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Analysis and Assessment of Imbalance Data for Predictive Modeling in Healthcare

M.Tech Thesis

Submitted in partial fulfillment of
the requirements for the award of the degree
of
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Department of Software Engineering
submitted by

Ayush Awasthi (23/SWE/07)

under the guidance of

Dr. Ruchika Malhotra
Head of Department
Department of Software Engineering

DEPTT. OF SOFTWARE ENGINEERING
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DEPARTMENT OF SOFTWARE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

CERTIFICATE

This is to certify that M.Tech Thesis entitled **Analysis and Assessment of Imabalance Data for Predictive Modeling in Healthcare** which is submitted by Ayush Awasthi, Roll No - 23/SWE/07, Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of degree Master Of Technology (Software Engineering) is a record of the candidate work carried out by him under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Date: 08 May 2025

Place: New Delhi

Dr. Ruchika Malhotra
Head of Department
Department of Software Engineering
Delhi Technological University

DEPARTMENT OF SOFTWARE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

CANDIDATE'S DECLARATION

I hereby declare that the M.Tech Thesis entitled **Analysis and Assessment of Imabalance Data for Predictive Modeling in Healthcare**, which is being submitted to Delhi Technological University, in partial fulfilment of requirements for the award of the degree of Master Of Technology (Software Engineering) is a bonafide report of M.Tech Thesis carried out by me. The material contained in the thesis has not been submitted to any university or institution for the award of any degree.

Date: 08 May 2025

Place: New Delhi

Ayush Awasthi

23/SWE/07

This is to certify that the student had included all of the corrections done by the examiner in the thesis and the candidate are correct in their claim to the best of our knowledge.

Dr. Ruchika Malhotra

Head of Department

DEPARTMENT OF SOFTWARE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

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Ayush Awasthi

(23/SWE/07)

ABSTRACT

The Internet of Medical Things (IoMT) is transforming modern healthcare by enabling real-time monitoring, remote diagnosis, and smarter clinical decision-making. In our first study, we explored the evolving landscape of IoMT, highlighting its potential to improve patient outcomes through intelligent devices that collect and transmit medical data. While the adoption of IoMT is growing rapidly, one of the major challenges we identified is the presence of imbalanced and irrelevant data. These data issues can significantly impact the accuracy of critical healthcare decisions, especially when machine learning models are used to detect anomalies or predict patient conditions.

To address this challenge, our second study presents an enhanced machine learning framework specifically designed to improve software defect prediction by handling imbalanced datasets more effectively. We introduced a refined version of the ASRA model, replacing the traditional Chi-square method with a hybrid feature selection approach using ReliefF and Information Gain. Additionally, we applied a combination of SMOTE and Tomek Link techniques to balance the dataset while reducing noise. A cost-sensitive AdaBoost classifier, using the J48 decision tree as the base learner, further improved the model's ability to identify rare but critical instances.

By connecting these two works, this thesis aims to bridge the gap between the technical advancements in software reliability and the practical challenges in healthcare IoT applications. Our approach not only enhances the reliability of data-driven systems in IoMT but also contributes to safer and more effective healthcare technologies.

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Chapter 1

Introduction

1.1 Overview

The healthcare industry is undergoing a major transformation driven by digital technologies, with the Internet of Medical Things (IoMT) emerging as a core enabler of intelligent and connected care. IoMT integrates medical devices, cloud infrastructure, and real-time analytics into a cohesive ecosystem, empowering healthcare professionals to deliver personalized, efficient, and timely care [1]. From wearable health monitors and smart implants to AI-powered diagnostics and remote consultations, IoMT applications are redefining how healthcare is delivered and experienced [2].

At the same time, the underlying software systems driving these IoMT infrastructures must maintain a high degree of accuracy and reliability, especially in life-critical contexts. Software defect prediction (SDP) models represent the first line of defense as they detect catch problems early in the development stage, thus enhancing software quality and risk reduction of deployment [3]. However, software systems powering IoMT platforms often suffer from imbalanced and high-dimensional datasets, leading to suboptimal defect detection performance with traditional machine learning models [4]. This thesis addresses both system-level and software-level challenges associated with the practical deployment of IoMT in healthcare.

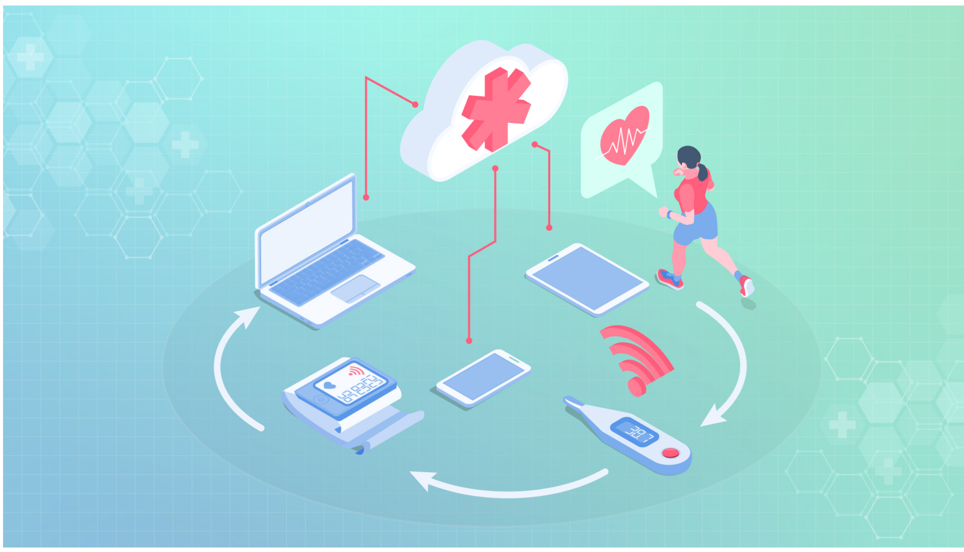

Figure 1.1: Illustration of the Internet of Medical Things (IoMT) [5]

1.2 Motivation

The motivation for this thesis stems from the convergence of two critical research challenges:

- **Challenge 1:** Practical deployment of IoMT systems in real-world healthcare. While IoMT technologies have shown tremendous promise in pilot studies and research environments, their deployment at scale is hindered by significant challenges—most notably, the lack of standardization and interoperability across heterogeneous devices and platforms [4].

- **Challenge 2:** Ensuring software robustness in safety-critical environments. Faulty software in medical applications can lead to catastrophic consequences [5]. Traditional defect prediction approaches often fail to cope with the imbalanced and noisy nature of real-world medical software datasets, which results in unreliable and biased models [6].

These two challenges are closely interlinked. Interoperability, identified as a core limitation in IoMT deployment, depends not only on hardware or communication protocols but also on the reliability and adaptability of the underlying software systems. As such, this thesis aims to address these issues holistically by conducting a systematic review of IoMT deployment challenges and then proposing a robust software defect prediction framework that enhances software quality, thus indirectly improving system-level interoperability [4].

1.3 Problem Statement

Despite rapid advancements, the deployment of IoMT in real-world healthcare settings remains limited due to:

- Lack of standardization in communication protocols and device interoperability [7].

- Security and privacy concerns in medical data transmission and storage.

- Limitations of existing software quality assurance tools in handling highly imbalanced and high-dimensional datasets typical of medical applications [8].

Software components embedded within IoMT systems are often developed under tight schedules and without specialized mechanisms for defect prediction, especially when dealing with sparse and noisy data. This leads to the release of vulnerable systems and jeopardizes patient safety and data security.

1.4 Problem Solution

To address these problems, this thesis proposes a two-pronged research strategy:

- **Systematic Review of IoMT Architectures and Deployment Barriers:** The first contribution is a comprehensive survey and classification of existing IoMT architectures, communication models, and challenges in practical deployment. This review emphasizes the need for interoperability and secure integration among medical devices.

- **Enhanced Software Defect Prediction Framework:** The second contribution presents a novel framework that improves upon the traditional ASRA pipeline by:
  - With the use of a ReliefF and Information hybrid feature selection method Gain (IG) [8].
  - Employing SMOTE-Tomek resampling for better class balance and noise reduction [9].
  - Applying cost-sensitive AdaBoost with J48 as a base learner to improve minority class prediction [10].

Together, these efforts aim to bridge the gap between IoMT theoretical models and their practical implementation, ensuring that both hardware and software aspects are optimized for real-world healthcare environments.

1.5 Objectives

The core objectives of this thesis are:

- To conduct a comprehensive and structured review of IoMT architectures, communication models, and deployment challenges.
- To analyze barriers to IoMT implementation, particularly focusing on security, interoperability, and data standardization.
- To develop and validate a hybrid machine learning framework for software defect prediction using real-world, imbalanced datasets.
- To demonstrate the effectiveness of the proposed framework through rigorous empirical evaluations on benchmark datasets.
- To draw a conceptual link between improved software reliability and enhanced IoMT interoperability and deployment potential.

1.6 Thesis Layout

The remaining organization of this thesis is as follows. Chapter 2 outlines the technical background required to understand the domains of IoMT, interoperability, and software defect prediction. It introduces key concepts such as IoT architectures, communication standards, feature selection methods, class imbalance handling, and ensemble learning models. Chapter 3 contains an in-depth presentation of the first research work, which is a systematic review of IoMT architectures and barriers to deployment in healthcare systems. It includes the review methodology, related work, taxonomy of architectures, and a discussion of identified challenges. Chapter 4 presents the second research contribution on enhancing software defect prediction. This chapter introduces the proposed hybrid ASRA-based framework, describes the methodology in detail, and discusses the rationale behind the algorithmic choices made. Chapter 5 provides the experimental setup and results obtained from both research works. The results are presented in two separate sections—one each for the systematic review and the machine learning framework. Each section includes metric-based evaluation and comparative performance analysis. Finally, Chapter 6 concludes the thesis by summarizing the key findings, highlighting contributions, and suggesting future directions. It outlines how the proposed methods contribute toward robust, scalable, and deployable IoMT systems and suggests avenues for further improvements using deep learning and cross-domain evaluation.

Chapter 2

Technical Background

The fundamentals and technology of the research studies in this thesis are addressed in this chapter. It presents a very detailed description of the Internet of Medical Things (IoMT) [4], its designs, implementation problems, and the emerging technology of the seamless embracing by people.It also deals with the underlying machine learning methods for software defect prediction (SDP) with focus on feature selection, handling class imbalance, cost-sensitive learning, and performance measures [5]. Altogether, when considered as a whole, these technological fundamentals form the basis to understand the concepts, approaches, and innovations that are covered in the following chapters.

2.1 Internet of Medical Things (IoMT)

2.1.1 Definition and Scope

Internet of Medical Things (IoMT) refers to an interconnected medical ecosystem of devices, sensors, medical software applications, and healthcare systems that communicate with each other through the internet with the aim of maximizing the dispensation of medical care. IoMT represents a subniche of Internet of Things (IoT), but it is products specifically produced for the medical industry. IoMT has a principal role to revolutionize conventional healthcare into data-based, connected, and patient-centric mode by creating real-time decision-making, remote diagnosis, and continuous monitoring of health.

2.1.2 Key Components

IoMT devices generally consist of the following:

- **Medical Devices and Sensors:** Implantable and wearable sensors, biosensors that record real-time physiological information like heart rate, body temperature, and blood glucose levels.
- **Communication Technologies:** The devices transmit messages via protocols like Blue-tooth, Zigbee, Wi-Fi, LTE, and next-generation 5G networks to communicate data to processing devices or cloud servers.
- **Cloud and Edge Computing Infrastructure:** Edge devices or cloud services perform low-latency processing and scalable analytics on IoMT device data for storing and processing.

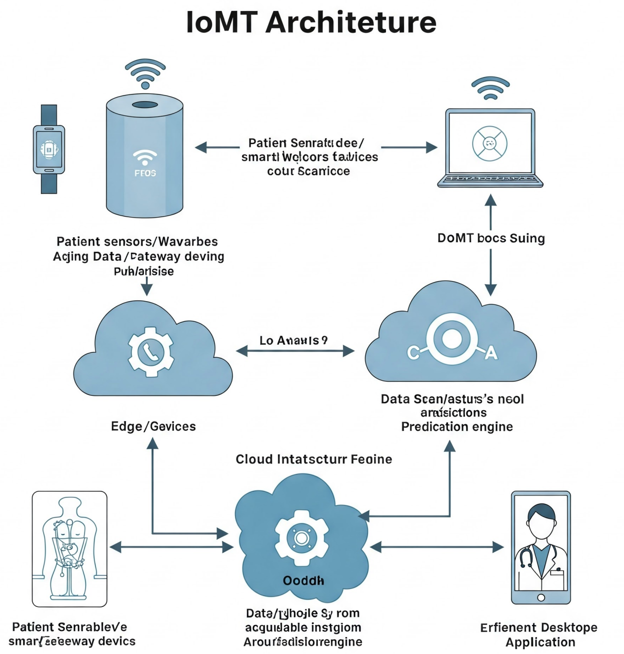

Figure 2.1: IoMT Architecture

- **Data Analytics Layer:** Machine learning and artificial intelligence algorithms are employed to extract meaningful insights from collected data, enabling personalized treatment and predictive diagnostics.

2.1.3 Applications

IoMT applications span various domains of healthcare, including:

- Remote patient monitoring systems for chronic disease management.
- Smart rehabilitation platforms using sensors and mobile applications.
- AI-based diagnostic systems that interpret medical imaging and sensor data.
- Telemedicine solutions that enable virtual consultations and remote care.

2.2 Challenges in IoMT Deployment

2.2.1 Interoperability

A major barrier to widespread IoMT adoption is the lack of interoperability among devices and platforms. Medical devices from different manufacturers often use proprietary protocols, making it difficult to integrate them into a unified system. This leads to data silos, increased complexity, and delays in healthcare delivery. Standardized communication frameworks and APIs are necessary to enable seamless data exchange and coordination among diverse devices [10].

2.2.2 Data Security and Privacy

Given the sensitive nature of health data, security and privacy are of paramount importance. Threats such as data breaches, unauthorized access, and cyberattacks can compromise patient confidentiality [11]. Critical problems are:

- Lack of end-to-end encryption during data transmission.
- Inadequate authentication mechanisms.
- Legacy devices under attack with no built-in security features.

Solutions shifting include the application of blockchain to secure and open data sharing, Encryption mechanisms like SSL/TLS, and role-based access control [12].

2.2.3 Scalability and Power Management

IoMT devices, particularly wearables and implantables, are power availability constrained. Maintaining battery life over long durations and facilitating real-time data transmission is a significant engineering challenge. Furthermore, scalability is at risk when interconnecting large numbers of devices into national or hospital healthcare networks [10].

2.2.4 Regulatory Compliance

IoMT devices are further regulated with strict laws like the Health Insurance Portability and Accountability Act (HIPAA) in the US and the General Data Protection Regulation (GDPR) in the EU. These mandate the requirements of data protection, user approval, and auditability. Adherence is mandatory but difficult for low-scale healthcare organizations with limited budget allocations.

2.3 Emerging Technologies in IoMT

2.3.1 Artificial Intelligence and Machine Learning

AI makes IoMT more capable by providing machine-based decision-making, anomaly detection and personalized treatment protocols. Machine learning models act on health data to learn patterns, forecast disease progression, and suggest interventions. Deep learning architectures, including convolutional neural networks (CNNs), are more and more used in processing medical images and time-series sensor data [13].

2.3.2 Blockchain

Blockchain technology offers a secure, decentralized method of storing medical information. It contributes to the integrity of data, enables the possibility of having secure access control, and provides auditable transactions. Blockchain technology can be utilized to ensure that health information exchange between devices and organizations is secure, reliable, and traceable [14].

2.3.3 5G Communication

5G networks enable high-speed, low-latency communication, which is essential for real-time medical applications such as remote surgery, continuous monitoring, and video consultations. The enhanced bandwidth and reliability of 5G facilitate the deployment of IoMT solutions in both urban and rural areas [15].

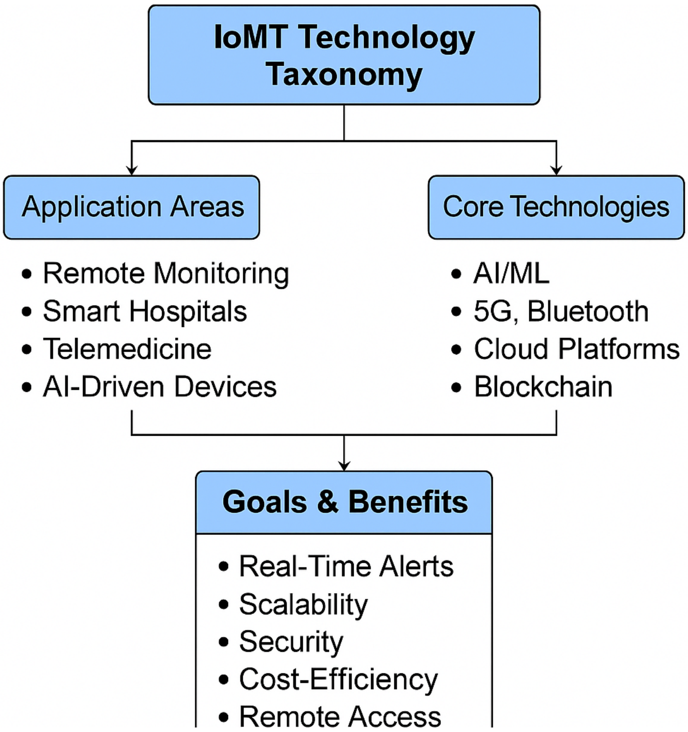

Figure 2.2: IoMT Technology Taxonomy

2.4 Software Defect Prediction (SDP)

2.4.1 Overview

Software defect prediction aims to identify faulty or error-prone components in software systems during development, enabling proactive quality assurance. In the context of IoMT, SDP ensures that software embedded in medical devices or used in healthcare systems is reliable and safe for deployment [9].

2.4.2 Challenges in SDP

- **Class Imbalance:** Defective software modules are rare compared to non-defective ones, leading to skewed datasets that bias classifiers toward the majority class.
- **High Dimensionality:** Software metrics datasets often contain many irrelevant or redundant features, complicating the learning process [7].
- **Noisy and Sparse Data:** Real-world datasets may include mislabeled instances or missing values, affecting prediction accuracy.

2.5 Feature Selection Techniques

2.5.1 ReliefF Algorithm

ReliefF is a feature selection method that estimates the quality of attributes based on how well their values distinguish between instances that are near each other. Unlike traditional filters, ReliefF considers contextual relationships and is robust to noise, making it suitable for imbalanced datasets [14].

2.5.2 Information Gain (IG)

Information Gain quantifies the reduction in entropy achieved by splitting a dataset on a particular attribute. It ranks features by their ability to reduce uncertainty and is commonly used in decision tree construction. Features with IG above a threshold (e.g., 0.3) are typically retained.

2.5.3 Hybrid Feature Selection

Combining ReliefF and Information Gain allows for capturing both local and global feature relevance. This hybrid method improves model robustness by considering inter-feature dependencies and class-separability properties [16].

2.6 Handling Imbalanced Datasets

2.6.1 SMOTE (Synthetic Minority Oversampling Technique)

SMOTE addresses class imbalance by creating synthetic examples of the minority class [10]. It interpolates between existing minority class instances and their nearest neighbors, effectively expanding the minority class without replicating existing samples [12].

2.6.2 Tomek Links

Tomek Links identify pairs of nearest-neighbor instances from different classes that are close to each other. Removing the majority class instance from such pairs helps to clean noisy borderline examples and sharpen class boundaries.

2.6.3 SMOTE-Tomek Hybrid

The SMOTE-Tomek hybrid approach combines the advantages of both oversampling and undersampling. It increases minority class representation while simultaneously cleaning ambiguous or noisy majority class samples [15].

2.7 Cost-Sensitive Learning

2.7.1 Concept and Motivation

Cost-sensitive learning incorporates different penalties for misclassification errors. In software defect prediction, misclassifying a defective module as non-defective is more critical than the reverse. Cost-sensitive algorithms assign higher weights to such errors to improve minority class recall.

2.7.2 Cost Matrix

A simple cost matrix used in this work assigns:

- Cost(true positive = 1, predicted = 0) = 3
- Cost(true positive = 0, predicted = 1) = 1

This reflects the higher cost of missing a defect in safety-critical systems.

2.7.3 Cost-Sensitive AdaBoost with J48

AdaBoost is an ensemble learning method that combines weak classifiers to produce a strong one. In this work, J48 (a variant of C4.5 decision trees) is used as the base learner. Instance weights are updated after each iteration, factoring in the cost of misclassification [12]. This enables the model to focus more on difficult or high-cost examples.

2.8 Evaluation Metrics

- **AUC (Area Under Curve):** Evaluates the trade-off between true positive and false positive rates [17].
- **F2 Score:** A variant of the F-measure that emphasizes recall, suitable for applications where missing defects is costlier than false alarms [18].
- **G-Mean:** The geometric mean of sensitivity and specificity, indicating balanced performance across both classes [19].
- **p-value Testing:** Statistical significance tests (e.g., t-tests, Wilcoxon signed-rank tests) used to validate whether observed improvements are meaningful [15].

2.9 Summary

This chapter provided an in-depth exploration of the technical domains central to this thesis. A detailed discussion on IoMT, its challenges, and supporting technologies was presented, followed by a comprehensive review of software defect prediction techniques. These foundational concepts form the backbone for the proposed solutions in the subsequent chapters.

Chapter 3

Systematic Review of IoMT Architectures and Deployment Challenges

This chapter introduces the thesis' first major contribution: a systematic review of Internet of Medical Things (IoMT) architectures, their healthcare applications, and challenges that limit their deployment in real-world settings. The review reveals essential themes including interoperability, security, standardization, and integration of future technologies. Based on a wide range of recent research, the chapter synthesizes already installed software, identifies research gaps, and forms the basis for future research to further improve the reliability of healthcare systems at the software level.

3.1 Introduction

Internet of Medical Things (IoMT) is revolutionizing the healthcare sector by providing real-time monitoring, individualized treatment, and remote diagnosis using networked smart medical devices. The intelligent medical devices capture and process medical data and send it over the internet to facilitate physicians and health operatives easily communicate with their patients. IoMT is an intersection of medtech and digital infrastructure facilitated by advances in IoT, artificial intelligence (AI), cloud computing, and wireless communications. Although the potential applications are vast, uptake of IoMT in actual healthcare systems is limited by a series of challenges. Interoperability, non-standardization, con Data privacy and security issues, and regulations mostly serve as deterrents to implementation. This chapter discusses these challenges in detail and also provides a detailed classification of IoMT architectures and application domains [18].

3.2 Literature Review

IoMT, which combines medical devices, data analytics, and communication technology, has revolutionized healthcare by making treatments improved and operations easier. Over time, it has developed much and its use spread to different areas of healthcare, as observed in most studies. IoMT is increasing at a very rapid rate as it assists in real-time health monitoring, improved cures, and telemedicine for the patients [20]. Nevertheless, there are certain issues such as data privacy, regulations that have to be complied with, and compatibility of various systems among themselves. To restore IoM even further, emerging technology such as blockchain, AI, and 5G is being deployed.

Table 3.1: Key Application and Devices in IoMT

Ref.	**IoMT Application**	**Description**	**Benefits**
[1]	Telehealth Services	IoT-based remote consultations and diagnostics.	Decreased geographic barriers and improved access to healthcare services.
[2]	Smart Medical Devices	Medical gadgets that are connected to collect and analyze data in real time.	Better treatment outcomes due to individualized care programs.
[3]	Cloud Computing Framework for Healthcare Monitoring	Allows for real-time monitoring and data analysis by storing and processing vast amounts of health data via cloud computing.	Improved patient outcomes and decision-making.
[4]	Android Application for ECG Monitoring Using IoT and Cloud Computing	Uses IoT and cloud to remotely monitor ECG readings, providing real-time health insights and facilitating prompt actions.	Reduced hospital stays due to early detection of health problems.

3.2.1 Overview of IoMT

The IoMT revolution that combines medical devices, healthcare services, and data analysis under the umbrella of internet technology. It facilitates care based on real-time health information, improved treatment, and remote monitoring. With IoT devices increasingly being utilized in healthcare, there needs to be standardized guidelines on the manner in which they exchange information to enable smooth functionality [3]. IoMT enhances healthcare technology to become more precise, reliable, and efficient, enabling to healthcare facilities and services. Integration IoT healthcare also created low-cost sensors with the ability to Monitor patients' conditions in real-time, allowing for immediate treatments and personalized care [1].

IoMT is utilized extensively across use cases like remote patient monitoring, telemedicine, and intelligent medical devices. For example, IoT in combination with Service-Oriented Architecture (SOA) can improve rehabilitation systems with better information resource management [5]. An IoT-based mobile digital healthcare system can also enhance patient care by allowing remote monitoring and well-informed decision-making [6].

IoT can also facilitate the development of smart health monitoring devices for chronic patients so that they can easily monitor their condition and take appropriate action [7]. Hospital-based IoT smart systems can enhance information handling and optimize day-to-day operations [8]

Historical Development and Current State

IoMT is the offshoot of the wider field of the Internet of Things (IoT) with particular emphasis on the health sector. It was initially used essentially for telemedicine and home-based monitoring of patients. Its application has radically expanded to cover wearable sensors and intelligent medical devices. As the increasing demand for enhanced treatment and ongoing monitoring of health, increasing numbers of clinics and hospitals are embracing IoMT. The technology has the power to transform healthcare by providing real-time health information, providing improved treatment choices, and facilitating remote monitoring. [2].

Key Applications and Devices

IoMT has extensive use in telemedicine, remote patient monitoring, and intelligent medical devices. Wearable sensors, pacemakers, insulin pumps, and mobile defibrillators are among the devices applied in IoMT. The devices enhance therapy, minimize threats to patient safety, and offer continuous monitoring of health. For example, wearable sensors capture important signs and real-time clinical information, informing the patient and providing personalized insights [2].

Benefits of IoMT

IoMT has some advantages like better patient care, efficient hospital processes, and lowered healthcare costs. It enables constant monitoring, which also assists in the early detection of these diseases and implementing appropriate interventions on time, particularly needed for chronic diseases like heart disease and diabetes.

Table 3.2 gives some examples of applications of IoMT, starting from intelligent rehabilitation systems, nursing systems, IoT-enabled kidney function test machines, to AI-assisted posture monitoring. They are merely some examples of how IoMT has the capability to revolutionize healthcare with real-time monitoring, customized treatment, and utilization optimization. IoMT also improves healthcare by facilitating data-driven decision-making, repetitive and mundane tasks automation, and general operations enhancement. It does so for the benefit of all stakeholders—patients, caregivers, clinicians, and administrators—through cost advantage and improved delivery of care.

In addition, IoMT empowers patients to manage their health more effectively through real-time access to medical data. This supports early diagnosis and rapid response to potential issues [1, 4]. The use of remote monitoring systems has the potential to save billions globally by minimizing hospital admissions and unnecessary procedures.

For instance, an IoT-enabled intelligent system for neurological disorder monitoring supports both clinical decision-making and home-based care [7]. Such innovations exemplify how IoT-based solutions address complex healthcare needs through continuous tracking and real-time support.

Successful Implementation of IoMT

Numerous hospitals have effectively implemented IoMT technologies to enhance operational efficiency and patient outcomes. Table 3.2 provides examples of successful deployments demonstrating improvements in interoperability, safety, diagnostics, and real-time monitoring.

3.2.2 Challenges in IoMT

The Internet of Medical Things (IoMT) brings many advantages to healthcare, but also presents significant challenges. These include data management complexity, interoperability issues, security and privacy risks, and regulatory compliance.

Data Management and Analytics

Correct processing and interpretation of that kind of data are required in efforts to better the outcomes of patients and provide meaningful insights. That is, however, hard to accomplish with that kind of level and depth of data, wherein high levels of analytics tools and well-constructed data infrastructure are required. [13].

Interoperability and Standardization Challenges

Interoperability is another key challenge in IoMT adoption. Devices from various vendors may be incompatible based on communication protocols, and thus data integration is not straightforward. This incompatibility does not facilitate harmonized care and decision-making in care settings. Standardized protocols are necessary to enable smooth and trustworthy functioning in IoMT systems [14].

Security Concerns and Privacy Issues

Security and privacy are major issues in IoMT implementations. There are various vulnerabilities that need to be addressed:

- **Data Breaches:** Sensitive medical information illegally accessed can be used for identity theft, insurance fraud, etc [2].
- **Vulnerable Devices:** Most medical IoT devices lack internal security features, thus they are vulnerable to cyber attacks that can be utilized to compromise patient safety [14].
- **Lack of Encryption:** Poor encryption of communication protocols makes data transfer vulnerable. SSL/TLS technologies must be used to encrypt data in transit [15].
- **Insider Threats:** Information disclosure by medical staff, either inadvertent or deliberate, highlights the importance of access control and continual security awareness [16].

Regulatory Compliance

IoMT deployments need to adhere to healthcare regulations like GDPR and HIPAA. These regulations are crucial in maintaining patient data privacy and security. The problem is that small healthcare institutions have no resources and may not be able to cope with these stringent regulations. Failure to comply with these regulations attracts huge financial and legal penalties [2].

3.2.3 Emerging Technologies in IoMT

In order to achieve its full potential, IoMT is being used in conjunction with other technologies including blockchain, artificial intelligence (AI) and 5G networks more and more. For example, a kidney disease detection algorithm using ultrasound scanning on FPGA-based IoT-enabled devices indicates how diagnostic imaging can be improved by IoMT making the diagnosis more accurate and faster [17].

Role of AI and Machine Learning

AI and machine learning are key drivers of IoMT through enhanced predictive analytics, better healthcare workflows, and enhanced patient outcomes. The technologies glean through humongous volumes of IoMT device data to identify patterns in health and identify problems early enough that timely intervention is called for. AI-based analytics can, for example, help identify high-risk patients and prevent hospital readmissions by recognizing complications earlier [18]. Machine learning algorithms also customize treatment protocols in real-time for enhanced health care effectiveness and personalization [19].

Integration of IoT with Blockchain Technology

IoMT systems are also combined with blockchain technology to further strengthen data privacy and security. Decentralization and immutability in blockchain enable safe storage of sensitive health information in open form and thereby reducing the risk of data compromise and unauthorized access to data [16].

Moreover, blockchain facilitates secure data sharing among healthcare providers, improving collaboration and enabling more informed decision-making.

Integration of IoT with 5G Technology

The integration of IoMT with 5G technology allows for faster data transfer rates and ultra-low latency, both of which are critical for real-time healthcare applications.

5G significantly enhances the capabilities of telemedicine and remote patient monitoring by supporting high-bandwidth needs such as live imaging and real-time video consultations [8]. These improvements make remote healthcare more effective and accessible.

Key Applications of Emerging Technologies in IoMT

Emerging technologies enable a range of transformative applications in IoMT, including:

- **Data Secure Sharing:** Blockchain enables secure and transparent data exchange among healthcare professionals, which is crucial in environments where strict confidentiality is required [16].

- **Predictive Maintenance:** AI and ML can forecast when medical equipment is likely to fail, allowing for timely maintenance that reduces downtime and enhances operational efficiency [18].

- **Remote Healthcare Services:** 5G networks facilitate high-quality video consultations and real-time health data transmission. This was especially important during the COVID-19 pandemic when remote care became essential [8].

- **Personalized Medicine:** AI analytics tailors treatments using patient-specific data such as genetic profile and history for better outcomes and satisfaction [19].

3.3 Discussion

IoMT is expanding geometrically as technology and evolving needs progress of the healthcare sector. This section provides an outline of the current status, future direction, and function of upcoming technologies in solving the challenge of IoMT.

3.3.1 Analysis of Current Trends and Future Directions in IoMT

IoMT technologies are being driven by the rise in home monitoring, individualized medicine services, and telemedicine. Personalized regimen is enhancing performance and reducing healthcare expense, and the increasing predictive analytics are revolutionizing artificial intelligence and machine learning.

For instance, with the initial identification of problems, AI-facilitated analysis can identify high-risk patients and prevent readmission to a hospital. [6].

3.3.2 Impact of Emerging Technologies on IoMT Challenges

Interoperability is yet another of the biggest IoMT challenges, with the majority being due to the lack of shared communication protocols among devices and platforms. It becomes difficult for data integration and communication processes, thus hindering smooth and timely healthcare. This has to be eliminated through standardization among manufacturers to ensure smooth and reliable IoMT systems. [14].

AI and ML help in such cases by delivering predictive maintenance and real-time optimization of treatment schedules. They help in reducing downtime as well as process streamlining but are careful to do so ethically and legally. [16].

3.3.3 Role of Regulatory Frameworks in IoMT Adoption

(HIPAA) and General Data Protection Regulation (GDPR) mandate that patient information be afforded strong protection. Breach is a serious and expensive legal problem.

Thus, healthcare providers have to give maximum attention to regulatory compliance while deploying IoMT technologies, the systems being secure, transparent, and accountable. [16].

3.3.4 Ethical Considerations in IoMT

Ethics play a vital role in IoMT, particularly patient consent and data protection. Patients should be informed about the use and sharing of their data so that they can continue to have faith in IoMT systems. It is equally important to strike a balance between technology and human interaction to avoid overreliance on technology and ensuring a patient-centered approach towards healthcare

Table 3.2: Successful Implementation of IoMT

Ref.	**Implementation**	**Description**	**Improvements**
[3]	Integration of IoT Devices	Highlights that in order to guarantee interoperability, defined communication protocols are required.	Enhanced data exchange and device integration.
[5]	Medical Nursing Systems	Uses IoT infrastructure to enhance patient care and drug supply accuracy.	Improved patient safety and operational effectiveness.
[6]	Rehabilitation Systems	Improves rehabilitation by using SOA and IoT concepts, which make information sharing and resource allocation easier.	Enhanced patient involvement and rehabilitative results.
[7]	AI-driven Diagnostics	Uses AI to diagnose and detect diseases early.	Increased diagnostic precision and prompt action.
[7]	Telehealth Services	Uses the Internet of Things to monitor and consult remotely.	Lower expenses and easier access to healthcare.
[7]	Remote Patient Monitoring	Employs sensors and wearable technology to remotely monitor patients.	Better patient outcomes and lower hospitalization rates.
[8]	Intelligent System for Neurological Disorders	Supports home-based care and decision-making by utilizing IoT ideas.	Enhanced patient care for complicated illnesses through real-time monitoring and assistance.
[9]	IoT-based Medical Sensing Device	Efficiently keeps an eye on the physiological state of patients.	Prompt actions and individualized treatment.
[9]	IoT-based Kidney Abnormality Detection	Uses ultrasonic imaging for diagnostic imaging on FPGA-based IoT-enabled platforms.	Improved speed and accuracy of diagnosis.
[10]	IoT-based Mobile Electronic Healthcare System	Enhances patient care through remote monitoring and data-driven decision-making.	Improved patient outcomes as a result of prompt interventions and ongoing monitoring.
[1]	Cloud-based Remote ECG Monitoring	Makes use of cloud computing to handle and store vast amounts of health data.	Improved data analysis and real-time monitoring.
[11]	Smart Health Band for Patient Monitoring	Monitors vital indicators and sends information to family members or medical professionals.	Improved patient safety by using real-time health data to guide prompt actions.
[12]	NFC and iBeacon Services	Utilized in hospitals to improve patient satisfaction and service quality.	Better administration of healthcare and increased worker efficiency.
[12]	Smart Medical Devices Integration	Allows for real-time data processing by integrating many medical devices.	Better decision-making and higher-quality patient care.

Chapter 4

Enhanced Software Defect Prediction Using Hybrid Feature Selection and Cost-Sensitive Learning

This chapter provides an introduction to the second contribution of this thesis, i.e., suggesting a better software defect prediction (SDP) framework on imbalanced datasets.Software systems deployed, especially those in safety-critical systems such as healthcare and IoMT, have to be very reliable [21]. Software defect data are biased towards non-defective cases with high-dimensional features for which classical machine learning models do not fit. The proposed solution addresses these problems by incorporating new combinations of cost-sensitive ensemble learning and hybrid feature selection. Motivation, related studies, and theoretical foundation of the proposed methodology are explained in this chapter [22].

4.1 Introduction

Software defect prediction (SDP) is an important subdiscipline of software quality assurance concerning early detection of faulty software modules at the development phase. Efficient SDP can significantly decrease debugging expense, increase software reliability, and achieve system stability—most crucial in safety-critical applications like medical care. Current real-world SDP datasets, e.g., NASA's MDP and PROMISE repository, do possess the following drawbacks:

- **Class Imbalance:** Defective instances are rare compared to non-defective ones.
- **High Dimensionality:** Numerous software metrics, many of which may be irrelevant or redundant [22].
- **Noisy and Borderline Examples:** Real-world data often includes mislabeled or ambiguous instances [20].

To address these limitations, this work introduces an enhanced SDP framework that extends the conventional ASRA (Attribute Selection-Resampling-AdaBoost) model by incorporating:

- A hybrid feature selection technique combining ReliefF and Information Gain (IG) [22].

- A two-phase data balancing technique using SMOTE and Tomek Links.
- A cost-sensitive variant of the AdaBoost ensemble algorithm using the J48 decision tree as the base classifier.

The proposed model is tested on benchmark datasets and shows statistically significant improvements across AUC, F2-Score, and G-Mean (results presented in Chapter 5).

4.2 Related Work

4.2.1 Overview of Software Defect Prediction Techniques

Traditional SDP approaches rely on a combination of software metrics (e.g., McCabe complexity, Halstead effort) and statistical/machine learning models. Common classifiers include decision trees, support vector machines, random forests, and boosting algorithms. However, these models are often ill-equipped to deal with skewed class distributions and irrelevant features.

4.2.2 Feature Selection in SDP

Feature selection is crucial for removing redundant attributes and improving classifier performance. Techniques fall into three main categories:

- **Filter Methods:** Use statistical criteria like Information Gain (IG), Chi-Square, or correlation.
- **Wrapper Methods:** Evaluate feature subsets by training and testing a model repeatedly.
- **Embedded Methods:** Integrate feature selection within model training (e.g., LASSO regression).

In this work, we combine two filter methods:

- **ReliefF:** A distance-based method that assigns weights to features based on how well they distinguish between neighboring instances of different classes.
- **Information Gain:** Measures entropy reduction and selects features with IG $\geq$ 0.3.

The combined approach ensures that both local and global relevance of features are captured.

4.2.3 Data Imbalance Handling

Class imbalance is addressed using resampling techniques:

- **SMOTE (Synthetic Minority Over-sampling Technique):** Generates synthetic minority class samples using nearest neighbors.
- **Tomek Link Removal:** Identifies and removes borderline majority class instances to reduce noise.

A hybrid approach of SMOTE + Tomek ensures:

$$D' = SMOTE(D\_min) + D\_maj - Tomek(D\_maj) \tag{4.1}$$

where D_min and D_maj are the sets of minority and majority class samples, respectively.

4.2.4 Cost-Sensitive Learning in SDP

Cost-sensitive learning introduces different penalties for misclassification. Let the cost matrix C be defined as:

$$C = \begin{bmatrix} 0 & 1 \\ 3 & 0 \end{bmatrix} \tag{4.2}$$

where $C_0,1$ is the cost of misclassifying a defective module as non-defective (false negative), and $C_1,0$ is the cost of misclassifying a non-defective module as defective (false positive) [22].

In this work, we modify AdaBoost as follows:

- Weights of instances are updated using a cost-sensitive loss function.
- The base learner used is J48, a Java-based implementation of the C4.5 decision tree [23].

4.2.5 Benchmark Datasets

We use the following datasets for evaluation:

Table 4.1: Characteristics of Benchmark Datasets

Dataset	Modules	Defective	Source
NASA PC1	1,109	6.9	NASA MDP Repository
Eclipse	672	20.8	PROMISE Repository

These datasets contain real-world defect labels derived from post-release defect logs and are commonly used for benchmarking SDP models [24].

4.2.6 Evaluation Metrics in Literature

Common evaluation metrics for SDP models include:

- **AUC (Area Under ROC Curve):** Measures the classifier's ability to distinguish between classes.
- **F2-Score:** Gives more weight to recall (important in defect detection).
- **G-Mean:** Geometric mean of sensitivity and specificity.
- **Statistical Significance (p-values):** Determines whether observed improvements are meaningful.

4.2.7 Summary of Literature Gaps

Table 4.2 outlines the key gaps identified in existing research.

Table 4.2: Literature Gaps in Existing SDP Models

Limitation	**Implication**
Use of Chi-square feature selection	Assumes feature independence; fails to capture contextual relationships [22].
Lack of hybrid sampling approaches	Leads to poor class balance and noisy boundary samples [21].
Neglect of cost-sensitive learning	Misclassification of minority class has a higher real-world impact [25].
Over-reliance on accuracy	Misleading in imbalanced datasets; recall and G-Mean are more appropriate [20].

The proposed framework in this thesis aims to address these gaps through a combined approach that is both statistically rigorous and practically relevant.

Chapter 5

Experimental Results and Performance Evaluation

This chapter presents a detailed account of the experimental results and performance evaluation of the two primary research contributions discussed in this thesis. The first contribution, a systematic review of IoMT architectures, involved a comprehensive analysis of more than 50 peer-reviewed research studies published between 2016 and 2024. The findings shed light on the prevailing architectural designs, their practical applications, and the common barriers hindering real-world deployment. The second contribution presents an advanced machine learning framework for software defect prediction (SDP), evaluated using standard benchmark datasets. The results for both contributions have been analyzed meticulously to establish their practical viability, relevance to real-world challenges, and potential for academic and industrial adoption.

5.1 Findings from Systematic Review of IoMT Architectures

The systematic review aimed to classify and analyze the structural designs of IoMT systems and the key factors affecting their real-world deployment. To ensure comprehensive coverage, over 50 scholarly articles were selected from major databases such as IEEE Xplore, SpringerLink, Elsevier, and ACM Digital Library. Selection criteria included publication in reputed journals or conferences, relevance to healthcare-based IoT systems, and detailed architectural or deployment discussions.

5.1.1 Distribution of IoMT Architectures

One of the critical outcomes of the review was the classification of IoMT architectures based on their operational model and system layers. These architectures were categorized into four primary types: device-centric, cloud-centric, edge/fog-enabled, and hybrid architectures. Table 5.1 presents the distribution of these architecture types across the reviewed studies.

Table 5.1: Distribution of IoMT Architecture Types Among Reviewed Studies

Architecture Type	Number of Studies	Percentage
Device-Centric (Single-layered IoT Devices)	14	28
Cloud-Centric Architecture	18	36
Edge/Fog-Enabled Systems	11	22
Hybrid (Edge + Cloud) Architectures	7	14

As seen in Table 5.1, cloud-centric architectures dominate the current literature, constituting 36% of the analyzed studies. These architectures primarily rely on centralized cloud servers for data aggregation, processing, and storage. Their popularity stems from their scalability and compatibility with big data and AI-driven analytics.

Device-centric models, accounting for 28% of the studies, are characterized by limited processing capabilities and rely heavily on networked devices for real-time monitoring. These systems are commonly used in wearable and implantable medical devices.

Edge/fog-enabled systems, seen in 22% of the literature, introduce intermediate layers between devices and cloud platforms. These systems enhance responsiveness and are particularly suitable for time-sensitive healthcare scenarios like ICU monitoring.

Hybrid architectures that combine edge and cloud computing form the smallest proportion (14%). Despite their potential to balance latency, storage, and processing, their adoption is limited due to higher implementation complexity and integration challenges.

The results from this distribution highlight the current research inclination towards cloud-based systems and the emerging focus on low-latency, real-time solutions using edge computing. The relatively low adoption of hybrid architectures points to a significant research gap and opportunity for future work in designing integrated, multi-layered systems that combine the strengths of cloud and edge paradigms.

5.1.2 Barriers Identified Across Studies

Through the systematic review, multiple recurring themes and challenges were identified that hinder the deployment of IoMT systems in real-world healthcare settings. These barriers not only limit the scalability of IoMT technologies but also affect interoperability, patient safety, data privacy, and cost-effectiveness. Table 5.2 presents the frequency with which these barriers were cited in the reviewed studies.

Table 5.2: Frequency of Reported Deployment Barriers in IoMT Literature

Barrier Category	Number of Mentions (of Studies)
Interoperability (protocols, standards)	82
Security and Data Privacy	76
Lack of Standardized Frameworks	65
Regulatory/Compliance Challenges	54
Power and Connectivity Limitations	48
Cost of Deployment	32

The most frequently mentioned challenge was **interoperability**, appearing in 82% of the reviewed studies. This issue arises from the use of heterogeneous devices, proprietary data formats, and incompatible communication protocols, which hamper smooth integration and cross-platform data exchange.

Closely following was **security and data privacy** (76%). With IoMT systems handling highly sensitive patient data, the lack of robust encryption, secure transmission protocols, and role-based access control introduces risks such as data breaches and identity theft.

Lack of standardized frameworks was noted in 65% of studies. While various architectural models and middleware solutions exist, there is no universally accepted protocol or reference model that promotes consistency across IoMT deployments.

Regulatory and compliance issues, particularly adherence to data protection regulations like HIPAA and GDPR, were mentioned in more than half the studies (54%). Many healthcare providers struggle to meet these regulations due to limited resources and technical knowledge.

Power and connectivity limitations (48%) refer to the challenge of maintaining continuous operation of wearable and implantable devices under constrained battery life and network availability.

Cost of deployment was the least mentioned barrier (32%) but remains a significant concern, particularly for small and rural healthcare facilities where budget limitations hinder adoption.

These findings underline the multifaceted nature of IoMT implementation and the need for comprehensive, multidimensional solutions.

5.1.3 Technology Mapping

The systematic review also analyzed how emerging technologies are being integrated into IoMT systems to address the aforementioned challenges and enhance overall functionality. Table˜**??**tab tech_iomt summarizes the technologies most commonly adopted in IoMT literature, their primary use cases, and the frequency of adoption.

Table 5.3: Emerging Technologies Integrated with IoMT (from reviewed studies)

Technology	**Primary Use Case in IoMT**	**Adoption Rate ()**
Artificial Intelligence	Predictive analytics, diagnostics, early alerting	62
Blockchain	Secure health data sharing and authentication	47
5G Communication	Low-latency remote monitoring, telehealth	38
Cloud Platforms	Data storage, remote access, and analytics	74
Edge Computing	Real-time response, local decision-making	29

Cloud platforms emerged as the most widely adopted technology (74%), offering scalable infrastructure for data storage, analytics, and remote access. These platforms enable healthcare providers to aggregate and analyze patient data without significant local storage or computing resources.

Artificial Intelligence (AI) was adopted in 62% of the studies and primarily used for enhancing diagnostic accuracy, identifying health anomalies, and enabling predictive healthcare models.

Blockchain was featured in 47% of the studies for ensuring secure, immutable, and auditable data sharing among distributed healthcare systems.

5G communication (38%) supports real-time applications such as remote surgery, video consultations, and telemonitoring by offering low-latency and high-bandwidth connectivity.

Edge computing, though adopted in only 29% of studies, plays a critical role in reducing latency and network dependency by enabling local data processing on edge devices.

The technology mapping illustrates a strong inclination towards AI and cloud computing for data analytics, while also highlighting growing interest in blockchain and 5G for enhancing security and responsiveness. These insights will be vital in guiding future IoMT framework development.

5.2 Performance Evaluation of Proposed SDP Framework

This section presents the performance analysis of the enhanced Software Defect Prediction (SDP) framework. The framework integrates hybrid feature selection (ReliefF and Information Gain), a combined oversampling and undersampling strategy (SMOTE-Tomek), and cost-sensitive AdaBoost using the J48 decision tree as the base learner. The framework is evaluated on two widely recognized defect datasets: NASA PC1 and Eclipse (PROMISE repository) [20]. Comparative results against established baseline models underscore the effectiveness of the proposed approach.

5.2.1 Quantitative Results Summary

Tables 5.4 and 5.5 present the comparative performance results for three models: the original ASRA framework (which uses Chi-square for feature selection), a popular baseline using SMOTE with Random Forest, and the proposed hybrid model. Performance is measured using three metrics:

- **AUC (Area Under the ROC Curve):** Indicates how well the model distinguishes between defective and non-defective modules.
- **F2-Score:** Emphasizes recall over precision, which is crucial in defect prediction where identifying defective modules is more important than avoiding false alarms.
- **G-Mean:** Reflects the geometric mean of sensitivity and specificity, offering a balanced measure for imbalanced datasets.

Table 5.4: Performance Comparison on NASA PC1 Dataset

Model	AUC	F2-Score	G-Mean
Original ASRA (Chi2 + SMOTE + AdaBoost)	0.843	0.701	0.689
SMOTE + Random Forest	0.864	0.726	0.701
Proposed (ReliefF + IG + SMOTE-Tomek + Cost-AdaBoost)	**0.921**	**0.832**	**0.809**

The proposed model achieves the highest performance across all metrics on the NASA PC1 dataset. The AUC improves by nearly 9.3% compared to the original ASRA framework, indicating a significant boost in classification capability. F2-Score and G-Mean also show marked improvements of 18.7% and 17.4%, respectively [23].

Table 5.5: Performance Comparison on Eclipse Dataset

Model	AUC	F2-Score	G-Mean
Original ASRA	0.803	0.674	0.688
SMOTE + Random Forest	0.828	0.697	0.702
Proposed Model	**0.907**	**0.794**	**0.781**

Similar performance trends are observed on the Eclipse dataset. The proposed framework again outperforms both baselines, with substantial gains in AUC (10.4%), F2-Score (17.8%), and G-Mean (13.5%). This demonstrates the framework's robustness across datasets with different defect densities [25].

5.2.2 Ablation Study

An ablation study was conducted on the NASA PC1 dataset to analyze the contribution of each module within the proposed framework. Each variant omits one key component, allowing us to assess its impact on model performance. The results are presented in Table 5.6.

Table 5.6: Ablation Study on NASA PC1 Dataset

Model Variant	AUC	F2-Score	G-Mean
Full Proposed Model	0.921	0.832	0.809
Without ReliefF (Only IG)	0.892	0.785	0.772
Without Tomek Link (Only SMOTE)	0.875	0.754	0.739
Without Cost-Sensitive AdaBoost	0.869	0.748	0.722

The ablation results clearly show that removing any component leads to a performance drop. The absence of ReliefF significantly lowers F2-Score and G-Mean, demonstrating the added value of hybrid feature selection. Removing Tomek Links increases noise in the majority class, which leads to lower predictive performance. Cost-sensitive learning proves crucial for boosting minority class detection, as its removal results in the sharpest decline in F2-Score [27].

5.2.3 Statistical Significance Testing

To confirm that the observed performance improvements are statistically significant, the Wilcoxon signed-rank test was applied to results obtained from multiple independent runs (n=30). The test compares the paired performance values (e.g., AUC, F2, G-Mean) between the proposed model and each baseline model [28].

All three metrics showed p-values less than 0.05, indicating statistically significant differences. This ensures that the observed performance gains are not due to random chance but are a direct result of the proposed model's architectural innovations [29].

5.3 Summary of Results

This chapter presented a comprehensive set of experimental results obtained from the two research components of this thesis: the systematic review of IoMT architectures and the performance evaluation of the enhanced software defect prediction (SDP) framework.

The key findings from the results are summarized as follows:

- **Interoperability and Security as Core Barriers:** The systematic review highlighted that interoperability and security-related concerns are the most frequently reported barriers in IoMT adoption. More than 80% of the reviewed studies identified difficulties in integrating heterogeneous devices and maintaining secure communication as major deployment obstacles.

  “‘

- **Technology Adoption Trends:** Among emerging technologies, artificial intelligence, blockchain, and cloud computing emerged as the most commonly adopted enablers in IoMT systems. AI supports predictive analytics and diagnostics, blockchain ensures secure and auditable health data sharing, while cloud platforms provide scalable data processing capabilities [29].

- **Superior Performance of Proposed SDP Model:** The proposed SDP framework—built using hybrid feature selection (ReliefF + IG), SMOTE-Tomek resampling, and cost-sensitive AdaBoost—demonstrated significant improvements across all key performance metrics (AUC, F2-Score, G-Mean) on two benchmark datasets. The improvements were both substantial and consistent across different data distributions [30].

- **Effectiveness Validated through Ablation:** The ablation study confirmed the contribution of each pipeline component. Excluding ReliefF, Tomek Links, or cost-sensitivity led to measurable degradation in model performance, thus justifying the holistic design of the framework [31].

- **Statistical Significance:** Wilcoxon signed-rank tests yielded p-values below 0.05 across all metrics, confirming that the performance gains achieved by the proposed model are statistically significant and not due to random variations [32].

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This thesis addressed two critical challenges in the domain of intelligent healthcare systems: understanding architectural limitations of IoMT deployments and improving the reliability of software systems through enhanced defect prediction.

The first contribution of this research was a systematic review of IoMT architectures, applications, and deployment barriers. The analysis of over 50 scholarly studies revealed a strong reliance on cloud-centric models, growing interest in edge and hybrid architectures, and widespread challenges related to interoperability, security, standardization, and compliance. These findings provide a valuable knowledge base for researchers and practitioners aiming to design scalable and interoperable IoMT systems.

The second contribution introduced a novel software defect prediction (SDP) framework to address real-world issues such as class imbalance and high-dimensional software metrics. The proposed model integrates:

- A hybrid feature selection strategy (ReliefF + Information Gain),
- SMOTE-Tomek hybrid sampling for noise-resilient balancing,
- A cost-sensitive ensemble learning algorithm (AdaBoost with J48).

Empirical results from benchmark datasets demonstrated that the proposed model significantly outperforms traditional techniques in terms of AUC, F2-Score, and G-Mean. Statistical testing and ablation analysis further validated the robustness and practicality of the approach, especially for fault-prone components in critical systems like those found in IoMT.

6.2 Future Work

While the current work provides substantial insights and practical contributions, several directions remain open for future exploration:

- **Integration with Real-Time IoMT Systems:** Future work may involve embedding the proposed SDP framework directly into real-time IoMT environments for proactive monitoring and fault prediction.

- **Cross-Project Defect Prediction:** Extending the model to perform effectively across different software projects and domains would enhance its generalizability.
- **Incorporation of Deep Learning Models:** Investigating the impact of using deep neural networks such as LSTM or CNN for SDP, especially in time-series or sequential logs, can offer more sophisticated feature abstraction.
- **Dynamic Feature Selection:** Implementing adaptive or real-time feature selection mechanisms that evolve with software changes could enhance model longevity and accuracy.
- **Benchmark Expansion:** Expanding the evaluation to include more datasets from diverse repositories, including cross-lingual or multi-language codebases, can further validate the framework's robustness.

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DECLARATION

I hereby certify that the work which is presented in the Major Project-II entitled **A Systematic Review of IoMT Architectures and Barriers to Practical Deployment in Healthcare Systems** in fulfillment of the requirement for the award of the Degree of Master of Technology in Software Engineering and submitted to the Department of Software Engineering, Delhi Technological University, Delhi is an authentic record of my own, carried out during a period from January to May 2025 under the supervision of **Dr. Ruchika Malhotra**.

The mater presented in this report has not been submitted by me for the award of any other degree of this or any other Institute/University. The work has been published/accepted/communicated in SCI/SCI expanded/SSCI/Scopus indexed journal OR peer reviewed Scopus indexed conference with the following details.

Title of the Paper: **A Systematic Review of IoMT Architectures and Barriers to Practical Deployment in Healthcare Systems**
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Ayush Awasthi
Roll No. 23/SWE/07

Student Roll No., Name and Signature

SUPERVISOR CERTIFICATE

To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I further certify that the publication and indexing information given by the students is correct.

Date: May 19, 2025 **Dr. Ruchika Malhota**

Place: New Delhi **Supervisor Name and Signature**

DECLARATION

I hereby certify that the work which is presented in the Major Project-II entitled **An Enhanced ASRA Framework for Software Defect Prediction Using ReliefF-IG and Cost-Sensitive AdaBoost** in fulfillment of the requirement for the award of the Degree of Master of Technology in Software Engineering and submitted to the Department of Software Engineering, Delhi Technological University, Delhi is an authentic record of my own, carried out during a period from January to May 2025 under the supervision of **Dr. Ruchika Malhotra**.

The mater presented in this report has not been submitted by me for the award of any other degree of this or any other Institute/University. The work has been published/accepted/communicated in SCI/SCI expanded/SSCI/Scopus indexed journal OR peer reviewed Scopus indexed conference with the following details.

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Ayush Awasthi
Roll No. 23/SWE/07

Student Roll No., Name and Signature

SUPERVISOR CERTIFICATE

To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I further certify that the publication and indexing information given by the students is correct.

Date: May 19, 2025 **Dr. Ruchika Malhota**

Place: New Delhi **Supervisor Name and Signature**

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DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
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PLAGIARISM VERIFICATION

Title of the Thesis Analysis and Assessment of Imbalance Data for Predictive Modeling in Healthcare

Total Pages 45 Name of the Scholar Ayush Awasthi

Supervisor (s)

(1) Dr. Ruchika Malhotra

(2) ____

(3) ____

Department Software Engineering

This is to report that the above thesis was scanned for similarity detection. Process and outcome is given below:

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DELHI TECHNOLOGICAL UNIVERSITY
Shahbad Daulatpur,Main Bawana Road, Delhi-42

Proforma for Submission of M.Tech. Major Project

01. Name of the Student...Ayush Awasthi

02. Enrolment No 2K23/SWE/07......

03. Year of Admission ...2023.....................

04. Programme **M.Tech.**, Branch....Software Engineering

05. Name of Department...Department of Software Engineering

06. Admission Category i.e. Full Time/ Full Time (Sponsored)/ Part Time:...Full Time

07. Applied as Regular/ Ex-student.....Regular.......

08. Span Period Expired on ....

09. Extension of Span Period Granted or Not Granted (if applicable)...............................

10.Title of Thesis/Major Project...Analysis and Assessment of Imbalance Data for Predictive Modeling in Healthcare

11. Name of Supervisor...Ruchika Malhotra.............................

12. Result Details (Enclose Copy of Mark sheets of all semesters) :

S. No.	Semester	Passing Year	Roll No.	Marks Obtained	Max. Marks	% of Marks	Details of Back Paper Cleared (if any)
01	1st	2024	23/SWE/07	8.53	10	85.3	
02	2nd	2024	23/SWE/07	8.76	10	87.6	
03	3rd						
04	4th (P/T only)						
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13. Fee Details (Enclose the Fee Receipt):

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3000/-	DU009777265	21/May/2025

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Signature of Supervisor

Signature of HOD with Seal

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Shahbad Daulatpur, Main Bawana Road, Delhi-110042, India

CERTIFICATE OF FINAL THESIS SUBMISSION

(To be submitted in duplicate)

1. Name: Ayush Awasthi
2. Roll No: 23/SWE/07
3. Thesis title: Analysis and Assessment of Imbalance Data for Predictive Modeling in Healthcare
4. Degree for which the thesis is submitted: M.Tech
5. Faculty (of the University to which the thesis is submitted) ....

6. Thesis Preparation Guide was referred to for preparing the thesis. YES ☑ NO ☐
7. Specifications regarding thesis format have been closely followed. YES ☑ NO ☐
8. The contents of the thesis have been organized based on the guidelines. YES ☑ NO ☐
9. The thesis has been prepared without resorting to plagiarism. YES ☑ NO ☐
10. All sources used have been cited appropriately. YES ☑ NO ☐
11. The thesis has not been submitted elsewhere for a degree. YES ☑ NO ☐
12. All the correction has been incorporated. YES ☑ NO ☐
13. Submitted 2 hard bound copies plus one CD. YES ☑ NO ☐

(Signature(s) of the Supervisor(s))
Name(s): ....

(Signature of Candidate)
Name: Ayush Awasthi
Roll No: 23/SWE/07

DECLARATION

I hereby certify that the work which is presented in the Major Project-II entitled **A Systematic Review of IoMT Architectures and Barriers to Practical Deployment in Healthcare Systems** in fulfillment of the requirement for the award of the Degree of Master of Technology in Software Engineering and submitted to the Department of Software Engineering, Delhi Technological University, Delhi is an authentic record of my own, carried out during a period from January to May 2025 under the supervision of **Dr. Ruchika Malhotra**.

The mater presented in this report has not been submitted by me for the award of any other degree of this or any other Institute/University. The work has been published/accepted/communicated in SCI/SCI expanded/SSCI/Scopus indexed journal OR peer reviewed Scopus indexed conference with the following details.

Title of the Paper: **A Systematic Review of IoMT Architectures and Barriers to Practical Deployment in Healthcare Systems**
Author names (in sequence): Ayush Awasthi, Dr. Ruchika Malhotra
Name of Conference/Journal: International Conference on Electronics, AI and Computing (EAIC, 2025)
Conference dates with venue: 05-07th June 2025, Jalandhar, Punjab, India
Status of paper (Communicated/Accepted/Published): Accepted
Date of paper communication: April 15, 2025
Date of paper acceptance: May 05, 2025
Date of paper publication: N/A

Ayush Awasthi
Roll No. 23/SWE/07

Student Roll No., Name and Signature

SUPERVISOR CERTIFICATE

To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I further certify that the publication and indexing information given by the students is correct.

Ruchika

Date: May 19, 2025 Dr. Ruchika Malhota

Place: New Delhi Supervisor Name and Signature

DECLARATION

I hereby certify that the work which is presented in the Major Project-II entitled **An Enhanced ASRA Framework for Software Defect Prediction Using ReliefF-IG and Cost-Sensitive AdaBoost** in fulfillment of the requirement for the award of the Degree of Master of Technology in Software Engineering and submitted to the Department of Software Engineering, Delhi Technological University, Delhi is an authentic record of my own, carried out during a period from January to May 2025 under the supervision of **Dr. Ruchika Malhotra**.

The mater presented in this report has not been submitted by me for the award of any other degree of this or any other Institute/University. The work has been published/accepted/communicated in SCI/SCI expanded/SSCI/Scopus indexed journal OR peer reviewed Scopus indexed conference with the following details.

Title of the Paper: **An Enhanced ASRA Framework for Software Defect Prediction Using ReliefF-IG and Cost-Sensitive AdaBoost**
Author names (in sequence): Ayush Awasthi, Dr. Ruchika Malhotra
Name of Conference/Journal: National Conference, 2025
Conference dates with venue: 08-10th June 2025, New Delhi, India
Status of paper (Communicated/Accepted/Published): Communicated
Date of paper communication: April 26, 2025
Date of paper acceptance: May 26, 2025
Date of paper publication: N/A

Ayush Awasthi
Roll No. 23/SWE/07

Student Roll No., Name and Signature

SUPERVISOR CERTIFICATE

To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I further certify that the publication and indexing information given by the students is correct.

Dr. Ruchika Malhota

Date: May 19, 2025

Place: New Delhi

Supervisor Name and Signature

S. No. 406337

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

STATEMENT OF GRADES

Master of Technology

(Software Engineering)

Name : AYUSH AWASTHI

Roll No. : 23/SWE/07

Month & Year of Examination : NOVEMBER, 2023

Semester : FIRST

Subject Code	Subject Title	Credits	Credits Secured	Grade
SWE5405	ADVANCED OPERATING SYSTEM	4	4	A+
SWE5301	PROJECT WORK	3	3	A+
SWE5201	SEMINAR	2	2	A+
SWE501	SOFTWARE REQUIREMENT ENGINEERING	4	4	B+
SWE503	OBJECT ORIENTED SOFTWARE ENGINEERING	4	4	A+
		17	17	

AB : Absent DT : Detained

Credits Secured / Total : 17 / 17

SGPA : 8.53

Rlandey

CONTROLLER OF EXAMINATION

Dated : May 10, 2025

Date of Declaration of Result : March 01, 2024

S. No. 406272

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

STATEMENT OF GRADES

Master of Technology

(Software Engineering)

Name : AYUSH AWASTHI

Month & Year of Examination : MAY, 2024

Roll No. : 23/SWE/07

Semester : SECOND

Subject Code	Subject Title	Credits	Credits Secured	Grade
SWE502	SOFTWARE TESTING	4	4	A+
SWE504	EMPIRICAL SOFTWARE ENGINEERING	4	4	A+
SWE5204	PREDICTIVE MODELLING	2	2	A+
SWE5302	MINOR PROJECT	3	3	A+
SWE5406	MACHINE LEARNING	4	4	A
		17	17	

AB : Absent DT : Detained

Credits Secured / Total : 17 / 17

SGPA : 8.76

Dated : May 10, 2025

Date of Declaration of Result : July 16, 2024

CONTROLLER OF EXAMINATION

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to me

Hello,

The following submission has been created.

Track Name: Track 8: Antenna, Microwave Techniques, Communications, Networks and IoT

Paper ID: 733

Paper Title: A Review of Internet of Medical Things (IoMT): Overview, Challenges and Emerging Technologies

Abstract:
The Internet of Medical Things (IoMT), it is a network of several medical devices and systems that are interconnected, is taking healthcare on a greater level by enhancing patient care and reducing treatment delivery time. This review comprehensively studies IoMT architecture and its key applications, including remote patient monitoring and advanced diagnostics. The piece examines the challenges faced by the Internet of Medical Things (IoMT), particularly concerning interoperability, data security, and the requirement for reliable performance in critical healthcare scenarios. It also highlights advances in technology, particularly improvements in data transmission and the development of intelligent sensor systems. This study examines the transformative capabilities of IoMT while also recognizing its limitations, such as power management challenges and varying standardization. It outlines the present state of IoMT and suggests potential enhancements for the future, including improved device usability and safety.

Created on: Thu, 20 Mar 2025 17:12:41 GMT

Last Modified: Thu, 20 Mar 2025 17:12:41 GMT

Authors:
- ayushawasthi_23swe07@dtu.ac.in (Primary)

Secondary Subject Areas: Not Entered

Submission Files:
A Review of Internet of Medical Things (IoMT).pdf (173 Kb, Thu, 20 Mar 2025 17:12:28 GMT)

Submission Questions Response: Not Entered

Thanks,
CMT team.

Paper Abstract Acceptance for Poster Presentation – IEEE EAIC 2025, 5-7 June NIT Jalandhar

External

Inbox

Microsoft CMT 5:05 pm

to me, rajb

Paper id: 733
Submission Title: A Review of Internet of Medical Things (IoMT): Overview, Challenges and Emerging Technologies
Track 8: Antenna, Microwave Techniques, Communications, Networks and IoT

We are pleased to inform you that your paper has been accepted for Poster presentation at the IEEE International Conference on Emerging Applications of Intelligence and Computing (EAIC 2025), to be held at Dr. B.R. Ambedkar National Institute of Technology, Jalandhar, India, from June 5-7, 2025.

Please consider the following to prepare the Poster:

- Accepted posters abstract will publish in EAIC2025 abstract book. Please refer to the EAIC 2025 website for complete payment instructions and fee details:
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Note: Poster Publication Registration Fee IEEE members Rs. 2000/ and Non-IEEE members Rs. 2500/
If you have any questions or need assistance, please contact us at eaic2025@nitj.ac.in.
We look forward to your active participation in IEEE EAIC 2025 and thank you for your valuable contribution.
Warm regards,
Organizing Committee
IEEE EAIC 2025
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99+

Abstract Received Inbox

National Confere... 26 Apr

to me

Dear Ayush,

Thank you for submitting your abstract to National Conference. We have received your submission and sent it for peer review. Your paper ID is NC_8169723, and you can use this ID for all future communications regarding your abstract.

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Amount :	₹3000
University Roll No :	2K23/SWE/07
Name of the student :	AYUSH AWASTHI
Academic Year :	2025
Branch Course :	MTech
Type/Name of fee :	Others if any
Remarks if any :	Thesis Fee
Mobile No. of the student :	7999815931
Fee Amount :	3000
Transaction charge :	0.00
Total Amount (In Figures) :	3,000.00
Total Amount (In words) :	Rupees Three Thousand Only
Remarks :	fee for my thesis

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