Max Health

Engineering a User-Friendly Smartphone and Smartwatch Application with Intelligent Textiles Biosensors to Detect Arrhythmias, Dysglycemia, Neurological Diseases, and Predict Asthma Attack Risk

Ibrahim Al-Akash
VETERANS MEMORIAL HIGH SCHOOL, CORPUS CHRISTI, TX

ABSTRACT

The coronavirus pandemic has highlighted the need for remote health monitoring for chronic diseases. To help patients manage their conditions, a user-friendly smartphone application and clothing biosensor were developed to detect arrhythmias, measure glucose levels, detect neurological disorders, and predict asthma attack risk. The biosensor was comprised of a smart shirt to monitor electrocardiogram (ECG), seismocardiogram (SCG), and gyrocardiogram (GCG), and smart pants to monitor inertial measurement unit (IMU) data and extract gait characteristics. Three machine learning models were developed, trained, and tested. A multiclass support vector machine (SVM) uses cardiogram data to classify the user's heart rhythm as healthy, atrial fibrillation, atrial flutter, ventricular flutter, or ventricular tachycardia. A random forest regression model monitors glucose levels using cardiogram data and classifies the user's glucose level as healthy, hypoglycemic, or hyperglycemic. A random forest classification model uses gait analysis to classify the user's neurological condition as healthy, Parkinson's, Huntington's, or Amyotrophic Lateral Sclerosis. The models were tested on new data to eliminate overfitting the models. The arrhythmia classifier achieved 98% accuracy, glucose monitor accuracy of 93%, and neurological classifier accuracy of 100%. To predict asthma attack risk, a program was developed which extracts asthma trigger data from APIs and smartphone data and then uses it in a decision matrix risk assessment (DMRA) to predict, low, medium, or high risk. The program was successful in testing and debugging. These results are promising, as they indicate the system may be a viable solution for patients with chronic diseases.

I. BACKGROUND

Cardiac disease is the world's leading killer, claiming more than 17 million lives per year (WHO, 2017). Many of these deaths could be prevented by monitoring the heart's rhythm. With proper monitoring, the number of lives lost to cardiac disease can be reduced.

Diabetes is on the rise, with 400 million adults diagnosed with diabetes, and 3.7 million deaths due to high blood glucose and diabetes (WHO, 2020). To better manage diabetes, patients must often check their glucose levels to understand when to take their medications and how they respond to them. To do this, patients can get a continuous glucose monitor implanted. This method is not ideal since it opens the door to infection and can result in scarring. Additionally, these implants are expensive, with prices reaching as high as $1,400 (Tenderich, 2019). This greatly limits accessibility to patients, which forces them to opt for low-tech alternatives such as blood test strips. With a more cost-effective and non-invasive alternative to glucose monitoring, patients can better deal with their diabetes, and the mortality rate can be reduced.

According to the Asthma and Allergy Foundation of America, more than 24 million Americans have asthma, and each year, approximately 2 million asthma attack victims visit the emergency room (2019). Asthma triggers are often overlooked by asthmatic patients, causing them to panic and mismanage the situation in case they suffer an asthma attack. With asthma risk prediction, patients can prepare better and reduce their chances of having an asthma attack.

Every year, about 60,000 Americans are diagnosed with Parkinson's disease (Parkinson's Foundation, 2018), 200,000 are at risk of developing Huntington's disease (NORD, 2007), and at least 16,000 are living with ALS at any given time (ALS Association, 2019). These neurological diseases are progressive, meaning they get worse over time. With early diagnosis, patients can receive better treatment and reduce the severity or even stop the disease entirely from progressing. A convenient neurological screening method can help patients deal with these illnesses.

The coronavirus pandemic highlighted the need for remote solutions to monitor patients' health. American doctors have reported seeing half as many patients as they normally would because of the virus (Scott, 2020). To add to this problem, hospitals were being filled to capacity, forcing doctors to choose whom to take care of and whom to let go. To prevent this from happening again, a remote health monitoring system can be used to help patients manage their illnesses without having to visit a doctor.

This research aims to create a low-cost, non-invasive, wearable, user-friendly system to monitor a user's health continuously and accurately detect arrhythmias, monitor glucose levels, detect neurological diseases, and predict asthma attack risk autonomously.

II. RELATED WORKS

Arrhythmia Detection

The electrocardiogram (ECG) is routinely used in cardiology to assess a patient's cardiovascular health, which records the heart's electrical signals that initiate a heartbeat. Hospitals usually use a 12-lead ECG, which requires 10 electrodes to be placed around the patient's chest to recreate the heart's motion in three dimensions (3D). In some cases, patients are asked to wear a Holter monitor for 24 to 48 hours, the ECG is saved to a local storage, and the doctor manually reads the ECG signals. This approach can be useful for diagnosing arrhythmias; however, real-time, autonomous diagnosis is not implemented. Also, the Holter monitor is outdated, as it was invented in 1962 (Telemetry in the clinical setting, 2008). Various studies have been done for classifying arrhythmias using machine learning; however, previous models are computationally expensive, inaccurate, or require hospital-grade 12-lead ECG data negating the feasibility of implementing them for continuous monitoring. Recently, a study was conducted regarding the combined use of inertial measurement units (IMUs) and a 1-lead ECG to reduce the number of electrodes while compensating for the loss of electrode data (Yang & Tavassolian, 2017). Seismocardiography (SCG) and gyrocardiography (GCG) use IMU data to extract the heart's three-dimensional (3D) motion from the chest's acceleration and gyration as the heart beats. Feature extraction is performed on this data to recreate the same features extracted from a 12-lead ECG. With this new cardiogram data acquisition method, an improved version of the Holter monitor can be developed, detecting arrhythmias in real-time.

Glucose Monitoring

Not until recently, patients used to rely on finger-prick blood tests to monitor their glucose levels. With this invasive method being expensive, uncomfortable for patients, and impractical for continuous monitoring, much research has been done attempting to develop alternative glucose monitoring methods. Minimally invasive continuous glucose monitors (CGMs) can be inserted subcutaneously; however, these devices are expensive, costing upwards of $1,000 (Diabetic Warehouse, 2018). This limits patients' accessibility to an affordable solution. Other research has been done on creating non-invasive glucose monitors using optical sensors (Klonoff, 1997). One study explored the use of near-infrared reverse iontophoresis to detect glucose levels non-invasively; however, this method cannot be used continuously as patients must have the sensor attached to their finger or earlobe (Jain, Joshi, & Mohanty, 2019). Another study explored the use of sweat-based glucose monitoring; however, this monitor is difficult to fabricate, requiring expensive manufacturing equipment (Gao, et al., 2017). Sweat-extraction methods must be improved for practical implementation. In 2011, a study was published examining the effects of glucose levels on heart rhythm, and the researchers found that dysglycemia does correlate strongly with cardiogram data (Nguyen, Su, & Nguyen, 2012).

Neurological Disease Detection

Several medical tests can be performed to assess a person's neurological condition, which may include a neurological exam, genetic screening, brain scans, and other examinations. Some recent studies discuss the effectiveness of gait pattern analysis for diagnosing neurological diseases. In these studies, gait characteristics are extracted from cameras, pressure sensors, inertial measurement units, or any combination thereof. These systems require expensive equipment, costing more than $200 per test, and controlled environments to track the patient's motion. This approach limits accessibility to patients and delays the diagnosis of neurological disorders.

Asthma Risk Prediction

No continuous real-time asthma risk prediction techniques are currently available. Sometimes doctors ask patients to use a spirometer to predict the patients' risk of an asthma attack and grade the severity of their asthma; however, this is only temporary as it is not practical for patients to use a spirometer throughout the day. Another way doctors are trying to mitigate asthmatic patients' risk of suffering an asthma attack is to educate patients on asthma triggers. While this may benefit the patients temporarily, there are too many factors that could trigger an asthma attack for them to confidently determine asthma attack risk on their own on a daily basis.

III. PROPOSED APPROACH

Engineering Constraints

The proposed Max Health system must be able to acquire health parameters non-invasively, remotely, and continuously. The apparatus must be easy to implement, with little to no technical knowledge required for set up, and it must be low-profile. The entire system must be cost-efficient, below $50. The user-interface (UI) must be simple and easy to understand. The system must detect arrhythmias, dysglycemia, and neurological diseases with statistically significant (p<0.05) accuracy.

Hardware Design Overview

To allow for ease-of-use and mitigate the intrusive and uncomfortable nature of previous devices, wearable biosensors were built. To acquire biomedical signals continuously, a smart shirt and smart pants were engineered using Arduino electronics components. The smart shirt biosensor is comprised of an Arduino Uno microcontroller to process and transmit the signals, an AD8232 1-lead ECG module to gather electrocardiogram data, an MPU-6050 IMU sensor to measure z-axis acceleration seismocardiogram data and x-axis rotation of the heart gyrocardiogram data, an HC-05 Bluetooth module to send data to the smartphone, and a 3,050 mAh power supply. The smart pants biosensor incorporates an Arduino Uno microcontroller, an HC-05, five MPU-6050 IMUs to measure 3D motion of the hip, knees, and ankles to extract gait pattern characteristics, a TCA9548A I2C multiplexer, and a 5,000 mAh power supply **(Figure 1)**.

Software Design Overview

To detect arrhythmias, dysglycemia, and neurological disorders, and predict asthma attack risk, a smartphone and smartwatch companion application was developed. Signals from the shirt and pants biosensors are processed by the Arduino Uno, transmitted to the smartphone application, and real-time data is displayed in the UI. The smartwatch watch face is paired with the smartphone to enable the user to view their biological metrics at a glance. Additionally, users have the option to replace the Max Health watch face with another watch face of their liking and view the parameters in the dedicated Max Health watch application as needed. The app also enables the user to add their doctor's contact information for notifications of any health abnormalities. If a health anomaly is detected, both the user and the doctor receive a short message service (SMS) notification indicating the specific disease classified.

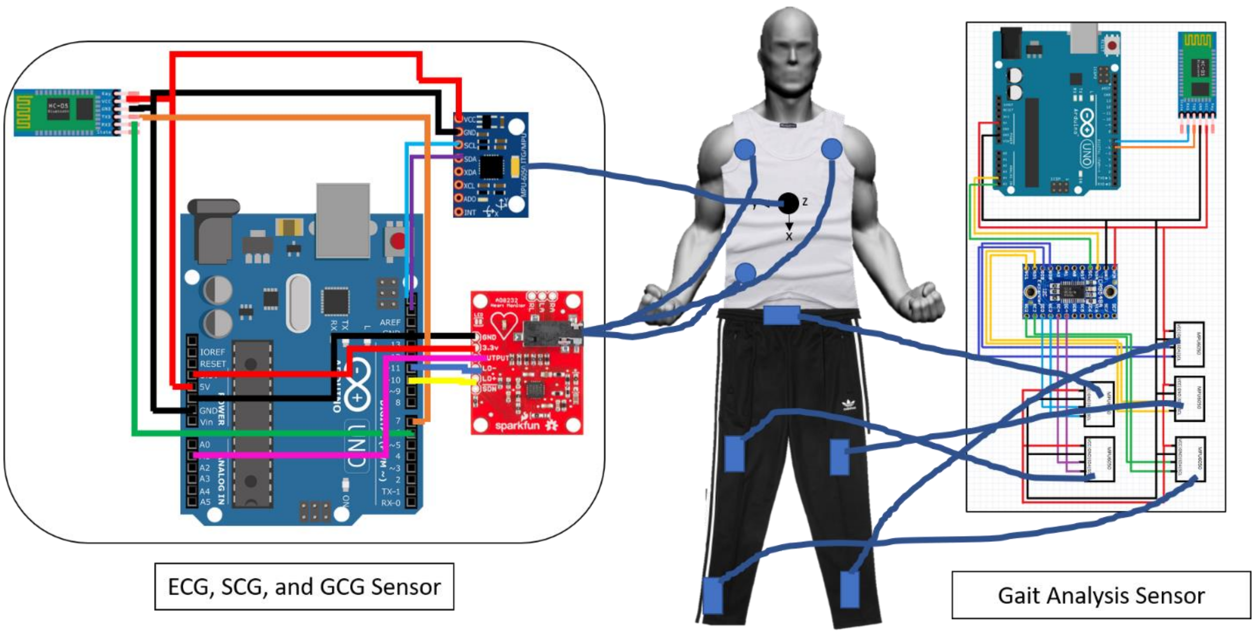


Figure 1: *Circuit diagram of proposed intelligent textiles biosensor system.*

IV. METHODOLOGY

A. Signal Preprocessing

Arrhythmia and Glucose

Data from the Physionet 12-lead ECG Arrhythmia MIT-BIH database was used for training the arrhythmia machine learning classifier and D1NAMO database for training the glucose machine learning regression model (Moody & Mark, 2001; Dubosson, et al., 2018). The MIT-BIH dataset included annotated ECG recordings from 47 patients with various arrhythmias. The D1NAMO dataset included CGM and ECG recordings from 29 patients totaling to 1550 hours of recordings. First, the ECG signals are resampled from 360 Hz to 125 Hz to help the model generalize the data. Then, the data was balanced to improve classification performance, and finally, the data was augmented via lossless transformations, including upscaling and downscaling the x-axis and y-axis. This effectively increases the size of the training dataset five-fold and further aids in model generalization.

Gait Analysis

Data from the Physionet Gait in Neurodegenerative Diseases annotated database was used for training the neurological diseases machine learning classifier (Hausdorff, et al., 2000). The dataset included gait characteristics from 68 patients such as left and right stride, left and right swing, left and right stance, left to right ratio, double stance, and total elapsed gait cycle time extracted from preprocessed force-sensitive resistor sensor data.

B. Feature Extraction Methods

Wavelet Transform and Autoregressive Modeling

Wavelet transform (WT) and autoregressive modeling (AM) were used to generate feature vectors representing the ECG waveform to recognize heart rhythm characteristics (Zhang & Zhao, 2005). The WT function of an ECG signal $f(x)$ is described as:

$$W_x f(x) = f(x) * \Psi_s(x) = \frac{1}{s}\int_{-\infty}^{+\infty} f(t)\, \Psi\left(\frac{x-t}{s}\right) dt,$$

where $f(x)$ is the WT of the signal, Ψ is the wave function, x is the basic wavelet, and s is the scale factor.

The Mallat algorithm is used to calculate the cardiogram digital signal's $f(n)$ dyadic WT:

$$S_{2j} f(n) = \sum_{k \in Z} h_k S_{2j-1} f(n - 2^{j-1}k) = a_j, a_j$$

$$W_{2j} f(n) = \sum_{k \in z} g_k\, S_{2j-1} f\left(n - 2^{j-1}k\right) = d_j, d_j,$$

where a_j, a_j are low-frequency factors that approximate the initial signal, S_{2j} is a smoothing operator, and d_j, d_j are high-frequency factors that are the details of the initial signals.

AM predicts future behavior based on past behavior. When there are values in a time series that are correlated, it is used for forecasting the values that precede and succeed them. The process is modeled as:

$$s[n] = \sum_{i=1}^{\rho} x[i]s[n-i] + e[n]$$

Where the signal at time instant n is $s[n]$, the ith coefficient of the model is $x[i]$, noise is $e[n]$, and the order is ρ.

Concatenated WT and AM coefficients for feature classification comprise the feature vector. The following fiducial markers are extracted: aortic-valve opening (AO), mitral-valve closing (MC), isovolumic movement (IM), aortic-valve closing (AC), mitral-valve opening (MO), isovolumetric contraction time (ICT), left ventricular ejection time (LVET), isovolumetric relaxation time (IRT), P wave, QRS complex, T wave, and U wave.

Madgwick Filter

To extract features from IMU sensor data, a Madgwick filter is used (Al-Fahoum & Abadir, 2018). The Madgwick filter estimates the IMU sensor's attitude using the following steps: 1) Receive accelerometer and gyroscope data from the sensors. 2) Compute orientation increments from accelerometer data (gradient step) and gyroscope measurements (numerical integration). 3) Combine the measurements from both the accelerometer and gyroscope to find the estimated attitude ${}^{I}_{W}\hat{q}_{est,\,t+1}$. Repeat these steps for every time instant.

1)

$$I_{a_{t+1}}$$

$$I_{\omega_{t+1}}$$

2)

$$\nabla f\left({}^{I}_{W}\hat{q}_{est,t}, W_{\hat{g}}, I_{\hat{a}_{t+1}}\right) = J^{T}\left({}^{I}_{W}\hat{q}_{est,t}, W_{\hat{g}}\right) f\left({}^{I}_{W}\hat{q}_{est,t}, W_{\hat{g}}, I_{\hat{a}_{t+1}}\right)$$

$$-\beta \frac{\nabla f\left({}^{I}_{W}\hat{q}_{est,t}, W_{\hat{g}}, I_{\hat{a}_{t+1}}\right)}{\left\| f\left({}^{I}_{W}\hat{q}_{est,t}, W_{\hat{g}}, I_{\hat{a}_{t+1}}\right)\right\|}$$

$$\frac{1}{2}\, {}^{I}_{W}\hat{q}_{est,t} \otimes \left[0, I_{\omega_{t+1}}\right]^{T}$$

3)

$${}^{I}_{W}\hat{q}_{est,\,t+1}$$

where I and W denote inertial and world frames, q denotes the quaternion orientation, a is the measured acceleration, g is the acceleration due to gravity, $W_{\hat{g}}$ denotes the normalized gravity vector, $I_{\hat{a}}$ denotes the normalized acceleration movements, ω is the measured angular velocity from the gyroscope, $\otimes$ indicates quaternion multiplication, β denotes the adjustment filter, and J is the Jacobian matrix.

C. Machine Learning Models

Multiclass Support Vector Machine

A support vector machine (SVM) classifies data by finding the hyperplane that maximizes the distance between two or more classes (Berwick, 2003). A multiclass SVM can separate the data into more than two classes. Support vectors define the hyperplane. To classify arrhythmias, the kernel trick was utilized. The kernel trick transforms existing data into higher-dimensional data, which makes it easier for the algorithm to classify the data into groups. The kernel function implemented in the arrhythmia classifier is the Gaussian kernel. The SVM classifies the cardiogram into healthy, atrial flutter, atrial fibrillation, ventricular tachycardia, or ventricular flutter. To maximize the margin between the groups, the solution for the algorithm must satisfy these two relations, where the vector W contains the weights of the coefficients of the hyperplane **(Figure 2)**:

$$W = \sum_{i=1}^{l} a_i y_i x_i \,, \quad \sum_{i=1}^{l} a_i y_i = 0$$

Random Forest

A random forest (RF) machine learning model is an ensemble of decision trees (Koehrsen, 2018). To make a prediction, the RF averages the decisions of all the trees. The Gini index is used when performing RF classification. This is the equation used to determine the branching of nodes on the decision tree (Schott, 2019):

$$Gini = 1 - \sum_{i=1}^{C} (p_i)^2$$

where c and p_i are the number of classes and relative occurrence of the class, respectively.

This formula determines which of the branches is more probable to occur using the class and probability, by finding the Gini of each branch on a node. An RF regression model was used for the glucose monitor, and an RF classification model was used for neurological disease detection **(Figure 2)**.

D. Asthma Attack Risk Prediction Program

A programmatic solution was developed to predict the risk of an asthma attack. The program extracts real-time asthma trigger data from a suite of application programming interfaces (APIs), including IQAir, OpenWeatherMap, AirNow, and Open-Elevation APIs and smartphone motion and medication tracking. Air Quality Index (AQI), smoke and fires locations, temperature, humidity, altitude, physical activity, and medication use are input to a decision matrix risk assessment (DMRA) algorithm and a risk assessment of low, medium, or high risk is output **(Figure 2)**.

E. Application Development and Machine Learning Deployment

To deploy the machine learning models to the smartphone application, each model was pre-trained, saved, and converted to TensorFlow Lite (TFLite) models. These TFLite models were then implemented in the Android Studio smartphone application. The smartwatch companion app was built in Tizen Studio. To pair the phone app data with the smartwatch, the Samsung Accessory Protocol (SAP) API was integrated into the Android Studio code. The machine learning predictions take place in the backend, and the user is notified of any health abnormalities via SMS notifications. This approach was chosen to make the UI simpler for ease of use.

F. Hardware Signal Transmission

ECG, SCG, and GCG

Electrode sensor signals are filtered by a combination of a two-pole high pass filter and a three-pole low pass filter and sent to the phone via Bluetooth **(Figure 3)**. This is done to filter out noise from the sensor data acquisition **(Figure 4)**. IMU sensor signals are input to a Madgwick filter, and the cardiogram features from the SCG and GCG are extracted. The fiducial markers are then fed to the pre-trained arrhythmia classification and glucose monitor machine learning algorithms **(Figure 5)**. The shirt sensor detects when an electrode is disconnected by sourcing a small current into the electrodes. The IMU sensors can also detect when the shirt is doffed and stop recording signal data.

Gait Pattern Characteristics

IMU sensor signals from the hip, knees, and ankles are input to a Madgwick filter, and the gait pattern characteristics are extracted **(Figure 3)**. Then, the features are fed to the pre-trained neurological disease classification machine learning algorithm **(Figure 5)**. Programmed threshold filters ensure the signals from the pants sensors are not collected for excessive motion, indicating running, jumping, or other extreme movements, and it is not collected for motion below a certain threshold, such as sitting, sleeping, or standing. Furthermore, the IMU sensors automatically stop recording signals when the pants are doffed.

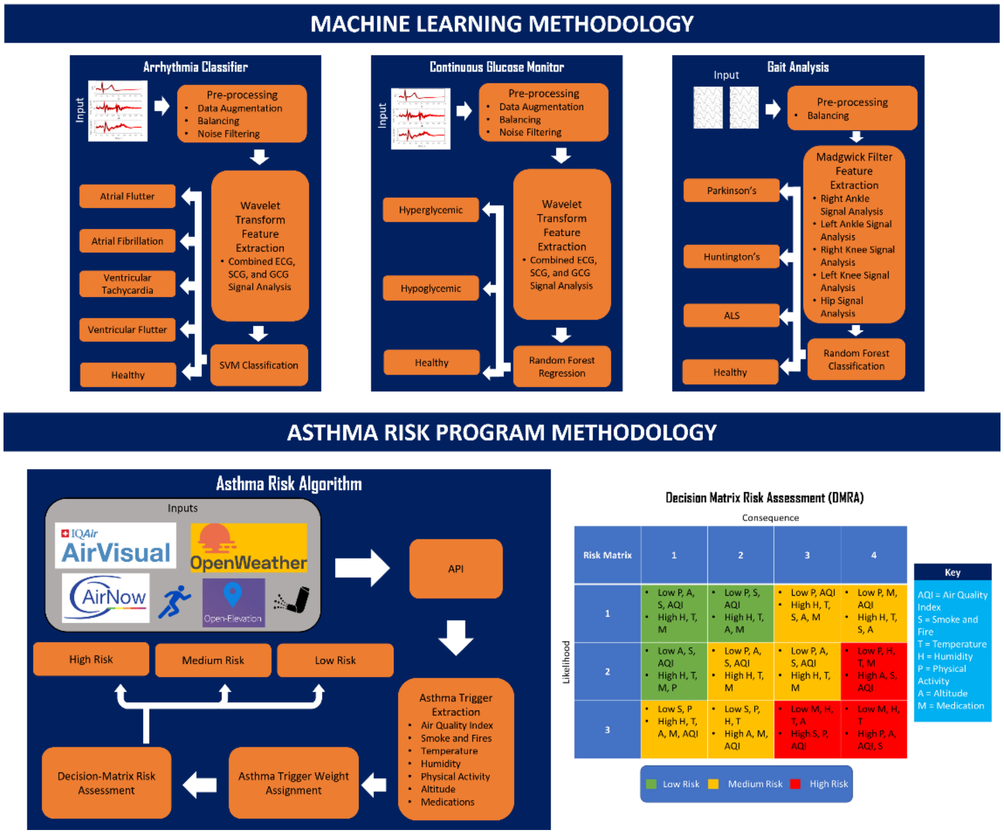


Figure 2: *Software methodology. (Top Left) Arrhythmia machine learning classifier (Top Center) Glucose machine learning classifier (Top Right) Neurological disease machine learning classifier (Bottom) Asthma risk prediction program.*

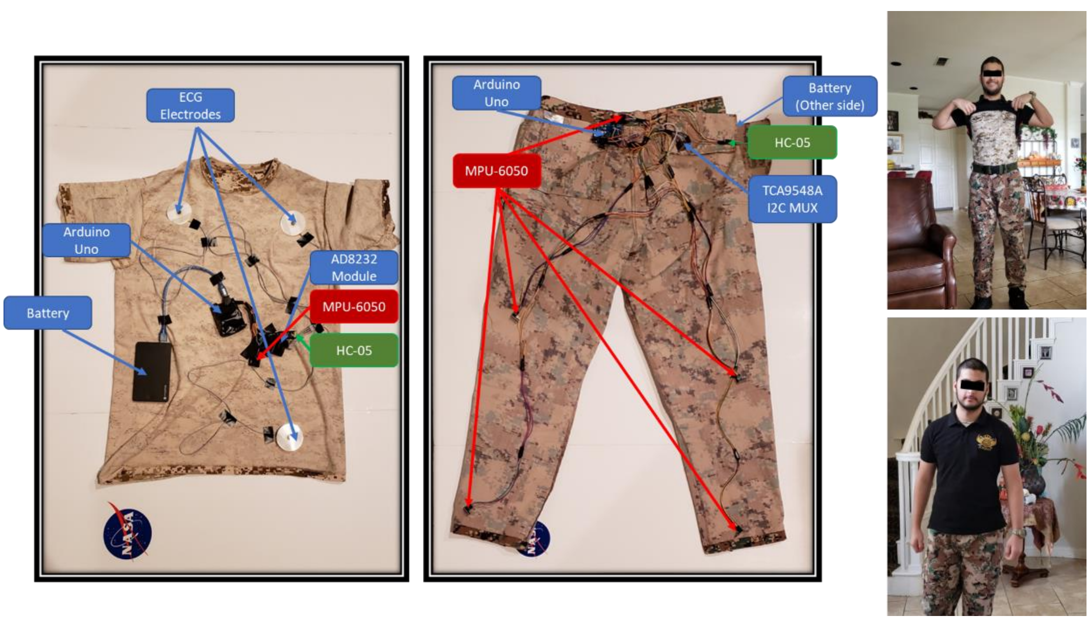


Figure 3: *Prototype intelligent textile biosensor system. (Left) Shirt biosensor for acquisition of cardiogram signals. (Center) Pants biosensor for acquisition of gait pattern features. (Right) Researcher donning the system.*

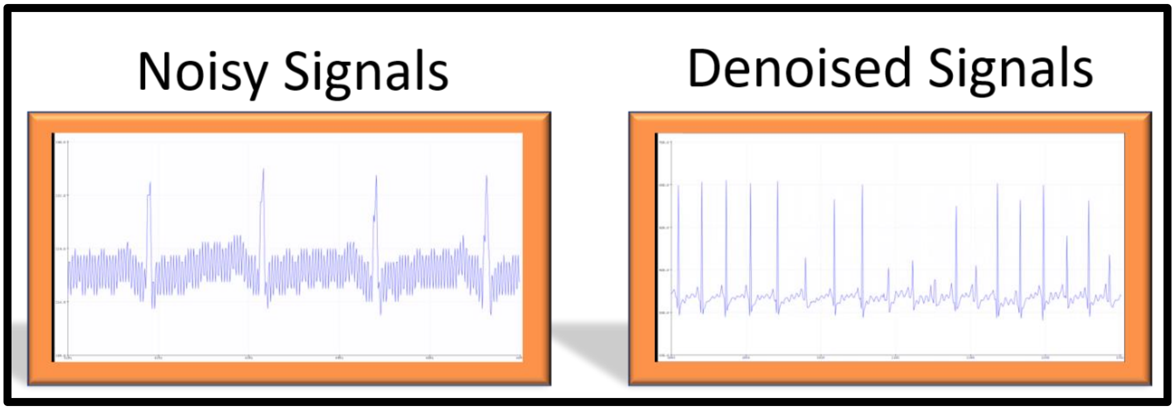
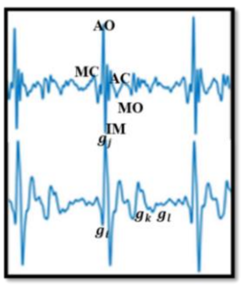
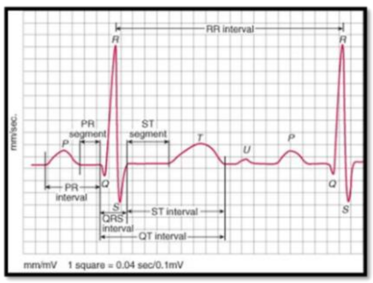


Figure 4: *Signal denoising. Raw ECG signal (left) and processed ECG signal (right).*





SCG Signal	Meaning
AO	Aortic-Valve Opening
MC	Mitral-Valve Closing
IM	Isovolumic Movement
AC	Aortic-Valve Closing
MO	Mitral-Valve Opening

GCG Signal	Meaning
g_i-g_j Interval	Isovolumetric Contraction Time
g_j-g_k Interval	Left Ventricular Ejection Time
g_k-g_l Interval	Isovolumetric Relaxation Time

ECG Signal	Meaning
P Wave Duration	Atrial Depolarization
PR Interval	Impulse Conduction
PR Segment	Baseline of ECG
QRS Duration	Ventricular Depolarization
RR Interval	Heart Rate
ST Segment	Between Ventricular Depolarization & Repolarization
TP Interval	Period of Electrical Inactivity
QT Interval	Time Taken to Depolarize and Repolarize

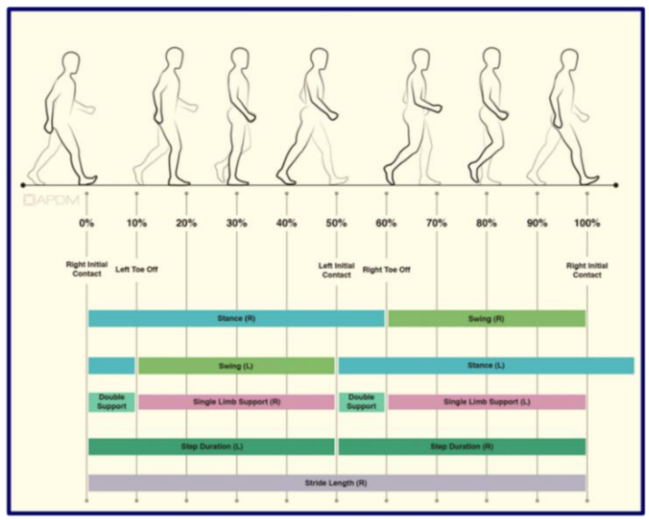


Figure 5: *Fiducial Markers: (Left) Cardiogram signals and their meaning (pictures from https://www.scirp.org/html/2-9101505/20b971d4-6b81-47cb-abb6-1faa019864ef.jpg). (Right) Gait pattern characteristics (picture from https://www.apdm.com/wp-content/uploads/2014).*

V. RESULTS

To evaluate the Max Health prototype, three levels of testing were conducted: diagnosis testing, software testing, and hardware testing. In diagnosis testing, the three machine learning models were tested on new data separate from the training data by manually splitting the original datasets into 80% training and 20% testing. This was done to realistically simulate new data for the models to analyze. In doing so, it can be determined whether models were generalizing well or simply overfitting the data. Confusion matrices were output, and statistical characteristics were calculated, including accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and F1 score **(Figure 6, Table 1)**:

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

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

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

$$PPV = \frac{TP}{TP + FP}$$

$$NPV = \frac{TN}{TN + FN}$$

$$F1\ Score = \frac{2 \times PPV \times Sensitivity}{PPV + Sensitivity}$$

These are commonly used in the field of biomedical engineering to evaluate prototypes and are widely accepted to use in comparisons to other approaches. The arrhythmia classifier results showed the model was 98% accurate with 98% sensitivity and 94% specificity, 98% PPV and 94% NPV, and 98% F1 score. The dysglycemia classifier results showed the model was 93% accurate with 97% sensitivity and 86% specificity, 92% PPV and 94% NPV, and 94% F1 score. The neurological disease classifier results showed the model was 100% accurate with 100% sensitivity and 99% specificity, 100% PPV and 100% NPV, and 100% F1 score. Moreover, McNemar's test was used to calculate the correlation between the machine learning models' predicted diagnosis and the true diagnosis, and all three models' p-values were <0.001, indicating a statistically significant correlation.

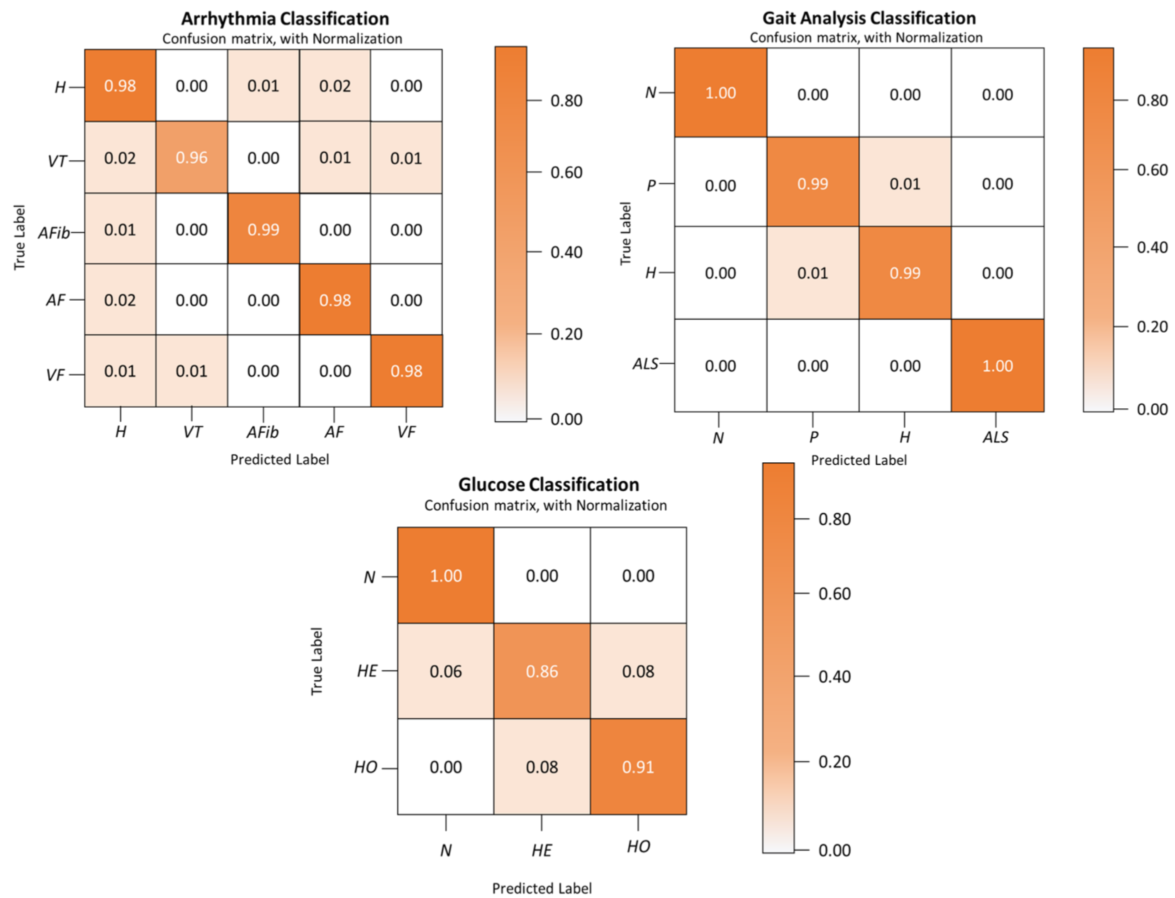


Figure 6: *Machine learning models confusion matrices. (Top Left) Arrhythmia classifier results; H-Healthy VT-Ventricular Tachycardia AFib-Atrial Fibrillation AF-Atrial Flutter VF-Ventricular Flutter. (Top Right) Neurological disease classifier results; N-Healthy P-Parkinson's H-Huntington's ALS-Amyotrophic Lateral Sclerosis. (Bottom) Glucose classifier results; N-Healthy HE-Hyperglycemia HO-Hypoglycemia.*

Classifier	Accuracy	Sensitivity	Specificity	PPV	NPV	F1	McNemar's Chi-Squared Statistic (Corresponding *p*-Value)
Arrhythmias	98%	98%	94%	98%	94%	98%	4828 (p<0.001)
Glucose	93%	97%	86%	92%	94%	94%	9091 (p<0.001)
Neurological Diseases	100%	100%	99%	100%	100%	100%	600 (p<0.001)

Table 1: *Machine learning models performance metrics.*

In software testing, the application underwent testing and debugging to ensure signals were successfully being input to the TFLite models, and predictions were being output. The asthma risk prediction program also underwent testing and debugging to confirm that real-time data from the APIs and the smartphone were being inputted to the DMRA, and the correct risk assessment was output. Furthermore, the smartwatch application underwent testing and debugging to verify that the application was paired to the smartphone, and the correct data was transmitted to the watch.

In hardware testing, the smart clothing biosensors signal transmission was tested in multiple conditions to simulate realistic scenarios and determine the feasibility of using the prototype for continuous monitoring. Signals from the shirt sensor were recorded while the user was sitting, walking, and running **(Figure 7)**.

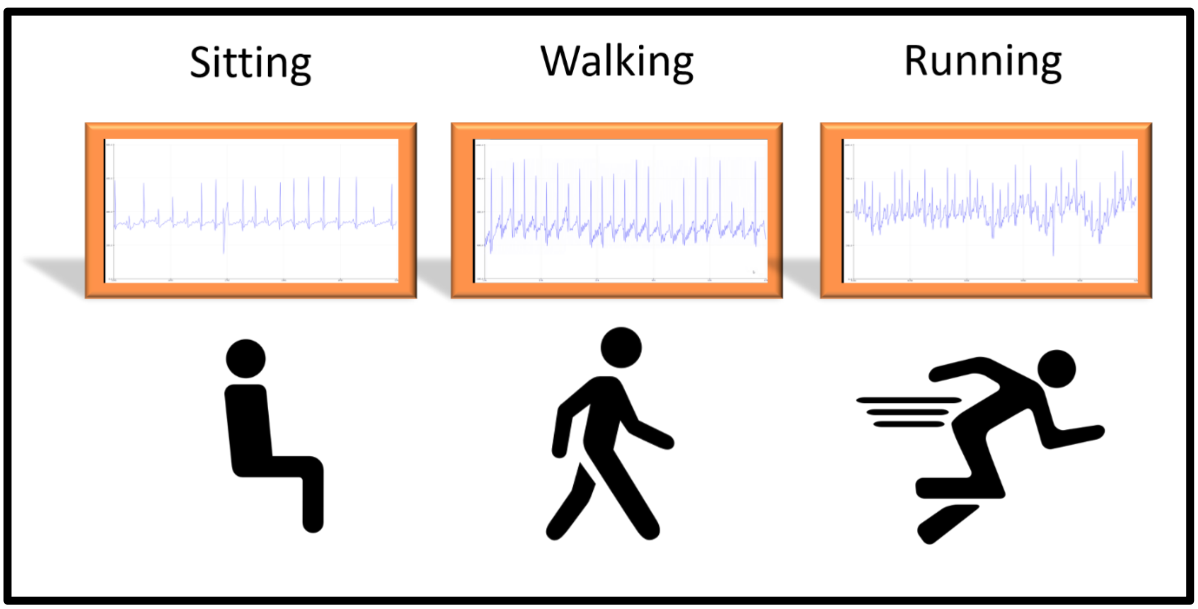


Figure 7: *ECG signal transmission while sitting (left), walking (center), and running (right).*

The measurements were indicative of heart rate increasing with more strenuous activity, which shows that the system was working properly. Additionally, in testing and debugging, the smartphone application correctly classified the user's heart rhythm as healthy. The cardiogram signals were being displayed in real-time in the UI. The smartphone application also was able to correctly classify the user's glucose level as healthy and provide an estimate of the user's glucose level in real-time, which was displayed in the UI. The shirt sensor successfully detected when the electrodes were misplaced or when the shirt was doffed, and the signal recording was shut off. Signals from the pants sensor were recorded while the user was walking back and forth, and the smartphone application successfully classified the user's neurological condition as healthy. IMU sensor signals were transmitted to the smartphone application in real-time and displayed in the UI **(Figure 8)**. The asthma risk prediction is a programmatic solution, and therefore only testing and debugging was conducted. The pants sensor successfully detected when there was excessive motion or too little motion and when the pants were doffed, and signal recording was shut off. Finally, battery testing was conducted to ascertain whether the sensors can be used continuously throughout the day, with the shirt sensor having on average, a battery life of 36 hours and 48 minutes, and the pants sensor having on average, a battery life of 26 hours and 24 minutes **(Figure 9)**.

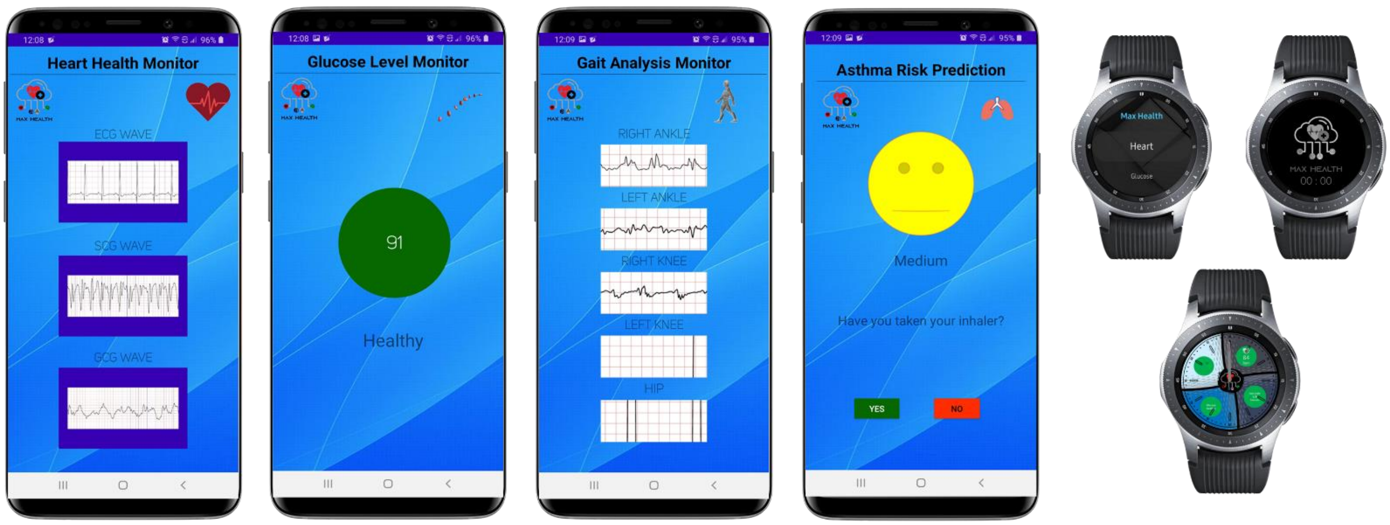


***Figure 8**: Smartphone and smartwatch user-interface. Screens from left to right: Cardiogram signals ECG (top), SCG (center), GCG (bottom); Glucose level (mg/dL); Gait tracking IMU signals right ankle (top), left ankle (2nd from top), right knee (center), left knee (2nd from bottom), hip (bottom); Asthma attack risk assessment prediction (top), medication tracking (bottom). Smartwatch screens: (Top Left) Dedicated smartwatch application dashboard, (Top Right) Low-power always-on-mode, (Bottom) At-a-glance watch face.*

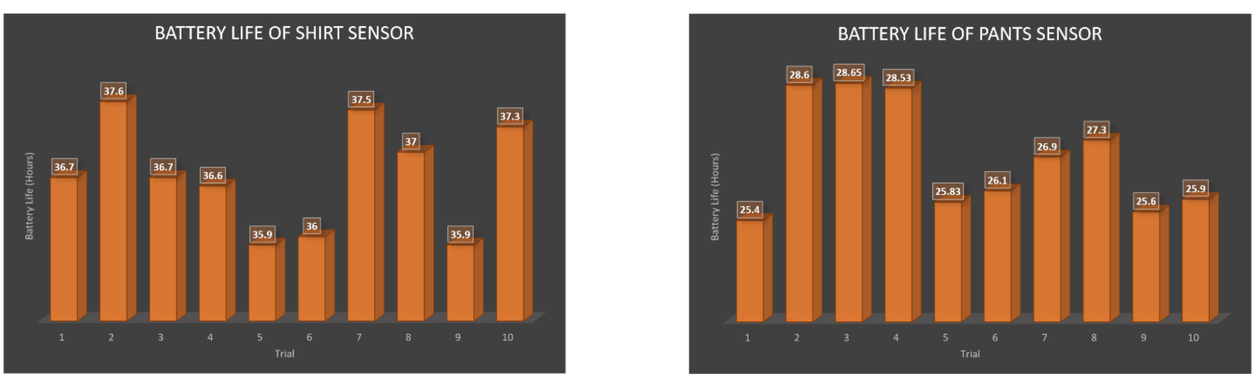


***Figure 9**: Battery testing results for shirt biosensor (left) and pants biosensor (right).*

VI. DISCUSSION

This project aimed to engineer a device that can non-invasively and continuously monitor health parameters and detect arrhythmias, dysglycemia, neurological diseases, and predict asthma attack risk. The prototype uses intelligent textiles biosensors to measure heart rhythm and gait metrics, which are then used in machine learning algorithms to classify the user's condition as healthy or unhealthy and specify the health abnormality detected. A multiclass SVM was used to classify arrhythmias, an RF regression model was used to classify glucose levels, and an RF classification model was used to classify neurological diseases. A multiclass SVM was chosen for the arrhythmia classifier because it is among the simplest models used in arrhythmia detection, and in past research, it was found to give high accuracies. RF was used for the glucose and neurological disease detection since RF models are simple, easy to set up, require less data in training, and they give high accuracies. Due to these factors, the aforementioned machine learning models are gaining popularity in the field of medicine. The proposed health monitoring system demonstrates results similar to or better than state-of-the-art approaches that use more complicated procedures to acquire health parameters and perform data analysis **(Table 2)** (Apple Inc., 2018; Samsung, 2018; Rajpurkar, Hannun, Haghpanahi, Bourn, & Ng, 2017; Morales, 2020; García, 2018; Wadwa, Laffel, Shah, & Garg, 2018; Bailey, 2017; Ťupa, et al., 2015; Dehzangi, Taherisadr, & Changalvala, 2017).

A possible explanation for the system's high performance is the utilization of efficient feature extraction methods and multiple levels of data augmentation. Incorporating these techniques allows for the machine learning models to generalize well and make accurate predictions on new data the algorithms have never seen before. The system is also much cheaper than current systems, costing a mere $22.12 **(Table 3)**. This is possibly the first prototype to be developed that can non-invasively, remotely, and continuously monitor arrhythmias, glucose, neurological diseases, and predict asthma attack risk simultaneously. Furthermore, classification is done on-device, meaning that patients do not have to be connected to the internet to have these classifiers working. This enables remote monitoring and diagnosis in even the most isolated areas. Another advantage of the proposed system is its versatility allows for monitoring many health parameters continuously. In doing so, the system can detect diseases in their early stages, which can potentially help patients receive better treatment. Also, the system's superior performance can provide patients with ease of mind and help doctors by providing valuable data about the user's health.

There were some key limitations in this study that should be mentioned. First, the system was only tested on myself, so initial hardware results may be biased. Further testing is required to validate the system on multiple users. To circumvent this issue, the system was tested in multiple conditions to realistically simulate continuous health monitoring. The results demonstrated that the system was successful. Second, the system was only tested on a healthy subject, yet the true test of the Max Health platform will need to be on subjects with these illnesses. To deal with this problem, the system underwent testing and debugging in which patient data from the testing dataset was input to the machine learning models. Finally, the prototype can be improved by miniaturizing the electrical components using application specified integrated circuits.

For future expansions of this project, the intelligent textile biosensors can be used to monitor additional conditions. With more data, the pants gait analysis sensors can be used to monitor arthritis and help patients track the progress of therapeutic interventions. By collecting more data, the shirt cardiogram sensors can be used to monitor respiration, which can then be implemented in the asthma risk software to improve risk assessment. With further machine learning training on larger datasets, the neurological disease classifier can be used to monitor the progression of the neurological disease and determine the severity. As more research is done concerning the use of IMU sensors and cardiogram analysis, the applications of this system can reach beyond its initial purpose.

Approach	Accuracy	Types of Arrhythmias	Biological Data Acquisition Method	Cost	Continuous	Mobile
Proposed	98%	5	Shirt Sensor (ECG + SCG + GCG)	$11.53	Yes	Yes
Apple	98%	2	Finger ECG	$399.00	No	Yes
Samsung	97%	2	Wrist PPG	$329.99	Yes	Yes
Rajpurkar et al. (Stanford)	81%	12	Chest Patch ECG	$360.00	Yes	No
KardiaMobile	95%	2	Finger ECG	$149.00	No	Yes

Approach	Accuracy	Biological Data Acquisition Method	Cost	Continuous	Invasive
Proposed	93%	Shirt Sensor (ECG + SCG + GCG)	$11.53	Yes	Non-invasive
Garcia	91%	Near-Infrared Sensor	$149.99	No	Non-invasive
Wadwa et al.	95%	Subcutaneous Electrochemical Sensor	$899.99	Yes	Minimally Invasive
Bailey	99%	Full Implant Fluorescence Sensor	$6,000	Yes	Invasive

Approach	Accuracy	Biological Data Acquisition Method	Cost	Mobile
Proposed	100%	Pants IMU Sensors	$10.59	Yes
Ťupa et al.	97%	Camera + Pressure Plates	$199.99	No
Dehzangi et al.	91%	Lab IMU Sensors	$364.73	No

Table 2: *Feature comparisons with previous approaches. (Top) Arrhythmia classifier (Center) Glucose classifier (Bottom) Neurological disease classifier.*

Item	Purpose	Specifications	Quantity	Total Cost
Arduino Uno	Microcontroller	Power Consumption: 45 mA; Length: 68.6 mm; Width: 53.4 mm; Weight: 25 g	2	$8.98 USD
MPU 6050 IMU Sensor	1 sensor measures the accelerations and gyrations of the heart. The remaining 5 sensors are used for gait analysis.	Power Consumption: 3.9 mA; Length: 21.2 mm; Width: 16.4 mm; Weight: 2.1 g	6	$4.98 USD
AD8232 ECG Sensor	Sensor records electrical signals of heart.	Power Consumption: 0.17 mA; Length: 5 mm; Width: 5 mm; Weight: 13.5 g	1	$4.83 USD
HC-05 BLE Module	Allows Bluetooth communication between phone and Arduino	Power Consumption: 30 mA; Length: 28 mm; Width: 15 mm; Weight: 3 g	2	$2.77 USD
TCA9548A I2C Multiplexer	Enables connections for multiple MPU 6050 modules with the Arduino	Power Consumption: 100 mA; Length: 30.6 mm; Width: 17.6 mm; Weight: 1.8 g	1	$0.56 USD
	Total System Cost			$22.12

Table 3: *Bill of Materials (BOM) for proposed approach.*

VII. CONCLUSION

The low cost, non-invasive nature, and ease of use of this proposed system provide a viable solution for patients with chronic disease as well as healthy people to monitor their health. The Max Health system can help users survive deadly arrhythmias by alerting them before it occurs, allowing ample time for them to locate a hospital and get their heart checked. Max Health can help with diabetes management by monitoring glucose levels and asthma patients with risk assessment, potentially encouraging them to take necessary precautions in case of an asthma attack. The proposed system can aid in early diagnosis of neurological disorders, which can lead to better treatment and slowing the progress of the disease. This system can provide patients with ease of mind and help doctors by providing valuable data about the user's health. In addition to the health benefits provided by this system, Max Health is much cheaper than current medical systems. Furthermore, the Max Health system is reusable, meaning that patients do not have to deal with maintenance issues or resupplying. This system is entirely contained within the clothing and can easily be implemented to any shirt or pants the user owns, with no technical experience required to set up the Max Health system. The methodology used in this project is novel, and to my knowledge, this is the first device of its kind to monitor these four health parameters simultaneously. The arrhythmia classifier is unique in that it uses lossless transformation techniques to augment the data, extracts features using WT and AM, and classifies arrhythmia by utilizing a multiclass SVM. The glucose monitor is innovative in that it can detect hypoglycemia and hyperglycemia solely from cardiogram signals, which, to my knowledge, has never been done before. The gait analysis for neurological diseases classifier is original in that the Madgwick filter is used for attitude estimation, a Random Forest model is used for classification, and the monitoring is continuous. The asthma risk prediction application is the first of its kind that can make predictions without the use of a spirometer. The results for the system are promising, indicating the machine learning algorithms are 98% accurate at classifying arrhythmias, 100% accurate at gait analysis classification of neurological diseases, and 93% accurate at classifying glucose levels. The hardware is also compatible with continuous monitoring of health parameters, with the sensors' battery life lasting more than 24 hours. This data supports the conclusion that the proposed Max Health system is a practical solution for non-invasive, continuous health monitoring. With further development and validation testing, the system can be improved and deployed for commercial use.

REFERENCES

Al-Fahoum, A., & Abadir, M. (2018). Design of a Modified Madgwick Filter for Quaternion-Based Orientation Estimation Using AHRS. *International Journal of Computer and Electrical Engineering*.

ALS Association. (2019, May). *About ALS*. Retrieved from ALS Association - Rocky Mountain Chapter: http://webco.alsa.org/site/PageServer/?pagename=CO_1_WhoGets.html#:~:text=Approximately%205%2C000%20people%20in%20the,cases%20occur%20without%20family%20history.

Apple Inc. (2018, December). *Using Apple Watch for Arrhythmia Detection*. Retrieved from Apple: https://www.apple.com/healthcare/docs/site/Apple_Watch_Arrhythmia_Detection.pdf

Asthma and Allergy Foundation of America. (2019, June). *Asthma Facts and Figures*. Retrieved from AAFA: https://www.aafa.org/asthma-facts/

Bailey, T. S. (2017). Clinical Implications of Accuracy Measurements of Continuous Glucose Sensors. *Diabetes Technology & Therapeutics*.

Berwick, R. (2003). *An idiot's guide to support vector machines (SVMs).* Cambridge, MA: Massachusetts Institute of Technology.

Dehzangi, O., Taherisadr, M., & Changalvala, R. (2017). IMU-Based Gait Recognition Using Convolutional Neural Networks and Multi-Sensor Fusion. *Sensors*.

Diabetic Warehouse. (2018). *DEXCOM G6 SENSORS & G6 TRANSMITTER COMBO*. Retrieved from Diabetic Warehouse: https://www.diabeticwarehouse.org/products/dexcom-g6-sensors-g6-transmitter-combo?utm_medium=cpc&utm_source=google&utm_campaign=Google%20Shopping&utm_campaign=gs-2018-09-13&utm_source=google&utm_medium=smart_campaign&gclid=Cj0KCQjwg8n5BRCdARIsALxKb96uH4EG

Dubosson, F., Ranvier, J.-E., Bromuri, S., Calbimonte, J.-P., Ruiz, J., & Schumacher, M. (2018). The open D1NAMO dataset: A multi-modal dataset for research on non-invasive type 1 diabetes management. *Informatics in Medicine Unlocked*.

Gao, W., Emaminejad, S., Nyein, H., Challa, S., Chen, K., Peck, A., . . . Javey, A. (2017). Fully integrated wearable sensor arrays for multiplexed in situ perspiration analysis. *Nature*.

García, A. (2018). Nonlinear transfer function's approach to non-invasive glucose measurement. *International Journal of Biosensors & Bioelectronics*.

Guvenir, H. A., Acar, B., Demiroz, G., & Cekin, A. (1997). A supervised machine learning algorithm for arrhythmia analysis. *Computers in Cardiology*.

Hausdorff, J. M., Lertratanakul, A., Cudkowicz, M. E., Peterson, A. L., Kaliton, D., & Goldberger, A. L. (2000). Dynamic markers of altered gait rhythm in amyotrophic lateral sclerosis. *Journal of Applied Physiology*.

Hilbel, T., Helms, T. M., Mikus, G., Katus, H. A., & Zugck, C. (2008). Telemetry in the clinical setting. *Herzschr Elektrophys*.

Jain, P., Joshi, A. M., & Mohanty, S. P. (2019). IGLU 1.0: AN ACCURATE NON-INVASIVE NEAR-INFRARED DUAL SHORT WAVELENGTHS SPECTROSCOPY BASED GLUCOMETER FOR SMART HEALTHCARE. *arXiv*.

Klonoff, D. C. (1997). Noninvasive Blood Glucose Monitoring. *Diabetes Care*.

Koehrsen, W. (2018, August 30). *An Implementation and Explanation of the Random Forest in Python*. Retrieved from Towards Data Science: https://towardsdatascience.com/an-implementation-and-explanation-of-the-random-forest-in-python-77bf308a9b76

Moody, G., & Mark, R. (2001, February 24). The Impact of the MIT-BIH Arrhythmia Database. *IEEE Eng in Med and Biol*. Retrieved from Physionet: https://physionet.org/content/mitdb/1.0.0/

Morales, D. (2020, February 18). *The Dr. AFib Review of the KardiaMobile*. Retrieved from Dr. AFib: https://drafib.com/blog/2018/11/5/kardiamobile-kardiaband-review

Nguyen, L. L., Su, S., & Nguyen, H. T. (2012). Identification of Hypoglycemia and Hyperglycemia in Type 1 Diabetic Patients Using ECG Parameters. *IEEE EMBS*.

NORD. (2007). *Huntington's Disease*. Retrieved from National Organization for Rare Disorders: https://rarediseases.org/rare-diseases/huntingtons-disease/

Parkinson's Foundation. (2018). *Statistics*. Retrieved from Parkinson's: https://www.parkinson.org/Understanding-Parkinsons/Statistics#:~:text=Approximately%2060%2C000%20Americans%20are%20diagnosed,are%20diagnosed%20before%20age%2050.

Rajpurkar, P., Hannun, A., Haghpanahi, M., Bourn, C., & Ng, A. (2017). Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks. *arXiv*.

Samsung. (2018, April 13). *Detecting AFib with wearables*. Retrieved from Samsung: https://www.samsung.com/us/ssic/detecting-afib-with-consumer-wearables/

Schott, M. (2019, April 25). *Random Forest Algorithm for Machine Learning*. Retrieved from Medium: https://medium.com/capital-one-tech/random-forest-algorithm-for-machine-learning-c4b2c8cc9feb

Scott, D. (2020, April 27). *Coronavirus has created a crisis for primary care doctors and their patients*. Retrieved from Vox: https://www.vox.com/2020/4/27/21231528/coronavirus-covid-19-primary-care-doctors-crisis

Tenderich, A. (2019, March 18). *Diabetes Mine*. Retrieved from Healthline: https://www.healthline.com/diabetesmine/eversense-implantable-cgm-alerts-insertion-cost-trials#1

Ťupa, O., Procházka, A., Vyšata, O., Schätz, M., Mareš, J., Vališ, M., & Mařík, V. (2015). Motion tracking and gait feature estimation for recognising Parkinson's disease using MS Kinect. *BioMedical Engineering OnLine*.

Wadwa, P. R., Laffel, L. M., Shah, V. N., & Garg, S. K. (2018). Accuracy of a Factory-Calibrated, Real-Time Continuous Glucose Monitoring System During 10 Days of Use in Youth and Adults with Diabetes. *Diabetes Technology & Therapeutics*.

WHO. (2017, May 17). *Cardiovascular Diseases*. Retrieved from World Health Organization: https://www.who.int/en/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

WHO. (2020, June 8). *Diabetes Factsheet*. Retrieved from World Health Organization: https://www.who.int/news-room/fact-sheets/detail/diabetes

Yang, C., & Tavassolian, N. (2017). Combined Seismo- and Gyro-cardiography: A More Comprehensive Evaluation of Heart-Induced Chest Vibrations. *IEEE Journal of Biomedical and Health Informatics*.

Zhang, L., & Zhao, Q. (2005). ECG Feature Extraction and Classification Using Wavelet Transform and Support Vector Machines. *IEEE Neural Networks and Brain*.