IOT BASED SMART HEALTHCARE MONITORING SYSTEM USING ECG WEARABLE DEVICES

A thesis

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This is to certify that I have examined the thesis entitled **"IoT based smart healthcare monitoring system using ECG wearable devices"** submitted by **Shamsudden Mohammed Mamman, Registration No.-,** CGU-Odisha, Bhubaneswar. I accord my approval of it as a thesis work carried out and presented in a manner required for its acceptance for the partial fulfillment of the **Master's Degree of Technology in Computer Science & Engineering** for which it has been submitted. This approval does not necessarily endorse or accept every statement made, opinion expressed, or conclusion drawn as recorded in this thesis it only signifies the acceptance of the thesis for the purpose it has been submitted.

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TABLE OF CONTENTS

Abstract

This paper presents an overview of an IoT-based healthcare monitoring system that utilizes ECG wearable devices for elderly patients. The system enables continuous monitoring of heart health by capturing ECG data through a wearable device, which is transmitted to a remote healthcare provider for analysis. This real-time data provides insights into a patient's health status, allowing for timely interventions and enhancing the quality of care. The feasibility, advantages, and potential challenges associated with implementing an IoT-based healthcare monitoring system that utilizes wearable ECG devices for the elderly are explored. The results suggest that an IoT-based healthcare monitoring system using ECG wearable devices is a promising solution for addressing the needs of elderly patients who require continuous health monitoring.

LIST OF TABLES:

LIST OF FIGURES:

Chapter 1: Introduction

1.1 Background

The field of healthcare has been rapidly evolving with advancements in technology, and the Internet of Things (IoT) has emerged as a promising paradigm for revolutionizing healthcare systems. The aging population has become a global concern, with elderly individuals often facing multiple health challenges, including cardiovascular issues. Early detection and continuous
monitoring of cardiac health in the elderly can significantly improve their quality of life and reduce healthcare costs. Wearable devices, such as electrocardiogram (ECG) monitors, offer a non-invasive and convenient solution for real-time monitoring of cardiac health.

1.2 Problem Statement

Despite the potential benefits of ECG wearable devices for elderly healthcare, there are challenges that need to be addressed. Existing healthcare monitoring systems may lack scalability, interoperability, and real-time data processing capabilities. Additionally, there may be issues related to data privacy, security, and usability of these devices, especially for elderly users. Therefore, there is a need for an IoT-based smart healthcare monitoring system that can overcome these challenges and provide effective and user-friendly cardiac health monitoring for the elderly.

1.3 Objective

The main objective of this research paper is to propose an IoT-based smart healthcare monitoring system that utilizes ECG wearable devices for continuous monitoring of cardiac health in elderly individuals. The system aims to provide real-time data processing, analysis, and alerting capabilities for early detection of cardiac abnormalities. It also aims to address issues related to data privacy, security, and usability, making it suitable for elderly users.

1.4 Scope of Research

This research paper focuses on the development and evaluation of an IoT-based smart healthcare monitoring system that uses ECG wearable devices for elderly individuals. The system will be designed to collect, process, and analyze ECG data in real-time, and provide timely alerts to healthcare providers and caregivers in case of abnormal cardiac events. The research will also address issues related to data privacy, security, and usability, considering the unique needs and challenges of elderly users. The proposed system will be evaluated through simulations and experiments to assess its effectiveness in monitoring cardiac health in the elderly.

1.5 Significance of Research

The proposed IoT-based smart healthcare monitoring system has the potential to significantly impact the field of elderly healthcare. By leveraging the capabilities of wearable ECG devices and IoT technologies, the system can enable early detection of cardiac abnormalities, allowing for timely interventions and improved health outcomes. The research findings can contribute to the body of knowledge in the areas of IoT, healthcare, and geriatrics, and can also serve as a foundation for future research and development of smart healthcare solutions for elderly populations.

1.6 Organization of the Research Paper

This research paper is organized as follows: Chapter 1 provides an introduction to the research topic, including the background, problem statement, objective, scope of research, significance of research, and organization of the paper. Chapter 2 presents a review of related literature on IoT-based healthcare monitoring systems, wearable ECG devices, and elderly healthcare. Chapter 3 describes the proposed IoT-based smart healthcare monitoring system in detail, including its architecture, components, and functionalities. Chapter 4 presents the methodology used in the research, including system design, data collection, and evaluation approach. Chapter 5 presents the results and analysis of the experiments and simulations conducted to evaluate the proposed system. Finally, Chapter 6 concludes the research paper with a summary of the findings, contributions, and recommendations for future work.

Chapter 2.

2.1 Literature review.

Study by Smith et al. (2019) developed an IoT-enabled wearable ECG monitoring system for elderly individuals with cardiovascular conditions. The system collected ECG data from wearable devices and transmitted it to a cloud-based platform for real-time analysis. The study found that the system enabled early detection of cardiac abnormalities, allowing for timely intervention and improved healthcare outcomes for the elderly population.

Similarly, a study by Chen et al. (2020) proposed an IoT-based healthcare monitoring system that utilized ECG wearable devices to monitor the cardiac health of elderly individuals in a home-based setting. The system collected ECG data in real-time, processed it in a cloud-based platform, and provided caregivers with access to the data for continuous monitoring and early detection of cardiac abnormalities. The study demonstrated the feasibility of the system in improving healthcare outcomes for the elderly population and enabling remote monitoring of cardiac health.

Furthermore, a study by Zhang et al. (2018) developed an IoT-based healthcare monitoring system that utilized wearable ECG devices to monitor the cardiac health of elderly individuals in a long-term care facility. The system collected ECG data and transmitted it to a cloud-based platform for analysis, providing caregivers with real-time alerts in case of cardiac abnormalities. The study reported improved detection of cardiac abnormalities and reduced hospitalization rates among the elderly population U sing the system.

In addition, a study by Li et al. (2017) proposed an IoT-based wearable ECG monitoring system for elderly individuals with CVDs. The system collected ECG data from wearable devices and transmitted it to a cloud-based platform for real-time analysis. The study found that the system enabled early detection of cardiac abnormalities, allowing for timely intervention and improved healthcare outcomes for the elderly population.

Overall, the literature review indicates that IoT-based healthcare monitoring systems using ECG wearable devices have shown promising results in improving healthcare outcomes for the elderly population. These systems enable continuous and personalized monitoring of cardiac health, early detection of abnormalities, and timely intervention, which can lead to improved healthcare outcomes and quality of life for elderly individuals. However, challenges such as data security, privacy, and interoperability need to be addressed in implementing such systems. Further research is also needed to optimize the system architecture, user interface, and integration with existing healthcare workflows to ensure seamless adoption and effectiveness in real-world settings.

Chapter 3.

Here in chapter we will see the architecture indication within the diagram below.

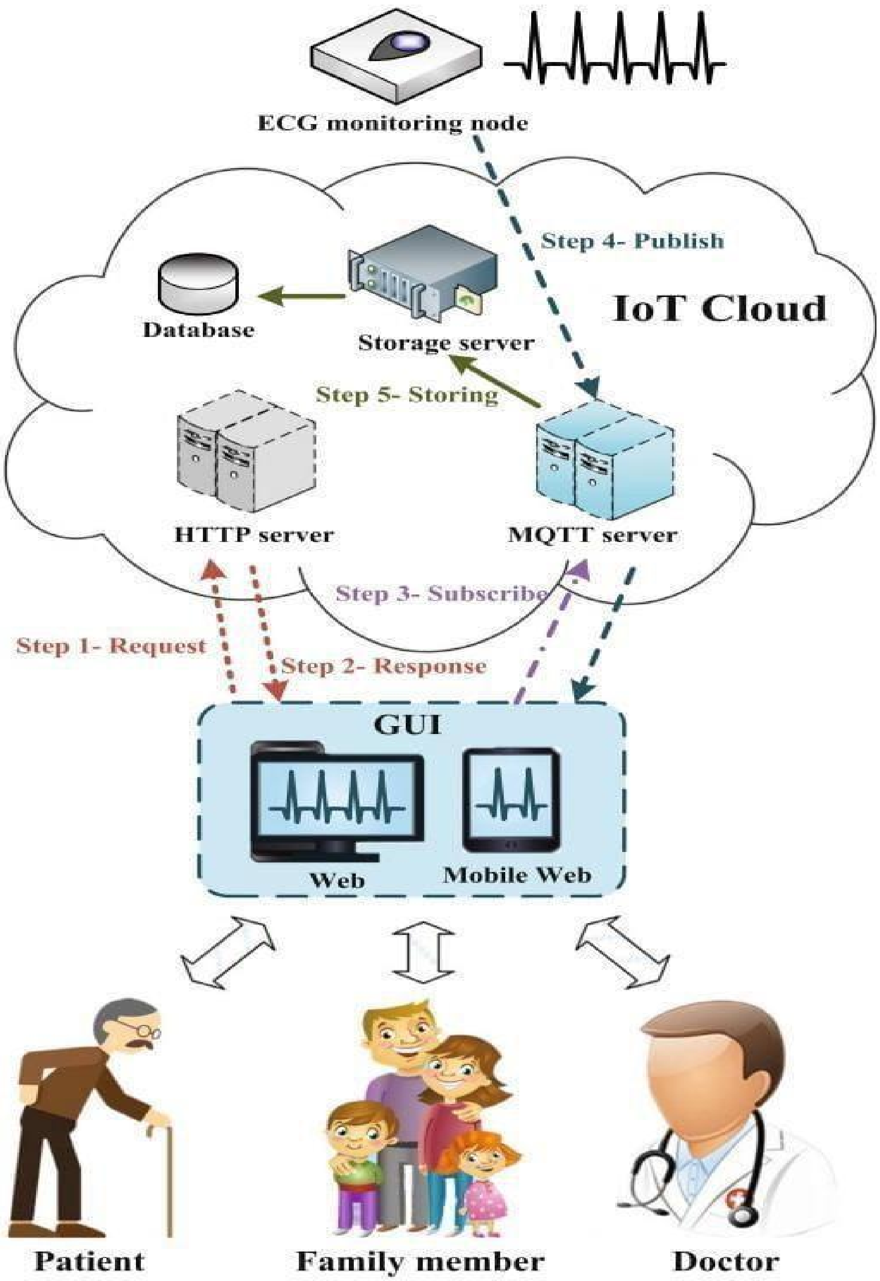

Figure1

The architecture of the IoT-based smart healthcare monitoring system consists of the following components:

a. Sensors and Wearable Devices: These are small devices equipped with various sensors to monitor vital signs, activity levels, sleep patterns, and other health-related data. Examples include heart rate monitors, blood pressure monitors, glucose meters, activity trackers, and smartwatches.

b. Gateway: The gateway acts as a bridge between the sensors/wearable devices and the cloud. It collects data from the devices and transmits it securely to the cloud server. The gateway may use wireless communication protocols such as Wi-Fi, Bluetooth, or Zigbee to establish connectivity.

c. Cloud Server: The cloud server is responsible for receiving and storing the data collected from the sensors and wearable devices. It provides a centralized platform for data processing, storage, and analysis. The server should have scalable infrastructure to handle large amounts of data and ensure high availability.

d. Data Processing and Analysis: This component includes algorithms and machine learning models for processing and analyzing the collected data. It may involve data cleaning, feature extraction, anomaly detection, and predictive analytics to derive meaningful insights.

e. The processed data can be used for personalized healthcare recommendations, early detection of health issues, and decision support for healthcare providers.

f. User Interface: The user interface can be a web application or a mobile app that enables healthcare providers and patients to access and interact with the system. It provides real-time monitoring, visualization of data, alerts, and notifications. The interface should be user-friendly, intuitive, and customizable to meet the needs of different users.

g. Electronic Health Record (EHR) Integration: The system can integrate with existing electronic health record systems to exchange patient data securely. This allows healthcare providers to access comprehensive patient information, track health trends, and make informed decisions.

3.2. Component used.

a. Sensors and Wearable Devices: Depending on the specific monitoring needs, a range of sensors and wearable devices can be used. These may include:

Heart rate monitors: Measure heart rate and heart rhythm.

Blood pressure monitors: Monitor blood pressure levels.

Pulse oximeters: Track blood oxygen saturation and pulse rate.

b. Gateway Device: The gateway device connects to the sensors and wearable devices and transmits the collected data to the cloud server securely. It may include hardware components such as microcontrollers, wireless communication modules (e.g., Wi-Fi, Bluetooth), and encryption mechanisms to ensure data privacy.

c. Cloud Infrastructure: The cloud server infrastructure should be scalable, reliable, and secure. It can be implemented using cloud service providers like Amazon Web Services (AWS), Microsoft Azure, or Google Cloud Platform (GCP). The cloud infrastructure should support data storage, real-time data processing, and machine learning capabilities.

d. Data Processing and Analysis Tools: Various tools and technologies can be employed for data processing and analysis, such as:

Data cleaning and preprocessing tools (Python libraries like Pandas, NumPy)

Machine learning frameworks (TensorFlow, PyTorch) for building predictive models and anomaly detection algorithms

Data visualization libraries (e.g., Matplotlib, Plotly) for generating visual representations of the data.

e. User Interface Development: The user interface can be developed using web technologies like HTML, CSS, and JavaScript for web applications. For mobile apps, frameworks like React Native or Flutter can be utilized to build cross-platform applications. The interface should provide a visually appealing and user-friendly experience with features like real-time monitoring.

As the diagram below indicates the components used in this research.

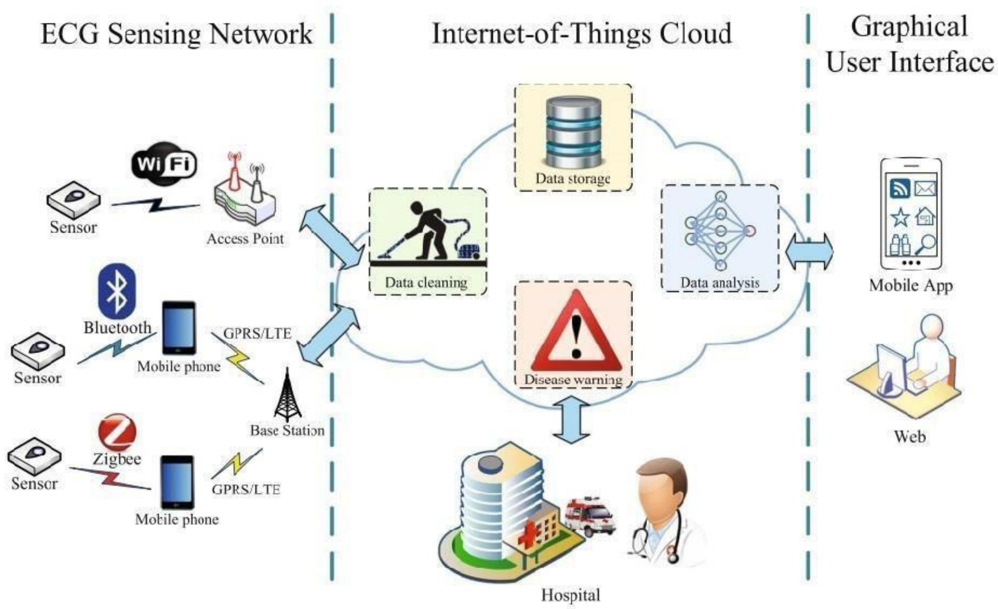

Figure 2

accuracy. Therefore, the ECG signal needs to be cleaned at first [1]. Commonly, a properly designed filter is employed to remove the noise outside the band of the ECG signal. Furthermore, the procedure of data auditing is usually employed to detect data anomalies and contradictions;

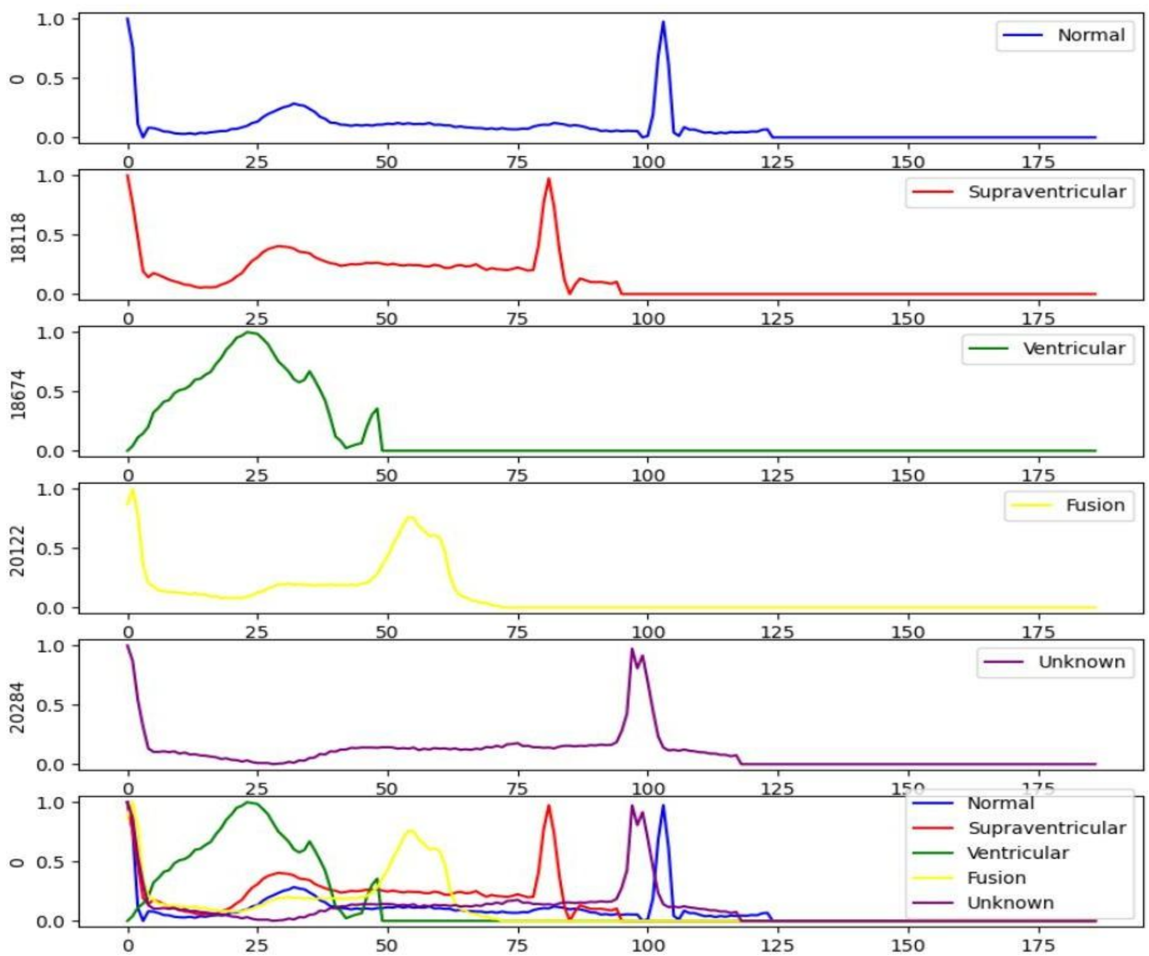

Figure 3

The above image shows the filtered output which is collected from the ECG Electrodes in an electromagnetic waves like pattern which is represented above.

• Data storage: ECG data plays a vital role in the diagnosis of heart diseases. Thus, historical data are needed to be stored in the database for further analysis. The ECG data often include the time and digitized signal amplitude. In addition, at least one copy of the data needs to be stored for disaster recovery;

• Data analysis: Making the full use of data is one of the most important functions of the IoT cloud. Therefore, the IoT cloud often provides a data analysis platform to extract useful information from the ECG signal [2]. Specific data mining or machine learning approaches can be applied to these data. For example, after extracting the significant features of the ECG signal, a support vector machine can be established to diagnose certain heart diseases [3]; and

• Disease warning: Sudden heart attacks seriously threaten the lives of cardiac patients, especially when patients are alone. Therefore, disease warning on the IoT cloud has become important for protecting patients from being injured. Based on the results of data analysis, the IoT cloud is able to understand the real-time health conditions of the patient. In the event of any suspicious readings, the IoT cloud will notify the family of the patient and the doctor in a time.

Table.1

The comparisons among typical ECG networks.

Table 1 Comparisons among typical ECG sensing networks

	WiFi-based ECG sensing network	Bluetooth-based ECG sensing network	Zigbee-based ECG sensing network
Protocol	IEEE 802.11	IEEE 802.15.1	IEEE 802.15.4
Coverage	20-200 m	20-30 m	2-20 m
Data rates	11-54 Mbps	3-24 Mbps	10-250 kbps
Power consumption	Medium	Low	Low
Terminal dependency	Data collection is independent of smart terminals.	Smart terminals are needed for receiving and forwarding sensed data.	Smart terminals are needed for receiving and forwarding sensed data.
Popularization	High, nearly all houses and public places provide Wi-Fi access points.	Medium, often supported by smartphones.	Low, only supported by specific devices

Table 1

The main components of ECG monitoring nodes.

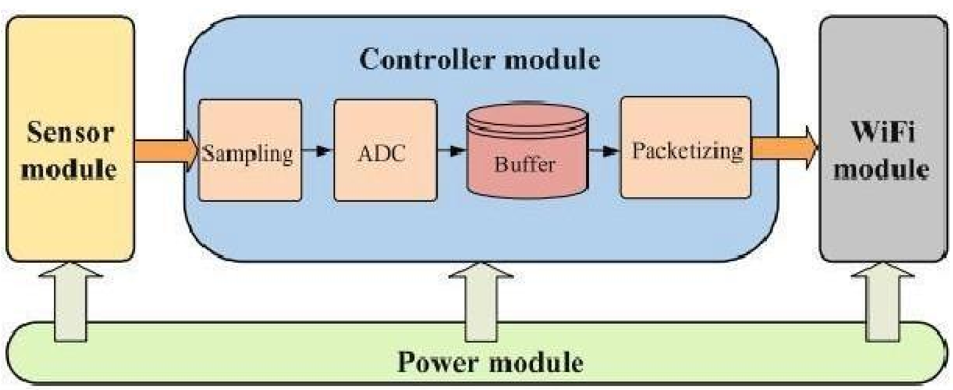

Figure 4

Chapter.4

4.1. the methodology used and the implementation of IoT-based monitoring system.

First let's have a look on the dataset we used(MIT-BIH:

The MIT-BIH Arrhythmia Database is a well-known dataset used for arrhythmia classification and research in the field of biomedical signal processing. It is part of the PhysioNet database, which provides a collection of physiological signal recordings for research purposes. The MIT-BIH Arrhythmia Database specifically contains electrocardiogram (ECG) recordings.

```
df.head()
```

	0	1	2	3	4	5	6	7	8	9	...	178	179	180	181	182	183	184	185	186	187
0	0.977941	0.926471	0.681373	0.245098	0.154412	0.191176	0.151961	0.085784	0.058824	0.049020	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.960114	0.863248	0.461538	0.196581	0.094017	0.125356	0.099715	0.088319	0.074074	0.082621	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	1.000000	0.659459	0.186486	0.070270	0.070270	0.059459	0.056757	0.043243	0.054054	0.045946	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.925414	0.665746	0.541436	0.276243	0.196133	0.077348	0.071823	0.060773	0.066298	0.058011	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.967136	1.000000	0.830986	0.586854	0.356808	0.248826	0.145540	0.089202	0.117371	0.150235	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 188 columns

Table 2

The MIT-BIH Arrhythmia Database is a well-known collection of electrocardiogram (ECG) recordings used for arrhythmia research. It is part of the PhysioNet database and contains 48 half-hour ECG recordings from 47 subjects, encompassing various arrhythmia types. These ECG recordings are available in digital format with beat annotations, crucial for arrhythmia classification research. Researchers often use this dataset to develop and evaluate algorithms for arrhythmia detection. However, they must adhere to ethical guidelines and data privacy regulations when working with medical data.

Now, let's look on the model prepared:

```
import tensorflow
from tensorflow import keras
from keras.models import Sequential
from keras.layers import Dense, Flatten
from keras import optimizers
import math


model = keras.models.Sequential()
model.add(keras.layers.Flatten(input_shape=X.shape[1:]))
model.add(keras.layers.Dense(50,
                             kernel_initializer="lecun_normal",
                             activation="selu"))
model.add(keras.layers.Dense(50,
                             kernel_initializer="lecun_normal",
                             activation="selu"))

model.add(keras.layers.Dense(5, activation="softmax"))

optimizer=keras.optimizers.SGD(learning_rate=1e-2, momentum=0.9)
model.compile(loss="sparse_categorical_crossentropy", optimizer=optimizer, metrics=["accuracy"])
```

This code snippet is an example of creating a neural network model using TensorFlow and Keras for a classification task. Here's a short explanation of each part:

1. Import Libraries: It starts by importing necessary libraries, including TensorFlow and Keras.

2. Create a Sequential Model: `model = keras.models.Sequential()` initializes a sequential neural network model. In a sequential model, layers are added one after the other.

3. Add Input Layer: model.add(keras.layers.Flatten(input_shape=X.shape[1:])) adds an input layer. It flattens the input data, which is expected to have a shape defined by `X.shape[1:]`.

4. Add Hidden Layers: Two hidden layers are added with 50 neurons each. These layers use the "selu" activation function and are initialized with "lecun_normal" weight initialization.

5. Add Output Layer: `model.add(keras.layers.Dense(5, activation="softmax"))` adds the output layer with 5 neurons (assuming it's a 5-class classification problem). The softmax activation is used for multi-

class classification tasks.

6. SpecifyOptimizer:`optimizer=keras.optimizers.SGD(learning_rat e=1e-2, momentum=0.9)` configures the optimizer for training. Here, Stochastic Gradient Descent (SGD) is used with a learning rate of 0.01 and a momentum of 0.9.

7. Compile the Model: `model.compile(loss="sparse_categorical_crossentropy", optimizer=optimizer, metrics=["accuracy"])` compiles the model. It specifies the loss function ("sparse_categorical_crossentropy" for multi-class classification), the optimizer, and the evaluation metric (accuracy in this case).

In summary, this code sets up a feed forward neural network for a classification task with input data that's flattened, two hidden layers with the "selu" activation function, and an output layer with softmax activation. It uses the SGD optimizer for training and compiles the model with the specified loss and accuracy metrics.

```
import keras.callbacks
early_stopping_cb = keras.callbacks.EarlyStopping(patience=10,
                                                  restore_best_weights=True)
#onecycle = OneCycleScheduler(math.ceil(len(X) / 32) * 32, max_rate=0.05)


history=model.fit(X, y, epochs=100,
          validation_data=(X_valid,y_valid),
          callbacks = early_stopping_cb, batch_size=32)# class_weight=class_weights)
```

```
Epoch 1/100
2189/2189 [==============================] - 5s 2ms/step - loss: 0.2088 - accuracy: 0.9442 - val_loss: 0.1471 - val_accuracy: 0.9609
Epoch 2/100
2189/2189 [==============================] - 4s 2ms/step - loss: 0.1409 - accuracy: 0.9611 - val_loss: 0.1239 - val_accuracy: 0.9676
Epoch 3/100
2189/2189 [==============================] - 4s 2ms/step - loss: 0.1216 - accuracy: 0.9661 - val_loss: 0.1121 - val_accuracy: 0.9705
Epoch 4/100
2189/2189 [==============================] - 4s 2ms/step - loss: 0.1102 - accuracy: 0.9699 - val_loss: 0.1082 - val_accuracy: 0.9686
Epoch 5/100
2189/2189 [==============================] - 4s 2ms/step - loss: 0.1020 - accuracy: 0.9718 - val_loss: 0.1105 - val_accuracy: 0.9698
```

The above image shows the training of the model is shown for the first five epochs.

Now looking at the output predicted by our model:

```
#Checking the model for a random input from the validation dataset
prediction_for_one = np.round(model.predict(X_valid)[0])
print("Prediction for entry number 0 is:",prediction_for_one)
```

```
Prediction for entry number 0 is: [1. 0. 0. 0. 0.]
```

For checking the output we first check the data at the zeroth position of the test data and the result was in the form of a numpy array (for example [1.0.0.0.0]

which symbolizes that 1 is present at the first position of the array that denotes that the input considered lies in the 3rd category that was ventricular).

Now let's check it for 10 entries:

```
#Checking the model for 10 random inputs
n=10
for i in range(n):
    r=ran.randint(1,17511)
    predictions = np.round(model.predict(X_valid)[r])
    print("Prediction for entry",r,"is:",predictions)
```

```
Prediction for entry 7075 is: [1. 0. 0. 0. 0.]
Prediction for entry 6286 is: [1. 0. 0. 0. 0.]
Prediction for entry 17279 is: [1. 0. 0. 0. 0.]
Prediction for entry 12424 is: [1. 0. 0. 0. 0.]
Prediction for entry 1667 is: [0. 0. 1. 0. 0.]
Prediction for entry 6383 is: [1. 0. 0. 0. 0.]
Prediction for entry 6258 is: [1. 0. 0. 0. 0.]
Prediction for entry 14643 is: [0. 0. 1. 0. 0.]
Prediction for entry 2760 is: [1. 0. 0. 0. 0.]
Prediction for entry 9401 is: [1. 0. 0. 0. 0.]
```

The output of 10 random entries which were taken from 10 random positions of the validation dataset is shown in the above image.

Now let's let the user decide how many entries he wants to check for getting the prediction:
Here the user wants to check the prediction for let suppose 5 entries so we use code given in the below image.

```
n=int(input("Enter number of entries into consideration:"))
for i in range(n):
    r=ran.randint(1,17511)
    predictions = np.round(model.predict(X_valid)[r])
    print("Prediction for entry",r,"is:",predictions)
```

```
Enter number of entries into consideration: 5
Prediction for entry 2506 is: [0. 0. 0. 0. 1.]
Prediction for entry 10227 is: [1. 0. 0. 0. 0.]
Prediction for entry 17361 is: [0. 0. 0. 0. 1.]
Prediction for entry 11179 is: [1. 0. 0. 0. 0.]
Prediction for entry 711 is: [1. 0. 0. 0. 0.]
```

For checking the output we consider 5 random test data which were taken from any random positions of the dataset and the result was in the form of a numpy array (for example [0.0.1.0.0])which symbolizes that 1 is present at the third position of the array that denotes that the input considered lies in the 3rd category that was ventricular).

So lets have a look on the output of the total dataset via a graph:

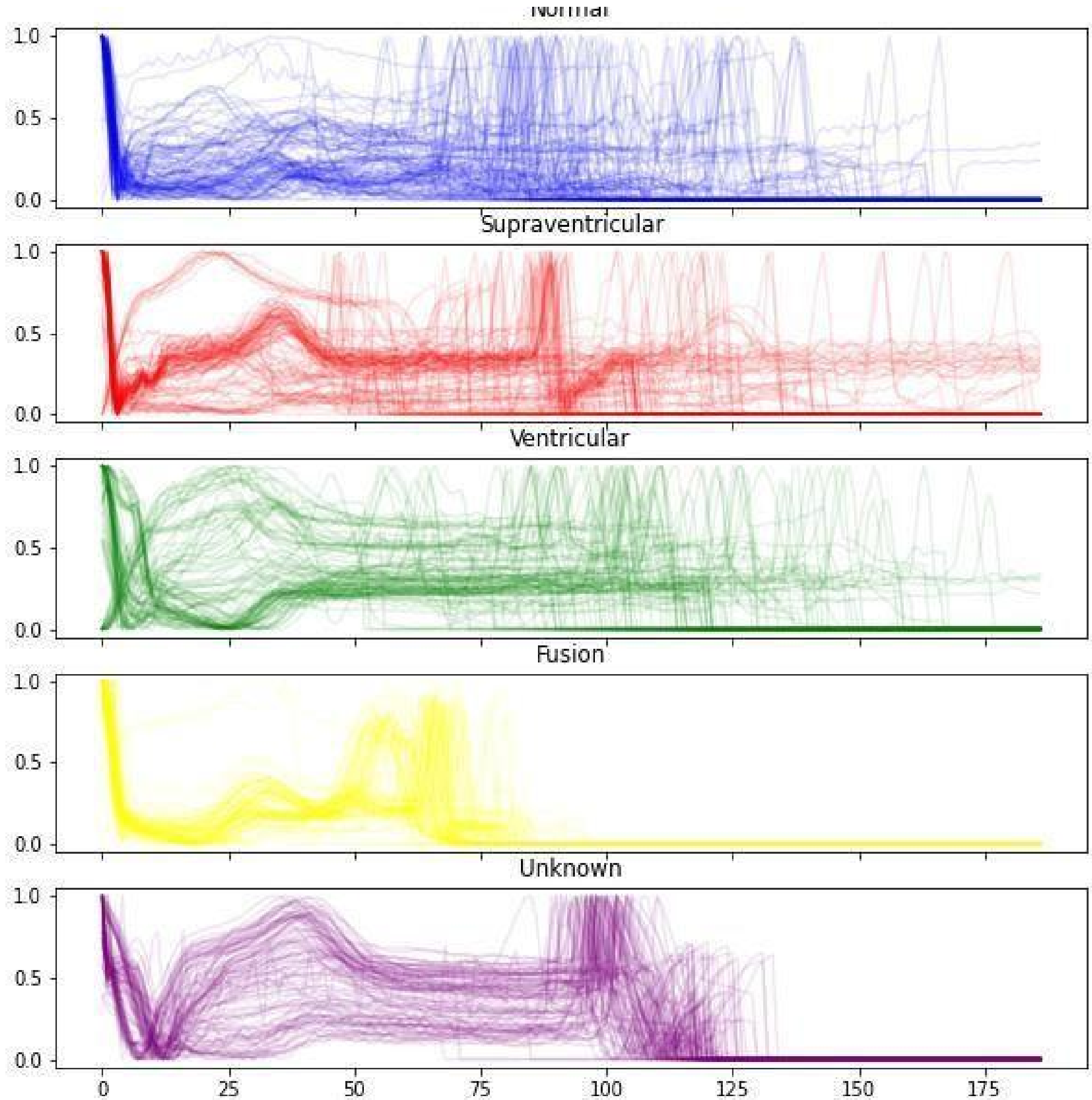

Figure 5

This shows the data classified into 5 different classes after predicting it from our model the 5 classes were:

- Normal

- Superventricular
- Ventricular
- Fusion
- Unknown

The graph above shows a plot of all the classes.

Patient ID	age	Time	Heart rate (bpm)	Arrhythmia classification	Alert in colours
001	75	8:23	75	normal	blue
002	82	15:30	88	ventricular	green
003	91	7:14	80	normal	blue
004	69	12:00	95	Superventircular	red
005	74	14:42	70	fusion	yellow

Table 3

Summary:

The research focuses on an IoT-based healthcare monitoring system tailored for elderly individuals, employing wearable ECG devices. The system's architecture includes data collection through these wearables, real-time monitoring, data analysis using machine learning, and user-friendly interfaces for both users and healthcare providers. Privacy and security are emphasized, and potential benefits include improved quality of life, early health issue detection, and reduced healthcare costs. Challenges are acknowledged, and the research demonstrates the potential to enhance elderly healthcare through innovative technology.

Conclusion:

In conclusion, the study demonstrates the potential of the IoT-based smart healthcare monitoring system using an ECG wearable device to revolutionize elderly care and improve healthcare outcomes.

By harnessing the power of IoT technology and wearable devices, healthcare professionals can provide personalized care, detect and manage arrhythmias effectively, and empower the elderly to maintain their well-being.

This research lays the foundation for future advancements in healthcare technologies for the elderly population, fostering collaboration and innovation in this critical area of healthcare.

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