LiveHeart: AI-Augmented Lifestyle Habit Monitoring System for Decision Making in Digital Care Pathway

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Abstract

The advancement of interoperable digital technology has had remarkable impacts on society especially in the healthcare area. Ischemic heart disease is a major cause of disability and premature death in many parts of the world that can still be mitigated through lifestyle changes. While the existing mHealth solutions that encourage users to maintain healthy lifestyle habits do exist, they lack the reliable advice of healthcare professionals to monitor patient's lifestyle habits remotely. The process of manually collecting patient data for analysis and clinical testing can also be time-consuming for healthcare professionals. Therefore, this study proposed a web-based information system to monitor lifestyle habits and habit-change of people prone to heart disease. The system collects lifestyle habit data from a smartwatch and smartphone. Then, the system utilizes machine learning techniques to classify the patient's lifestyle habit data such as diet, exercise, and sleep. Furthermore, the system is used to upload echocardiograms during the echocardiography test in the hospitals and receive the echocardiography results. The data analytical results are visualized on an intelligent dashboard that can be viewed by doctors using the web application. The system is expected to support doctors in decision-making for digital care pathways in order to provide timely intervention for lifestyle modifications.

Keywords 1

Heart Disease, Habit Change, Digital care pathway, Internet of Things, Machine learning, Classification, Web-based Application

1. Introduction

Ischemic heart disease and stroke are considered as the global leading causes of long-term disability and premature death [1]–[7]. The primary risk factors that contribute to heart disease and stroke are unhealthy diet, physical inactivity, and tobacco use [8]. The American Heart Association has defined ideal cardiovascular health based on a set of risk factors that can be mitigated through lifestyle changes such as eating a healthy diet and engaging in consistent physical activity [9]. Practicing these habits to maintain good cardiovascular health could help to minimize medical care expenditures [10].

Personnel in the healthcare sector have been utilizing wearable sensors to monitor the health of patients. Physical sensors are used to collect biomedical data which is pre-processed before being sent to a cloud infrastructure to be stored and analyzed through machine learning techniques to produce a diagnosis. These results are interpreted and visualized in the form of intelligent dashboards that can be easily understood by patients and health workers. However, the existing studies did not

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facilitate the change of lifestyle habits other than physical activity. Their main gap is related classifying patients' lifestyle habits for providing timely advice from the doctor and for better decision making. [11]–[13]. Therefore, this study proposed a web-based system based on Internet of Things (IoT) and big data analytics which speeds up the decision-making process for doctors so they can focus on prescribing advice for disease prevention and treatment.

Studies have shown that healthy lifestyle changes can contribute to the risk reduction of developing heart disease [14]–[16]. Most telehealth solutions that use machine learning and big data analytics to facilitate the adoption of healthy lifestyle habits focus on exercise and physical activity, but not other lifestyle habits like maintaining a healthy diet or regulating blood pressure [17], [18]. While mHealth solutions like Samsung Health and Google Fit that encourage users to maintain healthy habits do exist, they lack the reliable advice of a health professional to guide them to take care of their heart health.

For most of the existing clinical decision support systems, doctors still need to manually collect lifestyle habit data from patients, such as uploading CSV files or manually keying in data, before they can analyze the data, which can be time-consuming. Furthermore, echocardiography is a recommended method to detect the early onset of heart disease, but echocardiography function has rarely been integrated in clinical decision support systems [19].

Therefore, this study proposes a web-based system to monitor the habit-change and biomedical data of heart disease patients which consists of diet habits, exercise habits, sleeping habits. The system collects lifestyle habit data from devices and carries out machine learning on the data to generate an overall report of the patient's risk of developing heart failure. The results of data analytics are visualized in the form of an intelligent dashboard to be viewed by doctors to gain insights from their patients' data. The system is expected to provide an effective diagnosis of patients and thereby support doctors in decision-making for digital care pathway so they can focus on prescribing advice for habit adjustment to mitigate disease.

This paper introduced the proposed LiveHeart information system and reviewed the existing studies. The system requirements, design, development methodology, data analytics, tests, and evaluation are included afterwards. The paper is finally wrapped up with concluding remarks and future directions.

2. Related Works

2.1. Heart Disease and Lifestyle Habit

Coronary heart disease, also known as ischemic heart disease and coronary artery disease, occurs when a blockage forms in the blood vessels that supply blood to the heart, reducing the supply and causing the heart muscle cells to die. This blockage is usually made up of fatty deposits such as cholesterol. As a result, patients suffering from coronary heart disease experience a form of chest pain [20].

An important, controllable risk factor for coronary heart disease is lifestyle habits – these include unhealthy diet, physical inactivity, tobacco use and excessive alcohol consumption, as these activities contribute to the narrowing of the blood vessels that supply blood to the heart. As such, the risk of coronary heart disease can be managed by adopting healthy habits, such as eating more fruits and vegetables, reducing salt intake, engaging in daily physical activity, and managing blood pressure [21].

There are a number of existing risk assessment systems that assess the 10-year risk of cardiovascular disease mortality such as Framingham [22] and SCORE [23]. However, the studies conducted to develop these systems were limited to the American and European regions. As for heart disease specifically, the Get With the Guidelines-Heart Failure risk score is used to predict in-hospital mortality [24], while the Seattle Heart Failure Model predicts the 1-, 2- and 3-year survival of heart failure patients [25]. Again, these models were developed on a dataset of patients in the American region.

On the other hand, poor-quality diet, low physical activity, and emotional stress can lead to obesity, which in turn can lead to hypertension and diabetes, which are risk factors for heart failure with reduced ejection fraction. Adherence to diets rich in plant-based foods such as food and vegetables and low-sodium diets has been associated with a lower incidence of heart failure. The risk can also be lowered by carrying out enough physical activity to balance out calorie intake [27] and sleeping 7-8 hours a day [28-29]. Overall, healthier lifestyle habits are associated with a lower risk of developing heart failure, and vice-versa [14]–[16].

2.2. Habit Classification

Since healthcare systems are very sensitive, they require high accuracy to provide a reliable solution for doctors' decision making. Thus, this section focuses on the comparison of different classification algorithms to find the most suitable one with the best accuracy for classifying lifestyle habit data. Various studies were conducted for habit classification. For instance, random Forests algorithm was used to classify eating occasions as meals or snacks, achieving an accuracy of 84% with time, location, and time since last intake as the most informative features [30]. Furthermore, feeding gestures were used as an indicator of caloric intake and thus used Random Forests to differentiate between 10 types of feeding gestures, achieving an accuracy of 94% [31]. In another study, Random Forests was utilized to classify food consumption level as overeating, undereating and as usual, where a combination of self-reported features such as social and mood and passive smartphone sensing features such as battery level and accelerometer measurements yielded an accuracy of 87.81% [32].

Using Random Forests to predict the probability of an individual reaching their daily step count based on step count data collected from a wrist-worn activity tracker yielded an accuracy of 93% [33]. Support Vector Machine (SVM) was used in another study to classify ambulation, cycling, sedentary and other activities based on accelerometer data [34]. When the classification uncertainty estimated by the SVM exceeded a set threshold, the proposed algorithm requested for the ground truth activity label from the user and updated the classification model. This method achieved an accuracy of 89.2% Davidson et al. carried out a pilot study to predict two classes of RPE (RPE≤15 "Somewhat hard to hard" and RPE>15 "Hard to very hard" on Borg's 6–20 scale) based on time-series data collected from a smartwatch such as heart rate and peak oxygen consumption [35]. Convolutional Neural Network (CNN) was used for classification with an accuracy of 86.0%.
Another study collected raw respiratory signals and used balanced bootstrapping and Long Short-term Memory (LSTM) to detect sleep apnea, achieving the best accuracy of 77.2% on the abdominal respiratory belt signal [36]. An ensemble of bagged tree classifier, which is a combination of the bagging algorithm and decision tree classifier, was used in one study to classify sleep disorders as healthy, insomnia, sleep-disordered breathing, and REM behavior disorder. The authors used a pre-processing technique that used 30-seconds epoch of ECG signal. The classifier used sleep quality parameters such as wakefulness, total time in bed and REM and achieved an accuracy of 86.27% [37]. In another study, ECG signals were subjected to 5-level wavelet decomposition and norm features were extracted to be fed to a KNN classifier with 10-fold cross-validation to classify healthy sleep and insomnia in various sleep stages, achieving an accuracy of 97.87% for the REM sleep stage [38].

2.3. Echocardiogram Classification

There have been a limited number of studies that integrate echocardiogram classification into home-based clinical decision support systems. The existing studies [39-42] did not extend the diagnosis of heart chamber abnormalities to predict the risk of developing heart disease and did not have the potential to explore early detection of heart disease.

Back Propagation Neural Network (BPNN), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM) were used by [40] to classify the echocardiogram as normal, dilated cardiomyopathy or hypertrophic cardiomyopathy. Left ventricle measurements are extracted, and principal component analysis (PCA) and discrete cosine transform (DCT) are applied in this study to reduce the dimensionality of the data. The results showed that BPNN classifier with PCA features had the best accuracy of 90.2%.

Furthermore, the CNN model was developed by [41] for echocardiogram viewpoint classification. The proposed CNN model was developed for image segmentation of selected echocardiographic views to locate cardiac chambers, and the output was used to derive cardiac chamber measurements such as area, volume, and mass. The authors also developed separate CNNs to detect 3 types of heart diseases: hypertrophic cardiomyopathy, pulmonary arterial hypertension, and cardiac amyloidosis in A4c and PLAX views, achieving C-statistics of 0.93, 0.87

and 0.85 respectively.

Another study was done by [39] segmenting the main field of view in echocardiograms before utilizing an ensemble of CNN models for viewing the classification. Then, the U-Net was used to segment the left ventricle in A4c images before utilizing a CNN model to detect left ventricular hypertrophy. This method of performing image segmentation before classification resulted in detection of left ventricular hypertrophy with an accuracy of 91.2%. The authors also trained a semi-supervised Generative Adversarial Network (GAN) on labeled and unlabeled echocardiograms to detect left ventricular hypertrophy, achieving an accuracy of 92.3%.

Finally, a CNN model was developed by [42] for segmenting the left ventricle of the heart, predicting ejection fraction, and classifying heart failure with reduced ejection fraction. The end systolic volume, end diastolic volume and ejection fraction were included as features for training. The model was able to classify heart failure with reduced ejection fraction with an area under the curve of 0.97.

3. Development Methodology

This study is developed using the Agile methodology. Agile methodology is chosen to provide more flexibility in revising the analysis, design, and implementation of the system in the event that the system does not meet user requirements. As the system has many modules which require the integration of web development, machine learning and database management, it is more efficient to develop basic functionalities in earlier iterations and develop finer-grained functionalities in later iterations, with regular testing so that bugs can be fixed early in development. Using the Agile methodology, feedback can be continuously collected which is useful for improving the functionality of the system. For this study, the system requirements were collected from healthcare professionals as well as people prone to heart disease. Ethic approval was granted to collect data for system requirement gathering as well as acceptance testing.

The LiveHeart system was developed using basic web programming languages with a Flask application server and a MySQL cloud database. The system makes calls to a RESTful API to retrieve habit data and uses Random Forests and decision trees with selected features to classify the healthiness level of the data. The system also uses 3D CNNs to classify echocardiograms into "normal" and "low ejection fraction". It visualizes the results of data analysis in an intelligent dashboard. In addition, the system generates reports outlining the relationship between the patient's lifestyle habits and their heart health and allows the doctor to annotate and store these reports for future viewing.

LiveHeart is able to automate the collection of lifestyle habit data by collecting data through IoT devices such as smartphone and smartwatch, allowing doctors to receive real-time updates of patient's habit-change. Moreover, LiveHeart helps doctors to gain meaningful insights from data visualizations of analyzed habit data to support decision-making in digital care pathway. LiveHeart also speeds up the clinical workflow of diagnosis, treatment, and prevention through the application of machine learning.

3.1. System Overall Architecture and Module Design

The proposed solution is a web-based system to monitor habit-change and echocardiogram of heart disease patients. The patient can upload lifestyle habit data to their own personal devices while the patient is at home and the data can be received by the system to be viewed by the doctor at the hospital. The system can also be used at the hospital for nurses to upload echocardiograms during the echocardiography test and receive the echocardiography results.

The data for diet habits, exercise habits and sleeping habits of heart disease patients is collected from a smartwatch and the Samsung Health mobile application. This data is stored in a cloud database that can be accessed via a desktop application with an Internet connection.

In the web-based system, machine learning is carried out to classify the healthiness level of the patient's diet habit data, exercise habit data and sleeping habit data separately. The healthiness level is classified into five categories: very unhealthy, unhealthy, moderate, healthy, and very healthy.

The average healthiness level of the patient's diet, exercise and sleep are calculated to determine the patient's forecasted heart health. An overall healthiness level that is unhealthy indicates that the patient has a risk of developing heart failure with reduced ejection fraction, while an overall healthiness level that is moderate to healthy indicates that the patient has normal heart function.

A web application is developed (Figure 1) to enable the doctor to view the results of habit-change and biomedical data analysis on a digital dashboard, visualized in the form of graphs and tables. heart disease.

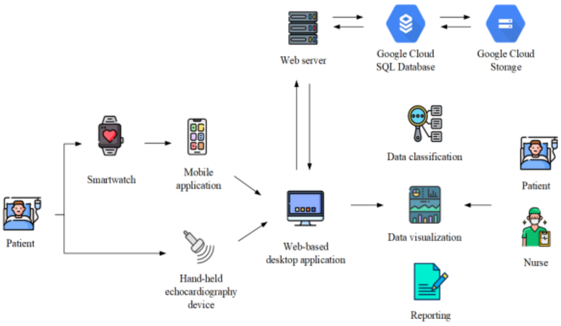

Figure 1: Overall architecture diagram for LiveHeart

The web application also generates a report that summarizes the patient's lifestyle habits and their impact on the patient's heart health, as well as a list of preventive measures to improve the patient's health. The doctor can annotate these reports, which are stored so they can be viewed anytime as a form of electronic health record. This feature supports doctors in the decision-making process of prescribing advice for habit adjustment to minimize the risk of

The overall architecture diagram of the proposed system is shown in Figure 1. The proposed system consists of four main modules which are user management, Internet of Things (IoT) device, habit classification, and intelligent dashboard.

A two-tier architecture was chosen for this web-based system because it is simple to develop and make modifications. As the back-end server is completely developed using Python, machine learning models can be directly run on the server without the need of an API. The two-tier architecture of the system is shown in Figure 2.

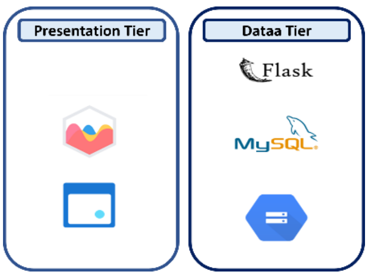

Figure 2: 2-tier architecture of the LiveHeart system

4. System Implementation and Data Analytics Results

4.1. Data Collection

To use this application, the patient must first have the Samsung Health mobile application installed on their smartphone. Secondly, the patient must have a smartwatch that is paired with their smartphone and the Samsung Health application. Thirdly, the patient must have the FitnessSyncer mobile application installed, and must enable FitnessSyncer to read diet, exercise, and sleep data from Samsung Health. FitnessSyncer is an application that aggregates data from multiple health and fitness applications and has an API that allows users to access their own data.

For this study, data was collected from only one patient for few months to successfully design and develop the system first. The process of habit data collection from the user-facing side is as follows: the patient records exercise and sleep data while wearing a smartwatch, which is simultaneously recorded in the Samsung Health mobile application; for diet data, the patient records a meal on the Samsung Health mobile application. Then, the patient opens the FitnessSyncer mobile application and allows FitnessSyncer to read their habit data from Samsung Health by selecting their Samsung Health data source and pressing the "Sync Now" button. The habit data from Samsung Health gets uploaded to the FitnessSyncer server and becomes accessible to the LiveHeart system. The Habit-change chart on the intelligent dashboard is updated with the healthiness level of the newly uploaded habit data. Figure 3 shows the example of Samsung Smartwatch used for data collection in this study as well as the sample collected data in Samsung health application.

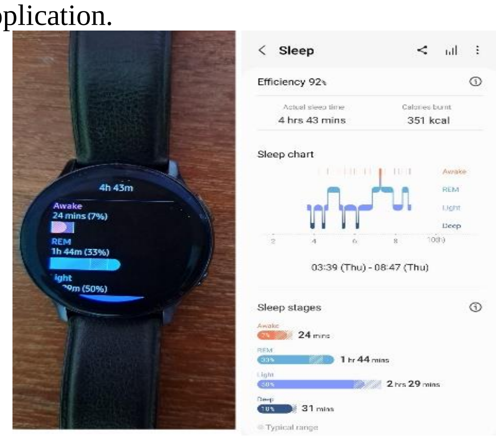

Figure 3: SmartWatch and the sample of collected data in Samsung Health

4.2. Habit Classification

The feature importance based on Mean Decrease in Impurity (MDI) of the Random Forests classifier is used for diet classification using the Scikit-learn library. The MDI is defined as the total decrease in node impurity weighted by the probability of reaching that node, averaging over all trees in the ensemble. Based on the feature importance shown in Figure 4, we can infer that the calories per serving have a significantly larger effect on the healthiness level of diet compared to other features.

The diet dataset consists of 293 rows of data where each row contains the nutrient intake of a meal taken on a particular day. The diet data was collected using the Samsung Health mobile application. The exercise dataset consists of 141 rows of data where each row contains information about an exercise activity undertaken on a particular day. The exercise data was collected using a smartwatch and the Samsung Health mobile application. The sleep dataset consists of 123 rows of data where each row contains information about an individual's sleep for a particular night. The sleep data was also collected using a smartwatch and the Samsung Health mobile application. The data in all three lifestyle habit datasets was collected from 1 October 2019 to 31 January 2020.

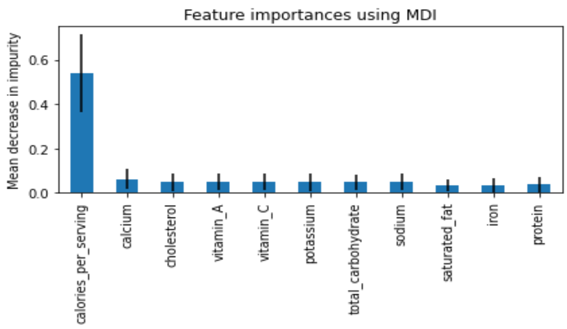

Figure 4: Feature importance chart for diet classification

In all three lifestyle habit datasets, each row is labelled with a level of healthiness within the range of 1-5, where 1 is the least healthy and 5 is the healthiest. The data labeling was verified by experts. As such, the habit classification consists of three main objectives as follows:

- To classify the healthiness level of diet as 1 (very unhealthy), 2 (unhealthy), 3 (moderate), 4 (healthy) or 5 (very healthy)
- To classify the healthiness level of exercise as 1 (very unhealthy), 2 (unhealthy), 3 (moderate), 4 (healthy) or 5 (very healthy)
- To classify the healthiness level of sleep as 1 (very unhealthy), 2 (unhealthy), 3 (moderate), 4 (healthy) or 5 (very healthy)

The decision tree and Random Forest models were used for classification. For diet classification, the ReliefF algorithm with 50 nearest neighbors was used to select 11 relevant features for training, and the data was divided into a training dataset and a testing dataset using a 70-30 split ratio. For sleep classification, the ReliefF algorithm with 30 nearest neighbors was used to select 10 relevant features for training, and the data was divided into a training dataset and a testing dataset using 80-20 split ratio. For exercise classification, all features were selected for training as feature selection did not improve the accuracy of the model, and the data was divided into a training dataset and testing dataset using 80-20 split ratio. The exercise data was also pre-processed by removing rows that contained cells with zero values and converting the type of workout activity into numerical values. The selected features for each habit classification are listed in Table 2.

Table 2
Selected features for habit classification

Diet	Exercise	Sleep
- Calories per serving - Calcium Cholesterol - Vitamin A - Vitamin C - Potassium - Total carbohydrates - Sodium - Saturated fat - Iron - Protein	- Total time spent for activity - Type of workout activity - Workout duration - Distance travelled - Average speed - Maximum speed - Workout calories - Workout steps - Average heartbeat - Maximum heartbeat - Average cadence - Maximum cadence	- Percentage of light sleep - Percentage of deep sleep - Percentage of awake phase - Percentage of -REM sleep - Sleep efficiency - Total sleep time - Calories burned - Actual sleep time - Alcohol intake - Eating dinner within 2 hours before sleep

The performance metrics of diet classification, exercise classification and sleep classification are shown in Table 3, 4, and 5 respectively. For diet classification, only the metrics for three categories of healthiness level are reported as the diet data only consisted of data that was labelled with a healthiness level of 1-3.

Table 3
Performance metrics of diet classification

Algorithm	Class	Precision	Recall	F1-score	Accuracy (%)
Decision tree	1	0.88	0.91	0.89	87.50
	2	0.88	0.86	0.87	
	3	0.86	0.86	0.86	
Random Forests	1	0.90	0.90	0.90	89.77
	2	0.86	0.89	0.87	
	3	1.00	0.92	0.96	

The best accuracy obtained for the diet, exercise and sleep classifiers were 89.77%, 90.00% and 68.00% respectively. Based on these performance metrics, the Random Forest classifier was chosen for diet classification, the decision tree classifier for exercise classification and the decision tree classifier for sleep classification in the developed system.

Table 4
Performance metrics of exercise classification

Algorithm	Class	Precision	Recall	F1-score	Accuracy (%)
Decision tree	1	1.00	1.00	1.00	90.00
	2	0.50	1.00	0.67	
	3	1.00	0.80	0.89	
	4	1.00	1.00	1.00	
	5	0.86	0.86	0.86	
Random Forests	1	1.00	0.50	0.67	70.00
	2	0.00	0.00	0.00	
	3	0.50	0.60	0.55	
	4	0.71	0.71	0.71	
	5	0.83	1.00	0.91	

Table 5
Performance metrics of sleep classification

Algorithm	Class	Precision	Recall	F1-score	Accuracy (%)
Decision tree	1	1.00	0.50	0.67	68.00
	2	0.75	0.50	0.60	
	3	0.67	0.57	0.62	
	4	0.55	1.00	0.71	
	5	1.00	0.75	0.86	
Random Forests	1	1.00	0.50	0.67	52.00
	2	0.67	0.33	0.44	
	3	0.42	0.62	0.50	
	4	0.67	0.80	0.73	
	5	0.33	0.25	0.29	

4.3. Echocardiogram Classification and Segmentation

This section focuses on the details of echocardiogram classification as one of the main features of the system. The echocardiography dataset used in this study is the EchoNet-Dynamic Dataset taken from the Stanford University School of Medicine [42].

A Convolutional Neural Network (CNN) based on the ResNet (2+1)D architecture was designed to take in echocardiography videos as input, and predict the value of ejection fraction. 32 frames were sampled from each video across a period of 2 before being loaded into the model. The model was built using the Torchvision library from the PyTorch machine learning framework and trained by running a Python script on the command-line for 2 epochs until it reached a validation loss of 167.145, before the model weights were saved. The performance metrics of ejection fraction prediction are shown in Table 6.

An if-else statement is used to set the classification of the echocardiogram based on the value of ejection fraction predicted by the model. If the ejection fraction predicted by the model is less than 55, the echocardiogram is classified as “low ejection fraction”. Otherwise, the echocardiogram is classified as “normal”. This classification, along with the value of ejection fraction is saved to the database.

Table 6
Performance metrics of ejection fraction prediction

Algorithm	R2 score	MAE	RMSE
ResNet (2+1)D	-0.944	7.46	10.41

A CNN model based on the DeepLabV3 ResNet50 architecture was built to carry out semantic segmentation of the left ventricle in the echocardiogram. Each video is divided into blocks of frames before being passed through the model. The model was built using the Torchvision library from the PyTorch machine learning framework and trained for 5 epochs until it reached a validation loss of 0.0401. The performance metrics of echocardiogram segmentation is approximately 0.912.

Both models were built based on the deep learning model for beat-to-beat cardiac function assessment developed by [43]. For both models, 2099 echocardiography videos were selected for training, 600 for validation and 300 for testing.

In the Echocardiography section on the Patient page, the nurse can click on a button in the top-right corner that redirects them to a page to upload an echocardiogram in .AVI format. Once the file is uploaded, the system runs the ejection fraction prediction and echocardiogram segmentation models on the echocardiogram.

First, the predictEF() function is run and a ResNet (2+1)D model is constructed. The ejection fraction prediction model weights, stored on the local file system as "ef_model_weights.pt", are loaded into the model using the torch.load() method and the model is run. Next, the drawLeftVentricle() function is run and a DeepLabV3 ResNet50 model is constructed. The echocardiogram classification model weights, stored on the local file system as "segmentation_model_weights.pt", are loaded into the model using the torch.load() method and the model is run.

After the models have been run, the nurse is redirected back to the Echocardiography section, where they can view a log of previous echocardiography results, which consists of the amount of ejection fraction and the classification of the echocardiogram. Both the doctor and nurse can click on the play button on each log to view the echocardiogram uploaded at that time, with a blue overlay over the left ventricle. This will help them to verify the ejection fraction prediction. The user interface of the Echocardiography section is shown in Figure 5.

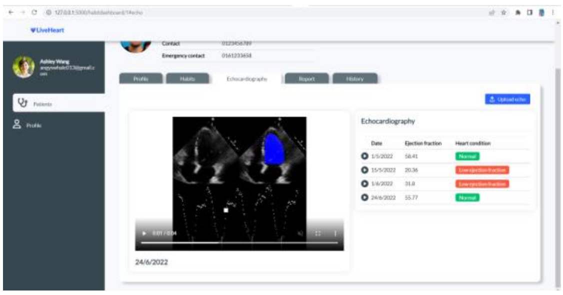

Figure 5: User interface of the Echocardiography section of patient page

4.4. Intelligent Dashboard and User Interfaces

For the habit dashboard, the system uses the Flask-SQLAlchemy extension to retrieve habit data from the cloud database, transforms the data into the desired format and renders the data in a dashboard format using the jinja2 template engine. Some of the user interfaces are randomly selected and shown in Figure 6-10.

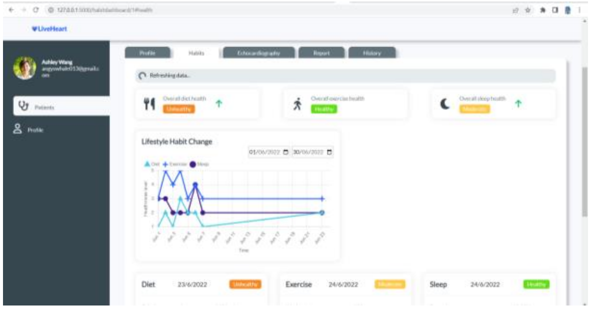

Figure 6: User interface of habit dashboard (doctor view)

Users can view detailed information about the habit on a certain day by viewing the three diet information cards. The data is visualized in a way that highlights the important data to guide doctors in decision-making.

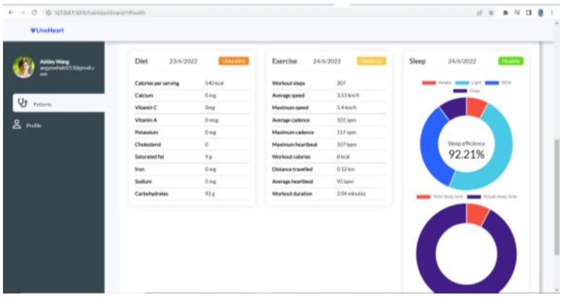

Figure 7: User interface of intelligent dashboard (doctor view)

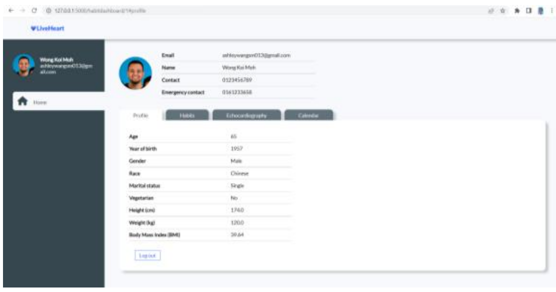

Figure 8: User interface of Homepage (Patient View)

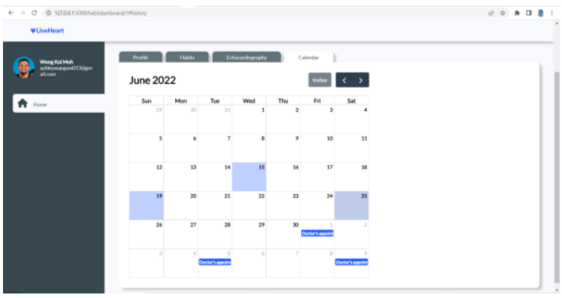

Figure 9: User interface of the Calendar section of the homepage (patient view)

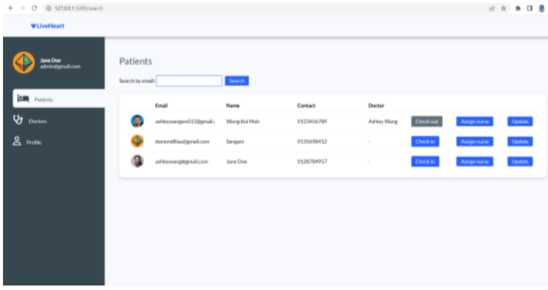

Figure 10: User interface of the Patient List page (admin view)

5. Discussion and Conclusion

If we define digital care pathway for heart disease as Figure 11, decision making can be integrated into the various steps. For instance, to identify people at risk for heart disease, decision-making may be used to choose the right risk assessment tools and screening procedures. Healthcare professionals and developers can choose which individual risk variables to consider, including age, family history, blood pressure, cholesterol levels, and lifestyle choices, and can create algorithms to determine the total cardiovascular risk score. After receiving personalized risk evaluations, users may decide what preventative steps to take. Furthermore, decision making can occur during the development of personalized treatment plans for individuals with heart disease. Based on the patient's medical history, diagnostic tests, and risk factors, healthcare providers can make decisions regarding medication choices, lifestyle modifications, and intervention strategies. The digital platform can provide recommendations based on evidence-based guidelines, assisting healthcare providers and patients in making informed decisions about the most appropriate treatment options.

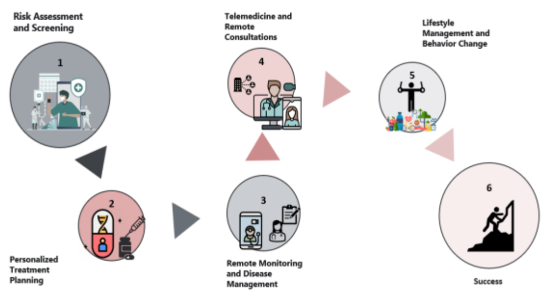

Figure 11: Digital health care pathway for people prone to heart disease.

In addition, decision making can be incorporated into remote monitoring systems for heart disease. The frequency and intensity of monitoring vital signs, such as heart rate, echocardiography, heartbeat sounds, blood pressure, heart rate, and oxygen saturation, can be set by healthcare professionals dependent on the patient's condition. Healthcare professionals can decide whether there is a need for additional medical treatments, lifestyle changes, or drug adjustments based on the data gathered.

Decision making can occur during virtual consultations with cardiologists and other healthcare professionals. Patients can discuss their symptoms, test results, and treatment progress, and healthcare providers can make decisions regarding medication adjustments, diagnostic tests, or referrals to other specialists. Patients can actively participate in these discussions, ask questions, and provide input on the decision-making process. Finally, decision making is involved in guiding individuals with heart disease to make healthy lifestyle choices. The digital platform can provide personalized recommendations for diet, exercise, stress management, and smoking cessation. Users can make decisions about adopting and adhering to these lifestyle changes based on their preferences and goals, with the guidance and support of healthcare providers.

LiveHeart combines the analysis of a variety of lifestyle habit data with input from doctors to professionally guide patients prone to heart disease to adopt healthier lifestyle habits. Furthermore, the proposed system is able to classify lifestyle habit data, classify echocardiograms, visualize data analytics on an intelligent report and manage reports of patients' overall health.

This study contributes to SDG3 and SDG9, which are Good Health and Well-being and Industry, innovation, and infrastructure respectively. With accelerated decision-making processes in digital care pathway for heart disease, the availability of doctors and nurses can be freed up to treat a larger number of patients who are suffering from heart disease. This addresses the reoccurring problem of health worker shortage. Furthermore, with the help of IoT, doctors can continue to monitor patient's health and provide timely habit intervention even while the patient is at home and not physically at the hospital. Meanwhile, the patient receives the benefit of having convenient access to healthcare facilities. Timely lifestyle habit management can help to gradually improve the cardiovascular health of heart disease patients if the system were to be implemented on a larger scale, contributing to the long-term plan to reduce the burden of non-communicable diseases.

The proposed for monitoring lifestyle habits can help with decision making by providing valuable data and insights. By continuously tracking and analyzing lifestyle habits such as exercise, diet, sleep patterns, and stress levels, individuals can gain a deeper understanding of their behaviors and their impact on health and well-being. This data can then be used to make informed decisions about lifestyle changes, goal setting, and preventive measures. For example, if the system detects a lack of physical activity or poor dietary choices, it can prompt the individual to adjust and provide recommendations for healthier alternatives. Ultimately, the system empowers individuals to make more informed decisions about their lifestyle choices, leading to improved overall health and well-being.

The proposed system includes the features for monitoring echocardiography that can provide valuable information and aid in decision making related to cardiovascular health. By continuously monitoring and analyzing echocardiographic data, such as heart function, chamber size, and blood flow patterns, healthcare professionals can gain insights into the condition of the heart. This information can be used to diagnose and monitor various cardiac conditions, assess treatment effectiveness, and make informed decisions regarding patient care. For example, if abnormalities are detected in the echocardiography results, healthcare providers can determine the appropriate interventions, such as medication adjustments or surgical procedures. The system can also help track changes over time, enabling healthcare professionals to assess the progression or improvement of a cardiac condition and adjust treatment plans accordingly. Ultimately, the system enhances decision making by providing objective data and assisting healthcare professionals in delivering optimal care for patients with cardiovascular conditions.

It is important to note that the integration of decision making into the digital care pathway for heart disease should involve collaboration between healthcare providers, researchers, and developers. The decisions made should be based on evidence-based guidelines, clinical expertise, and patient preferences to ensure optimal patient outcomes and engagement.

The future direction would be related to functionalities to manage other lifestyle habits that are risk factors for heart disease, such as the regulation of blood pressure, blood glucose and intervention for smoking habits. ChatGPT can be integrated into the system for consultation and recommendations. However, expert confirmation is required. Additionally, the IoT device module of the system could be extended to collect data from other IoT devices such as blood pressure and blood glucose monitoring devices. Finally, the system could benefit from having the functionality to predict the upcoming change in lifestyle habits in the future.

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