From Wearable Device to OpenEMR: 5G Edge Centered Telemedicine and Decision Support System

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Keywords: IoT, 5G, Wearable Communication, Mobile Edge Computing, Cloud/Edge, Artificial Intelligence, OpenEMR, Atrial Fibrillation.

Abstract: The Internet of Things (IoT) is developing rapidly, with applications across various fields and industries. In healthcare, wearable devices and the Internet of Medical Things (IoMT) have tremendous potential for improvements in the quality of telemedicine and producing medical insights and discoveries. Massive Machine Type of Communication (mMTC) in 5G further reduces latency and enhances connectivity in supporting wearables and IoMT, which provides a promising infrastructure for telemedicine. Although cloud computing reduced the computation and storage load on wearable devices significantly, the massive amounts of data produced by wearable devices and IoMT introduce challenges for latency and storage in the cloud. Additionally, applications will need to navigate the regulation and compliance laws related to handling sensitive and private health data, adding complexity to the accessibility and distribution of such innovations. This study first examined the current frameworks for wearable devices in 5G telemedicine implementation and discussed existing challenges. We then proposed a multi-layer 5G mobile edge computing (MEC) centered telemedicine design that dynamically integrates wearable devices with OpenEMR electronic health records system. The multi-layer design includes the IoT layer, MEC layer, Network layer, and Application layer. Near-real-time artificial intelligence (AI) components and electronic health record (EHR) instances are automatically deployed to and removed from the MEC layer to keep cloud computing capabilities closest to the infrastructure edge when a user is associating and disassociating with a 5G bases station, respectively. Lastly, we demonstrate a proof of concept by designing and implementing a system for detecting atrial fibrillation (Afib) over the design we proposed. Afib detection has the character of predictable trending, random occurrence of adverse events, and urgent care needed when happening. These characters requires a low latency, large range coverage and high throughput infrastructure. The proposed approach provides a distributed solution addressing the requirements for Afib detection. This approach can be used for other applications in telemedicine beyond Afib detection.

1 INTRODUCTION

The Internet of Medical Things (IoMT) improves multiple aspects in healthcare, including asset management in hospitals, patients' vitals remote monitoring, treatment compliance monitoring, smarter medication, assisted living, and telemedicine, etc. In IoMT, various medical devices or sensors, smartphones, imaging devices, personal digital assistants, and electronic health records (EHR) integrate and act as core parts of the system (Latif et al., 2017). At present, wearable biomedical/health devices are developing rapidly, offering advantages such as the continuity of medical services and real-time capture of health data. Wearable devices consist of sensors placed on the body to capture and monitor data. Ranging from fitness trackers and smartwatches to augmented reality (AR)/virtual reality (VR) glasses, wearable devices in healthcare collect data on a variety of measures such as heart rates, sleeping cycles, locations, and steps, etc. (Haghi et al., 2017). Wearable devices offer easier access, mobility, and convenience for users and medical personnel and have already demonstrated applications in fall identification and prevention, physical activity monitoring, sports medicine, patient education, diabetes care management, and more (Min Wu and Jake Luo, 2020). The emerging and integration of artificial intelligence (AI) and machine learning (ML), big data, and IoT has enhanced the degree of intelligence of wearable devices

Wang, Y., Tran, P. and Wojtusiak, J.
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DOI: 10.5220/0010837600003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 5: HEALTHINF*, pages 491-498
ISBN: 978-989-758-552-4; ISSN: 2184-4305

(Zhang et al., 2020). Combined with 5G technology, these technologies have the potential to revolutionize the healthcare industry, facilitating exciting research and development towards this direction in the field of telemedicine (Latif et al., 2017).

In current implementations of telemedicine over the IoMT monitoring in the both Long Term Evolution (LTE) and Wi-Fi system, three different types of operation exist. The first category is wearable devices to collect health data and connect to the cloud in the data network. In the cloud, AI may take place to provide diagnostic or predictive analysis for physicians or patients, and decision-making support for treatment or management (Zhang et al., 2020). The second category is for IoMT devices to run in an accessory mode and tether to a local connected mobile device for data storage and processing. An IoMT in the accessory mode is connected to a mobile phone through Wi-Fi or Bluetooth for raw data transmission, and most of the data analysis is processed on the mobile phone. The limitation of this model is the requirement of mobile phone presence within Wi-Fi/Bluetooth coverage, which is usually within 10 meters. The third category is for wearable devices to perform in standalone mode. For IoT in standalone mode, the connection to a base station is through cellular technology directly, and local data analysis occurs without any connection to the cloud. However, computing and energy limitations continue to hinder these devices' ability to process data locally. Additionally, there are limitations in hardware cost, size, and the number of devices able to connect to the base station at a given time.

Wearable devices are limited by power and storage constraints, hardware size, and computing capability and are subject to high hardware costs. Thus, most current IoMT devices adopted the second and third category model by sending their data to mobile devices with more computation power or further connecting to the clouds for processing (Sun et al., 2018). Existing technology such as LTE-Advanced and Wi-Fi are gradually evolving to fit the needs of wearable communication in telemedicine. However, besides the aforementioned limitations, telemedicine over the IoT will generate an unprecedented amount of data requiring transmission, analysis, and storage and face challenges such as security, latency, and connectivity under the current LTE infrastructure.

Furthermore, IoMT devices handles sensitive and private data, but the current regulations and policy of data generated by wearable data are not sufficient. Unlike traditional health or medical data required to comply with HIPAA regulations, HIPAA protection does not extend to wearables and Apps. Integrating wearable devices with regulated EHR systems like OpenEMR offers advantages of HIPPA protection and the creation of new applications. The cyber security of healthcare data is more stringent than other areas, and health data is frequently the target of cybercriminals. Despite several digital transformations, the ”healthcare industry remains highly susceptible to compromises of valuable health information” (Chernyshev et al., 2019). Security breaches and data leakage not only result in reputation and/or financial harm for the healthcare provider/facility but may also threaten patients' well-being or health. Weak health data protection and security measures may result in detrimental and costly consequences, such as identity theft, fraudulent insurance claims, ordering drugs for resale, or even harmful or fatal patient care.

According to a study by Shahriar et al., EHR applications in general ”suffer from implementation level vulnerabilities impacting HIPAA requirements,” and open-source EHR systems are not excluded from such vulnerabilities (file manipulation, SQL injection, possible flow control, etc.) (Shahriar et al., 2021). However, open-source solutions (OSS) have already been gaining traction in the scientific hardware community for their evidence of cost-effectiveness, and technological sophistication (Pearce, 2017). In the healthcare industry, open-source EHR systems are gaining more attention as adoption rates are increasing, helping to overcome barriers such as excessive cost and lack of interoperability (Latif et al., 2017). Besides its cost-effectiveness, open-source EHR systems offer more flexibility, less vendor lock, and increased control over data; customers utilizing OSS have more say and control in how data is stored and used, as compared to proprietary systems. OpenEMR is a popular and widely used open-sourced EHR system and one of the few OSS EHR systems certified by the Office of the National Coordinator (ONC) of the US Department of Health and Human Services.

An important application area of the wearable device is cardiology disease detection. Atrial fibrillation (Afib) is a quivering or irregular heartbeat (arrhythmia) that can lead to blood clots, stroke, heart failure, and other heart-related complications. At least 2.7 million Americans are living with Afib. Its prevalence is 1- 2% of the general population, and it is associated with increased risk of mortality and morbidity (Behar et al., 2017). Physicians' review of the patient's signs and symptoms, medical history, and physical examination including Electrocardiogram (ECG), Holter monitor, Event Recorder, Echocardiogram, Blood tests, Stress test, and Chest X-ray are required for Afib diagonisis. Asymptomatic Afib is more difficult to detect and can go undiagnosed for extended periods of time. Undetected Afib poses more risk to the patient and may have devastating consequences if diagnosed too late. Wearable devices are a non-invasive, convenient way to monitor cardiac rhythms, possibly aiding in the earlier detection of asymptomatic Afib. Afib detection through wearable devices has the characters of temporal based trending, adverse event random occurrences, and urgent care needed when it happens. These three characters determine stringent requirements of a desired solution: seamless geographic coverage, complex computation support, and low latency, secure connection. Our proposed 5G edge-centered telemedicine and decision support system fits the use case scenario and provides a reliable and scalable solution. Thus, as the proof of concept, we have designed and implemented an Afib detection model deployed to the 5G edge-centered system built and connected to an OpenEMR system. An extension to other medical models can easily be added to it.

2 SYSTEM DESIGN

2.1 5G Network Framework for Telemedicine

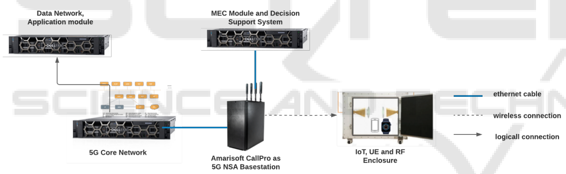

Figure 1: Hardware Implementation.

Despite the fact that the advantages on physical coverage of cellular network, IoMT devices in telemedicine generates a massive amount of data, some of which may require rapid analysis - such immense and diverse data needs are not supported by the current 4G/LTE infrastructure (Li, 2019). Latency, bandwidth, quality of service (QoS), reliability, and a massive number of connectivity are just some of the challenges associated with IoT on the current infrastructure. Moving forward, telemedicine will need support for a massive number of devices, standardization, energy-efficiency, device density, and security (Ahad et al., 2020). To build effective alarm or decision support models, secure exchange of data across various platforms is required. The 5G network is highly attractive in these regards due to its high speed, massive number connection characteristic, low latency, flexibility in Radio Area Network (RAN), and security enhancement due to network slicing for verticals. Especially, mMTC networks enable the long battery life,low latency, and high coverage density with support up to a million devices in a square kilometer which are crucially for massive scale, ultra-low-cost hardware.

The implemented hardware platform depicted in Fig.1 consists of a User Equipment (UE), Base Station (BS), Core Network (CN), MEC. The detailed information for the setup can be referred to at (Wang et al., 2021).

2.2 MEC Centered Design

Due to wearable devices' computing and energy constraints, telemedicine applications based on IoMT cannot be executed locally on the terminals, nor should all health data be uploaded to the cloud for analysis either. Deploying cloud computing in the current framework with massive amounts of data generated by IoT will introduce high data analysis latency and storage costs, placing tremendous pressure on the cloud and causing challenges to the network bandwidth and end-to-end delay (Zhang et al., 2020). IoT devices and cloud computing alone cannot fulfill the demands of wearable communication. Instead, mobile edge computing (MEC) should be utilized in tandem with IoT technology, artificial intelligence, and cloud computing components.

MEC has characteristics of decentralization, data localization, and low latency. MEC allows real-time intelligent decision-making by reducing network delay and transmission costs during the classification and assignment of QoS. By removing most of the computing needs of the IoT devices, IoT devices become 'lighter,' essentially only collecting and transmitting data and performing simple computations. This may save on hardware costs and improve the battery usage and performance speed of the wearable device. Utilizing a MEC layer also reduces strain on the cloud. The MEC Edge layer does not eliminate the need for a cloud computing layer, but rather the two layers communicate and work together to enhance the capabilities of the proposed system. MEC layer handles the pre-processing of data and data analysis before transmitting data to the cloud for storage and further management. The cloud computing layer performs big data analysis, mining, and sharing to train and upgrade the AI algorithm model that gets pushed to the edge nodes.

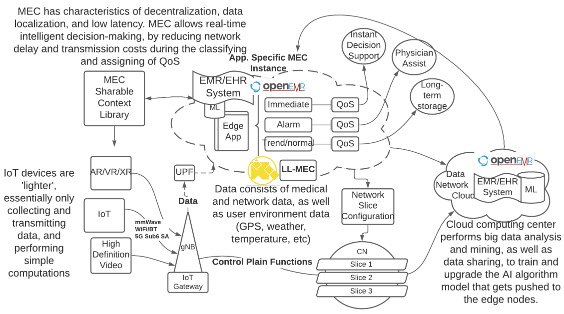

Figure 2: Proposed Telemedicine System Design.

2.3 OpenEMR-based Distributed System

A primary concern related to wearable device usage relates to the security and governance of data sharing. IoMT generated medical data storing in the centralized storage system leads to a single point of failure, privacy, and security concern (Kumar and Tripathi, 2021). HIPAA protection not extending to wearables and Apps creates another area of concerns for personal health data privacy and security. Wearable data should be stored in secure, regulated personal health clouds or electronic health records with opt-in systems, advance security measures, and transparent privacy policies in place (Bayoumy et al., 2021) in the desired scenario. In the proposed system design, the data storage challenges are addressed by a distributed open source EMR based architecture.

OpenEMR is a widely used open-sourced software for electronic health records and medical practice management solutions, utilized in more than 100 countries worldwide with an estimated usage by 100,000 medical providers serving greater than 90 million patients internationally. OpenEMR leverages one of the largest communities of users, volunteers, and contributors dedicated to developing and maintaining its software, making it a superior alternative to proprietary counterparts and more comprehensive than emerging applications. OpenEMR is ONC Certified as a Complete EHR, having achieved complete Meaningful Use certification with Release 5.0 and beyond. Compared to other popular open-sourced EHR systems like GNU Health, OpenMRS, and OSHERA VistA, OpenEMR has the highest functionality and is among the top for performance (Purkayastha et al., 2019). Utilizing OpenEMR supports interoperability and industry standards and reduces the burden of seeking new regulation compliance and additional security measures by making use of a popular existing electronic health records platform. According to its website, it offers HIPAA-friendly security features such as database connection encryption support, fine grained access control objects, the ability to encrypt patient documents, and industry-standard password hashing.

As with other open-sourced software, one of the most significant benefits of OpenEMR in the healthcare industry is that it is free and can easily be downloaded from one of the repositories (Syzdykova et al., 2017). Unlike proprietary electronic medical records systems, smaller health settings can utilize and adapt OpenEMR to their needs. Open-sourced systems are flexible, cost-efficient, offer freedom to try before buying and avoid vendor lock-in. These advantages help relieve health disparities by allowing for greater distribution and accessibility of electronic health records worldwide.

2.4 Proposed System Architecture

Our proposed system integrates 5G technology with wearable devices to capture physiological indicators in real-time and send them to the edge and cloud. Physiological indicators may include EKG data, heart rate, oxygen saturation, and other measures captured via wearable devices. As shown in Figure 2, four modules constitute the system: IoT module, MEC module, Network module, and Application module. Protocols of communications between the modules are defined. A layer structure is used for the module design. Each module is an abstract virtual machine that provides a cohesive set of services through a managed interface (Bass et al., 2013). With this design, layers imbue a system with portability through the ability to change the underlying computing platform, network, hardware, or application update. The connection among the four modules is shown in Figure 3.

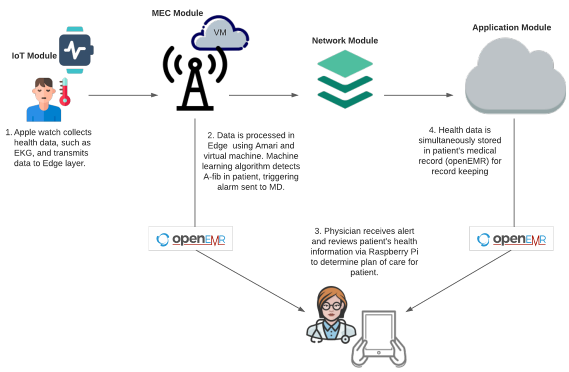

Figure 3: System Component Connection.

The IoT Module is responsible for the acquisition of health-based data and relative ambient data. It is also responsible for transmitting the data to the infrastructure, defined by the modules' protocol. The category of data acquisition affects the selection of data transmission. The physical layer data transmission attribution data is also recorded for security and acquisition anomaly detection.

The MEC Module is the main component for deploying OpenEMR instances, anomaly detection, real-time decision support, long-term data storage, and data merging to centerized data storage in the cloud. When a user is an associate with a gNodeB, the OpenEMR instance will be deployed on MEC with user customization and relevant user data sync up from the center OpenEMR location. Acquisition data from these patients will be transmitted to and analyzed at the MEC in real-time manners. The system will perform instant decision support, physician assistant alarm, and plan for long-term data backup based on the results and resources requested. When a user disassociate with the base station, a clearing up process will be launched to release the resources in the MEC and hand over to the next base station. This edge based design significantly reduce the latency by bring the data analysis closer to users and avoiding the routing to core network and enables the real-time decision support. Firewall and security features located on the MEC provide security enhancement to all instances.

The Network Module includes data transmission from gNB/MEC to the core network. Traffic security and efficiency is the primary responsibility for network module. The network data are also used for anomaly detection combined with acquisition data. Network slicing are used for directing the traffic, isolating context, and enhance network performance.

The Application Module is responsible for centralized application data management in the cloud. Long-term analysis and trending, non-real-time machine learning models are running in the application module.

2.5 System Implementation and Automation

To test the system design and implementation, a Apple Watch Series 6 was selected as the wearable device during the implementation. ECG, heart rate, and blood oxygen data were collected. This data from the Apple Watch is sent via 5G technology to the MEC layer, where pre-processing and analysis occur to detect atrial fibrillation. Studies suggest wearable devices, like the Apple Watch, may be effective and convenient tools to diagnose asymptomatic or symptomatic atrial fibrillation and/or other arrhythmia (Bayoumy et al., 2021). Using artificial intelligence, MEC determines the classification of health data as either 'trend/normal,' 'alarm,' or 'immediate' and assigns the appropriate QoS resources. If abnormalities are detected, and 'immediate' or 'alarm' classifications are triggered, MEC can quickly alert 911 services or medical personnel and the user; this is the benefit of edge computing - tasks are performed at the edge of the network, reducing both the distance of data transmission and communication delay. Therefore, critical decision-making tasks can occur in a real-time manner. OpenEMR software was installed on a Raspberry Pi device and handles the cloud's storage and management of health data. Raspberry Pi is a low-cost computer that acts as the server in this design, continuously running script to handle Apple Health files and pre-process then process data for insertion into the OpenEMR database. The MEC layer works alongside the cloud, pulling relevant data from existing records in OpenEMR to enhance its artificial intelligence and pushing data to the OpenEMR database in the cloud for long-term storage and further management. The transmission of data between the Apple Watch and the MEC layer and to and from the cloud is performed via 5G technology to ensure high QoS, low latency, massive connectivity and enhanced security. In Figure 4, the flowgraph of the system implementation is shown.

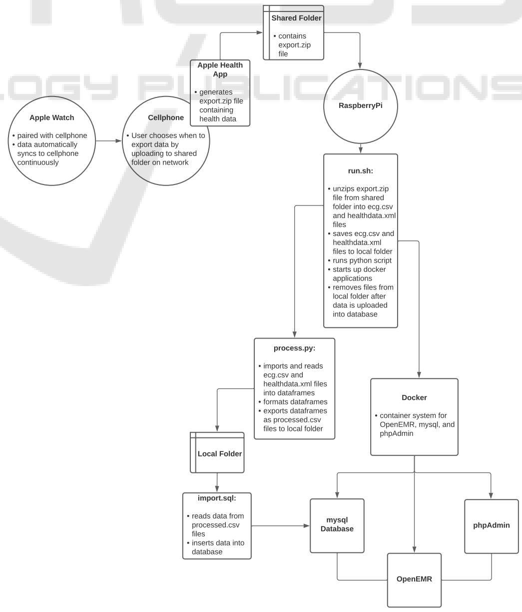

Figure 4: Apple Watch Based IOT connecting to 5G Edge System Automation.

3 SYSTEM PROOF OF CONCEPT: ATRIAL FIBRILLATION DETECTION IN 5G TELEMEDICINE NETWORK

In this session, we have designed and implemented Atrial fibrillation (AF) detection system based on the previously discussed framework. The model is trained using data from single-lead ECG plots generated by AliveCor devices. ECG recordings were collected using the AliveCor device and made available in (Clifford et al., 2017). A database of 8528 single-lead ECG and their annotations were used for training and testing. Four categories of ECG recordings were present in the databases: atrial fibrillation (A), normal sinus rhythm (N), other rhythms (O), and noisy recordings. Using this as proof of concept in the proposed system, we focused on the detection of type A: atrial fibrillation detection.

This is a proof of concept for the 5G Edge Centered Decision Support System with OpenEMR For Wearable Devices. Figure 5 shows the flowgraph of the Afib detection system itself. Figure 6 offers the integration and deployment of the system shown in Figure 5 to the 5G Edge Centered Telemedicine and Decision Support System. When a user device associates to the 5G network, the gNB that the device is associated with or in the process of handing over to will start creating the OpenEMR instance with the associated patient records and the Edge App instance. Relevant trained non-near-real time models are transferred from the data network to MEC on Edge App. As shown in Figure.6, Feature extraction, feature-based Afib detection model, R Cycle sample-based Afib detection model will be transmitted to the Edge app from the data network to MEC. Context data, including location, weather, road condition, etc., will also be accessible by the Edge App. As patient data are transmitted to the gNB and MEC, the data will be instantly processed by feature extraction, Afib model detection, and generating the results. One of the three potential types of results will be generated, Afib Detected, Low Detection Confidence, and normal result. The Afit detected result needs immediate attention, with an alarm being sent with the highest QoS. The low detection confidants need a physician's decision and assist with the second level of QoS. The normal results will be saved for long-term monitoring. As the patients disassociate with the current gNB(A) or handover to the next gNB(B), the process will be relaunched in the next gNB(B); meanwhile, the existing patient data and Edge App will be removed from the current gNB(A).

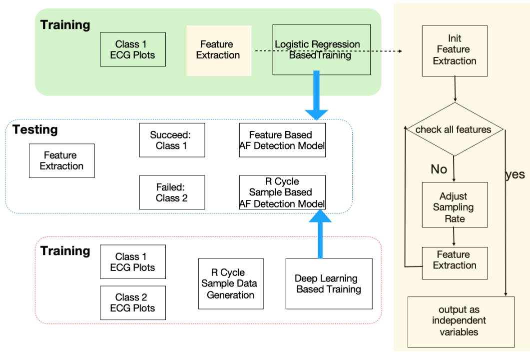

Figure 5: Flowgraph of Afib Detection.

Preprocessing is needed to extract features from ECG plots. The cardinal features of atrial fibrillation are an absence of coordinated depolarization of the atria (absence of P waves on the ECG) and unpredictable depolarization of the ventricles (no pattern to R wave occurrence on the ECG). As shown in Figure 1, The P wave represents the depolarization of the left and right atrium and corresponds to atrial contraction, and the QRS complex includes the Q wave, R wave, and S wave.

In general, some features are used to describe ECG medically. The commonly used features are ECG Signal quality, Heart Beats / Cardiac Cycles, and Heart Rate Variability (HRV). In HRV, there are a set of parameters used to describe the ECG signal, including CVSD, HF, LF, RMSSD, Shannon, Power, Triang, ULF, VHF, VLF, cvNN, madNN, mcvNN, meanNN, medianNN, pNN20, pNN50 and dNN. These are the basic features we used in our model.

8528 data samples are used for analysis. The length of each data sample is 9,000 to 18,000, recording 30 seconds to 60 seconds of ECG. Figure 7 shows an element overlap illustration of when aligning with the peak of the R wave of a normal ECG. Figure 8 shows an element overlap illustration of when aligning with the peak of the R wave with AF detected.

For the data processing part, we first categorize ECG plots by extracting essential Cardio and HRV features from the ECG. If we can extract them, the ECG plots are categorized as class 1. If the features are not extractable due to the low quality or abnormal ECG, then the plots are categorized as class 2. Here, we use a python library called NeuroKit (Dominique Makowski,) for the feature extraction.

Results show that there are 1.2% class 2 ECG plots and 98.8% class 1 ECG plots. For class 1 ECG, we use 27 features extracted from Table 1 to prepare for the data. We can reach an F1 score of 0.76.

For class 2 ECG plots, we need to take a closer look at them. Among the 104 ECG plots, there are

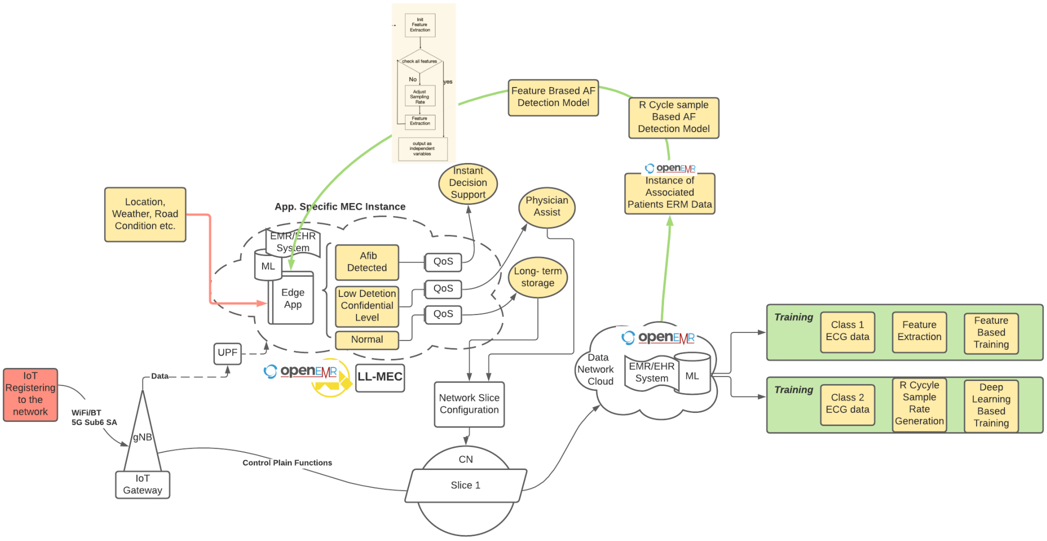

Figure 6: Flowgraph of Afib Detection Over the Proposed Telemedicine System.

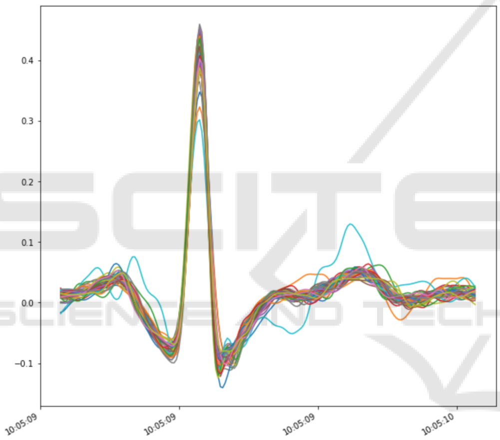

Figure 7: Normal ECG R Wave Overlap Illustration.

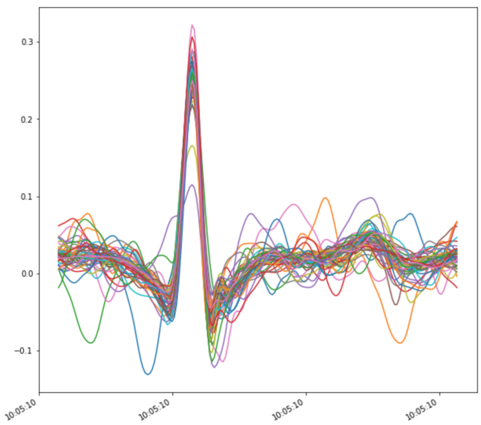

Figure 8: ECG with AF R Wave Overlap Illustration.

5% normal ECG, 13% AF, 66% Other Abnormal, and 15% noise. 95% of them are abnormal ECG plots. This will explain the reason why the features can be extracted. For the 5% normal ECG, the quality of the ECG plots also shows low. The experimental results are shown in Figure 10. The real-time AFib de-

	Optimal Recall Threshold = 0.12	Optimal F1 Threshold = 0.35
F1	0.708	0.760
Precision	0.664	0.750
Recall	0.849	0.772
Accuracy	0.886	0.939
Training AUC	0.925	0.925
Testing AUC	0.932	0.932

Figure 9: Result of The AFib Detection Model.

tection from the apple watch is validated in our system. Depending on the watchOS version, two types of data sources are supported - a pdf format image and the raw data file. As shown in Figure 10, when the available data source is a pdf image, our system converted it into an accepted data format for the detection model.

4 CONCLUSIONS

This study proposed a 5G mobile edge computing (MEC) based telemedicine design integrating wearable devices with an Open-EMR electronic health records system. This design has multiple modules: the IoT module, MEC module, Network module, and Application module. A near-real-time artificial intelligence (AI) components and electronic health record

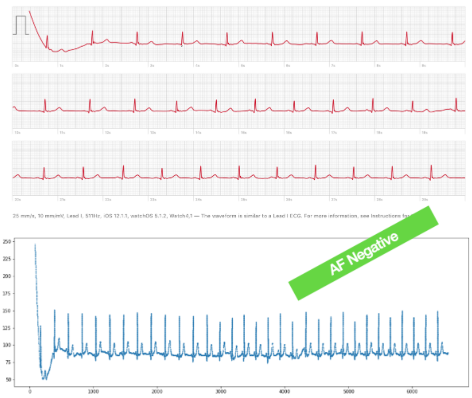

Figure 10: Result of Apple Watch ECG image detection.

(EHR) instances are deployed to the MEC layer, enabling cloud computing capabilities on the network edge. 5G technology further improves the latency and connectivity necessary to support wearables and IoMT in telemedicine. A proof of concept implementation of atrial fibrillation (Afib) detection with frequency predictable by trending, adverse event random occurrence, and urgent care needed when happens are evaluated. Future work includes applications in telemedicine beyond Afib detection and further development of the telemedicine work with mmWave and integration with other technologies.

ACKNOWLEDGEMENTS

This work was funded by the Commonwealth Cyber Initiative (CCI), research, innovation, and workforce initiative of the Commonwealth of Virginia.

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