International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 11 Issue: 11 | Nov 2024 www.irjet.net p-ISSN: 2395-0072

REAL TIME HUMAN ACTIVITY RECOGNITION FOR ELDERLY CARE IN SMART HOME

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Abstract - *Recognizing and predicting human activities in smart homes is increasingly important for enhancing resident's quality of life and safety. One key feature of smart home systems is the ability to recognize human activities in real-time, enabling automation, improving energy efficiency, and offering personalized assistance. This model introduces a method for real-time human activity recognition using the K-Nearest Neighbors (K-NN) algorithm in a smart home environment. Sensor data from various sources, such as motion, pressure, temperature and sound sensors is collected to identify and classify different activities performed by residents. The K-NN algorithm is chosen for its simplicity, robustness, and effectiveness in handling multi-dimensional data. By analyzing patterns in sensor data, the system accurately predicts activities such as walking, sitting, cooking and falling. The process includes sensor data collection, data preprocessing, feature extraction, and the implementation of K-NN for classification. The systems performance is evaluated using a dataset collected from a simulated smart home, demonstrating high accuracy in real-time activity recognition. This approach is particularly useful for applications like elderly care where understanding and predicting human behavior is critical for ensuring safety and efficiency.*

Key Words: **Real-Time Human Activity Recognition, Machine Learning, Sensors, KNN Algorithm, Elderly Care.**

1. INTRODUCTION

Smart home technologies play a crucial role in enhancing the quality of life for elderly individuals living alone, addressing the growing need for remote monitoring solutions due to the challenges faced by youngsters who live far from their elderly parents. In this context, the proposed system leverages the K-Nearest Neighbors (KNN) algorithm for real-time Human Activity Recognition (HAR) in smart homes. By analyzing sensor data, the system effectively classifies a range of activities, including walking, sitting, sudden falls etc. The primary objective is to ensure the safety of elderly individuals while providing peace of mind to their family members through real-time updates on their elderly people activities.

1.1 MOTION SENSOR

The motion sensor detects any physical movement within a defined area. This is crucial for tracking whether an individual is active or stationary, enabling the system to monitor daily activities such as walking, entering or exiting a room, or detecting prolonged inactivity. By identifying these movements, the motion sensor helps in distinguishing between regular behaviors and potential concerns. These sensors are typically placed in high-traffic areas like hallways, living rooms, or entryways to capture comprehensive movement data across the home.

1.2 PRESSURE SENSOR

A pressure sensor measures the force or weight applied to a surface, making it especially useful for determining whether a person is sitting, standing, or lying down. For example, it can detect when someone sits on a chair or lies on a bed, providing valuable information for recognizing regular activities, such as rest or relaxation, and abnormal events like sudden collapses. These sensors are often placed on chairs, beds, or on the floor in key locations where individuals frequently sit or lie down. This helps the system track important behavioral patterns and detect irregularities in posture.

1.3 TEMPERATURE SENSOR

The temperature sensor continuously monitors the ambient temperature in various areas of the home. This is useful for detecting environmental changes that may indicate specific activities, such as an increase in temperature when someone is cooking or using an appliance, or a sudden drop when a window is left open or if the heating system fails. In elderly care, this sensor can also detect changes in room temperature that may impact the individual's comfort or health, such as extreme cold or heat, which could signal a dangerous situation. These sensors are typically placed in living areas, kitchens, or other rooms where temperature changes are critical to monitor.

1.4 SOUND SENSOR

Sound sensors detect variations in noise levels, which can be helpful in identifying irregularities like shouting, banging, or sudden noises that may indicate distress or emergencies. They can detect sounds associated with normal conversations, television noise, or sudden outbursts of noise that could signal a fall or a cry for help. Sound sensors complement other sensors by providing an auditory layer of context that enhances the system's responsiveness to potential emergencies. They are usually placed in living rooms, bedrooms, or other areas where noise levels could indicate activity or concern.

2. EXISTING SYSTEM

The existing system for activity recognition employs six different machine learning algorithms, including SVM, KNN, Random Forest, Logistic Regression, MLP, and Decision Tree. While these algorithms aim to improve accuracy, the system becomes highly complex due to the integration of multiple models and sensor fusion, making the process resource-intensive. Despite leveraging various models, the overall accuracy of activity recognition remains low, largely due to noise and inconsistencies in sensor data. Furthermore, the use of wearable devices, sensors, and cameras introduces privacy concerns, making the system less suitable for users who prioritize privacy. Additionally, the reliance on multiple algorithms and sensors demands significant computational power, resulting in slower processing times and higher operational costs.

3. PROPOSED SYSTEM

The proposed system simplifies activity recognition by using only the K-Nearest Neighbors (KNN) algorithm, reducing complexity and resource requirements compared to systems with multiple algorithms. It relies on non-intrusive sensors, such as motion, sound, pressure, and temperature sensors, ensuring privacy while improving accuracy through comprehensive sensor input. By avoiding cameras and focusing on fewer algorithms, the system is more efficient and easier to manage. Correct coding practices and thorough testing ensure reliable outputs, making the system suitable for real-time monitoring of elderly activities with enhanced performance and privacy.

3.1 ARCHITECTURE DIAGRAM

The system integrates various sensors - pressure, sound, motion, and temperature to provide comprehensive monitoring for safety in smart homes. The pressure sensor detects changes in weight or force to recognize activities like sitting or lying down, while the sound sensor identifies sound variations that may indicate movements or disturbances. The motion sensor tracks activity or inactivity, distinguishing between normal behaviors like walking and irregular ones like falling. The temperature sensor monitors environmental changes, helping detect activities such as cooking or potential emergencies. Data from these sensors is aggregated, cleaned, and processed to extract key features, which are then classified using the K-Nearest Neighbors (KNN) algorithm. This allows the system to differentiate between regular and irregular activities. If irregularities like falls or unusual sounds are detected, alerts are sent, and all activities are logged for future analysis, improving safety and user experience over time.

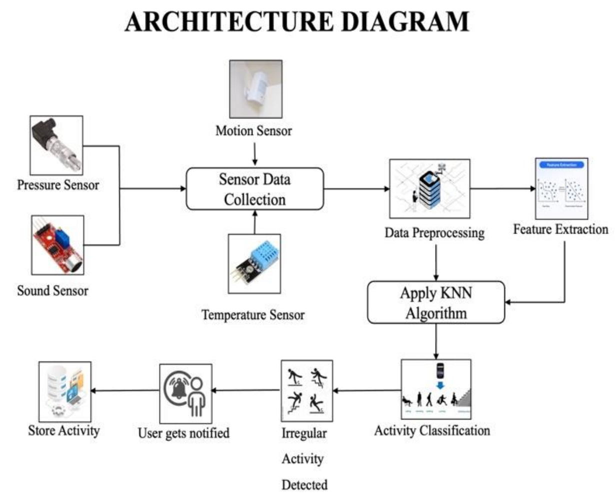

Fig – 1: Architecture Diagram

4. DATA FLOW DIAGRAM

The system starts by initializing and preparing sensors, including motion, pressure, sound and temperature, to collect real-time environmental data in a smart home. The sensors continuously gather information about the elderly's activities, which is then preprocessed to remove noise and inconsistencies. This cleaned data is fed into the k-Nearest Neighbors (KNN) algorithm for activity classification. The system checks if the activity is recognized; if not, it collects more data to improve accuracy. Recognized activities are categorized into regular and irregular events, with notifications sent to caregivers if an irregular activity, such as a fall, is detected. All activities are stored in the database for future analysis, ensuring continuous monitoring and data flow unless reprocessing is required.

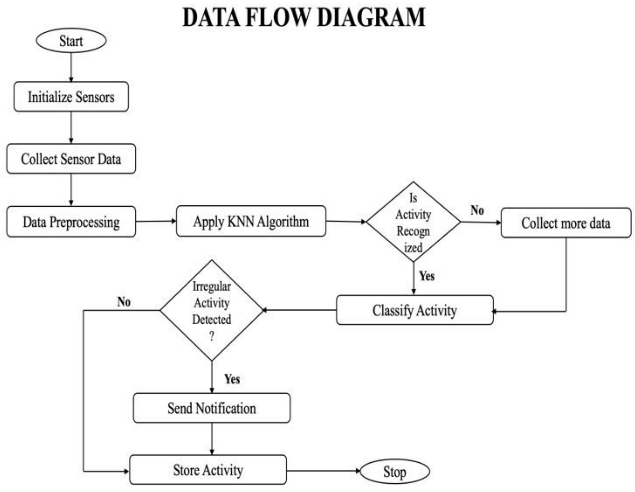

Fig – 2: Data Flow Diagram

5. MODULES

- Data Collection
- Data Preprocessing
- Feature Extraction
- Activity Recognition
- Notification and Storage

5.1 DATA COLLECTION

The Data Collection forms the core of the system, connecting to various sensors strategically placed around the smart home environment. These sensors include motion, pressure, sound, and temperature sensors, each serving a distinct purpose. Motion sensors detect physical movement, helping identify activities like walking, sitting, or falling. Pressure sensors measure the force applied to surfaces, such as chairs or beds, to detect whether the individual is sitting or lying down. Sound sensors capture noise levels, detecting sounds such as shouting or sudden loud noises, which can be critical for identifying emergencies. Temperature sensors monitor room temperature, helping the system recognize activities like cooking or identify environmental changes that could affect the elderly person's well-being. The collected data is continuously transmitted to the microcontroller, ensuring that the system remains updated with real-time information. This module is essential for maintaining a continuous flow of data from the sensors to the processing unit, allowing the system to monitor the elderly's activities effectively.

Pressure	Temperature	Motion	Sound	Activity
1.2	22.5	1	0.5	Walking
1.8	22	0	0	Sitting
0	21.8	0	1.5	Unusual Sound
1.5	23	1	0.3	Cooking
0	19.5	0	0	Prolonged Inactivity
0	20	0	3.5	Shouting
2	22.2	1	0.7	Walking
0	25.5	0	0	Temperature Change
1.4	23.1	0	0	Sleeping
1.6	22.4	0	1.7	Fall

Fig – 3: Data Collection

5.2 DATA PREPROCESSING

Once the raw sensor data is collected, the Data Preprocessing cleans and prepares it for analysis. This stage involves several important tasks to ensure the data is usable and accurate. First, noise removal is applied to filter out any irrelevant or erroneous readings, which may occur due to sensor malfunctions or external interference. Next, the module handles missing values, filling in any gaps where sensor data might be incomplete, ensuring the dataset is as complete as possible for analysis. Normalization is another key function of this module, as different sensors produce data on varying scales. For example, temperature readings are on a different scale than pressure readings. Normalization adjusts the values so that they can be compared accurately. Finally, the module filters out irrelevant information, focusing only on the data directly related to activity recognition. This process results in a clean, consistent dataset, which is then passed on to the feature extraction module. This ensures that the machine learning model receives high-quality input, leading to better performance and more accurate predictions.

Pressure	Temperatur	Motion	Sound	Activity
0	21.8	0	1.5	Unusual Sound
0	19.5	0	0	Prolonged Inactivity
0	20	0	3.5	Shouting
0	25.5	0	0	Temperature Change
1.6	22.4	0	1.7	Fall

Fig – 4: Data Preprocessing

5.3 FEATURE EXTRACTION

The Feature Extraction is responsible for identifying the most relevant patterns from the preprocessed sensor data. This is a crucial step because the effectiveness of the KNN algorithm depends on the quality and relevance of the features extracted. The module analyzes the cleaned data and extracts key indicators of activities. For instance, it might extract features such as the frequency and duration of movement from the motion sensor, pressure changes from the pressure sensor, sound intensity patterns from the sound sensor, and temperature fluctuations from the temperature sensor. These features encapsulate important aspects of the elderly's behavior and are essential for distinguishing between different activities. The module also reduces the dimensionality of the data by focusing on only the most important features, which improves the computational efficiency of the system. After extracting these features, the data is prepared for classification by the KNN algorithm, ensuring that the system can effectively differentiate between activities like walking, sitting, or falling.

5.4 ACTIVITY RECOGNITION

The Activity Recognition is where the core classification process takes place. It uses the K-Nearest Neighbors (KNN) algorithm to classify activities based on the features extracted from the sensor data. The KNN algorithm works by comparing the real-time data collected from the sensors with historical data that has been labelled as specific activities. By analysing the distance between data points, the algorithm can identify the most likely activity being performed at any given moment. The simplicity and low computational complexity of the KNN algorithm make it well-suited for real-time applications in smart homes. This module provides fast and accurate classifications by leveraging inputs from multiple sensors, ensuring that the system can make reliable predictions.

Fig – 5: Walking

Fig – 6: Sleeping

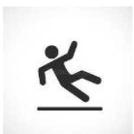

Fig – 7: Falling

Fig – 8: Unusual sound

5.5 NOTIFICATION AND STORAGE

The Notification and Storage handles both real-time alerts and long-term data management. When the system detects an irregular activity, such as a fall or prolonged inactivity, it immediately sends real-time notifications to family members or caretakers. These alerts can be sent via mobile apps, SMS, or email, ensuring that the elderly individual's support network is informed of potential emergencies. Additionally, this module logs all recognized activities - both regular and irregular - into a SQL database for long-term storage. This allows for historical analysis of the individual's activities, which can be useful for identifying trends or changes in behavior over time. By storing this data, caretakers and family members can access detailed reports on the elderly person's daily routines, providing valuable insights for ongoing care. This module ensures that the system not only responds to immediate concerns but also contributes to long-term monitoring and analysis.

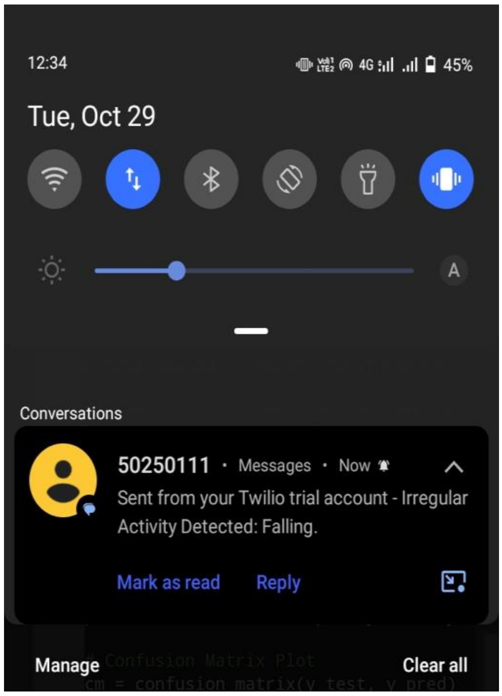

Fig – 9: Alert Notification

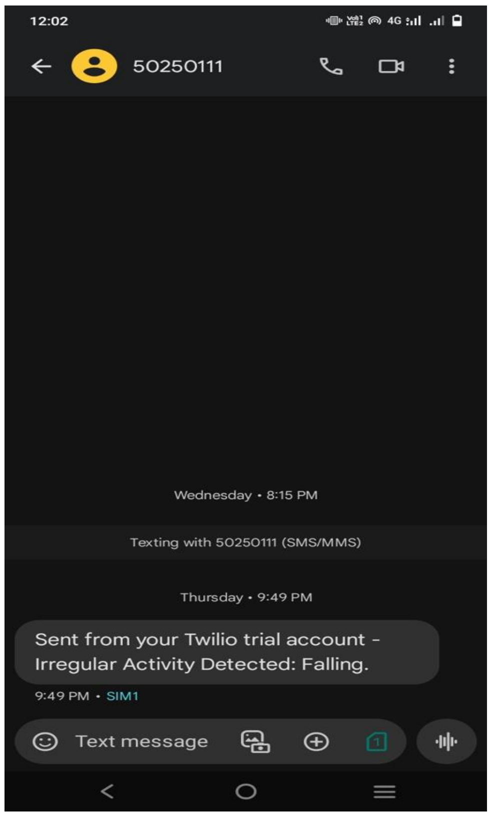

Fig – 10: Alert Message

6. CONCLUSIONS

The system provides continuous real-time monitoring to enhance the safety of elderly individuals in smart homes using motion, pressure, sound, and temperature sensors with the K-NN algorithm to classify activities. It supports independent living by ensuring reliable assistance during emergencies, sending immediate notifications to caregivers via SMS or email. With non-intrusive sensors that prioritize privacy, the system serves as a privacy-conscious alternative to camera-based surveillance while maintaining high accuracy and minimizing false alarms for effective monitoring.

7. ACKNOWLEDGEMENT

We extend our heartfelt thanks to Mrs. S.MARIA SOBANA, Assistant Professor in the Department of Computer Science and Engineering, for her invaluable guidance and encouragement throughout the development of this project. We are also grateful to our peers and the faculty of K.L.N. College of Engineering for their support and feedback. Finally, we appreciate the contributions of all the researchers whose works have provided the foundation for our study.

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