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Development of Smart Health Screening System for Rural Communities in the Philippines

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Abstract: The Philippines, surveyed as part of the 23 chosen countries worldwide, is producing 80% of global mortality burden due to chronic diseases and 50% full disorder burden because of noncommunicable diseases (NCDs) throughout the world. To prevent the rapid growth of diseases, and in some cases to prevent worsening of health conditions, screening is strongly recommended that can identify the symptoms while at their early stages. There are some laboratory tests that a patient can undergo. If it determined that a disease has emerged, further examinations can also be conducted to confirm the diagnosis. However, for people in rural areas, it is just an additional problem because of the cost and time consumption. This paper presents a smart health screening system that aims to ease and enhance the quality of life in rural communities. The developed program was composed of mobile applications, different medical devices, and sensors that screen-specific health parameters and predict the individual probability of having a cardiovascular disease such as diabetes, hypertension, and heart attack by implementing Random Forest classifier. The parameters include Blood Pressure (BP), Heart Rate (HR), Oxygen Saturation (SPO2), Body Mass Index (BMI), Blood Glucose (BG), and Cholesterol Level (Chol). To measure the effectiveness and reliability of the system, the proponents conducted an accuracy test by comparing the data collected by the system to the standard test done in a clinic. The result of the study using Random Forest Classifier which automates a health screening and prediction of cardiovascular diseases specifically diabetes, heart attack, hypertension achieved 98% accuracy in determining the probability of having heart diseases compared to the data gathered from Rosario Reyes Health Center and Ospital ng Sampaloc in Manila.

Keywords: Biomedical devices, Cardiovascular Disease, Health Monitoring, Health Screening, Remote Monitoring

1. Introduction

Technology in the developing world is considered to play an essential role in various global advancements that includes the evolution in health services. A combination of medical devices and sensors integrated with middleware and software that adjusts to the current standard of the internet is the focal thought for the Internet of Things [1]. Sensors in the market is continuously made smaller in size, cost-efficient but progressively dominant at the same time. As competition arises, companies are consistent in exerting efforts to build sensors in the maximum extent of development.

Noncommunicable diseases (NCDs) such as Cardiovascular Disease (CVD), Cancer, Diabetes, and Chronic Respiratory Disease (CRD), being the top cause of global mortality rate, are responsible for the 41 million deaths annually which are also equivalent to 71% human deaths of the world [2]. Cardiovascular Diseases (CVDs) are the leading cause of death internationally [2]. Based on a 2016 report, an estimation of 17.9 million people is reportedly dead because of CVDs, equivalent to 31% of deaths worldwide, and 85% are causes of Stroke and Myocardial Infarction (Heart Attack).

In the Philippines, for the last 50 years, the mortality rate due to NCDs became twice in number, including an estimate of 70% cases in association with the top 10 causes of deaths domestically [3]. Among the 23 surveyed international countries, the Philippines contributes to about 80% of the global mortality burden due to chronic disorders and 50% of full disorder burden because of NCDs [4].

In this study, a low-cost health screening and monitoring system was proposed. The study specifically aims to (1) utilize low-end health screening devices and medical sen-

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sors that analyze the health parameters including Heart rate (HR), blood pressure (BP), oxygen saturation (SpO2), blood glucose (BG), cholesterol, and body mass index (BMI). Lastly, is to (2) evaluate the overall system in terms of accuracy and efficiency.

The system focuses on screening a specific health parameter and predicting diseases such as diabetes, heart attack, hypertension by utilizing sensors, microcontrollers, Android application, and a machine learning algorithm. The patient's vital parameters are measured using a health screening system in just a few minutes. Pre-programmed in the microcontroller are sensors data and interfacing with a thermal printer. The system is compatible with Android phones and tablets. An Android application is used as detecting screen to allow the patient to screen their vital body parameters with an algorithm for predicting disease. The system has an offline database for the gathered data that was established for maintaining data privacy and for the admins to have access to medical records anytime. This study is for screening Heart rate (HR), blood pressure (BP), oxygen saturation (SpO2), blood glucose (BG), cholesterol, and body mass index (BMI). These given parameters can help to monitor if the patient has a chance of having diabetes, hypertension, and heart attack.

2. Related Works

Resembling the advances in Health Screening applications, various ventures of significant writings have made. For example, an Android mobile application developed by Omer and AlSalihi, named "HealthMate" functioning together with integrated health sensors for health monitoring [5]. A web-based app developed for medical practitioners. Raj, Jain, and Arif [6] developed "HEMAN" aimed to use a software called LabVIEW, also for health monitoring and for the gathered health parameters to be analyzed.

For Smart Health Monitoring System that was developed by Khan and Chattopadhyay [7], it aims to utilize the health sensors that are integrated with a microcontroller Arduino UNO for data reading in the Serial Monitor.

Mobile application and desktop software are both created to function as health monitoring devices. A system that allows medical professionals to monitor patients who are beyond to reach in their real-time and extending their capabilities to monitor multiple health status all connected to a single device. It is a Real-time Patient Monitoring System that was developed by Uddin, Alam, and Banu [8]. Another one, a proposed low-cost smart wireless monitoring system in the Android platform by researchers Kumar and Venkatesan [9].

Meanwhile, in [10] and [11], a system was developed that measures and correlates pH levels of sweat to an individual's pre-cognitive condition. LoRaWAN and Internet transmitted the data. In [12], the characterization of a pH test strip based on LED optical absorbance created a pH measuring device. The potentiometric method was used in [13] to observe changes in the hormonal balance due to ovulation in women.

On the other hand, disease diagnosis can use image processing. In [14], the researchers have developed a fingernail image diagnostic device that can detect circulatory diseases while in [15], they constructed a health evaluation device through tongue images. Images of microscopic urine constituents were analyzed in [16] and [17] using Prewitt operators and edge detection methods for disease recognition. Evaluated Skin images in [18] for the diagnosis of skin diseases.

The referenced projects discussed were used as a reference to build up the Smart Health Screening System in the early stage. Also, a foundation plan to design and build up this system utilized the results of this system.

3. System Architecture

A patient health parameter was decisive and studied for the threshold values for different analyses. Figure 1 shows the system architecture of the device. The input parameters of the system are Height and weight, Oxygen Saturation (SpO2), Heart rate, Blood pressure, Blood Glucose, and cholesterol. For the process, it includes data gathering that is composed of two sections: data acquisition and a machine learning model (Random Forest).

The patient needs to stand and place his or her index finger in the sensor. After detecting all the health parameters required, it will serve as an input of the system. Sensors data are pre-programmed by microcontrollers while the medical device data manually inputted in a mobile application.

The Random Forest algorithm serves as the classifying and predicting model for an Android-based disease prediction system. This system can calculate the individual possibility of having a detailed cardiovascular ailment due to its performance characteristics and accuracy. Using data from patients of Rosario Reyes Health Center and Sampaloc Hospital in Manila City tests the machine learning models used in the app to get the accuracy of the algorithm.

The proponents used Basic4Android for designing mobile application interface, and for the connection of microcontroller to Android application, B4Abridge is applied. The Android application allows the user to screen and predict disease. After analyzing, it will generate a printed copy for the patient medical diagnostic.

4. Materials and Methods

Materials used are listed below:

a. Hardware Development

- CK-101 Digital Blood Pressure device
- EasySure GCU (Glucose, Cholesterol, Uric Acid)
- HX711 weight sensor

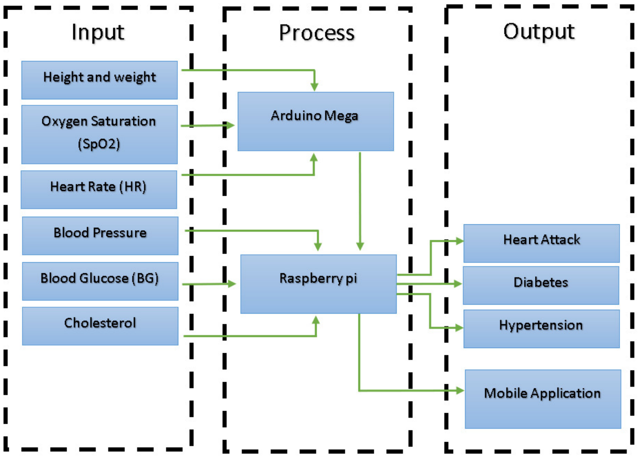

Figure 1. System Architecture of Smart Health Screening System

- Thermal printer
- MAX30100 - Pulse and Oxygen in Blood Sensor (SPO2)
- HC-SR04 – Height Sensor
- Load cells
- Arduino Mega
- Raspberry Pi 3

b. Software Development

- Java
- Python
- Basic4Android
- B4A bridge
- MySql
- Operating system (mobile) - Android OS

c. Health Parameters

To get an authentic result of an in wellbeing, predict pattern, and screening for health, we gathered some of the evaluated health parameters. It shows the personalized and overall image of an individual. Health attributes and parameters with their corresponding values and remarks are shown in Table I. These are used in arranging the collected data. Random Forest algorithm was implemented in training of these data gathered [19], [20], [21], [22].

5. System Description

One of the main latest implications of the Philippines is insufficient medical equipment and facilities that lead to the well-being situation of the persons in provincial areas [23]. Every single citizen must receive equal medical attention, but one of the factors that they did not is the access because of the distance. In this paper, the developed health care screening structure was a low-cost build system that matches perfectly and reflects the requests of the people int the countryside.

The access due to distance problem is the primary preference of this paper thus, to lift that problem, the device designed in this project is portable to carry around in case of traveling.

The developed device is made of low-cost sensors and components unlike with the high-end medical equipment which cannot be reached or utilized in far-flung communities. A lower cost was aimed for this device so it can be availed by the rural communities. Simultaneously, it delivered the medical attention which the public want. In this system, the proponents used both noninvasive and invasive devices. The researchers utilized commercially available medical kits for measuring blood pressure, blood glucose, and cholesterol level. For measuring height, weight, oxygen saturation and heart rate the proponents used some medical sensors.

6. System Design

A. *Hardware Interface*

The Hardware Design shows in Figure 2, comprises the assembly of the device, medical devices and sensors, a tablet, microcontroller, and a thermal printer. This device looks like a biomedical sensor kit in which it aids for a health condition to be monitored and can screen the patient's health parameter by simply scanning their hand. This system provides a printed copy of their medical diagnosis.

B. *Schematic Diagram*

In the Smart Health Screening system, the proponents utilized the Arduino Mega 2560 as a microcontroller for the input data acquisition. Due to its multiple inputs and output pins is the reason why Arduino Mega was selected. The Arduino comprises of the health sensor boards such as the HX711 (Weight Sensor), MAX30100 (Oxygen Saturation and Heart Rate Sensor), and HC-SR04 (Height Sensor) connected all circuit boards required for the system. It also includes the HC-05 Bluetooth module as a communication device between the microcontroller and the Android device, and the thermal printer for the physical output of the system. Arduino IDE is the programming platform that will be used for the boards to be interconnected and for the sensitivity of each health sensor.

After the data acquisition of the Arduino Mega, the Raspberry Pi 3 will receive the data via direct connection of USB cable. Raspberry Pi 3 is a cost-efficient, mini-computer board which is highly capable of computing and programming. It has 1 gigabyte of RAM, capable already of running Python, which is the required programming software for the system's prediction system and has a Micro SD slot as its storage where the .csv files wherein the

TABLE I. List of Health Parameters

No.	Attribute	Health Parameter	Value	Remarks
1	age	Age	-	-
2	sex	Sex	0 1	Female Male
3	bmi	Body Mass Index	0 (18.5-22.9) 1 (23-24.9) 2 (25-29.9) 3 ($\geq$ 30)	Normal Overweight Pre-obese Obese
4	maxhr	Maximum Heart Rate	0 (60-90) 1 (>90) (in bpm)	Normal Abnormal
5	bos	Blood Oxygen Saturation	0 (95-100%) 1 (<94%)	Normal Hypoxemia
6	fbs	Fasting Blood Sugar	0 (<100 mg/dL) 1 (101-125) 2 (>126)	Non-diabetic Pre-diabetes Diabetic
7	bpsys	Blood Pressure (systolic)	0 (<120) 1 (120-139) 2 (>140)	Normal At Risk High
8	bpdio	Blood Pressure (diastolic)	0 (<80) 1 (80-89) 2 (>90)	Normal At Risk High
9	chllvl	Cholesterol Level	0 (<200 mg/dL) 1 (201-239) 2 ($\geq$240)	Desirable Borderline High
10	sm	Smoking	0 1	False True
11	famhis	Family History	0 1	False True
12	alchl	Alcohol	0 1	False True
13	stress	Stress	0 1	False True
14	hrtbrn	Heartburn	0 1	False True
15	dt	Diet	0 1	False True
16	shrtnssbrth	Shortness of Breath	0 1	False True
17	exrcs	Active Exercise	0 1	False True
18	cp	Chest Pain	0 1	False True
19	num	Disease	0 1	False True

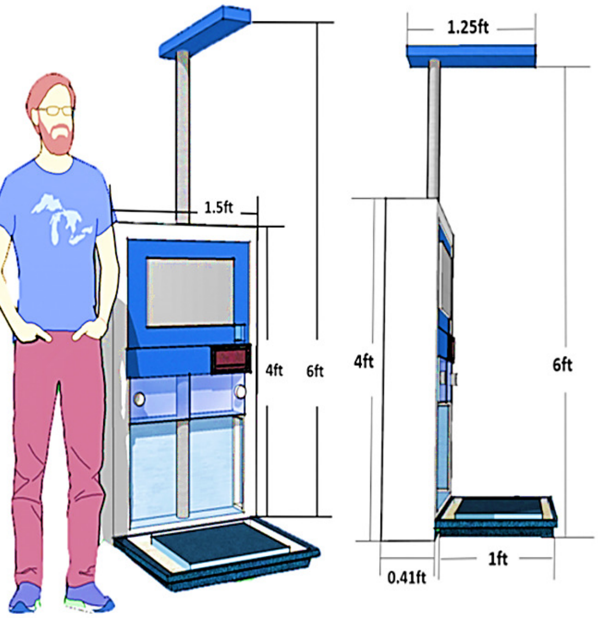

Figure 2. Hardware Design of Smart Heallth Screening

medical data of the users are stored. Another thing is its compatibility with the Android platform, the way that it is capable of applying the prediction system on an Android device is one of the main reasons why Raspberry Pi 3 was there as the core processing unit of the prediction system of the project.

Figure 3 shows the Smart Health Screening schematic diagram. The circuit includes HX711 (Weight Sensor), MAX30100 (Oxygen Saturation and Heart Rate Sensor), HC-SR04 (Height Sensor), HC-05 Bluetooth module, thermal printer, Arduino Mega, Raspberry Pi 3 and other miscellaneous components (USB header).

C. Mobile Application

Figure 4 shows the developed mobile application. Every tab view has a different function for the system that includes getting patient information, displaying patient and record information, manual input of medical parameters, medical questions, and display of results. The connected Android-powered device will display the data once it all regathered by the system. Then after that, the users will receive printed copies of their summarized medical results. It also includes the reference ID code. Since the database will be offline, medical records will maintain its security for the Data Privacy Act of the Philippines.

The application is in the Android platform simply because it is convenient and to be user-friendly. Also, the system's management purposes include an interface for both admin and patient. They can both view personal data, but as an admin, there will be added privileges.

On the Android application, the new patient will fill up the personal information and medical assessment. Next, the health monitoring system will administer the medical testing. The patient's health history can be viewed by searching its name and can also get a hardcopy result. The general data of the system will be displayed in the admin and doctor's module.

D. Random Forest Classifier

Random Forest is a regression and classification model. It generates decision trees for every characteristic, proper overfitting to its training set, deflect outliers of lost values by obeying information analysis phases, pre-processing information. It is a method for developing an active model where weak models are collected. Figure 5 shows the several decision trees done by the random forest tree matching the system [19], [20], [21]. Random forest classifier was used in this study because it achieved the highest accuracies [20] and the most dependable metrics [21] among the commonly used classifier algorithms.

To determine the possibility of the patient to have cardiovascular diseases, the Random Forest Classifier is selected because of its high percentage accuracy and also, there is no system of health screening that utilized a random forest algorithm for prediction of heart disease. Data collected from hospitals were trained using the said algorithm represented by a pseudocode in Figure 5. A similar random forest classifier can be found in ref. [22]. Parameters of the random forest (R_F) are first defined such as number of features (number_features), number of trees (number_trees), size of the samples (size_of_sample), maximum depth (maximum_depth), minimum sample size (minimum_size), train, and test. Then, in line 2, a list was created for the storage of data which generates a tree structure. Lastly, in the last lines, a loop was initialized so that random dataset sub-instances will be created which in turn generates a decision tree and the resulting prediction or forecast engine. After the data are trained, the proposed prediction engine system is tested. The system will start by first setting the medical sensors and Arduino. Sensors will be attached to the individual patient's body part. After the data were gathered from the sensors and processed by the Arduino, decision making will be executed via the prediction engine. Then, the possibility of a patient of having the disease diagnosed with diabetes, cardiovascular disease, or none will be shown.

```
1. define R_F(train, test,
maximum_depth, minimum_size,
size_of_sample, number_trees,
number_features):
2.      trees = enumerate()
3.      for i in range(number_trees):
4.      sample = subsample(train,
size_of_sample)
5.      tree = construct_tree(sample,
maximum_depth, minimum_size,
number_features)
6.      trees.append(tree)
```

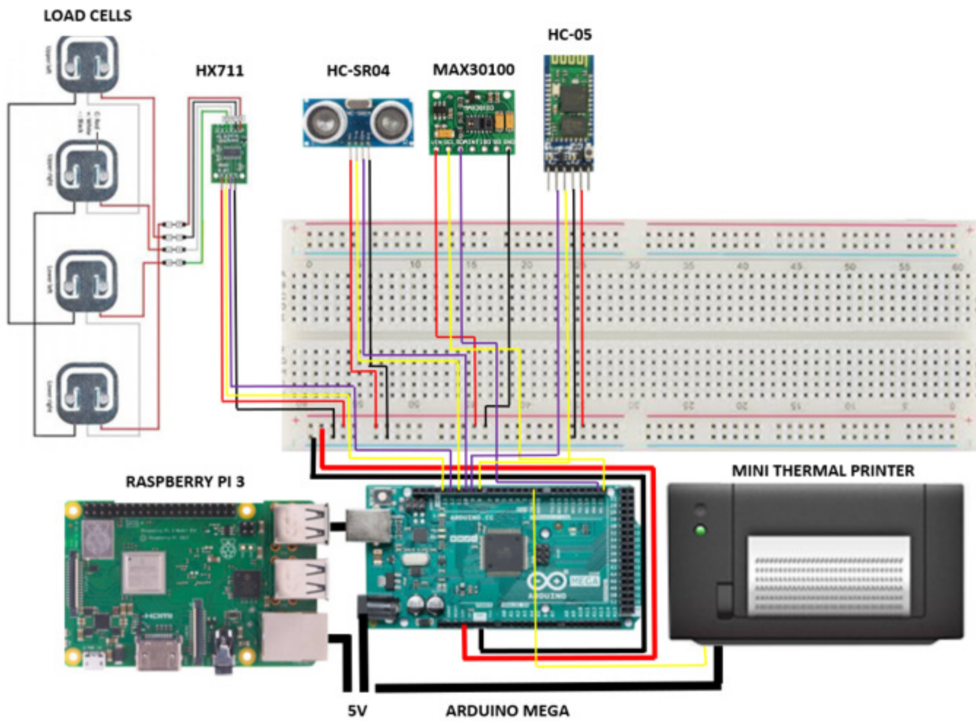

Figure 3. Web Application Interface

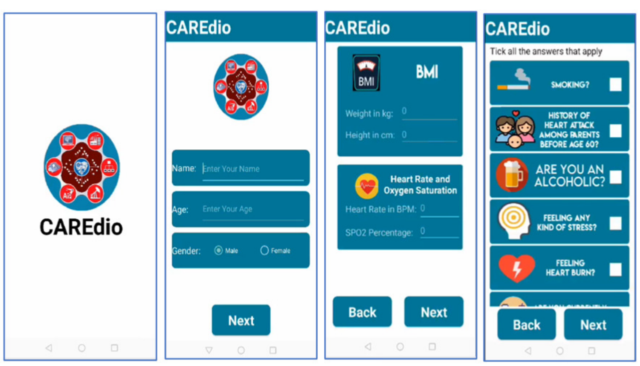

Figure 4. Web Application Structure Diagram

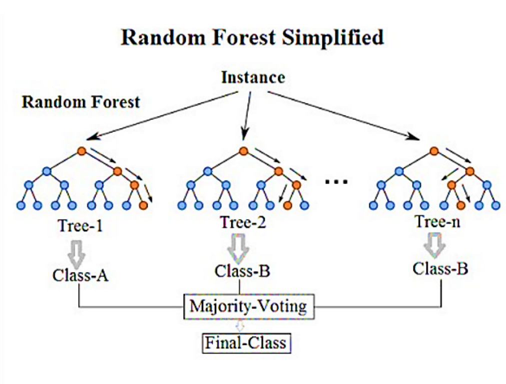

Figure 5. Potential Hydrogen (pH) Sensor Readings with Correction Response

```
forecasts = [bagging_forecast(trees ,row) for row in test]
return(forecasts)
```

7. System Results

The patient's data was gathered at the Ospital ng Sampaloc (Hospital of Sampaloc) and Rosario Reyes Health Center in Manila, Philippines. The accuracy of the samples was determined using Random Forest Classifier written in Python. Collected data includes patients with diabetes, hypertension, heart attack, with and without other types of cardiovascular disease.

Table II shows the random forest accuracy for diabetes, heart attack, hypertension, and other types of diseases. The confusion/correlation matrices between health parameters or attributes for hypertension, heart attack, diabetes, and other heart diseases are presented in Figures 6, 7, 8, and 9, respectively. The accuracy and precision scores, recall, f1-score, AUC, and mean absolute error for every disease are illustrated in Table III. Accuracy scores greater than 0.90 were achieved by our proposed system in predicting diabetes, heart attack, and hypertension diseases unlike in predicting other diseases that has a 0.87 accuracy score. For most groups, above 0.90 was attained for precision and recall. For all the groups, above 0.88 was achieved for the f1-score. A low sensitivity was evident for the "other diseases" group which is mostly because of including various diseases.

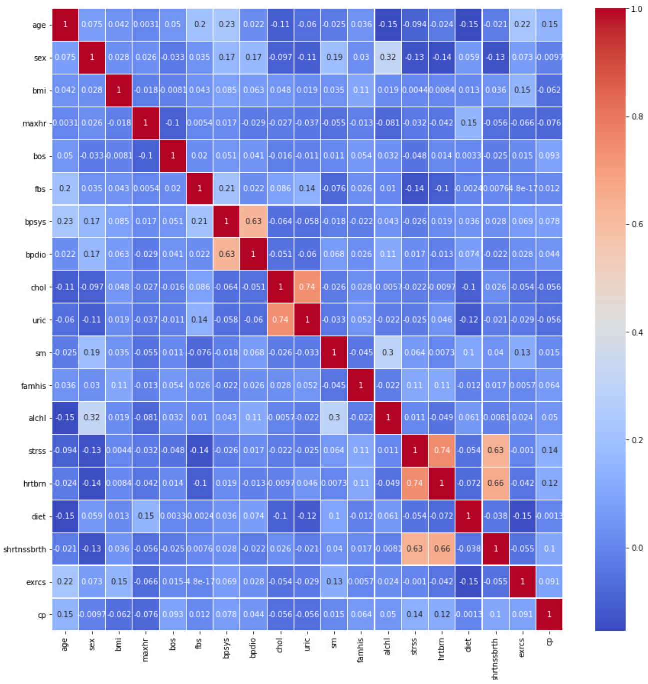

Figure 6. Confusion/correlation matrices between health parameters or attributes for hypertension

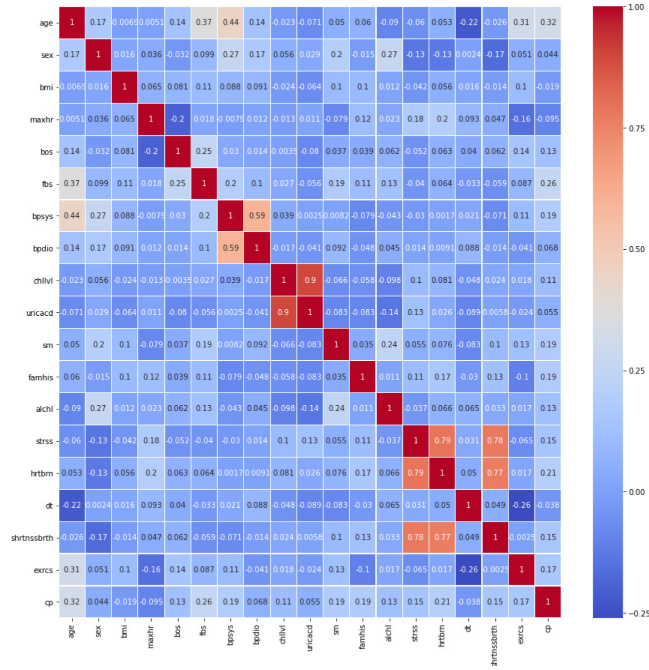

Figure 8. Confusion/correlation matrices between health parameters or attributes for diabetes

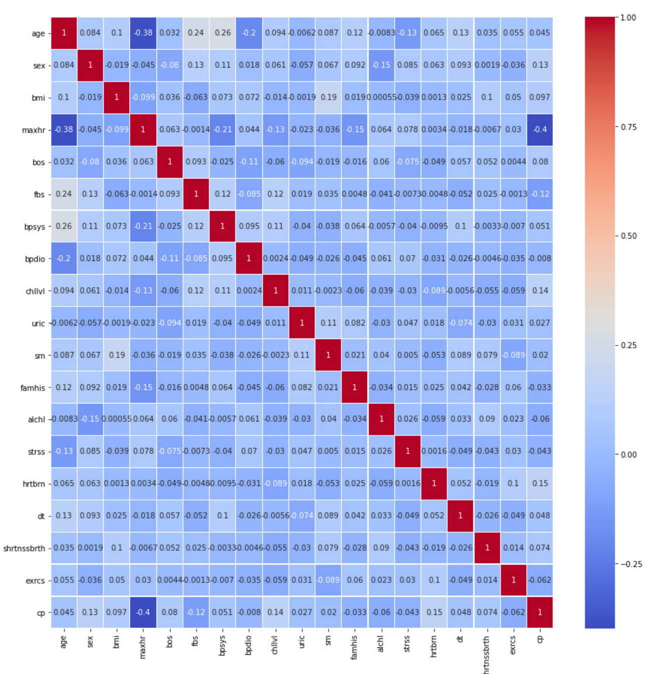

Figure 7. Confusion/correlation matrices between health parameters or attributes for heart attack

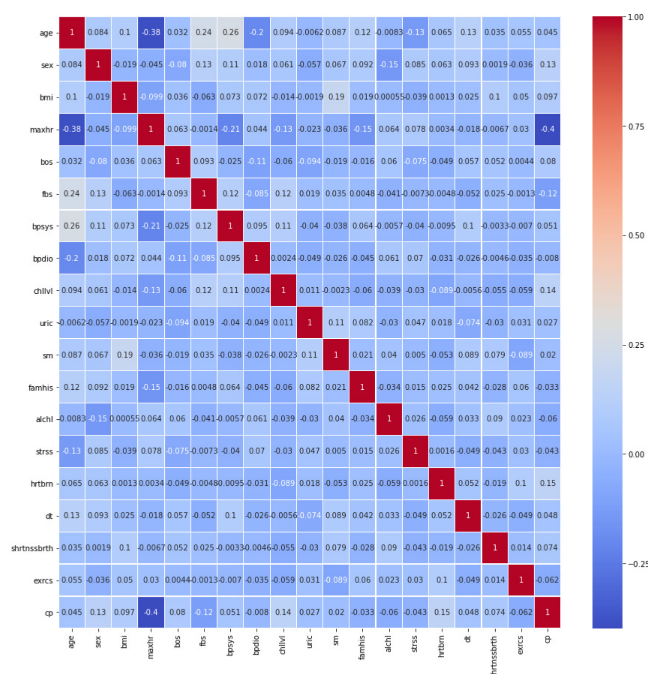

Figure 9. Confusion/correlation matrices between health parameters or attributes for other heart diseases

TABLE II. Fish Growth in Each Setup

Disease	Random Forest
Diabetes	91.67%
Heart Attack	90.12%
Hypertension	98.77%
Others	87.96%

Tables IV, V, VI, and VII present the system's output result for diabetes, hypertension, heart attack, and other CVDs, respectively, compared with the data collected from Ospital ng Sampaloc and Rosario Reyes Health Center in Manila. The proponents tested their mobile application against multiple validation subsets of our dataset by randomly selected 20 data as our test set, and applied our screener to this test set, calculating disease probabilities.

Tables IV, V, VI, and VII show that 20 out of 20 (100%), 19 out of 20 (95%), 20 out of 20 (100%), and 20 out of 20 (100%) data samples are matched for diabetes, hypertension, heart attack, and other CVDs, respectively. The proposed device matched with the outcome from the collected dataset producing the possibility of an individual of having diabetes, hypertension, heart attack, and other CVDs.

Lastly, Table VIII shows the comparison of proposed work with the prior works. Apparently, the proposed work can classify the greatest number of diseases (at 4) using only 1 machine learning algorithm (random forest) with a very high accuracy of more than 87% compared to the prior works. It also has the greatest number of health parameters or features. Most of all, it has the highest accuracy of detecting a certain disease i.e., hypertension at 98.77%.

8. Conclusion

The Development of Smart Health Screening using Random Forest Classifier which automates a health screening and cardiovascular diseases prediction (hypertension, diabetes, heart attack) achieved 98% accuracy in determining the probability of having heart diseases (20 diabetes, 20 heart attack, 19 hypertension, and 20 other CVDs) matched the results of system prediction compared to data gathered from Rosario Reyes Health Center and Ospital ng Sampaloc in Manila.

For future work, this study could be improved by using additional medical sensors for an extensive scope of detecting other types of diseases. Lastly, an application is recommended that can collect and save the readings of sensors to a CSV file automatically.

Acknowledgment

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TABLE III. Accuracy Score, Precision, Recall, F1- score, AUC, Mean Absolute Error for Each Disease

	Accuracy Score	Precision	Recall	F1-Score	AUC	Mean Absolute Error
Heart Attack	0.91	0.91	0.90	0.89	0.78	0.098
Diabetes	0.98	0.98	0.98	0.98	0.95	0.017
Hypertension	0.98	0.99	0.99	0.99	0.99	0.012
Others	0.87	0.88	0.88	0.88	0.88	0.120

TABLE IV. Trial for Patient's Data with Diabetes

Patient	Has Diabetes	System Output	Note
1	Yes	70%	Matched
2		94%	
3		89%	
4		98%	
5		91%	
6		94%	
7		80%	
8		96%	
9		98%	
10		86%	
11		96%	
12		93%	
13		51%	
14		97%	
15		78%	
16	No	10%	
17		2%	
18		7%	
19		18%	
20		12%	

TABLE VI. Trial for Patient's Data with Heart Attack

Patient	Has Disease	System Output	Note
1	Yes	88%	Matched
2		60%	
3		72%	
4		84%	
5		83%	
6		80%	
7		82%	
8		83%	
9		91%	
10		91%	
11		82%	
12		86%	
13		87%	
14		92%	
15		84%	
16	No	8%	
17		19%	
18		15%	
19		7%	
20		22%	

TABLE V. Trial for Patient's Data with Hypertension

Patient	Has Disease	System Output	Note
1	Yes	70%	Matched
2		97%	
3		96%	
4		78%	
5		91%	
6		90%	
7		99%	
8		88%	
9		91%	
10		90%	
11		90%	
12		86%	
13		88%	
14		87%	
15		89%	
16	No	31%	
17		71%	Mismatched
18		10%	Matched
19		13%	
20		18%	

TABLE VII. Trial for Patient's Data with Other Heart Diseases

Patient	Has Disease	System Output	Note
1	Yes	80%	Matched
2		56%	
3		59%	
4		95%	
5		86%	
6		88%	
7		51%	
8		100%	
9		79%	
10		95%	
11		91%	
12		95%	
13		55%	
14		86%	
15		98%	
16	No	4%	
17		0%	
18		2%	
19		9%	
20		4%	

TABLE VIII. Comparison of Proposed Work with Prior Works

	[24]	[25]	[26]			[27]	This work
Year	2017	2018	2018			2019	2021
Number of Health Parameters/ Features	13	14	9 (Breast Cancer)	8 (Diabetes)	13 (Heart Disease)	18	19
Classified Diseases	Heart Disease	Heart Disease	Breast Cancer	Diabetes	Heart Disease	Heart Disease	Diabetes Heart Attack Hypertension Other cardiovascular diseases (CVDs)
Algorithm	Naïve Bayes KNN Decision Tree Random Forest	Naïve Bayes Random Forest	Logistic Regression (LR) Decision Tree (DT) Random Forest (RF) Support Vector Machine (SVM) AdaBoost (AB)			Naïve Bayes Random Forest	Random Forest
Accuracy	Naïve Bayes (56.19%) KNN (73.41%) Decision Tree (66.31%) Random Forest (76.23%)	Naïve Bayes (87.20%) Random Forest (83.72%)	LR (95.71%) DT (94.29%) RF (97.14%) SVM lin (97.14%) SVM rbf (95.71%) AB (98.57%)	LR (95.71%) DT (74.03%) RF (81.82%) SVM lin (85.71%) SVM rbf (66.23%) AB (80.52%)	LR (87.1%) DT (70.97%) RF (77.42%) SVM lin (83.87%) SVM rbf (54.84%) AB (83.87%)	Naïve Bayes (61.96%) Random Forest (92.44%)	Diabetes (91.67%) Heart Attack (90.12%) Hypertension (98.77%) Other CVDs (87.96%)

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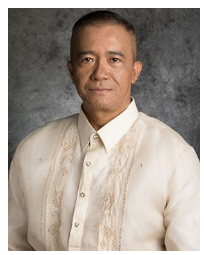

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