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PERSONAL HEALTHCARE MONITORING USING INTELLIGENT MULTIMODAL ACTIVITY RECOGNITION

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ABSTRACT

Intelligent recognition of multimodal human activities plays a vital role in modern personal healthcare systems by enabling continuous monitoring and analysis of human behavior. This approach utilizes data from multiple sources such as wearable sensors, smartphones, cameras, and environmental devices to accurately identify physical activities and health-related patterns. By combining different data modalities like motion, audio, and visual inputs, the system can achieve higher accuracy and robustness compared to single-source methods. Advanced techniques including machine learning and deep learning are used to process and analyze the collected data, allowing real-time detection of activities such as walking, running, sleeping, and abnormal behaviors. These systems can assist in early detection of health issues, provide personalized recommendations, and support elderly care and remote patient monitoring. Overall, multimodal activity recognition enhances the efficiency, reliability, and effectiveness of personal healthcare solutions.

Keywords:
Multimodal Activity Recognition, Personal Healthcare, Wearable Sensors, Machine Learning, Deep Learning, Human Activity Monitoring, Smart Healthcare

I. INTRODUCTION

The rapid advancement of technology has significantly transformed the field of personal

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healthcare, enabling smarter and more efficient ways to monitor human health and daily activities. One of the key developments in this area is **human activity recognition (HAR)**, which focuses on identifying and analyzing physical activities performed by individuals. Accurate recognition of daily activities such as walking, sitting, sleeping, and exercising is essential for health monitoring, disease prevention, and overall well-being.

Traditional activity recognition systems often rely on a single data source, such as wearable sensors or smartphone data. However, these systems may face limitations in accuracy and reliability due to noise, missing data, or variations in user behavior. To overcome these challenges, **multimodal activity recognition** has emerged as an advanced approach that integrates data from multiple sources, including accelerometers, gyroscopes, cameras, microphones, and environmental sensors.

By combining different types of data, multimodal systems provide a more comprehensive understanding of human activities and improve recognition performance. Advanced techniques such as **machine learning and deep learning** are used to process and analyze large volumes of heterogeneous data, enabling real-time and accurate activity detection. These intelligent systems are particularly useful in personal healthcare applications, including elderly care, fitness tracking, rehabilitation, and remote patient monitoring.

II. LITERATURE REVIEW

Research on human activity recognition (HAR) has evolved significantly with the advancement of sensing technologies and artificial intelligence. Early studies focused on **single-modal approaches**, primarily using data from wearable sensors such as accelerometers to detect basic physical activities. These methods applied traditional machine learning algorithms like decision trees, support vector machines, and k-nearest neighbors to classify activities, achieving moderate accuracy under controlled conditions [1].

As limitations of single-modal systems became evident, researchers began exploring **multimodal activity recognition**, which integrates data from multiple sources such as wearable devices, smartphones, and vision-based systems. These approaches improved recognition accuracy and robustness by capturing complementary information from different modalities [2].

With the rise of deep learning, more advanced models such as **convolutional neural networks (CNNs)** and recurrent neural networks (RNNs) have been applied to

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automatically learn features from raw sensor and video data. These models have shown superior performance in recognizing complex and dynamic human activities compared to traditional methods [3]. Additionally, hybrid architectures combining CNNs and long short-term memory (LSTM) networks have been used to capture both spatial and temporal patterns in activity data.

Recent research also emphasizes **context-aware and real-time activity recognition systems** for healthcare applications. These systems can monitor patient behavior continuously and detect anomalies such as falls or irregular movements, which are critical for elderly care and remote health monitoring [4].

III. EXISTING SYSTEM

The existing systems for human activity recognition in personal healthcare primarily rely on **single-modal data sources**, such as wearable sensors (accelerometers, gyroscopes) or smartphone-based sensing. These systems use traditional machine learning algorithms to classify activities like walking, sitting, or running based on sensor data patterns. While they are simple and cost-effective, their performance is often limited in real-world scenarios.

One major limitation of existing systems is their **dependency on a single data source**, which makes them sensitive to noise, sensor errors, and missing data. For example, wearable sensors may produce inaccurate readings due to improper placement or user movement variations. Similarly, vision-based systems depend heavily on lighting conditions and camera angles, which can affect accuracy.

Additionally, many existing approaches struggle with recognizing **complex and overlapping activities**, especially in dynamic environments. They often fail to capture contextual information, such as location or user behavior patterns, which is important for accurate activity understanding in healthcare applications.

Another drawback is the **lack of real-time processing and adaptability**. Some systems require significant computational resources and are not optimized for continuous monitoring, making them less suitable for real-time healthcare applications like elderly care or emergency detection.

IV. PROPOSED SYSTEM

The proposed system focuses on the **intelligent recognition of multimodal human activities** by integrating data from multiple sources to improve accuracy, reliability, and real-time performance in personal healthcare applications. Unlike existing single-modal approaches, this system combines inputs from **wearable sensors**

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(accelerometer, gyroscope), **smartphones**, and optionally **vision-based devices** to capture a comprehensive view of human activities.

The system begins with **data acquisition**, where multimodal data is continuously collected from different sensors and devices. This is followed by a **data preprocessing stage**, which includes noise removal, normalization, synchronization of multiple data streams, and segmentation into meaningful activity windows.

In the next stage, **feature extraction and fusion** are performed. Relevant features are extracted from each modality, such as motion patterns from sensors and contextual information from environmental data. These features are then fused using early fusion or late fusion techniques to create a unified representation of the activity.

The core of the system is a **deep learning-based model**, such as a hybrid architecture combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This model is capable of capturing both spatial and temporal patterns in the data, enabling accurate recognition of simple and complex activities.

The system also includes a **real-time activity recognition module**, which continuously analyzes incoming data and classifies activities such as walking, running, sitting, sleeping, and abnormal behaviors like falls. A **health monitoring and alert module** is integrated to notify caregivers or users in case of unusual or risky activities.

V. METHODOLOGY

The proposed system follows a structured methodology to accurately recognize multimodal human activities for personal healthcare. The process begins with the **data collection phase**, where data is gathered from multiple sources such as wearable sensors (accelerometer, gyroscope), smartphones, and optional vision-based devices. This multimodal data provides diverse and complementary information about user activities.

Next is the **data preprocessing stage**, which involves cleaning and preparing the collected data. Noise and irrelevant signals are removed, missing values are handled, and data from different sensors is synchronized. The continuous data is then segmented into smaller time windows to represent individual activities effectively.

In the **feature extraction phase**, meaningful features are derived from each modality. For sensor data, features such as mean, variance, frequency components, and motion patterns are extracted. For visual or contextual data, spatial and temporal features are identified. These features capture important

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characteristics needed for activity classification.

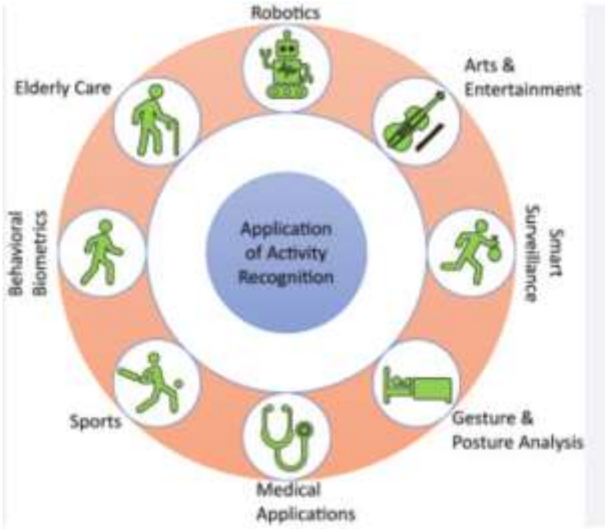
The system then performs **feature fusion**, where data from different modalities is combined. This can be done using early fusion (combining raw data) or late fusion (combining outputs of individual models). Fusion improves accuracy by utilizing complementary information from multiple sources.

In the **model training phase**, machine learning or deep learning models are trained using labeled datasets. Advanced models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are used to learn both spatial and temporal patterns in the data.

During the **activity recognition phase**, the trained model processes real-time input data and classifies activities such as walking, sitting, running, and sleeping. The system continuously monitors user behavior and detects abnormal activities.

VI. SYSTEM MODEL

System Architecture



VII. RESULTS AND DISCUSSIONS

In above screen user is login and after login will get below page

In above screen user can click on ‘Load & Process Kuhar Dataset’ link to load dataset and then will get below page and this dataset available inside ‘Dataset’ folder which is showing below

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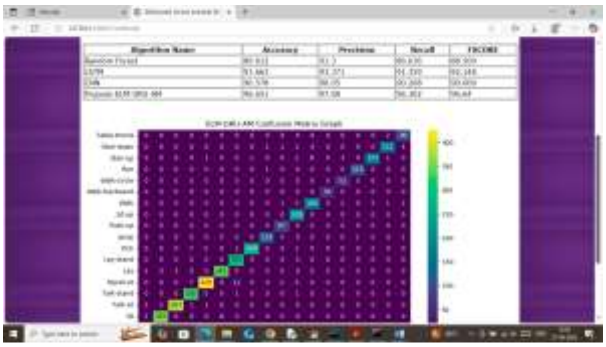
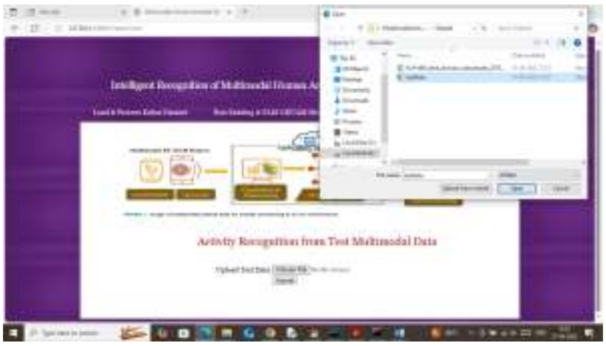
Above Kuhar dataset will be loaded to application and then will get below page

In above screen in first two lines can see number of records and number of features loaded from dataset. In red line can see number of features selected by ELM from total 1800 features and then can see different class labels loaded from dataset. In next lines can see train and test size and now click on 'Run Existing & ELM-GRUAM Models' link to train all models and then will get below page



In above screen in table format can see accuracy, precision, recall, FSCORE of all existing and propose algorithms. In above screen can see Propose ELM-GRU-AM got 96% accuracy which is higher than all existing algorithms. In confusion matrix graph x-axis represents Predicted Labels and y-axis represents true labels and then different colour boxes in diagonal represents correct prediction count and remaining blue boxes represents incorrect prediction count which are very few. Now click on 'Activity Recognition' link to upload test data and then predict activities



In above screen selecting and uploading 'testData.csv' file and then click on buttons to get below output

In above screen in first column can see some values from test data and then in second

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column can see recognized or predicted activities.

VIII. CONCLUSION

The intelligent recognition of multimodal human activities plays a significant role in advancing personal healthcare systems. By integrating data from multiple sources such as wearable sensors, smartphones, and environmental devices, the proposed approach overcomes the limitations of traditional single-modal systems and provides improved accuracy and reliability in activity detection.

The use of advanced techniques like machine learning and deep learning enables the system to effectively analyze complex patterns and recognize a wide range of human activities in real time. This capability is especially valuable in applications such as elderly care, fitness monitoring, rehabilitation, and remote patient supervision.

Overall, the proposed multimodal activity recognition system enhances healthcare by enabling continuous monitoring, early detection of abnormal behaviors, and personalized health insights. It contributes to improving the quality of life and supports the development of smarter and more efficient healthcare solutions.

IX. FUTURE WORK:

Future work in intelligent recognition of multimodal human activities for personal healthcare can focus on improving accuracy, adaptability, and real-world applicability of the system. One important direction is the integration of **advanced deep learning models**, such as transformer-based architectures, to better capture complex temporal and contextual relationships in multimodal data.

Another key area is the development of **lightweight and energy-efficient models** that can run on wearable devices and smartphones, enabling continuous monitoring without high power consumption. This will make the system more practical for daily use.

Future research can also explore **personalized activity recognition**, where models adapt to individual user behavior, lifestyle, and health conditions to provide more accurate and meaningful results. Additionally, incorporating **context-aware systems** that consider location, environment, and user routines can further enhance recognition performance.

Improving **data privacy and security** is another important aspect, especially when handling sensitive healthcare data. Techniques such as federated learning and secure data transmission can be implemented to protect user information.

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XI. REFERENCES

[1] J.V.ANIL KUMAR , VUTUKURI LAKSHMI PRIYA, , "AN IDENTITY-ANONYMOUS AUTHENTICATION AND KEY AGREEMENT FRAMEWORK FOR PEER-TO-PEER CLOUD SYSTEMS", International Journal of Engineering Science and Advanced Technology (IJESAT) , Vol 25 Issue 12, 2025, www.ijesat.com, https://doi.org/10.64771/ijesat.2025.039, Page 306 to 316, ISSN:2250-3676, 2025.

[2] J.V.Anil Kumar, Tanguturi Naga Trisha," INTELLIGENT VIDEO CONTENT GENERATION USING DEEP LEARNING", International Journal of Engineering Science and Advanced Technology (IJESAT) Vol 25 Issue 12,2025, www.ijesat.com, https://doi.org/10.64771/ijesat.2025.044, Page 357 to 364, ISSN:2250-3676, 2025.

[3] J.V. Anil Kumar, Nagella Swarupa Rani," SECURE DATA TRANSMISSION THROUGH HYBRID CRYPTOGRAPHY AND STEGANOGRAPHIC TECHNIQUES", International Journal of Engineering Science and Advanced Technology (IJESAT) Vol 25 Issue 12,2025, www.ijesat.com, https://doi.org/10.64771/ijesat.2025.046, Page 373 to 383, ISSN:2250-3676, 2025.

[4] Ordóñez, F. J., & Roggen, D., "Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition," *Sensors Journal*, 2016.

[5] Hammerla, N. Y., Halloran, S., & Plötz, T., "Deep, Convolutional, and Recurrent Models for Human Activity Recognition Using Wearables," *IJCAI*, 2016.

[6] Wang, J., Chen, Y., Hao, S., Peng, X., & Hu, L., "Deep Learning for Sensor-Based Activity Recognition: A Survey," *Pattern Recognition Letters*, 2019.

[7] Chen, L., Hoey, J., Nugent, C. D., Cook, D. J., & Yu, Z., "Sensor-Based Activity Recognition," *IEEE Transactions on Systems, Man, and Cybernetics*, 2012.

[8] Bulling, A., Blanke, U., & Schiele, B., "A Tutorial on Human Activity Recognition Using Body-Worn Inertial Sensors," *ACM Computing Surveys*, 2014.