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HUMAN ACTIVITY RECOGNITION: A DUAL PERSPECTIVE ON DEEP LEARNING AND HEALTHCARE MONITORING

Thesis Submitted
In Partial Fulfillment of the Requirements for the
Degree of

MASTERS OF TECHNOLOGY
by RESEARCH
in
Data Science

by
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ACKNOWLEDGEMENT

॥ गुरुर्ब्रह्मा गुरुर्विष्णुः गुरुर्देवो महेश्वरः ॥
॥ गुरुः साक्षात् परं ब्रह्म तस्मै श्री गुरवे नमः ॥

I am thankful to God for His strength, resilience and guidance throughout this journey. First of all, I would like to acknowledge my guide, Dr. Abhilasha Sharma, for giving her valuable advice and guidance during the entire process of doing this research. Her valuable advice and way of approaching the matter were very helpful for doing this task. Her belief in me boosted my morale and made me think clearly in order to do this research. I just can't say how much my confidence in her has helped me with this thesis; if it wasn't for her, this wouldn't have been possible. I would also like to thank Dr. Roshni Singh for her technical inputs, her collaborative approach towards the project. The attitude she took when talking about it, and her constant encouragement during the course of my research and M.Tech journey. She brought her experience and ideas to the table, offering valuable insights and perspectives to the practical work. I would like to express my love and gratitude to my parents for being always by my side, giving me their love and encouragement in all my endeavors, and guiding me all my life. It is thanks to them and their motivating atmosphere that I would not have been able to reach my objectives. This journey has been a real strength through their unwavering faith in me. I want to thank my friends, colleagues and peers for their companionship, encouragement, and academic camaraderie that has helped balance and bring positivity during this journey. I would like to thank them all for their support, love, and guidance for this thesis.

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CANDIDATE'S DECLARATION

I, Somanshu Gupta hereby certify that the research work which is being presented in the thesis entitled "Human Activity Recognition: A Dual Perspective on Deep Learning and Healthcare Monitoring" in partial fulfillment of the requirements for the award of the Degree of Master of Technology by Research in Data Science, submitted in the Department of Software Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from August 2024 to May 2026 under the supervision of Dr. Abhilasha Sharma. The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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This is to certify that the student has incorporated all corrections suggested by the examiners into the thesis, and the statement made by the candidate is correct to the best of our knowledge.

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Certified that Somanshu Gupta (24/RSE/06) has carried out their research work presented in this thesis entitled "Human Activity Recognition: A Dual Perspective on Deep Learning and Healthcare Monitoring" for the award of Master of Technology by Research from Department of Software Engineering, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the student himself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

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Human Activity Recognition: A Dual Perspective on Deep Learning and Healthcare Monitoring

Somanshu Gupta

ABSTRACT

In recent years, Human Activity Recognition (HAR) has become a significant research field in the healthcare monitoring area as it involves the analysis and interpretation of various human behavioral patterns by employing wearable sensors, smartphones, Internet of Things devices and intelligent computational algorithms. The recent breakthroughs in deep learning have resulted in the development of HAR applications ranging from elderly care to rehabilitation monitoring, assisted living and remote patient supervision. But current HAR systems have a number of limitations, such as distinguishing similar activities is challenging, handling subtle differences in the behavior is difficult, limited anomaly detection ability and lack of interpretability in a healthcare setting. This research gives a thorough survey about deep learning-based HAR techniques and introduces a new HAR framework for healthcare applications that is enhanced by incorporating change-point detection and anomaly analysis mechanisms. The proposed framework is based on Density-Based Spatial Gradient-Aligned Clustering of Applications with Noise for pattern identification, Gated Recurrent Temporal Echo Memory Unit for activity recognition, Generative Cross-Window Temporal Attention Adversarial Network for change-point detection, Memory-Augmented Hidden Information Bayesian Markov Model for uncertainty estimation, and Semantic Distance Regularized Autoencoder for anomalous activity detection. The framework is tested on the MHEALTH dataset following the pre-processing, dimension reduction and multi-domain feature extraction. The experimental results showed that the proposed model had the activity recognition accuracy of 98.91%, precision of 98.92%, recall of 99.06% and F-measure of 98.99%. The proposed autoencoder model had lower reconstruction errors and better clustering quality for anomaly detection. The proposed framework has been successfully applied to healthcare-related HAR applications such as monitoring of elderly, rehabilitation support, remote healthcare supervision, and smart assisted living system.

Keywords: Human Activity Recognition, Machine Learning, Deep Learning, Healthcare Monitoring, Change-Point Detection, Anomaly Detection, Wearable Sensors.

LIST OF PUBLICATIONS

International Conferences

1. Gupta, S. and Sharma, A., 2025. Human Activity Recognition: A Review of Deep Learning Approaches. In *Proceedings of the 1st International Conference on Artificial Intelligence and Sustainable Innovation (ICAISI-2025)*. **(Scopus-Indexed, Accepted and Presented, 31st May 2025)**
2. Gupta, S. and Sharma, A., 2026. GRTEMU-Based Human Activity Recognition with Change Point Detection for Healthcare Monitoring. In *Proceedings of the 4th Doctoral Symposium on Human Centered Computing (HUMAN-2026)*. **(Scopus-Indexed, Accepted and Presented, 29th March 2026)**

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
HAR	Human Activity Recognition
IoT	Internet of Things
DBSGACAN	Density-Based Spatial Gradient-Aligned Clustering of Applications with Noise
GRTEMU	Gated Recurrent Temporal Echo Memory Unit
GCWTAAN	Generative Cross-Window Temporal Attention Adversarial Network
MAHI-BMM	Memory-Augmented Hidden Information Bayesian Markov Model
HMM	Hidden Markov Model
SDRAE	Semantic Distance Regularized AutoEncoder
CNNs	Convolutional Neural Networks
RNNs	Recurrent Neural Networks
LSTMs	Long Short-Term Memory Networks
GRUs	Gated Recurrent Units
ML	Machine Learning
DL	Deep Learning
PCA	Principal Component Analysis
LIME	Local Interpretable Model-Agnostic Explanations
MF	Mean Frequency
MMS	Min-Max Scaling
RMS	Root Mean Square
SMA	Signal Magnitude Area
ZCR	Zero Crossing Rate
FFT	Fast Fourier Transform
GAN	Generative Adversarial Network
AE	AutoEncoder
SAE	Sparse AutoEncoder
VAE	Variational AutoEncoder
KDE	Kernel Density Estimation
MSE	Mean Square Error
MAE	Mean Absolute Error
RE	Reconstruction Error
SS	Silhouette Score
FPR	False Positive Rate

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FNR	False Negative Rate
DBI	Davies-Bouldin Index
GMM	Gaussian Mixture Model
KCP	Kernel Change Point
DTW	Dynamic Time Warping
BNN	Bayesian Neural Network
CRF	Conditional Random Field
KF	Kalman Filter

CHAPTER 1

INTRODUCTION

Human Activity Recognition (HAR) can be defined as one of the most interesting areas of Artificial Intelligence, healthcare analytics, and pervasive computing. The idea of HAR systems implies activity recognition of a person using analysis of data acquired from various kinds of sensors, including wearable gadgets, mobile phones, accelerometers, gyroscope sensors, cameras, and Internet of Things (IoT) monitoring devices [1], [2].

1.1 Background

With the increasing need for developing intelligent patient monitoring systems in recent years, HAR has recently gained a great deal of significance for healthcare applications. Observing the activities of daily living enables health care workers to determine the general status of a person and to identify and treat or assist them in the event of any issues. Intelligent activity recognition systems are significant and are applied in many domains such as rehabilitation programs, elder-care services, assisted living systems, fitness and wellness assessment programs, and remote healthcare monitoring [3, 4].

Previously, classical HAR algorithms mainly relied on methods of feature extraction and rule-based classification, which has to be manually designed. Although they were effective in laboratory settings, they could not handle noisy signals, various types of movement and combination of actions [5], [6]. This is why more recent HAR systems have turned to the use of neural network architectures like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and Gated Recurrent Units (GRUs) that have the ability to learn features automatically from raw signals [7], [8], [9]. Both easy and complex activity recognition had high accuracy on these models.

Despite the advantages of deep learning approaches, HAR faces some challenges. Currently existing models may have difficulty differentiating activities of the same type and recognizing behavior alterations indicating health problems [10], [11]. Any change in a patient's usual behavior pattern may indicate particular health issues. Therefore, there is a need to develop intelligent activity recognition systems that combine HAR capabilities with anomaly and change-point detection methods.

1.2 Human Activity Recognition in Healthcare

Intelligent monitoring systems have been adopted in healthcare systems to increase efficiency, enhance patient safety, and enable continuous monitoring of patients' well-being. Among all these intelligent monitoring systems, the HAR system has become the most important and widely used. It has become an integral part of the analysis of

individuals' activities to monitor their behavior and provide relevant information on their mobility status, physical state, and overall health [12], [13].

The use of the HAR system is widespread across various branches of healthcare, from elderly and rehabilitation monitoring to assisted living and chronic disease management to remote patient monitoring. Modern HAR systems in healthcare are primarily based on wearable technology, smartphones, accelerometers, gyros, and IoT devices to monitor activity and movement [14]. The collected data is then used with machine learning (ML) and deep learning (DL) techniques to analyze and provide insights to guide appropriate actions in healthcare emergencies. Activity recognition also enables healthcare experts to detect abnormal activity, such as falls, mobility issues, or behavioral abnormalities [15].

However, several issues and problems are associated with healthcare-oriented HAR systems. One problem is that human movements are highly variable and may affect recognition accuracy, and noisy sensor data can further worsen recognition accuracy; similarly, differences between activities can make recognition challenging. In addition to this, most of the available HAR systems find it difficult to detect abnormal activity or change points [16], [17], [18].

1.3 Research Motivation

The growing use of intelligent healthcare systems has driven a need for reliable HAR systems that continuously monitor human behavior and activities. It is essential for many applications, including elderly care, rehabilitation assistance, assisted living, and remote patient monitoring. Recognition of activities and early detection of abnormal behavioral patterns could help health experts to provide better care to patients and intervene at the right time [4], [13].

Despite DL helping improve the performance of existing HAR methods, some practical issues remain with these models. The problem that many HAR models face relates to the inability to differentiate between similar activities based on their movements and detect slight changes in the behaviors of individuals, which could indicate deteriorated health conditions [10]. In healthcare applications, small differences in individual behavior, such as walking more slowly, making inconsistent movements, or remaining inactive for a while, can be considered critical indicators of some diseases. Nevertheless, existing systems mostly focus on recognizing primary activities rather than secondary ones [18], [19].

Another major issue concerns the poor interpretability and trust in modern DL-based healthcare systems. Many existing models operate as black boxes, making it difficult to understand the reasoning behind their predictions [11]. Given these problems, the current study aims to propose an improved HAR system using DL methods in combination with change-point detection strategies.

1.4 Problem Statement

It has been observed that significant improvements in HAR have been achieved through the adoption of ML and DL techniques. However, current models still have drawbacks and need to be adapted to be applied to healthcare applications. These frameworks can be compromised by variation in human movement, noise in sensor data and with overlapping activities.

The major problem is associated with the possibility of recognizing activities with similar motion features. It might become challenging for scientists [10], [16]. It is noteworthy that slight changes in motion patterns during various activities can indicate an impending physical/mental disease. But most of the existing frameworks are focused on recognizing more general types of activities, rather than detecting subtle differences in behavior patterns [18], [19].

Another limitation of contemporary frameworks is their inability to effectively recognize abnormal activities or transitions. Abnormal activities, such as prolonged immobility, abnormal motion patterns, or sudden changes in activity, can indicate potential health threats. Also, several frameworks developed through DL approaches act as black box models that make their decision process hard to comprehend [11].

Therefore, there is a need for an improved framework that efficiently recognizes various activities and identifies any differences or changes in behavior. There is also a need for anomaly detection capabilities within a framework that can be successfully used in healthcare applications.

1.5 Research Objectives

The main purpose of this research will be to develop a more effective approach to human activity recognition in healthcare monitoring by increasing recognition accuracy and detecting abnormal behavior early. Accordingly, the current paper aims to suggest the combination of deep learning and change-point detection techniques for overcoming the limitations of existing frameworks used for recognizing HAR in healthcare environment. Therefore, the following research objectives are suggested:

- Examining and analyzing human activity recognition processes, especially those based on DL techniques utilized in healthcare monitoring systems
- Determining the weaknesses of currently available HAR systems with regard to handling noisy sensor data, overlapping activities, small changes in behavior, and anomalies.
- Developing a DL-based human activity recognition framework that can recognize both static and dynamic activities from data generated by sensors.
- Introducing change point detection methods into the new framework to allow for

the identification of small changes and anomalies in activity patterns associated with healthcare.

- Improving the learning capabilities of the model to enable effective recognition of long-range patterns in sequential activity data.
- Increasing the interpretability and reliability of activity recognition results in healthcare monitoring systems.
- To evaluate the performance of the proposed framework using appropriate performance metrics and compare its effectiveness with existing approaches.

CHAPTER 2

LITERATURE REVIEW

HAR can be applied to many domains, such as healthcare, surveillance, intelligent environment, sports analytics, and assisted living, thus explaining the emergence of HAR as a field. As a result of the increasing use of wearable devices, intelligent computing systems and sensor technology, there is a demand for reliable systems capable of accurately recognizing activities. In healthcare situations, activity recognition has a critical function in continuous monitoring, elderly care, rehabilitation aid, as well as identifying unusual activity.

Over the years, numerous ML and DL algorithms have been developed for HAR applications, based on data from wearable sensors, smart phones, cameras, and IoT devices. While ML algorithms have been traditionally used for the classification of handcrafted features, DL has been shown to have superior pattern recognition abilities from unstructured sensor data. CNNs, RNNs, LSTMs, neural networks and hybrid DL models are found to be successful in HAR [20].

However, despite the success of DL algorithms, there are some challenges involved in HAR within healthcare applications. Some of these challenges include sensor data noise, overlapping activities, difficulties identifying subtle changes in behavior, and the inability of most algorithms to detect anomalies in human behavior. Hence, a detailed analysis of the state of the art is necessary to understand recent advances and shortcomings in the field. The current chapter provides a complete review of various techniques, sensing technology, DL approaches, healthcare applications, anomaly detection, and other recent advances relevant to the field of HAR.

2.1 Fundamentals of Human Activity Recognition

The automatic recognition and categorization of human activities from sensory input collected from various devices is referred to as HAR. These systems can recognize activities based on human behaviors, including running, walking, sitting, standing, sleeping, and many other actions [1]. Therefore, the main goal of Human Activity Recognition is for an intelligent system to understand and predict human behavior in real-world scenarios.

Typical HAR systems include data acquisition, pre-processing, feature extraction, activity recognition/classification, and result interpretation stages. Various types of sensors and equipment are used for collecting sensory data. Wearable sensors, smartphones, cameras, accelerometers, gyroscopes, and other IoT devices are examples of sensors used in HAR [2]. After acquisition, the data needs to be preprocessed to filter out potential noise and anomalies from sensor inputs before analysis. As the next step, the extracted features are classified into predefined classes.

Human activities are usually divided into two categories based on whether they

require a static posture. Static human activities involve little body motion, such as sitting, standing, and sleeping. On the other hand, dynamic activities include any motion-related actions, including walking, jogging, running, and ascending stairs [21]. In most cases, dynamic activities are more difficult to recognize due to variations in speed and environmental conditions. Moreover, activities with very similar motions often pose problems for classification in an HAR system.

Various factors affect the effectiveness of the systems, including sensor data quality, preprocessing techniques, feature extraction methods, and classification algorithms [22]. In the initial phases of development of HAR, classical ML algorithms along with manually extracted features were extensively used [2], [5]. Nowadays, the advances in DL algorithms make it possible to achieve better recognition and prediction results using raw sensor data. As a consequence, current research advancements have considerably improved HAR in practice.

2.2 Sensors and Datasets Acquisition

A vital component in gathering data concerning human activity, human motion, human physiology, and the environment is sensors. Sensors affect the efficiency and reliability of activity recognition algorithms significantly by their quality and types. The recent advances in sensing technologies, and IoT devices, enable the collection of large amounts of real-time activity data for healthcare and smart monitoring applications [23].

One of the most popular technologies used for sensing human activities is wearable sensors. They comprise sensors such as accelerometers, gyroscopes, body-mounted smartwatches, Fitbit or other sensors that monitor body position and physical activity [24]. Accelerometers are used to measure linear acceleration and orientation changes, while gyroscopes record rotational motion. Wearable sensors are cheap, compact and can be readily integrated into smart phones. Applications of HAR systems based on wearable sensors in healthcare monitoring, physical therapy, senior health monitoring, and fitness tracking are common.

Apart from wearable sensors, vision-based and ambient sensing are also used to recognize human activities. Vision-based HAR uses visual sensors, such as cameras and depth sensors, to capture body posture and motion. Ambient sensors are represented by smart home devices and wireless sensors that monitor human activities based on the surrounding environment [12], [25]. Even though such approaches produce rich information, issues such as privacy concerns, lighting problems, occlusions, and computational requirements may arise.

Data acquisition is an essential stage, and the quality of the collected data directly affects recognition accuracy. Sensors acquire signal data in the form of sequences that need to be preprocessed before analysis. Some popular methods for data preprocessing are noise reduction, data normalization, segmentation, and feature extraction. Public data collections for HAR include UCI HAR, WISDM, PAMAP2, MHEALTH, and other datasets. Data samples consist of human body movements

recorded in different environments.

2.3 Machine Learning and Deep Learning Approaches for Human Activity Recognition

Various ML techniques have been used to develop HAR systems for identifying and categorizing human activities from sensor data [26], [27], [28]. Conventional ML techniques largely depend on handcrafted feature engineering, where statistical, temporal, and frequency domain features are extracted from raw sensor data and used in activity recognition [29], [25], [30], [31]. Numerous algorithms, such as Decision Tree, KNN, SVM, Random Forest, Naïve Bayes, and Hidden Markov Model (HMM), have shown satisfactory performance in recognizing simple activities in controlled environments [6], [30], [33]. Of these techniques, SVM and Random Forest have been extensively applied due to their excellent classification performance and their ability to handle multidimensional sensor data.

Even though they have performed well in the conventional ML setting, conventional ML has some disadvantages in HAR. First, although by now most ML models need to be manually engineered, with lots of effort and domain knowledge. Second, handcrafted features do not tend to encode the complex spatiotemporal relationships between real-world activities [5]. Lastly, conventional ML models fail to perform well in the presence of noisy sensor signals, overlap of activities and the variations in human activities. These problems have inspired the application of DL in developing HAR systems [34].

DL techniques have greatly improved the recognition ability of HAR systems by automatically learning meaningful representations of activities directly from raw sensor data [2]. CNNs have been widely applied to extract spatial and temporal features from sequential activities and have been successful in recognizing both simple and complex activities [35], [36]. Similarly, RNNs, especially LSTMs and GRU models, are highly effective in capturing temporal dependencies and relationships among sequential activities [9], [37]. Hybrid DL models combining CNN and LSTM models have been proposed for simultaneously capturing spatial and temporal features from sensor data [4], [38], [39]. In [40], a Convolved Normalized Pooled Block was used for extracting low-level features, and the Identity and Basic Blocks extracted residual features for handling sequential dependencies, providing high sensitivity and specificity but with the disadvantage of high computational costs. Recently, attention and Transformer models have been developed to model complex activity relationships [41].

Despite promising results in developing DL-based HAR systems, several challenges remain unsolved. Firstly, most DL models require large amounts of labeled data and significant computing power during training [42]. Secondly, distinguishing activities that share similarities and detecting slight behavioral changes are still difficult challenges, especially for health-oriented HAR systems [10], [16]. Another problem is the opacity of most DL models, making them black boxes with little transparency in decision-making.

2.4 Anomaly Detection and Change-Point Detection in Human Activity Recognition

The importance of anomaly detection in HAR systems cannot be overstated, as some behaviors may indicate potential risks to patients' health. Abnormal behavior in terms of falls, prolonged inactivity, strange movements, or any other abnormal changes in routine behavior must be detected in order to ensure efficient patient monitoring [17], [18]. However, traditional HAR systems are primarily focused on identifying predefined activities and have a limited ability to detect anomalies or deviations from routine activities. Thus, researchers have started employing different anomaly detection techniques in HAR systems along with DL technologies, such as autoencoders or recurrent neural networks [11], [19].

Change-point detection is another important technique for HAR systems, as it can be used to identify points where there are significant changes in sequential activity data. Such changes may indicate reduced movement speeds or other abnormalities that can indicate potential physical and neurologic conditions. The combination of change-point detection technology with the DL HAR system will improve the ability to detect nuances in activity that traditional classification techniques miss. Nevertheless, unresolved issues remain in detecting changes and processing noisy data.

2.5 Comparative Analysis of Existing Studies

A large number of studies on ML and DL models for HAR using wearable devices and healthcare monitors have been conducted. DL models such as CNN, RNN, LSTM, GRU, and hybrid models have shown improved effectiveness in recognizing human activities based on sensor inputs [4], [9], [35]. The use of ensemble models, attention mechanisms, and hybrid approaches in learning spatiotemporal features and enhancing activity recognition accuracy within the healthcare sector has also gained considerable research attention [38], [43].

However, current models have several drawbacks, such as having not been able to distinguish between the activities, poor performances in anomaly detection, interpretability problems, and noise in the input data provided by the sensors [18, 37, 38]. The following Table 2.1 presents a comparative study of some of the existing HAR literature that has limitations.

Table 2.1. Comparative Analysis of Existing Studies

Authors	Approach Used	Key Contribution	Limitations
Yang et al. [44]	DCNN	Extracted high-level features from sensor data	Limited evaluation on large datasets
Singh et al. [37]	RNN	Improved activity classification accuracy	Limited uncertainty handling

Murad and Pyun [9]	Deep RNN	Learned temporal dependencies effectively	Difficulty modeling long-range dependencies
Zeng et al. [36]	CNN	Achieved high recognition accuracy using mobile sensors	Restricted parameter flexibility
Bevilacqua et al. [35]	CNN	Recognized lower-limb activities using wearable sensors	Limited handling of complex activities
Wang et al. [11]	CNN-LSTM with HMM	Combined activity recognition with behavior prediction	Lack of interpretability
Alaghbari et al. [19]	DNN and LSTM	Activity recognition and anomaly detection	Difficulty distinguishing similar activities
Khatun et al. [38]	CNN-LSTM with Self-Attention	Improved spatiotemporal learning	Required large labeled datasets
Bhattacharya et al. [43]	Ensemble Deep Learning	Enhanced elderly healthcare monitoring	Overfitting issues
Gaud et al. [45]	Multiheaded CNN-LSTM	Improved recognition performance in healthcare	Limited training data

2.6 Research Gaps

The literature review shows that there has been considerable success in HAR by applying ML and DL algorithms. According to several researchers, CNN, RNN, LSTM, GRU, and hybrid DL models achieved better performance when it comes to activity classification using DL-based techniques [4], [9], [35]. One of the most crucial drawbacks of the current HAR approaches is their inability to recognize subtle behavioral changes and abnormal activity transitions in healthcare scenarios.

Another critical issue faced by HAR algorithms is detecting activities with almost identical movements and handling noisy sensor input [10], [16]. Current approaches have been unable to capture long-term dependencies within activity sequences. Furthermore, DL models currently used in HAR applications work as black boxes; therefore, their interpretability in healthcare is low [11].

Finally, according to the literature review, little attention has been paid to

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developing an HAR approach based on DL capable of detecting behavioral anomalies in healthcare. Thus, improvements in activity analysis, especially in identifying subtle behavioral changes and anomalies in patients' health status, are required.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter explains the research methodology that was used for implementing the proposed framework for HAR in healthcare monitoring. The proposed framework merges DL technologies with change-point detection and anomaly analysis techniques to enhance the HAR's performance and its capacity to detect small variations in behavioral attributes that could signal a potential health-related problem.

In the process of the aforementioned research methodology, a number of steps have been taken. These encompass data collection and preprocessing, data dimensionality reduction, feature extraction and selection, activity recognition, change-point detection, uncertainty estimation and anomalous activity detection. The data gathered from the sensors is then preprocessed. Then, the processed data is analyzed for activity recognition with the proposed Gated Recurrent Temporal Echo Memory Unit (GRTEMU) model. Furthermore, change point detection and anomaly analysis techniques have been successfully applied to detect anomalies and changes in behavior pattern.

The proposed framework and detailed description of the data set preparation, activity recognition process, anomaly detection methods and experimental evaluation procedures are described in the subsequent sections.

3.1 Overview of the Proposed Framework

This research aims to propose an improved HAR framework for healthcare monitoring through incorporating DL techniques along with change-point detection and anomaly analysis techniques.

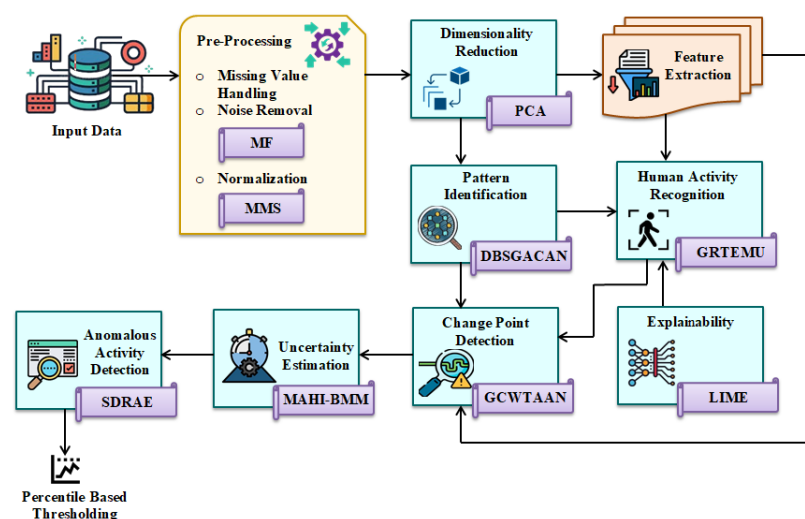


Fig. 3.1. Block Diagram of the Proposed Framework

The proposed framework aims to enable accurate recognition of human activities and detection of fine-grained behavioral differences and abnormal behavioral patterns

that could be a sign of potential health-related problems. The overall methodology consists of several steps: Data collection, Data pre-processing, Dimensionality reduction, Feature extraction, Activity recognition, Uncertainty estimation, Change-point detection, Anomaly detection. Figure 3.1 shows the overall framework of the proposed work. First, the sensor-generated activity data from HAR dataset publicly available for healthcare analysis are gathered. The collected data are then processed and undergo multiple pre-processing steps such as filling missing values, noise filtering, and normalization to enhance data quality and consistency for further analysis. The sensor data is then preprocessed and dimensionality reduction is done using Principal Component Analysis (PCA) to reduce the computation complexity and redundant information in the sensor data. To analyze the activities effectively, meaningful statistical, temporal, and frequency-domain features are extracted by multi-domain feature extraction techniques.

The patterns are identified by the Density-Based Spatial Gradient-Aligned Clustering of Applications with Noise (DBSGACAN) approach to increase the recognition of complex overlapping tasks. The extracted patterns and features are then given to the proposed GRTEMU model. The GRTEMU model is an improved version of the conventional GRU model that adds Temporal Echo Memory to provide better learning of long-range temporal dependencies in sequential activity data. Besides, **Local Interpretable Model-Agnostic Explanations (LIME)** are also used **to enhance the interpretability of the** recognition process and to give transparent decision analysis for healthcare applications.

After activity recognition, change-point detection is performed by Generative Cross-Window Temporal Attention Adversarial Network (GCWTAAN) to detect critical behavioral change points and activity differences. This identified change-point information is subsequently analyzed by Memory-Augmented Hidden Information Bayesian Markov Model (MAHI-BMM) to derive uncertainty and subtle anomalies. Finally, the Semantic Distance Regularized Autoencoder (SDRAE) is used to detect anomalous activities with percentile-based thresholding. The proposed framework is capable of delivering precise activity recognition, robust anomaly detection, and enhanced healthcare monitoring capabilities through their integration.

3.2 Data Acquisition and Preprocessing

The suggested framework uses MHEALTH [46] dataset. The data set includes body-motion and physiological sensor data from 10 participants during different physical activities. Both static and dynamic human movements are common in healthcare related applications and are recorded. All data samples are collected in a dataset with 1,215,745 data samples, 80% of which are used as a training set and the other 20% as a testing set of data for the framework.

Firstly raw sensor data is gathered and processed for further analysis. As the data from real world sensors are inevitably incomplete, noisy and inconsistent, several pre-processing steps are applied to the data to enhance the quality of the data and to ensure reliable activity analysis. For missing values within the dataset, the method of

replacing missing values with the mean of the sensor readings for that data is used. Noise is then reduced by Median Filter (MF), which filters out any sudden spikes and irregular movements from the sensors while maintaining the activity transitions and movement patterns. Then, Min-Max Scaling (MMS) is used to rescale the sensor data to a uniform range for more stable model training and efficiency.

After preprocessing, the procedure of dimensionality reduction is carried out using PCA to minimize the data size and eliminate redundancy contained in the readings from sensors. PCA is used to reduce the original data in the high-dimensional sensor to a smaller number of principal components that retain most of the variance. This process optimizes computation and simplifies training of the proposed framework.

The activity data is further processed using dimensionality reduction then multi-domain feature extraction is utilized to obtain meaningful features from the data. A number of statistical, temporal and frequency domain features are extracted from the sensor signals, including the following: Mean, Median, Standard Deviation, Variance, Root Mean Square (RMS), Signal Magnitude Area (SMA), Zero Crossing Rate (ZCR), Fast Fourier Transform (FFT) coefficients, Spectral Entropy, and Wavelet coefficients. The features extracted from these can give detailed information about human motion patterns, and lead to correct recognition of both static and dynamic activities in the proposed framework.

3.3 Proposed Human Activity Recognition Framework

The proposed approach involves a pattern identification, activity recognition using DL and explainability mechanisms, which will enhance the performance of healthcare monitoring. Preprocessed and extracted features from the sensors are then analysed to generate meaningful activity patterns and correctly identify various human activities. The proposed framework can deal with complex activity sequences, overlapping movements and temporal dependencies in activity data, which are frequently found in healthcare-related activity data.

3.3.1 Pattern Identification Using DBSGACAN

The first stage of pattern identification is carried out by DBSGACAN. The proposed approach extends the existing DBSCAN algorithm using the concept of Gradient-Aligned Distance for better detection of overlapping and closely related activity patterns. This allows the framework to have strong discrimination between similar activities and be tolerant of noisy sensor information.

Let the dimensionality-reduced data be represented as $\hat{J}$. The Gradient-Aligned Distance ($\hat{D}$) between two points is computed as:

$$h_p = \{(n, n') \in \hat{J} | \hat{D} \leq E_{ps}\}, h_p \geq \hat{r} \quad (3.1)$$

where, n and n' are the points initialized from $\hat{J}$, the epsilon (E_{ps}) and the minPts $\hat{r}$ also chosen from $\hat{J}$.

$$\widehat{D} = \mathfrak{S}^{dist}(n, n')[1 + \eta \|\nabla v(n) - \nabla v(n')\|] \quad (3.2)$$

$\mathfrak{S}^{dist}$ signifies the distance between n and n' , ∇v signifies the density field's gradient regarding n and n' , η signifies the tuning parameter, and h_p implies the core points. Next, for each h_p , the cluster c^* is initialized, and the density-reachable points are added to c^* .

$$c^* = \{h_p\} \cup \{h_p | \widehat{D} \leq E_{ps}, \widehat{D} \in h_p\} \quad (3.3)$$

This process continues until all h_p are assigned to the appropriate clusters. After determining h_p and c^* , the final clusters give the identified patterns from $\hat{f}$, and it is denoted as $\tilde{\rho}$. The pseudocode for the DBSGACAN approach is given as follows,

Pseudocode of the DBSGACAN

Input: Dimensionality-reduced outcome $\hat{f}$

Output: Identified patterns, $\tilde{\rho}$

Begin

Initialize n, n' and η

For each $\hat{f}$ **do**

Choose, (E_{ps}) and $(\hat{r})$

Identify core points, h_p

Apply, $\widehat{D} = \mathfrak{S}^{dist}(n, n')[1 + \eta \|\nabla v(n) - \nabla v(n')\|]$

If h_p is identified {

Create $c^* = \{h_p\} \cup \{h_p | \widehat{D} \leq E_{ps}, \widehat{D} \in h_p\}$

Add density reachable points

 } **else** {

Return h_p

 } **end if**

Iterate until all c^* are formed

Obtain $\tilde{\rho}$

End For

Return $\tilde{\rho}$

End

The identified patterns are then used to efficiently perform activity recognition using the proposed DL framework.

3.3.2 Human Activity Recognition Using GRTEMU

For activity recognition, the proposed GRTEMU model is employed. The model extends the conventional GRU architecture by integrating Temporal Echo Memory to improve the learning of long-range temporal dependencies within sequential sensor data. Let the extracted feature sequence be represented as:

$$F^{ext} = \{F_1^{ext}, F_2^{ext}, \dots, F_{pq}^{ext}\} \quad (3.4)$$

where, F^{ext} signifies the extracted features as well as pq denotes the extracted features.

Let F^{ext} and $\tilde{\rho}$ be represented as $\tilde{Z}$. In Figure 3.2, the proposed GRTEMU's structural diagram is shown.

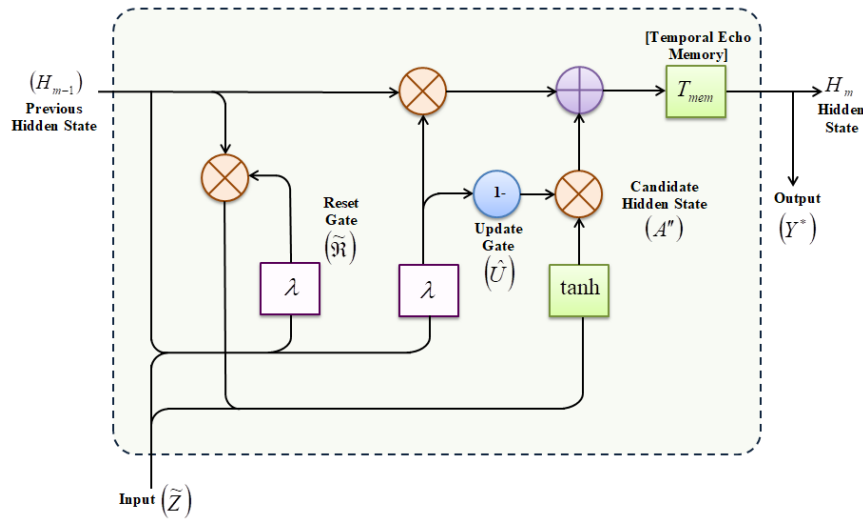


Fig. 3.2. Structural Diagram of the Proposed GRTEMU Classifier

Reset Gate: The reset gate $\tilde{\mathfrak{R}}$ determines from $\tilde{Z}$ which previous information should be retained or discarded.

$$\tilde{\mathfrak{R}} = \lambda[(\alpha' * [H_{m-1}, \tilde{Z}] + \beta')] \quad (3.5)$$

where, H_{m-1} represents the previous hidden state at time, α' implies the reset gate's weight, β' signifies the reset gate's bias, and ε denotes the sigmoid activation function.

Update Gate: $\tilde{Z}$ is fed into the update gate. It controls the amount of previous information preserved in the hidden state as,

$$\hat{U} = \lambda[(\hat{\alpha} * [H_{m-1}, \tilde{Z}] + \hat{\beta})] \quad (3.6)$$

where, $\hat{U}$ denotes the update gate and $\hat{\alpha}$ and $\hat{\beta}$ represent the weight and bias of the update gate, respectively.

Candidate Hidden State: The candidate hidden state (A'') is computed as:

$$A'' = \tanh[(\alpha'' \times [\tilde{\mathfrak{R}} \otimes H_{m-1}, \tilde{Z}] + \beta'')] \quad (3.7)$$

where, α'' and β'' signify the weight and bias, and $\tanh$ represents the hyperbolic tangent activation function.

3.3.3 Temporal Echo Memory

To improve long-range dependency learning, Temporal Echo Memory is incorporated into the GRU framework. The echo memory stores decayed representations of previous hidden states and provides additional contextual information during activity

recognition.

The Temporal Echo Memory is computed as:

$$T_{mem} = \chi(\Omega_{m-1}(A'')) + \chi'(H_{m-1}) \quad (3.8)$$

where, T_{mem} denotes the outcome of Temporal Echo Memory, Ω_{m-1} represents the echo memory, and χ and χ' signify the memory decay factor and memory accumulation factor, respectively.

The final hidden state (H_m) is obtained as:

$$H_m = (1 - \hat{U}) + (\hat{U} \times H_{m-1}) + (\lambda'' \times T_{mem}) \quad (3.9)$$

The outcome of H_m represented as Y^* denotes the recognized human activities. The pseudocode for the proposed GRTEMU is given below,

Pseudocode for the GRTEMU

Input: $\tilde{Z}$

Output: Recognized human activities, Y^*

Begin

Initialize b' , ϕ_{loss} , $\ddot{q}$, l'' , $\dot{y}$ and l'

For each $\tilde{Z}$ **do**

Compute reset gate, $\tilde{R}$

Perform update gate, $\hat{U} = \varepsilon[(\hat{\alpha} * [H_{m-1}, \tilde{Z}] + \hat{\beta})]$

Evaluate, A''

Apply, $T_{mem} = \chi(\Omega_{m-1}(A'')) + \chi'(H_{m-1})$

Derive, H_m

Obtain Y^*

If (*recognizedoutcome* == *satisfied*) {

Terminate

} **else** {

Repeat

} **end if**

End For

Return Y^*

End

The proposed GRTEMU model effectively recognizes activities such as standing, sitting, walking, jogging, cycling, climbing stairs, and other healthcare-related activities.

3.3.4 Explainability Using LIME

To improve interpretability and transparency within the proposed framework, LIME is incorporated into the activity recognition process. It provides explanations for individual predictions by analyzing the contribution of input features to the model's decisions. This improves the interpretability of the proposed healthcare-oriented HAR

framework and supports reliable decision-making in practical healthcare monitoring applications.

Let the selected activity instance from Y^* be represented as x' . Perturbed samples are generated around x' to create a set of perturbed instances ($\check{p}$). Further, by using the prediction model ($\hat{h}$), the predictions for ($\check{p}$) are obtained as,

$$L_p = \hat{h}(\check{p}) \quad (3.10)$$

where, L_p represents the predicted outcome. The weights $\tilde{W}$ are assigned for each sample L_p and L_{p+1} .

$$\tilde{W} = \exp\left(-\frac{d^{ist}(L_p, L_{p+1})^2}{\wp^2}\right) \quad (3.11)$$

where, (d^{ist}) is the distance measured between L_p and L_{p+1} , and $\wp$ denote the kernel width. Finally, based on $\tilde{W}$, the surrogate model $\tilde{\delta}$ is obtained as,

$$\tilde{\delta} = R'' + \sum \tilde{W} * L_p \quad (3.12)$$

where, R'' represents the regularization term.

3.4 Change-Point Detection and Anomaly Analysis

After activity recognition, the proposed framework performs change-point detection and anomaly analysis to identify abnormal behavioral patterns and subtle variations in activity sequences. In healthcare monitoring applications, detecting sudden or gradual changes in human activities is important for recognizing potential health-related abnormalities at an early stage. The proposed framework integrates DL and probabilistic analysis techniques to improve anomaly detection performance and support reliable healthcare monitoring.

3.4.1 Change-Point Detection Using GCWTAAN

Initially, change-point detection is carried out using the GCWTAAN. The proposed model enhances the conventional Generative Adversarial Network (GAN) by incorporating a Cross-Window Temporal Attention mechanism to capture temporal variations across sequential activity windows. This improves the framework's ability to identify significant behavioral transitions and subtle variations in activity.

Let F^{ext} , $\tilde{\rho}$, and Y^* be represented as $\tilde{\omega}$, which is provided to the generator network g^{en} . The Cross-Window Temporal Attention is applied in the generator network to model sequence variation rather than collapsing into a narrow pattern.

$$\tilde{I} = \hat{\mu} \times g^{en}(\tilde{\omega}, e'') \quad (3.13)$$

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$$\hat{\mu} = \sum \Sigma s \left(\frac{q_{ue} \times \tilde{k}}{\sqrt{\lambda}} + B'' \right)_{max} \quad (3.14)$$

where, $\tilde{I}$ depicts the generated data, e'' signifies the random noise, $\hat{\mu}$ denotes the CWTA mechanism, s_{max} illustrates the softmax function, and q_{ue} , $\tilde{k}$, and $\tilde{v}$ represent the queries, keys, and values derived from $\tilde{\omega}$, respectively. The discriminator network M_{dis} evaluates whether the generated samples are real or fake.

$$M_{dis} = \hat{\mu} \times \tilde{\tau}[\tilde{I}] \quad (3.15)$$

where, $\tilde{\tau}$ represents the discriminator function. The discriminator produces an output based on the probability condition $\mathfrak{R}''$.

$$\mathfrak{R}'' = \begin{cases} \vartheta', & \text{if } M_{dis} = 1 \\ \vartheta'', & \text{if } M_{dis} = 0 \end{cases} \quad (3.16)$$

where, ϑ' denotes the generated real data and ϑ'' signifies the generated fake data. The generator loss $\tilde{I}_{loss}$ and discriminator loss M_{loss} are calculated as,

$$\tilde{I}_{loss} = \Omega_{\tilde{I}} [M_{dis}(\tilde{I}(\vartheta''))] \quad (3.17)$$

$$M_{loss} = \Omega_{M_{dis}} [M_{dis}(\vartheta')] - \Omega[M_{dis}(\vartheta'')] \quad (3.18)$$

where, $\Omega_{\tilde{I}}$ and $\Omega_{M_{dis}}$ denote the expectancy operator over $\tilde{I}$ and M_{dis} , respectively. Based on $\tilde{I}_{loss}$ and M_{loss} , the change points are detected, and it is denoted as C^{dec} .

3.4.2 Uncertainty Estimation Using MAHI-BMM

Following change-point detection, uncertainty estimation is performed using the MAHI-BMM. The proposed model enhances the conventional HMM by incorporating memory-augmented hidden states to improve long-range temporal dependency learning and uncertainty estimation.

The hidden states (Q) are defined using the Memory-Augmented Hidden States $\hat{\phi}$ as,

$$\hat{\phi} = \tilde{\vartheta}(C^{dec}, Q, K'') \quad (3.19)$$

where, K'' signifies the memory vector as well as $\tilde{\vartheta}$ characterizes the controller function. The observation sequence (Q''), initial probabilities ($\tilde{Q}$), transition probabilities (Q'''), and observation probabilities $\tilde{Q}$ are initialized from C^{dec} . The probability of the observation sequence (Q'') is computed based on $\hat{\phi}$, and it is given as,

$$P_{rob} = \sum (\hat{\phi} * Q'') * Q''' \quad (3.20)$$

where, P_{rob} indicates the probability of (Q''). After determining P_{rob} , the maximum

log-likelihood in $\tilde{Q}$ is evaluated based on $(\ddot{Q})$ and P_{rob} using the Viterbi algorithm as,

$$\tilde{\Phi} = \max[\ddot{h} * (\ddot{Q}, \ddot{Q})] \times P_{rob} \quad (3.21)$$

where, $\tilde{\Phi}$ denotes the maximum log-likelihood in $\tilde{Q}$, $\max$ represents the maximum function, and $\ddot{h}$ implies the previous hidden state. Based on $\tilde{\Phi}$, the number of hidden states is selected using the Bayesian Information Criterion as,

$$u'' = -2 \ln(\tilde{\Phi}) + \hat{s} \ln(j') \quad (3.22)$$

where, u'' denotes the selected hidden states, $\ln$ represents the natural logarithm, and $\hat{s}$ and j' signify the estimated parameters and number of observations derived from $\tilde{\Phi}$, respectively. Thus, from u'' , the uncertainties are estimated, and it is denoted as $\hat{\tau}$.

3.4.3 Anomalous Activity Detection Using SDRAE

Finally, anomalous activities are detected using the SDRAE with percentile-based thresholding. The model learns the normal behavioral distribution of activity data and identifies abnormal activities based on reconstruction errors.

The encoding $\tilde{L}$ is performed based on $\hat{\tau}$, and it is given as,

$$\tilde{L} = \ddot{y}(V^{wei}(\hat{\tau}) + b') \quad (3.23)$$

where, $\ddot{y}$ signifies the sigmoid activation function, V^{wei} and b' denote the encoder's weights and biases, respectively. The reconstructed output is obtained as,

$$K^d = \ddot{y}(V^*(\tilde{L}) + b^*) \quad (3.24)$$

where, K^d characterizes the reconstructed outcome and V^* and b^* correspond to the decoder's weights and biases.

The reconstruction loss with Semantic Distance Regularization is computed as:

$$\varphi^{err} = \sum \hat{\omega} \|K^d - K^{d+1}\|_2^2 \quad (3.25)$$

where, $\hat{\omega}$ signifies the assigned semantic similarity weight and φ^{err} represents the reconstructed error.

Activities that produce reconstruction errors above the defined percentile threshold are classified as anomalous. The integration of GCWTAAN, MAHI-BMM, and SDRAE enables the proposed framework to reliably detect change points, estimate uncertainty, and identify anomalies for healthcare monitoring applications.

3.5 Experimental Setup, Implementation Details, and Evaluation Metrics

The proposed framework is tested and assessed with the MHEALTH dataset. The data

set is divided into a training set and a test set consisting of 80% of the data used for training the proposed models and 20% used for the test. The following stages of the implementation process encompass the preprocessing stage, feature extraction stage, activity recognition stage, change-point detection stage, uncertainty estimation stage and anomaly detection stages to evaluate the overall efficiency of the proposed framework.

The developed framework is evaluated experimentally with respect to the activity recognition and identification of abnormal individual behaviors. Further, the proposed GRTEMU-based system and its anomaly detection modules are benchmarked against other existing systems with respect to state of art in activity recognition, temporal learning and anomaly detection performance. Furthermore, another analysis of the framework's ability to recognize complex activity sequences, overlapping activities and other subtle behaviors relevant to the healthcare monitoring is performed.

The performance of the proposed framework is measured in terms of: Accuracy, Precision, Recall, F1-Score, Sensitivity and Specificity. The accuracy shows the overall effectiveness of the activity recognition; Precision and Recall show the performance of the framework in recognizing relevant activities and detecting anomalies, respectively. A combined measure that displays the results of both Precision and Recall is called the F1-Score. Lastly, Sensitivity and Specificity are used to assess the performance of the anomaly detection and healthcare monitoring.

CHAPTER 4

RESULTS AND DISCUSSION

The experimental results and performance analysis of the proposed HAR framework for healthcare monitoring is presented in this chapter. The proposed model combines activity detection based on DL and change point detection / anomaly analysis in order to enhance the activity recognition accuracy and to successfully detect the abnormal behavior. The framework is evaluated with several activity recognition, anomaly detection, pattern identification, change-point detection and uncertainty estimation performance metrics.

The experimental analysis is based upon the effectiveness of the proposed GRTEMU based model, the DBSGACAN clustering based approach, the GCWTAAN based change-point detection framework, the MAHI-BMM uncertainty estimation model, and the SDRAE anomaly detection system. The results are also compared with previous methods to demonstrate the improvements made on the recognition accuracy, temporal dependency learning, clustering quality and anomaly detection performance.

The detailed performance analysis and comparative evaluation of the proposed framework are presented in the following sections.

4.1 Performance Analysis of Anomaly Detection

The performance of the SDRAE algorithm is compared with the Autoencoder (AE), Sparse Autoencoder (SAE), Variational Autoencoder (VAE), and Kernel Density Estimation (KDE) models based on Mean Squared Error (MSE), Mean Absolute Error (MAE), Reconstruction Error (RE), and Silhouette Score (SS), as shown in Table 4.1.

Table 4.1. Performance analysis of the proposed and existing models

Methods	MSE	MAE	RE	SS
Proposed SDRAE	0.01245	0.01147	0.02145	0.9845
AE	0.05652	0.05546	0.06847	0.8123
SAE	0.10476	0.11243	0.11216	0.7812
VAE	0.41541	0.42458	0.43254	0.7359
KDE	0.83547	0.89684	0.82148	0.6784

From the above table, it can be observed that the proposed algorithm performs efficiently, with MSE = 0.01245, MAE = 0.01147, RE = 0.02145, and SS = 0.9845. On the other hand, the AE, SAE, VAE, and KDE algorithms have larger errors and lower Silhouette scores. The efficient performance of the proposed algorithm is due to the introduction of Semantic Distance Regularization to the model.

4.2 Performance Analysis of Human Activity Recognition

The efficiency of the GRTEMU model is evaluated against the performance of GRU,

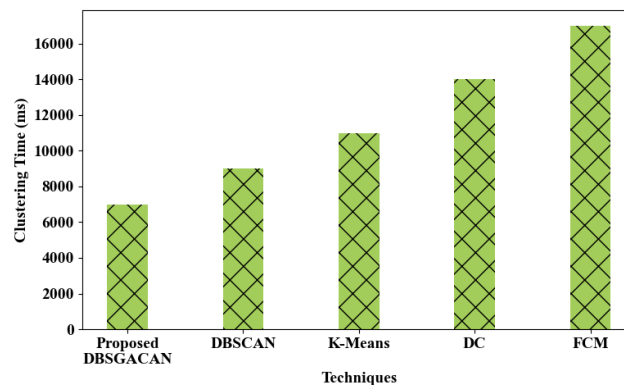
LSTM, RNN, and DNN models presented in Table 4.2. The GRTEMU model achieves higher measures: accuracy equals to 98.91%, precision 98.92%, recall 99.06%, F-measure 98.99%, sensitivity 99.06%, and specificity 98.73%, combined with the decrease in False Positive Rate (FPR) and False Negative Rate (FNR) measures to 1.2689 and 0.93701, respectively. Existing models demonstrate relatively low results on the mentioned metrics, with mean accuracies, precisions, and recalls of 92.48%, 92.02%, and 94.37%, respectively. The improvement in the algorithm's performance can be explained by using Temporal Echo Memory in the GRU.

Table 4.2. Numerical Validation of the Proposed and Traditional Methods

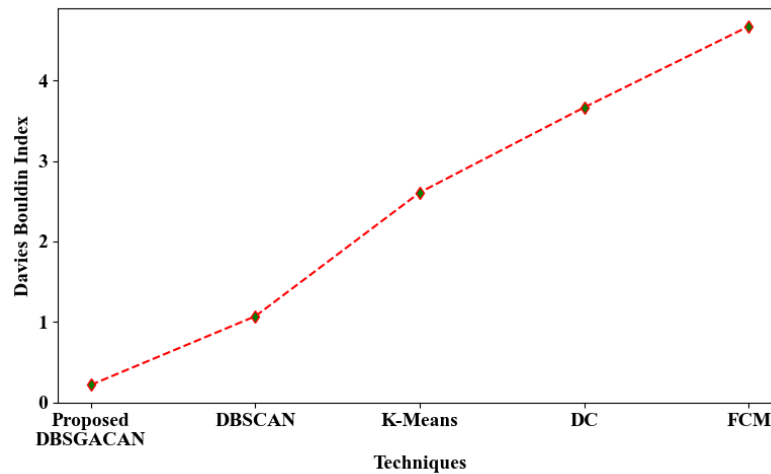
Techniques	Accuracy (%)	Precision (%)	Recall (%)	F-Measure (%)	Sensitivity (%)	Specificity (%)	FPR	FNR
Proposed								
GRTEMU	98.91	98.92	99.06	98.99	99.06	98.73	1.2689	0.93701
GRU	96.85	96.93	97.28	97.10	97.28	96.34	3.6590	2.714
LSTM	93.76	93.02	95.62	94.30	95.62	91.59	8.4093	4.371485
RNN	91.50	90.70	93.85	92.25	93.85	88.76	11.2302	6.147891
DNN	87.80	87.42	90.71	89.04	90.71	84.30	15.6967	9.282132

4.3 Performance Evaluation of Pattern Identification, Change Point Detection, and Uncertainty Estimation

The proposed DBSGACAN is benchmarked based on clustering time and Davies-Bouldin Index (DBI) against DBSCAN, K-Means, Density Clustering, and Fuzzy C-Means as illustrated in Fig. 4.1. The clustering time achieved by DBSGACAN is 7008 ms, and its DBI value is 0.2171. It outperforms all other existing methods because of its lower DBI value and clustering time. This improvement is due to DBSGACAN using the Gradient-Aligned Distance in addition to DBSCAN.



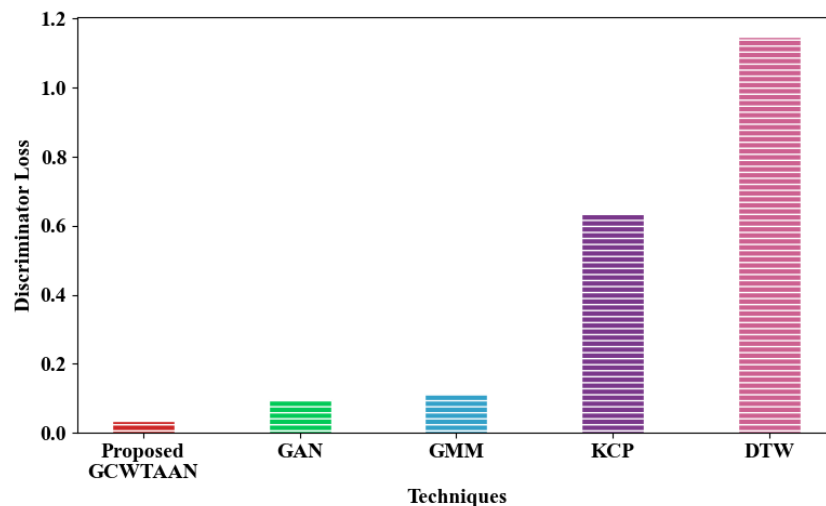
(a)



(b)

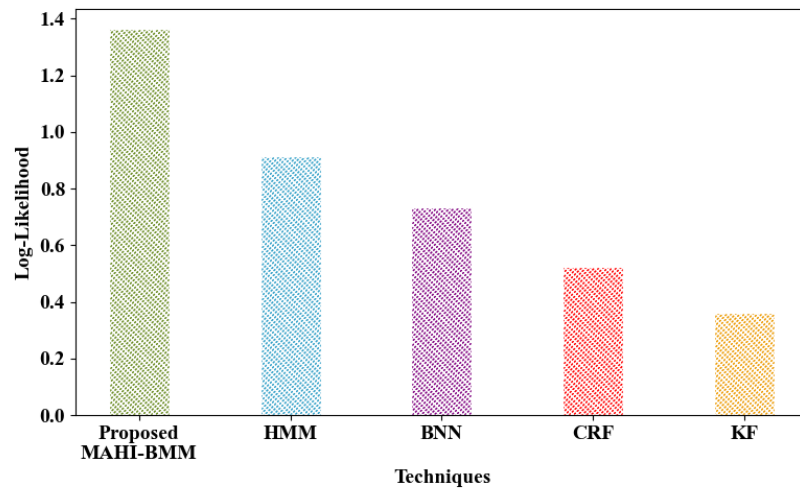
Fig. 4.1. (a) Clustering Time and (b) Davies-Bouldin Index Analysis

The proposed GCWTAAN is benchmarked against GAN, Gaussian Mixture Model (GMM), Kernel Change-Point (KCP), and Dynamic Time Warping (DTW) using the discriminator loss, as illustrated in Fig. 4.2. The discriminator loss of GCWTAAN is 0.03563, whereas all other approaches achieve higher discriminator losses. The reason for GCWTAAN's better performance is that it incorporates Cross-Window Temporal Attention within the GAN framework to effectively capture temporal variations.

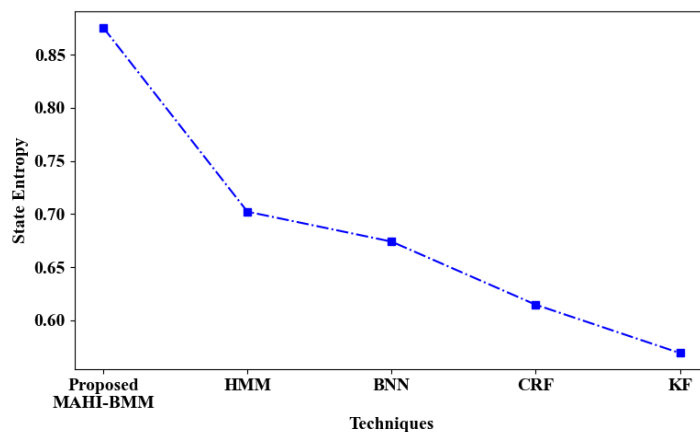
**Fig. 4.2.** Discriminator Loss Analysis

Finally, MAHI-BMM is benchmarked against HMM, Bayesian Neural Network (BNN), Conditional Random Field (CRF), and Kalman Filter (KF) based on Log-Likelihood (LL) and State Entropy (SE) as illustrated in Fig. 4.3. The reason for the superior performance of MAHI-BMM is due to its use of Memory-Augmented Hidden States and Bayesian Information Criterion-based state selection technique. Thus, it can

model long-term dependencies effectively and obtains high values for both SE and LL metrics (0.8756 and 1.3658).



(a)



(b)

Fig. 4.3. Performance Analysis of the Proposed and Traditional Methodologies in terms of (a) Log-Likelihood and (b) State Entropy

4.4 Ablation Study

An ablation study is conducted to determine the role played by the relevant components in the proposed framework. To investigate the effectiveness of the system, DBSGACAN and Temporal Echo Memory are eliminated, one by one, from the system. If the components are not used, the efficiency of activity recognition and anomaly detection decreases, it is observed.

A downside of excluding DBSGACAN is that it does not allow efficient classification and grouping of similar patterns. As a consequence, overlapping activities are not classified properly. Likewise, without Temporal Echo Memory in GRTEMU, one can't learn long-range temporal dependencies. Thus, the efficiency of activity recognition is low.

4.5 Comparison with Existing Works

In order to test the effectiveness of the proposed framework, it is compared with other human activity recognition algorithms currently in use such as ResNet-50, a feed-forward deep neural network (FDNN), and CNN. The results of comparison are presented in Table 4.3 below.

It can be stated that GRTEMU outperforms contemporary approaches in terms of accuracy and precision for recognition of human activities. Factors possibly explaining this advantage may include drawbacks of existing approaches such as the problem of vanishing gradients, overfitting, or inability to capture temporal characteristics. However, the superiority of the proposed framework is mainly determined by the use of DBSGACAN for pattern recognition and incorporation of Temporal Echo Memory into the GRTEMU model. At the same time, while the GRTEMU framework achieves adequate results on the MHEALTH data set, generalization ability needs further research on other healthcare data sets.

Table 4.3. Comparative Validation of the Proposed and Prevailing Works

References	Techniques	Accuracy (%)	Precision
[47]	ResNet-50	83.57	98.32%
[48]	FDNN	89.91	97%
[49]	CNN	97.20	-
[50]	CNN	97.78	-
[51]	CNN	93.82	0.94
Proposed	GRTEMU	98.91	98.92%

4.6 Chapter Summary

This chapter discusses the empirical assessment and performance analysis of the suggested healthcare monitoring framework. The GRTEMU-enabled HAR method, DBSGACAN clustering algorithm, GCWTAAN change-point detector, MAHI-BMM uncertainty measurement methodology, and SDRAE anomaly detection technique jointly perform significantly better in various measures compared to other systems.

The findings demonstrate that the suggested framework achieves excellent recognition accuracies, efficient anomaly detections, improved clustering performance, and reliable learning of temporal dependencies. The comparative analysis, along with the ablation study, proves the efficiency of the framework in solving complex healthcare activities-related activity recognition and anomaly detection tasks.

CHAPTER 5

CONCLUSION, FUTURE SCOPE AND SOCIAL IMPACT

This chapter presents the concluding remarks of the research work together with important future research directions and the broader social impact associated with DL-based HAR systems for healthcare monitoring.

5.1 Conclusion

This research offers an advanced framework for healthcare monitoring based on HAR. This work consists of an assessment of the state-of-the-art approaches in addition to analyzing how DL can help enhance activity classification. It can be seen from the analysis that deep learning approaches have significantly boosted the performance of HAR systems due to the ability of such algorithms to conduct automatic feature learning and temporal activity analysis. Nonetheless, there is a range of drawbacks in current approaches, including a poor ability to separate activities, anomaly detection problems, interpretability issues, and a lack of effectiveness in handling minor behavior differences in healthcare monitoring settings.

As a solution to the mentioned limitations, this paper offers an advanced, healthcare-based framework that utilizes DBSGACAN for pattern detection, GRTEMU for activity recognition, GCWTAAN for change point detection, MAHI-BMM for uncertainty estimation, and SDRAE for anomalous activities detection. The benefits of the introduced DBSGACAN lie in the improved clustering and better sensitivity to minor differences in activities, whereas GRTEMU allows improving learning of long-term temporal relationships via the integration of Temporal Echo Memory in GRU networks. In addition, incorporating LIME improved the interpretability of the activity recognition process for healthcare applications.

The experimental evaluation demonstrated the effectiveness of the proposed framework in activity recognition, anomaly detection, pattern identification, and uncertainty estimation. The proposed GRTEMU achieved higher accuracy, precision, recall, F-measure, sensitivity, and specificity of 98.91%, 98.92%, 99.06%, 98.99%, 99.06%, and 98.73%, respectively, while maintaining lower false-positive and false-negative rates. Similarly, the proposed SDRAE achieved lower reconstruction errors and higher clustering quality for anomalous activity detection. The GCWTAAN and MAHI-BMM models also demonstrated improved performance in change-point detection and uncertainty estimation through effective temporal dependency modeling and behavioral variation analysis.

The proposed framework can be used for several healthcare applications, such as elderly care, remote patient monitoring, Rehabilitation tracking, Fall risk assessment, wearable-based healthcare systems, and Smart assisted living. As a result, by detecting minute patient behaviors and activities, the framework will support early diagnosis and continuous patient monitoring, helping healthcare practitioners. The use of wearable sensors and IoT monitoring technology would make this application of the

framework more feasible.

5.2 Future Work

Though the results obtained in this study prove to be encouraging, there still exist some drawbacks of the framework.

1. Firstly, the use of various DL and probabilistic methods makes this framework computationally complex, which challenges its real-time application.
2. Secondly, the experiments in this study were based solely on the MHEALTH dataset, so the framework's generalization ability needs to be confirmed through testing on other healthcare datasets.
3. The improvement of the efficiency of computational operations in order to make the real-time deployment of the framework possible would be an interesting topic for further research.
4. Additional research may also explore multimodal, emotion-aware HAR frameworks that integrate physiological and behavioral data from patients within the healthcare context.
5. Furthermore, advanced explainable artificial intelligence techniques and lightweight DL architectures may be investigated to improve interpretability, scalability, and real-world applicability of healthcare-oriented HAR systems.

5.3 Social Impact

The suggested framework offers diverse applications within the context of healthcare, which include, but are not limited to, eldercare, patient monitoring, rehabilitation support, fall risk assessment, healthcare systems with wearable sensors, and assisted living systems. With the help of the proposed framework, which is able to detect behavioral changes as well as atypical behavior, healthcare professionals are better able to deliver medical interventions and monitor patients continuously.

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I hereby certify that the work which is presented in the Research Work entitled **“Human Activity Recognition: A Dual Perspective on Deep Learning and Healthcare Monitoring”** in fulfillment of the requirement for the award of the Degree of Master of Technology by Research in Data Science and submitted to the Department of Software Engineering, Delhi Technological University, Delhi is an authentic record of my own, carried out during a period from August 2024 to May 2026 under the supervision of **Dr. Abhilasha Sharma**.

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Author names (in sequence): Somanshu Gupta, Abhilasha Sharma

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Conference dates with venue: 30-31st May 2025, Suresh Gyan Vihar University, Jaipur, Rajasthan, India

Status of paper (Communicated/Accepted/Published): Accepted

Date of paper communication: April 01, 2025

Date of paper acceptance: April 26, 2025

Date of paper publication: N/A

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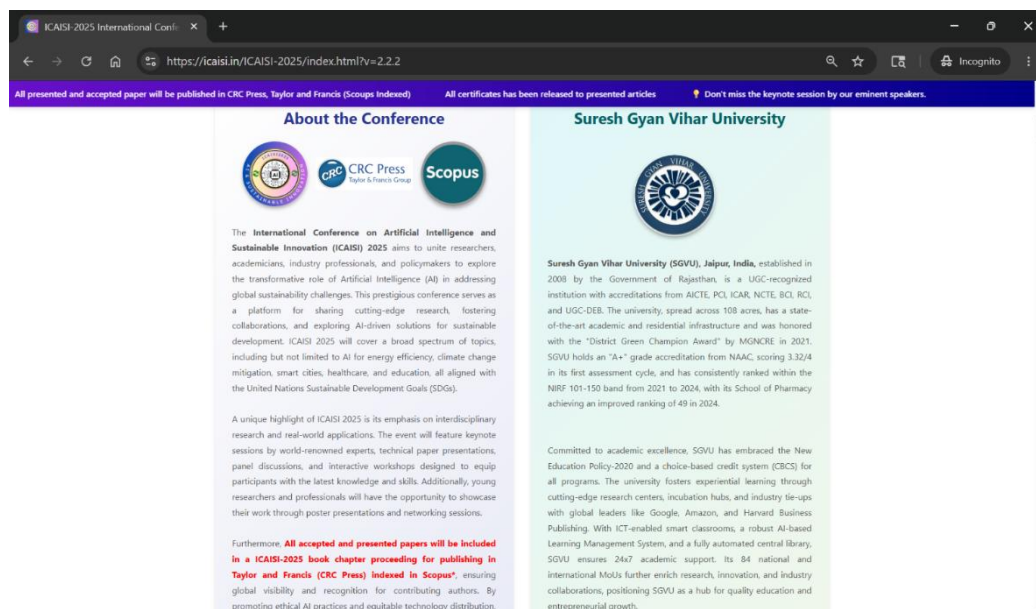
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Author names (in sequence): Somanshu Gupta, Abhilasha Sharma

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Conference dates with venue: 28-29th March 2026, Offbeat CCU, Kolkata, West Bengal

Status of paper (Communicated/Accepted/Published): Accepted

Date of paper communication: February 08, 2026

Date of paper acceptance: March 12, 2026

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Somanshu Gupta is currently pursuing the Master of Technology by Research degree in Data Science from the Department of Software Engineering, Delhi Technological University, Delhi, India. His thesis entitled *“Human Activity Recognition: A Dual Perspective on Deep Learning and Healthcare Monitoring”* investigates the application of deep learning techniques for intelligent healthcare-oriented Human Activity Recognition systems, with particular emphasis on activity recognition, anomaly detection, change-point detection, and wearable sensor-based healthcare monitoring.



His research interests include Human Activity Recognition, Deep Learning, Healthcare Monitoring Systems, Machine Learning, and Wearable Sensor-based Intelligent Systems. He has worked extensively in the area of healthcare-oriented Human Activity Recognition using deep learning techniques and anomaly detection methods.

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