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INTEGRATION OF INTERNET OF THINGS AND HEALTH RECOMMENDER SYSTEMS

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INTEGRATION OF INTERNET OF THINGS AND

HEALTH RECOMMENDER SYSTEMS

A Project

Presented to the

Faculty of

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In Partial Fulfillment

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by

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ABSTRACT

The Internet of Things (IoT) has become a part of our lives and has provided many enhancements to day-to-day living. In this project, IoT in healthcare is reviewed. IoT-based healthcare is utilized in remote health monitoring, observing chronic diseases, individual fitness programs, helping the elderly, and many other healthcare fields. There are three main architectures of smart IoT healthcare: Three-Layer Architecture, Service-Oriented Based Architecture (SoA), and The Middleware-Based IoT Architecture. Depending on the required services, different IoT architecture are being used. In addition, IoT healthcare services, IoT healthcare service enablers, IoT healthcare applications, and IoT healthcare services focusing on Smartwatch are presented in this research. Along with IoT in smart healthcare, Health Recommender Systems integration with IoT is important. Main Recommender Systems including Content-based filtering, Collaborative-based filtering, Knowledge-based filtering, and Hybrid filtering with machine learning algorithms are described for the Health Recommender Systems. In this study, a framework is presented for the IoT-based Health Recommender Systems. Also, a case is investigated on how different algorithms can be used for Recommender Systems and their accuracy levels are presented. Such a framework can help with the health issues, for example, risk of going to see the doctor during pandemic, taking quick actions in any health emergencies, affordability of healthcare services, and enhancing the personal lifestyle using recommendations in non-critical conditions. The

proposed framework can necessitate further development of IoT-based Health Recommender Systems so that people can mitigate their medical emergencies and live a healthy life.

ACKNOWLEDGEMENTS

With all my heart, I would like to express my appreciation to Dr. Nasrin Mohabbati and Dr. Conrad Shayo for encouraging me to develop my project. I am also grateful to have my supportive family and friends who have been there for me no matter what. There were ups and downs during the project timeline, and I am proud of myself for getting through all the bitterness and sweet moments. Along with this project, I am excited to go to the next chapter of my life with more adventures and experiences.

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CHAPTER ONE:

INTRODUCTION

“The goal is to turn data into information, and information into insight.”- Carly Fiorina

With the advent of the 4th industrial revolution and the development of 5G technology, the Internet of Things (IoT) is increasingly being used in our daily lives. For example, the importance of IoT in healthcare has recently risen due to COVID-19 pandemic around the world. It is expected that people will receive sufficient medical help and improve their quality of life due to the use of IoT in the medical field (Islam et al., 2015). IoT-based healthcare systems are being used in enhancing remote health monitoring, personal fitness programs, monitoring chronic diseases, looking after the elderly people, and many other medical fields.

Embedded prediction and intelligence capacity in IoT devices enables Remote Patient Monitoring (RPM), thus notifying patients about impending emergencies before they turn into severe health problems (Ahmed & Kannan, 2021). According to a study conducted by Center of Connected Health Policy “50% of the readmission rate is reduced by 30 days after using remote patient monitoring (RPM) for heart failure patients” (Nasrullah, 2021). Another study conducted by the Consumer Technology Association (CTA) showed that 49% of patients had improved medical outcomes with employment of RPM and 42% of patients took more ownership in health after using RPM (Pennic, 2019). In addition, the Centers for Medicare and Medicaid Services has found out that using RPM in Chronic Care Management programs decreased readmissions of patients (Schurrer et al., 2017).

Remote Monitoring is a technology that assists in patient care. It can collect and use a patient's biometric information such as blood pressure, glucose levels, and oxygen saturation and then analyze the health data to transmit to their healthcare providers (Hemanth et al., 2021). RPM accumulates patient's biometric data from wearable devices, patch-based sensors, Bluetooth biometric devices, Smartphones, etc. Therefore, integration of IoT and RPM systems lets users track their health condition. The ALTITUDE study discovered that 50% of mortality rates in between one to five years decreased for patients who had remote monitoring devices compared to patients who had in-person medical checkup (Powell et al., 2013). Moreover, the outbreak of COVID-19 has led to people paying more attention to RPM and IoT in healthcare, since it was hard to see a doctor since the virus has contagiousness. Recently, RPM became standard care to the patients who have implantable cardiac devices (Slotwiner et al., 2015).

Problem Statement

According to the Centers for Disease Control and Prevention (CDC) report, 41% of U.S. adults delayed or avoided healthcare treatment because of concerns of COVID-19 in 2020, this included 12% of urgent care patients and

32% of routine care patients (Czeisler et al., 2020). Also, the CDC reported that emergency visits for taking care of heart attack, stroke, and hyperglycemic crises have declined since the beginning of the pandemic situation. This medical situation would cause a more fatal crisis in public health. Avoidance of urgent care and routine care could diminish a patient's chance to manage their health conditions, and even further, the detection of diseases. Therefore, a contactless healthcare system should be more actively used on a daily basis. Utilizing an AI based healthcare system, IoT, and wearable devices could be the next chapter of healthcare. It is critical for people to take care of themselves to prepare for another situation similar to a pandemic. Throughout the COVID-19 pandemic, we have been made aware of the importance of contactless healthcare treatment. It is possible that we could encounter another pandemic which made meeting others dangerous because of the contagious virus.

Also, some diseases require immediate health treatment, such as a stroke, heart attack, and appendicitis. Anyone is susceptible to these time sensitive diseases, and they can happen anytime. The most important thing to prevent those diseases is to keep track of any symptoms and connect to a medical center right away when the symptoms appear. Using medical IoT sensors shows a patient's vital signs which are blood cholesterol, heart rate, blood pressure, and other biological data depending on the patient’s installed sensors (Akhbarifar et al., 2020).

In addition, the main problem of healthcare in the United States is affordability. The study conducted by Kaiser Family Foundation in 2019 discovered that 29% of Americans decided not to take their medication at the doctor's direction because of the cost of the prescription (Leonhardt, 2020). The overall studies implied that we need to develop affordable devices to keep track of personal health conditions. Therefore, it is important to study this project to allow reduction of doctors visit costs and enhance the quality of healthcare (Akmandor & Jha, 2017). Therefore, people could prepare for an emergent medical situation and acquire knowledge about their health condition and that treatment that is needed.

According to Gallup (2019), “25% of Americans report that they have encountered medical treatment in a delay due to the medical cost” (Saad, 2021). In addition, another study conducted by the American Cancer Society (2019) found out that “56% of Americans have experienced medical financial difficulties” (American Cancer Society, 2019). Those two studies implied that many Americans cannot get medical treatments in time because of the medical cost. The utilization of IoT can decrease the cost of medical treatment. In addition, people can keep track of their health before severe diseases occur.

Considering all the above problems and challenges, this project will mainly be focused on 1. how IoT would help to monitor personal health and 2. how IoT integration with the Health Recommender Systems can enhance immediate attention to the health conditions and affordability of healthcare by personal recommendations.

Purpose

The purpose of this project is to present an overview of Data, Artificial Intelligence (AI), Internet of Things (IoT), Internet of Medical Things (IoMT), Mobile Health (mHealth), Wearable devices, Recommender System, and Health Recommender Systems as well as how such technologies can play an important role in fast and affordable healthcare services. Also, the objectives of the project are to highlight how individuals can manage their health through IoT and how IoT and Health Recommender Systems integration can provide more advanced health treatment.

Research Questions

This study aims to show how modern technology can be utilized for personalized health-related recommendations. Therefore, people can manage their personal health on a daily basis before critical medical emergencies happen. It also helps to take quick action in case of emergencies. Following are the research questions that will be addressed in this study.

- What healthcare services can be provided by Internet of Things?

- What Internet of Things healthcare applications have been developed for people?
- How do Health Recommender Systems work?
- What kind of machine learning algorithms are used in Health Recommender Systems?
- How can recommender systems be used in the healthcare sector?
- How can integration of Internet of Things and Health Recommender Systems improve responsiveness in identifying and treating health issues?

Structure

This project is organized as follows: In Chapter 2, literature and past studies in the related topics are reviewed. In Chapter 3, Internet of Things in smart healthcare is discussed with architecture of smart IoT healthcare, IoT healthcare services, and IoT healthcare applications. In Chapter 4, the Health Recommender Systems using machine learning algorithms are reviewed. In Chapter 5, a framework of IoT-based Health Recommender Systems is suggested with a case study that is implemented by using Python to show evaluating accuracy of machine learning algorithms, the important health parameters of heart diseases, and correlation between the features of heart diseases. Chapter 6 discusses conclusion remarks and the future work.

CHAPTER TWO:

LITERATURE REVIEW

To discuss the integration of Internet of Things (IoT) and Health Recommender Systems, it is critical to know how previous works have been done and set the starting point. Therefore, following concept represents: Data, Artificial Intelligence (AI), Internet of Things (IoT), Mobile Health (mHealth), Wearable devices, Recommender System, and Health Recommender Systems for discussing the integration of IoT and Health Recommender Systems.

Data

Data in healthcare is generated in enormous quantities on a daily basis. With that being said, the utilization of big data in healthcare can improve healthcare treatment so the patients will decrease the medical impact on their body. Generally, big data analysis consists of 6 V's: volume, variety, velocity, veracity, validity, and volatility (Jagadeeswari et al., 2018). Among the characteristics, the three main features are volume, variety, and velocity. Volume shows the quantity of the information to attain the respective goals. Variety refers to the type of data that can be stored and analyzed. For example, variety in big data can be videos, sounds, text, etc. Velocity tells the speed of when the big data is generated or delivered to another (Kaur & Mann, 2017).

Artificial Intelligence (AI)

Artificial Intelligence (AI) is a technology which immerses human intelligence so that computers have perception ability, learning ability, and an ability to understand natural language through the computer programs (Kaur & Mann, 2017). AI systems rely on their input data. AI in healthcare supports the patient's health monitoring with, for example, vital checks in real time (Kaur & Mann, 2017). In addition, AI systems can explore the patients' data, and then, providing personalized health monitoring, recommendation, and treatment.

Internet of Things (IoT)

The Internet of Things (IoT) is a physical object that has a network connection (Vermesan & Friess, 2013). There can be different types of devices, such as medical instruments, home appliances, Smartwatch, industrial systems, people, buildings, vehicles, and Smartphones. These devices are connected and communicate with each other based on the required protocols to enable personal online monitoring, process administration, tracing, and positioning (Vermesan & Friess, 2014). IoT in healthcare can support health monitoring systems, wearable health monitoring, remote health monitoring, Smartphone health monitoring, etc. (Sahu et al., 2020). Patients keep monitoring their vital health conditions, for instance, body temperature, blood pressure, blood glucose, respiration rate, and pulse rate, using the sensor which is attached in the patient's body (Kumar &

Gandhi, 2018). Monitored patient’s vital health condition can be used for disease prediction and further treatment (Madakam et al., 2015). Moreover, the monitored data can be stored in the repository so that healthcare professionals have access to the data for future medical treatments (YIN et al., 2016).

Internet of Medical Things (IoMT)

The Internet of Medical Things (IoMT) is the combination of Internet of Things (IoT) with medical devices (Razdan & Sharma, 2021). IoMT is aimed to manage patients’ health by using sensors implanted in medical objects and transmitting the monitored data via network so that patients can communicate with their healthcare providers (Vishnu et al., 2020). According to Figure 1, the collected data from patients goes to the healthcare professionals, and then, feedback goes back to the patients. In the near future, most medical devices could connect and be monitored through the internet by healthcare professionals. Such systems will reduce the cost of medical treatment and allow faster access to medical care. In addition, IoMT with the integration of AI, big data, and cloud computing will accelerate the IoMT usage in healthcare.

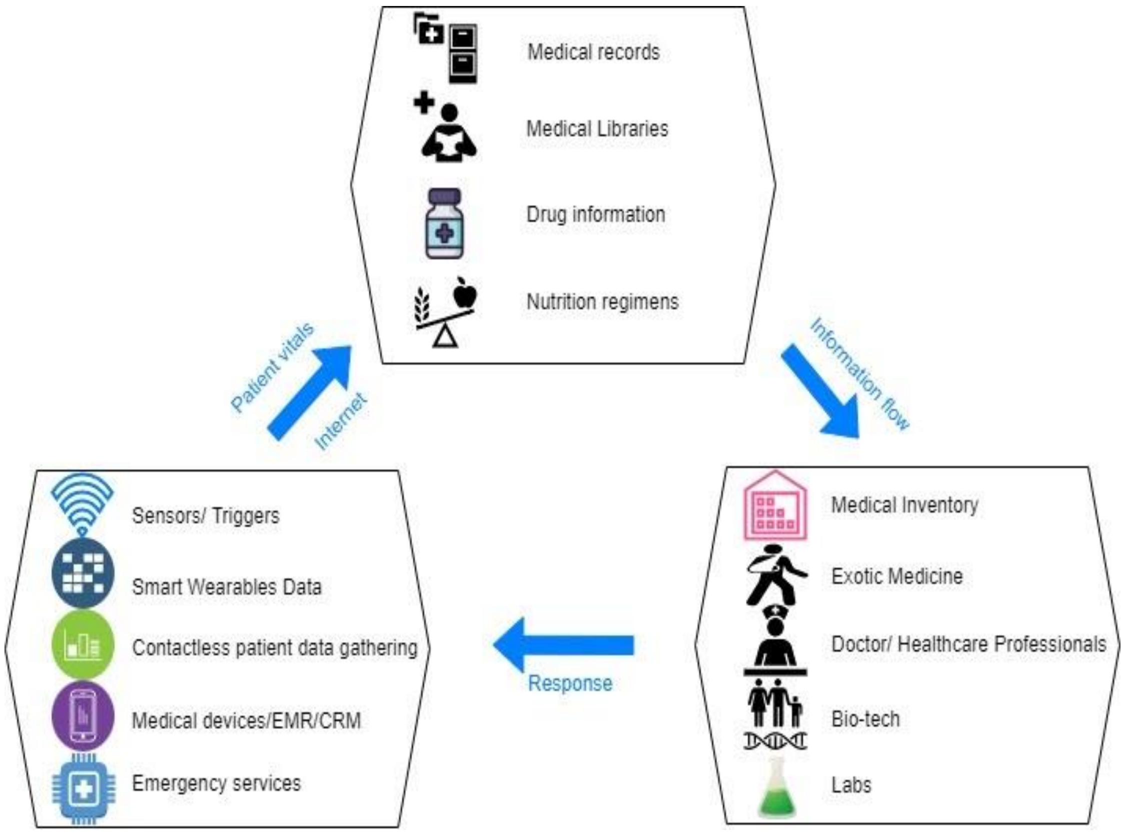

Figure 1. IoMT applications (Razdan & Sharma, 2021)

Mobile Health (mHealth)

Mobile Health (mHealth) is the utilization of mobile communication with network technology for healthcare (Dutta et al., 2017). mHealth apps collect user's health information, nutrition, and wellness so that the apps can help people with chronic diseases. In addition, users can track their workout schedule and diet nutrition. Therefore, mHealth apps improve the user's overall health condition by collecting user's health related data. mHealth has been widely used for communication between healthcare providers and patients and delivery for healthcare services (Dutta et al., 2017). In Table 1 below, it shows what mHealth apps are available and the description of apps.

Table 1. mHealth Apps for general healthcare

Apps	Description
Health Assistant	Keeps track of a wide range of health parameters such as body water and fat, weight, BP, body temperature, lipids, the glucose level, and various physical activities.
Healthy Children	Can search for pediatricians by location and request their advice for quick answers.
Google Fit	Tracks the suer's walking, running, and cycling activities.
Calorie Counter	Keeps track of food consumed by the user as well as their weight and measurements, among others.
Water Your Body	Reminds the user to drink water every day and tracks his or her water-drinking habits.
Noom	Helps to achieve personal health goal with advising healthier habits and check user's weight logging, step counting, and water tracking.
Pedometer	Records the number of steps the user takes and displays related information such as the number of calories burned per a unit of time.
Period Calendar	Keeps track of the best periods, cycles, and ovulation dates and helps the user achieve or prevent pregnancy.
Period Tracker by GP Apps	Keeps track of periods and forecasts fertility.
Instant Heart Rate	Measures the heart rate by using the smartphone's built-in camera to sense changes of the color of the fingertip, which is directly related to the pulse.

Cardiax Mobile ECG	Serves as a companion app for Cardiac Windows full-scale and 12-channel personal computer ECG system.
ECG Self-Monitoring	Serves as an automatic ECG device by registering ECG data based on the built-in “ECG self-check” software.
ElektorCardioscope	Displays ECG data through a wireless terminal.
Runtastic Heart Rate	Measures the heart rate using built-in camera on a real-time basis.
Heart Rate Monitor	Checks the heart rate on a real-time basis.
Kardia	Manages heart care from home with EKG recordings and share heart data with user’s doctor.
Blood Pressure Watch	Collects, tracks, and analyzes a Blood Pressure and share the user’s data via dropbox, Google Drive, and email.
Blood Pressure	Helps to control user’s blood pressure using build-in features but not measure blood pressure.
OnTrack Diabetes	Tracks blood glucose and medication to help manage diabetes.
Real Thermometer	Measures body temperature and get report.
Body Temperature App For Fever	Keeps track of body temperature and identifies its severity.
Medisafe Meds & Pill Reminder	Reminds the user of medication times.
Dosecast medication Reminders	Reminds the user of medication times, tracks the inventory, and maintains a log for drug management.
Rehabilitation Game	Serves as interactive game facilitating the auditory rehabilitation of patients with hearing loss.
iOximeter	Calculates the pulse rate and SpO_2
Eye Care Plus	Tests and monitors the vision.
SkinVision	Keeps track of the user’s skin health and enables the early discovery of any skin disorder.
AsthmaMD	Keeps track of the patient’s asthma.
Fight CF (cystic fibrosis)	Keeps track of the user’s cystic fibrosis status.
Hearing Test	Tests various aspects of hearing.
uHear	Allows for the self-assessment of hearing.
Relax Noise 3	Helps to stay focused in a noisy environment.
ReSound Tinnitus Relief	Helps to relieve tinnitus.
BetterSleep	Aids sleep and relieves insomnia.
Sleep Cycle	Manages sleep apnea.

FallSafety Home -Personal Alert	Monitors human activity and issues alerts on falling
Fall Detection -Fall Alert Saves Lives	Detects a fall and generates alerts when a device fall occurs.
Calm	Helps the user mediate, relax, and sleep.
Headspace: Meditation & Sleep	Helps the user to do a meditation and to manage stress.
Daily Yoga	Offers yoga, Pilates, and meditation sessions with the smart coach and track user’s activity.

(Islam et al., 2015)

Wearable Devices

The definition of wearable devices is the devices that can be attached to clothing and the human body with receptors and transducers (Xie et al., 2020). Wearable devices can do patient monitoring, asset monitoring, tracking, early medical interventions, and drug management (Banerjee et al., 2017). It can be used in healthcare for cardiovascular diseases, Alzheimer, Parkinson’s disease and other psychological diseases, asthma, obesity, and in-hospital monitoring. Moreover, wearable devices not only support personalized health services but also individualized portable devices and sensors (Guk et al., 2019). Portable devices can be divided into wrists, body clothes, feet, heads, and body sensor controlling devices (Kamišalić et al., 2018).

Table 2. Application of disease and examples of commercial wearable devices

Disease	Monitoring	Product Category	Commercial Product
Cardiovascular disease	Heart rate Pulse rate	Wrist Watch/band	HEM series of OMRON
Fitness tracking	Heart rate, Calories burned, activity level, Heart rate variability, Body temperature, Cardiac electrical activity (ECG)	Smart jewelry Ear appliance Watch/band	Ear-o-smart Cosinuss' One Apple Watch Samsung Galaxy Watch
Cognitive disorder	GPS	Wrist Watch/band	Vega GPS bracelet
Sleep or stress related disease	Heart rate variability, Heart rate	Wrist Watch/band Smart jewelry Patch	Airo Health anxiety tracker Oura ring Motiv ring Go2Sleep Kenzen Patch Vital Scout
Metabolic disorder	Glucose Hydration	Wrist Watch/band Ear appliance Patch	GlucoWatch G2-Biographer GlucoTrack Symphony FreeStyle Libre Dexcom Patches LVL
Mosquito-borne diseases	Temperature Sweat patterns	Smart jewelry	TermoTell bracelet
Skin disease & UV related disease	Level of UV	Smart patch Smart jewelry	MyUV Patch Netatmo JUNE
Respiratory diseases	Audio signal, heart rate, accelerations Cardiac electrical activity (ECG)	Wrist Watch/band Smart patch	LG Watch Urbane W150 Moto 360 2nd Generation Savvy patch ECG sensor XYZlife Patch BC1

Skeletal system diseases	Movement postural variation gait	Smart shoes	CUR Smart Pain Relief Valedo

(Guk et al., 2019)

Recommender System

Recommender System is a decision-making system used to filter information depending on user's preferences, interest, and previous activity (Isinkaye et al., 2015). Therefore, it is helpful for users to make their choice by giving out suitable options in the information overloaded world (Sahoo et al., 2019). Recommender System can be divided into seven different systems, such as content-based filtering, collaborative-based filtering, knowledge-based filtering, hybrid filtering, context-aware based filtering, demographic-based filtering, and social-based filtering (Ertuğrul & Elçi, 2019)

Health Recommender Systems

The Health Recommender System (HRS) is a system that applies the Recommender System in healthcare. Health Recommender Systems provide medical information that is related to the patient's medical history (Archenaa & Anita, 2017). Health Recommender Systems can provide patients personalized guidance into Clinical Diagnosis Systems (CDS) and provide personal recommendations, for example, diet recommendations, follow-up alerts, list of diagnosis, preventative care alerts, etc (Archenaa & Anita, 2017). The Quantified Self (QS) is a concept of self-tracking of personal health conditions in physical, biological, behavioral, or environmental information (Erdeniz et al., 2019). In addition, the QS system will include more recommendation systems to support the users using wearable devices, mobile phones, biosensors, and cloud services. In the basis of Quantified-Self (QS), Virtual Coach, Virtual Nurse, and Virtual Sleep Regulator can be used for improving personal health conditions. Virtual Coach helps to schedule a workout plan and Virtual Nurse supports a physical activity plan depending on the user's medical history and Virtual Sleep Regulator assists insomnia users to improve their sleep quality by recommending their sleep plan and physical activity. For example, collaborative filtering-based recommender systems use K-Nearest Neighbors (KNN) approach to find similarities among the population and recommend a topic that might be interesting and helpful for the targeted users by high chances (Erdeniz et al., 2019).

In this chapter, Data, Artificial Intelligence (AI), Internet of Things (IoT), Internet of Medical Things (IoMT), Mobile Health (mHealth), Wearable devices, Recommender System, and Health Recommender Systems have been reviewed. The literature review helps to understand how various technologies can come together to help monitoring personal health conditions. It also gives an insight to develop an idea which is an integration of IoT and Health

Recommender Systems. Therefore, this study is focused on highlighting how can integration of IoT and Health Recommender Systems help responsiveness and affordability in healthcare.

CHAPTER THREE:

INTERNET OF THINGS IN SMART HEALTHCARE

The Internet of Things (IoT) is the physical object having a connection with the network and embedded with technologies and sensors so that devices could communicate with other tools and systems over the network. IoT makes industries such as health, wearables, transportation, CCTV, manufacturing, agriculture, smart cars, traveling, banking and smart homes develop their potential (Nawara & Kashef, 2020). Using IoT guarantees industries to track, monitor, communicate, and operate their remote devices for their users.

IoT could enhance its capability integrating with big data, Cloud computing, and AI. AI is a broad concept of technology that aims to create human intelligence in computer programs. Machine learning is a subset of AI that tries to train machines/computer programs to learn (IBM Cloud Education, 2020). This project studies the IoT integration with recommender systems as a machine learning technique and a subset of AI.

Architecture of Smart IoT Healthcare

Current developments in computational power and server-based computing have strengthened the use of AI systems in many industries (Maranda et al., 2018). Such developments also have enabled reusability of AI tools with connected devices and correlated sensors. There are three most commonly used

IoT architectures: Three-Layer architecture, Service-Oriented based Architecture (SoA), and Middleware-based architecture (Lombardi et al., 2021). These architectures are explained in detail below.

Three-Layer Architecture

Three-Layer Architecture consists of perception layer, network layer, and application layer (Lombardi et al., 2021). Perception layer is the first phase of interacting with environments and certain objects by collecting the data and information (Lombardi et al., 2021). At this level, devices and sensors should be able to communicate with the target so that they could exchange information. Also, devices are equipped with computing abilities to use smart technologies, self-identification, self-diagnosis, and self-testing (Abdmeziem et al., 2015). In addition, there are special characteristics in smart objects, such as communication, identification, addressability, sensing and actuation, embedded information processing, localization, and user interface (Lombardi et al., 2021). Communication is the essential aspect of the perception layer for updating data and services and for attaining their goals. Identification is the key property to be individually identified. Addressability makes the objects reachable to do a remote control and configuration. Sensing and actuation is the part of the perception layer responsible for collecting information and data from the surrounding situation and utilizing it using sensors and actuators. Embedded information processing is a critical feature for calculation functions to process the outcome of devices and sensors. Localization is also an important feature to track the physical location of devices and users. User interface gives a proper platform to communicate with users. Table 3 shows most used technologies for operating smart devices (Čolaković & Hadžialić, 2018).

Table 3. Most used technologies in the IoT field

Scheme	Used Technologies
Communication	Zigbee, Bluetooth, Wi-Fi, Near Field Communication (NFC), Radio-Frequency IDentification (RFID), etc.
Identification	Electronic Product Code (EPC), Ubiquitous Code (uCode), Quick Response (QR), etc.
Addressability	IPv4, IPv6
Sensing e Actuation	Micro Electro-Mechanical Systems (MEMS) e Micro-Opto-Electro-Mechanical Systems (MOEMS), embedded sensors, etc.
Embedded information processing	Field Programmable Gate Array (FPGA), Programmable Logic Controller (PLC), microcontrollers, Single-board computer, System-on-Chip (SoC).
Localization	Global Position System (GPS), Galileo, etc.
User interface	Displays, remote control, etc.

(Čolaković & Hadžialić, 2018)

The Network layer conveys the information and data from the perception level to the application layer. In this layer, it has all network technologies and protocols to obtain a stable connection. There are different kinds of protocols used in IoT devices and the protocols are decided depending on the given situation such as the need for a certain transmission speed, the usage of each node, and the network scale (Lombardi et al., 2021). Wired networks offer more reliability and faster transmission (Sharma & Gondhi, 2018). Wireless sensor networks (WSN) refer to a network configuration of sensor nodes and can monitor the surrounding environment using sensors (Ghazal et al., 2021). WSN makes it possible to install an inaccessible situation and need fewer human resources. Furthermore, using wireless protocol eases the ability to add and remove the nodes when needed.

The Application layer has essential software to provide a specific service to users. This is the stage that utilizes all the information and data which is saved, filtered, and processed from the previous layer with analytic software so that the data can be used in real IoT applications, such as smart wearable. This layer also is referred to as a middleware. There are many platforms that implement IoT applications such as Amazon AWS, Xively, and Microsoft Azure (Lombardi et al., 2021).

Service-Oriented Based Architecture (SoA)

Service-Oriented Based Architecture (SoA) is the one of the most commonly used architecture styles that is able to connect various functional units of applications using interfaces and protocols (Lombardi et al., 2021). SoA is composed of the perception layer-the network layer-the service layer-the application layer. The newly added service layer manages service discovery, service interfaces, service management, and service composition.

The Middleware-Based IoT Architecture

The Middleware-Based IoT Architecture is also called a five-layer architecture (Ngu et al., 2016). The Middleware-Based IoT architecture consists of the perception layer-the network layer-the middleware layer-the application layer-the business layer. The Middleware-Based IoT architecture style has a strength in connecting between data, applications, and users. Particularly, the middleware layer has features that can collect and filter the obtained information from the previous layer and process the data discovery and give an access control of connected devices for applications. There are four advantages of the Middleware-Based IoT architecture. It supports a variety of applications, and it also can be able to run on various platforms and operating systems. Also, it dispenses computing and the communication service among networks, applications, and devices. Additionally, it helps standardized protocols to perform and it also provides standard interfaces while supporting portability and standardized protocols to do interoperability. Lastly, with a Middleware-Based IoT architecture, it provides a secure interface for the applications. Figure 2 shows most commonly used IoT architectures (Lombardi et al., 2021).

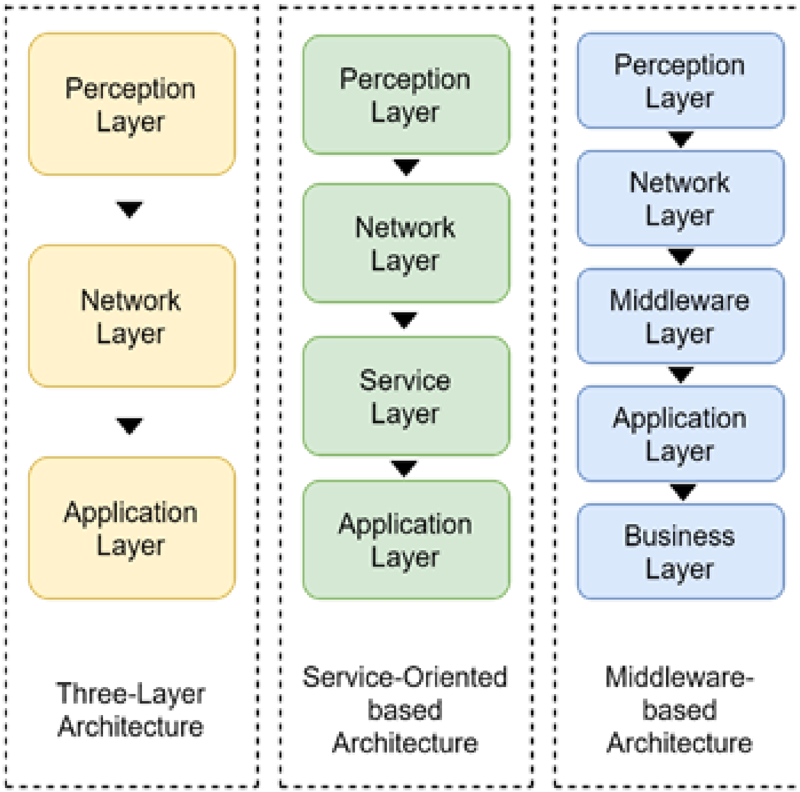

Figure 2. Most commonly used IoT Architectures (Lombardi et al., 2021)

IoT Healthcare Services and Applications

IoT-based healthcare systems are expected to improve the remote health monitoring, personal fitness program, monitor the chronic diseases, look after the elderly people, and many other medical fields (Islam et al., 2015). In this section, IoT healthcare is explained by dividing it into services, service enablers and applications. We also highlighted the IoT healthcare services focusing on Smartwatch.

A. IoT Healthcare Services

IoT-based healthcare services are aimed to reduce the cost of healthcare services, enhance the quality of people’s life, and improve the user’s experience. IoT healthcare services are categorized as Ambient assisted living (AAL), Mobile Health (mHealth), Wearable device, Adverse drug reaction, Community healthcare monitoring, Children health information, Cognitive computing, and Blockchain (Islam et al., 2015). Those have been outlined below.

Ambient Assisted Living (AAL). Ambient assisted living is a IoT healthcare service that is powered by artificial intelligence (Pradhan et al., 2021). It is utilized for elderly people to live their life more comfortably and safely. This healthcare service provides autonomy and assistance for elderly individuals if an emergency happens. IoT-based AAL architecture systemically provides healthcare services to elderly people and disabled people (Shahamabadi et al., 2013). The bottom line of the technology to apply this architecture in AAL uses IPv6-based low-power wireless personal area networks (6LoWPAN) for active communications, Radio Frequency Identification (RFID) and Near-Field Communications (NFC) for using passive communications. This technological architecture has been enlarged by integrating algorithms to detect elderly individuals’ problems in regard to medical care with a professional medical knowledge. Moreover, when medical emergency situations occur in elderly people, emergent detectors keep monitoring their chronic conditions and medical emergencies (Sandeepa et al., 2020).

Mobile Health (mHealth). Mobile Health (mHealth) is based on the mobile phone platform using network systems to communicate, compute, and medical sensors for healthcare services. The patients are able to share their personal health data using a network area with their healthcare provider. Through the network, healthcare providers can access patient's health data, diagnose symptoms, and actively provide treatment (Pradhan et al., 2021). Diabetic patients can monitor their glucose level using mHealth technology so that patients can manage their hypoglycemia (Istepanian et al., 2017). mHealth real-time monitoring technology can detect abnormal signals of heart activity and notify the condition to patients (Chuquimarca et al., 2020).

Wearable Devices. Wearable devices are devices that humans can attach to their body and wear it (Xie et al., 2020). Wearable devices are noninvasive and have potential to develop in different ways for human use. In other words, it could be developed by integrating with different sensors in wearable devices for people's healthcare, such as watches, shirts, shoes, and wristbands (Singh et al., 2020). The sensors that input in the wearable devices accumulate all the health data from the patients and it is uploaded on the specific databases. Some wearable devices are able to connect to mobile applications through the network.

IoT-enabled health monitoring devices can provide remote health monitoring with several embedded sensors in heartbeat, blood pressure, and body temperature (Wan et al., 2018). In addition, Electrocardiogram (ECG) and Electromyography (EMG) are also utilized in IoT-based wearable systems (Kelati et al., 2018). Therefore, Wearable devices can be utilized as monitoring systems for patients' chronic conditions, such as sleep apnea, Parkinson disease, obesity, post-traumatic stress disorder (PTSD), asthma, panic disorder, cardiovascular diseases, pulmonary conditions, and hypertension (Piwek et al., 2016).

Adverse Drug Reaction (ADR). Adverse Drug Reaction (ADR) is defined as “unpleasant or injurious reaction to patients occurred from intaking of medicinal product” (Coleman & Pontefract, 2016). The ADR is an intrinsically generic response and might happen by taking a single dose of medication or prolonged administration or composite result from combination of different kinds of drugs. The IoT-based ADR system is using a unique barcode/NFC-enabled device to recognize each drug at the individual patient's terminal (Jara et al., 2010). The drug's compatibility with the patients results in the patient's personal allergic history and electronic health record. In addition, the IoT-based prescription Adverse Drug Event (prescADE) has been developed to help decrease the ADE so that patients can improve their healthcare services (Nakhla et al., 2018). Moreover, patch testing in ADR has been proposed. Patch testing supports the detection of T-cell-mediated/non-immediate drug eruptions (Gonçalo & Bruynzeel, 2020).

Community Healthcare Monitoring. Community Healthcare monitoring can be defined as a concept that institutes a healthcare network covering a local community (Islam et al., 2015). This healthcare service originated from an IoT-based network system around a residential area, private clinic, and city hospital. The concatenated community healthcare monitoring services are considered as a cooperative network system so that it has to meet collective technical requirements for collaborative healthcare services. IoT-based healthcare monitoring systems in a rural area found out to be more energy-efficient. In addition, for a better cooperative network, it is necessary to incorporate authentication and authorization mechanisms. The community healthcare network is considered as a “virtual hospital” and a resident healthcare information service platform is founded on a four-layer structure. The medical facilities and the service platform are sharing data to obtain people’s health records and to access remote medical advice (Wang et al., 2012).

Children Health Information. Children Health Information is aimed to let children and their parents know about their children’s overall health condition including children’s nutritional values, psychological condition, and behavior. One study developed an IoT-based framework which can monitor a child's psychological and physical state and also suggested an IoT-based healthcare network where a medical device can connect with a mobile app (Sutjiredjeki et al., 2020). The system requires individual physical parameters such as heart rate, height, temperature, SpO2, and weight so this information can be analyzed by the doctors or health professionals over the mobile app. In addition, it is possible for parents and teachers to monitor children's food habits using m-health service (Briseno et al., 2012).

B. IoT Healthcare Service Enablers

In this subsection, the technologies that enhance analytics in healthcare services have been reviewed such as cognitive computing and blockchain.

Cognitive Computing. Cognitive Computing is a system that can analyze the problems in the human brain. Upon the development of artificial intelligence, now IoT-based devices are integrated with the artificial intelligence and sensor technology to imitate the algorithms of the human brain to solve the problem. Moreover, Cognitive Computing plays a big role in analyzing patterns in a massive amount of data (Behera et al., 2019). Cognitive Computing also improved the capacity of a sensor to process healthcare data and adjust to the environment. Utilizing the cognitive computing in the IoT system supports healthcare providers to keep track of a patient's condition and give a better treatment. Smart healthcare system based on the EEG which is using Cognitive Computing can make a decision about the pathological state of the patient (Amin et al., 2019). It also helps the patients who are in a medical emergency such as stroke and heart attack. One study also has proposed a mechanism of transmission of the cognitive data so that it helps to detect, record, and analyze individual patient’s health data (Kumar et al., 2019). Furthermore, when it comes to the emergent situation, Cognitive Computing transmitted the patient's health data with priority.

Blockchain. Blockchain technology is employed to solve the data fragmentation problems. It also supports the healthcare centers to build up a connection in the data repositories (Satamraju & B, 2020). Data fragmentation is a crucial point of secure data sharing (Pradhan et al., 2021). Data fragmentation can cause information gaps between healthcare providers. Therefore, the use of blockchain technology in the healthcare sector can solve the data fragmentation problem and reduce the barriers that can result in delaying the treatment process of patients. In addition, blockchain technology guarantees the security of sharing sensitive medical information and improves transparency between the patients and doctors. There are three reasons why the blockchain technology can secure the transmission as follows:

1. It has an immutable ledger that people are allowed to manage and control. Once the record is saved in the ledger, it is not changeable. Moreover, the ledger should follow a prebuilt regulation.

2. The blockchain technology has been distributed and is able to operate at the same time from various devices and computers.

3. The blockchain also follows the regulation and data exchange policies including a smart contract system. The smart contract system handles identity and access permission of electronic medical reports (EMRs) which are saved in

the blockchain. It only gives out permission to doctors to go through EMRs for their patients. The healthcare data gateway (HDG) through an app utilizes blockchain technology (Yue et al., 2016). It provides authorities to patients for saving their medical information along with the privacy policy.

C. IoT Healthcare Applications

IoT healthcare applications are used and focused by the patients. Therefore, healthcare applications are more toward the user based. In this section, IoT healthcare applications are covered such as Electrocardiogram (ECG) Monitoring, Glucose Level Sensing, Blood Pressure Monitoring, Body Temperature Monitoring, Oxygen Saturation Monitoring, Asthma Monitoring, Mood Monitoring, Medication Management, Rehabilitation System, and Wheelchair Management.

Electrocardiogram Monitoring (ECG). Electrocardiogram (ECG) describes the heart's electrical activity by reason of depolarization and repolarization of atrium and ventricles (Pradhan et al., 2021). ECG provides fundamental rhythms of the heart muscles. It also indicates abnormalities of cardiac symptoms such as arrhythmia, myocardial ischemia, and prolonged QT interval (Drew et al., 2004). The utilization of IoT technology has discovered the capacity of application in detecting early heart abnormalities with ECG monitoring application. One study has found out an IoT-based ECG monitoring application which is using receiving processors and wireless data acquisition systems (Liu, 2012). It used a search automation method for detecting cardiac abnormalities on a real time basis. A low-powered small ECG monitoring system that was integrated with a t-shirt had a biopotential chip for collecting ECG data (Wu et al., 2019). The earned data is transferred to the end-users with a Bluetooth function, and it can be visualized with a mobile app. An ECG monitoring system can operate long-term and continuous monitoring through the incorporation of nanoelectronics, IoT, and big data (Bansal & Gandhi, 2019). A compressive sensing optimizes the power consumption and conducts a better ECG monitoring performance (Djelouat et al., 2020). ECG monitoring system and fall detection using IoT technology can keep track of elderly patients' health conditions (Al-Kababji et al., 2019). It uses a cloud-based server and integrates with a mobile application.

Glucose Level Sensing. Glucose Level is the most important measure for people who are suffering from diabetes. Diabetes is a metabolic disease that causes high blood glucose levels in a prolonged period. Monitoring glucose level shows each pattern of blood glucose level so that patients can prepare for their meals, medication, and activities according to their blood glucose level. As IoT technologies grow, there are different kinds of wearable gadgets that have been developed for monitoring blood glucose level using IoT technologies. IoT-based noninvasive real-time glucometers for monitoring blood glucose levels in wearable sensors are linked to the healthcare providers through IPv6 connectivity (Istepanian et al., 2011). A glove for evaluating blood glucose level uses a Raspberry Pi camera with a laser beam (Alarcón-Paredes et al., 2019).

With a Raspberry Pi camera, there are pictures of fingertips for analyzing the diabetic condition of the users. An algorithm measures glucose level by employing double moving average of IoT architecture (Valenzuela et al., 2020). In addition, optical sensors use light signals reflected from the patient's body to calculate the glucose level from the human body.

Blood Pressure Monitoring. Blood Pressure is a mandatory test for most of the diagnostic procedures at the hospital. Wearable cuffless gadgets can measure systolic and diastolic pressure (Xin & Wu, 2017). The data monitored by a wearable cuffless gadget is saved in the cloud system. Moreover, Fog computing and cloud computing has been used for measuring Blood Pressure in IoT-based systems (Guntha, 2019). Using fog computing and cloud computing make systems to monitor Blood Pressure in long-term and real-time manner. Also, Convolutional Neural Networks (CNN) models based on a deep learning system can evaluate the systolic pressure and the diastolic blood pressure (Chao & Tu, 2017). Blood pressure measurement system uses Photoplethysmography (PPG) and the ECG signal (Dinh et al., 2017). The blood pressure was analyzed by the attached microcontroller module. It also stored the recorded data in the cloud storage.

Body Temperature Monitoring. Body temperature is an important part of any diagnostic procedure in healthcare services since body temperature provides a vital sign of maintenance of homeostasis (Ruiz et al., 2009). In addition, a little change in body temperature can affect the human body and can be fatal. Therefore, it is important to keep track of body temperature for doctors to decide about a patient's health condition for further treatment. Using a temperature thermometer is a typical way of measurement. However, IoT-based technologies have developed a way to monitor body temperature in a more comfortable and stable way. 3D-printed wearable devices can be put on the ear (Ota et al., 2017). The tympanic membrane in the ears makes a device to check the core body temperature using an infrared sensor. This device is combined with a wireless sensor and data processing system. Moreover, the device is not affected by the surrounding environment or by any other physical activities so that it can measure the human body temperature with integrity. IoT-based temperature monitoring system that can store the data in the database and be able to display on a web page allowing people to access it with their desktop or a mobile phone (Gunawan et al., 2020). The system has been developed using Arduino and Raspberry Pi. In addition, wearable devices with a lightweight sensor for measurement of an infant's body temperature in real-time could be reported to their parents when a critical change of temperature happens (Zakaria et al., 2018).

Oxygen Saturation Monitoring. Pulse oximetry is a proper way of oxygen saturation measurement and a crucial parameter in healthcare analysis. It is the noninvasive method which reduces conventional issues from previous methods and makes it possible to do real-time monitoring. Integrating IoT-based technology and pulse oximetry has improved the capability of healthcare application. An alarm system can notify a patient's oxygen saturation level when it reaches a critical point (Agustine et al., 2018). The alarm system was combined with a WLAN router using the Blynk server and pulse oximeter. Also, noninvasive tissue oximeters can calculate the blood oxygen saturation including pulse parameters and heat rate (Fu & Liu, 2015). In addition, monitored data can be transmitted through the server using communication technologies so that the data is used for doctor’s reference about the patients.

<u>Asthma Monitoring</u>. Asthma is one of the hardest chronic diseases that can cause fatal effects on a person's breathing and airways. When airways shrink, it causes critical health problems such as shortness of breath, chest pain, wheezing, and coughing. The only way of controlling asthma is using an inhaler or nebulizer when it happens. IoT-based smart sensors monitor respiratory rate in asthma patients (Shah et al., 2018). The monitored data of patients also was saved in a cloud server that allows caregivers to access diagnostic and monitoring objectives. A respiratory monitoring system with an alarm system uses a LM35 temperature sensor for measurement of the respiratory rate (Raji et al., 2016). This system was conducted by observing the air of inhalation and exhalation from the patients. The monitored data were transmitted to the health center and can be seen on a web server. In addition, this system automatically transmitted an alarm to the patient when a threshold level was reached. A system is developed which is able to monitor their condition, warn the health

condition of the patients, and suggest a proper medication to be administered (Gundu, 2020). Moreover, the system analyzed the environmental condition for the patient's health and directed the patients to change their position for their health. IoT-based devices integrated with machine learning, big data analysis, and cloud computing has suggested to monitor asthma more effectively (Prasad, 2020). Most potential features of monitoring asthma in the near future are utilizing the IoT-based asthma monitoring system (Hui et al., 2021).

Mood Monitoring. Mood monitoring is tracking of a person's emotional state that can be used for stabilizing a healthy mental state. Specifically, mood monitoring can be used for dealing with mental diseases, and it also supports healthcare professionals to manage their patients who are having a bipolar disorder, depression, stress, and so on. In addition, it is helpful for people to understand their mental condition by self-monitoring their emotional state. Mood mining approach using a CNN network for evaluating and categorizing individual moods in 6 categories which are happy, sad, calm, excited, distressed, and angry (Alam et al., 2017). Meezaj is an interactive system for measurement of real-time mood (Ahmad, 2020). Also, there is a system that can communicate with the people regarding their stress level (Pandey, 2017). The stress level can be utilized in designing IoT-based systems so that people prevent any further acute condition from occurring. MoodRecord is a platform that can monitor patients with bipolar disorder using Smartphones at home (Codina-Filbà et al., 2021). It is recorded user activity and requires users to answer questions and asks users to record video of themselves that is designed by physicians (Codina-Filbà et al., 2021).

Medication Management. Medication noncompliance causes a threat to personal health and public health. It also generates huge financial waste all over the world. As people are getting older, medication nonadherence occurs along with individual conditions such as dementia and cognitive decline. Many research has been developed for tracking the patient's medication compliance by using IoT applications. A smart medical box reminds people to take their medicine (Bharadwaj et al., 2017). In addition, the smart medical box can calculate the vital health parameters such as temperature, ECG, blood oxygen level, and blood glucose level. The recorded data is transmitted to the cloud server and can be accessed by patients and doctors through the mobile app. There is a system that monitors the condition of medication storage such as humidity and temperature so that the medication can be maintained in an ultimate storage environment for medicine (Karagiannis & Nikita, 2020). Saathi is a medication monitoring system for women who are in vitro fertilization (IVF) treatment (Wadibhasme et al., 2020). It is especially critical to take medication on time for women who are in the IVF process.

Rehabilitation System. Rehabilitation system is an essential physical medicine for restoring the functional ability of the patients who are suffering from disability (Pradhan et al., 2021). The Rehabilitation system is designed to identify the problem and assist patients to return to their normal life. The application of IoT with rehabilitation can be used for the treatment of cancer, stroke, sports injury, and physical disabilities (Qi et al., 2018). A smart walker rehabilitation system monitors the patient's walking pattern using a multimodal sensor and then analyzes the movement metrics (Nave & Postolache, 2018). The system was also utilized with a mobile app so that doctors have access to the recorded data and provide diagnostic reports. In addition, a sports rehabilitation system that can monitor the temperature, electromyography (EMG), motion posture, and electrocardiogram (ECG) has been developed and gives feedback to the athletes (Pradhan et al., 2021). The monitored data can be used in healthcare professionals for prediction of a patient's recovery process and plan of further rehabilitation program (Pradhan et al., 2021).

Wheelchair Management. A wheelchair assists patients with restricted mobility in a physical and psychological way. However, using a wheelchair can be limited to the patients who have brain damage. IoT-based steering system utilizes an obstacle avoidance system in a real-time basis (Lee et al., 2017). The system was designed to use image processing techniques of the recorded real-time basis videos. A smart wheelchair was utilized by multiple sensors, cloud computing, and mobile technologies (Ghorbel et al., 2018). A smart wheelchair system has a mobile app for active interaction between patients and the wheelchair, the caregivers. Moreover, it allows caregivers to monitor the wheelchair movement from a distance. IoT-based wheelchair monitoring system makes it possible to control with hand gestures (Garg et al., 2018). It is a useful controlling system for those who are having quadriplegia. The system used RF sensors in hand gloves for controlling the wheelchair. In addition, the information collected by the sensors was transmitted to the server for storing in the cloud which enables doctors and caregivers to access the data and refer to the patient's diagnosis. Advanced version of smart wheelchair can monitor the wheelchair activity and provide obstacle detection features, head mat, foot mat, and an umbrella (Kumar et al., 2020).

D. IoT Healthcare Services Focusing on Smartwatch

About 20% of Americans currently own smart wearable devices, thus the global market is expected to reach $70 billion by 2025 with a 25% of annual growth rate (Polaris Market Research, 2020). Among the variety of smart wearable devices, Smartwatches have been developed with the combination of mobile technology and medical devices so that Smartwatches can monitor users' health including cardiovascular parameters. There are numerous Smartwatches that have been developed. According to a report conducted by Counterpoint Research, the following numbers are Smartwatches global market share in 2021: Apple occupies 33.5%, Huawei 8.4%, Samsung 8%, iMoo 5.1%, Fitbit 4.2%, Other 40.8% (Lim, 2021). In this section, Apple watch and Samsung Galaxy watch will be compared.

Apple Watch. According to the Apple website[1] The Apple Watch 7 provides heart rate notifications, irregular rhythm notifications, fall detection, and has an electrocardiogram (ECG) app which has a heart sensor (Apple, 2021). The ECG has been approved by the Food and Drug Administration (FDA) for determining atrial fibrillation (AF) symptoms (Walters et al., 2016). The ECG app can monitor atrial fibrillation and sinus rhythm and it also asks users to input health symptoms. The monitored data can be shared with healthcare providers. Hence, if the user has serious symptoms, the ECG app prompts them to call emergency services. The ECG app can only be used to obtain information and medical consultation through the devices with personal healthcare providers before taking any action. Therefore, users can keep monitoring their heart condition before going to see a doctor and after. The Apple watch also uses Photoplethysmography (PPG) which can do continuous monitoring and has an algorithm that allows users to detect atrial fibrillation (AF) symptoms by themselves (Isakadze & Martin, 2020). PPG is generated by a pulse oximeter which lights the skin and measures any change in light absorption and is useful for measuring the heart rate. Through the PPG technology can monitor a tachogram showing heartbeats and apply it to the algorithm so that it can detect the pulse irregularity and AF. However, using PPG to monitor AF is not approved by the FDA (Dickson et al., 2021).

[1] http://www.apple.com/healthcare/apple-watch/

Samsung Galaxy Watch. According to the Samsung website[2] The Samsung Galaxy Watch 4 can monitor users' blood oxygen level (SpO_2), heart rate, steps, distance, calories, sleep stages (Awake-REM-Light-Deep), active time, and stress (Samsung, 2021). The Samsung Galaxy Watch can also measure users' weight, skeletal muscle, fat mass, body fat, BMI, body water, and BMR (Westenberg, 2021). Samsung employs BioActive Sensor (including PPG, ECG, and bioelectrical impedance (BIA) sensor) which enables the Galaxy Watch to calculate the ECG in a real time basis so that users can monitor their abnormal heart rate using the ECG and share the monitored result with their phone. It also manages users' sleep quality since it tracks users' sleep stages, including snoring and blood oxygen levels while users are sleeping. The Samsung Galaxy Watch also can be used in tracking users' working out routine and burning calories with GPS. Table 4 shows the comparison between Apple Watch and Samsung Galaxy Watch (Apple, 2021; Westenberg, 2021).

Table 4. Comparison between Apple Watch and Samsung Galaxy Watch

Feature	**Apple**	**Samsung**
Model	Apple Watch Series 7	Galaxy Watch 4
Release Month	October 2021	August 2021
Height	41mm, 45mm	40mm, 44mm
Width	35mm, 38mm	39.3mm, 43.3mm
Depth	10.7mm	9.8mm

[2] https://www.samsung.com/us/watches/galaxy-watch4/

Weight	32g-51.5g (depending on material)	25.9g, 30.3g
Display	Retina LTPO OLED	AMOLED
Display size	1.4-inch 1.77-inch	1.19-inch, 1.36-inch
Features	GPS, GLONASS, Galileo, QZSS, and BeiDou Compass Always-on altimeter Water resistant 50 meters Blood oxygen sensor (Blood Oxygen app) Electrical heart sensor (ECG app) Third-generation optical heart sensor International emergency calling Emergency SOS Accelerometer (Up to 32 g-forces with fall detection) Gyroscope Ambient light sensor Speaker Microphone Apple Pay GymKit	GPS, GLONASS, Beidou, and Galileo Accelerometer Barometer Gyroscope Geomagnetic sensor Ambient light sensor Samsung BioActive sensor: optical heart rate (PPG), electrocardiogram (ECG), bioelectrical impedance analysis sensor (BIA) Ambient Light HRM Samsung Pay
Ability	Blood Oxygen, Heartrate, ECG, Irregular rhythm notifications, Fall detection, Steps, Distances, Speed, Calories, Exercise, Sleep, Elevation, Active time, Respiratory rate	Blood oxygen level (SpO2), Heart rate, Steps, Distance, Calories, Sleep stages (Awake-REM-Light-Deep), Active time, Stress, Weight, Skeletal muscle, Fat mass, Body fat, BMI, Body water, and BMR

(Apple, 2021; Westenberg, 2021)

As we discussed IoT healthcare services, service enablers and applications in this chapter, IoT has the ability to overcome human limitations and physical difficulties. Among the variety of IoT services, Smart Watches have been considered as commonly used wearable technology with combination of Smartphones to help peoples' health monitoring. As we can see the usefulness of health monitoring through wearable devices, it implies that the integration of IoT and Health Recommender Systems would create more possibilities in human life.

CHAPTER FOUR:

HEALTH RECOMMENDER SYSTEMS

Integration of IoT and Recommender Systems in healthcare can support people to pay more attention to their personal health and wellness. Recommender Systems are aimed to assist people to make decisions when they are short on knowledge where there are several options available to choose from (Ricci et al., 2011). Recommender systems are utilized in predicting the user preferences of certain items (Bobadilla et al., 2013). The recommender systems have been used for helping a process of decision making in e-commerce, transportation, healthcare, agriculture, and media (Fayyaz et al., 2020). In particular, the Health Recommender Systems provide medical information that is related to the patient's health improvement and medical treatment along with patients' health records. Health Recommender Systems contribute to the advancement of healthcare services by offering patient centric health information to the healthcare professionals and patients in a proper moment. Moreover, Health Recommender Systems deliver the patient's medical information which is monitored data from wearable devices and personal medication history to the Clinical Diagnosis System (CDS) so that the patient can have a recommendation, such as diagnosis, medication refills, health insurance plans, follow-up, drug interaction alert, and diet recommendations regarding their health. Health Recommender Systems in IoT improve convenience feature of Health

Recommender System to the users. For example, the Holter monitor is one of the portable electrocardiograms (ECG) devices that can do remote monitoring regarding heart related disorders (Sana et al., 2020). However, it is difficult to carry around due to the big size, thus the usage has been reduced. Regarding the size problem, wearable devices have been represented for its convenience and remote monitoring in a long-term period. One of the advantages of IoT-based Health Recommender Systems can be the convenience for patients to monitor their health with less effort.

The core concept of a recommender system can be shown using the following function below (Adomavicius & Tuzhilin, 2005):

$$f: R \times I \rightarrow X$$

R means all the users and I means possible recommended items. Where f implies that utility of function about a certain item $i \in I$ to a user $r \in R$. X refers to the final recommendation including some of items that users have not used before but might like. Recommended items were listed by expanding the utility function. In addition, the following formulation can be used (Adomavicius & Tuzhilin, 2005).

$$\forall r \in R,\ i'_r = \arg\max_{i \in I} f(r, i).$$

Above the formula implies that to all the users $r \in R$, the recommender system decides to choose a certain item $i'_r \in I$ which can maximize the utility of function to the users. The result of predicting the utility of certain items is depending on the selected recommendation algorithms. There are four main recommendation techniques: content-based filtering, collaborative-based filtering, knowledge-based filtering, and hybrid recommendation systems which are discussed below (Zhang et al., 2020).

Main Recommender Systems and Algorithms

Content-Based Filtering

Content-based filtering employs an item's description for forecasting its utility along with user's preferences (Shardanand & Maes, 1995). Content-based recommender systems pursue a goal that recommends similar items based on an individual user's previous interest. In formal terms, the utility $f(r, i)$ of certain items i for a user r is calculated by the utility $f(r, i_v)$ from a user r to certain items $i_v \in I$ that is similar to item i. Most commonly used retrieval technique is using a keyword-based model, called the vector space model (Salton et al., 1975). Content-based recommender systems follow user's consumption records to find a user's interest on specific items and store them in the user's profile. The profiling process can encounter a binary classification problem. At this step, classic methods can be used such as Naïve Bayes, decision trees and nearest neighbor algorithms (Sebastiani, 2002). Content-based recommender system filters and matches the item representation with the user profile (Zhang et al., 2020). Moreover, the result is forwarded and the unmatched items that users dislike is removed. Content-based recommender system is on the basis of item representation and individual user. Therefore, it has enough information to predict the user's preferences. Also, this system has no cold-start problem since it can recommend new items to the individual users. In addition, this system is able to explain clearly about the recommendation result. However, the content-based recommender system is having a problem which are new user issues, over-specialization, data sparsity, and scalability (Balabanović & Shoham, 1997). Besides, it encounters the limitation to the variety of recommended items which means it keeps recommending the similar item for users. Furthermore, the items are not able to be represented in a specific form which is required to use a content-based recommender system.

<u>Collaborative-Based Filtering</u>

Collaborative-based filtering is aimed to predict unknown results by making a user-item rating matrix depending on a user's item preferences or choices (Sahoo et al., 2019). The users who have not ever rated certain items will get the recommended items according to the positive rating by other users. In formal terms, the utility $f(r, i)$ of a certain item i is calculated by the similar users $r' \in R$ experienced the utility of the assigned item $f(r', i)$. Collaborative-based filtering systems can be divided into memory-based collaborative-based filtering and model-based collaborative-based filtering (Zhang et al., 2020). Memory-based collaborative-based filtering uses the nearest neighbor algorithm. The recommendation computes possible ratings of certain items depending on the user's neighborhood user or item. In addition, memory-based collaborative-based filtering uses heuristic algorithms for calculating similarity values on users or items and it is also divided into user-based collaborative-based filtering and item-based collaborative-based filtering (Deshpande & Karypis, 2004). The memory-based collaborative filtering is easy to implement and an effective application. However, it has a cold-start problem. So, it is hard to predict if the user and items are new on the system. Even if an item is not a new product but unpopular, it is hard to get a rating from the consumers. It is especially hard to offer a recommendation in a real-time basis since the heuristic process needs time to provide a recommendation. This drawback is partially figured out by item-based collaborative filtering using a pre-calculated and pre-stored matrix. Model-based collaborative-filtering utilizes a machine learning/ data mining technique. When the ancillary information is integrated with the rating matrix, the model-based collaborative-filtering system brings out great outcomes. Matrix factorization won the Netflix Prize in 2009 and it has been ranked as the most popular algorithm (Koren et al., 2009). Matrix factorization can solve the sparsity problem (Luo et al., 2016). Even though users rated only a few items, they still can acquire an accurate recommendation using the matrix factorization. In addition, matrix factorization can integrate with other information so that it is easy to finish up the user profile and assist recommender systems performance (Liu et al., 2015).

Due to the shortcomings of content-based filtering such as cold-start problems, scalability, over-specialization, and data sparsity, there are studies to overcome the problem combining with Naive Bayes classification (Ghazanfar & Bennett, 2010). Therefore, it increases the accuracy and coverage of experimental results by integrating the collaborative filtering and Naive Bayes classification. In addition, the Bayesian model with collaborative filtering resulted in providing a recommendation which shows good prediction as matrix factorization (Valdiviezo-Diaz et al., 2019). Collaborative filtering with decision trees is also being used with dimensionality reduction and separate decision trees in every attribute (Wu, 2019). Moreover, using Reversed collaborative filtering (RCF) and K-Nearest Neighbors (KNN) perform accurate predictions with filtering inaccurate results and help to quickly find similar users. RCF is based on finding rated items using the KNN graph (Park et al., 2015). Collaborative filtering with KNN and gradient boosting method is developed (Lu et al., 2018). Collaborative filtering with KNN enhances the calculation of similarity of items and users for obtaining more relevant information and Collaborative filtering with gradient boosting method is also used for predicting the items' score.

Knowledge-Based Filtering

Knowledge-based filtering is on the basis of existing knowledge, regulation about item functions and user needs (Burke, 2002). Knowledge-based recommender system possess knowledge which is extracted from previous records of the user. The knowledge includes constraints, problems, and solutions

(Zhang et al., 2020). Case-based reasoning employs previous cases to resolve the current problem using the knowledge-based system (Aamodt & Enric, 1994). With knowledge-based filtering system, it finds similarities among the products, and it requires organized representations. The knowledge-based recommender system can especially be used in health decision support, financial services, and house sales since these services need certain domain knowledge and specific situations (Felfernig et al., 2011). Moreover, a knowledge-based recommender system does not suffer from having a new item/user problem because this system is storing the knowledge already (Felfernig & Burke, 2008). Moreover, users can make constraints about the outcome of recommendation. The disadvantage of this system is that the knowledge-based recommender system costs high to set up and manage the knowledge base system (Zhang et al., 2020).

Hybrid Filtering

Hybrid filtering system comprises collaborative-based filtering and content-based filtering for enhancing the performance and accuracy of the recommender system (Sahoo et al., 2019). Content-based filtering systems do not include all the opinions for recommending items (Chavan et al., 2021). In addition, it has a limitation of providing a recommendation if it is in the user’s interest. Collaborative-based filtering has a weakness that the systems are not able to provide recommendations if the item has not been rated which is called a cold-start problem. On the other hand, hybrid filtering systems can overcome the limitations from content-based filtering and collaborative-based filtering. Moreover, it consists of a combination of different recommender techniques so that it will increase the accuracy and optimal recommendations compared to a single recommender system (Schafer et al., 2007). In the healthcare perspective, a user profile can be extracted from a Personal Health Record (PHR). With using a PHR, it can solve the cold-start problem in the collaborative filtering system. Hybrid filtering is aimed to earn more accurate results and enhance the performance of algorithms. Hybrid filtering has been divided into seven strategies, such as weighted, mixed, switching, feature combination, feature augmentation, cascade, and meta-level filtering (Fayyaz et al., 2020).

Health Recommender Systems have been developed and immersed into our daily life to enhance our health and life through the utilization of filtering technologies. For example, sending motivational messages about the possibility of making a difference in their behavior using hybrid filtering recommender systems is helpful for smokers to quit smoking (Hors-Fraile et al., 2016). In addition, Health Recommender Systems have been developed to make recommendations for dietary needs depending on the patients' medical history and body features using machine learning algorithms and deep learning algorithms such as Long Short-Term Memory (LSTM), recurrent neural network, and Naive Bayes (Iwendi et al., 2020). For psychological recommender systems, it has been suggested that knowledge-based recommender system recommend patients for naturopathy, music therapy, and art therapy so that they can improve their psychological symptoms (Gyrard & Sheth, 2020). Moreover, it was possible to find rare diseases using a hybrid recommender system which is a combination of collaborative-based filtering and context-based filtering (Almeida et al., 2020).

Machine Learning Algorithms

There are different machine learning algorithms used in Recommender System to predict and filter for identifying the disease depending on the data type and needed implementation results. Support Vector Machine (SVM) is one of the supervised learning models. This model has been used for analyzing data for regression and classification analysis. In particular, SVM efficiently implements non-linear and linear data by using the kernel types which are mapping the inputs to the high-dimensional spaces (Mahesh, 2020). In addition, SVM-based collaborative filtering has been proposed to improve the precision and efficiency of recommendations (Chang et al., 2019). There is multi-criteria collaborative filtering with SVM which enhances precision of recommendation (Nilashi et al., 2014).

The Decision Tree (DT) algorithm is also one of the supervised machine learning algorithms (Ibrahim & Abdulazeez, 2021). DT keeps dividing the dataset until it solves classification or regression problems. The tree is made by a training process and final leaf nodes means the final decisions. The DT algorithm is also used to detect breast cancer.

The Naive Bayes (NB) algorithm is a classification algorithm that uses a statistical method and probability method (Yaswanth & Riyazuddin, 2020). NB algorithm is utilized in the classification of documents and filtering emails. This machine learning algorithm is characterized by its simplicity and usefulness with large amounts of data in most of the field.

The K Nearest Neighbors (KNN) algorithm uses Euclidean distances between data to earn neighbors (Urgiriye & Bhartiya, 2020). It is one of the most widely used algorithms to resolve any regression and classification issues. The K value can discover the similar cases that exist for the new case and find a similar category with the new case. Therefore, the value of K should be decided carefully to not result in overfitting.

The Random Forest algorithm is an ensemble model used to predict the nearest neighbors and the main idea for the ensemble is that a group of models forming a strong model (VijiyaKumar et al., 2019). The benefit of random forest classifiers is that they have concise running time and can handle missing data and unbalanced data. Subtree created by the dataset can choose the class in the dataset. Random forest algorithms can be used for diagnosing heart disease (Meshref, 2019).

The Logistic Regression algorithm is one of the supervised learning algorithms which can resolve in the formatting of binary classification by employing mathematical models with logistic function which is a sigmoid function for modeling the data (Kumar, 2020). Logistic Regression is characterized by simplicity of execution, training-based effectiveness, ease of regularization, and computational efficiency.

The Extreme Gradient Boosting (XGBoost) algorithm is applied for classification and prediction of problems due to the efficiency, portability, and flexibility of the algorithms (Kao et al., 2020). XGBoost is based on gradient boosting. XGBoost algorithms solve the over-fitting problem and improve the computational resources. XGBoost can draw the result by simplification of the objective functions with the high computational speed (Fan et al., 2018).

In this chapter, Recommender Systems are elaborated with highlighting Healthcare Recommender Systems. There are four main Recommender Systems which are content-based filtering, collaborative-based filtering, knowledge-based filtering, and hybrid filtering. The usage and applications of Health Recommender Systems does not have an adequate number of studies in the past. However, Health Recommender Systems have the potential to expand the scope of improving human life. Moreover, various machine learning algorithms which can be used in recommender systems have been reviewed in this chapter. Therefore, an IoT-based Health Recommender Systems is suggested in the next chapter based on the investigated machine learning algorithms. The suggested framework also includes utilizing the Middleware-based IoT architecture for the purpose of integration.

CHAPTER FIVE:

CASE STUDY AND DISCUSSION

The Internet of Things (IoT) and Health Recommender Systems are presented in the previous chapters. The importance and advantage of integrating IoT and Health Recommender Systems are also presented which can enhance the quality of human life and wellness. IoT can broaden the scope of Health Recommender Systems usability for various healthcare areas. In addition, a case study is presented in this chapter to indicate how different machine learning methods can be used for Health Recommender Systems and how effective they are for the case under study.

IoT-Based Health Recommender Systems Framework

In this chapter, an IoT-based Health Recommender Systems Framework is suggested. The framework uses the Middleware-based IoT architecture. Figure 3 shows the proposed IoT-based Health Recommender Systems Framework developed in this study.

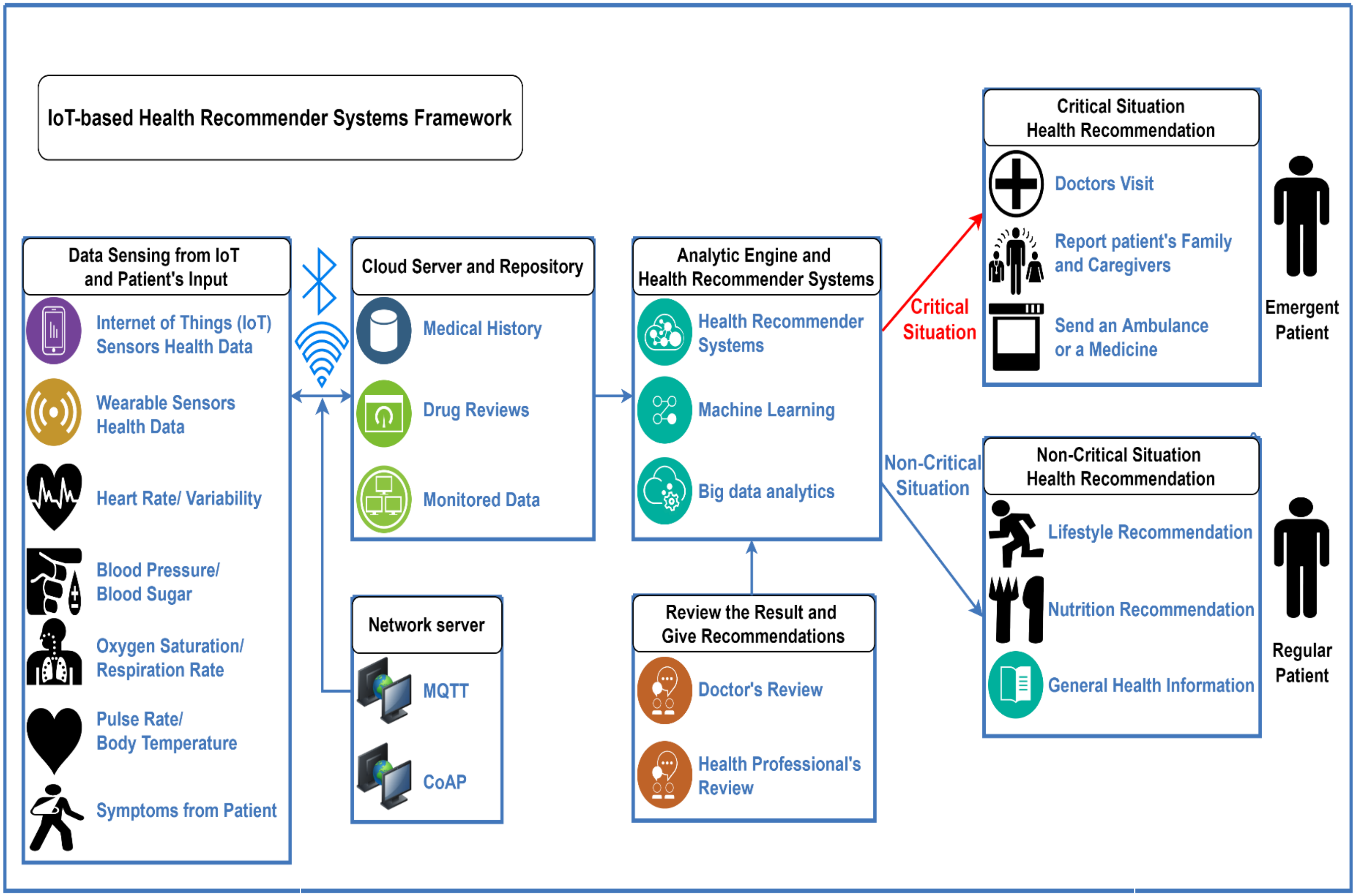

Figure 3. IoT-based Health Recommender Systems framework

The framework is based on Middleware-based IoT architectures, so it has 5 layers: perception layer, network layer, middleware layer, application layer, and business layer. As Figure 3 shows, in the perception layer the system will start with sensors health data from IoT devices and wearable devices such as Smartphone, Smartwatch to perceive important medical parameters, for example, heart rate, heart variability, blood pressure, blood sugar, oxygen saturation, respiration rate, pulse rate, body temperature, and any symptoms input from patients. This information from users is being monitored and saved in the cloud server using the network layer. In the network layer, MQTT and CoAP can be used depending on needs. Message Queue Telemetry Transport (MQTT) is a lightweight messaging protocol that can deliver messages from remote locations (Ansari et al., 2018). Constrained Application Protocol (CoAP) is an internet application protocol for constrained devices, and it allows constrained devices to communicate with the wider internet which uses similar protocols. In the middleware layer, monitored data, drug reviews, and medical history for each individual will be saved in the cloud server and repository to check whenever it is needed. Moreover, the cloud server and repository can be shared with users and healthcare providers since it is important to know about critical information for both. In the application layer, the most important analytic software is being executed. All the data recorded from users and information in cloud servers are being analyzed in this layer using Recommender System, Machine Learning algorithms, and big data analytics. In addition, the results from the analytic engine and recommendation system should be reviewed and advised by the doctors and health professionals to proceed to the next layer. The business layer can be divided into two categories which are critical and non-critical situations depending on the results from the application layer. If the user's health condition is critical, IoT devices will recommend to the emergent patient to see a doctor, report to their patient's family or caregivers, and send over an ambulance to patients or deliver a medicine from the hospital through the quick delivery medium. Otherwise, it would notify the user lifestyle recommendations, nutrition recommendations, and general health information to the non-critical situation patient through the IoT devices.

Case Study

Various machine learning algorithms have been reviewed in the previous chapter. The types of algorithms which show higher accuracy performance are implemented using Python in this chapter. In addition, the most important features for an occurrence of heart diseases are discussed by using a data source from the University of California, Irvine (Janosi et al., 1988). The dataset consists of 303 observations and 14 variables. 14 variables are age, sex, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiographic results, maximum heart rate, exercise induced angina, old peak, slope of the peak exercise ST segment, number of major vessels, thalassemia value, target. 303 observations vary the age range between 29 to

77. The accuracy output on each model is Support Vector Machine and K-Nearest Neighbors: 88.52 %, Random Forest: 86.88%, Logistic Regression, Extreme Gradient Boosting, and Naive Bayesian: 85.24%, and Decision Tree: 81.96%. In this case study, seven machine learning methods including Support Vector Machine, Decision Tree, K-Nearest Neighbors, Random Forest, Extreme Gradient Boosting, Naive Bayesian, and Logistic Regression are implemented to develop different Health Recommender Systems for the patients with heart diseases. Then, the accuracy of each recommendation system has been calculated to show the effectiveness of each method for the under-study dataset. Appendix A includes the Python code of all seven implemented machine learning methods. Figure 4 shows accuracy of different machine learning algorithms that are being used in the case study based on the heart diseases dataset. The accuracy is calculated by comparing the model output on the test data with the pre-known labels of data (i.e., 0 means the patient does not have heart diseases, 1 means the patient does have heart diseases). For each algorithm the accuracy is calculated to show how many times the model can predict the output correctly. The values are multiplied by 100 to be shown in percentage.

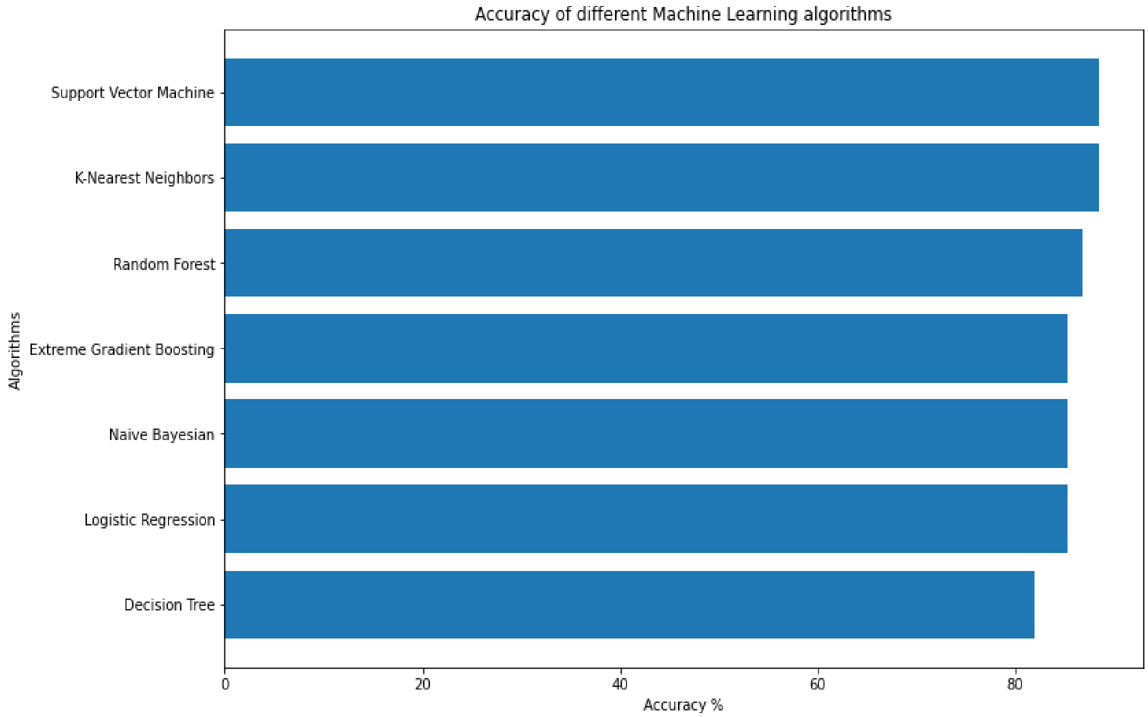

Figure 4. Accuracy of different Machine Learning algorithms

According to the barplot in Figure 4, Support Vector Machine (SVM) algorithms and K Nearest Neighbors (KNN) are both the same with the highest accuracy, 88.52%. This means that both algorithms can predict the possibility of heart diseases from the patients. SVM has less of a possibility of overfitting and can manage linear data and non-linear data. SVM has weaknesses in dealing with large quantities of dataset. The implemented data set subject was 303 and 14 variables, so SVM can achieve high accuracy in this case study result. On the other hand, KNN has strength in multiclass problems and is used for classification and regression problems. Even though KNN has high sensitivity to irrelevant and high computation, it showed high accuracy in this study.

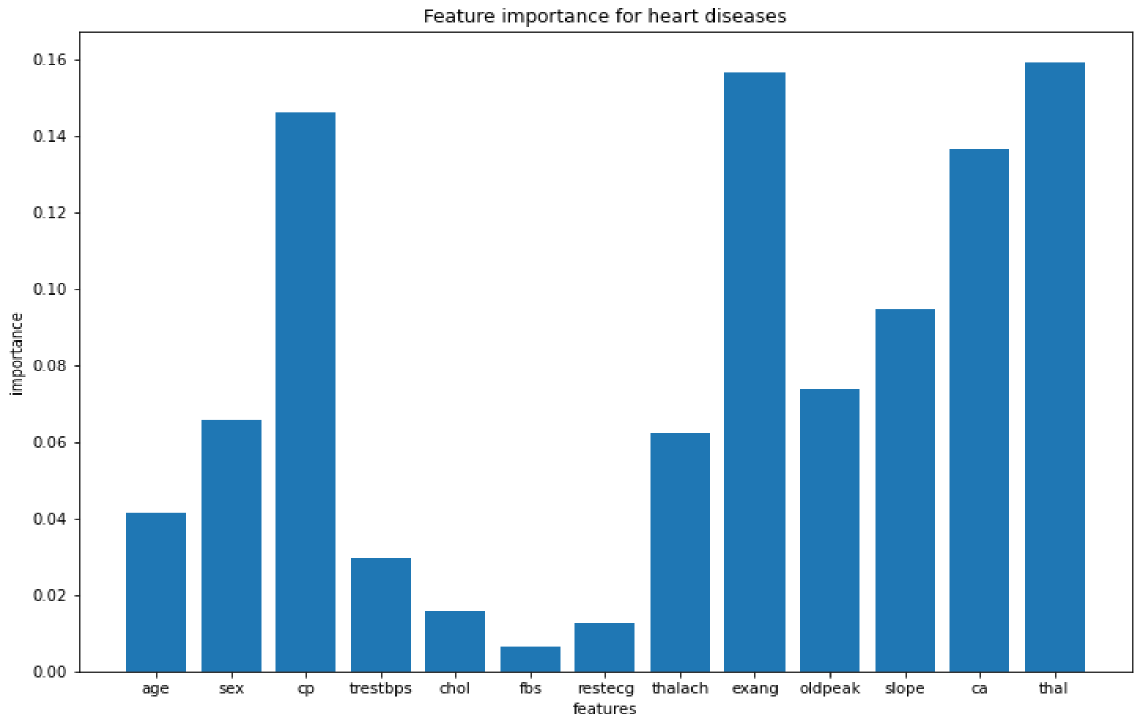

Figure 5. Feature importance for heart diseases

Figure 5 shows what features have an impact on the occurrence of heart diseases. The feature importance is calculated by using feature importance (except the target data) using a XGBoost. The conducted features include the following: age, sex, chest pain type (cp), resting blood pressure (trestbps), serum cholesterol (chol), fasting blood sugar (fbs), resting electrocardiographic results (restecg), maximum heart rate (thalach), exercise induced angina (exang), old peak, slope of the peak exercise ST segment (slope), number of major vessels (ca), thalassemia value (thal). Among these features, thalassemia value, exercise induced angina, and chest pain type are the most influential components to heart diseases. ECG should be used in most heart disease cases to proceed with treatment or testing. Therefore, ECG technology in wearable devices allow users to monitor the irregular rhythm of their heart.

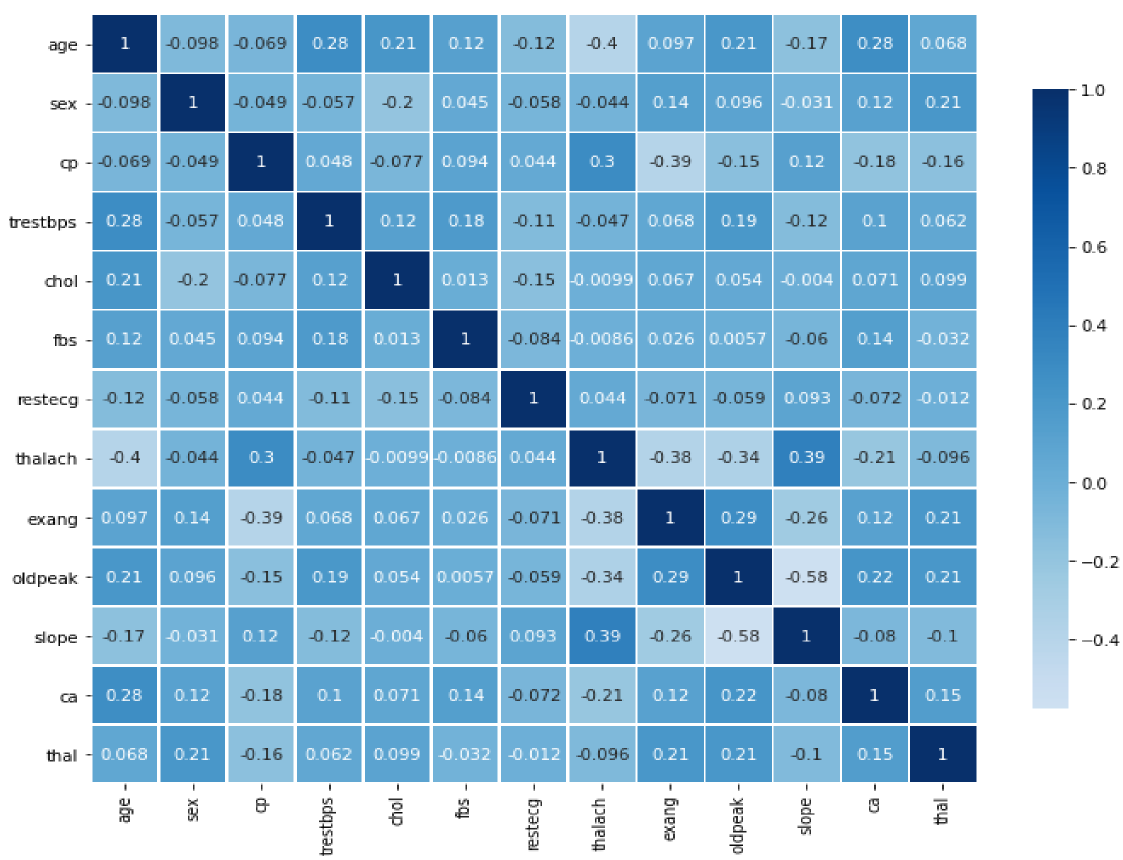

Figure 6. Correlation between the features of heart diseases

Figure 6 represents the correlation between the features of heart diseases. The most correlated value is 0.39 which shows correlation between maximum heart rate (thalach) and the slope of the peak exercise ST segment (slope). ST segment is elevated by early repolarization, acute ischemia, ventricular dyskinesia, and injury from pericarditis (Kashou et al., 2021).

In this chapter, an IoT-based Recommender System framework has been suggested and the case study was implemented showing the accuracy of machine learning algorithms to predict heart diseases and the feature importance of heart diseases and correlation between the features of heart diseases. SVM algorithms and KNN algorithms resulted in higher accuracy compared to other algorithms to predict heart disease occurrences rates. Such methods can be utilized in the proposed IoT-based framework to recommend patients appropriate actions based on their situation. For example, if the recommender system classifies the patients in high risk of heart diseases it will call the emergency and notify the family of the patient. In case of non-emergency, the recommender system will specify what the patient should do to avoid any future discomfort. The system is capable of finding important features for patients with possible heart diseases (such as thalassemia value, exercise induced angina, and chest pain type) and recommend actions to improve their health and be conscious of their condition. The proposed framework helps address some challenges, for example, the risk of going to the doctor in case of pandemic, taking quick actions in case of emergency conditions, affordability of healthcare services, and improving the living habits by considering recommendations in non-emergency situations.

CHAPTER SIX:

CONCLUSION AND FUTURE WORK

Conclusion

This project is aimed to develop an IoT-based Recommender System framework for coupling IoT and Health Recommender Systems. This project presents the architecture of smart IoT in healthcare, IoT healthcare services, IoT healthcare service enablers, IoT healthcare applications, and IoT healthcare devices focusing on wearable devices, especially a Smartwatch. In addition, this project describes the Recommender Systems with machine learning algorithms which is applicable to the Health Recommender Systems in many ways. The integration of IoT and Health Recommender Systems will enhance people's wellness, detect diseases earlier and provide medical advice to patient’s IoT devices or wearable devices. This case study is conducted with data about heart diseases. Through the case study, the accuracy of machine learning algorithms regarding health-related issues are high in Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) algorithms. This study can be helpful for people who need to develop a health-related recommender system using machine learning algorithms. The feature importance for heart diseases and the correlation between the features of heart diseases can support people who need information regarding long term actions to prevent heart diseases.

As the project reaches the finish line, answers to each research question are provided in this section. This project investigated the IoT healthcare services which are Ambient Assisted Living, mHealth, Wearable Devices, Adverse Drug Reaction, Community Healthcare Monitoring, and Children Health Information. IoT healthcare service enablers are Cognitive Computing and Blockchain. In addition, IoT healthcare applications are ECG, Glucose Level Sensing, Blood Pressure Monitoring, Body Temperature Monitoring, Oxygen Saturation Monitoring, Asthma Monitoring, Mood Monitoring, Medication Management, Rehabilitation System, and Wheelchair Management for enhancing people's wellness and overcoming physical limitations. Content-based filtering, collaborative-based filtering, knowledge-based filtering, and hybrid filtering are described with machine learning algorithms for the understanding how the Health Recommender Systems work. Also, this study shows the usage of Health Recommender Systems in helping to quit smoking, to balance dietary nutrition, to relieve psychological symptoms, and to detect rare diseases. With the understanding of IoT in healthcare and Health Recommender Systems, the IoT-based Health Recommender Systems framework is developed in this study for improving responsiveness in identifying the health problem on a daily basis and treating the health-related issues rapidly and conveniently. Therefore, the suggested framework aims to help people to monitor their health-related issues so that they can prevent any health emergencies and live their healthy life. Moreover, the integration of IoT and Health Recommender Systems ultimately can provide affordable health treatment with commercialization and popularization.

The goal of this study is accomplished by investigating healthcare services and healthcare applications using IoT so that we know how to manage individual health through the IoT. In addition, this project suggests the framework of IoT and Health Recommender Systems to elaborate that the framework can provide more advanced health treatment. Therefore, it can enhance in five aspects which are affordability, convenience, responsiveness, treatment, and wellness of humans.

Commercializing the integration of the IoT and Health Recommender Systems can result in the reduction of health treatment costs by monitoring individual health on a daily basis and it can also recommend medical advice through doctors and healthcare professionals. Among the many IoT, Smartwatches can be the medium of the popularization of the suggested framework by developing the medical sensors in the Smartwatch due to its popularity and convenient feature to wear. The IoT devices are widely used in human life which lead to the fast responsiveness in health emergencies and provide quick treatment using Health Recommender Systems. IoT in healthcare can be the next innovation in people’s flourishing life and even utilization of the Health Recommender Systems can induce the better version of healthy human life by monitoring personal health in case of pandemic and can provide recommendations for a healthy lifestyle recommendation, nutrition recommendations and for general health information.

Future Work

While implementing this project, there are limitations of building up a framework and implementing a case study. If relevant studies are published more frequently, it would further support studies regarding the integration of IoT and Health Recommender Systems. This project did not specifically focus on disease since this project mainly focuses on the coupling of IoT and Health Recommender Systems. The integration of IoT and Health Recommender Systems highlights how each particular disease can be a new direction of research for the future. Also, implementation with the algorithms of Health Recommender Systems using specific IoT devices can be compared in future studies.

APPENDIX A:

PYTHON CODE FOR CASE STUDY

PYTHON CODE FOR CASE STUDY

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from collections import Counter
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import
confusion_matrix,accuracy_score,roc_curve,classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
from mlxtend.classifier import StackingCVClassifier

data = pd.read_csv('heartdata.csv')
data.head()

data.info()

y = data["target"]
X = data.drop('target',axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,
random_state = 0)

print(y_test.unique())
Counter(y_train)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

a1 = 'Logistic Regression'
lr = LogisticRegression()
model = lr.fit(X_train, y_train)
lr_predict = lr.predict(X_test)
lr_conf_matrix = confusion_matrix(y_test, lr_predict)
lr_acc_score = accuracy_score(y_test, lr_predict)
```

```
print("confussion matrix")
print(lr_conf_matrix)
print("Accuracy of Logistic Regression:",lr_acc_score*100)
print(classification_report(y_test,lr_predict))

a2 = 'Naive Bayesian'
nb = GaussianNB()
nb.fit(X_train,y_train)
nbpred = nb.predict(X_test)
nb_conf_matrix = confusion_matrix(y_test, nbpred)
nb_acc_score = accuracy_score(y_test, nbpred)
print("confussion matrix")
print(nb_conf_matrix)
print("Accuracy of Naive Bayesian model:",nb_acc_score*100)
print(classification_report(y_test,nbpred))

a3 = 'Random Forest Classfier'
rf = RandomForestClassifier(n_estimators=20, random_state=12,max_depth=5)
rf.fit(X_train,y_train)
rf_predicted = rf.predict(X_test)
rf_conf_matrix = confusion_matrix(y_test, rf_predicted)
rf_acc_score = accuracy_score(y_test, rf_predicted)
print("confussion matrix")
print(rf_conf_matrix)
print("Accuracy of Random Forest:",rf_acc_score*100)
print(classification_report(y_test,rf_predicted))

a4 = 'K-NeighborsClassifier'
knn = KNeighborsClassifier(n_neighbors=10)
knn.fit(X_train, y_train)
knn_predicted = knn.predict(X_test)
knn_conf_matrix = confusion_matrix(y_test, knn_predicted)
knn_acc_score = accuracy_score(y_test, knn_predicted)
print("confussion matrix")
print(knn_conf_matrix)
print("Accuracy of K-NeighborsClassifier:",knn_acc_score*100)
print(classification_report(y_test,knn_predicted))

a5 = 'DecisionTreeClassifier'
dt = DecisionTreeClassifier(criterion = 'entropy',random_state=0,max_depth = 6)
dt.fit(X_train, y_train)
dt_predicted = dt.predict(X_test)
dt_conf_matrix = confusion_matrix(y_test, dt_predicted)
dt_acc_score = accuracy_score(y_test, dt_predicted)
```

```
print("confussion matrix")
print(dt_conf_matrix)
print("Accuracy of DecisionTreeClassifier:",dt_acc_score*100)
print(classification_report(y_test,dt_predicted))

a6 = 'Support Vector Classifier'
svc =  SVC(kernel='rbf', C=2)
svc.fit(X_train, y_train)
svc_predicted = svc.predict(X_test)
svc_conf_matrix = confusion_matrix(y_test, svc_predicted)
svc_acc_score = accuracy_score(y_test, svc_predicted)
print("confussion matrix")
print(svc_conf_matrix)
print("Accuracy of Support Vector Classifier:",svc_acc_score*100)
print(classification_report(y_test,svc_predicted))

a7 = 'Extreme Gradient Boosting'
xgb = XGBClassifier(learning_rate=0.01, n_estimators=25,
max_depth=15,gamma=0.6, subsample=0.52,colsample_bytree=0.6,seed=27,
                reg_lambda=2, booster='dart', colsample_bylevel=0.6,
colsample_bynode=0.5)
xgb.fit(X_train, y_train)
xgb_predicted = xgb.predict(X_test)
xgb_conf_matrix = confusion_matrix(y_test, xgb_predicted)
xgb_acc_score = accuracy_score(y_test, xgb_predicted)
print("confussion matrix")
print(xgb_conf_matrix)
print("Accuracy of Extreme Gradient Boosting:",xgb_acc_score*100)
print(classification_report(y_test,xgb_predicted))

%matplotlib inline
imp_feature = pd.DataFrame({'Feature': ['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs',
'restecg', 'thalach',
     'exang', 'oldpeak', 'slope', 'ca', 'thal'], 'Importance':
xgb.feature_importances_})
plt.figure(figsize=(12,8))
plt.title("Feature importance for heart diseases")
plt.xlabel("features")
plt.ylabel("importance")
plt.bar(imp_feature['Feature'],imp_feature['Importance'])
plt.show()

model_ev = pd.DataFrame({'Model': ['Decision Tree','Logistic Regression','Naive
Bayesian','Extreme Gradient Boosting','Random Forest',
```

```
                'K-Nearest Neighbors','Support Vector Machine'], 'Accuracy':
[dt_acc_score*100,lr_acc_score*100,

nb_acc_score*100,xgb_acc_score*100,rf_acc_score*100,knn_acc_score*100,sv
c_acc_score*100]})
model_ev

%matplotlib inline
plt.figure(figsize=(12,8))
plt.title("Accuracy of different Machine Learning algorithms")
plt.xlabel("Accuracy %")
plt.ylabel("Algorithms")
plt.barh(model_ev['Model'],model_ev['Accuracy'])
plt.show()
corr=data.corr()
corr
data = data.drop(['target'],axis =1)
plt.figure(figsize=(10,10))
sns.heatmap(X.corr(), vmax=1, center=0, square=True, linewidths=.5,
cbar_kws={"shrink": .6}, annot=True, cmap='Blues')
plt.tight_layout()
plt.show()
```

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