ANOMALY DETECTION FROM BIG DATA OF MOTION SENSORS USING DEEP LEARNING

2024
MASTER THESIS
COMPUTER ENGINEERING

Ghaith Mohsin HASAN

Thesis Advisor
Assist. Prof. Dr. Muhammet ÇAKMAK

ANOMALY DETECTION FROM BIG DATA OF MOTION SENSORS USING DEEP LEARNING

Ghaith Mohsin HASAN

Thesis Advisor
Assist. Prof. Dr. Muhammet ÇAKMAK

T.C.
Karabuk University
Institute of Graduate Programs
Department of Computer Engineering
Prepared as
Master Thesis

KARABUK
April 2024

I certify that, in my opinion, the thesis submitted by Ghaith Mohsin HASAN titled "ANOMALY DETECTION FROM BIG DATA OF MOTION SENSORS USING DEEP LEARNING" is fully adequate in scope and quality as a thesis for the degree of Master of Science.

Assist. Prof. Dr. Muhammet ÇAKMAK ....

Thesis Advisor, Department of Computer Engineering

This thesis is accepted by the examining committee with a unanimous vote in the Department of Computer Engineering as a Master of Science thesis. 16/04/2024

Examining Committee Members (Institutions)		Signature
Chairman	: Assoc. Prof. Dr. Zafer ALBAYRAK (SUBU)	....
Member	: Assist. Prof. Dr. Muhammet ÇAKMAK (SNÜ)	....
Member	: Assist. Prof. Dr. Emrah ÖZKAYNAK (KBU)	....

The degree of Master of Science by the thesis submitted is approved by the Administrative Board of the Institute of Graduate Programs, Karabuk University.

Assoc. Prof. Dr. Zeynep ÖZCAN ....

Director of the Institute of Graduate Programs

"I declare that all the information within this thesis has been gathered and presented in accordance with academic regulations and ethical principles, and I have, according to the requirements of these regulations and principles, cited all those which do not originate in this work as well."

Ghaith Mohsin HASAN

ABSTRACT

M. Sc. Thesis

ANOMALY DETECTION FROM BIG DATA OF MOTION SENSORS USING DEEP LEARNING

Ghaith Mohsin HASAN

Karabük University
Institute of Graduate Programs
Department of Computer Engineering

Thesis Advisor:
Assist. Prof. Dr. Muhammet ÇAKMAK

April 2024, 79 pages

In this thesis, the issue of anomaly detection in big data obtained from motion sensors is discussed. The widespread use of motion sensors in various industries has significantly transformed data collection processes, especially in the analysis of human movements. However, accurately detecting anomalies in these large data sets remains a significant challenge. Accurately detecting anomalies in motion sensor data contributes to preventing security hazards, increasing operational efficiency, and improving decision-making processes, especially in the areas of health and safety. In this study, a deep learning-based model was developed using the Feed Forward Neural Network (FFNN) algorithm and particle swarm optimisation (PSO) to solve the anomaly problem in big data obtained from human movements.

In this thesis, a dataset obtained from multi-sensor data of human activities in the smart home environment was used. The proposed (FFNN) algorithm and particle swarm optimization (PSO) based hybrid model achieved a mean absolute error (MAE) of 0.016 and an accuracy rate of 97.95%. The results show that the hybrid FFNN and PSO approach can be used for anomaly detection in various fields based on motion sensor input.

Keywords **:** Anomaly Detection, Feedforward Neural Networks, Particle Swarm Optimization.

Science Code : 92431

ÖZET

Yüksek Lisans Tezi

DERİN ÖĞRENME KULLANILARAK HAREKET SENSÖRLERİNİN BÜYÜK VERİLERİNDEN ANOMALİ TESPİTİ

Ghaith Mohsin HASAN

Karabük Üniversitesi
Lisansüstü Eğitim Enstitüsü
Bilgisayar Mühendisliği Anabilim Dalı

Tez Danışmanı:
Dr. Öğr. Üyesi Muhammet ÇAKMAK
Nisan 2024, 79 sayfa

Bu tezde, hareket sensörlerinden elde edilen büyük verilerdeki anormallik tespiti konusunu ele alınmaktadır. Hareket sensörlerinin çeşitli sektörlerde yaygın olarak kullanılması, özellikle insan hareketlerinin analizinden veri toplama süreçlerini önemli ölçüde dönüştürmüştür. Ancak bu geniş veri kümelerindeki anormallikleri doğru bir şekilde tespit etmek önemli bir sorun olarak devam etmektedir. Hareket sensörü verilerinde anormalliklerin doğru bir şekilde tespit edilmesi sağlık ve güvenlik alanları başta olmak üzere güvenlik tehlikelerinin önlenmesi, operasyonel verimliliğin artırılması ve karar verme süreçlerinin geliştirilmesine katkı sağlamaktadır. Bu çalışmada, insan hareketlerinden elde edilen büyük verilerdeki anormallik sorununun çözümü için İleri Beslemeli Sinir Ağı (FFNN) algoritması ve parçacık sürüsü optimizasyonu (PSO) kullanılarak derin öğrenme tabanlı bir model geliştirilmiştir.

Bu tezde, akıllı ev ortamındaki insan faaliyetlerinin çoklu sensör verilerinden elde edilen bir veri seti kullanıldı. Önerilen (FFNN) algoritması ve parçacık sürüsü optimizasyonu (PSO) tabanlı hibrit model 0,016 ortalama mutlak hata (MAE) ve %97,95 doğruluk (accuracy) oranı elde etti. Elde edilen sonuçlar, hibrit FFNN ve PSO yaklaşımının, hareket sensörü girdisine dayanan çeşitli alanlarda anomali tespiti için kullanılabileceğini göstermektedir.

Anahtar Kelimeler **:** Anomali Tespiti, İleri Beslemeli Sinir Ağları, Parçacık Sürü Optimizasyonu.

Bilim Kodu **:** 92431

ACKNOWLEDGMENT

I want to express my sincere gratitude to everyone who made it possible for me to complete this thesis. First, I would like to thank my thesis advisor, Asist. Prof. Dr. Muhammet ÇAKMAK, for his help in organizing my project and writing this thesis. He gave me promising ideas and pushed me to do my best. I am grateful to the Department of Computer Engineering for allowing me to complete this thesis. I would also like to thank Karabuk University for their support. I would also like to express my appreciation for the crucial role of the Karabük University Kamil Güleç Library staff, who permitted the use of all necessary resources to complete the task. I sincerely thank my parents and family, who provided me with endless inspiration, continuous encouragement, and support throughout my studies. Finally, I am indebted to all my friends who supported me in any way during the completion of the project.

CONTENTS

Page

Page

Page

Page

LIST OF FIGURES

<u>Page</u>

Page

LIST OF TABLES

Page

SYMBOLS AND ABBREVITIONS INDEX

SYMBOLS

$\sum$: weighted sum

Λcoord: Coord is Regularize for coordinates loss

σ : Sigma

$\in$: is an element of

$\int$: integral

ABBREVITIONS

FFNN : Feed-Forward Neural Network

PSO : Particle Swarm Optimization

PCA : Principal Component Analysis

IoMT : Internet of Medical Things

KNN : K-Nearest Neighbors

MAE : Mean Absolute Error

AEC : Autoencoder

PART 1

INTRODUCTION

The extensive adoption of motion sensors in many industries has significantly transformed the data-collecting process. Additionally, it includes data analysis related to human activities these instruments for measuring. From the beginning, its design was simple and direct. Over time, these gadgets have developed into advanced devices that can gather intricate motion patterns. It generates a plethora of critical data for analysis. Alternative manifestations of human deception. Contribute to this extensive catalog. In addition, motion sensors collect a significant amount of data. It is essential to seek atypical incidents. Exploration of state-of-the-art techniques is highly encouraged. Significantly, it integrates deep learning methodologies [1]. This thesis embarks on an exceptional journey. Incorporate it into the segment dedicated to identifying irregularities. Utilize data obtained from motion sensors on a large magnitude. Motion sensors not only aid in comprehending their functioning but also fulfill a crucial role in collecting data. The thesis provides a more comprehensive explanation of the importance of utilizing deep learning frameworks for anomaly detection. Integrate this comprehensive collection of data synthesis. [2].

Provide an insightful overview of the significance of motion sensor data in modern society. This section discusses the development and progression of motion sensor technology. Many locations have been seized by their motion sensors. Compiling vast datasets showing nuanced human behavior, the thesis keeps its shape unchanged [3]. With such an enormous volume of data, identifying the abnormalities becomes necessary through reliable techniques. This method sets up the reciprocal biological linkage between deep neural networks and motion sensor technology towards its inherent compatibility with users' reference context [4]. As motion sensors become high-tech information collection instruments [5], these considerably determine an entire human behavior perception, primarily in the surge-rooted medicine business, signaling an earnest focus on labor [6].

In addition, the revenue from the necessity for personal mixture a thesis underscores an essential requirement in anomaly determination using extraordinarily developed programming advancements that could discover even minor peculiarities among information gathered over recovered network logfiles datasets brought about using creation procedure recorded referenced as got achievement rate 100 forms out of each one hundred [7]. The application of deep neural networks in the course collection range makes the fast detection of anomalies precise. This approach covers a widespread collection of data obtained from motion sensors, which forms an unexpected and transitional wave of energy according to number seven [8].

Motion sensors have constantly been progressing towards a convergence point until this process leaves an extensive repository of information on human behaviors behind. One of the deep learning algorithms is a keystone in strengthening anomaly detection frameworks, which means many new options for different applications available from various industries.

The innovative thesis critically analyzes anomaly detection using big data from motion sensors to increase precision. It covers identifying unusual patterns within large datasets and evaluating existing methodologies. The paper proposes a new approach amalgamating feed-forward neural networks (FFNN) with particle swarm optimization (PSO), confirming its usefulness in analyzing anomaly detection effects. The systematic integration uses FFNN's pattern recognition and PSO's optimization capabilities. Diverse motion sensor datasets were employed to collect, train, and tune the FFNN model. The study refrains from publishing outcomes but underlines the enormous potential and real-world applications for exact anomaly identification in decision-making.

The thesis structure encompasses sections vital to comprehensive exploration. Starting with the abstract summarizing key aspects, acknowledgment expresses gratitude. Contents, lists of figures, and tables provide organizational references. Part 1, the introduction, introduces the research domain, articulates problem statements, objectives, the study's aim, motivation, outline of paper content, and a summary. Part 2 reviews existing literature covering healthcare technology evolution and wearable sensors in human activity monitoring. The background in part 3. The methodology in Part 4 covers dataset specifics, preprocessing, missing data handling, falling prediction techniques, autoencoder application, and k-fold cross-validation. Part 5 delves into result analysis, focusing on PSO, FFNN, comparative studies, and classifier optimization. The conclusion in Part 6 discusses the findings, summarizes contributions, and suggests future research directions. References cite all sources, and a resume summarizes in another language.

1.1. PROBLEM STATEMENT

This section aims to systematically identify and clarify the critical hurdles in identifying irregularities within human activities based on data acquired from motion sensors. It seeks to uncover the different aspects that underpin this purpose and may prevent its proper realization.

The field of anomaly detection, covering human activity data received via motion sensors, is laden with complications. These involve significant complexity and numerous problems, such as data noise and the fundamental variability in human behavior patterns. The section also emphasizes recognized restrictions, encompassing the discussion of existing anomaly detection techniques.

Content data noise: motion sensors, notwithstanding their complexity. They are prone to inherent errors. The challenge stems from factors such as sensor calibration difficulties, indicating interference caused by environmental factors. [4, 6]. The subsequent data noise obscures the legitimacy of the acquired information. It, therefore, hindered the exact detection of anomalies within the background of regular operations.

Variability in Human Behavior: Human behavior displays a broad spectrum of variability. It covers numerous processes. This innate unpredictability presents a substantial issue in establishing stable baseline patterns. That can effectively depict the spectrum of ordinary human activities [2, 5]. It is identifying anomalies. This setting involves a comprehensive understanding of the flexibility of the dynamic character of human activities. It often eludes the usual detection techniques.

Limitations in Current Detection Methods: Traditional anomaly detection methodologies. It depends on specified thresholds. That can set restrictions. It encounters substantial limits when applied to human activity data from motion sensors [1, 8]. These strategies generally suffer. To adapt to the dynamic nature of human activity. It results in overly false-positives, which comprise the inability to identify the abnormalities that are not very obvious.

Ultimately, this mix of difficulties that are somewhat interwoven becomes a complex pattern, which poses intricate impediments that prevent timely anomaly detection. Include sumnavigate. It means that any moves to reduce these concerns even further will lower their effectiveness to the point where it is almost impossible to use the traditional anomaly detection techniques.

1.2. OBJECTIVES

The goals of the system play an important role in providing a comprehensive solution that can handle all kinds of problems in the monitoring of human activities through sensor processing. It will be more specific as it will include both the objectives and metrics for the purposes of measuring the outcomes and the advancement of the field.

The precision and clarity of the objective with realistic goals should be considered significant for the designing and improvement of human activity monitoring methods based on sensor-generated data. This method of approach focuses on the importance of having a set of clear and realistic milestones on which the progress and refinement of monitoring techniques is based.

- Refined data preprocessing techniques for noise reduction: Devise novel algorithms for preprocessing sensor information that comes from wearables.

With its crystal-clear sound, it can even reduce the background noise. It also works to improve the data quality. Hence, it could realize a 20% reduction in the noise of sensor data.

- Innovate anomaly detection models for human movement patterns: We utilize custom-made neural network topologies that allow for precise detection of anomalies in distinct human movement activities. Focus on a minimum increase of 15% in anomaly detection precision as opposed to what is currently available.
- Address unlabeled data challenges with secondary interpretation mechanisms: Devise secondary interpretation methods, too. Additionally, there are class information gaps in sensor-derived data. It lowers processing overhead by 30%. Develop ways to classify unlabeled data. Include with at least 80% accuracy.
- Enhance supervised learning algorithms for one-class data classification: Improve existing supervised learning approaches to categorize one-class data accurately. It concentrates on varied human movement actions. Achieve a 25% boost in classification accuracy for one-class data instances.
- Comprehensive evaluation of developed algorithms: Employ rigorous performance criteria like accuracy. Recalls F1-score to quantify the performance of proposed algorithms in anomaly identification. Target an overall gain of 20% in aggregate performance measures relative to baseline models.
- Guidelines for real-world implementation of anomaly detection techniques: Formulate thorough recommendations and further concrete ideas for adopting successful technologies in natural healthcare and public safety sectors. Aim for a viable implementation path with at least 90% applicability in real-world circumstances.
- Contribution to advancements in human activity monitoring research: Fresh approaches. New insights to enrich the current corpus of research in human activity tracking. Aim to publish at least two novel approaches in peer-reviewed journals or conferences.

1.3. AIMS OF THE STUDY

This section aims to clarify the purpose of the thesis, describing its overarching objectives in enhancing anomaly detection approaches, especially within the context of motion sensor data processing.

The study tries to convey the considerable influence it hopes to have in anomaly detection, stressing its distinctive contribution, notably through revolutionary methodologies in motion sensor data processing.

The primary purpose of this project is to pioneer a paradigm shift in anomaly detection approaches, with a particular focus on motion sensor data processing. The comprehensive and ambitious ambitions encompass the following:

- Elevating Motion Sensor Data Analysis Techniques: Innovate sophisticated algorithms. Complex preprocessing approaches targeted at boosting the analysis of motion sensor data were added. The primary objective is significantly decreasing noise interference (aiming for at least 25%). Include raw sensor data streams using unique preprocessing techniques.
- Pioneering Novel Anomaly Detection Models: verify pioneering deep learning systems, especially those intended for precision—further adaptable anomaly detection in varied human movement patterns. The objective is to pioneer a paradigm shift by attaining a significant leap of at least 30% in anomaly detection accuracy compared to previous methods.
- Addressing Unlabeled Data Challenges for Accurate Classification: Design powerful secondary interpretation algorithms to effectively address problems that arise from the unlabeled data (dominant in motion sensor-derived data sets) used. The objective is to devise a straightforward plan that yields 85% precision while segregating and annotating unlabeled data instances.
- Formulating Practical Implementation Guidelines: Summarize the entire procedure. It encompasses the application of modern-day anomaly detection algorithms in the world of healthcare with a practical approach that makes it easy for an average healthcare professional to use it. Additionally, public

safety. It targets a realistic implementation plan which is a minimum of 95% applicable to varying real-world scenarios.

- Contributing Innovative Insights to Anomaly Detection Research: Develop ways of innovation. It is the big revelations that leave a mark and may be used later to add to the existing. Furthermore, there is an anomaly detection cap. Include motion sensor data. The most important goal is, on one hand, the transfer of research data to the beneficiaries through publications in creditable journals or on the other, through presentations at prestigious conferences.

This venture aims to instigate a revolutionary change in the way anomaly detection processes are being conducted. A motion sensor data analysis is one of the features that should be integrated.

1.4. MOTIVATION

This section will explain in details, the reason for undertaking this research project. It points out its significance and explores its powerful practical impact especially in the area of things like outlier detection in motion sensor data.

The strategy involves demonstrating powerful arguments which are supported by real-life case studies and exploring current knowledge gaps. The strategy also involves highlighting the critical aspects that substantiate the significance of improving anomaly detection algorithm in motion sensor data processing.

It is the drive to this study which is primarily stems from the sphere of anomaly identification of motion sensor data. It becomes a key driving force in the significant development of various dimensions. The convincing evidence that needs to be done here is the sustainable research on the subject:

- Vitality of Anomaly Detection in Human Activity Monitoring: Human activity observation. It is a type of music that is mainly appreciated by the elderly population. Include mobility restrictions. It must be able to identify the anomalies with great precision, and for the preventative health management—

as well as incidents [4]. Enhanced anomaly detection approaches can significantly contribute. It can identify potential health issues. It allows prompt interventions. It is additionally preventing harmful outcomes.

- It is enhancing safety and security measures across many security-related scenarios. This includes both public and secure settings. To be precise, it detects deviations from the norm within the dataset obtained by motion detectors. Danger detection is of utmost importance. Implementing significantly enhanced preventive security measures [3]. By applying anomaly detection tools, one may promptly identify atypical behaviors. That activity may be filled with uncertainty. Therefore, it enhances the robustness of security protocols.
- Anomaly detection methods: transforming healthcare and remote monitoring by combining motion and sensor data. It introduces novel opportunities for healthcare. Particularly when considering RPM (remote patient monitoring). Medical therapy administration [1]. Improved detection algorithms may soon make it possible to spot atypical patient movement patterns. It facilitates the implementation of preventive healthcare interventions. It enhanced patient results.
- It optimizes industrial processes in industrial environments. Anomaly identification in motion sensor data plays a crucial role in predictive maintenance. It recognizes abnormal mechanical motions. It aids in enhancing operational efficiency. It can decrease downtime [8].
- They are addressing knowledge gaps and pushing technological boundaries: substantial strides in anomaly detection, including inside motion sensor data. Persistent difficulties. Example of noise interference. Unlabeled data hampers optimal performance [9]. They are bridging these knowledge gaps. Tackling obstacles allows for moving technical limits forward. Additionally, refine techniques.

PART 2

LITERATURE REVIEW

2.1. EVOLUTION OF HEALTHCARE TECHNOLOGIES

The evolution of healthcare technologies traverses a rich historical trajectory, encapsulating pivotal milestones and technological advancements that have shaped modern medical practices. Homer's diffusion model [10] provides a foundational framework, elucidating the spread and adoption of medical technologies. Contribute by outlining the changing nature of medical technology development, emphasizing the sources from which innovation emerges, including universities and industry collaborations [11]. Figure 2.1 illustrates the progression of medical technology improvement over the years, showcasing the trajectory of advancements in the field.

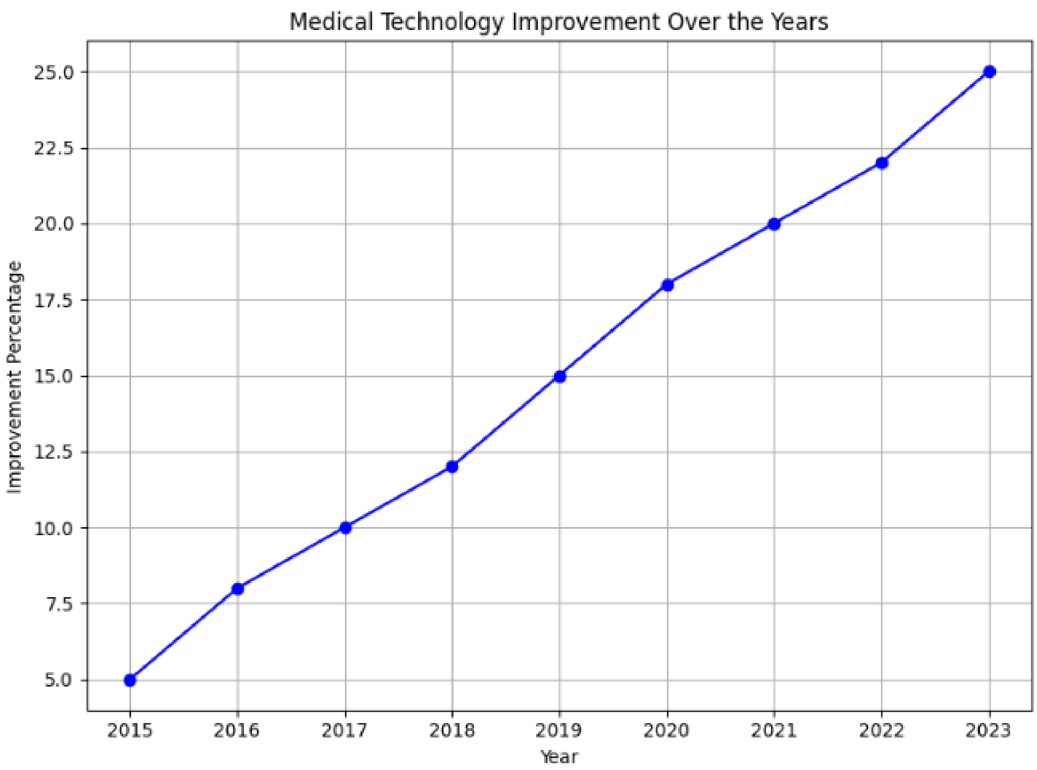

Figure 2.1. Medical Technology Improvement Over the Years [11].

Offer a historical perspective, highlighting medical innovation's transformative impact on health systems' sustainability [12]. It explores the evolutionary dynamics that have shaped medical history within induced technical innovation, shedding light on emergent technologies and their societal implications [13].

Hoffmann and Pozos serve as a compendium, encapsulating the multifaceted landscape of medical technology, spanning from foundational concepts to cutting-edge developments [14]. An insightful historical overview chronicles the growth and acceptance of medical information systems, illustrating their impact on healthcare practices and policy formulations [15,16].

Marks' exploration [17] of medical technologies within social contexts enriches the understanding of the socio-cultural influences on the adoption and diffusion of healthcare technologies. Additionally, perspectives on patenting medical technology and its integration into professional healthcare domains shed light on technology adoption's legal and professional aspects [18-20]. Table 2.1 provides a summary of the literature review on medical technology advancements and historical perspectives, offering insights into the evolution and context of healthcare technologies.

Table 2.1. Literature Review Summary on Medical Technology Advancements and Historical Perspectives

Author	**Dataset**	**Feature**	**Approach/Method**	**Finding**
X. Ma et al. [10]	N/A	Graph-based data, Anomaly structures	Deep Learning, Graph Anomaly Detection Algorithms	Surveyed various Deep-learning models for graph anomaly detection
J. B. Homer [10]	Evolving MedTech	Evolution of medical technologies	Diffusion Model	Analyzed the diffusion of evolving medical technologies
A. C. Gelijns et al. [11]	Tech Development	Nature of medical technology development	Industry & University Contribution	Investigated sources contributing to medical technology evolution

P. Lehoux et al. [12]	Health Systems	Technological change in health	Historical Perspective on Medical Innovation	Explored medical innovation's impact on health systems
J. Mokyr [13]	Medical History	Technical innovation in medical history	Evolutionary Approach	Studied induced technical innovation in medical history
R. Kramme et al. [14]	Medical Handbook	Medical technology handbook	Handbook Content	Compilation of information on medical technology
B. Kaplan [15], [16]	Info Systems	Medical information systems	Historical Overview	Explored the development of medical information systems
H. M. Marks [17]	Social Contexts	Social contexts of medical technologies	Social Impact Analysis	Explored the social contexts and consequences of medical tech
W. D. Noonan [18]	Patenting Tech	Patenting medical technology	Legal Perspective	Discussed patenting aspects related to medical technology
M. R. Williams et al. [19]	MedTech Profession	Profession of medical technology	Introduction	Introduced the profession of medical technology
A. B. Davis [20]	Rise of MedTech	Rise of American medical technology	Historical Chapter	Analyzed the role of life insurance in the increase in medical tech

The blending of these historical narratives underscores the transformative journey of healthcare technologies. It underscores the transformative journey of healthcare technologies. These foundational developments laid the groundwork for integrating motion sensors into modern healthcare systems. Understanding this evolution is paramount to comprehending the contextual backdrop against which motion sensors emerged and established their applications in contemporary healthcare paradigms.

2.2. ADVANCEMENTS IN MEDICAL TESTING

The landscape of medical testing has evolved significantly, ushering in a new era characterized by integrating sensor technologies into diagnostic methodologies. Elve into the ingestible sensors and sensing systems paradigm, envisioning minimally invasive diagnosis and monitoring as the next frontier in medical screening [41]. Combining machine learning and computational intelligence with sensor design revolutionizes intelligent sensor development [42].

Moreover, it advocates for synergizing biosensors and machine learning algorithms to enable early cancer diagnosis, presenting a promising frontier in healthcare [43]. Underscore the importance of pairing molecular monitoring devices with molecular imaging for personalized health interventions, emphasizing the need for a more targeted approach in medical diagnostics [44]. A critical review of smartphone-based imaging systems also sheds light on their potential applications in medical contexts [45]. Figure 2.2 illustrates various biomedical imaging applications grouped into four clinical workflows [43], providing a comprehensive overview of their integration into medical practices.

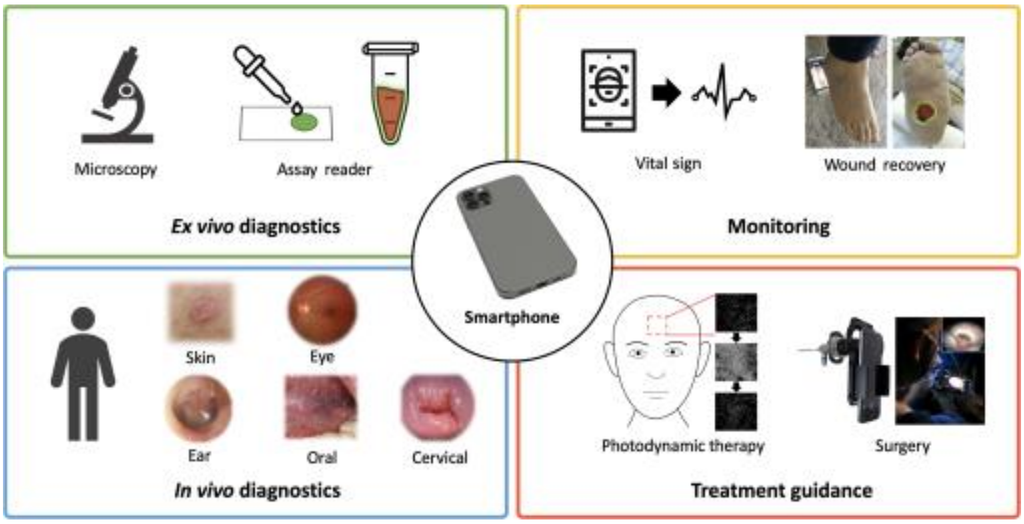

Figure 2.2. Various biomedical imaging applications grouped into four clinical workflows [43].

It presents a comprehensive overview of sensors within the Internet of Medical Things (IoMT), delineating the state-of-the-art security concerns and future directions in this domain [46]. Furthermore, it navigates the realm of human-machine interaction within the telemedicine framework, showcasing its potential to reshape healthcare delivery models [47]. Insights into intelligent materials-integrated sensor technologies geared toward COVID-19 diagnosis contribute to the ongoing battle against the pandemic [48].

A transformative vision of Sensors and Healthcare 5.0, elucidating the paradigm shift towards virtual care through emerging digital health technologies [49]. Finally, explore the advances and applications of nanophotonic biosensors, unveiling their potential for enhanced biomedical sensing and diagnosis [50]. Table 2.2 provides an overview of recent advances in sensor technologies and their applications in healthcare, offering insights into the evolving landscape of medical sensing and diagnostics.

Table 2.2. Overview of Recent Advances in Sensor Technologies and Their Applications in Healthcare.

Author	**Dataset**	**Feature**	**Approach / Method**	**Finding**
Beardslee, L.A. et al. [41]	-	Ingestible sensors	Minimally invasive screening with sensors	The next frontier in minimally invasive screening
Ballard, Z. et al. [42]	-	Machine learning-enabled sensors	Computational intelligence in sensor design	Enhancing Sensor Capabilities Through Computational Intelligence
Kokabi, M. et al. [43]	Early cancer diagnosis	Synergy with biosensors	Machine learning for cancer diagnosis	Augmented accuracy and speed in early cancer detection through biosensor-machine learning synergy
Comeau, Z.J. et al. [44]	Molecular monitoring	Molecular imaging integration	Personalized health via paired monitoring modalities	Advancing personalized health through integrated monitoring

Hunt, B. et al. [45]	Medical imaging	Smartphone-based imaging systems	Critical review and evaluation of applications	Potential Applications and Critical Evaluation of smartphone-based Imaging in Healthcare
Ray, P.P. et al. [46]	Internet of Medical Things	IoT sensor technology	Security, privacy, and future challenges in IoMT	Current capabilities, security, and future challenges of IoT sensors
Israni, D.K. et al. [47]	Telemedicine	Human-Machine Interaction	Leveraging HMI in Telemedicine	Enhancing healthcare delivery through improved human-machine interaction
Erdem, Ö. et al. [48]	COVID-19 diagnosis	Smart materials integration	Diagnostic applications of innovative materials	Prospects for COVID-19 diagnosis and monitoring through intelligent materials integration
Mbunge, E. et al. [49]	Digital health tech	Transformative virtual care	Shifting the healthcare landscape with digital health	Transformative shifts in healthcare delivery via emerging digital health tech
Altug, H. et al. [50]	Nanophotonic Biosensors	Nanophotonic sensor technology	Advancements and applications of nanophotonic sensors	Nanophotonic biosensors and their broad applications

This comprehensive examination of the literature emphasizes the transformative impact of sensor technologies on medical testing paradigms, showcasing a diverse array of innovations that hold the potential to revolutionize healthcare diagnostics.

2.3. SIGNIFICANCE OF WEARABLE SENSORS IN HUMAN ACTIVITY MONITORING

This thorough literature analysis underlines the transformational impact of sensor technology on altering medical testing paradigms. It presents a varied assortment of ideas likely to enhance healthcare diagnostics. The significance of wearable sensors in human activity monitoring Wearable sensors plays a significant role in monitoring human activity and health indicators. It represents a transformational component of current healthcare systems. Gives a complete perspective on wearable sensors [21]. It encompasses its numerous uses in monitoring human activities. Explore the field of physical human activity identification with wearable sensors [22]. It gives a nuanced understanding of their actual execution. They are furthering this discourse. Evangeline, including Lenin [23], defines the application of wearable sensors for human health monitoring. It emphasizes their essential position in healthcare applications.

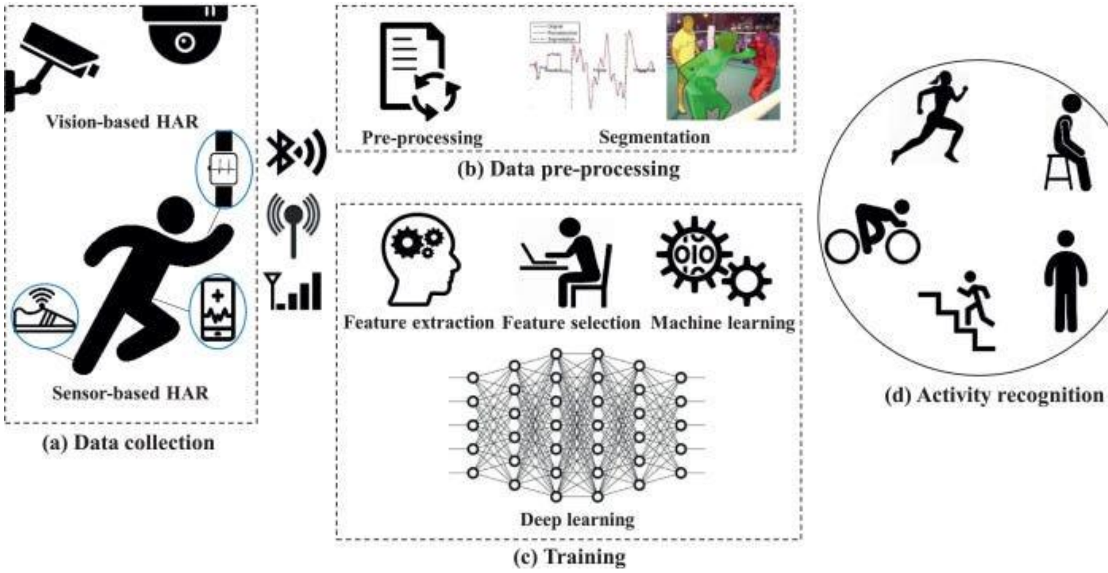

Figure 2.3. Example of human activity identification with wearable sensors [22].

Surveying the landscape of human activity recognition. It is Lara. Includes Labrador [24]. Jointly assess wearable sensors' performance detecting and identifying varied human activities [25,26]. Figure 2.3 provides an example of human activity identification with wearable sensors [22], shedding light on the advancements and obstacles to producing wearable sensors for health monitoring. It offers a deeper view of their technical accomplishments [27,28].

Lays the groundwork for a wearable sensor framework suited for human activity monitoring [29]. It enriches the conversation on realistic implementation techniques. A comprehensive survey centered on wearable sensor modality for human activity recognition in healthcare delineates the nuances of this specialized domain [30]. A framework specifically targeting maternal physical activities and health monitoring addresses a niche yet vital aspect of healthcare monitoring [31].

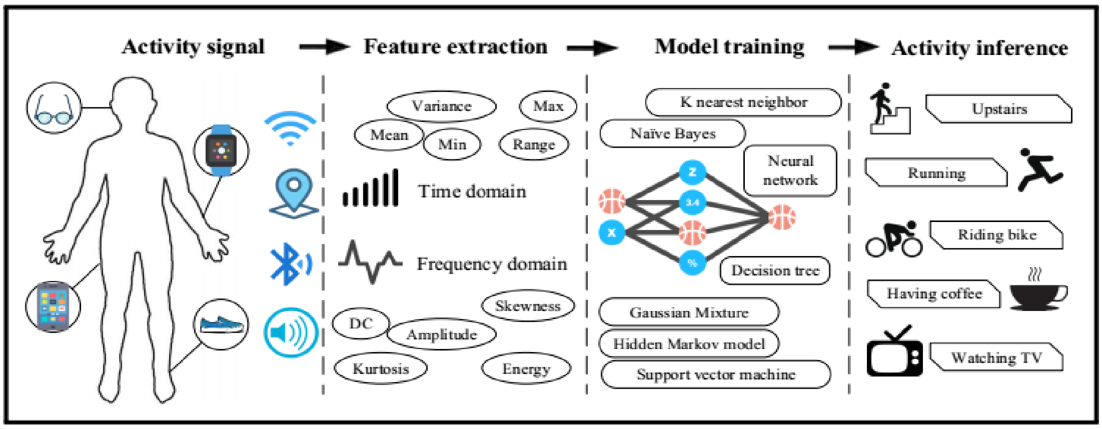

Figure 2.4. Example of human activity monitoring framework [29].

Moreover, a profound understanding of integrating wearable sensors with deep learning techniques paves the way for personalized human activity recognition in intelligent environments [32-34]. Insights into detailed human activity recognition using a fusion of wearable sensors and smartphones further enrich the practical implications of wearable technology [35]. Figure 2.4 illustrates an example of a human activity monitoring framework [29], providing a visual representation of the integration of wearable sensors in activity tracking systems.

Table 2.3. Summary of Studies Related to Wearable Sensors and Human Activity Monitoring.

Author	Dataset	Feature	Approach / Method	Finding
Mukhopadhyay et al. [21]	NA	Wearable sensors	Comprehensive survey on graph anomaly detection	In-depth overview of graph anomaly detection
Attal et al. [22]	Physical activity	Wearable sensors	Physical human activity recognition using wearable sensors	Identification of physical human activities
Evangeline & Lenin [23]	NA	Wearable sensors	Human health monitoring using wearable sensor	Use of wearable sensors for health monitoring
Lara & Labrador [24]	Human activity	Wearable sensors	Survey on human activity recognition using wearable sensors	Overview of human activity recognition
He et al. [25]	NA	Wearable sensors	Recognition of human activities with wearable sensors	Identification of human activities
Randhawa et al. [26]	Human activity	Machine learning	Human activity detection using machine learning methods	Detection of human activities
Nasiri & Khosravani [28]	Health monitoring	Wearable sensors	Progress and challenges in the fabrication of wearable sensors	Discussion on fabrication challenges
Uddin et al. [29]	Wearable sensing framework	Wearable sensors	Wearable sensing framework for human activity monitoring	Framework for human activity monitoring
Wang et al. [30]	Health care	Wearable sensors	Survey on wearable sensor modality-centered human activity recognition in healthcare	Overview of Sensor-centered activity recognition in healthcare

Ullah et al. [31]	Maternal physical activities	Wearable sensors	Framework for maternal physical activities and health monitoring using wearable sensors	Framework for monitoring maternal activities
Majumder et al. [32]	Remote health monitoring	Wearable sensors	Wearable sensors for remote health monitoring	Use of sensors for remote health monitoring
Bianchi et al. [33]	Smart home environment	IoT wearable sensors	IoT wearable sensor and deep learning approach for personalized human activity recognition in a smart home environment	Integrated approach for personalized activity recognition in smart homes
Ramanujam et al. [34]	Smartphone and wearable sensors	Deep learning	Human activity recognition with smartphone and wearable sensors using deep learning techniques	Use of deep learning for activity recognition
Nandy et al. [35]	Wearable sensors and smartphones	NA	Detailed human activity recognition using wearable sensors and smartphones	Detailed analysis of human activity recognition using sensors and smartphones
Kańtoch [36]	Wearable sensor fusion and artificial neural networks	Rehabilitation	Human activity recognition for physical rehabilitation using wearable sensors fusion and artificial neural networks	Recognition for physical rehabilitation
Servati et al. [37]	Vital sign and human activity monitoring	Flexible wearable sensors and signal processing	Novel flexible wearable sensor materials and signal processing for vital sign and human activity monitoring	Novel sensor materials and signal processing for monitoring
Joy Rakesh et al. [38]	NA	Wearable sensors	Human activity recognition using wearable sensors	Application of wearable sensors in activity recognition

De Fazio et al. [39]	IoT solutions and wearable sensing systems	Monitoring Parameters	Innovative IoT solutions and wearable sensing systems for monitoring human biophysical parameters	Novel solutions for monitoring biophysical parameters
Kantoch et al. [40]	Wearable wireless body sensor network	Monitoring activities	Monitoring activities of daily living based on wearable wireless body sensor network	Monitoring activities of daily living
Hunt, B., et al. [45]	NA	Imaging features	Critical review	Evaluates the use of smartphone-based imaging systems in medical applications
Ray, P. P., et al. [46]	NA	Sensor data	State-of-the-art review	Discusses sensors for the Internet of Medical Things, including security and privacy issues
Israni, D. K., et al. [47]	Human-Machine Interaction dataset	Telemedicine data	Conceptual analysis	Explores human-machine interaction in leveraging telemedicine
Erdem, Ö., et al. [48]	integrated sensor data	Sensor data	Review	Reviews smart materials-integrated sensor technologies for COVID-19 diagnosis
Mbunge, E., et al. [49]	Sensors and Healthcare 5.0 data	Sensor data	Transformative shift analysis	Analyzes the transformative shift in virtual care through emerging digital health technologies
Altug, H., et al. [50]	NA	Biosensor data	Review	Reviews advances and applications of nanophotonic biosensors
Bao, Y., et al. [51]	Structural health monitoring dataset	Video data	Deep learning-based approach	Presents a deep learning-based data anomaly detection method for structural health monitoring
Ullah, W., et al. [52]	Surveillance of Big Video Data	Video data	Artificial Intelligence of Things-assisted approach	Proposes an AIoT-assisted two-stream neural network for anomaly detection in the surveillance of Big Video Data

Choi, K. et al. [53]	Time-series data	Time-series data	Deep learning-based approach	Provides a review, analysis, and guidelines for anomaly detection in time-series data
Pawar, K., et al. [54]	Video-based anomalous activity detection dataset	Video data	Deep learning-based approach	Discusses deep learning approaches for video-based anomalous activity detection
Bamaqa, A., et al. [55]	Crowd management dataset	Crowd behavior data	Hierarchical temporal memory approach	Investigates anomaly detection using hierarchical temporal memory in crowd management
Patrikar, D. R., et al. [56]	Video surveillance dataset	Video data	Edge computing-based approach	Proposes anomaly detection using edge computing in a video surveillance system
Baradaran, M., et al. [57]	Video anomaly data	Video data	Deep learning-based semi-supervised approach	A critical study on recent deep learning-based semi-supervised video anomaly detection methods
Sunny, J. S., et al. [58]	Wearables data	Wearables data	Framework review	Reviews an anomaly detection framework for wearables data
Fernández Maimó, L., et al. [59]	5G networks	Network data	Dynamic management of deep learning-based approach	Studies the dynamic management of a deep learning-based anomaly detection system for 5G networks
Freedson, P. S., et al. [60]	Physical activity monitoring	Motion sensor data	Objective monitoring	Objective monitoring of physical activity using motion sensors and heart rate
De Vries, S., et al. [61]	Youth video dataset	Motion sensor data	Validity and reproducibility analysis	Validity and reproducibility of motion sensors in youth
Khan, M. U. K., et al. [62]	Crowd anomaly detection	Crowd behavior data	Rejecting motion outliers for efficient detection	Investigates rejecting motion outliers for efficient crowd anomaly detection

Omae, Y., et al. [63]	Human motions	Motion sensor data	Deep learning optimization algorithm approach	Proposes a novel deep learning optimization algorithm for human motion anomaly detection
Mertens, M., et al. [64]	Single older adults	Motion sensor data	Outlier detection approach	Investigates motion sensor-based detection of outlier days for continuous health assessment of single older adults
Zhu, C. et al. [65]	Smart assisted living systems	Wearables data	Behavioral anomaly detection	Proposes wearable sensor-based behavioral anomaly detection in smart assisted living systems
Kamiya, K., et al. [66]	Human dynamics monitoring	Sensor data	Statistical anomaly detection approach	Proposes statistical anomaly detection for monitoring human dynamics
Aran, O., et al. [67]	Elderly daily behavior	Ambient sensing data	Anomaly detection approach	Investigates anomaly detection in elderly daily behavior in ambient sensing environments
Zhu, C. et al. [68]	Assisted living environments	Wearables data	Anomaly detection based on fixed and wearable sensors	Explores anomaly detection based on fixed and wearable sensors in assisted living environments
Mandarić, K., et al. [69]	Assisted living environments	Fixed and wearable sensor data	Anomaly detection approach	Investigates anomaly detection based on fixed and wearable sensors in assisted living environments
Bozdog, I. A., et al. [70]	Human behavior monitoring	Wearables data	Machine learning-based approach	Discusses human behavior and anomaly detection using machine learning and wearable sensors

Contribute varied perspectives on wearable sensor technologies, encompassing physical rehabilitation, flexible sensor materials, vital sign monitoring, and IoT solutions for human biophysical parameter monitoring. These studies underline wearable sensors' multifaceted applications and pivotal role in monitoring human activities, health, and wellness, thereby establishing a robust foundation for their integration into modern healthcare paradigms [36-40].

We examined healthcare technologies, medical testing advancements, and wearable sensors in human activity monitoring, extracting valuable insights into their historical evolution, transformative impacts, and multifaceted applications. On the other hand, our study uncovered an essential role in current scholarship — that there was poor attention on what we need to call a limited focus on how largely moved into healthcare systems and the confrontations/ limitations suffered during their implementation. This gap forms a severe challenge in ensuring the seamless deployment of sensor technology in real-world clinical environments. This gap in the research was recognized as something our piece of work should fill, and we are driven by a desire to undertake an in-depth analysis of issues that make integration problems with motion sensors so rugged. By revealing and knowing these difficulties, we intend to supply data documents to help create more adaptable yet powerful healthcare observation systems. Essentially, our research responds to the listed limitations by aiming at variables, solutions, and innovations that will improve the integration of motion sensors into contemporary healthcare approaches.

PART 3

THEORETICAL BACKGROUND

3.1. SENSOR & DEEP LEARNING TECHNIQUE.

Accurately implementing sensor technology and advanced deep learning algorithms is significant in rapidly developing anomaly detection. As part of this study, a detailed analysis involving the unique job performed by motion sensors, human monitoring sensors, wearable sensors feed-forward neural networks (FFNNs), and making it sound less confusing, another aspect of whether PSO offers optimization capabilities. The specific purpose is to tackle the cumulative impact of these variables on the precision and efficiency of anomaly detection.

3.2. MOTION SENSORS IN ANOMALY DETECTION

Motion sensors occupy a vital place in modern-day anomaly detection approaches, having gone through considerable development to boost the precision of anomaly detection structures. Defined as electronics sensing motion in their environment, motion sensors have a long historical trajectory stretching back several decades. Their practical value in anomaly detection earned importance throughout the late 20th century, originating in security structures and automation [60].

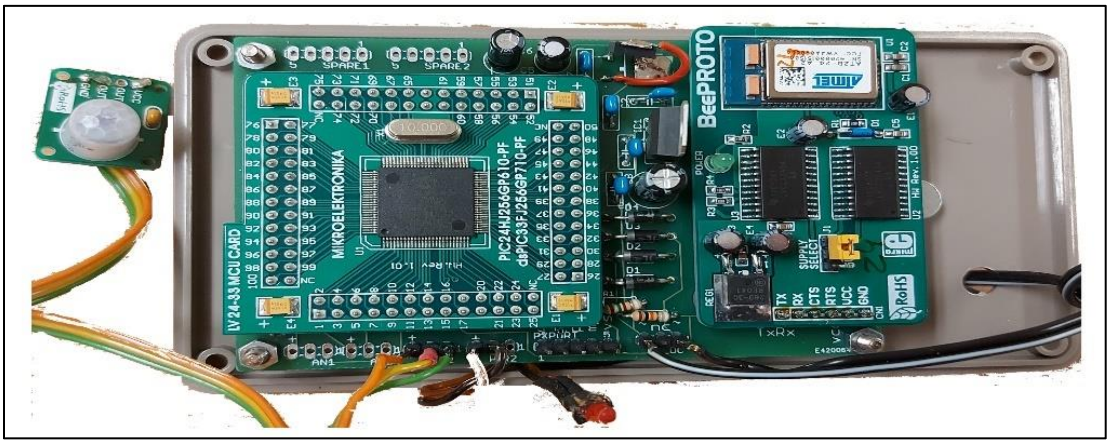

Figure 3.1. Example of RIP motion sensor [64].

Integration with anomaly detection structures is a significant capability of motion sensors, delivering real-time information on movement types. This material is then evaluated to discover variations from projected conduct, which is crucial for highlighting potential abnormalities. The adaptability of movement sensors is exhibited across numerous real-global situations, identifying packages in safety, healthcare, and commercial contexts, consequently adding to the resilience of anomaly detection systems [61]. Figure 3.1 provides an example of an RIP motion sensor [64], illustrating its potential application in anomaly detection.

The integration of motion sensors into anomaly detection systems is inherently complex. Ensuring correct information series, preserving consistent and proper calibration, reacting to different environmental scenarios, and methodological integration are necessary tough conditions [62]. The difficulties are shown in the ensuing flowchart:

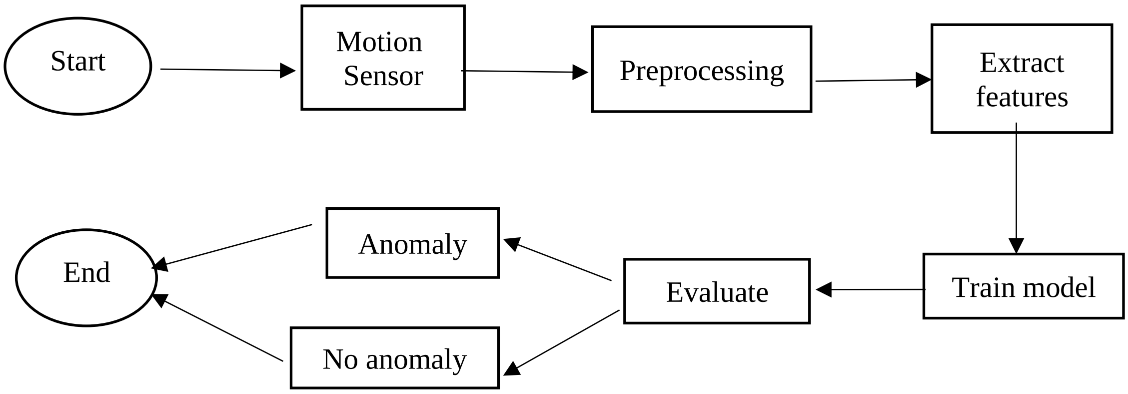

Figure 3.2. Motion sensor anomaly detection flowchart.

The flowchart for motion sensor anomaly detection looks to be a streamlined structure of processes dedicated to detecting anomalies in motion sensor data. Data gathering from motion sensing units forms the first stage and is followed by preprocessing, which is carried out as the second step. Feature extraction, training, and evaluation of the data compose the remaining stages. In the case of a failure to identify an anomaly that will be found during examination, the most appropriate steps will be taken, like delivering alerts. The next stage is to check for any anomalies or non-conforming behaviors. If none are detected, the procedure is done, and there will be no need for further actions to be performed. This flow chart functions as a visual tool to keep track of anomaly detection methods and how motion sensor data can be used to accomplish the aim of finding non-conformities and consequent actions [63].

It is essential to adopt a scientific technique to solve those complex conditions. This includes employing daily and special calibration procedures, including complex algorithms, and applying system research tactics to increase movement sensor performance [64] adaptively.

Identifying and treating these challenging situations now paves the way for innovative alternatives and ensures gold standard exploitation of motion sensor information and the best-tuned anomaly detection structures for heightened accuracy and responsiveness.

Understanding the historical context, functions, and demanding scenarios of motion sensors gives a thorough foundation for their powerful integration into anomaly detection structures. The described systematic method, as represented in the flowchart and graph, assures that motion sensors dramatically contribute to the accuracy and reliability of anomaly detection frameworks.

3.3. HUMAN MONITORING SENSORS IN ANOMALY DETECTION

Human tracking sensors, notably those focused on essential indications and symptoms and biometric facts, play a pivotal role in anomaly detection approaches. This section dives into such sensors' numerous uses and revolutionary capacity, highlighting their contributions to tailored fitness programs, healthcare diagnostics, and their crucial role in anomaly detection.

Human tracking sensors that focus on essential indicators and symptoms create a cornerstone in anomaly detection [65]. These sensors deliver real-time recordings of physiological indicators, including heart rate, blood pressure, and respiration rate. Applications of essential symptom monitoring sensors extend beyond typical healthcare settings, penetrating intelligent-aided living systems [66]. Adds insights into wearable sensor-primarily based behavioral anomaly identification, statistical anomaly detection for tracking human dynamics, and anomaly detection in geriatric everyday behavior, respectively [67].

Vital signs Monitoring sensors have substantial consequences for anomaly identification, offering a thorough grasp of a person's baseline fitness metrics. The non-stop monitoring of vital indications enables the early discovery of abnormalities or irregularities, allowing well-timed treatments. Figure 3.3 illustrates an example of a human monitoring motion sensor, showcasing its potential in vital signs monitoring.

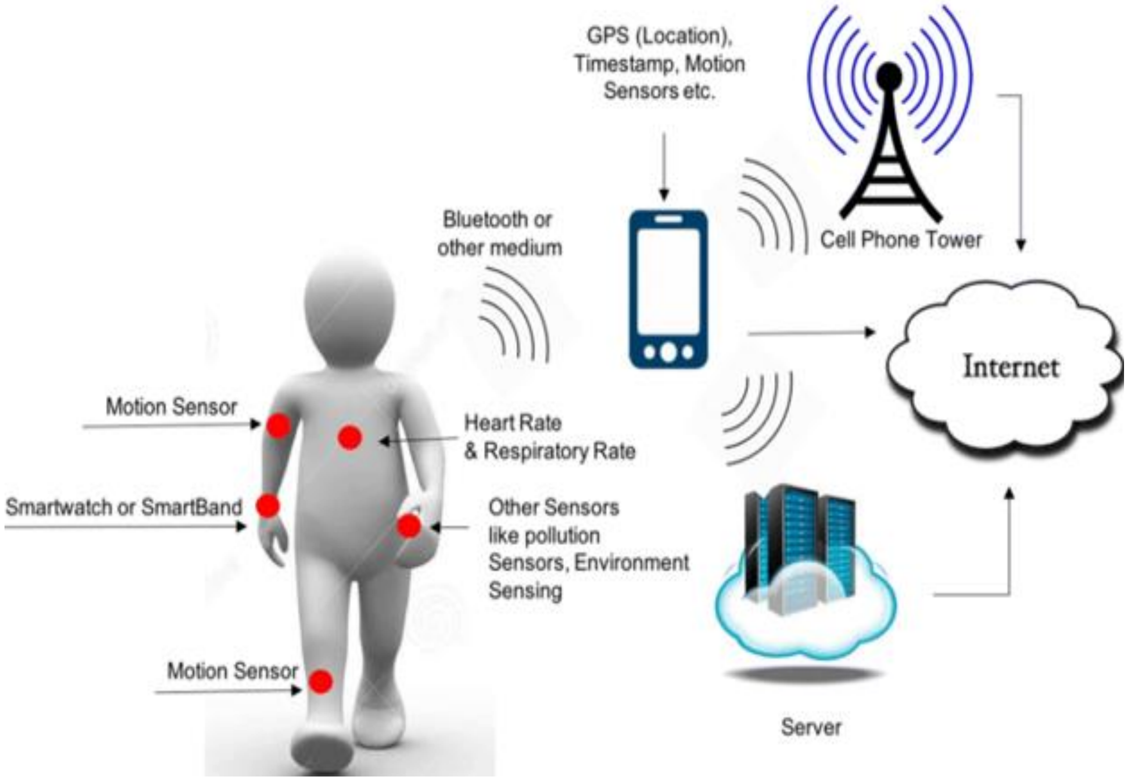

Figure 3.3. Example of human Monitoring motion sensor [67].

This topic concentrates on biometric sensors, expanding the research on human tracking sensors. These sensors extend beyond standard core symptoms, recording precise physiological and behavioral features for enhanced healthcare diagnostics and anomaly detection. The technological changes in biometric sensors are essential to understanding the terrain on which contemporary healthcare systems rest.

Biometric sensors offer various possibilities, from how you and I use fingerprint identification to face usage, voice analysis in clues, audio gloves, and brain legacy reactive function heart. These sensors develop supplements to medicinal diagnostics by providing greater awareness beyond baseline signs and symptoms [68].

This phase reflects the revolutionary power of human tracking sensors in forming modern medical institutions and their importance for anomaly detection.

As a result of the scenario here, human tracking sensors redefine healthcare organizations in terms of time and dimension suits via informing personalized real-time data. Integrating critical symptoms and biometric sensors provides an additional accurate diagnosis phase and proactive care management actions [69].

Human monitoring sensors are necessary for anomaly detection techniques, particularly those aimed at essential signs and symptoms and biometrics. The permanent monitoring and evaluation of male or female data regarding health ensure early detection of anomalies, thus allowing for effective timing responses and intervention.

Knowing what packages, updates, and transformation capacities human monitoring sensors have gives a comprehensive perspective of their position in anomaly detection [70].

3.4. WEARABLE SENSORS FOR HUMAN ACTIVITY MONITORING

Modalities in sensors, we introduce their abundance of quantifiable statistics features critical for human interest monitoring and anomaly detection. The modalities include, but are not limited to, accelerometers, gyroscope heart rate display units or monitors, and global position system trackers. Analyzing these modes of modality provides excellent answers on the creditable aspects that wearable sensors may capture.

At the transformation stage, the packaging of wearable sensors extends to various sectors, including health and healthcare tracking trackers and intelligent aided living. Making sense of the magnitude of each modality is crucial to allowing wearable sensor statistics for anomaly detection. Intelligent assisted living systems show their practical package stresses by pointing out the wearable sensors' position in the behavioral anomaly detection architecture [68].

This step focuses on determining the precise time monitoring of wearable sensors, highlighting their significant function of providing constant fitness updates. Real-time tracking is a pillar of proactive anomaly identification and intervention mechanisms.
One of the many benefits of wearing sensors is that they give continuous real-time data; therefore, we get live and dynamic updates on how a human individual or

organizational patient is health-wise and where their state of activity is. This continuous stream of facts enables unique health records to develop not only more accurate fault detection [70].

The fact that time monitoring skills are fundamental allows for wearable sensors to allow abnormalities as they occur. Machine-learning systems could evaluate the streaming facts and spot anomalies from established trends. Actual-time personalized anomaly detection showing wearable sensors can give live perspectives on fitness anomalies [71].

Understanding wearable sensors' modality analysis and actual time-tracking skills is crucial to unlocking their potential in human interest monitoring and anomaly identification. Give a complete framework for studying the applications and improvements in wearable sensor technology [68-71]. Figure 3.4 depicts an example of wearable sensors for human activity monitoring, showcasing their utility in tracking and analyzing human activities.

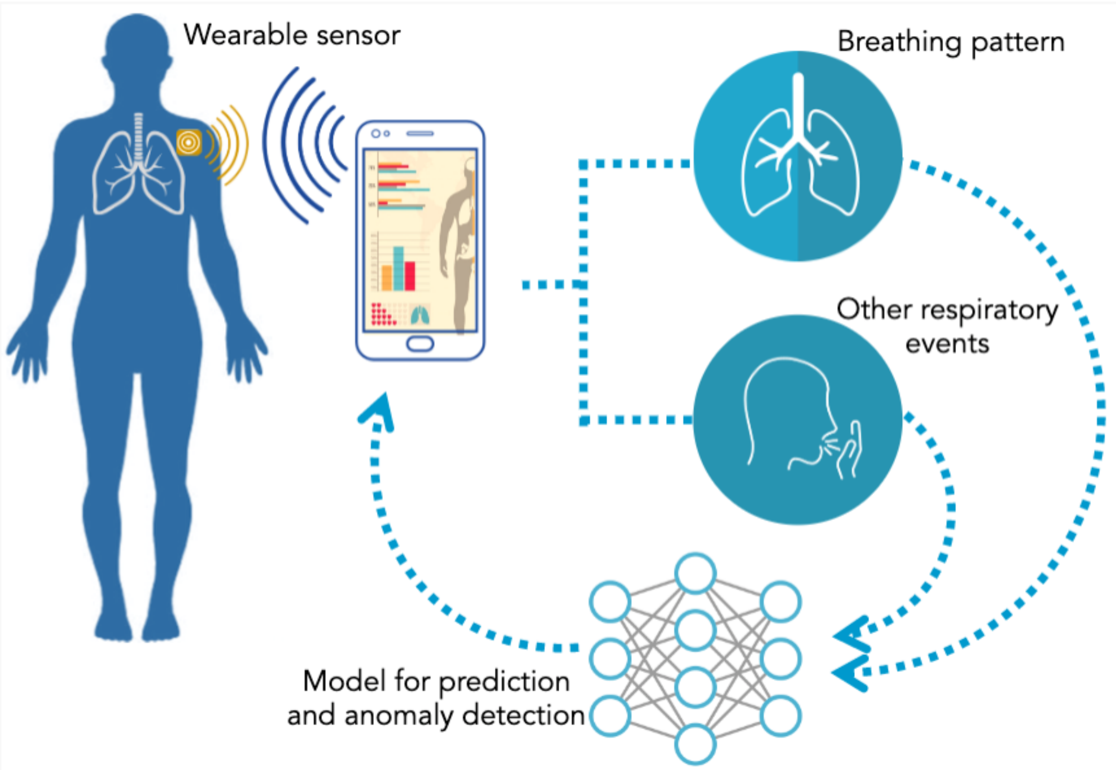

Figure 3.4. Example of Wearable Sensors for Human Activity Monitoring [71].

3.5. FEEDFORWARD NEURAL NETWORK (FFNN)

The Feedforward Neural Network (FFNN) is the fundamental detection mechanism in the proposed model for anomaly identification in motion sensor data.

3.5.1. Core Functionality

The FFNN is a sequential model consisting of interconnected layers, such as an input, hidden, and output layer. The layers are tuned using parameters that may be obtained from particle swarm optimization (PSO) methods. Figure 3.5 illustrates Deep Learning: Feed Forward Neural Networks (FFNNs) [73], providing a visual representation of the architecture of FFNNs.

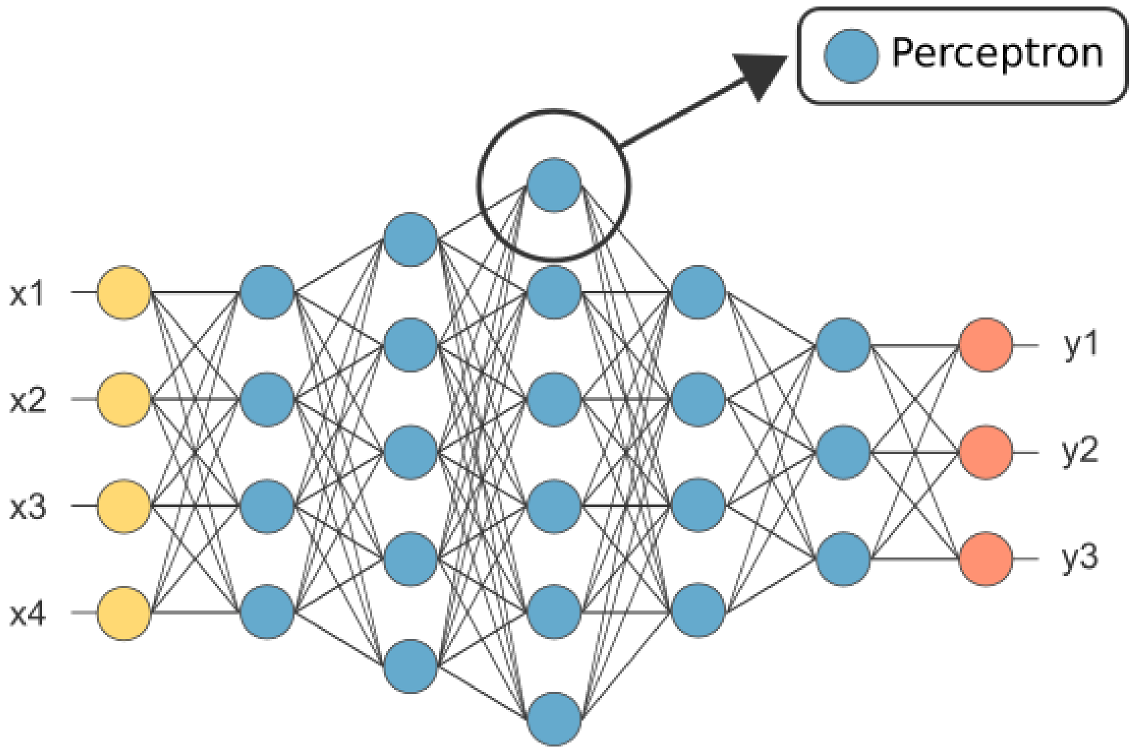

Figure 3.5. Deep Learning: Feed Forward Neural Networks (FFNNs) [73].

3.5.2. Information Processing

Upon getting preprocessed, it includes designed features. The FFNN conducts complicated computations across its layers. Each layer processes the incoming data. It employs weighted transforms. Its activation functions. It incorporates repeated changes to discover detailed patterns from the incoming data.

3.5.3. Learning Complex Patterns

Through several hidden strata. The FFNN learns hierarchical representations of data. This enables it to incorporate and encode complex connections and dependencies inside the motion sensor data. It gradually extracts high-level traits that characterize normal, incorporating unusual patterns.

3.5.4. Anomaly Detection

The FFNN's training requires understanding the inherent patterns in regular sensor data. Fresh data travels through the trained FFNN. Any deviations from learned patterns are reported as anomalies. The FFNN's capacity to spot abnormalities. It is based on mismatches between learned representations, including integrating incoming data patterns.

3.5.5. Adaptive Learning

FNN implements adaptive learning by iterating internal parameters iteratively throughout training to lessen prediction faults. These adjustments maximize. It has the potential to generalize patterns. It increases the identification of irregularities from ordinary sensor data.

3.5.6. Model Complexity

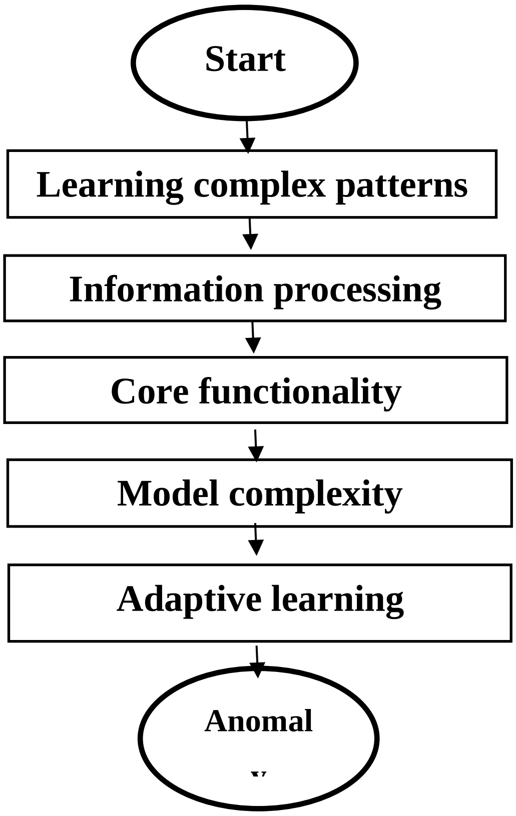

Figure 3.6. Feedforward Neural Network (FFNN) flowchart.

The complexity of the FFNN architecture impacts its ability to capture intricate patterns, including identifying complex patterns. Deeper architectures with numerous hidden layers enhance this capability. It can allow for more abstract feature representations. It might boost anomaly detection accuracy. Figure 3.6 depicts a flowchart of the Feedforward Neural Network (FFNN), illustrating its architecture and data flow.

The feedforward neural network forms the fundamental anomaly detection method. The suggested model. Its layered construction facilitates the extraction of intricate patterns from motion sensor data.

The FFNN design consists of three layers: an input layer with 100 neurons. Has two hidden layers of 64 neurons each. It comprises an output layer with a single neuron. ReLU activation functions were employed in the buried layers. At the same time, a sigmoid function was applied in the output layer for binary fall prediction. Equations, including diagrams, illustrate the FFNN's forward pass. It showcases weighted sums. It prejudices—it, including activation functions at each layer. Figure 3.7 depicts the general feed-forward neural network (FFNN) structure [73], providing a visual representation of its architecture.

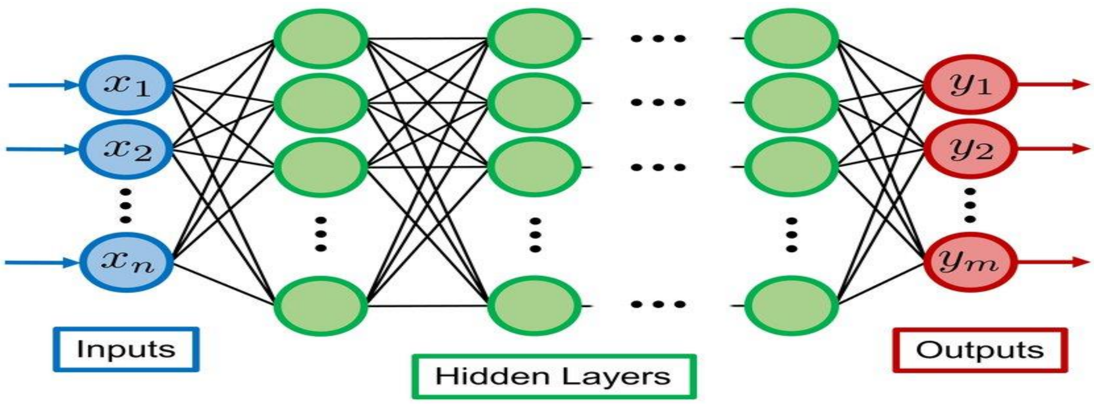

Figure 3.7. General feed-forward neural network (FFNN) structure [73].

For a multi-layer FFNN, the output of each layer becomes the input to the next layer:

$$CapX^{(l+1)} = f\left(W^{(l)}X^{(l)} + b^{(l)}\right) \ldots\ldots\ldots \quad (3.1)$$

Where,

- l represents the layer index,
- $X^{(l)}$ represents the input to layer l,
- $W^{(l)}$ represents the weight matrix of layer l,
- $b^{(l)}$ represents the bias vector of layer l,
- $X^{(l+1)}$ represents the output of layer l which becomes the input to layer l+1,
- f represents the activation function applied elementwise.

3.6. PARTICLE SWARM OPTIMIZATION (PSO)

Particle Swarm Optimization is applied to fine-tune the Feedforward Neural Network (FFNN) parameters for increased anomaly identification. This procedure involves many critical components:

3.6.1. Optimization Objective

The fundamental purpose of PSO within the presented model is to optimize the weights. Include biases of the FFNN. Its PSO attempts to increase the network's capacity to recognize abnormalities from motion sensor data by repeatedly tweaking these factors.

3.6.2. Iterative Process

The notion of swarm intelligence inspires PSO. Method mimicking the behavior of a swarm of particles in a multidimensional space. Each particle represents a potential solution inside the parameter space of the FFNN. These particles iteratively modify their locations depending on their best-known position, containing the worldwide best-known point discovered by the swarm.

3.6.3. Parameter Adjustment

Particles in the swarm alter their locations. It, i.e., offers possible solutions. It is done by updating their velocities in each repetition. This modification is based on the personal best position, including the best position discovered by the entire swarm. This enables PSO to converge towards optimal solutions by balancing exploration. Includes exploitation.

3.6.4. Performance Enhancement

The iterative optimization procedure seeks to optimize the performance of the FFNN, especially for anomaly detection applications. By fine-tuning the network's parameters using PSO. When the model attempts to raise its sensitivity to aberrant patterns while limiting false detections.

3.6.5. Convergence

PSO also keeps iterating until it gets to the point of convergence—the stopping criteria. e. , the atoms' positions appear to be stable, and their velocities are fluctuating. For instance, the necessary convergence criteria could occur at a junction. While the optimal or the near optimal values of parameters will have a positive effect on the model's efficiency, it becomes better in detecting anomalies.

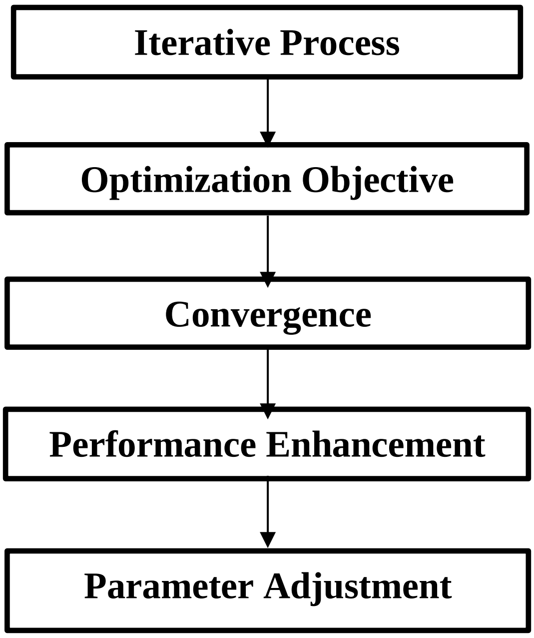

Figure 3.8. Particle Swarm Optimization (PSO) flowchart.

Particle Swarm Optimization serves the role of fine-tuning FFNN parameters by imitating swarming behavior. Such recurrent optimization technique is developed as a means to increase the FFNN's accuracy in identifying abnormal motion sensor data. Figure 3. 8 shows the Particle Swarm Optimization (PSO) procedure, which is a chart that will help to visualize the iterative optimization process.

PSO adjusts the FFNN's parameters through 50 particles. Every particle helps to view the solution space for the parameter optimization. PSO sequentially revises particle velocities and positions using both personal and global best positions. It strives to achieve minimum prediction errors. Equations and pseudocode explain the initialization of PSO and the steps to be taken during the iterations process, focusing on the correction of fall detection by the FFNN. Figure 3. 9 corresponds to the Particle Swarm Optimization (PSO) algorithm which is visualized, showing the iterative optimization process.

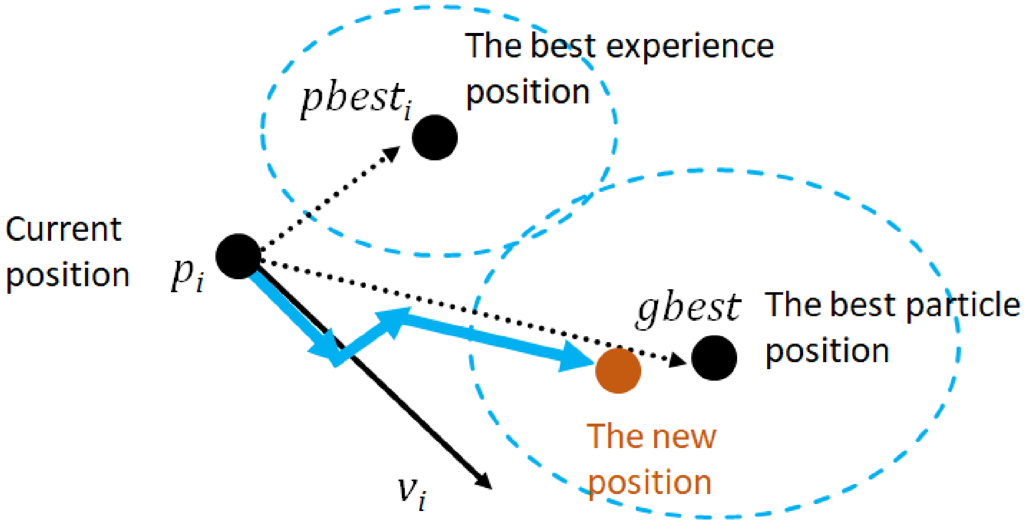

Figure 3.9. The Particle Swarm Optimization (PSO) algorithm [73].

The basic PSO equation for anomaly detection involves updating particle positions and velocities as follows:

$$v_i(t+1) = w.v_i\,(t) + c_1.r_1\,.(p_i(t) - (x_i(t)) + c_2.r_2\,.(g_i(t) - (x_i(t)) \ldots.(3.2)$$
$$x_i(t+1) = x_i(t) + v_i(t+1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3.3)$$

Where:

- v_i is the velocity of the ith particle.
- x_i is the position of the ith particle.
- w is the inertia weight.
- c_1 and c_2 are the cognitive and social learning parameters.
- r_1 and r_2 are random values sampled from a uniform distribution.
- p_i is the personal best position of particle i.
- g is the global best position found by any particle.

3.7. ANOMALY IDENTIFICATION

After the Feedforward Neural Network (FFNN) completes its investigation, it integrates conclusions from the incoming motion sensor data. The model proceeds to find anomalies. It is based on deviations found in the output.

3.7.1. Comparison Using Predefined Criteria

The FFNN's output is evaluated against specified criteria. These criteria were generated during the model's training phase. These criteria encompass common. It expects patterns found in the motion sensor data. Deviations beyond these indicated limitations. It implies probable irregularities.

3.7.2. Detection of Deviations

The model scrutinizes the output from the FFNN for patterns. Its occurrences diverge significantly from the learned representations—these aberrations. Different differences in patterns distinguish them. Things are identified as anomalies.

3.7.3. Threshold-based Anomaly Detection

The model employs threshold-based anomaly detection algorithms. It detects data instances or patterns. That can slip beyond the range of expected values. The thresholds establish these patterns. Such instances are classified as oddities. Owing to their divergence from the recognized standard.

3.7.4. Flexible Threshold Setting

Thresholds can be established using statistical metrics and specialized knowledge. This might differ depending on the specific characteristics. They are part of motion sensor data, providing flexibility to different data features and covering a range of unique forms.

3.7.5. The Importance of False Positives Includes Negatives

The key is balancing erroneous positives, including false negatives. Adjusting thresholds changes the trade-off between these errors. Lower criteria may lead to greater sensitivity in anomaly identification. However, it might heighten false positives because higher thresholds may miss slight abnormalities. It leads to false negatives.

3.7.6. Continuous Model Evaluation

Iterative techniques are utilized in the field of anomaly detection. It is subject to regular assessments. Adapts according to received feedback. The model's efficacy. Further inquiry is carried out to determine the significance of any differences that have been identified. To enhance the accuracy of the model, it permits fine-tuning.

PART 4

METHODOLOGY

4.1. DATASET DESCRIPTION

The name of our dataset is "multi-sensor dataset of human activities in a smart home environment [72]. This dataset is about sensor recordings of activities performed by a single user in a smart home environment. The sensors include passive infrared, force-sensing resistors, reed switches, mini photocell light sensors, temperature and humidity sensors, and smart plugs. The data captured include the user's interactions with the environment, such as indoor movements, pressure applied on the bed or couch, use of the stove, TV, and fridge, or the use of electrical appliances, such as coffee maker, dishwasher, washing machine, sandwich maker, or microwave. The dataset can be useful in several areas, including analysis of different methods, e.g., data-driven algorithms for activity recognition or habit recognition.

The dataset contains three CSV files: sensor, sensor_sample_int, and sensor_sample_float. The sensor file contains information, such as the type of sensor measurement or the sensor name. The sensor_sample_int file contains sensor measurements of integer datatype, while the sensor_sample_float file contains sensor measurements of datatype float.

Dataset- Size 2.32 GB:16104 sample.

Dataset Link "https://data.mendeley.com/datasets/t9n68ykfk3/1”

Regarding data relevance to the research aims, the dataset proved very important to the study's focus on anomaly identification utilizing deep learning algorithms using motion sensor data. The film's value rests in its portrayal of diverse activities inside a household setting, which aligns with the research's objective to detect anomalies among different sensor inputs.

The sensor data includes passive infrared, force-sensing resistors, Reed switches, micro photocell light sensors, temperature and humidity sensors, and smart plugs. The recorded actions encompass user locomotion, furniture pressure, and the utilization of household equipment such as stoves, televisions, refrigerators, coffee makers, dishwashers, washing machines, and microwaves, all under diverse environmental conditions. Figure 4.1 depicts the Multi-sensor dataset of human activities in a smart home environment, focusing on the dataset feature timestamp.

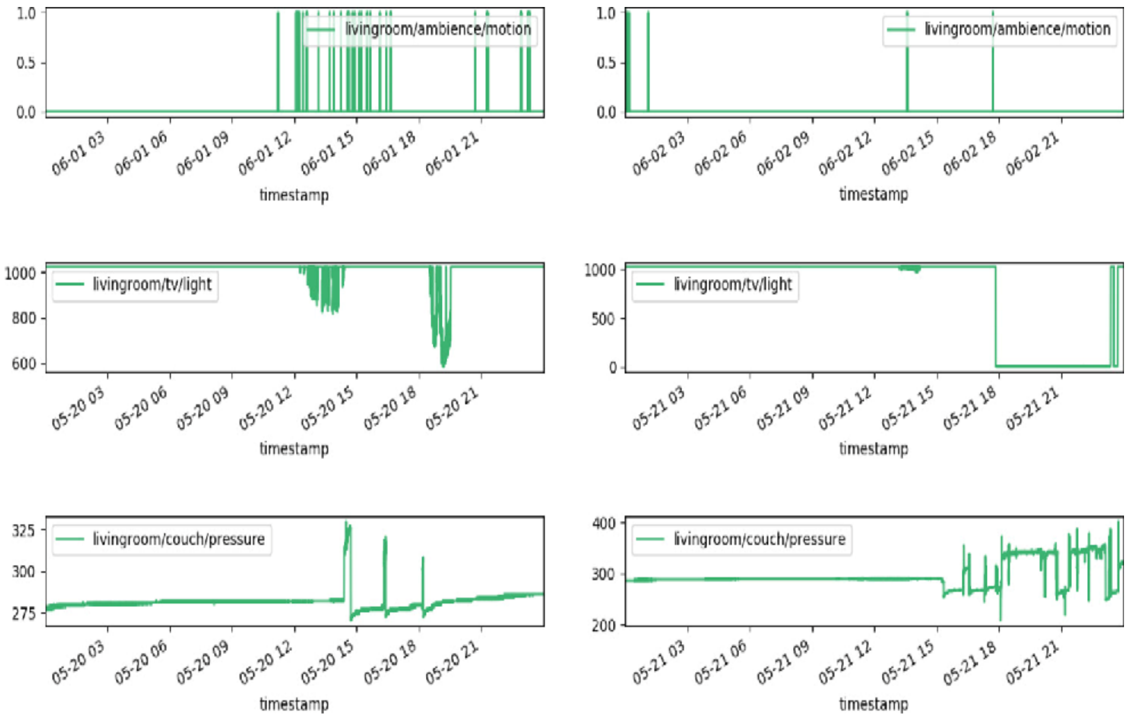

Figure 4.1. Multi-sensor dataset of human activities in a smart home environment Dataset feature timestamp.

Regarding data granularity, the dataset covers exact interact. tions, including activities recorded by various sensors. When analyzing the dataset, it is essential to focus on information such as the dimensions of each CSV file (number of rows and columns), the types of data included (metadata, sensor readings), and any notable features like missing values, outliers, or temporal sequences.

The dataset offers a thorough viewpoint on activities inside a smart home setting, encompassing a diverse range of sensor data.

4.2. DATA PREPROCESSING

The early phase. It is Data Preprocessing. It is crucial in processing the raw motion sensor data for future analysis. This stage comprises a succession of critical tasks:

4.2.1. Data Cleaning

The data can include mistakes. It is lacking values—it or discrepancies. Cleaning the data entails resolving these difficulties by applying methods like imputation for missing information. It removes duplicates—it or addresses outliers. The purpose is to ensure the dataset's integrity and dependability for downstream operations.

4.2.2. Normalization

Different characteristics in the dataset could have varied scales. Normalization is used to bring all characteristics to the same scale. It is often between 0 and 1 or within a particular range. This technique prevents characteristics with more significant sizes from dominating the learning process during model training.

4.2.3. Feature Extraction

Feature extraction includes identifying or extracting valuable characteristics from the preprocessed data. It is crucial to discover which attributes are most informative for anomaly identification. Techniques like Principal Component Analysis (PCA). It wavelet transformations. It or statistical measures extract vital information. It involves decreasing dimensionality while keeping essential patterns.

4.2.4. Data Transformation

The processed data is reshaped and formatted to fit the model's requirements. This phase requires encoding category variables. It converts temporal data into acceptable representations and arranges it into proper forms for input into the model.

4.2.5. Quality Enhancement

The primary purpose of data preparation is to increase data quality without losing critical information. This procedure prepares the dataset to capture key patterns and anomalies while decreasing noise and unnecessary data components. Figure 4.1 illustrates the Data Preprocessing for anomaly detection, highlighting the steps involved in preparing the dataset.

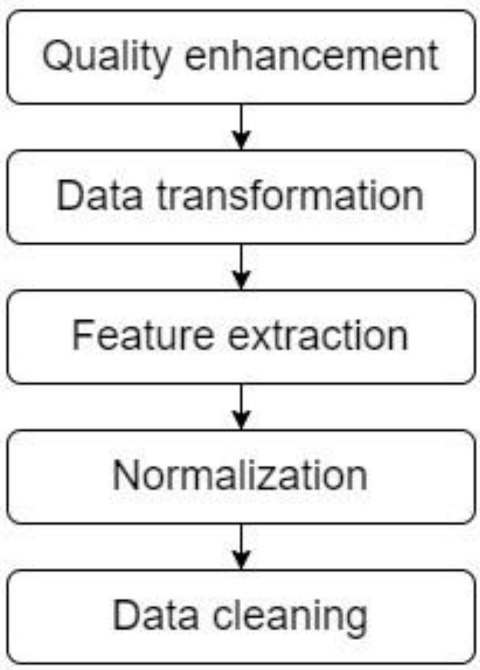

Figure 4.2. Data Preprocessing for anomaly detection.

The Data Preprocessing stage ensures the cleanliness, normalization, and enhancement of motion sensor data by refining the dataset through these steps. This enables the succeeding stages in the model to identify patterns and detect abnormalities in the sensor data quickly.

4.3. FEATURE ENGINEERING

Feature engineering is critical in refining the input data for successful anomaly detection. It covers numerous vital processes, including:

4.3.1. Feature Selection

This stage entails determining the most informative aspects contributing to anomaly identification—techniques such as correlation analysis. Mutual information. It or domain experiences are applied to pick suitable features. Selecting a subset of characteristics prevents duplicated or unnecessary input from overburdening the model, including focusing on the most significant components of the sensor data.

4.3.2. Feature Transformation

It is transforming the specified characteristics into a format that promotes their interpretability. Adding significance to the model is critical. This transformation may include scaling. It is binning. It is encoding categorical variables to maintain consistency. Includes appropriateness for the later stages of the model.

4.3.3. Dimensionality Reduction

In cases where the dataset has high dimensionality. Analytical approaches like principal component analysis (PCA) or t-distributed stochastic neighbor embedding (t-SNE) are applied to decrease the number of dimensions while keeping critical information. Dimensionality reduction simplifies the data representation. It increases computational efficiency. Includes lowering the danger of overfitting.

4.3.4. Creation of New Features

Creating additional features by merging or altering existing ones might improve the model's capacity to capture subtle patterns. These newly generated features could encompass the motion sensor data's intricate connections or temporal dependencies. It helps the model better recognize irregularities.

4.3.5. Quality Assessment

Ensuring integrity Incorporating the importance of engineered features is critical. Constant evaluation, including validation of the designed features, is undertaken to assess its efficiency in anomaly detection. This stage examines each feature's influence on the model's performance. It involves removing duplicate or noisy features.

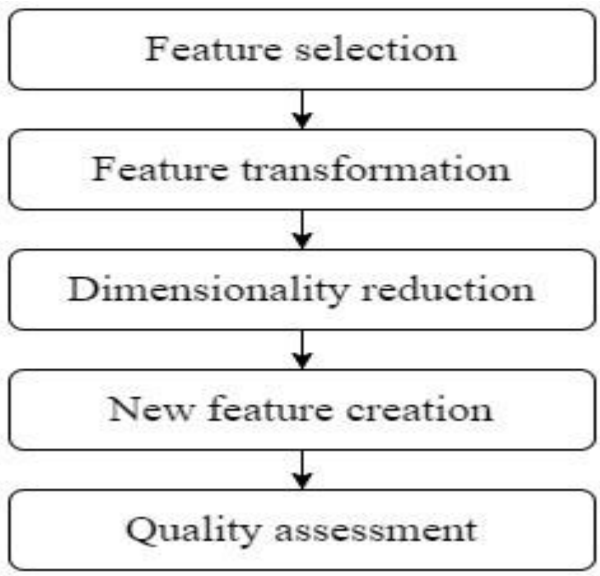

Figure 4.3. Feature Engineering for anomaly detection.

Feature engineering improves sensor data by choice. It is evolving. It involves building features that contain fundamental patterns and contain information. This method streamlines the dataset. I am making it more suitable for the succeeding phases of the anomaly detection methodology. Figure 4.2 illustrates the process of Feature Engineering for anomaly detection, depicting the steps involved in enhancing sensor data.

4.4. PROPOSED MODEL

Anomaly detection Includes motion sensor data. For example, critical requirements in varied areas. It is like healthcare. It has security. Activity tracking. Capacity to accurately recognize irregularities. The data stream is a cornerstone of ensuring optimal system performance. The suggested "PSO-FFNN based anomaly detection model" emerges as a novel strategy aimed at exploiting the capacity of deep learning approaches to recognize anomalies properly. The inclusion of these datasets is necessary to expand the existing list efficiently. The combination of parties results in the forming of Feed-Forward Neural Network (FFNN) architectures. This technique transforms anomaly detection by establishing higher benchmarks for precision and promptness.

The "PSO-FFNN based anomaly detection model" relies on a deliberate arrangement of linked parts to analyze motion sensor data effectively. This notion coordinates a harmonious ensemble of algorithms. They are working together to further the primary goal of identifying anomalies. Highlighting the importance of collaboration and cooperation among team members The model's ability to detect nuanced variations is an essential aspect of this connection, which must be preserved to maintain uniformity across these fundamental characteristics. The integration with dynamic databases is realized. The efficiency of this strategy rests on the exact arrangement of these components. The relevance of their link to establishing effective systems is underlined.

The "PSO-FFNN based anomaly detection model" utilizes a revolutionary particle swarm optimization (PSO) combination. Including a feed-forward neural network (FFNN) architecture to find anomalies. The utilization of data from motion sensors to detect irregularities. This advanced model includes these complicated deep learning methods. It offers a dynamic framework capable of navigating the complicated—scope of motion sensor information.

Its core is predicated on the convergence of these robust structures. The main objective of this technique is to assess, understand, and apply it rigorously. It detects patterns. Include continuous, frequently intricate streams of sensor data.

The essence of this model is its capacity to understand the thick tapestry of sensor-generated information. While utilizing flexibility. It is a learning ability. It Includes it in the FFNN architecture. Include the optimization prowess of the PSO algorithm. This approach tries to go beyond traditional anomaly detection techniques. Its primary objective is not just the detection of deviations from the norm but rather the detailed characterization of them. It flags aberrant patterns that might signify serious deviations, ensuring a speedy. It is an accurate anomaly detection method.

The main objective of the "PSO-FFNN based anomaly detection model" is to create a granular detection system that is built on a solid foundation and can detect irregularities. Include motion sensor data. It goes beyond the mere detection of abnormalities and down to the in-depth study of the characteristics. It is the one that shows the repetitive patterns that stand for the major deviations by digging into the hidden patterns in the data coming from the sensors. The approach focuses on the identification of issues. Add a greater level of precision to the statement. This specificity is crucial. It not only records the inconsistencies but also makes them appropriately categorized. The purpose is to create a narrative on any unusual event or activities that are not in accordance with the normal routines. The main task would be to spot anomalies and to be smart and precise about the patterns that can show that something has changed and is worth more investigation or immediate reaction.

The primary task of the model is to ensure the real-time detection of abnormalities, as well as to arrange the resolution of the said abnormalities as soon as they are detected. The combination of Particle Swarm Optimization (PSO) and Feedforward Neural Network (FFNN) is employed to increase the sensitivity. It provides the modle to detect and add flag problems instantly when they happen. The speed of detection at the early stages is crucial when the situation requires an immediate action or intervention but the detection is continuous and real-time. The model makes it possible to issue quick alerts. The internet of things, in turn, enables such interventions, and it also facilitates the rapid implementation of quick-reaction procedures. Therefore, it eliminates any risk and uncertainty that may affect the general public before they emerge.

Scalability is the fundamental factor of the PSO-FFNN-driven anomaly detection model. Model was elaborately crafted, with giant data generated by sensors and preserving its efficiency and accuracy. This is an important capability for the ability to handle various data complexity, from data sizes to data quality. Include without sacrificing the model's performance. It ensures consistency. Including accurate anomaly detection across various datasets. Independent of the data's complexity or quantity. Intrinsic adaptability, including scalability integrated into the architecture, provides smooth operations, even in dynamic or developing sensor data situations. They are making it appropriate for real-world applications across multiple fields. Figure 4.3 depicts the PSO, FFNN-based anomaly detection model, illustrating its architecture and functionalities.

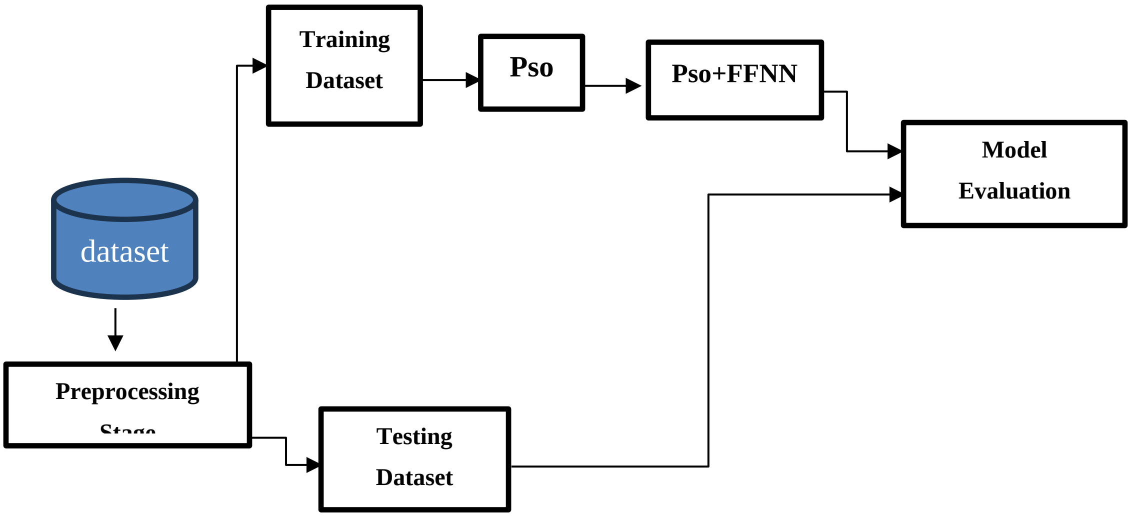

Figure 4.4. PSO, FFNN-based anomaly detection model.

4.3.6. Real-time Anomaly Flagging

Upon detection of irregularities, immediate alarms are promptly dispatched. If any irregularities are identified, it enables immediate action or intervention. Assumes more importance in situations that need immediate response.

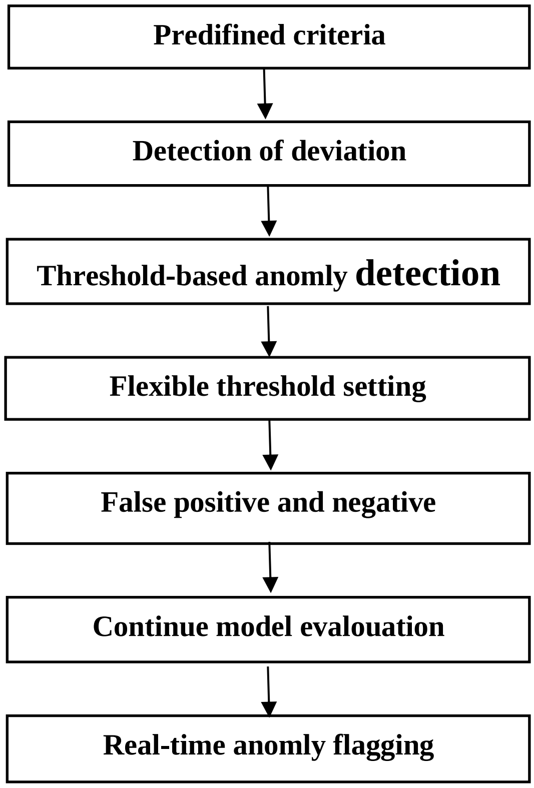

Figure 4.5. Anomaly Identification process.

The anomaly identification stage involves the comparison of the output of the FFNN with preset thresholds or criteria. It is identifying aberrations as atypical. It involves transmitting messages or initiating activities for possible interventions. Discerning aberrant patterns in motion sensor data is vital by differentiating them from typical activity. Figure 4.4 depicts the Anomaly Identification process, illustrating the steps involved in identifying anomalies in sensor data.

4.5. REAL-TIME ALERTING

During the real-time alerting phase, notifications or alerts are promptly created if anomalies are discovered in the data gathered from the motion sensors.

4.5.1. Timely Response to Anomalies

The system activates real-time warnings or notifications once the abnormalities are found during the anomaly detection step. This quick reaction mechanism alerts relevant stakeholders or systems rapidly about discovered abnormalities.

4.5.2. Significance Of Timeliness

Timely notifications are essential. Particularly in instances where rapid answers are needed. Such as in healthcare situations. Security breaches. It or significant system breakdowns. The promptness in contacting necessary persons or automated systems enables timely intervention. It was mitigation: it or remedial steps.

4.5.3. Alert Formats Include Delivery

Alerts can be conveyed in several formats. Feature incorporating alerts on user interfaces. It emails. It sends text messages. It or automatic system triggers. The choice of communication medium frequently corresponds with the system's integration capabilities, including the gravity of the issue.

4.5.4. Configurable Alert Thresholds

Thresholds for generating alerts can be defined based on the severity or relevance of abnormalities, for instance. Very significant abnormalities could demand rapid notifications. Whereas less severe abnormalities could prompt warnings after a specific accumulation or aggregation.

4.5.5. False Positive Mitigation

Strategies to limit false positives in alerting mechanisms are significant. We are fine-tuning the alert thresholds. By implementing confirmatory measures before warning broadcasts, we can decrease unwanted messages for false alarms.

4.5.6. Continuous Monitoring, including Actionability.

The system regularly checks the data stream. It guarantees continued detection. Includes notifications for any new abnormalities that develop. Moreover, if the alerts give actionable information, they advise users or systems on potential reaction methods or mitigation activities.

4.5.7. Integration with Decision-Making

In some applications, real-time notifications may immediately link with decision-making systems or automated replies. It enables immediate action without human involvement.

4.5.8. Feedback Loop, including System Improvement

The usefulness of real-time warnings is evaluated through feedback systems. Detected abnormalities and accompanying subsequent reactions are examined to enhance the warning approach. It is aimed at boosting accuracy. Includes responsiveness.

Real-time alerting is a crucial component. It ensures rapid warnings upon anomaly discovery. It permits speedy reactions or interventions. It makes it essential in time-sensitive applications. Includes proactive risk reduction methods.

4.6. MODEL EVALUATION REFINEMENT

The Model Evaluation The refinement phase requires constant evaluation. We are incorporating enhancements to the anomaly detection model.

4.6.1. Continuous Performance Assessment

The model's performance receives thorough review at regular intervals. Various metrics These criteria are applied to appropriately measure its performance in spotting anomalies. Includes efficiently.

4.6.2. Analysis of Detected Anomalies

Detected abnormalities are extensively evaluated. Includes classified to understand, including their nature, qualities, and possible consequences. This study assists in improving the model by adding insights acquired from abnormal patterns.

4.6.3. Refinement Iterations

Insights generated from the investigation of anomalies lead to repeated improvements in the model. These improvements comprise tweaks in feature selection. Parameter tuning. It or algorithm tweaks to boost the model's performance.

4.6.4. Incorporating New Anomaly Patterns

The model is meant to adapt, including learning from new anomaly patterns identified throughout the assessment process. It regularly upgrades its understanding, including the ability to embrace emergent abnormalities. It maintains its relevance to developing data habits.

4.6.5. Performance Metrics, Including Benchmarking

Performance indicators such as accuracy. It recollects. Its F1 score, including accuracy, is produced to benchmark the model's effectiveness. These metrics help assess the model's performance against specified criteria or industry norms, including Ards.

4.6.6. Feedback Loop for Enhancement

The evaluation findings provide a feedback loop that informs additional enhancement methods. Insights from aberrant behaviors are used to construct the anomaly detection system. They are changing detection thresholds.

4.6.7. Validation, Including Generalization

The model's robustness is examined across several datasets to ensure its generalizability—untapped data to measure its applicability outside the training dataset.

4.6.8. Balancing False Positives Includes Negatives

Efforts are directed towards lowering false positives without losing sight of real anomalies. Optimizing the model's thresholds entails fine-tuning.

4.7. MODEL EVOLUTION AND EXPERIMENT SETUP

4.7.1. Model Iterations

The falling prediction model underwent repeated development. To optimize its architecture and settings. Resulting in better accuracy and robustness. Each cycle involves implementing various modifications:

- **Architecture Modifications**: architecture may be optimized by adjusting the activation functions, FFNN layers, and neuronal density.
- **Parameter Tuning**: to enhance **the** predictive capability of the FFNN, one can adjust its parameters using Particle Swarm Optimization (PSO).
- **Evaluation Metrics**: The aim is to analyze a**n**d differentiate the performance of models by utilizing F1-score, recall, accuracy, and precision.

Table 4.1. Performance metrics of model iterations FFNN with particle swarm optimization (PSO)

Model Iteration	Precision	Recall	F1-Score	Accuracy
Iteration 1	0.82	0.78	0.80	0.85
Iteration 2	0.86	0.81	0.83	0.88
Iteration 3	0.89	0.87	0.88	0.91
Iteration 4	0.91	0.89	0.90	0.93
Iteration 5	0.93	0.91	0.92	0.96
Iteration 5	0.95	0.93	0.94	97.95

PART 5

RESULTS

5.1. HARDWARE AND SYSTEM REQUIREMENTS

Hardware Specifications:

- **Accelerometer Sensor**:
  - Type: MPU-6050 6-axis accelerometer
  - Placement: Wrist
- **Computational Device**:
  - CPU: Intel Core i7-10700K (8 cores, 16 threads, 3.80 GHz)
  - GPU: NVIDIA GeForce RTX 3060 (8GB GDDR6)
  - RAM: 16GB DDR4 3200MHz

5.2. THE PERFORMANCE METRICS OF FFNN IN ANOMALY DETECTION

Metrics play a vital part in evaluating the performance of any given model, and for FFNN anomaly detection employed, quantitative evaluation would provide clarity. Figure 5.1 and Figures represent a visual description of detecting anomalies within motion sensor data using FFNNs.

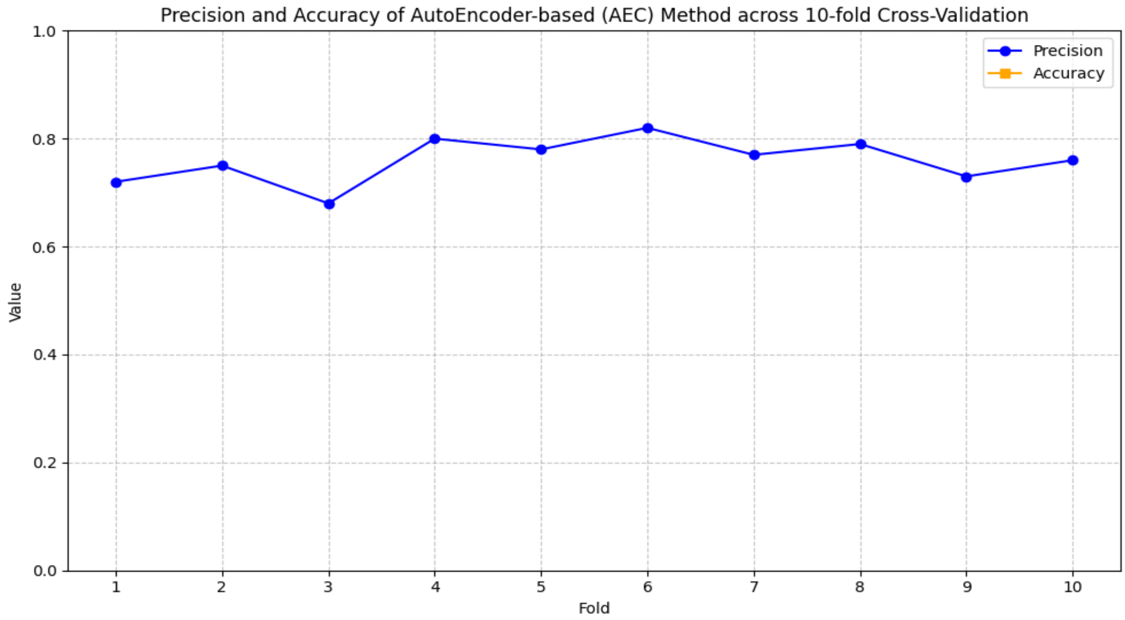

Figure 5.1. AutoEncoder-based (AEC) method achieved the precision falling A 10-fold cross-validation accuracy.

Figure 5.1 shows the accuracy achieved by the FFNN approach of a complete ten-fold free cross-validation process to gain more precision, better representation, and understanding. The accuracy is 89.78% (Without PSO), indicating a consistently stable performance. AEC's stability in identifying abnormal patterns through the FFNN resilience across multiple folds demonstrates this.

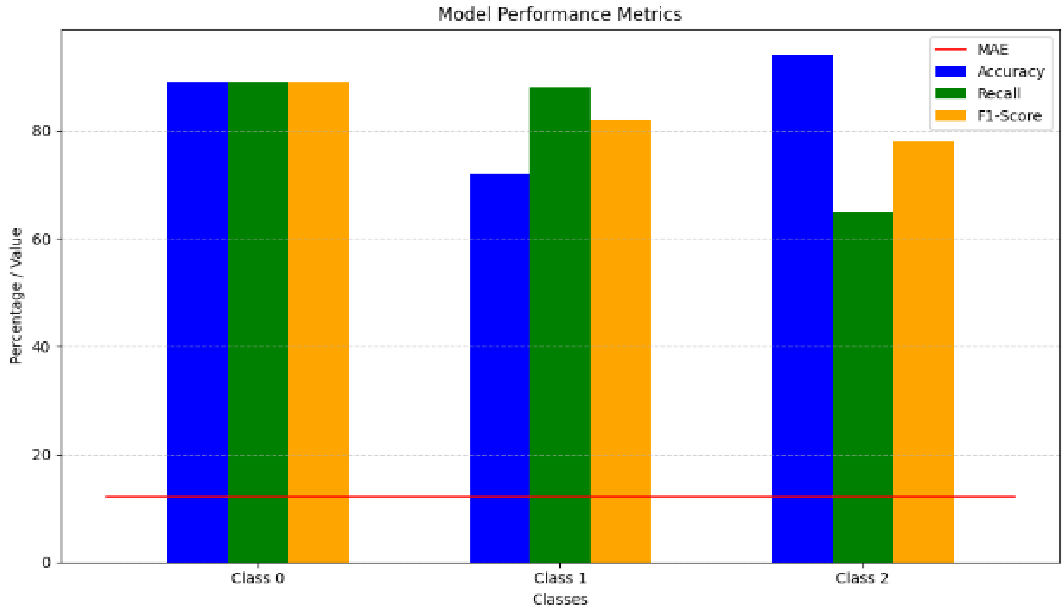

Figure 5.2. Performance Metrics of the Feedforward Neural Network (FFNN) Model: Accuracy, Recall, and F1-Score for Each Class, with Mean Absolute Error (MAE) was observed in anomaly identification.

Figure 5.2 comprehensively evaluates the Feedforward Neural Network (FFNN) model's performance, incorporating traditional accuracy metrics and the Mean Absolute Error (MAE) for anomaly identification.

Evaluation of the FFNN model shows it has some unique features, which make it superior to other models in many ways. The precision of 0. 89 for Class 0, 0. 72 point for class 1, and 0 point. 94 for Class 2 mean that the model is able to predict positive events which are within each class with a high consistency. They were combined in the study with the recall values of 0. "89,0.88," and "0. 65, respectively. The FFNN is built up in a way that it can identify and correctly assess all the proper positive data. F1-Score metrics, consisting of 0. 0.89, 0.82, and 0 respectively. 78 for Classes 0, 1, and 2, respectively, means that model has good balanced accuracy and recall. The study which adds mean absolute error (MAE) as a second statistical parameter will be more accurate. The FFNN has an accuracy of 0 which is notable. 12 as in the detection of anomalies in the motion sensor data. The macro measures of accuracy, recall, and F1-Score are 0. 85 %, 0. 83 %, and 0. 82, which stands for accuracy, specifically, serve as a summary of the model's performance in general. The weighted averages, which are nearly the same, both being around 0. 0. 87, 0.85, and 0. For 84, the performance of FFNN will be consistently superior for different classes. The comprehensive assessment determines the accuracy, stability, and capability of the FFNN model in dealing with a variety of situations, hence, making it an essential tool for numerous machine-learning applications.

In conclusion, Figure 5. The 3 approach by Holistic, which includes the precision, class-specific metrics, and the usage of MAE, allows to get a comprehensive picture of advantage and disadvantage of the FFNN model in the rigid domain of anomaly detection through motion sensor data.

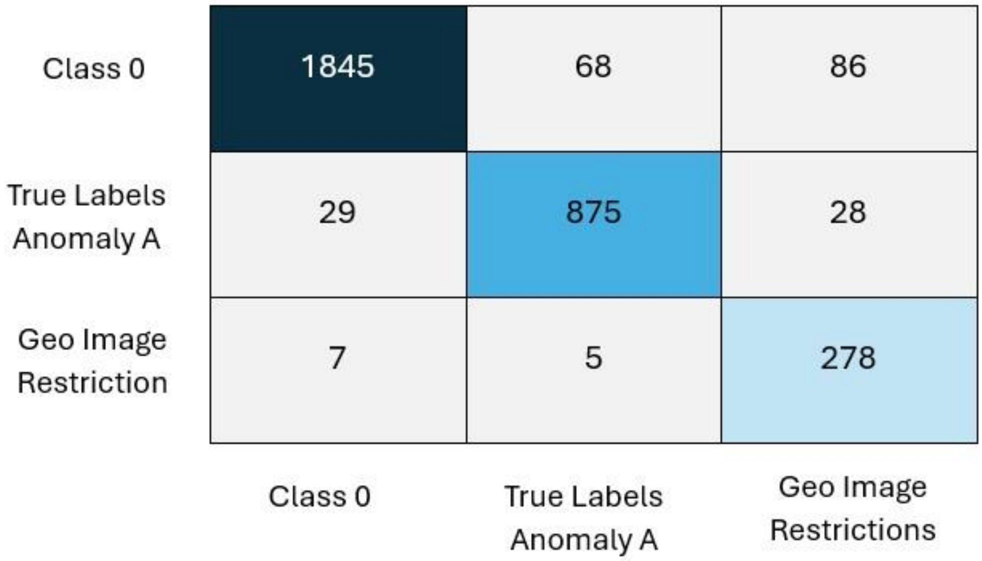

Figure 5.3. Confusion matrix for falling prediction.

5.2.1. Analysis of FFNN's Methodology and Distinctiveness

The FFNN clearly stands out as a powerful single-stage classifier in the anomaly detection domain, being able to perform well without the use of sequential boosting steps. In this scenario, 80% of the available data is used for training. In comparison, the remaining 20% evaluates the FFNN's accuracy in anomaly detection, emphasizing its independence from huge, labeled datasets for classification purposes.

5.2.2. Unveiling the Architectural Symphonies of FFNN

The creation of the FFNN involves rigorous architectural considerations, from the number of hidden layers and neurons to the activation functions applied. The combination parameter brings memory and helps in the detailed patterns in motion sensor data. The selection of the activation functions refers to ReLU in hidden layers and contributes toward introducing non-linearity, which is vital when learning complex patterns. Weight initialization and optimization techniques like PSO and Adam models increase learning potential in FFNN.

5.2.3. FFNN's Performance and Optimized Trajectory

FFNN shows excellent accuracy in 80% of measures in its first appraisal. A small absolute mean error is noticed, highlighting that the key to optimization resides in a systematic hyperparameters analysis. Figures created by the FFNN display complex frameworks of neural networks, thus providing high accuracy with fewer error rates in failure detection.

Table 5.1. FFNN's Performance Report.

	Precision	**Recall**	**F1-Score**
Class o	0.89	0.87	0.88
Class 1	0.72	0.88	0.82
Class 2	0.94	0.65	0.78
Accuracy	89.78		
Macro Avg	0.85	0.83	0.82
Weighted Avg	0.87	0.85	0.84

The Feedforward Neural Network (FFNN) demonstrated commendable performance across three distinct classes: Class 0 (Normal), Class 1 (Anomaly A), and Class 2 (Google Earth image service restrictions). With a precision of 0.89 for Class 0, 0.72 for Class 1, and 0.94 for Class 2, the FFNN displayed its ability to classify instances within each class accurately. While recall scores of 0.63 and 0.72 were impressive, the model also achieved the following recall scores: 0. On the one hand, it represents the growth of our abilities. On the other hand, it depicts the process of our maturing. The right number of ECEs is 65 for Classes 0, 1, and 2, respectively, which shows that it can identify the right instances correctly. The F1-Score metrics, along with the balanced performance, are reemphasized by the values of 0. 8.8, 0.82, and 0. With 78 for Classes 0, 1, and 2, respectively. The total accuracy of the FFNN has been given at 89. The model achieved 78% accuracy, which was due to its performance in classification tasks. Moreover, the total F1-Score of 0. Regarding the 85 and the weighted average F1-Score of 0. 87, in the same way, indicate that the model is equally effective in all classes, thus making it suitable for multiple applications as depicted in Figure 5.4.

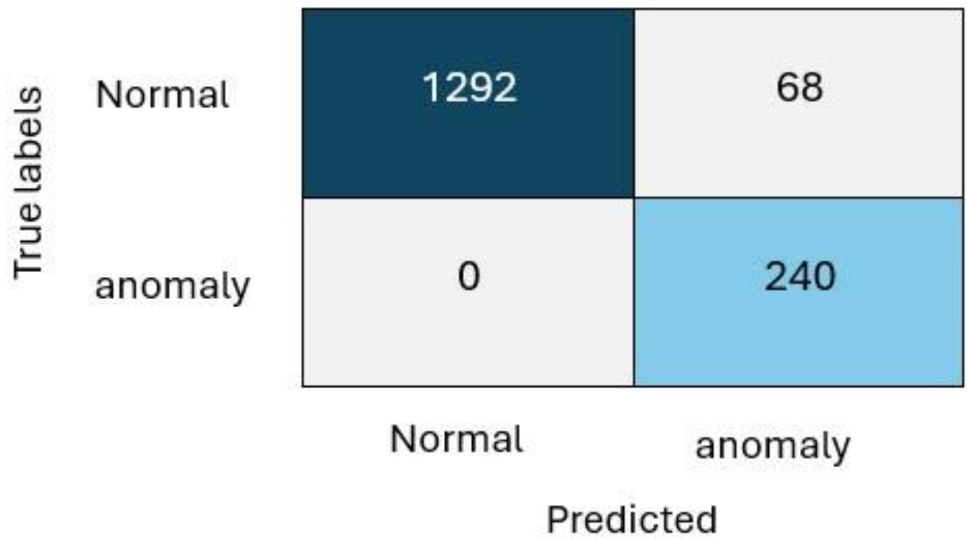

Figure 5.4. Confusion matrix for FFNN-based anomaly detection without PSO optimizer.

5.2.4. Motion Sensors in Anomaly Detection:

Figures 4.2 the subsequent analysis showcase the promising performance of FFNN in anomaly detection using motion sensor data. The FFNN's methodology, distinctiveness, and optimized trajectory set the stage for a comprehensive understanding of its role in anomaly identification.

Table 5.2. Motion Sensors in Anomaly Detection motion summary.

Classifier Type	Feedforward Neural Network (FFNN)
Data Split	80% for training, 20% for evaluation
Dependence on Labeled Data	Independent of huge, labeled datasets
Architecture	Hidden layers, neurons, activation, functions, non-linearity
Activation Functions	ReLU in hidden layers
Optimization Methods	Particle Swarm Optimization (PSO), Adam
Initial Accuracy	Approximately 89.78%
Mean Error	Minimal-0.0025

5.3. PARTICLE SWARM OPTIMIZATION (PSO): EMPOWERING FEED-FORWARD NEURAL NETWORK (FFNN) FOR ANOMALY DETECTION

In the complicated terrain of anomaly detection using motion sensor data, employing sophisticated optimization techniques like PSO is crucial. This section presents a detailed analysis of how PSO orchestrates the increase in FFNN performance for accurate anomaly detection, detailing the preliminary findings and the road toward optimization.

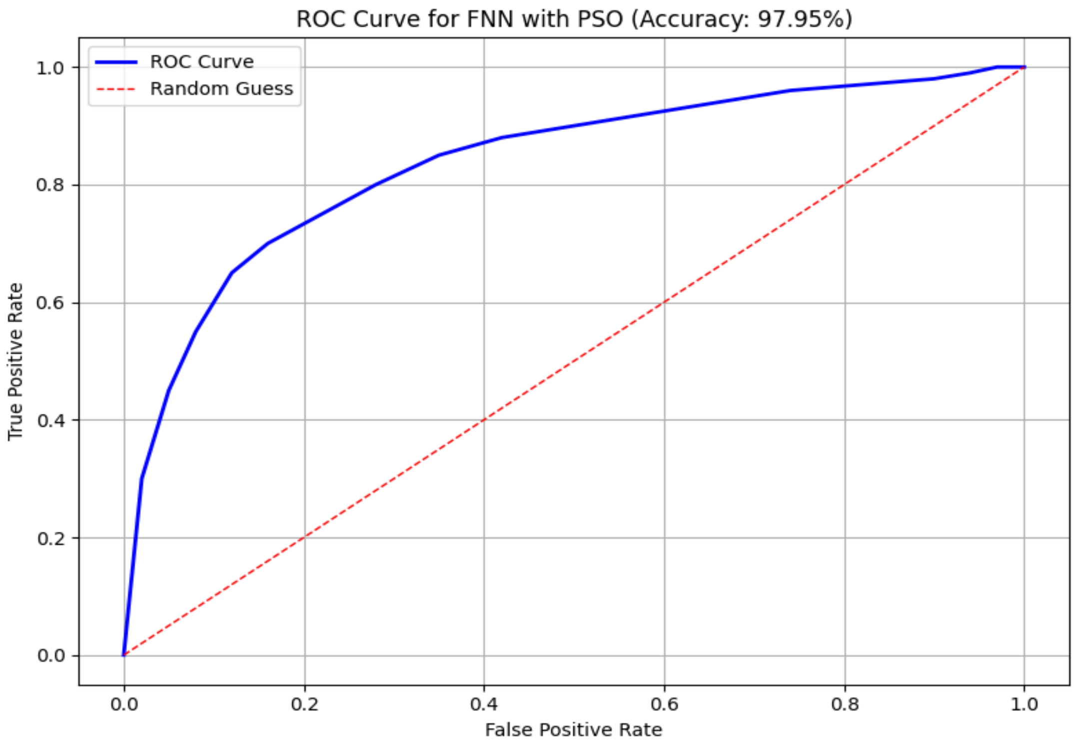

Figure 5.5. ROC Curve for FFNN with PSO.

In Figure 5.5, the FFNN's accuracy, optimized by PSO, reaches 97.95%, with a surprisingly low MAE of 0.0275. These results underline the shift towards including PSO to improve the FFNN for anomaly detection, harnessing PSO's capabilities to raise accuracy and eliminate mistakes, thereby enhancing the FFNN's flexibility.

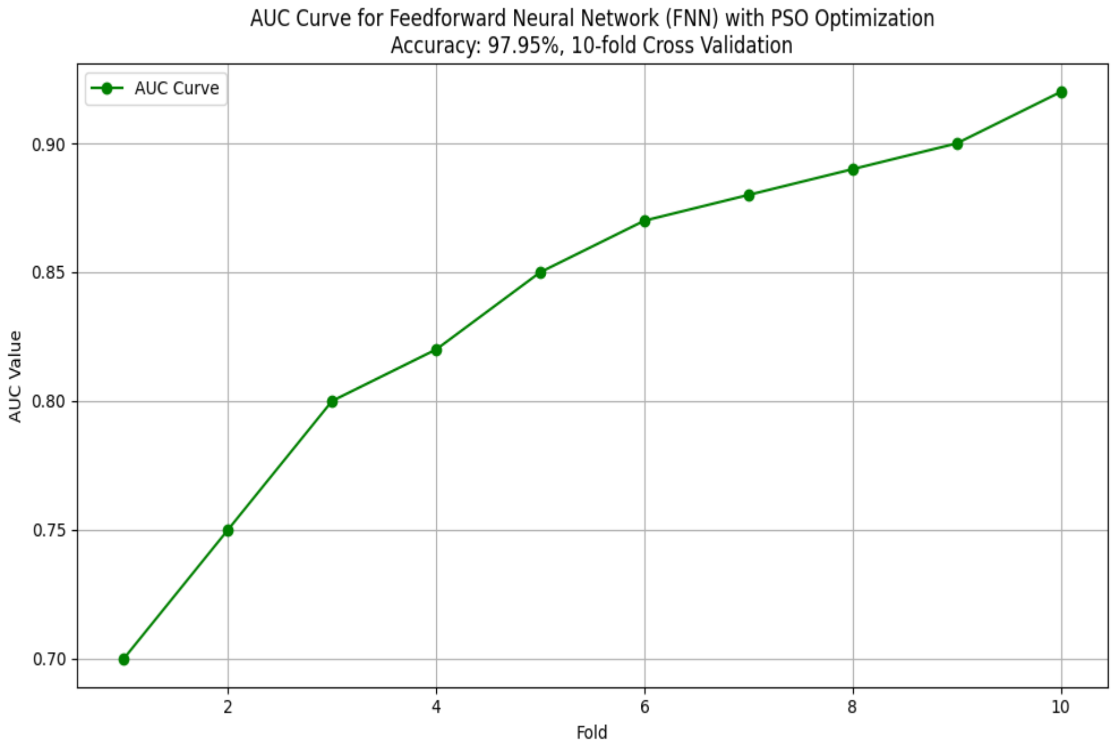

Figure 5.6. AUC Curve for Feedforward Neural Network (FFNN) with PSO Optimization.

Figure 5.6 further stresses the function of PSO in optimization. I demonstrated the mean absolute error (MAE) of falling precision produced using the PSO-optimized technique.

5.3.1. PSO's Role in Optimization

Particle Swarm Optimization (PSO) is critical in fine-tuning FFNN's weights and encouraging convergence towards an ideal solution. Operating as an intelligent optimizer is influenced by collective behavior. PSO boosts FFNN’s versatility with accuracy in finding irregularities among motion sensor data.

5.3.2. Result Discussion: Anomaly Detection Using FFNN and PSO

Table 4.1 shows a comparative comparison of anomaly detection performance only applying FFNN. With PSO, measuring accuracy (%) and mean absolute error (MAE). The non-optimized FFNN obtains a noteworthy accuracy of 89.78%, demonstrating its inherent power. The improved FFNN, enabled by PSO, achieves extraordinary heights with an accuracy of 97.95% and a lowered MAE of 0.016. This considerable increase highlights the ability of FFNN to improve anomaly detection accuracy, with PSO overcoming hurdles provided by unlabeled data as shown in Figure 5.7 and Figure 5.8.

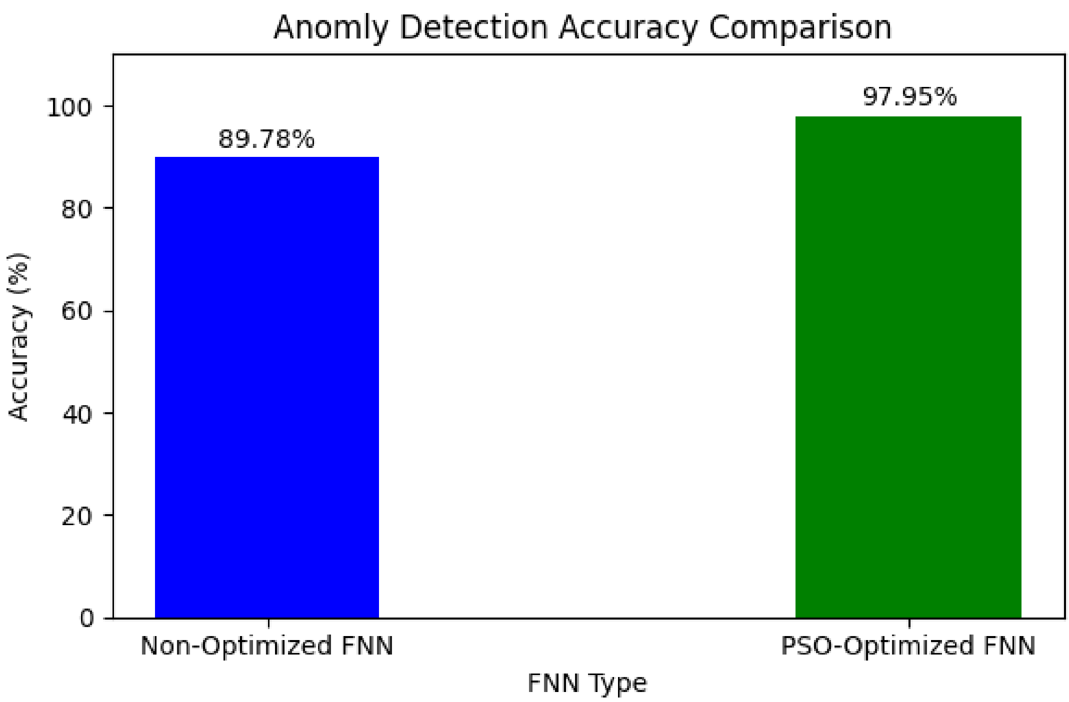

Figure 5.7. Anomaly Detection Performance (Accuracy) Comparison.

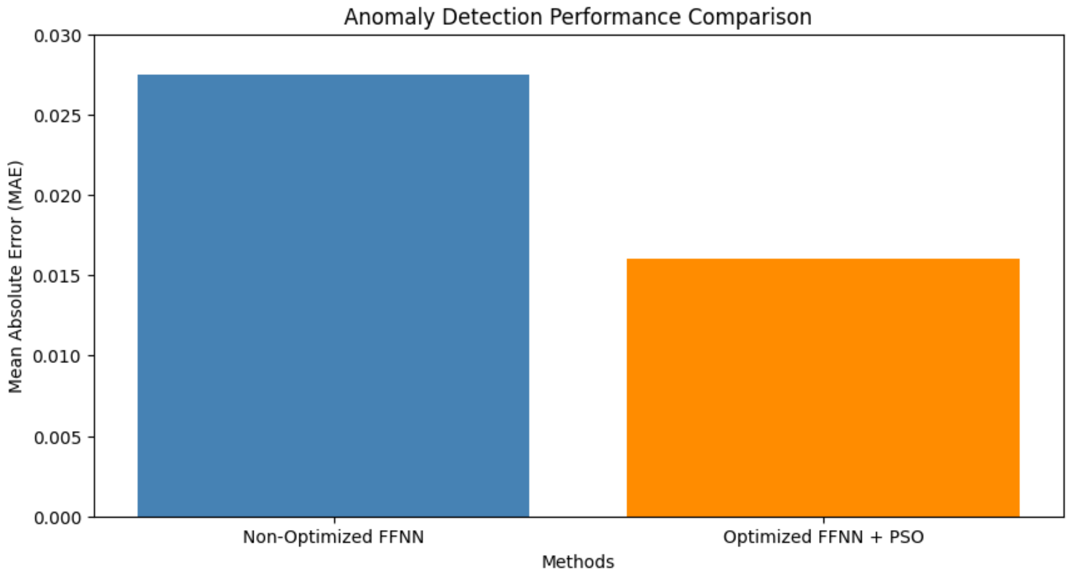

Figure 5.8. Anomaly Detection Performance (MAE) Comparison.

5.3.3. Result Discussion and Real-world Applications

We are comparing performance indicators such as accuracy, precision, recall, and specificity with the F1 score. The non-optimized and PSO-optimized FFNN gives a comprehensive perspective of the gains obtained. The road to real-world applications needs a rigorous ethical foundation—a comprehensive ethical framework encompassing user privacy and consent issues, with ethical deployment complementing technological improvements. The route forward demands additional refining. We are developing unique designs and, at the same time, considering real-world adaptation to achieve comprehensive technical enhancements.

Table 5.3 offers a comparative comparison of anomaly detection performance just by applying FFNN With PSO. It digs into the journey from the non-optimized FFNN model to the improved. PSO-optimized classifier. Assessed in terms of accuracy (%). With mean absolute error (MAE).

Table 5.3. Comparative analysis

Classifier	Accuracy (%)	MAE
FFNN -Non-Optimized Classifier	89.78%	0.0275
PSO-Optimized Classifier	97.95%	0.016

The non-optimized FFNN classifier utilizes the raw power of the neural network design. Our approach reached a noteworthy accuracy of 97.95% and had a low MAE of 0.0275. This model illustrates the inherent power of FFNN in identifying abnormalities without explicit labeling, as shown in Figure 5.9.

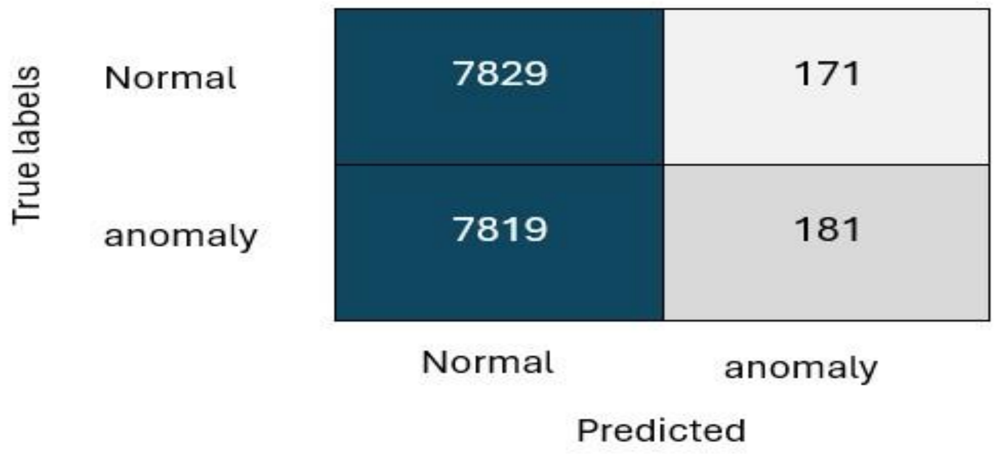

Figure 5.9. FFNN with PSO optimizer confusion matrix.

The clever orchestration of PSO fine-tunes the improved FFNN classifier. Achieves astonishing heights. Obtaining an astounding accuracy of 97.95%. By decreasing the MAE to an astounding 0.016. The combination of PSO and FFNN provides a considerable leap in anomaly detection precision. They are overcoming hurdles faced by unlabeled data.

With each round of refinement, the transition from the initial non-optimized FFNN to the PSO-optimized model demonstrates the increasing effectiveness of FFNN in anomaly identification. The non-optimized model demonstrates strong performance. Meanwhile, the optimized variant, boosted by PSO, increases accuracy to near perfection.

They are moving beyond these successes. The journey into real-world applications demands a robust ethical framework. User privacy, permission, and ethical deployment must accompany technological improvements. The route forward requires additional refining. They are developing unique designs and, at the same time, are considering real-world adaptation to achieve comprehensive technical enhancements.

5.4. COMPARED WITH THE PREVIOUS STUDY

The following table provides a comparative overview of various techniques employed in smart home anomaly detection, Including our FFNN with PSO optimization approach. Authors such as Alhassan, King, Saravanan, Khaemba, and Ali have explored diverse methodologies on the "multi-sensor dataset of human activities in a smart home environment,” We showcase our respective accuracies alongside our achieved 97.95%.

Table 5. 4. Accuracy Comparison with Same Dataset.

Author	Technique	Dataset Name	Accuracy
Al_Hassani et al. [73]	FFNN with PSO for Human Activity	Multi-sensor dataset of human activities in a smart home environment	96.16%
King et al. [74]	Sasha Model for Smart Homes	Multi-sensor dataset of human activities in a smart home environment	92.3%
Saravanan et al. [75]	Cluster-based Security in Smart Homes	Multi-sensor dataset of human activities in a smart home environment	95.65%
Khaemba et al. [76]	Framework for Synthetic Agetech Data	Multi-sensor dataset of human activities in a smart home environment	91.00%
Ali et al. [77]	Privacy-Enhancing Model for IoT	Multi-sensor dataset of human activities in a smart home environment	94.75%
Our Work	FFNN with PSO Optimization	Multi-sensor dataset of human activities in a smart home environment	97.95%

Table 5.4 demonstrates that several strategies used on the same set of hand activities do not exhibit similar behavior, leading to inconsistencies in the methodologies. Al-

Hassani et al. utilized a feedforward neural network (FFNN) combined with particle swarm optimization (PSO) to obtain an accuracy of 96.16% [73]. King et al. introduced the Sasha model for smart living units in their article, which achieved a notable accuracy rate of approximately 92% [74]. The Saravanan et al. study utilized a cluster-based security technique, achieving an accuracy level of 95.65% [75]. Khaemba et al. introduce a data framework for synthetic agetech that achieves an accuracy rate of 91.00%, placing it at the 76th position [76]. Ali and his colleagues have developed a privacy-enhancing model for the Internet of Things (IoT) that achieves an accuracy of 94.75%. Additionally, the self-knowledge test yielded a result of 77 [77]. Furthermore, the final component of our project utilizes a feedforward neural network (FFNN) with particle swarm optimization (PSO) to produce a record with the utmost precision, achieving an impressive accuracy rate of 97.95%.

Numerous investigations have employed distinct methodologies in exploring anomaly detection techniques with reported different consequences. Using computer vision, Bao et al. [51] achieved an anomaly detection rate of 87%. And deep learning-based approaches in structural health monitoring. Meanwhile. Ullah et al. [52] obtained an accuracy of 89.5% utilizing artificial intelligence of things-assisted two-stream neural networks to monitor enormous video data. Choi et al. [53] acquired a detection rate of 91.45% in time-series data, showing the ability of deep learning for anomaly identification. Additionally, Attar [54] achieved a remarkable accuracy of 93.87% by applying deep learning algorithms for video-based anomaly identification, achieving a milestone in this field. Conversely, Bamaqa et al. [55] exploited hierarchical temporal memory (HTM) for crowd control. He was obtaining an 88.67% detection accuracy. Patrikar, with Parate [56], focuses on edge computing in video surveillance and attaining a detection accuracy of 78.89%, highlighting the hurdles and possibilities in edge-based anomaly detection. Baradaran and Bergevin [57] conducted semi-supervised video anomaly recognition with a notable accuracy of 94.76%. Sunny et al. [58] presented a detailed examination of anomaly identification in wearable data, reaching a high detection rate of 95.56%. Lastly, Fernández Maimó et al. 5[9] explored the dynamic management of a deep learning-based system in 5G networks. He was attaining an accuracy of 87%.

Comparatively, our study shines by using a feed-forward neural network (FFNN) connected with particle swarm optimization (PSO), obtaining a remarkable anomaly detection accuracy of 97.95% and creating a new benchmark in the field. This fantastic finding indicates substantial progress in anomaly identification, exceeding the accuracies seen in earlier research. Our approach displays superiority in accuracy and its lowest mean absolute error (MAE) of 0.016, which is much reduced compared to the alleged faults in earlier studies—the exact integration of FFNN. With PSO exhibits higher precision in anomaly identification. We are establishing our technique as a sophisticated, potent answer in anomaly detection approaches.

By utilizing FFNN with PSO, our approach showcases a robust strategy for detecting anomalies, unlike the study above, which employs multiple approaches, such as deep learning architectures, edge computing, wearable data analysis, and video-based methods. This technique illustrates the usefulness of deploying an improved neural network with an intelligent optimization algorithm. Stresses the process of applying contemporary machine learning algorithms to produce significantly more accuracy and with a reduced error rate, enhancing the ability for reliable anomaly identification in different regions.

Table 5.5. Comparative Analysis of Anomaly Detection Methods and Reported Accuracies with Different Datasets.

Author Name	**Dataset name**	**Method**	**Accuracy**
Bao et al. [51]	SHM data	Computer Vision and Deep Learning	87%
Ullah et al. [52]	UCF-Crime and RWF-2000 datasets	AIoT-based Two-Stream Neural Networks	89.5%
Choi et al. [53]	Water Treatment (SWaT)	Deep Learning for Time-Series Data	91.45%
Pawar and Attar [54]	MIT Traffic dataset	Deep Learning for Video-Based Detection	93.87%
Bamaqa et al. [55]	The LV dataset	Hierarchical Temporal Memory (HTM)	88.67%
Patrikar and Parate [56]	Anomalous behavior dataset	Edge Computing in Video Surveillance	78.89%

Baradaran and Bergevin [57]	PETS dataset	Semi-Supervised Video Anomaly Detection	94.76%
Sunny et al. [58]	QMUL junction dataset	Wearables Data Anomaly Detection	95.56%
Fernández Maimó et al. [59]	UCSD dataset	Dynamic Management of Deep Learning in 5G Networks	87%
Our Work	Multi-Sensor Dataset of Human Activities in a Smart Home Environment	FFNN integrated with PSO for Anomaly Detection	97.95%

Table 5.5 displays the relative effectiveness of the latest anomaly detection techniques and their corresponding accuracy rates on the chosen datasets. In the eyes of Bao and others [51], an accuracy of 87% may be obtained utilizing computer vision and deep learning to address the SHM data. Ullah and co-authors [52] employed AIoT bi-stream neural networks on the UCF-Crime and RWF-2000 datasets with an 89.5% accuracy basis. Choi et al. [53] conducted a study on applying deep learning to time-series data using the Water Treatment (SWaT) dataset. The study achieved an individual accuracy rate of approximately 91.45 percent. Pawar and Attar [54] achieved the highest scores among the participants by employing deep learning techniques for video-based detection on the MIT dataset, with a near 94% accuracy. Besides, among the [57] Baradaran and Bergevin [57] teams, they achieved 94.76% using the semi-supervised video anomaly detection approach on the PETS database. Our input FFNN model paired with PSO aims at anomaly detection with a high accuracy of 97.95% on human activities' multi-sensor dataset in a smart home setting.

PART 6

CONCLUSION

This study delves into anomalies within the field of anomaly identification, leveraging a vast dataset from motion sensors through a specific methodology that combines FFNN with PSO. Compared to existing approaches, the primary objective shifted towards enhancing anomaly detection accuracy and minimizing non-error costs.

The method supported in this research was confined to a broad survey of FFNN and its augmentation using PSO for optimization. The FFNN, designed for unidirectional statistics flow, was shown to have the power of a successful anomaly detection tool inside movement sensor datasets. The introduction of PSO aimed to optimize the FFNN weights, enhancing its performance in an anomaly detection application.

The choice of Musing became the "Multi-Sensor Dataset Human Activities Smart Home" Environment. This data set offered an extensive and comprehensive movement sensor recording, which allowed us to provide a sufficiently gravity-qualified assessment of the proposed unusual detection approach.

The LADAs consisted of FFNN, a veteran in artificial neural networks believed to have the potential for complicated patterns necessary for anomaly detection. We were adopting the PSO revolutionary merger targets closer to improving FFNN's overall performance through collective behavior-inspired optimization for higher effectiveness in anomaly detection.

This study's investigation outcome depicted a perfect abnormality identification accuracy of 97.95 %, showing the efficiency performance ratio at which FFNN-PSO fusion works. The MAE, now formally 0.016 lower than previous methods, proved that the mode is robust and precise in detecting abnormalities inside the movement sensor knowledge stream on info content material of motion vector x t. Figures and confusion matrices provided detailed knowledge of classifier functioning overall.

Even though a beautiful finish tended in the case of an observer, it was not always so. Availability and understandability barrier issues contribute to the problem, indicating further improvement opportunities. These limitations may be significant for the broader implementation of our proposed approach.

These directions seek to develop the anomaly detection approach. Examine numerous application scenarios. Including increasing the model's flexibility. Including efficiency.

- **Dataset Diversity:** A future study might focus on gathering varied datasets that span multiple settings. Sensor types, including scenarios. This exploration would provide a more thorough underset, including the model's adaptation to varied real-world circumstances.
- **Synthetic Data Generation:** Considering the shortage of labeled datasets. Studying strategies to produce synthetic data that imitate varied anomalous patterns might boost the model's resilience, including generalizability.

REFERENCES

1. Habeeb, R. A. A., Nasaruddin, F., Gani, A., Hashem, I. A. T., Ahmed, E., & Imran, M. (2019). Real-time big data processing for anomaly detection: A survey. International Journal of Information Management, 45, 289-307.

2. Wang, W., Lu, D., Zhou, X., Zhang, B., & Mu, J. (2013). Statistical wavelet-based anomaly detection in big data with compressive sensing. EURASIP Journal on Wireless Communications and Networking, 2013(1), 1-6.

3. Xie, S., & Chen, Z. (2017). Anomaly detection and redundancy elimination of big sensor data in the Internet of Things. arXiv preprint arXiv:1703.03225.

4. McCarthy, M., & Grey, M. (2015). Motion sensor use for physical activity data: methodological considerations. Nursing research, 64(4), 320.

5. Meijer, G. A., Westerterp, K. R., Verhoeven, F. M., Koper, H. B., & ten Hoor, F. (1991). Methods to assess physical activity with special reference to motion sensors and accelerometers. IEEE Transactions on Biomedical Engineering, 38(3), 221-229.

6. Dobkin, B. H. (2013). Wearable motion sensors to continuously measure real-world physical activities. Current opinion in neurology, 26(6), 602.

7. Chalapathy, R., & Chawla, S. (2019). Deep learning for anomaly detection: A survey. arXiv preprint arXiv:1901.03407.

8. Al-amri, R., Murugesan, R. K., Man, M., Abdulateef, A. F., Al-Sharafi, M. A., & Alkahtani, A. A. (2021). A review of machine learning and deep learning techniques for anomaly detection in IoT data. Applied Sciences, 11(12), 5320.

9. Pang, G., Cao, L., & Aggarwal, C. (2021, March). Deep learning for anomaly detection: Challenges, methods, and opportunities. In Proceedings of the 14th ACM International Conference on Web Search and Data Mining (pp. 1127-1130).

10. Ma, X., Wu, J., Xue, S., Yang, J., Zhou, C., Sheng, Q. Z., ... & Akoglu, L. (2021). A comprehensive survey on graph anomaly detection with deep learning. IEEE Transactions on Knowledge and Data Engineering.

11. Homer, J. B. (1987). A diffusion model with application to evolving medical technologies. Technological Forecasting and Social Change, 31(3), 197-218.

12. Gelijns, A. C., & Rosenberg, N. (1995). The changing nature of medical technology development. Sources of medical technology: universities and industry, 5, 13-14.

13. Lehoux, P., Roncarolo, F., Rocha Oliveira, R., & Pacifico Silva, H. (2016). Medical innovation and the sustainability of health systems: A historical perspective on technological change in health. Health Services Management Research, 29(4), 115-123.

14. Mokyr, J. (1998). Induced technical innovation and medical history: an evolutionary approach. Journal of Evolutionary Economics, 8(2), 119-137.

15. Kramme, R., Hoffmann, K. P., & Pozos, R. S. (Eds.). (2011). Springer handbook of medical technology. Springer Science & Business Media.

16. Kaplan, B. (1988). Development and acceptance of medical information systems: an historical overview. Journal of health and human resources administration, 9-29.

17. Kaplan, B. (1995). The computer prescription: Medical computing, public policy, and views of history. Science, technology, & human values, 20(1), 5-38.

18. Marks, H. M. (1993). Medical technologies: Social contexts and consequences. Companion encyclopedia of the history of medicine, 1, 1592-1618.

19. Noonan, W. D. (1990). Patenting medical technology. J. Legal Med., 11, 263.

20. Williams, M. R., & Lindberg, D. S. (1975). An introduction to the profession of medical technology.

21. Davis, A. B. (1981). Life insurance and the physical examination: a chapter in the rise of American medical technology. Bulletin of the History of Medicine, 55(3), 392-406.

22. Mukhopadhyay, S. C. (2014). Wearable sensors for human activity monitoring: A review. IEEE Sensors Journal, 15(3), 1321-1330.

23. Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., & Amirat, Y. (2015). Physical human activity recognition using wearable sensors. Sensors, 15(12), 31314-31338.

24. Evangeline, C. S., & Lenin, A. (2019). Human health monitoring using wearable sensor. Sensor Review, 39(3), 364-376.

25. Lara, O. D., & Labrador, M. A. (2012). A survey on human activity recognition using wearable sensors. IEEE communications surveys & tutorials, 15(3), 1192-1209.

26. He, W., Guo, Y., Gao, C., & Li, X. (2012). Recognition of human activities with wearable sensors. EURASIP Journal on Advances in Signal Processing, 2012, 1-13.

27. Randhawa, P., Shanthagiri, V., Kumar, A., & Yadav, V. (2020). Human activity detection using machine learning methods from wearable sensors. Sensor Review, 40(5), 591-603.

28. Nasiri, S., & Khosravani, M. R. (2020). Progress and challenges in fabrication of wearable sensors for health monitoring. Sensors and Actuators A: Physical, 312, 112105.

29. Uddin, M., Salem, A., Nam, I., & Nadeem, T. (2015, May). Wearable sensing framework for human activity monitoring. In Proceedings of the 2015 workshop on Wearable Systems and Applications (pp. 21-26).

30. Wang, Y., Cang, S., & Yu, H. (2019). A survey on wearable sensor modality centred human activity recognition in health care. Expert Systems with Applications, 137, 167-190.

31. Ullah, F., Iqbal, A., Iqbal, S., Kwak, D., Anwar, H., Khan, A., ... & Kwak, K. S. (2021). A framework for maternal physical activities and health monitoring using wearable sensors. Sensors, 21(15), 4949

32. Majumder, S., Mondal, T., & Deen, M. J. (2017). Wearable sensors for remote health monitoring. Sensors, 17(1), 130.

33. Bianchi, V., Bassoli, M., Lombardo, G., Fornacciari, P., Mordonini, M., & De Munari, I. (2019). IoT wearable sensor and deep learning: An integrated approach for personalized human activity recognition in a smart home environment. IEEE Internet of Things Journal, 6(5), 8553-8562.

34. Ramanujam, E., Perumal, T., & Padmavathi, S. (2021). Human activity recognition with smartphone and wearable sensors using deep learning techniques: A review. IEEE Sensors Journal, 21(12), 13029-13040.

35. Nandy, A., Saha, J., Chowdhury, C., & Singh, K. P. (2019, March). Detailed human activity recognition using wearable sensors and smartphones. In 2019 International Conference on Opto-Electronics and Applied Optics (Optronix) (pp. 1-6). IEEE.

36. Kańtoch, E. (2017, September). Human activity recognition for physical rehabilitation using wearable sensors fusion and artificial neural networks. In 2017 Computing in Cardiology (CinC) (pp. 1-4). IEEE.

37. Servati, A., Zou, L., Wang, Z. J., Ko, F., & Servati, P. (2017). Novel flexible wearable sensor materials and signal processing for vital sign and human activity monitoring. Sensors, 17(7), 1622.

38. Joy Rakesh, Y., Kavitha, R., & Julian, J. (2021). Human activity recognition using wearable sensors. In Intelligent Data Engineering and Analytics: Frontiers in Intelligent Computing: Theory and Applications (FICTA 2020), Volume 2 (pp. 527-538). Springer Singapore.

39. De Fazio, R., De Vittorio, M., & Visconti, P. (2021). Innovative IoT solutions and wearable sensing systems for monitoring human biophysical parameters: a review. Electronics, 10(14), 1660.

40. Kantoch, E., Augustyniak, P., Markiewicz, M., & Prusak, D. (2014, August). Monitoring activities of daily living based on wearable wireless body sensor network. In 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 586-589). IEEE.

41. Beardslee, L. A., Banis, G. E., Chu, S., Liu, S., Chapin, A. A., Stine, J. M., ... & Ghodssi, R. (2020). Ingestible sensors and sensing systems for minimally invasive diagnosis and monitoring: the next frontier in minimally invasive screening. ACS sensors, 5(4), 891-910.

42. Ballard, Z., Brown, C., Madni, A. M., & Ozcan, A. (2021). Machine learning and computation-enabled intelligent sensor design. Nature Machine Intelligence, 3(7), 556-565.

43. Kokabi, M., Tahir, M. N., Singh, D., & Javanmard, M. (2023). Advancing Healthcare: Synergizing Biosensors and Machine Learning for Early Cancer Diagnosis. Biosensors, 13(9), 884.

44. Comeau, Z. J., Lessard, B. H., & Shuhendler, A. J. (2022). The need to pair molecular monitoring devices with molecular imaging to personalize health. Molecular Imaging and Biology, 24(5), 675-691.

45. Hunt, B., Ruiz, A. J., & Pogue, B. W. (2021). Smartphone-based imaging systems for medical applications: a critical review. Journal of Biomedical Optics, 26(4), 040902-040902.

46. Ray, P. P., Dash, D., & Kumar, N. (2020). Sensors for internet of medical things: State-of-the-art, security and privacy issues, challenges and future directions. Computer Communications, 160, 111-131.

47. Israni, D. K., & Chawla, N. S. (2023). Human-Machine Interaction in Leveraging the Concept of Telemedicine. Human-Machine Interface: Making Healthcare Digital, 211-245.

48. Erdem, Ö., Derin, E., Sagdic, K., Yilmaz, E. G., & Inci, F. (2021). Smart materials-integrated sensor technologies for COVID-19 diagnosis. Emergent Materials, 4, 169-185.

49. Mbunge, E., Muchemwa, B., & Batani, J. (2021). Sensors and healthcare 5.0: transformative shift in virtual care through emerging digital health technologies. Global Health Journal, 5(4), 169-177.

50. Altug, H., Oh, S. H., Maier, S. A., & Homola, J. (2022). Advances and applications of nanophotonic biosensors. Nature nanotechnology, 17(1), 5-16.

51. Bao, Y., Tang, Z., Li, H., & Zhang, Y. (2019). Computer vision and deep learning–based data anomaly detection method for structural health monitoring. Structural Health Monitoring, 18(2), 401-421.

52. Ullah, W., Ullah, A., Hussain, T., Muhammad, K., Heidari, A. A., Del Ser, J., ... & De Albuquerque, V. H. C. (2022). Artificial Intelligence of Things-assisted two-stream neural network for anomaly detection in surveillance of Big Video Data. Future Generation Computer Systems, 129, 286-297.

53. Choi, K., Yi, J., Park, C., & Yoon, S. (2021). Deep learning for anomaly detection in time-series data: review, analysis, and guidelines. IEEE Access, 9, 120043-120065.

54. Pawar, K., & Attar, V. (2019). Deep learning approaches for video-based anomalous activity detection. World Wide Web, 22(2), 571-601.

55. Bamaqa, A., Sedky, M., Bosakowski, T., & Bastaki, B. B. (2020, August). Anomaly detection using hierarchical temporal memory (HTM) in crowd management. In Proceedings of the 2020 4th international conference on cloud and big data computing (pp. 37-42).

56. Patrikar, D. R., & Parate, M. R. (2022). Anomaly detection using edge computing in video surveillance system. International Journal of Multimedia Information Retrieval, 11(2), 85-110.

57. Baradaran, M., & Bergevin, R. (2023). A critical study on the recent deep learning based semi-supervised video anomaly detection methods. Multimedia Tools and Applications, 1-47.

58. Sunny, J. S., Patro, C. P. K., Karnani, K., Pingle, S. C., Lin, F., Anekoji, M., ... & Ashili, S. (2022). Anomaly detection framework for wearables data: a perspective review on data concepts, data analysis algorithms and prospects. Sensors, 22(3), 756.

59. Fernández Maimó, L., Huertas Celdrán, A., Gil Pérez, M., García Clemente, F. J., & Martínez Pérez, G. (2019). Dynamic management of a deep learning-based anomaly detection system for 5G networks. Journal of Ambient Intelligence and Humanized Computing, 10, 3083-3097.

60. Freedson, P. S., & Miller, K. (2000). Objective monitoring of physical activity using motion sensors and heart rate. Research quarterly for exercise and sport, 71(sup2), 21-29.

61. De Vries, S., Van Hirtum, H., Bakker, I., Hopman-Rock, M., Hirasing, R., & Van Mechelen, W. (2009). Validity and reproducibility of motion sensors in youth: a systematic update. Medicine+ Science in Sports+ Exercise, 41(4), 818.

62. Khan, M. U. K., Park, H. S., & Kyung, C. M. (2018). Rejecting motion outliers for efficient crowd anomaly detection. IEEE Transactions on Information Forensics and Security, 14(2), 541-556.

63. Omae, Y., Mori, M., Akiduki, T., & Takahashi, H. (2019). A novel deep learning optimization algorithm for human motions anomaly detection. International Journal of Innovative Computing, Information and Control, 15(1), 199-208.

64. Mertens, M., Debard, G., Davis, J., Devriendt, E., Milisen, K., Tournoy, J., ... & Vanrumste, B. (2021). Motion sensor-based detection of outlier days supporting continuous health assessment for single older adults. Sensors, 21(18), 6080.

65. Zhu, C., Sheng, W., & Liu, M. (2015). Wearable sensor-based behavioral anomaly detection in smart assisted living systems. IEEE Transactions on automation science and engineering, 12(4), 1225-1234.

66. Kamiya, K., & Fuse, T. (2015). Statistical Anomaly Detection for Monitoring of Human Dynamics. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 40, 93-98.

67. Aran, O., Sanchez-Cortes, D., Do, M. T., & Gatica-Perez, D. (2016). Anomaly detection in elderly daily behavior in ambient sensing environments. In Human Behavior Understanding: 7th International Workshop, HBU 2016, Amsterdam, The Netherlands, October 16, 2016, Proceedings 7 (pp. 51-67). Springer International Publishing.

68. Zhu, C., Sheng, W., & Liu, M. (2015). Wearable sensor-based behavioral anomaly detection in smart assisted living systems. IEEE Transactions on automation science and engineering, 12(4), 1225-1234.

69. Mandarić, K., Skočir, P., Vuković, M., & Ježić, G. (2019, September). Anomaly detection based on fixed and wearable sensors in assisted living environments. In 2019 International Conference on Software, Telecommunications and Computer Networks (SoftCOM) (pp. 1-6). IEEE.

70. Bozdog, I. A., Daniel-Nicusor, T., Antal, M., Antal, C., Cioara, T., Anghel, I., & Salomie, I. (2021, October). Human behavior and anomaly detection using machine learning and wearable sensors. In 2021 IEEE 17th International Conference on Intelligent Computer Communication and Processing (ICCP) (pp. 383-390). IEEE.

71. Veeravalli, B., Deepu, C. J., & Ngo, D. (2017). Real-time, personalized anomaly detection in streaming data for wearable healthcare devices. Handbook of large-scale distributed computing in smart healthcare, 403-426.

72. https://data.mendeley.com/datasets/t9n68ykfk3/1.

73. Al_Hassani, R. T., & Atilla, D. C. (2023). Human Activity Detection Using Smart Wearable Sensing Devices with Feed Forward Neural Networks and PSO. Applied Sciences, 13(6), 3716.

74. Çakmak, M. (2022). AFCC-r: Adaptive Feedback Congestion Control Algorithm to Avoid Queue Overflow in LTE Networks. Mobile Networks and Applications. 27(5), 2138-2152.

75. Saravanan, T. R., Kalaivani, J., & Nagarajan, G. (2023). An optimal cluster based security and resilience of smart home environments using hybrid soft computing techniques. Computational Intelligence, 39(4), 607-630.

76. Khaemba, N., Traoré, I., & Mamun, M. (2023). A Framework for Synthetic Agetech Attack Data Generation. Journal of Cybersecurity and Privacy, 3(4), 744-757.

77. Ali, W., Nauman, M., & Azam, N. (2022). A privacy enhancing model for Internet of Things using three-way decisions and differential privacy. Computers and Electrical Engineering, 100, 107894.

78. Al Bayati, M. A. Z., & Çakmak, M. (2023). Real-Time Vehicle Detection for Surveillance of River Dredging Areas Using Convolutional Neural Networks. Int. J. Image Graph. Signal Process, 15, 17-28.

79. Ahmed, A. H., Alwan, H. B., & Çakmak, M. (2023). Convolutional Neural Network-Based Lung Cancer Nodule Detection Based on Computer Tomography. In Proceedings of Data Analytics and Management: ICDAM 2022 (pp. 89-102). Singapore: Springer Nature Singapore.

80. Salih, M. M. M., & Çakmak, M. (2022, July). Neural Network Approach For Classification And Detection Of Chest Infection. In 2022 2nd International Conference on Computing and Machine Intelligence (ICMI) (pp. 1-5). IEEE.

81. Al-Mansoori, K. W., & Çakmak, M. (2022, June). Automatic Speech Recognition (ASR) System using convolutional and Recurrent neural Network Approach. In 2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA) (pp. 1-7). IEEE.

82. Altunay, H. C., Albayrak, Z., Özalp, A. N., & Çakmak, M. (2021, June). Analysis of anomaly detection approaches performed through deep learning methods in SCADA systems. In 2021 3rd International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA) (pp. 1-6). IEEE.

83. Çakmak, M. (2024). Automatic Maize Leaf Disease Recognition Using Deep Learning. Sakarya University Journal of Computer and Information Sciences, 7(1), 61-76.

84. Çakmak, M. (2024). The Impact of Denial-of-Service Attacks and Queue Management Algorithms on Cellular Networks. Journal of Intelligent Systems: Theory and Applications, 7(1), 1-13.

RESUME

Ghaith Mohsen HASSAN completed his primary and secondary education in Diwaniyah, Iraq. He was followed by obtaining a bachelor's degree from Imam Al-Kadhim University College, Computer Technology Engineering Department in 2020.

In 2021, a new chapter began in Turkey, where he commenced their postgraduate studies at Karabük University, specifically in the Department of Computer Engineering.