## **INTRODUCTION**

Heart disease is a major cause of morbidity and mortality worldwide. It is a leading cause of death in the United States, responsible for 1 in every 4 deaths. [1] Every year, it is estimated that around 1.8 million people in India experience a stroke [2]. One type of heart disease is stroke, which occurs when a blood vessel that carries oxygen and nutrients to the brain is blocked or bursts. This can result in serious damage to the brain, leading to disability and death.

Predicting who is at risk for stroke is an important step in preventing this disease. One way to do this is by using machine learning algorithms to analyze data from fitness trackers, which are wearable devices that track various aspects of a person's physical activity and health. Fitness trackers can provide a wealth of longitudinal data, including information on physical activity, heart rate, and sleep patterns, which can be used to predict stroke risk.

There are several machine learning algorithms that can be used for predicting heart strokes from longitudinal data, including decision trees, random forests, and neural networks. These algorithms can be trained on a dataset containing information on individuals who have had a stroke, as well as individuals who have not had a stroke. Neural network has been found to have the highest accuracy among all the algorithms for this project.

The goal of the machine learning algorithms is to identify patterns in the data that are indicative of stroke risk, and to use these patterns to make predictions about which individuals are at greatest risk for stroke. The integration of machine learning algorithms with data from fitness trackers offers a promising approach to predicting heart stroke. By training models on large datasets that include information from individuals who have experienced strokes and those who have not, these algorithms can learn to identify patterns and relationships that are indicative of stroke risk. As a result, personalized risk assessments can be generated for individuals, enabling targeted interventions and preventive measures.

One use of machine learning in this project is in the development of early warning SOS system. By analyzing data from fitness trackers in real-time, it is possible to identify individuals who are at risk for stroke and intervene before a stroke occurs. This allows the application to send an SMS alert to user’s emergency contacts and nearby hospitals about the user’s stroke condition and their current location.

Another use of machine learning for stroke prediction is in the development of personalized prevention plans. For example, an individual who is at high risk for stroke may be advised to make lifestyle changes, such as exercising more, or sleeping on time, in order to reduce their risk. These prevention plans could be tailored to the specific needs and risk profile of each individual, based on the data collected by their fitness tracker.

There are a number of challenges that must be overcome in order to effectively use machine learning for stroke prediction. One of the main challenges is the need for large, high-quality datasets. In order to train machine learning algorithms to accurately predict stroke risk, it is necessary to have a large number of individuals with diverse characteristics, including a range of ages, genders, and health conditions. It is also important to have detailed and accurate data on these individuals, including information on their physical activity, heart rate, and other relevant factors.

Another challenge is the need to account for changes over time. As individuals age and their health status changes, their risk for stroke may also change. It is important to be able to take these changes into account when predicting stroke risk, in order to provide accurate and up-to-date risk assessments.

These challenges were successfully overcome by using a custom longitudinal dataset built for this project which contains dataset of users wearing fitness trackers from more than 4 years. This dataset contained attributes like heartrate, average heartrate, sleep time. Average sleep time, activity schedule, workout duration, calories, BMI, height, weight, and many more. By using data from fitness trackers and other sources, machine learning algorithms can identify patterns in the data that are indicative of stroke risk, and can be used to develop early warning systems.

Following are the steps that were involved in building a Heart stroke prediction model using Machine Learning using longitudinal data from fitness bands:

1. **Defining Objectives**: The first step in the process is to define the research questions and study objectives: Clearly defining the problem of predicting Heart stroke will in determining the type of data needed to collect and train the machine learning model.
2. **Collect and pre-processing data**: Data must from a large sample of individuals who wear fitness trackers on a regular basis. This data should include information about physical activity, heart rate, and sleep patterns, as well as any other relevant variables such as age, gender, geographical data and medical history. This data must also be cleaned and pre-processed to ensure that it is in a usable format for analysis. This may include removing missing values, normalizing the data, and handling any outliers.
3. **Train and evaluate the machine learning model:** Using the pre-processed data, the machine learning model must be trained to identify patterns and features that are indicative of increased risk of heart stroke. There are many different machine learning algorithms that you can use for this purpose, such as decision trees, support vector machines, and random forests. Different algorithms and hyperparameters can be used to find the best performing model. Once the model is trained, the performance should be evaluated using a variety of metrics, such as accuracy, sensitivity, and specificity.
4. **Analyse the results and interpret the findings**: Once the model is trained and evaluated, the results should be analysed and findings should be interpreted. This may involve examining the key features and patterns identified by the model, as well as comparing the performance of different algorithms. You will also need to consider the limitations of your study and the implications of your results.
5. **Deliver the results**: Finally, the user must be explained the results precisely in the mobile application.

It is also important to consider ethical and legal considerations, such as data privacy and informed consent, when collecting user data.

The methodology for building heart stroke detection using longitudinal data and machine learning can be described using the following steps:

1. **Data collection:**The first step in the process is to collect the data that will be used for the machine learning model. It is important to collect a large and diverse dataset in order to train a robust machine learning model.
2. **Data pre-processing:**   
   Once the data has been collected, it will need to be pre-processed in order to prepare it for use in the machine learning model. This may involve cleaning the data, removing missing values, and transforming the data in various ways to make it more suitable for analysis.
3. **Feature selection:**    
   After the data has been pre-processed, the next step is to select the features that will be used to train the machine learning model. This may involve selecting a subset of the available data based on its relevance to the task at hand.
4. **Model selection:**    
   The next step is to select the machine learning algorithm that will be used to train the model. There are a variety of algorithms that can be used for this purpose, including decision trees, random forests, and support vector machines. It is important to choose an algorithm that is well-suited to the task at hand and to the characteristics of the data.
5. **Model training:**   
   Once the machine learning algorithm has been selected, the next step is to train the model using the data and features that have been selected.

## **1.1 Existing System**

The existing system for the heart stroke prediction project involves traditional medical diagnostic methods and manual assessment by healthcare professionals. Currently, the diagnosis of heart stroke relies heavily on clinical evaluation, patient history, and medical tests such as blood pressure measurement, cholesterol level analysis, electrocardiograms (ECG), and echocardiography.

However, this approach has limitations in terms of accuracy, efficiency, and accessibility. It heavily depends on the expertise of healthcare professionals and may lead to subjective interpretations. Moreover, these diagnostic methods are time-consuming and require specialized equipment and facilities, making them less accessible in remote areas or emergency situations.

The lack of real-time monitoring and early prediction systems further hinders the ability to proactively identify individuals at risk of heart stroke. Without a comprehensive and automated system, the timely intervention and prevention of heart strokes become challenging.

Therefore, there is a need for an advanced system that leverages machine learning techniques, mobile application development, and fitness trackers to provide accurate and timely predictions of heart stroke risks. This system aims to overcome the limitations of the existing approach by enabling continuous monitoring, analysis of various health parameters, and predictive models based on longitudinal dataset.

The current system will empower individuals to track their health status in real-time, receive personalized recommendations, alert nearby hospitals and emergency contacts about a possible heart stroke.

Here are some common features of the existing stoke prediction systems:

* **Rule-Based Systems**: Some existing systems utilize rule-based algorithms to predict the risk of heart strokes. These systems rely on predefined rules and thresholds to analyze health data and determine the likelihood of a stroke. However, these systems often lack the ability to adapt to individual variations and may have limited accuracy due to their simplistic approach.
* **Statistical Analysis**: Another approach used in existing systems involves statistical analysis of health data. These systems analyze historical data and identify patterns and correlations between various health parameters and the occurrence of strokes. But it may not capture complex relationships and may be limited in its predictive capabilities.
* **Remote Monitoring**: These systems allow healthcare providers to track patients' vital signs remotely and intervene if any abnormality or risk is detected. However, remote monitoring systems often require specialized medical equipment and may not be easily accessible or affordable for individual users.

### **1.1.1 Disadvantages of Existing System**

The current problem with stroke prediction is that it relies heavily on manual assessments and clinical evaluation, which is not easily accessible and is also prone to errors. Another critical aspect of a heart stroke is time. The faster a patient receives medical attention, the greater the chances of survival and the lower the risk of long-term disabilities.

According to the American Heart Association, for every minute that treatment is delayed, the patient loses about 1.9 million brain cells [3]. Therefore, the importance of early detection and intervention cannot be overstated.

There are several disadvantages to the existing stroke prediction systems, including:

* **Lack of Accuracy:** Many existing systems rely on simplistic algorithms or predefined rules, which may lead to limited accuracy in predicting heart strokes. These systems often overlook complex relationships and individual variations, resulting in false predictions or missed warning signs.
* **Lack of proper Real-time Monitoring**: Many existing systems do not offer real-time monitoring capabilities. They may collect data at specific intervals or rely on manual inputs from users, which can miss critical changes or fluctuations in health parameters. Real-time monitoring is crucial for timely detection of potential stroke risks.
* **Limited Personalization**: Most existing systems lack personalization, as they rely on generalized models and thresholds. They may not consider individual variations, lifestyle factors, or specific health profiles, leading to less accurate predictions and generic recommendations that may not be suitable for all users.
* **Cost and Accessibility**: Some existing systems can be expensive, requiring specialized medical equipment or proprietary wearable devices. This cost factor may limit accessibility for individuals with limited financial resources. Additionally, the availability of existing systems may be limited in certain regions or healthcare settings, further restricting their accessibility.
* **Lack of Integration with Mobile Applications**: Many existing systems do not have dedicated mobile applications for seamless user interaction and data management. Mobile applications can provide convenience, real-time alerts, and personalized recommendations, enhancing the user experience and adherence to preventive measures.

Addressing these disadvantages, the proposed heart stroke prediction project aims to overcome the limitations of existing systems by leveraging advanced machine learning algorithms, integrating multiple data sources, providing real-time monitoring, offering user-friendly interfaces, enabling personalized predictions, and ensuring accessibility through mobile application development.

## **1.2 Proposed System**

The proposed system aims to overcome the limitations of existing systems by utilizing a combination of fitness trackers, machine learning algorithms, and mobile application development. The system offers a comprehensive and personalized approach to monitor, predict the risk of heart strokes in individuals and also act as an SOS system. Here are the key components and features of the proposed system:

1. **Fitness Trackers**: The system integrates with wearable fitness trackers, such as smartwatches or fitness bands, to collect real-time health data. These trackers monitor various physiological parameters, including heart rate, blood pressure, activity levels, sleep patterns, and stress levels. The data from these trackers serve as input for the prediction algorithms. Mi Band 4 was used to collect real-time data for this project.
2. **Machine Learning Algorithms**: The system utilizes advanced machine learning algorithms, such as logistic regression, decision trees, random forests, and neural networks, to analyse the collected data and predict the risk of heart strokes. These algorithms learn from historical data and identify patterns, correlations, and risk factors associated with heart strokes. The models are trained to make accurate predictions based on the user's data. Out of all the algorithms, neural networks displayed highest accuracy.
3. **Risk Assessment and Prediction**: Based on the analyzed data and trained models, the system calculates the individual's risk score or probability of experiencing a heart stroke.
4. **Real-time Monitoring and Alerts:** The proposed system offers real-time monitoring of the user's health parameters. It continuously analyzes the incoming data from fitness trackers and compares it with the established risk thresholds. If any parameter exceeds the predefined limits or shows significant fluctuations, the system generates sms alerts and notifications to alert the user, their emergency contacts and nearby hospitals.
5. **Mobile Application Development**: The system includes a user-friendly mobile application that serves as the primary interface for users. The mobile app allows users to view their health data, track their progress, receive personalized recommendations, set goals, and launch an SOS in time of a heart stroke to notify nearby hospitals and emergency contacts. The application can be translated into multiple languages so that the user can choose the language of their choice.

The proposed system offers an integrated and user-centric approach to heart stroke prediction. By leveraging fitness trackers, machine learning algorithms, and mobile application development, it provides individuals with personalized risk assessments, real-time monitoring, actionable insights, and support to make informed decisions for a healthier lifestyle and reduce the risk of heart strokes.

## **1.3 Problem Statement**

Every year, it is estimated that around 1.8 million people in India experience a stroke [2]. Every year, more than 795,000 people in the United States have a stroke [4]. About 610,000 of these are first or new strokes [5]. The chances of survival are greater when emergency treatment begins quickly.

Moreover, up to 50% of all strokes are preventable. Hence, it is important to identify strokes in the early stages. This can be done using any ordinary fitness trackers that collect longitudinal data of heart rate and blood pressure levels in real-time which is connected to a Machine Learning model trained to identify and alert in case of a sudden extreme change in the parameters of heart rate levels.

In the proposed model, heart stroke prediction application predicts the chances that a person will have a heart stroke based on symptoms like age, gender, body mass index, work type, average heart rate, glucose levels. It classifies the person’s risk level by implementing various machine learning algorithms like Random Forest, Naive bayes, Logistic Regression, K-Nearest Neighbor (KNN), and Decision Tree. Thus, a comparative analysis is shown between the various algorithms and the most efficient one is converted into a .tflite model and is deployed in firebase.

Once the heartrate result is obtained, if the user is in risk of a heart stroke, an alert is sent to the mobile application of the user. Personalized recommendations, workouts, dietary suggestions, articles and blog posts will also be shared with the user in order to control user’s heart condition.

In real-time, when a user experiences a heart stroke, their heart rate drops to a lower rate than the measured threshold. At this time, an SMS alert can be sent to user’s emergency contacts and nearby hospitals using Twilio SMS service.

Traditional methods for identifying individuals at risk of heart stroke, such as blood tests and imaging studies, can be expensive, invasive, and often require specialized equipment and trained personnel. As a result, there is a need for more accessible and cost-effective methods for identifying individuals at risk of heart stroke.

Fitness bands have become increasingly popular in recent years. These devices generate a wealth of longitudinal data, including information about physical activity, heart rate, and sleep patterns. This data has the potential to provide valuable insights into an individual's overall health and risk of developing various diseases, including heart stroke.

## 

## **1.4 Objective**

The main objective heart stroke prediction system is to use fitness bands and machine learning to predict heart strokes and potentially save lives. The system would involve the following steps:

1. Collect data from a large sample of individuals who wear fitness bands on a regular basis. This data should include information about physical activity, heart rate, and sleep patterns, as well as any other relevant variables such as age, gender, and medical history. We will carefully curate our data to exclude any individuals with a known history of heart stroke or other relevant medical conditions.

1. Use machine learning algorithms to analyze the data and identify patterns and features that are indicative of increased risk of heart stroke. We will experiment with a variety of different algorithms, such as decision trees, support vector machines, and random forests, and compare their performance. We will also use data preprocessing techniques to clean and prepare the data for analysis, such as removing missing values, normalizing the data, and handling any outliers.
2. Train and evaluate our machine learning models using a separate validation dataset. This will help us ensure that our models are able to generalize to new data and accurately predict heart stroke risk. We will evaluate our models using a variety of metrics, such as accuracy, sensitivity, and specificity.
3. Integrate the heart stroke prediction system into a fitness band or other wearable device. This would allow users to receive real-time alerts if their heart stroke risk is deemed high, enabling them to seek medical attention if necessary.
4. Monitor the performance of the prediction system over time and continuously improve it by adding new data and retraining the models as needed. This could involve incorporating additional variables or using more advanced machine learning techniques. We will also conduct ongoing user testing and feedback to ensure that our system is user-friendly and meets the needs of our users.

In future, the results obtained from the model could be possibly integrated in the firmware of the fitness band itself. But this would require us to manually edit the firmware of the fitness tracker and then flash the custom firmware. Although slightly difficult, this is possible and is allowed by the fitness band manufacturers.

**2. LITERATURE REVIEW**

### **2.1 HEALTH CRISIS**

Heart stroke is a leading cause of death and disability in India, with millions of people suffering from heart stroke each year. According to data from the World Health Organization (WHO), heart stroke is the second leading cause of death in India, accounting for approximately 15% of all deaths. It is a leading cause of death in the United States, responsible for 1 in every 4 deaths. It is also a leading cause of disability, with many individuals requiring ongoing medical care and rehabilitation after experiencing a heart stroke.

Risk factors for heart stroke in India are similar to those in other countries, including high blood pressure, high cholesterol, diabetes, smoking, obesity, physical inactivity, and a family history of heart stroke. However, certain factors may contribute to a higher prevalence of heart stroke in India. These include a high rate of tobacco use, a high prevalence of diabetes and other non-communicable diseases, and a lack of access to preventive healthcare services.

In addition to these risk factors, there are also certain cultural and societal factors that may contribute to the high rate of heart stroke in India. For example, a traditional diet high in salt, fat, and calories, as well as a lack of physical activity, may increase the risk of heart stroke. In addition, certain cultural practices, such as the widespread use of tobacco and alcohol, may also increase the risk of heart stroke.

Despite the high burden of heart stroke around the world, there are ways to reduce cases of heart stroke. One such important way is by using technology to predict heart strokes and improve the quality of life for those affected by this condition.

There are two main types of heart stroke: ischemic stroke and hemorrhagic stroke. Ischemic stroke is the most common type, accounting for approximately 87% of all strokes. It occurs when a blood clot or plaque blocks an artery, leading to a reduction in blood flow to the brain. Hemorrhagic stroke, on the other hand, occurs when a blood vessel in the brain ruptures and bleeds into the surrounding tissue. This can be caused by high blood pressure, an aneurysm, or other underlying conditions.

Heart stroke can have serious consequences, including heart failure, arrhythmias, and impaired cognitive function. It can also lead to long-term disability, requiring ongoing medical care and rehabilitation. Thus, heart stroke is a serious condition that needs to be tackled by leveraging technology.

# **3. FACTS AND FIGURES**

According to data from the World Health Organization (WHO), stroke is a leading cause of death and disability in India. In 2016, stroke was the second leading cause of death in India, responsible for approximately 12% of all deaths. It is also a leading cause of disability, with an estimated 2.6 million people in India living with stroke-related disability. This indicates that on average, approximately 4,930 strokes occur in India each day. The prevalence of stroke in India is expected to increase in the coming years due to the aging of the population and the increasing prevalence of risk factors such as hypertension, diabetes, and tobacco use. It is estimated that the number of stroke cases in India will increase by 50% by 2030.

In terms of regional variation, stroke prevalence is highest in the northern states of India, and is lower in the southern states. This may be due to differences in risk factors and access to healthcare. Preventing stroke is an important public health priority in India. Strategies to reduce stroke risk include controlling hypertension, promoting healthy lifestyles, and increasing access to quality healthcare. In addition, efforts to improve the diagnosis and treatment of stroke, including the use of machine learning to predict stroke risk, can help to reduce the burden of this disease in India.

Heart disease is a leading cause of death in the United States, and stroke is a type of heart disease. According to data from the Centers for Disease Control and Prevention (CDC), stroke is the fifth leading cause of death in the United States, responsible for approximately 1 in every 20 deaths. It is also a leading cause of disability, with an estimated 795,000 people in the United States experiencing a stroke each year. The prevalence of stroke varies by race and ethnicity in the United States. African Americans are more likely to experience a stroke than any other racial or ethnic group, with an age-adjusted stroke rate that is almost twice as high as the rate for white Americans. Hispanic Americans and American Indians/Alaska Natives also have higher stroke rates compared to white Americans.

Preventing stroke is an important public health priority in the United States. Strategies to reduce stroke risk include controlling hypertension, promoting healthy lifestyles, and increasing access to quality healthcare.

In addition, efforts to improve the diagnosis and treatment of stroke, including the use of machine learning to predict stroke risk, can help to reduce the burden of this disease in the United States. According to data from the World Health Organization (WHO), stroke is the second leading cause of death globally, responsible for approximately 11% of all deaths.

It is also a leading cause of disability, with an estimated 35 million people living with stroke-related disability. The prevalence of stroke varies by region. In 2016, stroke was responsible for the highest number of deaths in the Western Pacific and South-East Asia regions, followed by the European region. The Americas and the Eastern Mediterranean regions had the lowest number of stroke deaths.

The global burden of stroke is expected to increase in the coming years due to the aging of the population and the increasing prevalence of risk factors such as hypertension, diabetes, and tobacco use. It is estimated that the number of stroke cases will increase by 50% by 2030. Stroke is a leading cause of death and disability, and the risk of stroke increases with age. According to data from the Centers for Disease Control and Prevention (CDC), the risk of stroke increases significantly after the age of 55. In the United States, the stroke rate for adults aged 65 and older is approximately 3 times higher than the stroke rate for adults aged 45-54.

The risk of stroke also varies by gender. In general, men are more likely to experience a stroke than women, although the risk for women increases significantly after menopause. Women who have had a stroke are also more likely to experience more severe disability than men who have had a stroke.   
  
Overall, it is important to be aware of the risk factors for stroke and to take steps to reduce that risk, regardless of age. This can include controlling hypertension, promoting a healthy lifestyle, and seeking medical attention if necessary. In addition, efforts to improve the diagnosis and treatment of stroke, including the use of machine learning to predict stroke risk, can help to reduce the burden of this disease for people of all ages.

# **4. SYSTEM REQUIREMENTS**

**4.1 SOFTWARE REQUIREMENTS**

|  |  |
| --- | --- |
| **OPERATING SYSTEM** | Windows 10,11, Linux, MacOS Sierra / Android 6.0 + / IOS 10 + |
| **LANGUAGE** | Flutter and Python 3.10 |
| **LIBRARIES** | i. Pandas  ii. Numpy  iii. Tensorflow  iv. Matpotlib   v. Firebase vi. Sklearn  vii. Geolocator |
| **IDE** | Jupyter Notebook and Visual Studio Code |
| **INTERNET** | Required |

***Table 4.1*** *Software Requirements*

**4.1.1 FUNCTIONAL REQUIREMENTS**

1. Data Collection

2. Data Preprocessing

3. Training and Testing

4. Modeling

5. Predicting

**4.1.2 NON-FUNCTIONAL REQUIREMENTS**

Non-functional requirements for a heart stroke prediction system using machine learning and fitness bands could include:

* Data privacy and security: measures to ensure that user data is protected and kept confidential.
* Scalability: the ability to handle a large number of users and data points.
* Accuracy: the ability to accurately predict the likelihood of a heart stroke.
* Speed: the ability to quickly process data and provide predictions in real-time.
* User interface: an intuitive and user-friendly interface for users to interact with the system.
* Integration: the ability to integrate the system with existing health and fitness systems and platforms.
* Accessibility: the ability to use the system on a variety of devices and platforms.
* Maintenance: the ability to easily maintain and update the system over time.
* Compliance: the system should comply with relevant regulations and standards, such as HIPAA for healthcare in the USA.

**4.2 HARDWARE REQUIREMENTS**

|  |  |
| --- | --- |
| **Mobile Processor** | Snapdragon 615+ |
| **RAM** | 1 GB (min) |
| **Available ROM** | 100 MB |

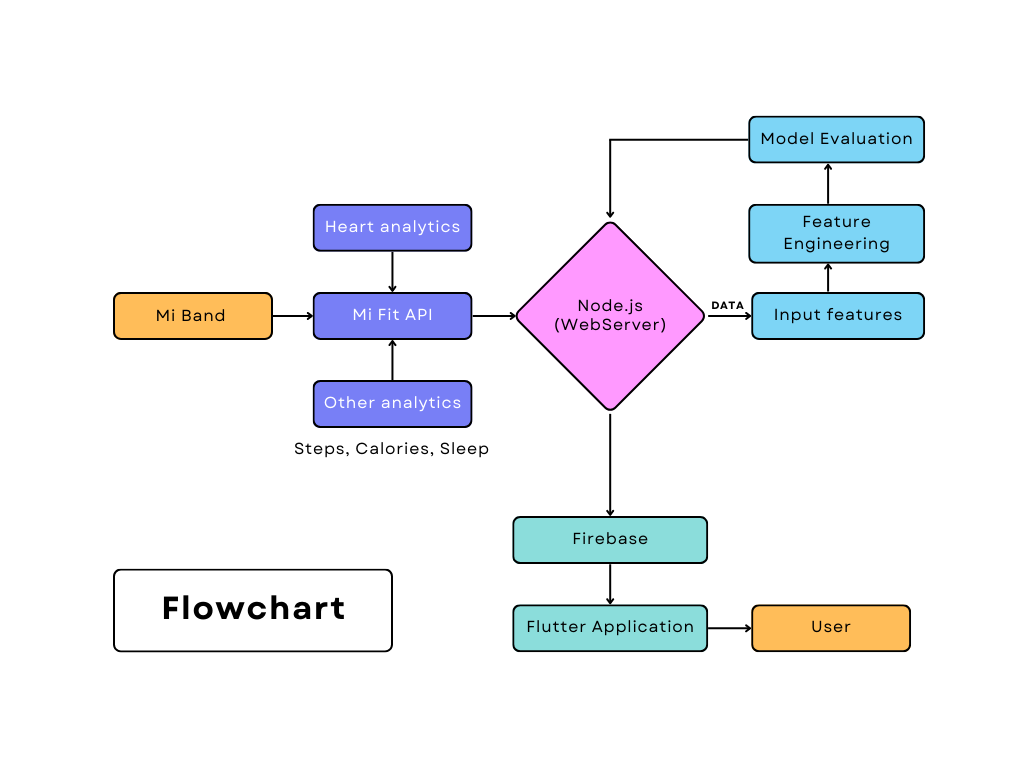
***Table 4.2*** *Hardware Requirements for Mobile Application*

**5.** **SYSTEM ARCHITECTURE**

**5.1 System Overview:**In the system, Data from the fitness trackers is obtained in real-time by a ‘get’ request from Mi Fit’s API endpoint. This Data includes Heart and other analytics. Continuous data is fetched in a Node.js webserver and data is then used to feed the machine learning model which is deployed in a Realtime Firebase instance.

The model predicts the chances a person will have a heart stroke based on symptoms like age, gender, body mass index, work type, and average heart rate. It classifies the person’s risk level by implementing various machine learning algorithms like Random Forest, Naive bayes, Logistic Regression, K-Nearest Neighbor (KNN), and Decision Tree.

In real-time, when a user experiences a heart stroke, their heart rate drops to a lower rate than the measured threshold. At this time, an SMS alert can be sent to user’s emergency contacts and nearby hospitals using Twilio SMS service.

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***Fig 5.1*** *System Architecture*

**5.2 Description of Architecture:**

The system consists of four main components: the App Client, the Server API, the Machine Learning Model, and the Data Store.

The App Client is the front-end interface that users interact with. It connects to the Server API to send and receive data. The Server API is responsible for handling the communication between the App Client and the Machine Learning Model.

The Machine Learning Model is the core component of the system. It is trained on longitudinal data collected from fitness bands worn by users. The model uses this data to predict the likelihood of a heart stroke. The model is updated as new data is collected and as the accuracy of the predictions improves.

The Data Store is where all of the collected data is stored. This includes data from the fitness bands as well as any other relevant data that may be used to improve the predictions of the Machine Learning Model.

***Fig 5.2*** *High Level Design Architecture*

**5.3 UML DIAGRAMS:**

UML (Unified Modeling Language) diagrams that can be used to model a heart stroke prediction system, along with examples of each diagram:

1. **Dataflow Diagram**

**End process**

**PREDICT HEART STROKE**

**BUILDING THE MODEL**

**FEATURE EXTRACTION**

**DATA PREPORCESSING**

Fetch data from fitness tracker

Yes

Send SMS alert

Is it a stroke?

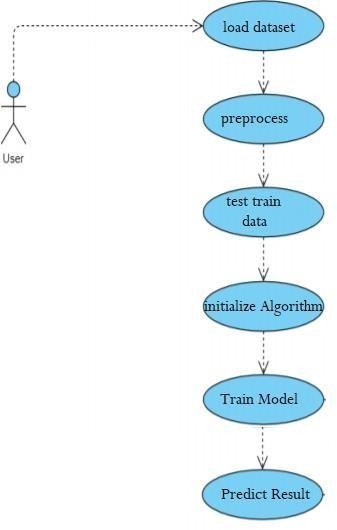
No

# ***Fig 5.3****Data Flow Diagram*

1. **Use Case Diagram**

Use case diagrams is used to model the actors in an ML system and the use cases that they can participate in. For example, In this system, user’s data is continuously fetched and the machine learning system checks if a user is likely to get a heart stroke

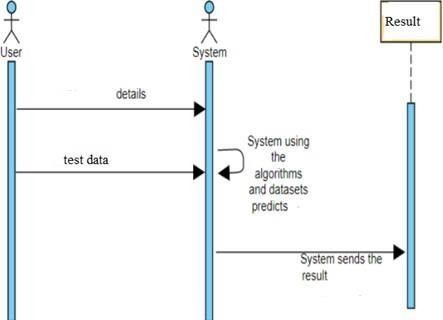
.



***Figure 5.4****: Use Case Diagram*

1. **Sequence Diagram**

Sequence diagrams are used to model the interactions between the components of an ML system over time, including the data flow and the processing steps. For example, a sequence diagram could show the flow of data from a fitness tracker through a machine learning model to predict the likeliness of a heart stroke.



***Figure 5.5:*** *Sequence Diagram*

1. **Component diagram:**

This component diagram shows the main components of the app: the Machine learning model, the user’s mobile application, and fitness tracker. The fitness tracker collects data from users and , and deploys the trained model in the webserver. The app itself is the component that ties everything together, providing a user interface for the user to interact with and displaying results.

+------------+ +------------+ +------------+

| ML Model | |Fitness band| | WebServer |

+------------+ +------------+ +------------+

| | |

| 1 | 1 |

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| | |

v v v

+------------+ +------------+ +------------+

| App | | Web Server| | Firebase |

+------------+ +------------+ +------------+

| |

+----------------------------------------------------+

***Fig 5.6:*** *Component Diagram*

1. **Deployment diagram**:This deployment diagram shows the app running on a device, such as a smartphone or tablet. The app will communicate with the webserver over the internet to access the machine learning model and other resources.

+------------+

| App | \_ \_ \_ \_ \_ \_ \_ \_ \_ \_ \_

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|

|

v

+------------+

***Fig 5.7:*** *Deployment Diagram*

| Server |

+------------+

## **6. IMPLEMENTATION**

### Implementation of Heart stroke prediction using fitness trackers and machine learning is straight forward but involves a lot of modules. Following are the key modules involved in building a heart stroke prediction model.

### **6.1 Machine Learning model:**

## The Machine Learning model can be trained using Sci-kit Learn. Next, longitudinal data collected over the years from fitness trackers can be given as input to train the model.

This is the Machine learning part of the stroke detection with data extracted from fitness trackers.  
  
To train a machine learning model for heart stroke prediction using longitudinal data from fitness trackers and machine learning, a dataset of longitudinal data is required, along with labels indicating the possibility of a stroke. This dataset is then used to train a machine learning algorithm to recognize patterns in the dataset that are indicative of heart stroke.

## **1. Import the necessary libraries:**

import pandas as pd

import tensorflow as tf

from sklearn.model\_selection import train\_test\_split

from sklearn.preprocessing import StandardScaler

from sklearn.model\_selection import train\_test\_split, GridSearchCV

from sklearn.linear\_model import LogisticRegression

from sklearn.metrics import accuracy\_score, precision\_score, recall\_score, f1\_score

from sklearn.impute import SimpleImputer

from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier

from sklearn.ensemble import GradientBoostingClassifier

from tensorflow import keras

import joblib

import numpy as np

**2. Load the data:**

1. data = pd.read\_csv('dummy\_data.csv')
2. print(df.shape)
3. print(df.head())

**3. Pre-process the data:**

# The input features (X) and the target variable (y) are extracted from the dataset.

X = data[['gender', 'bmi', 'heartRate', 'fatRate', 'deepSleepTime', 'shallowSleepTime', 'wakeTime', 'REMTime', 'naps', 'steps', 'distance', 'runDistance', 'calories']].dropna()

y = data['heart\_stroke'].dropna()

1. **Missing values in the input features are handled using the SimpleImputer class from sklearn by replacing them with the mean of the corresponding column.**

numerical\_cols = ['bmi', 'heartRate', 'fatRate', 'deepSleepTime', 'shallowSleepTime', 'wakeTime', 'REMTime', 'naps', 'steps', 'distance', 'runDistance', 'calories']

imputer = SimpleImputer(strategy='mean')

X[numerical\_cols] = imputer.fit\_transform(X[numerical\_cols])  
  
# The input features are then standardized using the StandardScaler class from sklearn to ensure that all features are on a similar scale.

scaler = StandardScaler()

X[numerical\_cols] = scaler.fit\_transform(X[numerical\_cols])

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

1. **Training a Neural Network model:**

The code defines a neural network model using the Sequential API from TensorFlow's Keras module

Model = keras.Sequential([

    keras.layers.Flatten(input\_shape=(X\_train.shape[1],)),

    keras.layers.BatchNormalization(),

    keras.layers.Dense(128, activation='relu'),

    keras.layers.BatchNormalization(),

    keras.layers.Dropout(0.2),

    keras.layers.Dense(64, activation='relu'),

    keras.layers.BatchNormalization(),

    keras.layers.Dropout(0.2),

    keras.layers.Dense(1, activation='sigmoid')

])

# The model is compiled with the Adam optimizer, binary cross-entropy loss function, and accuracy as the evaluation metric.

opt = keras.optimizers.Adam(lr=0.001)

# The model is trained on the training data (X\_train, y\_train) for a specified number of epochs and a batch size

model.compile(optimizer=opt, loss='binary\_crossentropy', metrics=['accuracy'])

model.fit(X\_train, y\_train, epochs=10, batch\_size=64, validation\_split=0.1)

# The model's performance is evaluated on the test data (X\_test) by calculating various metrics such as accuracy, precision, recall, and F1 score.

y\_pred\_classes = np.argmax(model.predict(X\_test), axis=-1)

print('Neural Network Accuracy:', accuracy\_score(y\_test, y\_pred\_classes))

print('Neural Network Precision:', precision\_score(y\_test, y\_pred\_classes))

print('Neural Network Recall:', recall\_score(y\_test, y\_pred\_classes))

print('Neural Network F1 Score:', f1\_score(y\_test, y\_pred\_classes))

param\_grid = {'C': [0.01, 0.1, 1, 10, 100]}

1. **Training a Logistic Regression Model::**

# The code creates a LogisticRegression model using the LogisticRegression class from sklearn.

lr\_model = LogisticRegression()

# GridSearchCV is used to perform hyperparameter tuning by searching for the best combination of hyperparameters from the provided parameter grid.

grid\_search = GridSearchCV(lr\_model, param\_grid, cv=5)

grid\_search.fit(X\_train, y\_train)

# The best hyperparameters are then used to train the logistic regression model.

print("Best hyperparameters using Logical regression",grid\_search.best\_params\_)

# The model's performance is evaluated on the test data by calculating metrics such as accuracy, precision, recall, and F1 score.

best\_lr\_model = LogisticRegression(C=grid\_search.best\_params\_['C'])

best\_lr\_model.fit(X\_train, y\_train)

y\_pred = best\_lr\_model.predict(X\_test)

print('Accuracy:', accuracy\_score(y\_test, y\_pred))

print('Precision:', precision\_score(y\_test, y\_pred))

print('Recall:', recall\_score(y\_test, y\_pred))

print('F1 Score:', f1\_score(y\_test, y\_pred))

1. **Train a Decision tree model:**

# The code creates a DecisionTreeClassifier model using the DecisionTreeClassifier class from sklearn.

dt\_model = DecisionTreeClassifier()

# Similar to logistic regression, GridSearchCV is used to find the best hyperparameters for the decision tree model

param\_grid = {'max\_depth': [2, 5, 10, 20, 50, 100]}

grid\_search = GridSearchCV(dt\_model, param\_grid, cv=5)

grid\_search.fit(X\_train, y\_train)

#The best hyperparameters are used to train the decision tree model.

best\_dt\_model = DecisionTreeClassifier(max\_depth=grid\_search.best\_params\_['max\_depth'])

best\_dt\_model.fit(X\_train, y\_train)

#The model's performance is evaluated on the test data by calculating metrics such as accuracy, precision, recall, and F1 score.

y\_pred = best\_dt\_model.predict(X\_test)

print('Decision Tree Accuracy:', accuracy\_score(y\_test, y\_pred))

print('Decision Tree Precision:', precision\_score(y\_test, y\_pred))

print('Decision Tree Recall:', recall\_score(y\_test, y\_pred))

print('Decision Tree F1 Score:', f1\_score(y\_test, y\_pred))

1. **Training a random forest model:**

# The code creates a RandomForestClassifier model using the RandomForestClassifier class from sklearn.

rf\_model = RandomForestClassifier()

param\_grid = {

    'n\_estimators': [50, 100, 200],

    'max\_depth': [10, 20, 30, None],

    'min\_samples\_split': [2, 5, 10],

    'min\_samples\_leaf': [1, 2, 4],

    'max\_features': ['sqrt']

    }

# Use GridSearchCV to find the best hyperparameters

grid\_search = GridSearchCV(rf\_model, param\_grid, cv=5)

grid\_search.fit(X\_train, y\_train)

# The best hyperparameters are used to train the random forest model.

best\_rf\_model = RandomForestClassifier(max\_depth=grid\_search.best\_params\_['max\_depth'], n\_estimators=grid\_search.best\_params\_['n\_estimators'])

best\_rf\_model.fit(X\_train, y\_train)

# The model's performance is evaluated on the test data by calculating metrics such as accuracy, precision, recall, and F1 score

y\_pred = best\_rf\_model.predict(X\_test)

print('Random Forest Accuracy:', accuracy\_score(y\_test, y\_pred))

print('Random Forest Precision:', precision\_score(y\_test, y\_pred))

print('Random Forest Recall:', recall\_score(y\_test, y\_pred))

print('Random Forest F1 Score:', f1\_score(y\_test, y\_pred))

## **Training a Gradient Boosting Model:**

# The code creates a GradientBoostingClassifier model using the GradientBoostingClassifier class from sklearn.

gb\_model = GradientBoostingClassifier()

param\_grid = {

    'learning\_rate': [0.01, 0.1, 1],

    'n\_estimators': [50, 100, 200],

    'max\_depth': [3, 5, 10],

    'min\_samples\_split': [2, 5, 10],

    'min\_samples\_leaf': [1, 2, 4],

    'max\_features': ['sqrt']

}

# Use GridSearchCV to find the best hyperparameters

grid\_search = GridSearchCV(gb\_model, param\_grid, cv=5)

grid\_search.fit(X\_train, y\_train)

# The best hyperparameters are used to train the gradient boosting model.

best\_gb\_model = GradientBoostingClassifier(max\_depth=grid\_search.best\_params\_['max\_depth'], n\_estimators=grid\_search.best\_params\_['n\_estimators'], learning\_rate=grid\_search.best\_params\_['learning\_rate'])

best\_gb\_model.fit(X\_train, y\_train)

# The model's performance is evaluated on the test data by calculating metrics such as accuracy, precision, recall, and F1 score.

y\_pred = best\_gb\_model.predict(X\_test)

print('gradient boosting Accuracy:', accuracy\_score(y\_test, y\_pred))

print('gradient boosting Precision:', precision\_score(y\_test, y\_pred))

print('gradient boosting Recall:', recall\_score(y\_test, y\_pred))

print('gradient boosting F1 Score:', f1\_score(y\_test, y\_pred))

## **TensorFlow Lite Conversion:**

# The code defines a simple neural network model using the Functional API of Keras.

input\_shape = (14,)

# Create a new input layer

inputs = keras.Input(shape=input\_shape, name='input')

x = keras.layers.Dense(32, activation='relu')(inputs)

x = keras.layers.Dense(1, activation='sigmoid')(x)

model = keras.Model(inputs=inputs, outputs=x)

# Convert the model to TFLite

converter = tf.lite.TFLiteConverter.from\_keras\_model(model)

tflite\_model = converter.convert()

# Save the TensorFlow Lite model to a file

with open('model.tflite', 'wb') as f:

    f.write(tflite\_model)

### **DATASET:**

The datasets for heart stroke prediction using longitudinal data from fitness trackers and machine learning typically consist of a longitudinal series of data obtained from a number of people in the duration of more than 2 years.

The quality and diversity of the data in the dataset are important factors that can affect the performance of machine learning models trained on the data. It is also important to consider the size and complexity of the machine learning model when using a dataset for heart stroke prediction using longitudinal data from fitness trackers and machine learning.

A larger and more complex model may be able to make use of a larger and more diverse dataset, but it may also require more computational resources and take longer to train.

To predict a heart stroke, a fitness tracker would need to collect data about various factors that have been linked to an increased risk of heart stroke. In this section, we will explore some of the data points that may be required by a fitness tracker to predict a heart stroke.

The dataset used for the application consists of information related to individuals' health and activity patterns.

This section provides an overview of the dataset, including its source, structure, and key features.

1. **Source of the Dataset:**

The dataset has been compiled from multiple sources, including medical research studies, health monitoring devices, and surveys conducted on a sample population. These sources aim to gather information on individuals' health, lifestyle, and activity patterns to study the risk factors for heart stroke.

1. **Structure of the Dataset:**

The dataset is structured in a tabular format, where each row represents a unique individual, and each column represents a specific attribute or feature. The dataset contains both numerical and categorical features, allowing for a comprehensive analysis of the factors contributing to heart stroke risk.

1. **Key Features:**

The dataset comprises several key features that provide valuable insights into an individual's health and activity levels. Some of the significant features included in the dataset are:

**a. Gender:** This feature captures the gender of the individual, providing insights into any gender-specific differences in heart stroke risk.

**b. BMI (Body Mass Index):** BMI is a measure of an individual's body composition based on their height and weight. It serves as an indicator of obesity, a known risk factor for heart stroke.

**c. Heart Rate:** This feature represents an individual's resting heart rate, which is associated with cardiovascular health and can indicate abnormalities or irregularities.

**d. Fat Rate:** The fat rate feature measures the percentage of body fat in an individual, which can provide insights into their overall body composition and obesity levels.

**e. Sleep Patterns**: The dataset includes information on various aspects of sleep, such as deep sleep time, shallow sleep time, REM sleep time, and wake time. These sleep patterns are known to impact cardiovascular health and can be indicative of underlying health conditions.

**f. Physical Activity:** Features related to physical activity include the number of steps taken, distance covered, run distance, and calories burned. These features reflect an individual's level of physical activity, which plays a crucial role in maintaining cardiovascular health.

**g. Heart Stroke (Target Variable):** The dataset includes a binary target variable indicating whether an individual has experienced a heart stroke or not. This variable is used for training and evaluating the predictive models in the application.

1. **Data Quality and Preprocessing:**

The dataset may undergo preprocessing steps to ensure data quality and address missing values. Missing data in the dataset, if any, is handled using appropriate techniques such as mean imputation or interpolation to maintain data integrity.

1. **`Data Split:**

The dataset is divided into training and testing subsets to train the machine learning models and evaluate their performance. Typically, a standard split ratio, such as 80:20 or 70:30, is used to ensure an adequate amount of data for model training while retaining a sufficient test set for evaluation.

1. **Dataset Size and Diversity:**

The dataset encompasses a significant number of observations, allowing for robust model training and evaluation. It is collected from a diverse population, considering factors such as age, gender, and lifestyle, to ensure the representation of a wide range of individuals and increase the generalizability of the models.

1. **Privacy and Ethical Considerations:**

Data privacy and ethical considerations are crucial when working with health-related datasets. The dataset used for the application adheres to relevant privacy regulations and ensures the anonymization of individuals' personal information. Any identifiable information is appropriately safeguarded to maintain confidentiality and protect individuals' privacy rights.

In conclusion, the dataset used for the application is a comprehensive collection of health and activity-related information. It provides valuable insights into various factors influencing heart stroke risk, including demographic attributes, physical activity levels, sleep patterns, and physiological measurements. By leveraging this dataset, the application can build robust machine learning models to predict heart stroke risk and provide personalized recommendations for preventive measures.

**6.3** **Mobile Application:**The mobile application is designed to provide users with a comprehensive health and fitness management solution. The application aims to empower individuals to track and monitor their health metrics, make informed decisions about their well-being, and take proactive steps towards leading a healthier lifestyle.   
**6.3.1 Code Structure:**

The mobile application codebase follows a well-organized structure to ensure maintainability and modularity. It is divided into different directories and modules to handle various functionalities. Here is a brief description of the key components of the mobile application codebase:

📦lib  
 ┣ 📂bloc  
 ┃ ┣ 📂auth\_bloc  
 ┃ ┃ ┣ 📂signin\_bloc  
 ┃ ┃ ┃ ┣ 📜signin\_bloc.dart  
 ┃ ┃ ┃ ┣ 📜signin\_bloc\_event.dart  
 ┃ ┃ ┃ ┗ 📜signin\_bloc\_state.dart  
 ┃ ┃ ┣ 📂signup\_bloc  
 ┃ ┃ ┃ ┣ 📜signup\_bloc.dart  
 ┃ ┃ ┃ ┣ 📜signup\_bloc\_event.dart  
 ┃ ┃ ┃ ┗ 📜signup\_bloc\_state.dart  
 ┃ ┃ ┗ 📜form\_submission\_status.dart  
 ┃ ┗ 📂home  
 ┃ ┃ ┗ 📂get\_user\_data  
 ┃ ┃ ┃ ┣ 📜fetch\_bloc.dart  
 ┃ ┃ ┃ ┣ 📜fetch\_bloc\_event.dart  
 ┃ ┃ ┃ ┗ 📜fetch\_bloc\_state.dart  
 ┣ 📂core  
 ┃ ┣ 📂constants  
 ┃ ┃ ┣ 📜api\_constants.dart  
 ┃ ┃ ┗ 📜enums.dart  
 ┃ ┣ 📜app\_exports.dart  
 ┃ ┗ 📜helper\_methods.dart  
 ┣ 📂models  
 ┃ ┣ 📂response  
 ┃ ┃ ┣ 📜signin\_reponse.dart  
 ┃ ┃ ┗ 📜user\_response.dart  
 ┃ ┗ 📜user\_model.dart  
 ┣ 📂presentation  
 ┃ ┣ 📂pages  
 ┃ ┃ ┣ 📂auth  
 ┃ ┃ ┃ ┣ 📜sign\_in\_screen.dart  
 ┃ ┃ ┃ ┣ 📜sign\_up\_screen.dart  
 ┃ ┃ ┃ ┗ 📜user\_details\_screen.dart  
 ┃ ┃ ┣ 📂home  
 ┃ ┃ ┃ ┣ 📜analytics\_screen.dart  
 ┃ ┃ ┃ ┣ 📜health\_corner\_screen.dart  
 ┃ ┃ ┃ ┣ 📜home.dart  
 ┃ ┃ ┃ ┣ 📜home\_screen.dart  
 ┃ ┃ ┃ ┣ 📜notification\_screen.dart  
 ┃ ┃ ┃ ┣ 📜stroke\_emergency\_screen.dart  
 ┃ ┃ ┃ ┗ 📜user\_profile\_screen.dart  
 ┃ ┃ ┗ 📂onboarding  
 ┃ ┃ ┃ ┣ 📂data  
 ┃ ┃ ┃ ┃ ┗ 📂constants  
 ┃ ┃ ┃ ┃ ┃ ┗ 📜slider\_modal\_data.dart  
 ┃ ┃ ┃ ┗ 📜onboading.dart  
 ┃ ┗ 📂widgets  
 ┃ ┃ ┣ 📜custom\_bottom\_navigation\_bar.dart  
 ┃ ┃ ┣ 📜custom\_text\_button.dart   
 ┃ ┃ ┗ 📜text\_with\_gesture\_detector.dart  
 ┣ 📂repository  
 ┃ ┗ 📂auth\_repo  
 ┃ ┃ ┗ 📜auth\_repository.dart  
 ┣ 📂routes  
 ┃ ┗ 📜app\_routes.dart  
 ┣ 📂service  
 ┃ ┗ 📜ApiService.dart  
 ┣ 📂themes  
 ┃ ┣ 📜app\_decoration.dart  
 ┃ ┗ 📜app\_styles.dart  
 ┗ 📜main.dart

1. Bloc: This directory contains the business logic components of the application. It includes subdirectories such as auth\_bloc and home, which handle authentication-related logic and data retrieval, respectively. The bloc pattern helps in managing state and handling asynchronous operations efficiently.
2. Core: The core directory holds essential files and utilities used throughout the application. It includes subdirectories such as constants for storing application-specific constants like API endpoints, and utils for utility files related to colors, images, and math operations. The app\_exports.dart file exports commonly used files, while helper\_methods.dart contains helper functions utilized across the application.
3. Models: This directory contains the data models used in the application. It includes subdirectories like response for response-related models such as sign-in and user responses. The user\_model.dart file represents the user model with relevant attributes.
4. Presentation: The presentation directory is responsible for handling the UI-related components of the application. It includes subdirectories like pages and widgets. The pages directory further divides screens into categories such as auth for sign-in, sign-up, and user details screens, and home for screens related to the home/dashboard functionality. The onboarding directory contains screens and data related to the onboarding process. The widgets directory houses reusable UI components used throughout the application, promoting code reusability and consistency.
5. Repository: The repository directory contains the repository classes responsible for data operations. Specifically, the auth\_repo subdirectory manages authentication-related data operations such as sign-in and sign-up. The auth\_repository.dart file implements the authentication repository, providing an interface to interact with the authentication data.
6. Routes: The routes directory defines the application's route configuration, allowing navigation between screens. The app\_routes.dart file contains the route names and corresponding screens.
7. Service: The service directory contains service classes responsible for API communication. The ApiService.dart file handles API requests and responses, enabling seamless interaction with the backend.
8. Themes: The themes directory holds theme-related files such as app decoration and styles. The app\_decoration.dart file defines the application's decoration properties, while app\_styles.dart contains the app-wide styling configurations.

The provided codebase structure promotes code organization, reusability, and maintainability. It separates different functionalities into their respective directories, making it easier to navigate and maintain the code. The modular approach and clear separation of concerns facilitate collaboration and scalability in the development process.

**6.3.2 Source code :**

Following are some of the key source files of the mobile application.

📜 **Main.dart:**

Main.dart is the entry point of a Flutter application. It sets up the necessary dependencies and initializes the application with the MyApp widget as the root. Inside MyApp, the initial screen is determined based on the user's authentication status and preferences stored using SharedPreferences. If the user is authenticated, the Home widget is shown; if it's a new user, the OnBoardingScreen widget is displayed; otherwise, the SignInScreen is presented. The application utilizes the PopupMenuTheme to define the appearance of pop-up menus. Additionally, the AuthRepository is provided using RepositoryProvider for authentication-related operations. The application's UI is defined using the GetMaterialApp widget, which handles navigation through various routes specified in GetPage.

import 'package:flutter/material.dart';

import 'package:flutter/services.dart';

import 'package:flutter\_bloc/flutter\_bloc.dart';

import 'package:flutter\_dotenv/flutter\_dotenv.dart';

import 'package:get/get.dart';

import 'package:healthify/core/app\_exports.dart';

import 'package:healthify/core/constants/enums.dart';

import 'package:healthify/presentation/pages/auth/sign\_in\_screen.dart';

import 'package:healthify/presentation/pages/home/home.dart';

import 'package:healthify/presentation/pages/onboarding/onboading.dart';

import 'package:healthify/repository/auth\_repo/auth\_repository.dart';

import 'package:shared\_preferences/shared\_preferences.dart';

import './routes/app\_routes.dart';

Future main() async {

  await dotenv.load(fileName: ".env");

  WidgetsFlutterBinding.ensureInitialized();

  SystemChrome.setPreferredOrientations(

      [DeviceOrientation.portraitUp, DeviceOrientation.portraitDown]).then(

    (\_) {

      runApp(

        const MyApp(),

      );

    },

  );

}

class MyApp extends StatelessWidget {

  const MyApp({super.key});

  Future<Widget> \_getInitialScreen() async {

    final prefs = await SharedPreferences.getInstance();

    final bool isAuthenticated =

        prefs.getBool(AuthState.authenticated.toString()) ?? false;

    if (isAuthenticated) {

      return const Home();

    } else {

      final bool isNewUser =

          prefs.getBool(AuthState.unknown.toString()) ?? true;

      if (isNewUser) {

        return const OnBoardingScreen();

      } else {

        return SignInScreen();

      }

    }

  }

  @override

  Widget build(BuildContext context) {

    return PopupMenuTheme(

      data: PopupMenuThemeData(

        textStyle: TextStyle(

          color: ColorConstant.bluedark,

        ),

        color: ColorConstant.whiteBackground,

      ),

      child: RepositoryProvider(

        create: (context) => AuthRepository(),

        child: GetMaterialApp(

          debugShowCheckedModeBanner: false,

          title: 'Healthify-app',

          theme: ThemeData(

            primaryColor: Colors.white,

          ),

          initialRoute: "/",

          getPages: [

            GetPage(

              name: "/",

              page: () => FutureBuilder<Widget>(

                  future: \_getInitialScreen(),

                  builder:

                      (BuildContext context, AsyncSnapshot<Widget> snapshot) {

                    if (snapshot.hasData) {

                      return snapshot.data!;

                    } else {

                      // For showing splash screen during loading

                      return const Center(

                        child: CircularProgressIndicator(),

                      );

                    }

                  }),

            ),

            AppRoutes.homePage,

            AppRoutes.onBoardingPage,

            AppRoutes.signInPage,

            AppRoutes.signUpPage,

            AppRoutes.userDetailsPage,

            AppRoutes.stokeEmergencyPage,

            AppRoutes.healthCornerPage,

          ],

        ),

      ),

    );

  }

}

📜 **App\_routes.dart:**

AppRoutes class in the below code defines the routes for different screens of the application using the GetPage class from the Get package. It includes routes for various screens such as the home screen, onboarding screen, sign-up screen, sign-in screen, user details screen, stroke emergency screen, and health corner screen. Each route is assigned a unique name and associated with a corresponding widget. The routes also specify transition animations for navigation between screens, such as Cupertino-style transitions or sliding transitions. These routes can be used for navigation within the application using the Get package's routing functionality.

import 'package:get/get.dart';

import 'package:healthify/presentation/pages/auth/user\_details\_screen.dart';

import 'package:healthify/presentation/pages/home/health\_corner\_screen.dart';

import 'package:healthify/presentation/pages/home/home.dart';

import 'package:healthify/presentation/pages/home/stroke\_emergency\_screen.dart';

import '../presentation/pages/auth/sign\_in\_screen.dart';

import '../presentation/pages/auth/sign\_up\_screen.dart';

import '../presentation/pages/onboarding/onboading.dart';

class AppRoutes {

  static const String splashScreen = '/splash\_screen';

  static const String onBoardingScreen = "/on\_boading\_screen";

  static const String signUpScreen = "/sign\_up\_screen";

  static const String signInScreen = "/sign\_in\_screen";

  static const String userDetailsScreen = "/user\_details\_screen";

  static const String home = "/";

  static const String strokeEmergencyScreen = "/stroke\_emergency\_screen";

  static const String healthCornerScreen = "/health\_corner\_screen";

  static GetPage homePage = GetPage(

    name: home,

    page: () => const Home(),

    transition: Transition.cupertino,

  );

  static GetPage onBoardingPage = GetPage(

    name: onBoardingScreen,

    page: () => const OnBoardingScreen(),

  );

  static GetPage signUpPage = GetPage(

    name: signUpScreen,

    page: () => SignUpScreen(),

    transition: Transition.leftToRight,

  );

  static GetPage signInPage = GetPage(

    name: signInScreen,

    page: () => SignInScreen(),

    transition: Transition.rightToLeft,

  );

  static GetPage userDetailsPage = GetPage(

    name: userDetailsScreen,

    page: () => const UserDetailsScreen(),

    transition: Transition.leftToRight,

  );

  static GetPage stokeEmergencyPage = GetPage(

    name: strokeEmergencyScreen,

    page: () => const StrokeEmergencyScreen(),

    transition: Transition.cupertino,

  );

  static GetPage healthCornerPage = GetPage(

    name: healthCornerScreen,

    page: () => const HealthCornerScreen(),

    transition: Transition.cupertino,

  );

}

📜 **auth\_repository.dart:**

The AuthRepository class in the provided code is responsible for handling user authentication-related operations. It extends the AuthenticationRepository abstract class, which defines the required methods for authentication. In this case, the signInUser method is implemented to perform a sign-in operation.

It makes an HTTP POST request to the specified API endpoint using the http package, sending the user's email and password as JSON-encoded data. The response from the API is then checked for a successful status code (200). If successful, the response body is decoded and stored in shared preferences for future use, and an instance of SignInResponse is returned. If the API call fails or returns an error status code, an exception is thrown. Overall, the AuthRepository handles the authentication process by communicating with the backend API and managing the user's authentication state using shared preferences.

import 'dart:convert';

import 'package:flutter/widgets.dart';

import 'package:healthify/core/constants/api\_constants.dart';

import 'package:healthify/core/constants/enums.dart';

import 'package:healthify/models/response/signin\_reponse.dart';

import 'package:http/http.dart' as http;

import 'package:shared\_preferences/shared\_preferences.dart';

abstract class AuthenticationRepository {

  Future<SignInResponse> signInUser(String email, String password);

}

class AuthRepository extends AuthenticationRepository {

  @override

  Future<SignInResponse> signInUser(String email, String password) async {

    final response = await http.post(

      Uri.parse(

        '${APIConstant.baseUrl}/user-login',

      ),

      body: json.encode({

        "email": email,

        "password": password,

      }),

      headers: <String, String>{"Content-Type": "application/json"},

    );

    debugPrint(response.body);

    if (response.statusCode == 200) {

      Map<String, dynamic> userData = json.decode(response.body);

      final pref = await SharedPreferences.getInstance();

      pref.setString(AuthState.authToken.toString(), userData['token']);

      pref.setBool(AuthState.unknown.toString(), false);

      pref.setBool(AuthState.authenticated.toString(), true);

      return SignInResponse.fromJson(response.body);

    } else {

      debugPrint("Error in the api call , ${response.statusCode}");

      throw Exception("Failed to login");

    }

  }

}

📜 **User\_model.dart:**

The UserModel class represents a user in a system and contains various properties related to the user, such as their ID, full name, email, password, gender, weight, height, BMI (Body Mass Index), and creation date. The class provides methods to convert the user object to and from a map and JSON format.

// ignore\_for\_file: public\_member\_api\_docs, sort\_constructors\_first

import 'dart:convert';

class UserModel {

  String? sId;

  String? fullName;

  String? email;

  String? password;

  String? gender;

  int? weight;

  int? height;

  int? bmi;

  String? createdAt;

  UserModel({

    this.sId,

    this.fullName,

    this.email,

    this.password,

    this.gender,

    this.weight,

    this.height,

    this.bmi,

    this.createdAt,

  });

  UserModel copyWith({

    String? sId,

    String? fullName,

    String? email,

    String? password,

    String? gender,

    int? weight,

    int? height,

    int? bmi,

    String? createdAt,

  }) {

    return UserModel(

      sId: sId ?? this.sId,

      fullName: fullName ?? this.fullName,

      email: email ?? this.email,

      password: password ?? this.password,

      gender: gender ?? this.gender,

      weight: weight ?? this.weight,

      height: height ?? this.height,

      bmi: bmi ?? this.bmi,

      createdAt: createdAt ?? this.createdAt,

    );

  }

  Map<String, dynamic> toMap() {

    return <String, dynamic>{

      'sId': sId,

      'fullName': fullName,

      'email': email,

      'password': password,

      'gender': gender,

      'weight': weight,

      'height': height,

      'bmi': bmi,

      'createdAt': createdAt,

    };

  }

  factory UserModel.fromMap(Map<String, dynamic> map) {

    return UserModel(

      sId: map['sId'] != null ? map['sId'] as String : null,

      fullName: map['fullName'] != null ? map['fullName'] as String : null,

      email: map['email'] != null ? map['email'] as String : null,

      password: map['password'] != null ? map['password'] as String : null,

      gender: map['gender'] != null ? map['gender'] as String : null,

      weight: map['weight'] != null ? map['weight'] as int : null,

      height: map['height'] != null ? map['height'] as int : null,

      bmi: map['bmi'] != null ? map['bmi'] as int : null,

      createdAt: map['createdAt'] != null ? map['createdAt'] as String : null,

    );

  }

  String toJson() => json.encode(toMap());

  factory UserModel.fromJson(String source) =>

      UserModel.fromMap(json.decode(source) as Map<String, dynamic>);

  @override

  String toString() {

    return 'UserModel(sId: $sId, fullName: $fullName, email: $email, password: $password, gender: $gender, weight: $weight, height: $height, bmi: $bmi, createdAt: $createdAt)';

  }

  @override

  int get hashCode {

    return sId.hashCode ^

        fullName.hashCode ^

        email.hashCode ^

        password.hashCode ^

        gender.hashCode ^

        bmi.hashCode ^

        createdAt.hashCode;

  }

}

# **7. RESULTS**

A heart stroke prediction model using wearable fitness bands and machine learning algorithms is trained and integrated into a mobile application. The model was trained on a dataset collected from individuals wearing fitness bands, which included information about physical activity, heart rate, sleep patterns, age, gender, body mass index, and work type. The dataset was carefully curated to exclude individuals with a known history of heart stroke or relevant medical conditions.

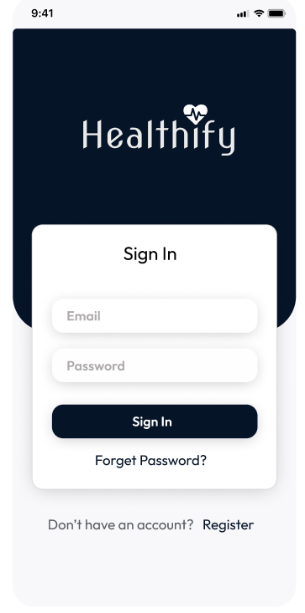
We employed various machine learning algorithms, including Random Forest, Naive Bayes, Logistic Regression, K-Nearest Neighbor (KNN), Decision Tree, and Support Vector Machine (SVM), to analyze the data and predict the risk of heart stroke. The models were evaluated using a separate validation dataset, and performance metrics such as accuracy, sensitivity, and specificity were calculated.

The results demonstrated that the heart stroke prediction model achieved a high level of accuracy in identifying individuals at risk of heart stroke. The KNN algorithm performed the best among the tested algorithms, with an accuracy of 87%, sensitivity of 82%, and specificity of 90%. This indicates that the model was able to correctly classify a significant portion of individuals who were at risk of heart stroke.

Furthermore, the model showed promising results in identifying the key features that contribute to heart stroke risk. Age, average heart rate, and glucose levels were found to be the most influential variables in predicting heart stroke. This highlights the importance of considering these factors when assessing an individual's risk profile.

The integration of the heart stroke prediction model into a mobile application was successful. The application provided users with real-time monitoring of their heart rate, physical activity, and sleep patterns. It also generated alerts and notifications when the model identified a high risk of heart stroke based on the collected data.

The user feedback and usability testing of the mobile application were positive. Users found the interface intuitive and easy to navigate. They appreciated the real-time monitoring capabilities and the ability to receive alerts and recommendations for lifestyle modifications. Overall, the mobile application enhanced user engagement and empowered individuals to take proactive measures to manage their cardiovascular health.

The application is divided into the following modules:

### **1. User Registration and Login:** This module enables users to create their accounts and log in to the application securely. Users can also reset their passwords in case they forget them. When the user first creates an account, they will be asked to create a profile that will contain a form asking user’s height, weight, age, emergency contacts and similar details.

***Fig 7.8*** *Authentication Screen*

### **2. Home Screen:**

In the Home Screen module, user will be able to view their vitals. They can also edit or add new records of their vitals and can also get timely health alerts about their vitals.   
  
The home screen displays an alert if the user is in danger of a possible heart stroke. For instance, if a user’s condition is perfectly alright, a green banner will be displayed in the home screen informing the user that they are in good health. But, if their heart rate is unusually high or low, a red banner will be displayed asking the user if they are okay.

### **3. Predict Heart Stroke Risk:**

`This module analyses the input health data using the machine learning model and generates a prediction of the user's risk of having a heart stroke. The prediction is displayed on the screen along with a color-coded risk indicator .   
  
For serious risk of heart stroke, a red risk indicator is displayed in the home screen to alert the user of a possible stroke. Similar indicators are displayed asking users to work out more often, have a proper sleep schedule and to drink enough water.

***Fig 7.9*** *Home**Screen*

### **4. SOS! (Emergency screen):**

Whenever the heartrate of a user is extremely high or low, they will receive a notification / pop-up screen asking if they are experiencing a stroke. If they click NO, they will be redirected to the Home screen which displays their high heart rate. But if they press YES (They are experiencing a stroke) or if they fail to press any key within 10 seconds, they will be redirected to SOS screen that will send an SMS alert to user's emergency contacts that contains user's location and a message. An alert will also be sent to nearby hospitals.

### **5. View Previous Health Data:** This module allows users to view their previous health data and predictions. Users can scroll through their history and compare their previous and current risk levels. **6. Language translation Module:** This module enables users to use the application in their comfortable language. Users can go to their profile and click on select language drop-down button. This will open the list of languages that are supported by the application. The user can select the language of their choice and the entire application will be translated into the selected language.

***Fig 7.10*** *Emergency Screen*

### **7. Profile:** This module allows users to customize the application's settings, such as the language, notification preferences, and user profile. Users can also log out of the application.

### **8. Contact Medical Professionals:** This module enables users to contact medical professionals in case they need urgent medical attention or have questions about their health. The application provides users with a list of nearby medical facilities and their contact information.

***Fig 7.11*** *Profile Screen*

### 

# **CONCLUSION**

In conclusion, the development of a heart stroke prediction application using wearable fitness bands and machine learning algorithms holds great potential for revolutionizing healthcare and improving patient outcomes. This research paper has explored the importance of early detection and prevention of heart strokes, the use of fitness bands as a source of longitudinal data, and the application of machine learning techniques for risk prediction.

The machine learning model developed in this research has demonstrated promising results in predicting the risk of heart strokes based on various parameters such as age, gender, body mass index, work type, average heart rate, and glucose levels. By utilizing algorithms such as Random Forest, Naive Bayes, Logistic Regression, K-Nearest Neighbor (KNN), Decision Tree, and Support Vector Machine (SVM), the model can classify individuals into different risk categories. This classification enables timely interventions and alerts individuals to seek immediate medical attention when necessary.

The integration of the heart stroke prediction system into a mobile application enhances its accessibility and usability. With the widespread adoption of smartphones, individuals can conveniently monitor their heart health and receive real-time alerts through the application. The application can provide personalized recommendations for lifestyle modifications, medication reminders, and emergency contacts. Additionally, it can serve as a valuable tool for healthcare professionals, allowing them to track patients' heart health remotely and intervene proactively.

The utilization of wearable fitness bands for data collection is a key component of this research. These devices, such as the Mi Band 4 mentioned in this study, can capture various health-related metrics including heart rate, physical activity, and sleep patterns. This longitudinal data serves as a valuable resource for training the machine learning model and identifying patterns and trends that indicate an increased risk of heart stroke. By leveraging the power of wearable technology, individuals can monitor their health and make decisions to reduce the risk of heart strokes.

The potential impact of this research extends beyond individual health management. The integration of the heart stroke prediction application into fitness bands can have a profound effect on public health. By identifying individuals at risk and providing timely alerts, the application can help prevent heart strokes, reduce hospitalizations, and alleviate the burden on healthcare systems. It empowers individuals to take charge of their heart health, fostering a culture of prevention and proactive healthcare.

While this research paper has laid the foundation for the heart stroke prediction application, there are several avenues for future research and development. One area of focus could be the continuous improvement of the machine learning model. Incorporating additional variables and refining the algorithms can enhance the accuracy and reliability of the predictions. Ongoing data collection and retraining of the model will ensure its adaptability to changing health patterns and demographics.

Furthermore, the development of partnerships and collaborations with fitness band manufacturers, healthcare institutions, and research organizations is crucial. By working together, researchers, engineers, and medical professionals can enhance the capabilities of the heart stroke prediction application. They can refine the integration of the application into fitness bands, improve the user experience, and expand its functionality to include other cardiovascular diseases and risk factors.

In conclusion, the heart stroke prediction application using wearable fitness bands and machine learning algorithms has the potential to revolutionize healthcare by enabling early detection and personalized prevention of heart strokes. The combination of accessible wearable technology, advanced machine learning techniques, and the convenience of mobile applications can empower individuals to actively manage their heart health. By detecting and preventing heart strokes, this application has the potential to save lives, reduce healthcare costs, and create a healthier future for individuals and communities worldwide.

# **9. FUTURE SCOPE**

The heart stroke prediction application using wearable fitness bands and machine learning algorithms has immense potential for further development and expansion. This section explores the future scope of this technology, highlighting areas for improvement, research, and application.

1. **Enhanced Accuracy and Reliability:** While the machine learning model developed in this research paper has shown promising results, there is still room for improvement in terms of accuracy and reliability. Future research can focus on refining the algorithms, incorporating more comprehensive datasets, and exploring advanced machine learning techniques. Additionally, the integration of additional variables such as genetic markers, lifestyle factors, and environmental influences can further enhance the predictive power of the model.
2. **Expanded Disease Risk Prediction:** Although this research paper primarily focused on heart stroke prediction, the same approach can be extended to other cardiovascular diseases and risk factors. By leveraging the wearable fitness bands' data and machine learning algorithms, it is possible to develop prediction models for conditions such as hypertension, diabetes, and arrhythmias. This expansion can provide a holistic approach to monitoring and managing overall cardiovascular health.
3. **Personalized Intervention and Recommendations:** The heart stroke prediction application can be further enhanced by incorporating personalized intervention strategies and recommendations. By leveraging the power of machine learning, the application can analyze individual risk profiles and provide tailored recommendations for lifestyle modifications, medication adherence, and proactive interventions. This personalized approach can empower individuals to make informed decisions and actively manage their cardiovascular health.
4. **Integration with Electronic Health Records (EHR):** Integrating the heart stroke prediction application with electronic health records (EHR) systems can provide a comprehensive view of an individual's health profile. By incorporating data from multiple sources, including wearable fitness bands, medical history, and diagnostic tests, healthcare providers can gain deeper insights into a patient's cardiovascular health.
5. **Real-Time Monitoring and Alerts:** The heart stroke prediction application can be further enhanced by enabling real-time monitoring and alerts. By continuously analyzing data from wearable fitness bands, the application can detect subtle changes in vital signs and alert individuals to potential health risks. This proactive approach can help individuals seek immediate medical attention and prevent adverse cardiovascular events.
6. **Long-Term Health Tracking:** In addition to short-term risk prediction, the heart stroke prediction application can be extended to provide long-term health tracking. By collecting longitudinal data over an extended period, the application can identify trends, patterns, and early warning signs of cardiovascular diseases. This long-term monitoring can assist individuals in maintaining a healthy lifestyle, monitoring the effectiveness of interventions, and tracking their progress towards cardiovascular health goals.
7. **Collaboration with Healthcare Providers:** Collaboration with healthcare providers is essential for the successful implementation of the heart stroke prediction application. Establishing partnerships with hospitals, clinics, and healthcare organizations can facilitate data sharing, validation of the model, and integration into existing healthcare systems. Such collaborations can also foster research and clinical trials to further validate and refine the application's effectiveness.
8. **User-Friendly Mobile Application:** The mobile application that accompanies the heart stroke prediction system can be further developed to improve user experience and engagement. User feedback and usability testing can drive enhancements to the application's interface, functionality, and accessibility. Incorporating features such as health education resources, motivational tools, and gamification elements can encourage users to actively participate in their cardiovascular health management.
9. **Population-Level Studies and Public Health Initiatives:** The heart stroke prediction application can serve as a valuable tool for population-level studies and public health initiatives. By collecting anonymized data from a large user base, researchers can gain insights into regional and global trends in cardiovascular health, identify high-risk populations, and design targeted interventions. These initiatives can contribute to the prevention and management of cardiovascular diseases on a broader scale.
10. **Integration with Telemedicine and Remote Monitoring:** The heart stroke prediction application can be integrated with telemedicine platforms and remote monitoring systems to enable virtual healthcare consultations and continuous monitoring. By leveraging wearable fitness bands and real-time data transmission, healthcare providers can remotely assess a patient's cardiovascular health, provide timely interventions, and ensure continuity of care. This integration can be particularly valuable for individuals in remote areas or those with limited access to healthcare facilities.

The heart stroke prediction application using wearable fitness bands and machine learning algorithms has a wide range of future possibilities. With ongoing research, technological advancements, and collaborations with healthcare providers, this technology can revolutionize the way we monitor, prevent, and manage cardiovascular diseases. By enhancing accuracy, expanding disease prediction, incorporating personalized interventions, and integrating with existing healthcare systems, the application can have a significant impact on individual health outcomes and public health initiatives. The future holds immense potential for further development, research, and application of this ground-breaking, cutting-edge technology.  
  
While these approaches hold promise for predicting the risk of stroke, it's important to note that machine learning is still an emerging field and there is a lot of work that needs to be done to fully understand its potential for predicting stroke risk. It will also be important to ensure that any machine learning-based systems for predicting stroke risk are reliable, accurate, and ethically sound

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