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RESEARCH ARTICLE

Advancing Healthcare and Elderly Activity Recognition: Active Machine and Deep Learning for Fine-Grained Heterogeneity Activity Recognition

SIDRA ABBAS[1], (Graduate Student Member, IEEE), GABRIEL AVELINO SAMPEDRO[2,3], (Member, IEEE), SHTWAI ALSUBAI[4], STEPHEN OJO[5], (Member, IEEE), AHMAD S. ALMADHOR[6], ABDULLAH AL HEJAILI[7], AND LUBOMIRA STRAZOVSKA[8]

[1]Department of Computer Science, COMSATS University Islamabad, Islamabad 44000, Pakistan
[2]Faculty of Information and Communication Studies, University of the Philippines Open University, Los Baños 4031, Philippines
[3]Center for Computational Imaging and Visual Innovations, De La Salle University, Malate, Manila 1004, Philippines
[4]College of Computer Engineering and Sciences, Prince Sattam bin Abdulaziz University, Al-Kharj 11942, Saudi Arabia
[5]Department of Electrical and Computer Engineering, College of Engineering, Anderson University, Anderson, SC 29621, USA
[6]Department of Computer Engineering and Networks, College of Computer and Information Sciences, Jouf University, Sakaka 72388, Saudi Arabia
[7]Faculty of Computers and Information Technology, Computer Science Department, University of Tabuk, Tabuk 71491, Saudi Arabia
[8]Faculty of Management, Comenius University in Bratislava, 82005 Bratislava, Slovakia

Corresponding authors: Lubomira Strazovska (lubomira.strazovska@fm.uniba.sk) and Sidra Abbas (sidraabbas@ieee.org)

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ABSTRACT This research explores the potential of technologies in human activity recognition among the elderly population. More precisely, using sensor data and implementing Active Learning (AL), Machine Learning (ML), and Deep learning (DL) techniques for elderly activity recognition. Moreover, the study leverages the HAR70+ dataset, providing insight into the daily activities of older individuals and AL-based ML and DL techniques to construct predictive models for these activities. The findings have implications for proactive and personalized elderly care, representing an approach to improving prediction performance in this domain. The research experiments are presented systematically, summarizing the outcomes of various machine-learning models across three iterative experiments. This research explored a diverse array of ML algorithms, including Random Forest (RF), Extreme Gradient Boosting (XGBoost), Logistic Regression (LR), K-Nearest Neighbors (KNN), Stochastic Gradient Descent (SGB) and DL methods such as Deep Neural Networks (DNN) and Long Short-Term Memory networks (LSTM) for experimentation. This research trained models on 7 activities: walking, shuffling, climbing stairs (up and down), standing, sitting, and lying down, and 4 activities separately: standing, sitting, walking, and lying down, using the same classifiers. Results reveal that LSTM achieved the best accuracy of 0.95% for 7 activities and 0.96% using RF on 4 actives, showing the potential of DL and ML techniques, particularly when integrated with AL, to enhance activity recognition rate, patient care, optimize medication strategies and improve the well-being of elderly individuals. Hence, the findings presented in this study have showcased the potential to enhance the quality of life for seniors using the blend of ML, DL and AL.

INDEX TERMS Active learning (AL), elderly activity recognition, human activity recognition (HAR), healthcare, deep learning (DL), machine learning (ML), lifestyle and technology.

I. INTRODUCTION

Older adults' well-being and quality of life have ascended to the forefront of healthcare and gerontology research in

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an era characterized by a rapid global demographic shift towards an aging population [1]. Likewise, physical function and health differ among older adults, and regular physical activity is crucial for maintaining function and independence in older age [2], [3], [4]. Subsequently, recognizing the diverse spectrum of daily physical behaviors exhibited by older individuals is a healthcare priority and a foundation for furthering their independence, enhancing their overall happiness and prolonging their healthy years [5]. Moreover, Human Activity Recognition (HAR) has emerged as an essential field in the ongoing search to improve the lives of older adults [6]. Most importantly, it offers the tantalizing prospect of automating the classification and continuous monitoring of the myriad activities that fill the daily lives of older individuals. Nevertheless, realizing the potential of robust HAR models tailored to the nuances of older adult behavior remains a complex endeavor. This study tackles this challenge head-on.

This study explores the potential of AL techniques within the context of HAR for older adults. Furthermore, HAR holds potential for older adults, whose daily activities span a wide spectrum from sedentary tasks like reading to dynamic movements like walking or exercising [7]. However, developing accurate and adaptable HAR models for this demographic is a formidable challenge. Moreover, older adults exhibit considerable activity variability, and collecting labeled data for such a diverse range of behaviors can be difficult; this is where AL enters the equation [8]. In addition, by judiciously selecting which instances to label interactively, AL can alleviate the data labeling burden, enhance model performance, and adapt the HAR system to the specific behaviors and contexts that older adults encounter daily. This study investigates the marriage of AL and HAR paradigms to advance the recognition and understanding of daily physical behaviors among older adults.

Existing literature has employed sensor-based and vision-based approaches to classify daily physical behaviors in older adults. Most importantly, studies have discussed context-aware activity recognition systems, emphasizing specialized models and datasets tailored to the elderly demographic [9]. While the existing literature provides valuable insights, there still needs to be a gap in leveraging AL techniques to classify daily physical behaviors in older adults. Moreover, AL, when integrated, has the potential to enhance recognition systems' accuracy and adaptability. Specifically, this study addresses this gap by introducing AL techniques into the classification process. This approach is intended to improve the precision and adaptability of recognizing daily physical behaviors in the elderly demographic. Moreover, the primary contributions of our study lie in the seamless integration of sensor-based data with AL strategies to train ML and DL models.

AL is an ML and DL technique at the forefront of this study. Subsequently, it fundamentally alters how ML and DL models learn from data [10]. Furthermore, in traditional ML and DL, models are passively fed labeled data for training, often requiring vast amounts of meticulously labeled samples [11]. Likewise, AL, however, introduces an interactive dimension [12]. Moreover, instead of merely consuming labeled data, it empowers the model to actively query the most informative, uncertain, or ambiguous data points for labeling, efficiently focusing its learning efforts where they matter most. This approach is especially advantageous in the realm of Human Activity Recognition. AL can be very helpful when recognizing different behaviors in older adults. In addition, this study acts as a vital conduit, bridging two significant domains: ML/DL and the multidimensional healthcare needs of older adults [13]. Likewise, the focus here is on AL, a methodology that addresses the trifecta of challenges common in HAR for this demographic–data scarcity, model generalization, and adaptability. Similarly, Within the pages of this paper, readers will thoroughly examine AL techniques that have proven successful in the domain of HAR. The paper expertly navigates readers through the optimal application of these AL strategies, each enhancing recognition and adaptability. Ultimately, the paper concludes with a compelling evaluation of these strategies' significant influence on identifying daily physical behaviors in older adults.

At its core, this study adds valuable information to what is already known about caring for older adults and using technology in healthcare. Moreover, a smart learning approach helps computer models better understand and adapt to the various things older people do daily. Overall, this could lead to more personalized healthcare, which would improve the lives of older people and their families.

A. CONTRIBUTIONS

- **Innovative Adaptation of Active Learning (AL):** Our research focuses on applying active learning methodologies to enhance the performance of ML and DL models to recognize activities in the elderly.
- **Comprehensive Model Evaluation and Fine-Tuning:** The paper presents a detailed analysis involving various models, including KNN, LR, NB, RF, SGD, XGBoost, DNN, and LSTM. The fine-tuning of these models using the HAR70+ dataset with AL is a distinctive aspect of our work. This comprehensive evaluation demonstrates our commitment to rigorously testing and improving predictive abilities.
- **Superior Performance Metrics:** The research findings indicate a significant increase in accuracy, precision, and recall improvements compared to the base paper. We achieved higher accuracy and superior F1 scores, especially in activities such as walking, sitting, and lying, showcasing the effectiveness of our proposed approach.
- **Potential Impact on Elderly Well-being:** Beyond the technical contributions, our study highlights the potential impact on the well-being of elderly individuals.

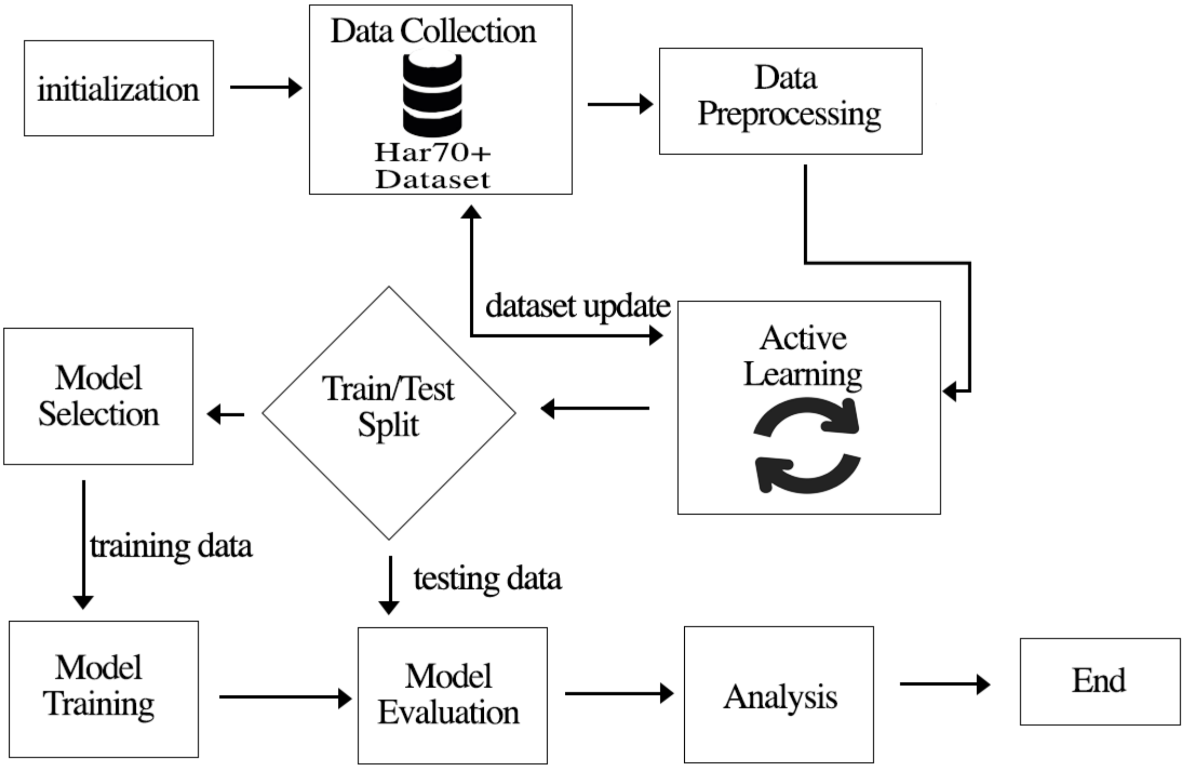


FIGURE 1. Employed methodology.

The blend of ML, DL, and AL, as presented in this research, demonstrates a commitment to enhancing the quality of life for seniors, a critical aspect that distinguishes our work in the broader context.

II. RELATED WORK

This section explored and examined the scholarly research about recognizing routine physical activities among elderly individuals [14], [15]. Furthermore, regular physical activity is essential for maintaining function and independence in older adults, and recognizing their diverse daily physical behaviors is crucial for enhancing overall happiness and prolonging healthy years [16]. Likewise, an inactive lifestyle can lead to declining mobility, muscle strength, and cardiovascular health, making older adults more susceptible to chronic conditions and loss of health. Hence, accurately classifying and monitoring their daily activities carries serious implications for healthcare interventions, tailored exercise programs, and lifestyle adjustments that can promote well-being and active aging. Subsequently, numerous studies have delved into sensor-based activity recognition for older adults. These investigations often involve wearable devices equipped with accelerometers, gyroscopes, and other sensors [17], [18]. These sensors capture motion and activity data, enabling the recognition of various physical behaviors [19]. For instance, researchers have employed wearable sensors to monitor gait patterns, detect falls, and distinguish between standing, sitting, and walking activities [20], [21]. In other words, these advancements have shown great promise in improving the safety and well-being of older adults, especially those living independently. As well as in parallel, vision-based systems have garnered attention as a means of activity recognition [22], [23]. These systems can track and classify activities in real time using cameras and computer vision algorithms [24]. For instance, researchers have demonstrated the capability of vision-based systems in identifying gestures, recognizing specific activities such as cooking or exercise, and even assessing overall mobility and health and have also incorporated a deep neural network that integrates convolutional layers with long short-term memory to recognize human activities [25]. These approaches offer a non-intrusive means of monitoring daily activities, particularly relevant in elder care.

AL, a pivotal aspect of this paper, has been explored extensively in ML and DL. AL involves smart strategies for selecting which data points to label, aiming to maximize learning efficiency [26]. The principle is that ML/DL models can achieve high performance with less labeled data by choosing the most informative or uncertain data points for labeling. This approach has proven valuable in domains where data labeling can be resource-intensive or impractical. Furthermore, AL has found applications across diverse domains, from natural language processing to image classification. For instance, in text classification,

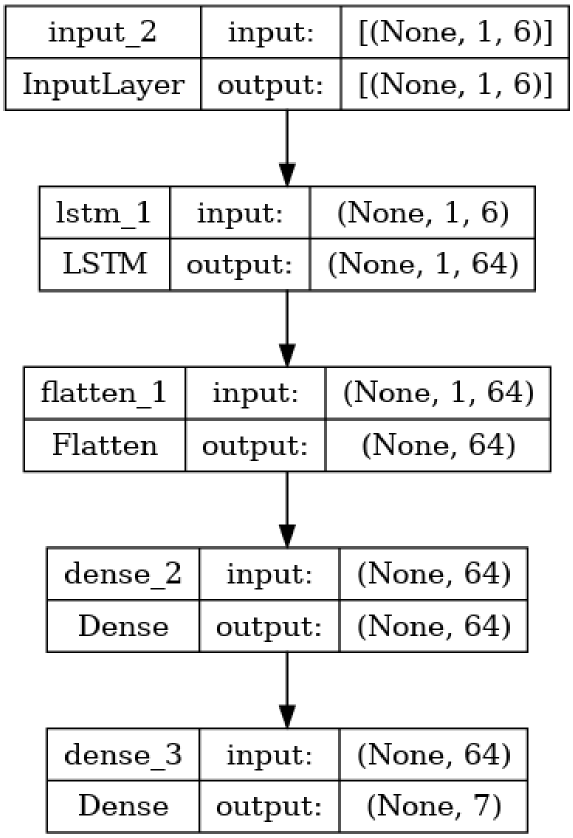


FIGURE 2. LSTM architecture.

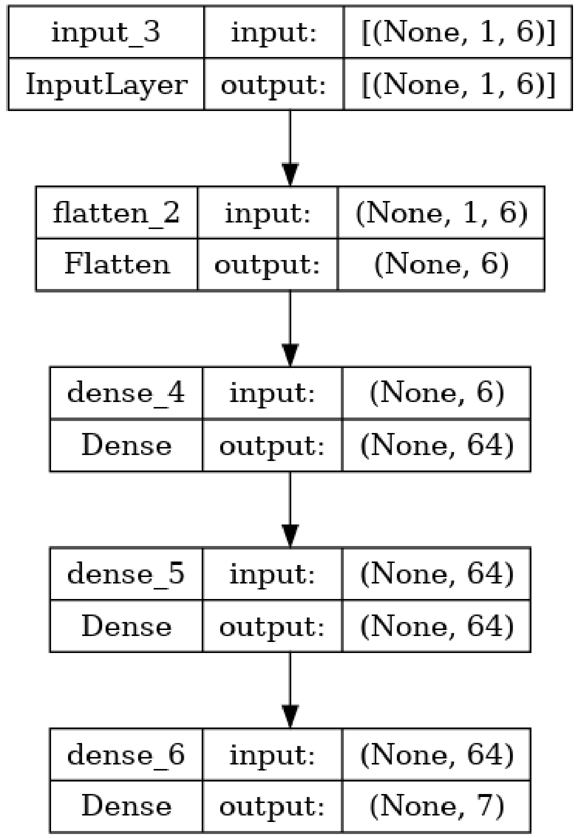


FIGURE 3. DNN architecture.

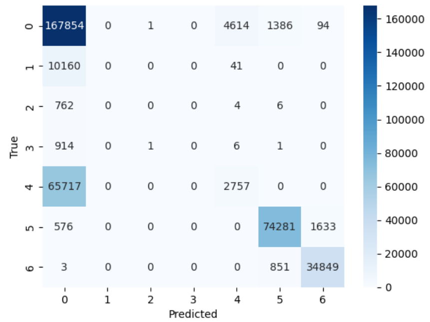
AL has been used to optimize the labeling of documents for sentiment analysis, reducing the labeling burden on human annotators [27]. Similarly, in image classification tasks, AL strategies have effectively selected the most informative images for model training. These successful applications underscore the adaptability and potential of AL techniques.

Various academic studies on classifying daily physical behavior in older adults have significantly contributed to the field [28], [29]. Specific studies focusing on Classifying Daily Physical Behavior in Older Adults have contributed significantly to the field. Moreover, these studies have addressed the unique challenges of recognizing and categorizing the diverse spectrum of daily physical activities in older individuals. By developing specialized models and datasets tailored to the elderly demographic, they have opened the door for more accurate and context-aware activity recognition systems [9]. Building upon the insights gained from this body of research, this paper seeks to enhance further the field's understanding and approach by incorporating AL techniques into classifying daily physical behaviors among older adults.

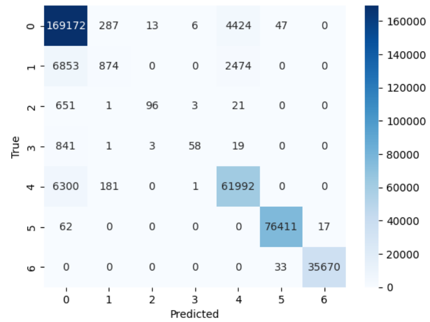
This paper bridges the activity recognition and AL domains for older adults. By integrating sensor-based and vision-based approaches with AL strategies, this study aims to enhance the accuracy and efficiency of recognizing daily physical behaviors in older adults. Hence, this innovative approach leverages the strengths of both domains, offering the potential for more effective, adaptable, and cost-efficient eldercare solutions.

III. METHODOLOGY

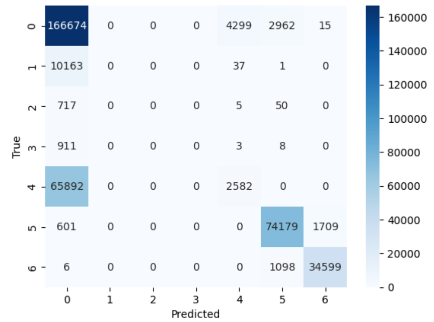
This study took a systematic approach to improve how activities are recognized in older adults, with the main goal of adding AL methods. The dataset is called "HAR70+," and it holds data about activities older adults do daily [30]. This dataset includes walking, shuffling, going up and down stairs, standing, sitting, and lying down. Likewise, the study developed models for 7 activities: walking, shuffling, climbing stairs (up and down), standing, sitting, and lying down, along with 4 activities: standing, sitting, walking, and lying. Each activity is carefully labeled to help this study's learning process. Moreover, the study starts with carefully preparing the "HAR70+" dataset, a vital step in preparing it for model training. Furthermore, this involved cleaning up the data to remove inconsistencies, addressing missing information, and adjusting features to ensure they were in the right scale or format. The research conducted an in-depth look at the dataset's characteristics through exploratory data analysis. This helped gain insights into the dataset and guided the decisions as the study progressed. In addition, in a significant move toward a better understanding older adults' daily activities, this study collected and organized data relating



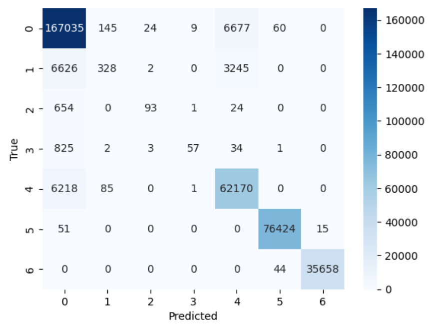
(a) AL-LR



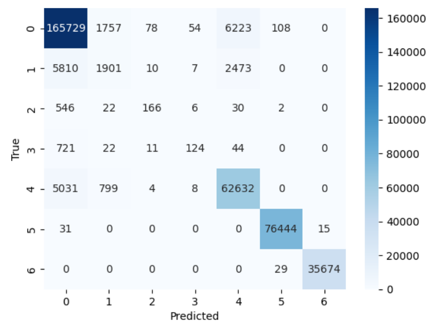
(b) AL-RF



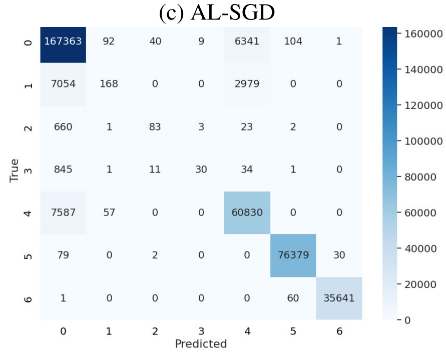
(c) AL-SGD



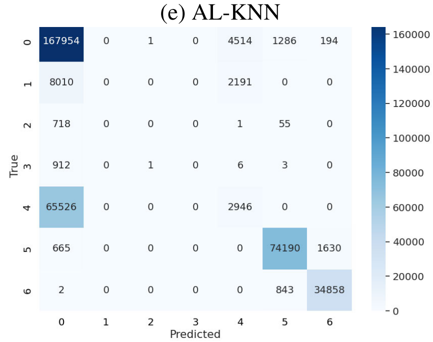
(d) AL-XGBoost



(e) AL-KNN



(f) AL-DNN



(g) AL-LSTM

FIGURE 4. **Confusion matrix of all classifiers.**

to their most common actions. These actions encompass everyday movements like walking, shuffling, climbing stairs (up and down), standing, sitting, and lying down. Likewise, recognizing the importance of these activities in older adults' lives, this study aimed to consolidate and structure the data associated with these routine actions. This simplified the study and analysis process and provided a clearer view of how older adults navigate their daily lives. This well-organized data is valuable for enhancing healthcare for older adults, making it more individualized and effective in promoting their overall well-being.

Figure 1 outlines the steps and approach used in this research. In addition, this study explored feature engineering to enable effective learning and model generalization. Algorithm 1 provides the workflow of the overall proposed approach. First, we collect the dataset and perform data pre-processing. Next, Feature selection and extraction techniques were applied, giving the machine-learning models a solid foundation to build their understanding. Subsequently, Recursive Feature Elimination was employed for feature selection for enhanced model performance, iteratively removing less important features. In addition, Principal Component Analysis served as a feature extraction technique, transforming the original features into uncorrelated principal components to reduce dimensionality while preserving essential information. Moreover, one of our study's defining aspects is applying AL strategies to the "HAR70+" dataset. More precisely, AL empowers the models to select which data points to label autonomously to maximize learning efficiency. This iterative process enables the models to continually improve their performance as they identify the most informative data samples for labeling. The study utilized three distinct iterations. Furthermore, for the modeling phase, the research explored various ML algorithms, including RF, XGBoost, LR, KNN, SGD and Neural Networks, such as Deep Neural Networks and Long Short-Term Memory

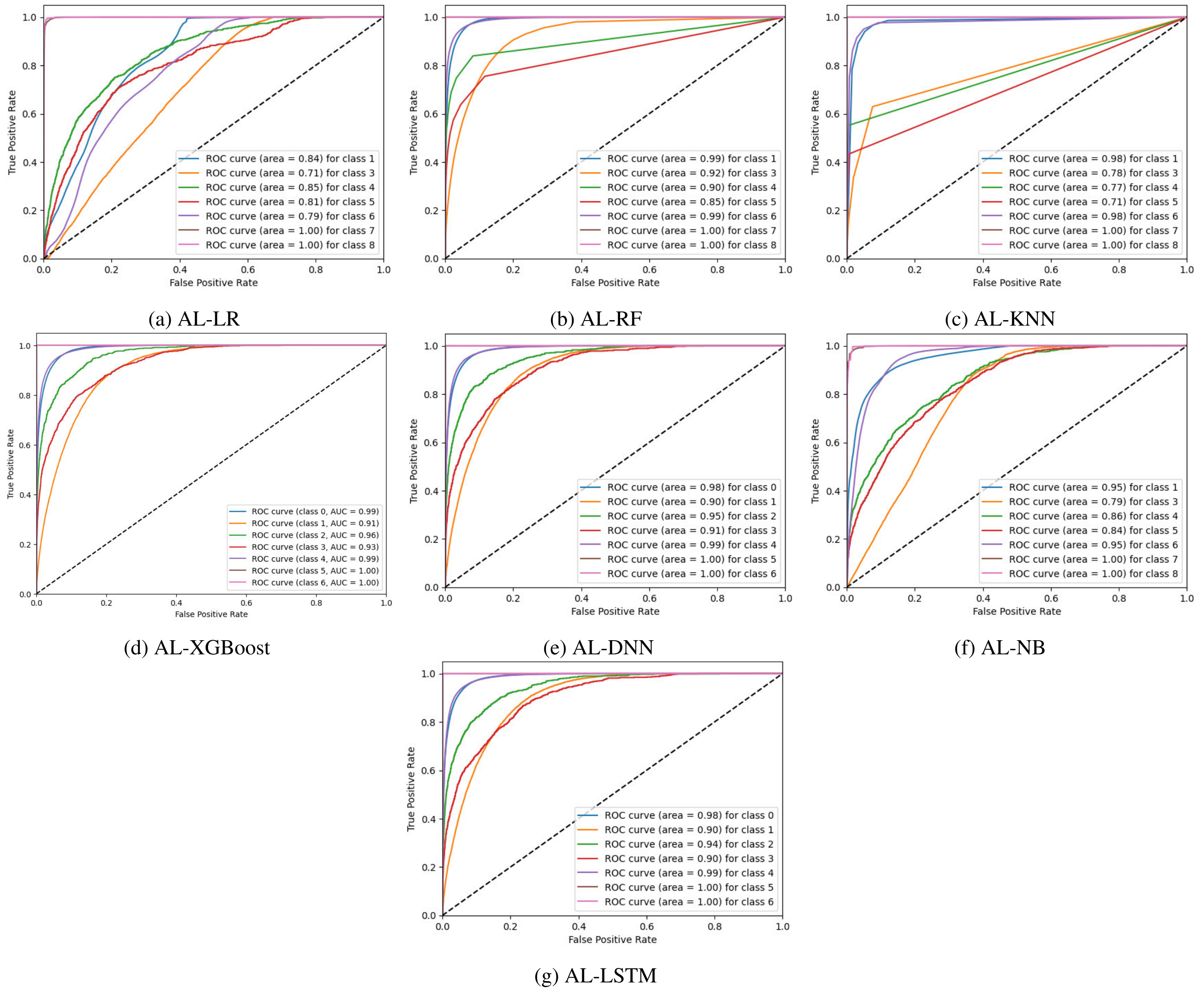


FIGURE 5. **ROC curves of all classifiers.**

Networks. These models were trained on the labeled data from the "HAR70+" dataset, and their performance was rigorously assessed using established metrics. Specifically, the "HAR70+" dataset was thoughtfully divided into training and testing sets, a common practice to evaluate model performance while guarding against overfitting. Additionally, this study employed cross-validation techniques to ensure the performance of the used models [31]. The utilized classifiers and their respective parameters in this study are presented in Table 1. Subsequently, from the raw sensor data in the "HAR70+" dataset, this study extracted relevant features that encapsulated the essence of each activity.

Figure 2 shows the LSTM architecture. It includes an LSTM layer with 64 units and a flattened layer. It concludes with two dense layers: one with 64 units and a 'relu' activation function and another with seven units and 'softmax' activation. Moreover, the model is compiled with the 'Adam' optimizer and uses 'categorical_crossentropy' as the loss function for multiclass classification, while accuracy is monitored during training. Figure 3 shows an architecture

TABLE 1. **Classifier parameters.**

Classifier	Parameters
DNN	- Hidden Layers: 2 - Units per Layer: 64 - Activation: ReLU
LSTM	- Units: 64 - Return Sequences: True - Activation: Relu
SGD	- loss: log - Max iteration: 1000
NB	- GaussianNB(all default)
KNN	- KNeighborsClassifier(all default)
LR	- LogisticRegression(all default)
XGBoost	- Max Depth: 3 - Learning Rate: 0.1
RF	- Number of Trees: 100 - Max Depth: None

Algorithm 1 Activity Recognition Algorithm

```
Data Collection: HAR70+ dataset
Data = C(D_HAR70+)
Preprocessing (Data)
P_Data ← Missing Data Handling (Data)
P_Data ← Categorical Encoding (P_Data)
P_Data ← Numerical Normalization (P_Data)
AL Technique: Begin labeled dataset with seed instances
for Each iteration do
    Get Uncertainty scores
    Select the most uncertain samples
    Look for original labels
    Retrain the model on the updated labeled dataset
    Evaluate model performance on the testing set
end for
Examine model performance metrics
Examine confusion matrix and ROC curve
```

with an input, flattened, and dense layers. More precisely, the deep learning model (1,6) input shape was chosen based on dataset characteristics and DL architecture demands. Given the nature of the input data, a one-dimensional input shape comprising six features has been chosen to maximize the model's efficacy in capturing crucial temporal patterns. This configuration seamlessly aligns with the data structure, empowering the model to learn and accurately represent the input features. Subsequently, the study has fine-tuned these models by adjusting hyperparameters and configurations to optimize their performance. This iterative process improved the initial architecture choices and resulted in a refined configuration. This configuration has shown increased performance on key metrics. The research adopted an approach infused with AL and followed an iterative path. Initially, models were trained on a limited labeled dataset from the "HAR70+" dataset. Subsequently, the models actively identified uncertain or informative samples from the "HAR70+" dataset for additional labeling. This dynamic process facilitated a deeper understanding of complex activities over successive iterations. To determine the effectiveness of the models, the study employed standard evaluation metrics such as accuracy, F1 score, precision, and recall [32]. These metrics provided comprehensive insights into how well the models recognized the daily physical behaviors of older adults using the "HAR70+" dataset. In sum, in the results and analysis, the study presented the outcomes of the experiments on the "HAR70+" dataset, shedding light on how AL techniques impacted the accuracy and efficiency of activity recognition for older adults. Moreover, the discussion involved the broader implications of these findings in the context of eldercare and healthcare technology. Moreover, also acknowledged the approach's limitations and identified promising avenues for future research. Overall, the presented methodology, intertwined with the "HAR70+" dataset and AL, includes a comprehensive approach to improving the lives of older individuals.

IV. RESULTS AND EXPERIMENTATION

This study presents a comprehensive analysis of experiments using various ML and DL models to recognize daily physical behaviors in older adults based on the "HAR70+" dataset. The primary objective was to identify the most effective model for this critical task while thoroughly examining the consistency and reliability of each approach. Table 2 displays the experimental results for all iterations on seven activities. Subsequently, KNN was the first model examined. Across three iterations, this study consistently achieved an accuracy of 93.50%. Moreover, this highlights the robustness of the KNN model in maintaining high accuracy levels, making it a promising choice for activity recognition. Further analysis is needed to explore precision and recall metrics to understand its performance better.

TABLE 2. Experimental results on 7 activities(All Iterations).

Model	Accuracy	F1 Score	Precision	Recall
KNN				
Iteration 1	0.9350	0.9287	0.9264	0.9350
Iteration 2	0.9350	0.9287	0.9264	0.9350
Iteration 3	0.9350	0.9287	0.9264	0.9350
LR				
Iteration 1	0.7633	0.6895	0.6886	0.7633
Iteration 2	0.7633	0.6895	0.6886	0.7633
Iteration 3	0.7633	0.6895	0.6886	0.7633
Naive Bayes				
Iteration 1	0.8117	0.8128	0.8464	0.8117
Iteration 2	0.8117	0.8128	0.8464	0.8117
Iteration 3	0.8117	0.8128	0.8464	0.8117
RF				
Iteration 1	0.9395	0.9283	0.9328	0.9395
Iteration 2	0.9395	0.9283	0.9330	0.9395
Iteration 3	0.9393	0.9281	0.9326	0.9393
SGD				
Iteration 1	0.7586	0.6841	0.6831	0.7586
Iteration 2	0.7586	0.6841	0.6831	0.7586
Iteration 3	0.7586	0.6841	0.6831	0.7586
XGBoost				
Iteration 1	0.9325	0.9196	0.9238	0.9325
Iteration 2	0.9325	0.9196	0.9238	0.9325
Iteration 3	0.9325	0.9196	0.9238	0.9325
DNN				
Iteration 1	0.9815	0.9876	0.9831	0.9823
Iteration 2	0.9845	0.9886	0.9895	0.9845
Iteration 3	0.9925	0.9996	0.9922	0.9925
LSTM				
Iteration 1	0.9815	0.9876	0.9831	0.9823
Iteration 2	0.9845	0.9886	0.9895	0.9845
Iteration 3	0.9925	0.9996	0.9922	0.9925

LR was next in line, producing an accuracy of 76.33% across all iterations. Although LR offers stable performance, it lags behind KNN in accuracy. Precision and recall values indicate potential limitations in capturing the intricate details of older adults' daily behaviors. Moreover, The Naive Bayes model, with an accuracy of 81.17% across iterations, demonstrated competitive performance compared to LR. Furthermore, it exhibited higher precision, suggesting proficiency in correctly classifying positive instances. However, a slightly lower recall indicates room for improvement in capturing all relevant activities. In addition, the RF model proved to be highly effective in its performance, showing an impressive accuracy of 93.95%. Its consistency and effectiveness make it a strong candidate for activity recognition. More precisely, the closely aligned F1 Score, precision, and recall values underscore its suitability for this task. Conversely, the SGD model exhibited lower accuracy at 75.86%. Precision, recall, and F1 Score values could have been more optimal, implying that more suitable choices may exist for this particular task. In addition, LSTM was the best model, with an average accuracy, f1score, precision, and recall of 0.9861, 0.9919, 0.9882, and 0.9864, respectively.

Figure 4 illustrates the confusion matrices for the classifiers utilized in this research. It can be noticed that classes 1, 2, and 3 are confused mostly by almost all of the classifiers. The rationale is that these classes resemble class 0 (walking). Subsequently, Figure 5 presents the Receiver Operating Characteristic (ROC) curves for a range of models practiced in this research. These graphical representations serve as a means to assess the effectiveness of binary classification models. Moreover, ROC curves describe the balance between True Positive and False Positive rates across various model thresholds or decision boundaries. Essentially, they allow measuring how well a model can distinguish between positive and negative classes, with a higher area under the curve signifying better discriminatory ability [33]. Specifically, in this context, the ROC curves provide insight into the performance of various models. More specifically, ROC curves offer a valuable means of evaluating a model's capability to differentiate between positive and negative classes. Overall, a larger area under the curve indicates enhanced discriminatory power. Hence, in this analysis, KNN and LSTM exhibit superior performance compared to other models, as evident in the figure. Lastly, experiments with XGBoost showed an accuracy of 93.25%, closely matching the RF model's performance. This suggests that both models offer similar accuracy levels and provide flexibility in selecting the most appropriate model for specific use cases. In summary, this study's extensive experimentation highlights the potential of KNN, RF, and XGBoost as models for recognizing daily physical behaviors in older adults. While KNN maintains good accuracy and consistency, RF and XGBoost offer competitive accuracy levels, making them preferable for more complex scenarios. The choice of the most suitable model depends on the specific needs and priorities of eldercare and healthcare technology applications. Further analysis, including fine-tuning and feature engineering, is recommended to optimize model performance and advance the field of eldercare research.

Table 3 displays performance metrics for an AL-based xgboost model, including precision, recall, F1-score, and support values for multiple classes. Moreover, it shows good performance in Class 5 and Class 6.

Furthermore, Table 4 presents performance metrics for an AL-based SGD model, with lower precision, recall, and F1-score in most classes, resulting in a lower weighted average F1-score.

TABLE 3. Xgboost performance based on AL.

Class	Precision	Recall	F1-Score	Support
Class 0	0.92	0.96	0.94	173950
Class 1	0.59	0.03	0.06	10201
Class 2	0.76	0.12	0.21	772
Class 3	0.84	0.06	0.12	922
Class 4	0.86	0.91	0.88	68474
Class 5	1.00	1.00	1.00	76490
Class 6	1.00	1.00	1.00	35702
Accuracy	-	-	0.93	366511
Macro Avg	0.85	0.58	0.60	366511
Weighted Avg	0.92	0.93	0.92	366511

TABLE 4. SGD performance based on AL.

Class	Precision	Recall	F1-Score	Support
Class 0	0.80	0.68	0.96	173950
Class 1	0.00	0.00	0.00	10201
Class 2	0.00	0.00	0.00	772
Class 3	0.00	0.00	0.00	922
Class 4	0.07	0.37	0.04	68474
Class 5	0.96	0.95	0.97	76490
Class 6	0.96	0.95	0.97	35702
Accuracy	-	-	76	366511
Macro Avg	0.42	0.42	0.40	366511
Weighted Avg	0.68	0.76	0.68	366511

Table 5 shows performance metrics for an AL-based RF model, achieving high precision, recall, and F1-score in several classes, leading to a strong overall performance and accuracy.

TABLE 5. RF performance based on AL.

Class	Precision	Recall	F1-Score	Support
Class 0	0.92	0.97	0.95	173950
Class 1	0.65	0.09	0.15	10201
Class 2	0.86	0.12	0.22	772
Class 3	0.85	0.06	0.12	922
Class 4	0.90	0.91	0.90	68474
Class 5	1.00	1.00	1.00	76490
Class 6	1.00	1.00	1.00	35702
Accuracy	-	-	94	366511
Macro Avg	0.88	0.59	0.63	366511
Weighted Avg	0.93	0.94	0.92	366511

Table 6 offers performance metrics for an AL-based Naive Bayes model. Class 5 shows high precision and F1 scores, while other classes have relatively lower performance metrics.

Table 7 offers performance metrics for an AL-based LR model. The model performs strongly for Classes 5 and 6, while other classes have lower precision, recall, and F1-score values.

The performance metrics for a KNN model based on AL are shown in Table 8. Subsequently, Class 5 and Class 6 achieve perfect F1-score, recall, and precision, producing

TABLE 6. Naive Bayes performance based on AL.

Class	Precision	Recall	F1-Score	Support
Class 0	0.94	0.72	0.82	173950
Class 1	0.07	0.04	0.05	10201
Class 2	0.00	0.00	0.00	772
Class 3	0.00	0.00	0.00	922
Class 4	0.56	0.95	0.71	68474
Class 5	0.97	0.94	0.96	76490
Class 6	0.90	0.95	0.93	35702
Accuracy	-	-	81	366511
Macro Avg	0.49	0.52	0.49	366511
Weighted Avg	0.85	0.81	0.81	366511

TABLE 7. LR performance based on AL.

Class	Precision	Recall	F1-Score	Support
Class 0	0.68	0.96	0.80	173950
Class 1	0.00	0.00	0.00	10201
Class 2	0.00	0.00	0.00	772
Class 3	0.00	0.00	0.00	922
Class 4	0.37	0.04	0.07	68474
Class 5	0.97	0.97	0.97	76490
Class 6	0.95	0.98	0.96	35702
Accuracy	-	-	76	366511
Macro Avg	0.43	0.42	0.40	366511
Weighted Avg	0.69	0.76	0.69	366511

a high weighted average F1-score, indicating overall good performance.

TABLE 8. The performance of KNN based on AL.

Class	Precision	Recall	F1-Score	Support
Class 0	0.93	0.95	0.94	173950
Class 1	0.42	0.19	0.26	10201
Class 2	0.62	0.22	0.32	772
Class 3	0.62	0.13	0.22	922
Class 4	0.88	0.91	0.90	68474
Class 5	1.00	1.00	1.00	76490
Class 6	1.00	1.00	1.00	35702
Accuracy	-	-	0.93	366511
Macro Avg	0.78	0.63	0.66	366511
Weighted Avg	0.93	0.93	0.93	366511

A. PERFORMANCE ANALYSIS OF ACTIVITY RECOGNITION CLASSIFIERS ACROSS FOUR CATEGORIES

The classification study reveals diverse performance outcomes among various classifiers for the activity recognition task in four activities: standing, sitting, walking, and lying. Table 9 presents the results on 4 activities. Moreover, Random Forest demonstrates good accuracy, consistently achieving 95.41%, with precision, recall, and F1 score metrics ranging from 95.37% to 95.41%. Conversely, Logistic Regression exhibits a comparatively lower accuracy of 76.29%, accompanied by modest precision, recall, and F1 score values of around 67.98%.

Likewise, Xgboost proves highly effective with a constant accuracy of 94.79% across all iterations, maintaining precision, recall, and F1 score metrics at 94.76% and

TABLE 9. Experimental results on 4 activities(All Iterations).

Model	Accuracy	F1 Score	Precision	Recall
Random Forest				
Iteration 1	0.9537	0.9533	0.9535	0.9537
Iteration 2	0.9539	0.9535	0.9537	0.9539
Iteration 3	0.9541	0.9537	0.9539	0.9541
Logistic Regression				
Iteration 1	0.7629	0.6798	0.6227	0.7629
Iteration 2	0.7629	0.6798	0.6227	0.7629
Iteration 3	0.7629	0.6798	0.6227	0.7629
Xgboost				
Iteration 1	0.9479	0.9477	0.9476	0.9479
Iteration 2	0.9479	0.9477	0.9476	0.9479
Iteration 3	0.9479	0.9477	0.9476	0.9479
KNN				
Iteration 1	0.9496	0.9497	0.9497	0.9496
Iteration 2	0.9496	0.9497	0.9497	0.9496
Iteration 3	0.9496	0.9497	0.9497	0.9496
Naive Bayes				
Iteration 1	0.8273	0.8324	0.8756	0.8273
Iteration 2	0.8273	0.8324	0.8756	0.8273
Iteration 3	0.8273	0.8324	0.8756	0.8273
SGD				
Iteration 1	0.7548	0.6723	0.6140	0.7548
Iteration 2	0.7548	0.6723	0.6140	0.7548
Iteration 3	0.7548	0.6723	0.6140	0.7548
LSTM				
Iteration 1	0.9431	0.9429	0.9428	0.9431
Iteration 2	0.9439	0.9439	0.9439	0.9439
Iteration 3	0.9444	0.9444	0.9445	0.9444
DNN				
Iteration 1	0.9463	0.9460	0.9459	0.9463
Iteration 2	0.9458	0.9453	0.9454	0.9458
Iteration 3	0.9467	0.9465	0.9464	0.9467

94.79%, respectively. Subsequently, KNN showcases good performance, consistently achieving an accuracy of 94.96% with precision, recall, and F1 score metrics around 94.97%. Naive Bayes delivers an accuracy of 82.73%, while SGD lags with 75.48%, both displaying balanced precision, recall and F1 score metrics. In addition, the deep learning models, LSTM and DNN, exhibit competitive accuracy values of 94.44% and 94.67%, respectively, with high precision, recall, and F1 score metrics. Overall, comprehensive insights into each classifier's strengths and weaknesses aid informed decision-making for deploying activity recognition systems.

Table 10 compares the accuracy results between the current study and base study [30] on a Human Activity Recognition dataset (HAR70+). The current study reports a higher accuracy than the base. The proposed approach achieved better F1 scores on walking, sitting, and lying while achieving almost equal results on standing activity. Results reveal the potential of DL and ML techniques, particularly when integrated with AL, to enhance activity recognition rate and patient care, optimize medication strategies, and improve the well-being of elderly individuals. Hence, the findings presented in this study have showcased the potential to enhance the quality of life for seniors using the blend of ML, DL and AL.

TABLE 10. Accuracy comparison in literature for 4 activities: standing, sitting, walking, lying.

Activities	[30]	ALRF
	F1 Score	F1 Score
Sitting	0.93	0.998
Walking	0.95	0.961
Standing	0.89	0.892
Lying	0.86	0.999

V. CONCLUSION AND FUTURE WORK

This study mainly focused on models with lots of labeled data. In the future, it might be worth looking into methods where the model can learn even when there is not a lot of labeled data available. Finally, testing the models in real healthcare settings to see how they affect the health and well-being of older adults would be an important step in future research. This study explored recognizing what older adults do daily to improve healthcare and monitor their well-being. Using a dataset called "HAR70+" that shows what older adults do daily, this research used ML and DL techniques to build strong models for predicting these activities. The study used models like KNN, LR, NB, RF, SGD, XGBoost, and LSTM, which all showed good results. Across three tries, the models showed different accuracy, F1 scores, recall, and precision. Based on the results, the LSTM model performed the best, with an average accuracy of 0.9861. In sum, this study shows that training ML and DL models to understand what older adults do is important, as it can help improve their healthcare and support. Hence, more work is needed, but this study shows that ML and DL can make a big difference in older adults' lives. This study can be expanded and improved in various ways. Firstly, including a more diverse group of older adults from different backgrounds and locations could make the model better understand daily routines. Likewise, Collecting data on more activities that older adults commonly do, such as cooking, cleaning, and leisure, could provide a more complete picture of their daily lives. Additionally, wearable technology with better sensors, like accelerometers and gyroscopes, could provide richer data for recognizing activities. Trying out another machine, deep, and reinforcement learning methods helps build more models that recognize complex patterns in what older adults do.

REFERENCES

[1] R. Owen, K. Berry, and L. J. E. Brown, "Enhancing older Adults' well-being and quality of life through purposeful activity: A systematic review of intervention studies," *Gerontologist*, vol. 62, no. 6, pp. e317–e327, Jul. 2022.

[2] K. M. Mathieson, J. J. Kronenfeld, and V. M. Keith, "Maintaining functional independence in elderly adults: The roles of health status and financial resources in predicting home modifications and use of mobility equipment," *Gerontologist*, vol. 42, no. 1, pp. 24–31, 2002.

[3] K. F. Reid and R. A. Fielding, "Skeletal muscle power: A critical determinant of physical functioning in older adults," *Exercise Sport Sci. Rev.*, vol. 40, no. 1, pp. 4–12, 2012.

[4] J. Angulo, M. El Assar, A. Álvarez-Bustos, and L. Rodríguez-Mañas, "Physical activity and exercise: Strategies to manage frailty," *Redox Biol.*, vol. 35, Aug. 2020, Art. no. 101513.

[5] A. Beswick, R. Gooberman-Hill, A. Smith, V. Wylde, and S. Ebrahim, "Maintaining independence in older people," *Rev. Clin. Gerontol.*, vol. 20, no. 2, pp. 128–153, May 2010.

[6] A. Hayat, F. Morgado-Dias, B. Bhuyan, and R. Tomar, "Human activity recognition for elderly people using machine and deep learning approaches," *Information*, vol. 13, no. 6, p. 275, May 2022.

[7] W. W. Hoeger, S. A. Hoeger, C. I. Hoeger, and A. L. Fawson, *Lifetime Physical Fitness and Wellness*. Boston, MA, USA: Cengage Learning, 2018.

[8] G. Dhiman, A. V. Kumar, R. Nirmalan, S. Sujitha, K. Srihari, N. Yuvaraj, P. Arulprakash, and R. A. Raja, "Multi-modal active learning with deep reinforcement learning for target feature extraction in multi-media image processing applications," *Multimedia Tools Appl.*, vol. 82, no. 4, pp. 5343–5367, Feb. 2023.

[9] K. T. Chui, B. B. Gupta, M. Torres-Ruiz, V. Arya, W. Alhalabi, and I. F. Zamzami, "A convolutional neural network-based feature extraction and weighted twin support vector machine algorithm for context-aware human activity recognition," *Electronics*, vol. 12, no. 8, p. 1915, Apr. 2023.

[10] R. Monarch and R. Munro, *Human-in-the-Loop Machine Learning: Active Learning and Annotation for Human-Centered AI*. New York, NY, USA: Simon and Schuster, 2021.

[11] A. Hamza, U. Hayat, W. Hussain, and A. Mumtaz, "Machine learning based classification of crystal system using rendered images from X-ray diffraction (XRD) dataset," in *Proc. 3rd Int. Conf. Artif. Intell. (ICAI)*, Feb. 2023, pp. 64–69.

[12] A. Sauer, R. B. Gramacy, and D. Higdon, "Active learning for deep Gaussian process surrogates," *Technometrics*, vol. 65, no. 1, pp. 4–18, Jan. 2023.

[13] Y. Wei, Y. Lil, M. Xu, Y. Hua, Y. Gong, K. Osawa, and E. Tanaka, "A real-time and two-dimensional emotion recognition system based on EEG and HRV using machine learning," in *Proc. IEEE/SICE Int. Symp. Syst. Integr. (SII)*, Jan. 2023, pp. 1–6.

[14] M. J. Aartsen, C. H. M. Smits, T. van Tilburg, K. C. P. M. Knipscheer, and D. J. H. Deeg, "Activity in older adults: Cause or consequence of cognitive functioning? A longitudinal study on everyday activities and cognitive performance in older adults," *J. Gerontol. Ser. B, Psychol. Sci. Social Sci.*, vol. 57, no. 2, pp. P153–P162, Mar. 2002.

[15] C. Röcke, M. Luo, P. Bereuter, M. Katana, M. Fillekes, V. Gehriger, A. Sofios, M. Martin, and R. Weibel, "Charting everyday activities in later life: Study protocol of the mobility, activity, and social interactions study (MOASIS)," *Frontiers Psychol.*, vol. 13, Jan. 2023, Art. no. 1011177.

[16] A. Moradell, J. A. Casajús, L. A. Moreno, G. Vicente-Rodríguez, and A. Gómez-Cabello, "Effects of diet—Exercise interaction on human health across a lifespan," *Nutrients*, vol. 15, no. 11, p. 2520, 2023.

[17] Y. Kaya and E. K. Topuz, "Human activity recognition from multiple sensors data using deep CNNs," *Multimedia Tools Appl.*, vol. 83, no. 4, pp. 10815–10838, Jan. 2024.

[18] L. Calisti and E. Lattanzi, "Real-time energy-efficient sensor libraries for wearable devices," in *PREPRINT (Version 1) Available at Research Square*, 2023, doi: 10.21203/rs.3.rs-3288932/v1.

[19] W. Taylor, S. A. Shah, K. Dashtipour, A. Zahid, Q. H. Abbasi, and M. A. Imran, "An intelligent non-invasive real-time human activity recognition system for next-generation healthcare," *Sensors*, vol. 20, no. 9, p. 2653, May 2020.

[20] R. Ganesan and Y. BevishJinila, "Sensor-based fog-cloud integrated human fall detection system using regression-based gait pattern recognition," *Research Square*, to be published.

[21] M. K. MacLean, R. Z. U. Rehman, N. Kerse, L. Taylor, L. Rochester, and S. Del Din, "Walking bout detection for people living in long residential care: A computationally efficient algorithm for a 3-axis accelerometer on the lower back," *Sensors*, vol. 23, no. 21, p. 8973, Nov. 2023.

[22] H. Shahverdi, M. Nabati, P. F. Moshiri, R. Asvadi, and S. A. Ghorashi, "Enhancing CSI-based human activity recognition by edge detection techniques," *Information*, vol. 14, no. 7, p. 404, Jul. 2023.

[23] D. R. Beddiar, B. Nini, M. Sabokrou, and A. Hadid, "Vision-based human activity recognition: A survey," *Multimedia Tools Appl.*, vol. 79, nos. 41–42, pp. 30509–30555, Nov. 2020.

[24] A. G. D'Sa and B. G. Prasad, "A survey on vision based activity recognition, its applications and challenges," in *Proc. 2nd Int. Conf. Adv. Comput. Commun. Paradigms (ICACCP)*, Feb. 2019, pp. 1–8.

[25] K. Xia, J. Huang, and H. Wang, "LSTM-CNN architecture for human activity recognition," *IEEE Access*, vol. 8, pp. 56855–56866, 2020.

[26] G. S. S. Lin, W.-W. Tan, H.-J. Tan, C.-W. Khoo, and K. I. Afrashtehfar, ''Innovative pedagogical strategies in health professions education: Active learning in dental materials science,'' *Int. J. Environ. Res. Public Health*, vol. 20, no. 3, p. 2041, Jan. 2023.

[27] U. Ahmed, J. C.-W. Lin, and G. Srivastava, ''Deep hierarchical attention active learning for mental disorder unlabeled data in AIoMT,'' *ACM Trans. Sensor Netw.*, vol. 19, no. 3, pp. 1–18, Aug. 2023.

[28] A. O. Jimale and M. H. M. Noor, ''Subject variability in sensor-based activity recognition,'' *J. Ambient Intell. Humanized Comput.*, vol. 14, no. 4, pp. 3261–3274, Apr. 2023.

[29] A. Snoun, T. Bouchrika, and O. Jemai, ''Deep-learning-based human activity recognition for Alzheimer's patients' daily life activities assistance,'' *Neural Comput. Appl.*, vol. 35, no. 2, pp. 1777–1802, Jan. 2023.

[30] A. Ustad, A. Logacjov, S. Ø. Trollebø, P. Thingstad, B. Vereijken, K. Bach, and N. S. Maroni, ''Validation of an activity type recognition model classifying daily physical behavior in older adults: The HAR70+ model,'' *Sensors*, vol. 23, no. 5, p. 2368, Feb. 2023.

[31] Z. Xiong, Y. Cui, Z. Liu, Y. Zhao, M. Hu, and J. Hu, ''Evaluating explorative prediction power of machine learning algorithms for materials discovery using k-fold forward cross-validation,'' *Comput. Mater. Sci.*, vol. 171, Jan. 2020, Art. no. 109203.

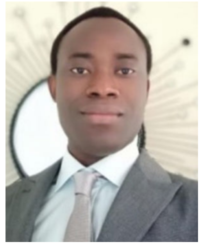
[32] M. Sokolova, N. Japkowicz, and S. Szpakowicz, ''Beyond accuracy, F-score and ROC: A family of discriminant measures for performance evaluation,'' in *Proc. Australas. Joint Conf. Artif. Intell.* Hobart, TS, Australia: Springer, Dec. 2006, pp. 1015–1021, 2006.

[33] K. Hajian-Tilaki, ''Receiver operating characteristic (ROC) curve analysis for medical diagnostic test evaluation,'' *Caspian J. Internal Med.*, vol. 4, no. 2, p. 627, 2013.

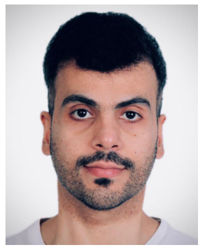
SIDRA ABBAS (Graduate Student Member, IEEE) received the B.S. degree from the Department of Computer Science, COMSATS University, Islamabad, Pakistan. Her research interests include computer forensics, machine learning, criminal profiling, software watermarking, intelligent systems, and data privacy protection.

GABRIEL AVELINO SAMPEDRO (Member, IEEE) is currently with the Faculty of Information and Communication Studies, University of the Philippines Open University, Laguna, Calabarzon, Philippines. His current research interests include the Internet of Things and artificial intelligence.

SHTWAI ALSUBAI is currently an Assistant Professor of computer science with Prince Sattam bin Abdulaziz University. His research interests include model-driven development for emerging technologies, big data processing and analytics, and graph transformation theory and its applications in machine learning and AI.



STEPHEN OJO (Member, IEEE) received the B.Sc. degree (Hons.) in electrical and electronics engineering from The Federal University of Technology Akure, Nigeria, in 2014, and the M.Sc. and Ph.D. degrees in information systems degree from Girne American University, Cyprus, in 2017 and 2021, respectively. He is currently an Assistant Professor with the Department of Electrical and Computer Engineering, College of Engineering, Anderson University, Anderson, SC, USA. Before Joining Anderson University, he was a Lecturer with Girne American University, Cyprus, where he taught courses in distributed computing, advanced programming, and electric circuits. He was also a Research Scholar with Vodafone Telecommunication Company, Cyprus, where he developed a multiplicative based model for signal propagation in wireless networks. He is a full-time Faculty Member with Anderson University, where he teaches computer programming, electric circuits, machine learning, artificial intelligence in wireless mobile networks, and biomedical applications. He has authored and coauthored several peer-reviewed journals. His research interests include wireless networks, machine learning for wireless mobile networks, machine learning, and AI in biomedical devices. He was awarded the Mobil and Full Ph.D. Scholarships throughout the bachelor's program.



AHMAD S. ALMADHOR received the B.S.E. degree in computer science from Aljouf University (formerly Aljouf College), Aljouf, Saudi Arabia, in 2005, the M.E. degree in computer science and engineering from the University of South Carolina, Columbia, SC, USA, in 2010, and the Ph.D. degree in electrical and computer engineering from the University of Denver, Denver, CO, USA, in 2019. From 2006 to 2008, he was a Teaching Assistant and the College of Sciences Manager with Aljouf University, where he was a Lecturer, from 2011 to 2012. Then, he became a Senior Graduate Assistant and a Tutor Advisor with the University of Denver, in 2013 and 2019, respectively. He is currently an Assistant Professor of CEN and VD with the Computer and Information Science College, Jouf University, Saudi Arabia. His research interests include AI, blockchain, networks, smart and microgrid cyber security, and integration, image processing, video surveillance systems, PV, EV, machine, and deep learning. His awards and honors include Aljouf University Scholarship (Royal Embassy of Saudi Arabia in D.C.), Aljouf's Governor Award for Excellency, and others.

ABDULLAH AL HEJAILI received the bachelor's degree in computer science from Tabuk Teachers College, Saudi Arabia, in 2007, and the master's degree in computer science from CLU, USA, in 2011. He is currently pursuing the Ph.D. degree with the Informatics School, University of Sussex. He is a Lecturer of computer science with the University of Tabuk. His research interests include technology-enhanced learning, image processing, virtual, augmented reality, motion capture, and education applications.

LUBOMIRA STRAZOVSKA is currently a Docent with the Department of Economics and Finance, Faculty of Management, Comenius University Bratislava. She studied at the Faculty of Philosophy, Comenius University Bratislava, and the Faculty of Business, University of Economics in Bratislava. She has long been devoted to management and artificial intelligence in research and publishing activities. At the same time, she also conducts a final thesis on these topics. She was the author of the first monograph on family business in Slovakia. She is the author of many valuable scientific outputs on the mentioned topics. In publishing, she is the author and coauthor of several university textbooks and texts and professional articles focused on the economic activity of small and medium-sized enterprises.