Powered Wearable Technologies for Dementia Care: Evaluating Activity Recognition Models and Dataset Challenges

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Abstract: Dementia is a progressive neurological condition affecting millions worldwide, posing significant challenges for patients and caregivers. Wearable technologies integrated with artificial intelligence (AI) provide promising solutions for continuous activity monitoring, supporting dementia care. This study evaluates the performance of various AI models, including tree-based methods and deep learning approaches, in recognizing activities relevant to dementia care. While the first excelled in handling class imbalances and recognizing common activities, deep learning models demonstrated superior capabilities in capturing complex temporal and spatial patterns. Additionally, a comprehensive analysis of 30 datasets revealed significant gaps, including limited representation of elderly participants, insufficient activity coverage, short recording durations, and a lack of real-world environmental data. To address these gaps, future work should focus on developing datasets tailored to dementia care, incorporating long-duration recordings, diverse activities, and realistic contexts. This study highlights the potential of AI-powered wearable systems to transform dementia management, enabling accurate activity recognition, early anomaly detection, and improved quality of life for patients and caregivers.

1 INTRODUCTION

Dementia encompasses a range of neurological disorders characterized by memory loss and cognitive decline (Winblad et al., 2016). Currently, over 55 million people worldwide live with dementia, and this number is projected to double by 2050, posing significant challenges for healthcare systems and families (World Health Organization, 2023). With aging populations and no cure available, the prevalence of dementia continues to rise.

As the condition progresses, symptoms may include disorientation, mood swings, confusion, severe memory loss, behavioural changes, and difficulties with speaking, swallowing, or walking (Lindeza et al., 2024). These challenges place a

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significant emotional and physical burden on both individuals and their caregivers, requiring substantial support from an early stage.

The role of caregivers is fundamental in supporting elderly individuals with dementia. However, it often presents significant challenges, including high rates of depression and stress, physical strain, and social isolation (Lavretsky, 2005). To address these challenges, enhancing caregiver support and implementing effective dementia monitoring are crucial.

Dementia monitoring offers numerous benefits. It helps prevent accidents by tracking movements and reducing risks associated with wandering. Enables long-term health tracking, providing valuable data for caregivers and healthcare professionals to make informed care and treatment decisions. Furthermore, monitoring reduces family anxiety by promptly alerting caregivers to potential issues and facilitates patient independence, allowing individuals with dementia to engage safely in activities both indoors and outdoors (Lin et al., 2008).

Wearable technology plays a pivotal role in monitoring individuals with dementia by providing non-invasive, continuous, and objective data on various physiological and behavioral parameters. These devices are generally well-accepted by both patients and caregivers, making them a practical solution for continuous monitoring (Husebo et al., 2020).

One notable application is GPS-enabled wearables, which help monitor mobility patterns and locate missing individuals with dementia, offering a non-intrusive way to track movements and prevent wandering (Cullen et al., 2022). Additionally, these devices can report detailed mobility outcomes, such as activity duration, out-of-home movements, and trajectory patterns (Cullen et al., 2022). They also provide insights into health indicators specific to dementia, including lower daily activity levels, decreased sleep efficiency, and greater circadian rhythm variability compared to controls(Cote et al., 2021).

For patients and caregivers, the comfort, convenience, and affordability of wearable devices are key priorities. Essential features include long battery life, water resistance, and an emergency button, which enhance usability and reliability (Stavropoulos et al., 2021).

The work presented in this paper is part of a larger project focused on developing a wearable device tailored to the unique needs and challenges of individuals with dementia. A study from this project highlights a significant gap in the availability of comprehensive devices, as most existing wearables fail to provide an integrated solution that includes activity monitoring (daily activities, daytime and nighttime patterns, activity and movement trends), real-time location tracking, fall detection, and SOS alert systems (Rocha et al., 2024).

The primary objective of this paper is to describe the available datasets obtained from wrist-worn wearables and evaluate the best AI architectures for predicting activities based on this data. This analysis provides critical insights into selecting and developing effective solutions for activity monitoring, which is an essential step toward enhancing the functionality of wearable devices for dementia care.

This paper is organized in seven sections. Section 2 presents the state-of-the-art advancements in AI and wearable technologies for dementia care, focusing on activity recognition and the challenges of developing effective models. Section 3 outlines the methodology employed, including dataset selection, preprocessing steps, and the AI models evaluated. Section 4 discusses the datasets analysed in this study, emphasizing sensor types, participant demographics, recording durations, and recorded activities. Section 5 provides a detailed analysis of model performance across various datasets, highlighting the strengths and limitations of different AI approaches. Section 6 discusses the implications of the findings, challenges encountered, and recommendations for future research. Finally, Section 7 concludes the paper, summarizing key insights and proposing directions for advancing AI-powered wearable technologies in dementia care.

2 STATE OF THE ART

In the field of dementia care, wearables and Artificial Intelligence (AI) are becoming increasingly significant, offering solutions for monitoring (Husebo et al., 2020), early diagnosis (Godfrey et al., 2019; Sashima, 2022), and improved quality of life (Wilmink et al., 2020).

2.1 Activity Recognition in Dementia Care

Activity Recognition are crucial in improving care for individuals with dementia. Through the use of wearable sensors and machine learning algorithms, these systems provide valuable insights into patients' daily activities, supporting caregivers in addressing deficits and improving care delivery (K. J. Kim et al., 2009). For instance, deviations from typical behaviour can be identified by analysing parameters such as time, location, and activity duration (Gayathri et al., 2015).

2.2 AI in Activity Recognition

AI plays a pivotal role in processing sensor data, identifying patterns, and recognizing activities. By extracting both spatial and temporal features, AI enhances the accuracy and efficiency of activity recognition systems (Khan et al., 2022).

AI algorithms can process streaming data in real-time, enabling dynamic recognition of human activities. For example, sliding window-based approaches combined with time-decay factors have been shown to improve recognition accuracy in dynamic environments, ensuring reliability even in complex, real-world scenarios (Krishnan & Cook, 2014).

One key advantage of AI-driven systems is their ability to identify new or unexpected activities not encountered during training. This adaptability enhances the system’s relevance to real-world conditions, making it better suited for the unpredictable nature of dementia care (Leite et al., 2021).

Different AI techniques offer unique benefits, and their applicability depends on factors like the complexity of activities, the nature of sensor data, and the amount of labelled data available.

2.2.1 Machine Learning Techniques

Machine learning (ML), a subset of AI, is widely used in activity recognition systems for its ability to learn patterns from data and generalize them to new scenarios.

Among traditional ML approaches, Support Vector Machines (SVMs) are particularly effective for tasks involving well-separated classes, achieving high accuracy in identifying activities such as walking, running, and sitting from wearable data (L. Cheng et al., 2017). Similarly, Random Forest (RF) is known for its resilience to noise and ability to classify multiple activities (Badawi et al., 2019), while K-Nearest Neighbors (KNN) is most suitable for datasets with fewer classes, working by comparing feature similarity (Murad & Pyun, 2017). Logistic Regression, with its computational efficiency and interpretability, is commonly used in binary classification tasks such as distinguishing between active and inactive states in wearable systems(Rabbi et al., 2021).

When it comes to Deep Learning approaches, Convolutional Neural Networks (CNNs) are effective in learning complex patterns from raw data, ideally for special feature extraction from sensor data (Khan et al., 2022). Recurrent Neural Networks (RNNs) such as Long Short-Term Memory (LSTM) networks can capture temporal dependencies in sequential activity data (Murad & Pyun, 2017). Gated Recurrent Units (GRUs), a variation of RNNs, are particularly effective for wearable time-series data, as they can predict transitions between complex activities, such as alternating sitting and standing, based on accelerometer and gyroscope readings (Erdaş & Güney, 2021).

Boosting algorithms like Extreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM) have also proven effective for wearable data. XGBoost is optimized for speed and scalability, making it suitable for identifying key sensor contributions and managing missing data in activity monitoring applications (Ge, 2023). On the other hand, LightGBM is particularly advantageous for processing large datasets and handling real-time data streams, making it an excellent choice for latency-critical tasks like fall detection and abnormal movement tracking (S. T. Cheng, 2017).

Each of these techniques offers unique benefits, and their applicability depends on factors like the complexity of activities, the nature of sensor data, and the volume of labelled data available.

2.2.2 Challenges

Wearable devices collected data is often noisy due to movement artifacts, environmental interference, or device misplacement. To address this, techniques such as feature disentanglement are employed to separate meaningful activity patterns from irrelevant noise (Su et al., 2022).

While deep learning methods like CNNs and LSTMs networks have proven effective for activity recognition, the integration of data from multiple sensors, such as accelerometers, gyroscopes, and heart rate monitors, introduces significant complexity. This fusion increases computational demands, posing challenges for both model training and deployment (Nweke et al., 2018).

Another limitation is the difficulty in generalizing activity recognition models across users with varying physical characteristics or across different environmental contexts. This often leads to reduced performance in real-world applications, highlighting the need for models that are adaptable to diverse scenarios (Lara & Labrador, 2013).

Wearables are limited by battery life and processing power, making energy-efficient AI models essential for real-time activity recognition, hybrid ensemble models and feedback-based adaptive sampling have been proposed to balance energy efficiency with recognition accuracy (Min & Cho, 2011).

3 METHODOLOGY

To train AI models for activity recognition, suitable datasets are essential. For our study, the ideal dataset includes data from accelerometers, gyroscopes, and heart rate sensors, as these sensors provide crucial insights into movement, orientation and physiological responses. The dataset should feature labelled activity data to facilitate supervised learning and encompass range of activities – such as walking, running, laying, sleeping, eating, and hygiene – that are particularly relevant to dementia care. Additionally, it is crucial for the dataset to include diverse participants, specifically older adults of both genders, as dementia predominantly affects this demographic. The selected datasets were used to train various AI models, including Support Vector Machines (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Extreme Gradient Boosting (XGBoost), Logistic Regression, Light Gradient Boosting Machine (LightGBM), and Gated Recurrent Units (GRU). Model performance was evaluated using metrics such as precision, recall, and F1-score for each class, along with overall accuracy, macro-average, weighted-average, and a confusion matrix to analyse classification outcomes.

4 DATASETS

To develop and evaluate AI models for activity recognition in dementia care, this study analysed 30 publicly available datasets commonly used in wearable activity and health monitoring research. These datasets were selected to explore their applicability in detecting activities relevant to dementia, such as walking, eating, sleeping, and fall-related movements.

4.1 Sensors

In this study, a total of 30 datasets were analysed to examine the types of sensors utilized for wearable activity and health monitoring systems.

Among these datasets, the most used sensors were accelerometers (ACC), which appeared in 22 datasets when combining data from wrist-mounted, chest-mounted, and general-purpose accelerometers. Accelerometers are foundational in wearable systems due to their ability to capture motion data, making them versatile for applications such as activity detection, fall monitoring, and posture analysis.

Gyroscopes (GYR) were the second most frequent sensor type, featured in 16 datasets. These sensors provide rotational motion data, complementing accelerometers in capturing more detailed movement patterns, especially for activities involving complex or rotational motions.

Heart rate (HR) sensors were present in 8 datasets, often used for applications requiring cardiovascular activity tracking.

Other sensors, such as temperature (TEMP) sensors and electrocardiograms (ECG), were found in 6 datasets each, highlighting their role in physiological and health monitoring. Electrodermal activity (EDA) sensors, which measure skin conductance changes and are used for stress detection, were utilized in 5 datasets. Additionally, respiration (RESP), oxygen saturation (SpO2), and photoplethysmography (PPG) sensors were included in a smaller number of datasets, primarily focusing on health monitoring and specific physiological applications. Figure 1 provides a visual representation of the number of datasets utilizing each sensor type. This analysis underscores the importance

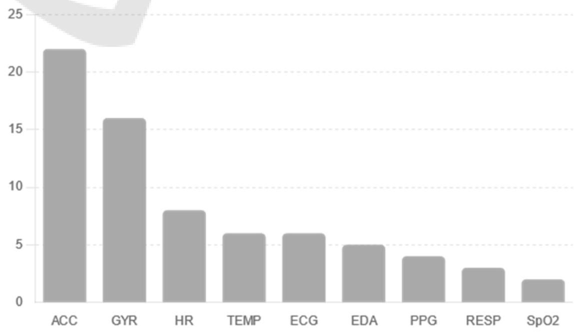

Figure 1: Frequency of Sensor Types Used in the Datasets - Accelerometer (ACC, m/s²); Gyroscope (GYR, rad/s); Heart Rate (HR, bpm); Temperature (TEMP, °C); Electrocardiography (ECG, mV); Electrodermal Activity (EDA, µS); Photoplethysmogram (PPG); Respiration (RESP, bpm); Oxygen Saturation (SpO2, %). The vertical axis represents the count of datasets containing each sensor type.

of accelerometers and gyroscopes as fundamental components in wearable systems for activity detection. However, the integration of physiological sensors, such as HR combines physical and health data to develop more comprehensive monitoring systems.

4.2 Participants Demographics

The demographic composition of participants in wearable datasets is crucial for developing activity recognition models tailored to elderly individuals with dementia. Since dementia predominantly affects older populations, datasets used for model training must reflect the physiological and behavioural characteristics of this demographic. Discrepancies in age, gender, or participant diversity can lead to models that fail to generalize effectively to real-world applications in dementia care.

The total number of participants across datasets varies significantly. Larger datasets such as the Parkinsons Disease Smartwatch dataset (PADS) (Julian et al., 2024), with 469 participants, and the Sleep Health and Lifestyle Dataset (Tharmalingam, 2023), with 374 participants. In contrast, smaller datasets like the OPPORTUNITY Activity Recognition (Roggen, Alberto, et al., 2010), and the Smartwatch Heart Rate Data Dataset (Biswas & Ashili, 2023), involve only a single participant.

The age range of participants varies, with most of the datasets focus on adults with a median age of 20-30 years, some of them being the Physical Activity Monitoring Dataset PAMAP2 (Attila, 2012), Objectively Recognizing Eating Behaviour and Associated Intake (OREBA) (Rouast et al., 2020), and Annotated Wearable Multimodal Biosignals recorded during Everyday Life Activities in Naturalistic Environments (ScientISST MOVE) (Saraiva et al., 2024), Figure 2.

Datasets targeting specific populations, like the elderly, include an older demographic. For example, the Wrist Elderly Daily Activity and Fall Dataset (WEDA-FALL) (Marques, 2022) has participants with a mean age of 50.48 years, while the Long-Term Movement Monitoring Database (Ihlen et al., 2015) includes participants aged 65–78 years.

Several datasets report near-equal gender representation. For example, the Sleep Health and Lifestyle Dataset (Tharmalingam, 2023) has a 51% male and 49% female split, enhancing model fairness and applicability across both genders. While others, such as the Wearable Stress and Affect Detection (WESAD) (Schmidt et al., 2018), are male dominated, with only 20% female participants, such biases may lead to models that underperform for underrepresented groups.

4.3 Duration of Recordings

To accurately model and monitor daily routines, datasets must capture a representative snapshot of an individual's activities throughout the day. Short recordings may only provide fragmented insights, while longer recordings enable a view of patterns, deviations, and anomalies. Extended datasets are particularly important for identifying changes in routines, such as prolonged inactivity, increased wandering, or disruptions in sleep patterns, which are critical indicators for dementia care.

For example, the Long-Term Movement Monitoring Database (Ihlen et al., 2015) provides 3 days of continuous data, the Smartwatch heart rate data (Biswas & Ashili, 2023), includes 1 month of data, and the Clemson All-day Dataset (CAD) (Hoover, 2020) spans for 354 days, making these datasets ideal for tracking routine behaviours over multiple days.

In contrast, the remaining 25 datasets in the review capture data for durations shorter than 24 hours, limiting their applicability for in-depth routine analysis, Figure 3.

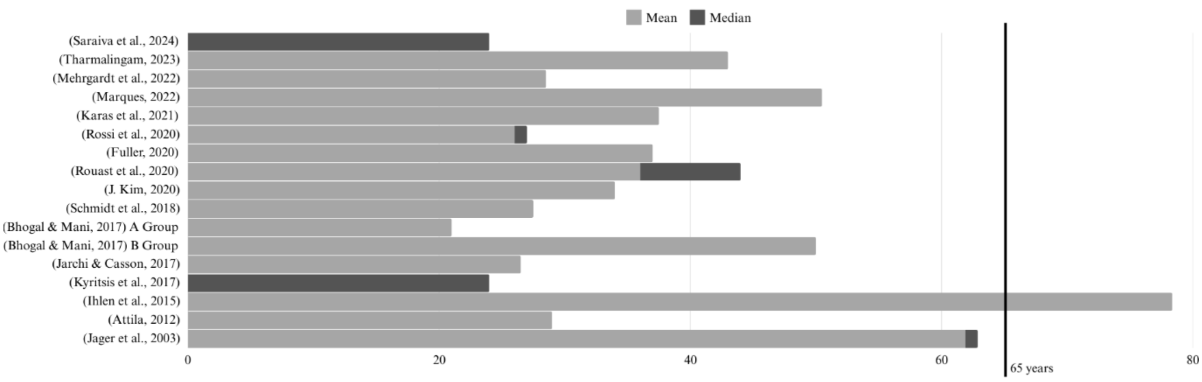

Figure 2: Age Distributions in Research Databases.

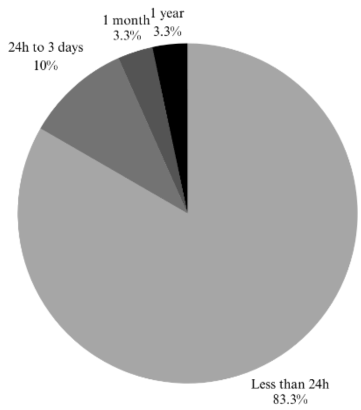

Figure 3: Duration Breakdown of Data Recordings.

4.4 Recorded Activities

Monitoring daily routines requires datasets that contain a wide range of activities typically performed throughout the day. This includes basic activities like walking, sitting, sleeping and eating, as well as more complex or irregular behaviours such as hygiene routines, wandering, or falling movements, as seen on Table 1.

Walking is the most frequently recorded activity across the datasets, appearing in 40% (12 datasets) of the reviewed datasets. Eating activities, essential for monitoring nutritional health and independence, are labelled in 20% (6 datasets). Sitting and sleeping activities are recorded in 13.3% (4 datasets) each, highlighting a focus on sedentary and rest-related behaviours.

In addition to these activities several datasets (11) include labels for miscellaneous activities that provide unique insights into daily routines and specific behaviours. For instance, the OPPORTUNITY dataset (Roggen, Alberto, et al., 2010) includes activities like "opening a door" and "drinking water," used for recognizing fine-grained motor skills. The PAMAP2 dataset (Attila, 2012) features labelled activities such as "ascending stairs", “descending stairs”, “watching TV”, “standing” and "house cleaning," capturing more dynamic and context-specific movements, particularly useful for training models that aim to recognize household activities. The WEDA-FALL dataset (Marques, 2022) focuses on fall-related activities and recovery movements, critical for fall detection systems, similarly, the Long-Term Movement Monitoring Database (Ihlen et al., 2015)focuses on prolonged activity tracking, offering continuous movement data collected over several days from older adults. Other datasets, like the ScientISST MOVE dataset (Saraiva et al., 2024), include transitions between activities such as "standing-to-sitting" and "sitting-to-lying," relevant for understanding changes in posture or transitions that may indicate health issues. The OREBA dataset (Rouast et al., 2020) targets eating behaviours by providing multimodal data for recognizing eating gestures and associated intake, contributing to dietary monitoring. The Sleep Health and Lifestyle Dataset (Tharmalingam, 2023) on the other hand, focuses on sleep patterns and lifestyle habits capturing detailed sleep metrics such as duration, efficiency, and disruptions, which are vital for understanding circadian rhythm irregularities often observed in dementia patients.

The WESAD (Schmidt et al., 2018), are focused on stress recognition, providing labelled data for different emotional states, including stress, amusement, and neutral conditions. These datasets often integrate physiological signals, such as heart rate variability (HRV), electrodermal activity (EDA), and respiratory patterns, alongside motion data.

Each of these datasets provides unique insights and data characteristics that enrich the development of AI models, enabling more comprehensive and accurate activity recognition systems tailored to dementia care.

5 MODEL PERFORMANCE ANALYSIS

To evaluate the effectiveness of machine learning models in activity recognition, we analysed the performance of multiple algorithms across various datasets. This section summarizes the results obtained for each dataset. Performance metrics, including precision, recall, and F1-score, were evaluated for models like Random Forest, K-Nearest Neighbors (KNN), and Gradient Boosting.

5.1 MMASH Dataset

The MMASH (Multimodal Activity Recognition in Smart Home Environments) (Rossi et al., 2020) dataset is a comprehensive dataset designed for activity recognition research. It includes data from multiple sensor types such as accelerometers, gyroscopes, magnetometers, and physiological sensors. Covering a wide range of activities, including basic actions like sitting, walking, and lying down, as well as complex activities such as eating or performing household tasks.

Table 1: Activity Types Captured in Wearable Activity Recognition Datasets.

Ref./ Activity	Walk	Sit	Sleep	Eat	Fall	Miscellaneous
(Saraiva et al., 2024)	x					x
(Guy et al., 2024)						x
(Nicoomanesh, 2024)	x		x			
(Julian et al., 2024)						
(Godzwon, 2024)						
(Tharmalingam, 2023)	x		x			x
(Grimaldi et al., 2023)	x	x			x	
(Mehrgardt et al., 2022)						
(Amin et al., 2022)						
(Marques, 2022)	x				x	x
(Karas et al., 2021)	x					x
(Rossi et al., 2020)	x	x	x	x		x
(Fuller, 2020)	x	x				x
(Hoover, 2020)				x		
(Rouast et al., 2020)				x		
(J. Kim, 2020)					x	x
(Walch, 2019)	x		x			
(Kyritsis et al., 2019)				x		
(Schmidt et al., 2018)						
(Jafarnejad, 2018)						
(Bhogal & Mani, 2017)						
(Jarchi & Casson, 2017)	x					x
(Kyritsis et al., 2017)				x		
(Ihlen et al., 2015)					x	
(Banos et al., 2014)	x	x		x	x	x
(Attila, 2012)	x					x
(Roggen, Calatroni, et al., 2010)						
(Jager et al., 2003)						
(Moody & Mark, 2001)						

Both the XGBoost and LigthGBM models consistently achieved higher accuracy, and F1-scores compared to other models. For instance, the XGBoost, demonstrated strong generalization with higher overall accuracy and consistently balanced precision and recall across activities, including underrepresented classes. With the LightGBM outperforming in handling imbalanced data, particularly for rare activities.

The Random Forest and Gradient Boosting models performed best for the generalized activities with large support values, such as sitting. However, the model struggled with specific or underrepresented activities such as large screen usage and sleeping.

Comparing to other models, the KNN underperformed, presenting low precision and recall values for most activities, due to the class imbalance.

5.2 ScientISST Dataset

The ScientISST Dataset (Saraiva et al., 2024) is a comprehensive and multimodal dataset designed for human activity and gesture recognition. It is particularly valuable for developing and evaluating machine learning models in scenarios requiring high precision and robustness, such as healthcare, wearable technology, and human-computer interaction.

The KNN and Random Forest models outperformed the other models, achieving nearly perfect results across most activities for accuracy, precision and F1-score, apart from the less frequent activities.

The CNN and GRU models performed well in recognizing frequent and sequential activities. CNN excelled at extracting spatial features, achieving high F1-scores for structured tasks like "Run" (0.95) and dynamic movements like "Jumps" (0.74). GRU effectively captured temporal dependencies, making it ideal for activities with transitions, such as "Lift" (F1-score: 0.83) and "Run" (F1-score: 0.93). The SVM model showed strong performance for well-separated and frequent activities. The MLP model demonstrated consistent performance for frequent and distinct activities, achieving an F1-score of 0.97 for "Run."

All models, however, struggled with nuanced gestures like "Greetings" and “jump” presenting reduced precision and recall.

5.3 PAMAP2 Dataset

The PAMAP2 (Physical Activity Monitoring for Aging People 2) (Attila, 2012) dataset is a collection of data designed to facilitate the development and evaluation of activity recognition algorithms. This dataset is widely utilized in the field of wearable computing and health monitoring, particularly for applications involving elderly care and fitness tracking.

The Random Forest and XGBoost models exhibit stellar performance, with nearly perfect precision, recall, and F1-scores close to 100% across a wide range of activities. This performance indicates their robust predictive capabilities and adaptability in managing diverse data types, particularly in complex activity scenarios such as 'nordic walking' and 'cycling'.

In a similar way, LightGBM, a gradient boosting model optimized for speed and reduced memory usage, offers substantial advantages for real-time activity recognition applications. Combining the robust framework of gradient boosting with enhancements designed to improve processing speed and efficiency, making it competitive for applications where quick response times are crucial.

The KNN model showed moderate performance with an overall accuracy of 91%. While it performed well on frequent activities like "Sitting" (F1-score: 0.98) and "Cycling" (F1-score: 0.96), its performance dropped for more complex and underrepresented activities, such as "Ascending Stairs" (F1-score: 0.74) and "Descending Stairs" (F1-score: 0.72).

The Logistic Regression model shows varying performance across different activities, reflecting some fundamental limitations in handling complex, multiclass problems. While it performs commendably in activities with clear distinctions, such as 'lying' and 'ironing', it faces challenges in activities requiring nuanced differentiation, such as 'standing' versus 'sitting'. This variation highlights the need for sophisticated feature engineering or advanced data preprocessing to bolster its effectiveness in more complex scenarios.

6 DISCUSSION

The findings of this study provide important insights into the development and optimization of AI models and wearable technologies for activity recognition in dementia care. However, a significant challenge is the lack of comprehensive datasets tailored to the unique requirements of this domain. Current datasets predominantly feature younger adults, offering limited representation of older individuals who are most affected by dementia, thereby reducing the applicability of AI models to the intended population. Additionally, existing datasets often fail to cover the full range of activities relevant to dementia care, such as hygiene routines, eating behaviors, wandering, and fall-related movements. This lack of comprehensive activity coverage limits the ability of AI systems to monitor the complex behaviors associated with dementia effectively.

Another limitation is the prevalence of short-duration recordings, which are insufficient for analyzing long-term activity patterns and deviations that are critical for dementia monitoring and detecting changes in routine or health status. Furthermore, most datasets are collected in controlled environments, which fail to capture the complexity and variability of real-world settings, such as homes or assisted living facilities where dementia patients typically reside. This discrepancy reduces the robustness and generalizability of models trained on such data. Additionally, many datasets suffer from significant class imbalances, with underrepresented activities leading to poor model performance for these specific behaviors. Addressing these limitations is essential to develop AI-driven wearable solutions that are accurate, robust, and capable of meeting the practical needs of dementia care.

Future datasets should prioritize the inclusion of elderly participants representing diverse genders and cognitive stages, ensuring that the data accurately reflects the population most affected by dementia. These datasets should aim to capture a comprehensive range of activities, including eating, hygiene routines, wandering, fall recovery, and activity transitions, as well as nighttime behaviours. To enable a deeper understanding of daily routines and their variations, it is essential to include long-duration recordings spanning multiple days or even weeks. Collecting data in naturalistic environments, such as homes or care facilities, will further enhance the validity of the datasets and significantly improve the robustness and generalizability of AI models developed for dementia care.

The performance evaluation of the AI models in this study highlights the strengths and limitations of different approaches for activity recognition in dementia care. Models such as Random Forest (RF), XGBoost, and LightGBM consistently demonstrated robust performance, excelling in handling class imbalances and accurately recognizing well-defined activities like walking, running, and sitting. Their resilience to noisy data and ability to generalize across common activity classes make them reliable choices for general activity monitoring.

However, despite these promising results, all models faced challenges in identifying less frequent and more nuanced activities, such as eating or transitions, due to limitations in dataset quality and class imbalances. The underrepresentation of these critical activities in the datasets hindered model performance, leading to reduced precision and recall for these classes. Moreover, the prevalence of short-duration recordings further constrained the models' ability to analyze long-term activity patterns, limiting their effectiveness in detecting behavioral trends and anomalies essential for dementia care.

These findings underscore the necessity of selecting and tailoring models based on specific application requirements. For general activity recognition tasks, tree-based models like XGBoost and LightGBM offer strong performance and efficiency. In contrast, deep learning approaches, such as CNNs and GRUs, are better suited for tasks that require detailed temporal and spatial analysis, particularly when handling complex or transitional activities. Addressing dataset limitations, including activity coverage, class balance, and recording duration, will be critical for enhancing model performance and ensuring their practical applicability in real-world dementia care scenarios.

7 CONCLUSION

This study highlights the potential of AI models and wearable technologies for activity recognition in dementia care, demonstrating the strengths of tree-based models like Random Forest, XGBoost, and LightGBM in handling class imbalances and recognizing common activities, as well as the capabilities of deep learning models such as CNNs and GRUs in capturing complex patterns and transitions. However, significant challenges remain, including the lack of comprehensive datasets that adequately represent the elderly population, encompass a diverse range of activities, and provide long-duration recordings in real-world environments. These limitations reduce the generalizability and effectiveness of AI models in detecting nuanced behaviors and long-term activity patterns critical for dementia monitoring.

To address these gaps, future research should focus on developing tailored datasets with enhanced demographic diversity, extended recordings, and realistic environmental contexts. Combining traditional and deep learning models into hybrid approaches can further optimize performance, while energy-efficient AI solutions will ensure real-time monitoring capabilities for wearable devices. By overcoming these challenges, AI-powered wearable technologies can play a transformative role in dementia care, enabling accurate activity recognition, early intervention, and improved quality of life for patients while reducing the burden on caregivers.

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