

*Ministry of Higher Education  
and Scientific Research  
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College of Science  
Department of Computer  
Science*



# **Simulation of Prediction Healthcare Model Using Markov Chain**

*A Thesis*

**Submitted to the Department of Computer Science College of  
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Requirements for the Degree of Master in Computer Science**

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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

﴿وَلَقَدْ آتَيْنَا دَاوُودَ وَسُلَيْمَانَ عِلْمًا ۖ وَقَالَا الْحَمْدُ لِلَّهِ

الَّذِي فَضَّلَنَا عَلَى كَثِيرٍ مِّنْ عِبَادِهِ الْمُؤْمِنِينَ﴾

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## الإهداء

أهدي جهدي المتواضع هذا إلى قذوتي ومثلي

الأعلى أبي الحبيب

إلى منبع الايثار أُمي الغالية

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إلى من هم سندي وعضدي اخوتي

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*Hala muhanad*

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## *Abstract*

The Internet of Things (IoT) is improving people's lives in more direct and practical ways. One of the most important systems and possible IoT applications is healthcare. It is extensively utilized in a variety of industries and has been developed in a number of ways to support human health, including using the Internet of Things to diagnose illnesses. It also influences the patient's state and the efficacy of the system. The capacities of the healthcare system will be enhanced by and monitor the conditions.

this thesis proposes a predictive model using only Received Signal Strength Indicator (RSSI) volatility. The proposed approach achieves the same function as conventional solutions that use a complex set of motion sensors.

The environment and other elements cause RSSI fluctuation experimental findings demonstrate the ambiguity of RSSI change when people move across the network area and support the applicability of the detection and prediction approach, under a specific situation and some relevant performance indicators, such as the probability of a complete section. The system unavailability is obtaining the system balance equations. For a deeper understanding and validation of the analytical findings, a detailed numerical assessment of chosen metrics is offered. Direct Solution and Markov Prediction were two models utilized to make predictions. The Markov Prediction result was also measured using the statistical scale Root Mean Square Error (RMSE), which is roughly 0.047, and the direct solution result was measured using the RMSE statistical measure that is approximately 0.00431. Direct action is the most effective solution.

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## *List Of Symbols*

| <i>Symbol</i> | <i>Meaning</i>                             |
|---------------|--|
| $\alpha$      | Initial Transition                         |
| $\beta$       | Response Transition                        |
| $p_i$         | Probability                                |
| $p(E_1)$      | Probability Of Event                       |
| $p(x)$        | Probability Function, Where X is the Input |

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### *List of Abbreviations*

| Abbreviations | Meaning                             |
|---------------|-------------------------------------|
| BLE           | Bluetooth Low Energy                |
| BSN           | Body Sensor Networks                |
| DSS           | Decision Support Systems            |
| FBTM          | Fuzzy-Based Treatment Model         |
| GPRS          | General Packet Radio Services       |
| IoT           | Internet Of Thing                   |
| ISM           | Industrial, Scientific, And Medical |
| MBAN          | Medical Body Area Network           |
| MD            | Medical Data                        |
| ML            | Machine Learning                    |
| MSFR          | Motion Sensor Failure Rate          |
| RFID          | Radio Frequency Identification      |
| RMSE          | Root Mean Square Error              |
| RSSI          | Received Signal Strength Indicator  |
| SMS           | Short Message Service               |
| WBAN          | Wireless Body Area Network          |
| MKB           | Medical Knowledge Base              |
| Wi-Fi         | Wireless Fidelity                   |
| WSN           | Wireless Sensor Network             |
| MOM           | Medical Ontology Model              |

***Chapter One***  
***General Introduction***

## **Chapter one General Introduction**

### **1.1 Introduction**

The success of sharing and connecting acquired medical data is crucial to the ultimate goal of improving healthcare practices and biomedical goods. Due to the rapid growth of health-related data, it needs to be correctly found so that important information can be found and turned into useful knowledge that could lead to better healthcare. The critical goal of Medical Data (MD) diagnosis is to be precise in identifying, predicting, and diagnosing illnesses. Therefore, it is crucial to develop and use realistic Machine Learning(ML) categorization techniques that accurately perceive and assess situations [1].

Healthcare systems are continually presenting new challenging aspects to their managers and decision-makers. The effectiveness of current healthcare systems must be able to assess how any changes to these systems would affect patient care [2]. The pursuit of quality improvement has gained importance in the healthcare sector. This trend is due mainly to the perception that improvement work is a means through which healthcare organizations may become safer, more efficient, and more capable of delivering higher-quality care particularly crucial during challenging economic times [3].

In the last study, it was shown that the triple structure of a health monitoring system using a Wireless Sensor Network (WSN) to monitor specific parts of the body continuously measures heart rate and temperature using a set of vital sensors, and this system achieved an accuracy of 95% using Markov modelling [4].

This work discusses WSN based Markov model. The Wireless Sensor Network (WSN) is a joint research path in the information, communication, and technology (ICT) fields, based on sensor technology, microelectromechanical technology, and wireless communication technology. The prevalence of wireless devices, especially those used in healthcare has exploded in recent years. Medical monitoring, memory improvement, medical data access, and emergency communication with healthcare providers through the use of Short Message Service (SMS) or General Packet Radio Services (GPRS) are just a few examples of the many ways in which Body Sensor Networks (BSN) systems have improved people's lives. Healthcare services can assist patients and their families by allowing them to remotely obtain and monitor physiological signs without having to disturb the patient's healthy lifestyle [5].

People choose to use motion sensors for these activities because of the properties of the sensors; otherwise, they would prefer a more practical solution. A new generation of passive (battery-less) sensors, Radio Frequency Identification (RFID) tags with embedded sensors, solves the issues with battery-operated wearables. Passive sensors are more lightweight and compact than battery-powered ones. Moreover, passive sensors don't need maintenance since they don't utilize the chemical energy kept in accumulators. Additionally, passive devices may be conveniently worn by fastening them to clothing, limiting the removal of the monitoring device, particularly by patients with cognitive impairment [6].

## **1.2 Related Work**

There are a large number of studies and research that dealt with the available model and improving the health care system, and we mention the following.

**1- R. Shinmoto, R. Visvanathan, S. Hoskins(2016)[8]:** In the previous study, a study was conducted on the efficiency of sensors for elderly patients who are monitored here. A wireless sensor that can be worn on their clothes was used for patients distributed in two rooms, and they were monitored based on a machine. The predictor of learning activity was focused on the reason for alerting them to leave the chair as well as the bed. The result was the chair exits for the first room were 94% and for the second room 95%, as well as the bed for the second room. The predictors were 67% and 78% respectively, while the F score was > 84% and 77% for bed exits. And the chair.

**2- U. Gogate and J. Baka, 2018 [4]:** In this study, we demonstrate the three-tier architecture of our prototype healthcare monitoring system, which uses a WSN to continually monitor specific body parts of patient parameters. Heart rate and body oxygen levels can be measured using a variety of biosensors, and the temperature is connected to an Arduino Nano board, and the data is relayed to a server. Wireless connection with the Node MCU ESP8266 Thing Speak, an internet of things (IoT) program, makes data available to doctors and caregivers on distant servers. Smartphone alerts can be used to notify cares in the event of an emergency. The system is beneficial for cardiac patients and can be utilized at home or in hospitals for infant and baby care and geriatric care. The system's accuracy is 95%, with a response time of 10 seconds.

**3- I. Singh, D. Kumar and S. Khatri, 2019 [9]:** This system is based on the cloud. The article proposed a framework for grouping adaptive e-healthcare services management. The suggested structure has been improved and now includes many divisions. The cloud design provides a web-enabled system that is integrated with specialists, drug specialists, radiologists, and research centre staff. This recommended engineering may also be successfully delivered in many sectors, including security, cost-cutting, associations, and instructional. The dynamic features of a mark are captured using digital services such as tablets. The essential highlights of the mark are isolated when it is being marked. These highlights are then pre-handled and saved as a format to create a pre-prepared dataset. It is suited for any size usage since it allows for even asset mounting and is thus suitable for massive purposes. In this proposed model, we can quickly check the efficiency as it saves time and money. They have saved a lot of time compared to others, from 20,000 to 15,000.

**4- Khayal 2020 [12]:** This modelling methodology offers chances to explain actual use patterns and trajectories for individuals and the population with chronic diseases when combined with data science tools. The result uses two examples first example System functions were abstracted to BE- TOS descriptions in this example: All Other, Test, Imaging, Evaluation and Management (E&M), and Processes. The following descriptors were used for aggregated places of service: home, office, outpatient, inpatient, and emergency room (ER). The knowledge base displays the system's capabilities in degrees of freedom. The test was (2 for home, 7 for office 7, outpatient 11, ER 16, and Inpatient 21). The first example made use of data from the previous 40 days of existence. Second example We picked the last 6 months of life for this example since it corresponds to previous end-of-life studies. During the sixth month before death (1/19).

**5- D. Akila, D.Balaganesh 2021[1]:** This research provides a Fuzzy Based Treatment Model (FBTM) which allows for early detection and treatment. In the first phase, a Medical Ontology Model (MOM) is constructed based on a Medical Knowledge Base (MKB). This will predict how likely it is that a patient may have an acute condition. Figure 8 displays the FBTM accuracy results. Heart attack prediction accuracy declines from 97% to 95.4%. Strokes decreased from 92% to 90%, while brain tumours decreased from 95% to 93.1%. Kidney failure decreased from 95.5% to 94%.for work.

**6- Latif & Mehryar, 2020 [15]:** They suggest an algorithm to monitor the patient. Compared to the MAS algorithm, O-MAS-R showed a 7.21 per cent average increase in CR of ECG datasets and an 8.25 per cent increase in EMG datasets. This wearable device has many sensors, including sensors for temperature and heart rate. The data will be collected from the sensors by the gadget in the form of biosignals, and then it will be wirelessly sent to a computer at the hospital for further storage and analysis.

**7-H.Wang,F.Zhang, Zhang[16]:** This latest study paper proposes a device-free person identification approach for employing the Received Signal Strength Indicator (RSSI) measurement of Wireless Sensor Network (WSN) with packet dropout based on ZigBee. The experimental findings demonstrate the unpredictability of RSSI change while a human moves over the network region and support the detection method's validity. attain 95 per cent accuracy.

**Table 1.1: Comparison Between the Proposed Systems and Related Methods.**

| Ref.   | Method or Algorithms  | Accuracy   |
|--|---|--|
| R. Shinmoto, R. Visvanathan, S. Hoskins(2016)[8] | ZigBee-compatible radio and a common set of physiological   | first room 94%, second room 95%  |
| U. Gogate and J. Baka, 2018 [4]                  | Uses WSN and type of sensor to monitor patient  | The system's accuracy is 95%, with a response time of 10 seconds.  |
| I. Singh, D. Kumar and S. Khatri, 2019 [9]       | Uses cloud and web this proposed model, we can quickly check the efficiency as it saves time and money  | They have saved a lot of time compared to others, from 20.000 to 15,000  |
| Khayal 2020 [12]                                 | This modelling methodology offers chances to explain actual use patterns and trajectories for individuals.  | The first example test was (2 for home, 7 for office 7, outpatient 11, ER 16, Inpatient 21)<br>Second example We picked the last 6 months of life for this example since it corresponds to previous end-of-life studies. During the sixth month before death (1/19). |
| D. Akilah, D. Balaganesh 2021[1]                 | a Fuzzy based treatment model (FBTM) The study predicts how likely it is that a patient may have an acute condition. Figure 8 displays the FBTM accuracy results                      | Heart attack prediction accuracy declines from 97% to 95.4%. Strokes decreased from 92% to 90%, while brain tumours decreased from 95% to 93.1%. Kidney failure decreased from 95.5% to 94%.for work.  |
| Latif & Mehryar, 2020 [15]                       | They suggest an algorithm to monitor the patient. Compared to the MAS algorithm, O-MAS-R  | Compared to the MAS algorithm, O-MAS-R showed a 7.21 per cent average increase in CR of ECG datasets and an 8.25 per cent increase in EMG dataset  |
| H. Wang, F. Zhang, Zhang[16]                     | a device-free person identification approach for employing Received Signal Strength Indicator (RSSI) measurement of Wireless Sensor Network (WSN) with packet dropout based on ZigBee | The experimental findings demonstrate the unpredictability of RSSI change while a human moves over the network region and support the detection method's validity. attain 95 per cent accuracy   |



### **1.3 Problem Statement**

The problem with this research is how to transfer patient data to the doctor. In light of the spread of viruses, it became necessary to communicate with the doctor through the system able to diagnose the patient's condition remotely, that is, by monitoring the patient via the WSN network, how to treat data and the signal that comes from the system that monitors the patient.

### **1.4 Aim of the Thesis**

Our model provides service besides the predicted status of patients to provide an assistant diagnosis for doctors to get accurate results. Building a system to increase the full service of the system: Transferring data in the sensors to monitor the patient to health care,

### **1.5 Outline of Thesis**

Besides this chapter, the surviving parts of this thesis include the following chapters:

**Chapter Two:** Within the context of the healthcare system, the second chapter will discuss the application of wireless sensor networks and the paradigm that underlies their use.

**Chapter Three:** This chapter outlines the produced model the predictive model, as well as provides an introduction to the processes of the proposed system.

**Chapter Four:** In this chapter, the findings and analyses that have been collected from the suggested system are explained.

**Chapter Five:** This chapter provides a list of conclusions that may be drawn from the findings of the work that was given, as well as some ideas for work that should be done in the future.