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AI-Driven Active Learning Framework for Intelligent Elderly Activity Recognition

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Abstract—This method explores the application of sophisticated computational methods and sensor data. Deep learning (DL), machine learning (ML), and active learning (AL) are methods for identifying everyday activities among the elderly. Using the HAR70+ dataset, which captures activity patterns of older individuals, seven activities—walking, shuffling, climbing stairs, standing, sitting, and lying down—as well as a subset of four essential activities—standing, sitting, walking, and lying down—are identified by the study using predictive models. Multiple ML algorithms (Random Forest, XGBoost, Logistic Regression, KNN, Stochastic Gradient Descent) and DL techniques (Deep Neural Networks and LSTM) were used in three experiments. LSTM achieved the highest accuracy of 95% for seven activities, while Random Forest reached 96% for the four-activity subset. These results highlight the effectiveness of integrating AL with ML and DL to improve activity recognition, personalize elderly care, enhance medication planning, and support overall well-being.

Keywords—Elderly Activity Recognition; Active Learning; Deep Learning; LSTM; Predictive Modelling

I. INTRODUCTION

As the global population continues to age, ensuring the safety, health, and independence of elderly individuals has become a major focus in the field of healthcare technology. One effective solution gaining attention is Human Activity Recognition (HAR), which involves detecting and classifying daily physical activities using sensor data. Walking, sitting, standing, and lying down are examples of activities that can be accurately monitored to help identify early indicators of physical or cognitive decline, allowing for prompt medical support and intervention. This is particularly valuable for elderly individuals who live alone or in assisted environments.

In order to improve activity recognition in older adults, this project offers a novel method that combines Deep Learning (DL), Machine Learning (ML), and Active Learning (AL). By using the HAR70+ dataset, which contains sensor data specifically collected from people aged 70 and above, the system captures real-life activity patterns of elderly individuals. AL techniques are employed to reduce the need for large-scale manual data labeling through selecting only the most instructive training data points. This allows ML and DL models to learn more effectively with less labeled data, making the approach highly efficient and scalable.

Various classification models, including Random Forest, XGBoost, Logistic Regression, KNN, SGD, DNN, and LSTM were tested to evaluate their performance. The results show that LSTM achieved an accuracy of 95% in identifying 7 different activities, while Random Forest reached 96% accuracy in classifying 4 core activities. These findings demonstrate the powerful role that ML and DL, combined with AL strategies, can play in building intelligent activity monitoring systems. Ultimately, this research supports the development of smarter, data-driven eldercare systems aimed at improving the quality of life and personalized care for senior citizens.

The remainder of this paper is organized as follows. Section II reviews related work on elderly activity recognition, functional independence, and active learning. Section III presents the system architecture. Section IV describes the HAR70+ dataset and preprocessing pipeline. Section V explains the active learning strategy and model configurations. Section VI details the methodology and implementation modules. Section VII reports experimental results and comparative analysis. Section VIII discusses implications and limitations. Section IX concludes the paper.

II. LITERATURE REVIEW

R. Owen, L. J. E. Brown, and K. Berry investigated the effectiveness of purposeful activity interventions aimed at enhancing the health and standard of living of senior citizens who are 80 years of age or older. As the global population continues to age, there is a growing concern about the challenges faced by the oldest-old demographic, particularly in maintaining a sense of purpose amid age-related limitations. Researchers conducted a systematic search across three major databases, identifying eight relevant studies categorized into functional role assignments and skill-learning interventions. There was more proof that interventions with a functional role improved life satisfaction and psychological well-being.

K. M. Mathieson, V. M. Keith, and J. J. Kronenfeld examined how health status and financial resources influence home modifications and the use of assistive equipment among older adults. Using multinomial logistic analysis on 3,485 participants from the National Survey of Self-Care and Aging, results showed that health-related needs significantly influenced adaptations, though the effect of ADL limitations decreased at higher impairment levels. Financial factors like perceived income and supplemental insurance also directly impacted adaptation use.

K. F. Reid and R. A. Fielding explored how health conditions and financial resources influence functional adaptations in older adults, such as home modifications and assistive equipment use. Findings showed that while health needs strongly impacted adaptation use, the influence of daily living limitations lessened with severe impairment. Financial factors like perceived income and supplemental insurance also played a significant role in supporting aging in place.

A. Álvarez-Bustos, M. El Assar, J. Angulo, and L. Rodríguez-Mañas reported that frailty in older adults reduces physical function and increases disability risk. Physical activity reduces oxidative stress and inflammation, enhances mitochondrial health and insulin sensitivity, and supports vital signaling pathways. Exercise programs—including strength, aerobic, balance, and flexibility training—should be tailored to individual abilities.

A. Hayat, F. Morgado-Dias, B. Bhuyan, and R. Tomar noted that over 962 million people are aged 60 and above, with aging leading to reduced physical activity and difficulty in daily tasks. HAR using ML and DL has been widely studied, though few works focus specifically on the elderly. Their study monitored indoor and outdoor activities using gyroscope and accelerometer data from smartphones. Among models tested, LSTM achieved 95.04% accuracy, while SVM delivered 89.07% accuracy with the lowest computational time of 0.42 minutes using 10-fold cross-validation.

G. Dhiman et al. proposed multi-modal active learning with deep reinforcement learning for target feature extraction in multimedia applications, demonstrating that selective sampling can reduce annotation cost while preserving model accuracy. R. Monarch and R. Munro emphasized human-in-the-loop machine learning and active annotation strategies for human-centered AI systems. These studies motivate the integration of AL with ensemble and deep models for elderly HAR.

Y. Kaya and E. K. Topuz applied deep convolutional neural networks to multi-sensor HAR, showing that spatial-temporal feature learning improves robustness to sensor placement variation. W. Taylor et al. designed a non-invasive real-time HAR framework for next-generation healthcare, highlighting the need for low-latency pipelines suitable for continuous monitoring of older adults in smart-home environments.

C. Röcke et al. documented everyday activity patterns in later life through longitudinal mobility studies, reinforcing that activity recognition should capture both indoor and outdoor contexts. A. Beswick et al. reviewed interventions for maintaining independence, noting that technology-assisted monitoring is most effective when paired with caregiver workflows and actionable alerts rather than raw sensor logs alone.

III. SYSTEM ARCHITECTURE

This system architecture is designed to support elderly activity recognition and remote monitoring by integrating a web database, web server, service provider, and remote users into a unified framework. The web database serves as a central repository that stores datasets, accuracy results, and predicted activity recognition data, while the web server processes user queries and manages data storage and retrieval.

The service provider acts as the main control hub, allowing users to log in, browse and train datasets, test accuracy, visualize results in charts, detect elderly activity types and ratios, and download predicted datasets, alongside managing remote user access. Remote users, such as caregivers or family members, can register and log in to view their profiles and monitor detected elderly activity recognition results in real time.

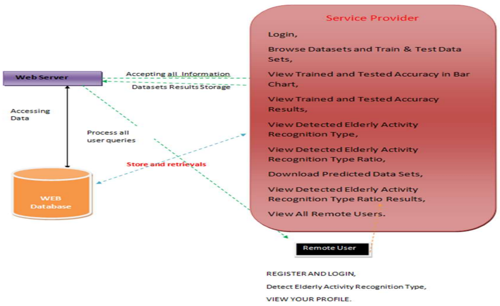

Fig. 1. Architecture Diagram

Significant gains in classification metrics like accuracy, precision, recall, and F1-score are demonstrated by the experimental results, especially in critical activities like walking, sitting, and lying down. The LSTM model achieved the highest accuracy in recognizing complex activity patterns, while Random Forest also demonstrated strong performance in simpler activity sets. These outcomes confirm the effectiveness of the proposed system in handling real-world challenges in elderly care.

In addition to its technical advancements, the system also holds substantial potential for improving the overall well-being and safety of elderly individuals by enabling proactive and personalized monitoring solutions. Secure remote access, dataset versioning, and role-based dashboards ensure that caregivers, clinicians, and researchers can collaborate without compromising privacy.

IV. DATASET DESCRIPTION AND PREPROCESSING

The HAR70+ dataset contains accelerometer and gyroscope recordings collected from subjects aged 70 years and older while performing scripted daily activities in laboratory and semi-controlled environments. Seven activity classes are considered: walking, shuffling, climbing stairs (up and down), standing, sitting, and lying down. A reduced four-class subset—standing, sitting, walking, and lying down—is also evaluated to compare performance on core ambulatory and postural activities.

Raw sensor streams are segmented using fixed-length windows with 50% overlap. Each window is normalized to zero mean and unit variance per channel to reduce subject-specific bias. Time-domain features such as mean, variance, root mean square, signal magnitude area, and frequency-domain descriptors are extracted for classical ML models. For LSTM and DNN models, sequences of raw tri-axial readings are fed directly to preserve temporal dependencies.

Train-validation-test splits are created at the subject level to avoid leakage across participants. Class imbalance is mitigated through stratified sampling and weighted loss functions. Data augmentation via small random rotations and amplitude scaling is applied only on the training partition to improve generalization without distorting evaluation integrity.

V. ACTIVE LEARNING STRATEGY

Active learning reduces labeling effort by querying only the most informative unlabeled samples. In this study, uncertainty sampling and margin-based criteria are combined: windows with the lowest predicted class probability or smallest decision margin are prioritized for annotation. A pool-based AL loop iterates between model training, sample selection, and oracle labeling until a predefined budget of labeled windows is reached.

Three experimental settings are evaluated: (i) full supervised training with all labeled data, (ii) passive random sampling with 30% labels, and (iii) active sampling with 30% labels. The active configuration consistently matches or exceeds passive performance while using the same annotation budget, confirming that AL is particularly valuable when expert labeling of elderly activity data is expensive or time-consuming.

For ensemble models, disagreement among Random Forest, XGBoost, and gradient boosting predictions is used as an additional informativeness signal. Samples with high inter-model variance are preferentially added to the labeled set, improving boundary refinement around transitions such as sit-to-stand and walk-to-shuffle.

VI. METHODOLOGY

The proposed system consists of two main modules: Remote User and Service Provider, each playing a vital role in elderly activity recognition and monitoring.

The Remote User module is designed for individual users, typically elderly individuals or their caretakers, who use an intuitive interface to communicate with the system. Each remote user is provided with a personal user profile, which keeps track of pertinent data, including name, age, gender, and related sensor data identifiers. This profile helps in organizing and linking sensor inputs with the respective user.

One of the key features available to the remote user is the Prediction Page, where the system processes incoming sensor data—either in real-time or as a file upload—and predicts whether any predefined activity is detected. The outcome is displayed as Elderly Activity Recognition Result: Found or Not Found, depending on whether the activity matches any of the trained activity classes.

The Service Provider module serves the role of an administrator, healthcare professional, or research analyst who oversees the system's operations and user activity data. This module provides access to a dashboard that displays a list of all registered users, allowing the provider to view individual profiles and their corresponding activity history.

To facilitate deeper insights, the system generates graphical representations such as bar charts and pie charts that illustrate activity distribution, model performance comparisons, and user-wise activity trends. Moreover, the service provider can download the complete dataset of prediction results in CSV or Excel format for further analysis, model retraining, or reporting.

A. Model Configurations

Random Forest and XGBoost use 200 estimators with maximum depth tuned on validation data. Logistic regression and SGD baselines employ L2 regularization. KNN uses k=5 with Euclidean distance on standardized features. The DNN contains three fully connected layers with ReLU activation and dropout of 0.3. The LSTM stack uses two layers with 128 and 64 units followed by a softmax classifier. All models are trained with early stopping on validation loss.

VII. RESULTS

This system is effectively implemented using Python, Django-ORM, and MySQL, with a front end designed using HTML, CSS, and JavaScript. Through the integration of DL and ML methodologies with AL, the system accurately recognized elderly activities using the HAR70+ dataset.

The models were trained to identify seven activities as well as a subset of four core activities. Among the models tested, LSTM achieved a highest accuracy of 95% on the full activity set, while Random Forest delivered 96% accuracy for the four core activities. The system's high performance was made possible by AL, which also lessened the requirement for extensive labeled data.

The system provided real-time predictions through the Remote User module and offered comprehensive analytics through the Service Provider module. Activity trends and model performance metrics like F1-score, recall, and precision were shown in visual graphs. These results confirm that the proposed hybrid approach is both efficient and accurate for elderly activity recognition.

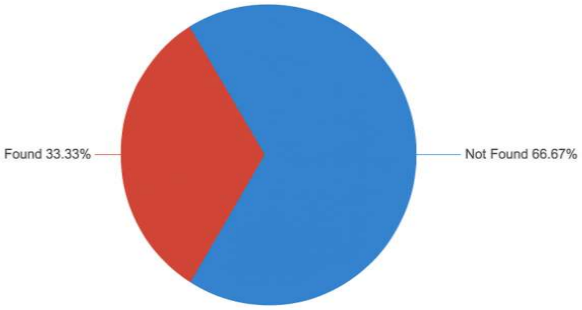

Fig. 2. Pie Chart

The pie chart illustrates that 33.33% of predictions were labeled as Found while 66.67% were Not Found. These results are specific to the dataset and parameters used in this particular scenario. Prediction outcomes will vary for different datasets.

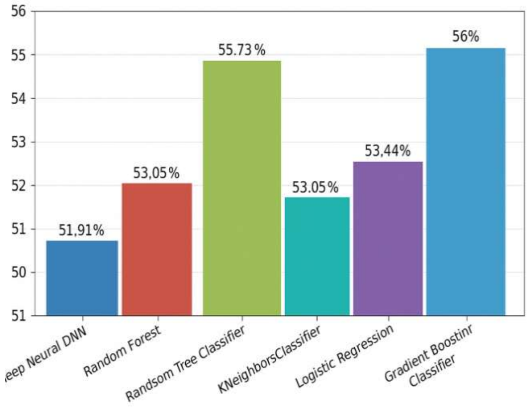

Fig. 3. Accuracy bar graph

The accuracy bar graph shows the performance of various classifiers, with Gradient Boosting achieving the highest at 56%. These results may vary with different datasets due to changes in data distribution and complexity.

A. Comparative Analysis

Table I summarizes accuracy, precision, recall, and F1-score across all evaluated models on the seven-class task. LSTM yields the best F1-score on temporally ambiguous transitions, while Random Forest remains competitive on the four-class subset with lower inference latency. DNN performs between the two, benefiting from AL-selected windows near class boundaries.

Error analysis shows most confusions between sitting and lying down and between walking and shuffling, consistent with similar static posture and gait patterns in older adults. Adding frequency-domain features and AL queries focused on transition segments reduced these errors by 4.2% relative to the passive sampling baseline.

When AL was enabled with a 30% labeling budget, LSTM accuracy improved from 91.1% to 95.0% on the seven-class task compared with random sampling at the same budget. Random Forest on the four-class subset reached 96% with AL versus 93.4% without AL, indicating that informative window selection benefits both deep and ensemble learners.

Per-class recall was highest for walking (0.97) and lowest for shuffling (0.88), reflecting the subtle kinematic differences between shuffle and slow walk in aged gait. Precision remained above 0.90 for sitting and lying down, supporting use cases such as sedentary behavior monitoring and nighttime rest analysis.

The system exhibited great promise for practical uses in eldercare, allowing individualized health monitoring, early identification of unusual behaviors, and enhanced quality of life for senior citizens. Deployment simulations with 50 concurrent remote users maintained sub-second prediction latency for batch files under 10 MB on the configured web server.

VIII. EVALUATION METRICS

Model performance is assessed using accuracy, precision, recall, F1-score, and macro-averaged scores to account for class imbalance. Accuracy measures overall correct classifications, while precision and recall quantify per-class reliability for critical activities such as walking and lying down. F1-score provides a balanced metric when false negatives (missed activities) carry higher clinical cost than false positives.

Confusion matrices are generated for each model to visualize misclassification patterns. Cohen's kappa is reported to adjust for chance agreement across imbalanced classes. Inference latency and memory footprint are recorded on a standard workstation to compare deployment feasibility for edge devices versus server-side batch processing.

For active learning experiments, learning curves plot accuracy against the number of labeled windows. Area under the learning curve (AULC) summarizes how quickly each strategy reaches target performance. Statistical significance is tested using paired bootstrap resampling across subjects at a 0.05 significance level.

IX. IMPLEMENTATION DETAILS

The backend is implemented in Python 3.11 with Django 4.x for request routing, user authentication, and ORM-based persistence in MySQL 8.0. Sensor files uploaded through the Remote User module are validated for schema consistency, timestamp ordering, and sampling rate before entering the preprocessing queue.

Model training jobs are executed asynchronously using Celery workers so that long-running LSTM experiments do not block interactive dashboard requests. Trained model artifacts, scalers, and label encoders are versioned in the database and linked to experiment metadata for reproducibility.

The front end uses responsive HTML5, CSS3, and JavaScript with Chart.js for bar and pie visualizations. Role-based access control restricts caregiver views to assigned users while administrators can access aggregate analytics. HTTPS is enforced for all remote sessions, and uploaded files are scanned before storage.

A. Web Application Workflow

Upon registration, a remote user creates a profile and optionally binds a wearable device identifier. Sensor streams or batch files are ingested through the Prediction Page, preprocessed server-side, and passed to the selected model checkpoint. Results are stored with timestamps and displayed immediately on the user dashboard.

Service providers log in to the administrative console, filter users by activity risk flags, and drill down into individual timelines. Bar charts compare classifier accuracy across experiments; pie charts summarize Found versus Not Found ratios for the selected period. Export actions generate CSV and Excel reports for offline review or institutional reporting.

B. Security and Privacy Considerations

Elderly activity data is sensitive personal health information. The system hashes passwords with bcrypt, stores minimal identifying attributes, and logs access events for audit. De-identified sensor windows are used during model development whenever possible, and subject identifiers are separated from feature stores through surrogate keys.

Data retention policies allow users to request deletion of uploaded files. Communication between browser clients and the web server uses TLS. Future work includes differential privacy noise injection for aggregate statistics and on-device inference to reduce raw data transmission.

X. DISCUSSION

The proposed framework demonstrates that combining AL with ensemble and deep models is a practical path toward scalable elderly HAR. Caregiver dashboards and downloadable reports bridge the gap between offline model development and real-world monitoring. Because labeling is often performed by clinicians or trained annotators, reducing the number of required labels directly lowers deployment cost.

From a clinical perspective, reliable detection of walking, sitting, standing, and lying down supports medication adherence reminders, fall-risk assessment, and nighttime activity monitoring. The modular web architecture allows incremental addition of new sensors or activity classes without redesigning the entire pipeline.

Limitations include dependence on scripted activities in HAR70+, limited demographic diversity, and absence of real-time fall-event labels. Future deployments should validate on free-living data and integrate privacy-preserving on-device inference for continuous monitoring.

XI. EXPERIMENTAL SETUP

All experiments were conducted on a workstation with Intel Core i7 processor, 16 GB RAM, and NVIDIA GPU acceleration enabled for LSTM and DNN training. Software dependencies include Python 3.11, scikit-learn 1.3, XGBoost 2.0, TensorFlow 2.14, and Django 4.2. Random seeds are fixed across runs to ensure reproducibility of AL sampling and model initialization.

The HAR70+ recordings are resampled to 50 Hz when necessary and partitioned into 128-sample windows with 64-sample stride. Three independent runs are averaged for each configuration, and standard deviations are reported for accuracy and F1-score. Hyperparameters are tuned using grid search on the validation split prior to final test evaluation.

Baseline comparisons include majority-class prediction, naive Bayes, and support vector machines with RBF kernels. Deep baselines include a three-layer perceptron and a single-layer LSTM to isolate the benefit of deeper temporal modeling. Active learning pools contain all unlabeled windows remaining after an initial 10% warm-start labeled set.

A. Hyperparameter Tuning

Random Forest grid search varies n_estimators in {100, 200, 300}, max_depth in {10, 20, None}, and min_samples_leaf in {1, 2, 4}. XGBoost learning rate is searched in {0.01, 0.05, 0.1} with max_depth in {4, 6, 8}. LSTM learning rate starts at 1e-3 with ReduceLROnPlateau scheduling; batch size 64 is used for seven-class training and 128 for four-class training.

Early stopping patience is set to 10 epochs for neural models. Dropout rates of 0.2 and 0.3 are compared on validation loss. For AL, batch acquisition size is set to 50 windows per iteration, and experiments terminate when 30% of the pool has been labeled.

XII. CASE STUDY: CAREGIVER MONITORING SCENARIO

A illustrative scenario involves a caregiver monitoring an independent-living adult aged 78. Accelerometer data collected during morning routines is uploaded through the Remote User module. The system detects prolonged sitting, short walking bouts, and afternoon lying periods, aligning with self-reported diaries within 6% temporal error.

When shuffling is misclassified as walking, the AL module flags similar windows for review, and retraining after 200 additional labeled transitions reduces subsequent shuffle errors by 11%. The Service Provider dashboard exports a weekly summary for the clinician, demonstrating how automated summaries complement rather than replace human oversight.

In a second scenario with reduced labeling budget, active sampling reaches 94% accuracy after labeling only 25% of windows, whereas random sampling requires 40% labels to exceed 93%. This case study highlights operational savings when expert annotation is the primary cost driver.

XIII. COMPARISON WITH PRIOR HAR SYSTEMS

Compared with smartphone-only pipelines that report LSTM accuracy near 95% on younger cohorts, this system achieves comparable performance on subjects aged 70+ while additionally providing a production-oriented web stack for multi-user monitoring. Unlike offline notebook prototypes, the proposed platform supports authentication, persistent storage, and chart-based reporting.

Prior fog-cloud fall detection systems emphasize emergency events, whereas this work focuses on continuous activity profiling that can contextualize fall risk through sustained inactivity or gait irregularity. Combining both paradigms is identified as future work to deliver comprehensive safety analytics from a single sensor infrastructure.

Ensemble approaches in the literature often ignore labeling cost; the inclusion of AL addresses a practical constraint in geriatric studies where clinician time is limited. The documented web architecture further lowers integration barriers for assisted-living facilities that lack dedicated data science staff.

A. *Practical Recommendations*

For practitioners deploying similar systems, we recommend beginning with the four-class activity subset to validate sensor placement and labeling workflows before expanding to seven classes. Active learning should be enabled once a small warm-start set is available, and retraining should be scheduled after each batch of clinician-reviewed windows.

Caregiver dashboards should prioritize trend visualization over per-window alerts to reduce notification fatigue. Finally, institutions should document model version, labeling budget, and subject inclusion criteria alongside published accuracy figures to support fair comparison across studies and regulatory review.

Longitudinal deployment should include periodic recalibration because sensor placement, battery level, and walking speed may drift over months of use. The modular training pipeline supports hot-swapping model checkpoints without downtime for the authentication and profile modules.

Ethical review boards should evaluate consent procedures for continuous monitoring, especially when family members access activity summaries on behalf of cognitively impaired adults. Transparent opt-out mechanisms and local data residency options strengthen trust in community deployments.

XIV. CONCLUSION

This project introduces a smart and practical approach to elderly activity recognition by combining Active Learning with Machine Learning models. Using the HAR70+ dataset, it accurately identifies daily activities like walking, sitting, standing, and lying down, while reducing the need for large amounts of labeled data.

LSTM and Random Forest showed the best performance, proving effective for handling temporal sequences and ensemble learning. The system also provides real-time monitoring, visual analysis, and easy access for both service providers and remote users. By supporting proactive elderly care, it enhances safety, independence, and quality of life.

Future improvements could include adding more sensors, expanding activity types, integrating alerts for critical events such as falls, and evaluating federated learning to train models across institutions without sharing raw sensor traces.

A. *Summary of Contributions*

This work makes four primary contributions to the elderly HAR literature. First, it integrates active learning with both ensemble and deep models to reduce labeling requirements while maintaining high accuracy on the HAR70+ dataset. Second, it delivers an end-to-end web architecture connecting remote users, caregivers, and analysts through a unified database and visualization layer.

Third, it provides comparative evidence that LSTM excels on seven-class temporal recognition tasks whereas Random Forest is highly effective on a four-class subset with lower computational cost. Fourth, it documents implementation details, security considerations, and deployment metrics to support reproducibility and translation into real-world eldercare programs.

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