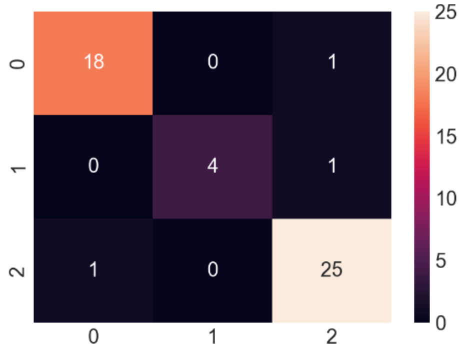

Figure 5a. Confusion matrix

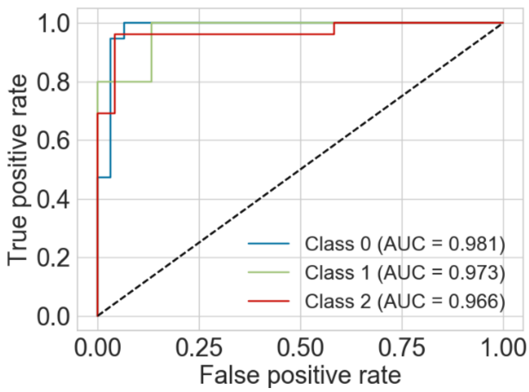

Figure 5b. AUC ROC curve of the model

The diagonal elements of the confusion matrix correspond to correctly predicted samples. In this analysis, a total of 47 out of 50 samples are accurately classified (94%). A total of 19 cases of Class 0 are predicted. Among these, 1 case (5.2%) is misclassified as Class 2. Additionally, 1 out of 5 Class 1 and 1 out of 26 Class 2 are incorrectly predicted. Class 0 and Class 2 achieve commendable F1-score values of 95% and 94%, while the F1 score for Class 1 stands at a lower 89%. To assess the model's performance across different classification thresholds, this paper employs the AUC-ROC curve, also known as the Receiver Operating Characteristic curve. Receiver Operating Characteristic (ROC) curve is a graphical method for assessing the classifier performance. It utilizes two key metrics: the true positive rate (TPR) and the false positive rate (FPR). These metrics are plotted on a two-dimensional graph, with the FPR on the x-axis and the TPR on the y-axis. The resulting ROC curve allows the comparison of the relative performance of different classifiers and evaluates whether a classifier performs better than random guessing. AUC stands for the Area Under the Curve and represents the area under the ROC curve. It measures the overall performance of the binary classification model. As both TPR and FPR range between 0 to 1, the AUC area always lies between 0 and 1, and a greater value of AUC denotes better model performance. The ROC AUC curve of the XGBoost model is presented in Figure 5b. The ROC curve of the prediction model demonstrates a strong asymptotic trend toward the line (y=1). The AUC for all three classes is relatively comparable, exhibiting only minor differences. The AUC for Class 0 exceeds that of Class 1 by 0.008, and the AUC for Class 1 surpasses that of Class 2 by 0.007. The AUC for all three curves is notably high, indicating that the model demonstrates strong accuracy in distinguishing between positive and negative cases. The performance of the model used in this paper with those of Houman, Li, and Chi is compared in Table 5 and Figure 6.

Table 5. Compared with other models.

Approach	***Model***	***Input data***
Houman S. et al.	ResNet50 (0%)	Chest CT Images
WeiTse Li et al.	XGBoost	Diagnosis, Risk Factors, CTScan, Signs and Symptoms, Temperature, XrayResults and etc.
D. Th. K. Chi, et al.	XGBoost	Diagnosis, Risk Factors, CTScan, Signs and Symptoms, Temperature, XrayResults and etc Initial PCR Diagnosis, Number Of Family Members Infected, Region.
This paper (Naveena et al.)	XGBoost	Vital Signs, Body Height and Weight, Demographic Data, reason and time of the visit.

The results showed that, although this model only requires simple input data, and easily and quickly collects data from a health kiosk and does not require specialized tests like the other three models (CTScan, XrayResults and etc), its accuracy level is only slightly lower than that of Chi and Li's model and higher than that of Houman's model.

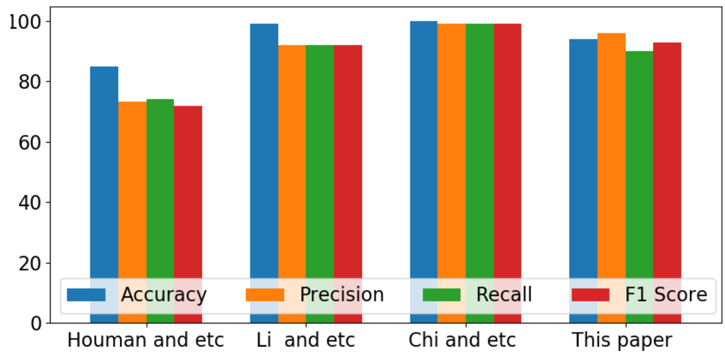

Figure 6. Performance of the model compared to other models

The model's performance underscores the feasibility of utilizing XGBoost for disease prediction based on demographic data, reason and time to visit, BMI, BSA and vital signs of patients. Once the AIoTM-1 device collects these data, it transmits the data to the AIU. The XGBoost model of the AIU processes the received data and classifies the patients according to types of respiratory infectious diseases. Final, the prediction results are sent back to the AIoTM-1 device for display on its touchscreen, provided that the installation of the device makes it possible.

4.3. Integration of the device into HMS and e-Health platforms

To facilitate seamless integration of the AIoTM-1 device into the HMS, the output package is designed under the HL7/RS-232 standard. An illustrative example of this package is presented in Figure 7.

```
EVN|A01|20241215150504
PID|||P-12145||NGUYEN TRUNG HIEU||19890612|M||||||||||HC-4-01-0110169972
PV1|1|O
OBX|1|NM|8302-2||167|cm||||R|||20241215150504
OBX|2|NM|29463-7||78|kg||||R|||20241215150520
OBX|3|NM|39156-5||28|kg/m2||||R|||20241215150520
OBX|4|NM|8462-4||81|mm[Hg]||||R|||20241215150625
OBX|5|NM|8480-6||124|mm[Hg]||||R|||20241215150625
OBX|6|NM|8867-4||86|bpm||||R|||20241215150625
OBX|7|NM|9279-1||19|bpm||||R|||20241215150715
OBX|8|NM|20564-1||95|%||||R|||20241215150715
OBX|9|NM|8310-5||36|Cel||||R|||20241215150835
OBX|10|TX|SARS-CoV-2||Negative||||R|||20241215150838
OBX|11|TX|Influenza||Negative||||R|||20241215150838
```


Figure 7. HL7-RS-232 output data

The packet comprises several segments, each serving a distinct purpose. The initial segment is the EVN (Event Type) segment, documenting the date and time on which the measurements are recorded. Following this, the PID (Patient Identification) segment contains pertinent patient identification information. The PV1 (Patient Visit) segment records data related to the patient's visit. Lastly, the OBX (Observation /Result) segment encompasses details related to body indices, vital signs, units and times of measurement, and predicted outcomes. The device is also equipped with APIs that facilitate information exchange with third-party software through a RESTful interface. A comprehensive list of these APIs is presented in Table 2. For instance, when a user employs the API to retrieve the results of the device's most recent record, the returned results will be displayed as illustrated in Figure 8.


```
{
    "resourceType": "Patient",
    "id": "AIoTM-1-20241215150504",
    "text": {"status": "generated"},
    "datetime": "2024-12-15T15:05:04",
    "health_insurance_code": "HC-4-01-0110169972",
    "patient_code": "P-12145",
    "full_name": {"first_name": "Nguyen", "middle_name": "Trung", "last_name": "Hieu"},
    "birthdate": "1989-06-12",
    "height": {"value": 167, "unit": "cm"},
    "weight": {"value": 78, "unit": "kg"},
    "BMI": {"value": 28, "unit": "kg/m2"},
    "diastolic_blood_pressure": {"value": 81, "unit": "mmHg"},
    "systolic_blood_pressure": {"value": 124, "unit": "mmHg"},
    "heart_rate": {"value": 86, "unit": "BPM"},
    "respiratory_rate": {"value": 19, "unit": "BPM"},
    "SPo2": {"value": 95, "unit": "%"},
    "body_temperature": {"value": 36, "unit": "°C"},
    "SARS-CoV-2": "Negative", " Influenza ": "Negative"
}
```


Figure 8. JSON output data

The data packet is structured in JSON format and encompasses several critical information fields. Among these fields are time and patient identification details, which include the patient code, health insurance card number, full name, and date of birth, as well as data pertaining to body indices and vital signs. Additionally, the packet includes units of measurement and predicted outcomes.

To enhance data security on the device, data encryption algorithms are employed to protect information during both transmission and storage (such as RSA and Diffie-Hellman). Additionally, the implementation of multi-factor authentication (MFA) techniques requires users to present multiple forms of verification before accessing medical data. Firewalls and intrusion detection systems also play a crucial role in protecting systems and devices from cyber-attacks.

5. FUTURE WORKS

In the future, the device will be deployed to collect larger datasets derived from clinical data sources in hospital settings. Additionally, the AIoTM-1 device has the potential to integrate additional security measures, such as facial recognition, fingerprint biometrics, and iris recognition, ensuring that only authorized individuals can log in and operate the device, thereby enhancing data security. Furthermore, blockchain technology can be used to securely store data and protect patients' personal information.

6. CONCLUSION

One of the challenges faced by health systems during epidemic outbreaks is managing a high volume of patients without optimal tools for patient classification according to types of respiratory diseases. In healthcare facilities, staff typically rely on vital sign measurement devices, particularly electronic thermometers, to classify patients exhibiting signs of fever. Patients with high temperatures are categorized as at risk of infectious respiratory diseases. However, to accurately determine a patient's health status, in-depth diagnostic tests, such as rapid test kits or PCR assays, are required. These methods, while effective, are often expensive, time-consuming, and labour-intensive. Furthermore, measuring a patient's temperature alone cannot differentiate between various respiratory diseases.

The integration of AI in the development of health kiosks offers a promising solution. These kiosks facilitate the rapid collection of patient data and represent an innovative approach for swiftly identifying high-risk positive cases. The AI model exhibit stable performance with a high level of accuracy, establishing a robust foundation for deployment across larger datasets derived from clinical data sources within hospital environments. Additionally, standardizing output data in HL7 format and developing a RESTful API for device communication allow seamless integration into medical systems and remote healthcare platforms within the IoT framework.

The experimental results presented in this article demonstrate the effectiveness of the applied methods in the device development. This study opens up a novel and practical direction for screening, classifying, and accurately predicting patients with diseases. Furthermore, this direction contributes to a cost reduction associated with medical examinations and treatment processes while also decreasing the turnaround time for test results.

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Manuscript received on 27 November 2024