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RESEARCH ARTICLE

Active Machine Learning for Heterogeneity Activity Recognition Through Smartwatch Sensors

SIDRA ABBAS[1], (Graduate Student Member, IEEE), SHTWAI ALSUBAI[2], MUHAMMAD IBRAR UL HAQUE[3], (Senior Member, IEEE), GABRIEL AVELINO SAMPEDRO[4,5], (Member, IEEE), AHMAD ALMADHOR[6], (Member, IEEE), ABDULLAH AL HEJAILI[7], AND IRYNA IVANOCHKO[8]

[1]Department of Computer Science, COMSATS University Islamabad, Islamabad 44000, Pakistan
[2]College of Computer Engineering and Sciences, Prince Sattam bin Abdulaziz University, Al-Kharj 11942, Saudi Arabia
[3]Electrical Engineering Department, Sir Syed University of Engineering and Technology, Karachi 75300, Pakistan
[4]Faculty of Information and Communication Studies, University of the Philippines Open University, Los Baños 4031, Philippines
[5]Center for Computational Imaging and Visual Innovations, De La Salle University, Malate, Manila 1004, Philippines
[6]Department of Computer Engineering and Networks, College of Computer and Information Sciences, Jouf University, Sakaka 72388, Saudi Arabia
[7]Computer Science Department, Faculty of Computers and Information Technology, University of Tabuk, Tabuk 71491, Saudi Arabia
[8]Faculty of Management, Comenius University Bratislava, 82005 Bratislava, Slovakia

Corresponding authors: Iryna Ivanochko (iryna.ivanochko@fm.uniba.sk) and Sidra Abbas (sidraabbas@ieee.org)

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ABSTRACT Smartwatches with cutting-edge sensors are becoming commonplace in our daily lives. Despite their widespread use, it can be challenging to interpret accelerometer and gyroscope data efficiently for Human Activity Recognition (HAR). This study explores active learning integrated with machine learning, intending to maximize the use of smartwatch technology across a range of applications. The previous research on the HAR lacks promising performance, which could make it difficult to make highly accurate recognition. This paper proposes a novel approach to predict human activity from the Heterogeneity Human Activity Recognition (HHAR) dataset that integrates active learning with machine learning models: Random Forest (RF), Extreme Gradient Boosting (XGBoost), K-nearest Neighbors (KNN), Decision Tree (DT), Gradient Boosting (GB) and Light Gradient Boosting Machine (LGBM) classifier to predict heterogeneous activities accurately. We evaluated our approach to these models on the HHAR dataset that was generated using an accelerometer and gyroscope of smartwatches. The experiments are evaluated on 3 iterations where the results demonstrated that the proposed approach predicts human activities with the highest F1-Score of 99.99%. The results indicate that this approach is the most accurate and effective compared to the conventional approaches and baseline.

INDEX TERMS Active learning, machine learning, smart watch, wristwatch, activity recognition, gyroscope, accelerometer.

I. INTRODUCTION

Heterogeneous Human Activity Recognition (HHAR) provides a thorough understanding of human behavior, which includes analyzing various behaviors using many data modalities, including visual, auditory, and sensor data. In this dynamic industry, integrating active learning approaches becomes essential to support systems' robustness and context awareness. By carefully choosing and labeling data points, active learning helps machine learning models effectively adjust to human behavior's subtleties. The intricacy of combining data from several sources, possible synchronization

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problems, and privacy considerations related to managing various data kinds are obstacles, too. Notwithstanding these difficulties, the field's capacity to provide complex understandings of human behavior emphasizes how critical it is to resolve these problems to apply the solutions in the actual world successfully. This article involves an evolving approach of machine learning called active learning that carefully chooses which data points to label so that the model can determine which examples are the most instructive. In exploring the field of activity recognition using active learning approaches, this article offers a new, iterative method to improve the accuracy and effectiveness of machine learning models.

The pursuit of improving classification accuracy continues to be a crucial problem in the constantly changing field of machine learning [1]. Employing efficient methodologies is essential for creating precise and trustworthy predictive models, given the explosion in the amount of data available and the complexity of real-world situations. Active learning, which selects the most useful data points iteratively, can greatly enhance model performance [2]. This article explores a detailed study that aims to improve classification accuracy by utilizing active learning techniques and thorough model comparisons. Smartwatches are developing into personalized health companions that offer real-time biometric data analysis and health trend tracking in addition to their sensor capabilities [3]. They conveniently interact with smartphone apps, enabling users to set wellness objectives, track sleep habits, and get prompt notifications [4]. Additionally, these gadgets promote community among users by encouraging people to participate in social fitness challenges and collectively adopt healthier lifestyles [5]. Our research intends to take advantage of these developments by utilizing the rich data from accelerometers and gyroscopes, improving the accuracy of predictive models and enabling users to make knowledgeable decisions about their daily activities and health.

Smartwatches are less accurate than other monitoring tools like cameras, radar, infrared sensors, etc. Their sensor range is restricted, they rely on line of sight, and their specialized functions are limited. Still, the widespread adoption of smartwatches in our daily lives creates a compelling potential for improving activity prediction and personal health management [6]. Realizing wristwatch technology's full potential is critical since more people rely on these gadgets to track their daily activities, evaluate their fitness, and control health factors [7]. These gadgets are data-rich platforms that can record minute details of human movements and interactions. They include several accelerometers, gyroscopes, and cutting-edge communication protocols like Bluetooth and Wi-Fi [8]. However, the best use of this abundance of data for precise predictive modeling is still a considerable barrier. The urgent need to close this gap between data collection and insightful conclusions serves as the driving force for our research. Our work intends to revolutionize how these devices perceive user actions by examining cutting-edge machine-learning approaches adapted to wristwatch sensor data, providing accurate health predictions and individualized suggestions. By doing this, we enable people to actively manage their health and contribute to continuous developments in wearable technology, paving the way for a healthier and more informed society.

In addition to meeting people's immediate needs, our research advances bigger societal objectives. Preventive healthcare practices and individualized health interventions are becoming more important as the demands on the world's healthcare systems rise [9]. As portable health companions, smartwatches have the potential to be a game-changer in this paradigm shift [10]. These technologies can enable proactive health management, potentially decreasing the strain on healthcare infrastructures and improving the standard of care by precisely forecasting behaviors, finding patterns, and providing timely health recommendations [11]. This drive emphasizes the societal impact of our research, which aims not only to provide individuals with practical knowledge but also to advance the conversation on preventive healthcare practices in a society that is becoming more digitally and globally linked. This paper makes the following contributions.

- This paper significantly advances the field of Human activity recognition using active learning approaches. The main contribution of this research work is a comprehensive evaluation of six popular machine learning algorithms integrated with active learning: RF, XGBoost, DT, GB, KNN, and LGBM. This investigation focuses on the interaction between active learning and several classifiers that aid in selecting the best approach.
- We use cutting-edge active learning to improve activity recognition and uncertainty sampling to improve accuracy. Our method deliberately includes difficult cases and shows a considerable improvement in accuracy over conventional techniques.
- After evaluating the results in 3 iterations, evaluation measures demonstrate that the activity can be predicted with the highest accuracy and F1-score of 99.99%. The final results indicate that our active learning approach is the most effective and accurate; it increases the recognition rate from conventional and state-of-the-art methods.

The article is organized into the following main parts. Section II explains the previous and related work in activity recognition and their advancement. Section III describes the approach used to create better results. Section IV of this paper contains the experimental analysis and results, and the Final section V concludes the article and provides future work.

II. LITERATURE REVIEW

Authors in [12] proposed a unique and portable deep learning framework for HHAR in sophisticated Internet of Things applications. The framework addresses issues with HHAR, including the variety of sensors, the complexity of human actions, and the constrained computing power of IoT devices. The Hierarchical Multiscale Extraction (HME) module employs a collection of residually connected Shuffle Group Convolutions (SG-Convs) that extract and learn picture representation from various receptive fields. As a result, the framework can extract local and global properties from the sensor data. Meanwhile, the ISCA module concentrates on the most informative features, so the framework's accuracy increases while its computing complexity decreases. The suggested approach beat numerous cutting-edge techniques in terms of accuracy and efficiency. When tested against three publicly available HHAR datasets, the framework attained an average accuracy of 99.5% on the WISDM dataset.

Authors in [13] suggested a new time series data imaging and fusing framework for wearable sensor-based HAR. The framework handles HAR's difficulties, including the large dimensionality of sensor data, the difficulty separating features from time series data, and the requirement for real-time recognition. The sensor data is converted into images by the time series imaging component, making it simpler to do feature extraction and recognition. The framework creates images from the sensor data using a sliding window method. Each image represents a series of sensor readings taken inside the window. The framework does picture fusion and recognition using a deep neural network (DNN), and a labeled collection of sensor data and images is used to train the DNN model. The suggested framework was tested on two publicly available HAR datasets. In terms of accuracy and efficiency, it outperformed various cutting-edge techniques, including Long Short-Term Memory LSTM) networks, Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN) trained on raw sensor data. For instance, the proposed framework attained an average accuracy of 97.0% on the HHAR dataset.

Authors in [14] suggested KU-HAR, an open dataset for HHAR. Its collection included information from 90 users who used their smartphone's accelerometer and gyroscope sensors to conduct 18 different tasks. The exercises included standing, sitting, walking, jogging, jumping, and other indoor and outdoor activities. Participants were asked to complete each exercise for a set period to gather the data, which was gathered at a 100 Hz sampling rate. Raw activity samples and subsamples were used to partition the dataset into two halves. The raw activity samples represented the initial information gathered from the participants. The subsamples with 3 seconds of data for each activity were taken from the raw activity samples. The dataset has 20750 subsamples and a total of 1945 raw activity samples. The dataset is balanced since each activity had an equal number of samples. The dataset has been used to test several HAR algorithms and has been proven to work well for HAR in several contexts. The authors trained an RF classifier on the dataset, and the classifier had a subsample accuracy of 89.7%.

Authors in [15] proposed a deep learning method for Complex Activity Recognition (CAR) using various wearable device sensors. It is an end-to-end model that systematically collects characteristics and learns the sequential details of complex activities, dubbed DEBONAIR (Deep learning-based multimodal complex human activity recognition). Firstly, temporal and spatial features are extracted from the sensor data using RNN and CNN. Then, sensor fusion is used to understand the connections between the various features; it uses a fully connected neural network. A fully connected neural network layer is used to discover the connections between the fused features and the various activity classes. The research authors used two open datasets of complicated activities to evaluate DEBONAIR. On both datasets, the results demonstrated that DEBONAIR outperformed cutting-edge CAR techniques. For instance, DEBONAIR attained an accuracy of 98.7% on the WISDM dataset.

Authors in [16] suggested a change point-based data segmentation integration heterogeneous ensemble strategy for activity recognition, known as HEA-DSeg (Heterogeneous Ensemble Approach with Data Segmentation), to increase the precision and robustness of activity recognition. It combines the strengths of various machine learning techniques with change point detection. The sensor data is divided into various activity segments using a change point detection method, and then the features are extracted from segmented sensor data. After that, an ensemble classification module divides the segmented sensor data into various activity classes by combining the predictions of various machine learning methods. The paper's authors used two open activity recognition datasets to evaluate HEA-DSeg. The outcomes demonstrated that, on both datasets, HEA-DSeg beats cutting-edge activity recognition techniques.

A resource-constrained federated learning (FL) framework for HAR with diverse labels and models was suggested by [17] known as Resource-Constrained FL with Heterogeneous Labels and Models for HAR (RCFLA-HAR). It addresses the difficulties given by statistical and model heterogeneities across users and the constrained resources of mobile devices. The process of distilling transforms the local models of each user into student models while minimizing the size and complexity of the student model; it combines all users' distilled student models into one big model. In this module, the student models are aggregated using a weighted averaging technique, where the relative performance of each student model determines the weights. The authors assessed RCFLA-HAR, and the findings showed that RCFLA-HAR performs better than state-of-the-art FL techniques for HAR, even in contexts with limited resources. RCFLA-HAR, for example, achieved 95.1% accuracy on the HHAR dataset.

Authors in [18] suggested a framework for recognizing HAR using several smartphone sensors known as DailyHAR; it effectively recognizes various daily activities by fusing sensor data with machine learning algorithms. The data from the smartphone's sensor is cleaned and prepared, combined with the preprocessed data from the various sensors. The relevance of each sensor for HAR is considered using a weighted average technique to combine the sensor data. That data is divided into many activity classes of the fused features. It uses machine learning approaches like Support Vector Machines (SVMs) or RFs to categorize the features. The paper's authors used two open datasets of HAR activities to evaluate DailyHAR. On both datasets, the results demonstrated that DailyHAR outperformed cutting-edge HAR techniques. For instance, DailyHAR achieved a 99.2% accuracy rate on the WISDM dataset.

Authors in [19] proposed a new DiamondNet neural network-based architecture for heterogeneous sensor attentive fusion for HAR. DiamondNet greatly enhances HAR performance by utilizing the power of several sensor modalities and attention mechanisms. The feature extraction module derives robust characteristics from each sensor modality by denoising and extracting the most pertinent features. After that, the attention-based GCN creates new heterogeneous multisensor modalities by adaptively utilizing the possible connections between various sensors. The attentive fusion subnet combines a global attention mechanism and shallow features to efficiently calibrate various feature levels across many sensor modalities. This guarantees that all the features are fairly weighted and combined, leading to a more reliable and precise HAR model. Analyzed DiamondNet results using three open HAR datasets. The outcomes demonstrated that DiamondNet beats cutting-edge HAR techniques on all three datasets. For instance, DiamondNet achieved a 99.5% accuracy rate on the WISDM dataset.

Authors in [20] suggested a unique context-aware HAR heterogeneous hyper-graph neural network (HHGNN) model. The HHGNN model can use contextual information from sensor data, user profiles, and social network data to increase HAR accuracy. There are two primary parts to the HHGNN model: a heterogeneous hyper-graph neural network and a feature extraction module. A dataset of HAR actions with labels trains the HHGNN model. The association between the features from various data sources and the user's behavior is taught to the model during training. After training, the model can forecast user behavior based on fresh, unlabeled data. A public dataset of HAR actions was used to evaluate the HHGNN model. According to the results, the HHGNN model beats cutting-edge HAR techniques on the dataset. For instance, the HHGNN model has a 93.1% accuracy rate.

Authors in [21] suggested a Heterogeneous Clustering Approach for Human Activity Recognition (HCA-HAR); it tackles the difficulties of data heterogeneity and the requirement for interpretable outcomes in HAR. HCA-HAR comprises three primary parts: feature extraction, heterogeneous data clustering, and activity interpretation. Data from various sensors are grouped into several activity groupings using the heterogeneous data clustering module. It uses a new heterogeneous data clustering technique that considers the various feature types and their associations, and the activity interpretation module interprets the activity clusters to provide activity labels that are understandable to humans. Based on an open dataset of HAR activities, the research authors evaluated HCA-HAR. The outcomes demonstrated that, on the dataset, HCA-HAR beats cutting-edge HAR clustering techniques. For instance, HCA-HAR achieved a 95.1% accuracy rate.

III. PROPOSED APPROACH

The steps of our proposed approach are described in this section, including dataset information, features and the machine learning algorithm using active learning approaches. Figure 1 visually represents our proposed approach.

A. DATASET SELECTION

A dataset of human activity recognition information gathered from cellphones and smartwatches is called the Heterogeneity Activity Recognition (HHAR) dataset. It was developed to reflect various sensor types and authentic environments in actual deployments. Data on activity recognition and data from still experiments make up the dataset. The accelerometer and gyroscope, two motion sensors frequently present in smartphones and smartwatches, provide readings for the activity recognition data. Data was gathered from 9 participants who used cellphones and smartwatches while engaging in 6 activities. The exercises included walking, running, sitting, standing, lying down, and stair climbing. The accelerometer records from stationary devices are included in the still experiment data. The dataset classes are shown in Figure 2, which are the same in both datasets of accelerometer and gyroscope.

The HHAR dataset accurately depicts the sensor heterogeneities that can be anticipated in actual deployments; the HHAR dataset is exceptional. This indicates that a wide range of smartphone and smartwatch models were used in a wide range of use cases to acquire the data. This increases the difficulty of the dataset for machine learning algorithms to learn from while increasing its realism. A variety of research papers on human activity recognition have made use of the HHAR dataset. It has been employed to assess various machine learning algorithms, create fresh feature extraction and classification techniques, and look at how sensor heterogeneities affect the effectiveness of human activity recognition. 8 smartphones and 4 smartwatches contributed to the data. Here, we focused on the data collected from smartwatches that LG and Samsung made. The environment and scenario for activity recognition were created to generate numerous activity primitives realistically. Users took two separate routes for bicycling and walking, and two sets of stairs were used for climbing and descending.

B. FEATURE DESCRIPTION

In the HHAR dataset, each column in the file has a separate data value, and each row represents a single sample. A more thorough description of each column is provided in Table 1. The user's activity when the sample was collected is indicated by the ground truth activity labels ' Biking', 'Sitting', 'Standing', 'Walking', 'Stair Up', and 'Stair down'.

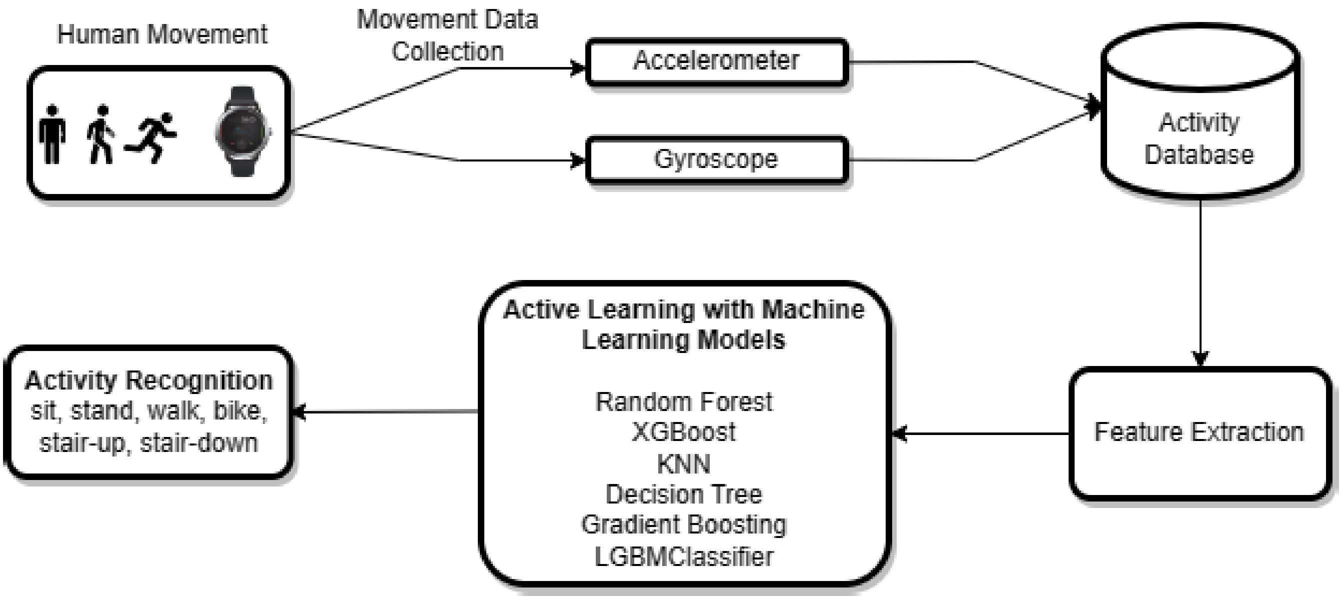


FIGURE 1. Workflow of active learning approach on HHAR.

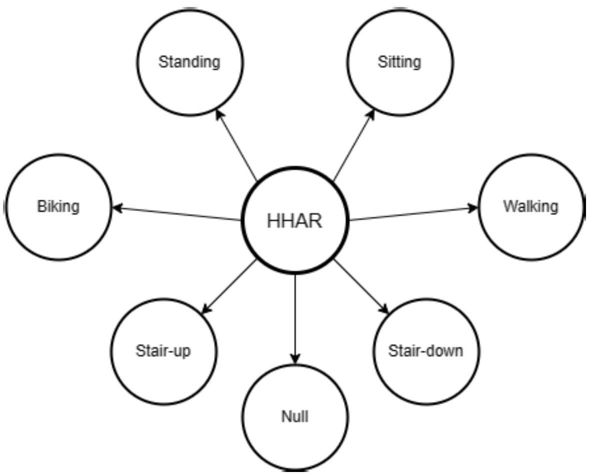


FIGURE 2. Target classes in HHAR dataset.

TABLE 1. Feature description.

Column name	Description
Arrival time	The moment data collection system got the sample
Creation time	The moment sample on the smartwatch was created
x	The x-axis's acceleration
y	The y-axis's acceleration
z	The z-axis's acceleration
User	The user's ID who was sporting a smartwatch
Model	The smartwatch's design
Device	The smartwatch's unique serial number
gt	The sample's ground truth activity label

C. ACTIVE LEARNING

Active learning is essential when gathering labeled data requires many resources or is expensive. Active learning works by incrementally improving the machine learning model's performance with less labeled input [22]. Active learning takes an initial set of labeled data, and an unlabeled dataset is used to start the procedure. It carefully chooses each iteration's unlabeled dataset's most confusing or uncertain data point [23]. The decision function's prediction probabilities are used to measure this uncertainty, allowing the model to pinpoint situations where it is least confident in its predictions. The active learning procedure ensures that the model focuses on the trickiest cases by repeatedly identifying these uncertain samples, boosting overall accuracy. The uncertain sample expands the training set and is added to the labeled dataset. On this revised dataset, the model is retrained, improving its comprehension of the intricacy of the data. The chosen sample is eliminated from the test set to prevent repetition in subsequent iterations. After training, the model's predictions are contrasted with the actual labels of the remaining test samples. Several performance metrics are calculated to assess the model's performance in each iteration, including accuracy, F1-score, precision, and recall. The active learning algorithm can correctly track the model's growth thanks to this thorough examination. Active learning improves the learning process by iteratively choosing the most instructive instances. The algorithm concentrates on the data points that offer the most learning value, speeding the labeling process instead of labeling random or redundant occurrences. As a result, active learning is a powerful tool in machine learning, especially when working with small amounts of labeled data. This makes it crucial in practical applications where getting labeled samples is difficult or expensive.

The technique presented in Algorithm 1 offers an iterative active learning strategy to improve machine learning models. It employs an approach known as uncertainty sampling to choose and add particular samples to the training dataset systematically. RF, DT, XGBoost, KNN, GB, and LightGBM are just a few of the classifiers used by the algorithm.

The F1-Score measure and accuracy are used to evaluate performance. The approach greatly enhances the precision and overall performance of the model by utilizing different machine-learning models and active learning strategies. Each algorithm helps forecast human activities and produces reliable, comparable outcomes. The specific features of each algorithm will be covered in more detail in the following sections. This algorithm first separates the dataset into training and testing sets using the train_test_split function. A machine learning model is initialized by the training_model function in preparation for further training. The fit technique trains the model using the available labeled data, and predict_proba forecasts class probabilities for test set samples. The algorithm chooses the most ambiguous sample in the test set using Xtest. Drop to remove it from the test set and append it to the labeled training data. The accuracy, f1_score, precision, recall, and accuracy scores are used to assess the model's predictions.

1) RANDOM FOREST WITH ACTIVE LEARNING

To iteratively improve the model's accuracy, the RF classifier with an active learning approach is a flexible ensemble learning method. This procedure begins by separating the available labeled data (X_train and y_train) from the unlabeled data (X_test and y_test). The code uses prediction probabilities across several iterations to choose the data point with the greatest uncertainty intelligently. The labeled dataset is then supplemented with this sample, allowing the model to concentrate on difficult cases. The questionable sample is taken from the test set to avoid repeat evaluations. Following training, performance metrics, including accuracy, F1 score, precision, and recall, are computed by comparing the model's predictions with the actual labels. The active learning loop continues, improving the model's comprehension of intricate patterns. Equation (1) represents the prediction mechanism utilized by random forest.

$$\hat{y} = \text{argmax}_k \left(\sum_{i=1}^{N_{\text{trees}}} \mathbb{I}(y_i = k) \right) \tag{1}$$

The RF model's ability to handle high-dimensional data and identify complex correlations within the dataset is one of its key benefits. Furthermore, it has integrated feature importance measures that help with feature selection and understanding the underlying data dynamics by highlighting each feature's significance in the prediction process. Important hyperparameters that impact the model's performance are the number of estimators, maximum tree depth, splitting criterion, and minimum sample requirements for splitting nodes. The Random Forest model's ensemble diversity makes it easy to include it with active learning techniques, especially uncertainty sampling.

2) XGBOOST WITH ACTIVE LEARNING

A powerful GB technique, the active learning approach with the XGBoost classifier iteratively improves model accuracy.

Algorithm 1 Active Learning With Machine Learning Classifier and Evaluation Metrics

Require: X (Features), Y (Labels)

Split the dataset into training and testing sets: $X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}} = \text{train\_test\_split}(X, Y, \text{test\_size} = 0.25)$
Initialize empty lists: *accuracies*, *f1_measure_list*, *precision_list*, *recall_list*
Number of Iterations = 3
for i in range(Number of Iterations) **do**
  Initialize a model: $model = \text{training\_model}()$
  Train the model using the current labeled data: $model.\text{fit}(X_{\text{train}}, y_{\text{train}})$
  Get the uncertainty scores for the samples in the test set: $uncertainty = \text{model.predict\_proba}(X_{\text{test}}).\text{max}(\text{axis} = 1)$
  Get the index of the most uncertain sample: $uncertain\_sample = \text{uncertainty.argmax}()$
  Add the uncertain sample to the labeled data
  $X_{\text{train}} = \text{concat}(X_{\text{train}}, [X_{\text{test}}.(uncertain\_sample)])$
  $y_{\text{train}} = \text{concat}(y_{\text{train}}, [y_{\text{test}}.(uncertain\_sample)])$
  Remove the uncertain sample from the test set:
  $X_{\text{test}} = X_{\text{test}}.\text{drop}(index = uncertain\_sample)$
  $y_{\text{test}}.\text{pop}(uncertain\_sample)$
  $y_{\text{pred}} = \text{model.predict}(X_{\text{test}})$
  Calculate evaluation metrics:
  $accuracy = \text{accuracy\_score}(y_{\text{test}}, y_{\text{pred}})$
  $f1\_measure = \text{f1\_score}(y_{\text{test}}, y_{\text{pred}})$
  $precision = \text{precision\_score}(y_{\text{test}}, y_{\text{pred}})$
  $recall = recall\_score(y_{test}, y_{pred})$
  Append the metrics to the respective lists:
  Print the results:
  $\text{print}(Iterationi + 1 : Accuracy, F1Score, Precision, Recall$
end for
Get the iteration with the best accuracy, F1 measure, precision and Recall
Print the best accuracy, F1 measure, Precision, Recall

The iterative approach starts with separating the labeled data (X_train and y_train) from an unlabeled dataset (X_test and y_test). Using the prediction probabilities derived from the XGBoost model, it chooses the test set predictions that are most uncertain throughout each iteration. The training set is enriched by adding the sample with the highest level of uncertainty to the labeled data. This unsure sample is subsequently eliminated from the test set to prevent duplicates. On the new test set, the model makes predictions, and accuracy measures, including accuracy, F1 score, precision, and recall, are computed. This active learning cycle continues, testing the model's understanding with difficult examples. The XGBoost classifier ensures that the model learns from the most instructive data points, resulting in higher accuracy over iterations. The XGBoost classifier is renowned for its robustness and speed in processing complicated datasets. The technique effectively takes advantage of the XGBoost classifier's advantages, making it useful in active learning settings when data labeling requires many resources. The prediction function for XGBoost is represented in equation (2).

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i, \theta_k) \tag{2}$$

This active learning-based activity detection system demonstrates the power of the XGBoost algorithm as a reliable classification tool. The method uses XGBoost's built-in ability to model intricate relationships inside data by carefully selecting crucial hyperparameters. Among these, the "n estimators" hyperparameter regulates the number of boosting rounds, allowing the model to enhance its forecasts progressively. The "max depth" parameter limits the depth of each decision tree and influences the complexity of learned patterns. To benefit from the tree-based models that form the basis of this technique, we select "gbtree," XGBoost's default booster.

3) K-NEAREST NEIGHBOR WITH ACTIVE LEARNING

KNN is an instance-based, non-parametric learning method that may be used for classification and regression applications. KNN was used in our environment to categorize data points. Using prediction probabilities produced by the trained KNN model, the algorithm determines the sample from the test set that is the most uncertain in each iteration. The labeled training data is then combined with the uncertain sample, representing the data point where the model has the least confidence. KNN classifies new data points according to the majority class among their KNN, where "k" is a user-defined parameter designating the number of nearby data points considered. The KNN model's comprehension of the underlying patterns in the data is improved by iteratively adding the most uncertain samples to the labeled dataset. The KNN classifier can adjust and enhance its predictions over consecutive iterations thanks to the iterative selection of these difficult examples. KNN excels in circumstances with complicated and non-linear decision boundaries because of its capacity to detect local patterns in the data.

$$\hat{y} = \text{argmax}_j \left(\sum_{i=1}^{k} \mathbb{I}(y_i = j) \right) \tag{3}$$

Equation (3) represents the classification of the predicted class for new data points. Notable is the 'n neighbors' parameter of the KNN, which controls the number of neighbors utilized in prediction. The default value of 5 is applied in this case. The 'n neighbors' parameter greatly impacts how well the model works and behaves. Because the KNN classifier uses a tiny value, it is sensitive to slight oscillations in the data and can catch complicated patterns in the feature space. To enhance the model's ability to identify intricate assault patterns, the instance with the greatest uncertainty score is appended to the labeled data. The KNN classifier and its "n neighbors" parameter are integrated into this active learning-based assault detection method. This method uses the KNN algorithm's adaptability to changing data distributions and its capacity to highlight complex feature space relationships.

4) DECISION TREE WITH ACTIVE LEARNING

The DT algorithm is a popular machine-learning method for classification and regression applications. Recursively dividing the dataset into subgroups according to the most important attribute at each step is how it operates. The result of this process is a structure that resembles a tree, with nodes denoting the features, branches denoting the decisions based on those data, and leaves denoting the results (class labels or numerical values). For classification tasks, the projected class for new data points falling into the leaf nodes is the majority class in those nodes. The mean (or another measure) of the target values in the leaf node serves as the predicted value for regression tasks. We used an active learning approach utilizing a DT classifier that dynamically enhances its prediction capabilities on each iteration. The active learning process improves the model's comprehension of complex data patterns by carefully concentrating on the situations when the model's predictions are unsure. DTs are popular in many applications because of their interpretability and capacity for category and numerical information. The prediction function DT models are represented in equation (4):

$$\hat{y} = f(X) = \sum_{l=1}^{K+1} y_l \cdot \mathbb{I}(X \in R_l) \tag{4}$$

The iterative architecture employed the uncertainty sampling technique to identify test set instances with the highest model prediction uncertainty level, improving activity recognition. By gradually including these instances in the labeled training data, the Decision Tree's accuracy and ability to identify intricate assault patterns are enhanced. The default value of the "max depth" option determines the depth of the decision tree. A shallow tree ensures a generalized model and avoids overfitting, whereas a deep tree could lead to overfitting. Using the "predict proba" function, the probability estimates of the examples that belong to each class were determined. The instance with the highest uncertainty score is selected and added to the training set to increase the model's capacity to handle complicated and uncertain situations.

5) GRADIENT BOOSTING WITH ACTIVE LEARNING

Our active learning strategy relies heavily on GB, a powerful ensemble learning technique, to iteratively improve model predictions. In active learning, uncertainty is dealt with by locating the data points that are the most ambiguous, enabling the model to gain knowledge from these difficult situations. GB constructs DTs sequentially, improving model accuracy by concentrating on incorrectly classified or ambiguous samples. The system carefully chooses and labels data points through repetitions of active learning, assuring the model's continuous improvement. In this iterative process, weak learners are integrated to create a strong, correct model, harnessing the boosting power of GB. GB improves performance and reduces labeling work by incorporating active learning principles, making it an effective technique when labeled data is expensive or rare. Softmax function for GB is represented in equation (5), it is mostly used for multiclassification problems:

$$\hat{y}_{i,k} = \frac{e^{\eta \cdot h_k(x_i)}}{\sum_{j=1}^{K} e^{\eta \cdot h_j(x_i)}} \tag{5}$$

The ''n estimators'' parameter, which has its default value set, indicates how many boosting steps will be conducted. By avoiding overstretching this parameter, the model determines the optimal number of phases for effectively minimizing mistakes. Furthermore, the ''max depth'' parameter determines the maximum depth of every tree. While a shallower tree avoids overfitting, a deeper tree can better catch intricate patterns. The default value of this parameter is maintained to ensure the model's balanced performance. Every iteration employs the concept of uncertainty sampling by selecting test set examples with the greatest uncertainty scores.

6) LIGHT GRADIENT BOOSTING MACHINE WITH ACTIVE LEARNING

Due to its exceptional efficiency and accuracy in active learning contexts, it implements the LightGBM algorithm. LightGBM is a gradient-boosting system that uses a histogram-based learning strategy, making it especially suitable for big datasets. LGBM excels in active learning by efficiently managing the selection of ambiguous samples. The learning process is considerably accelerated by its capacity to build DTs top-down leaf-wise, facilitating quick adaption to difficult situations. The fundamental idea of active learning, emphasizing instructive data points, fits in perfectly with LightGBM's advantages. The iterative process of sample selection and model refining becomes particularly effective when LGBM is used inside an active learning framework.

$$\hat{y}_{i,k} = \frac{e^{\sum_{k=1}^{K} w_k \cdot h_k(x_i)}}{\sum_{j=1}^{K} e^{\sum_{k=1}^{K} w_k \cdot h_k(x_i)}} \tag{6}$$

Equation (6) represents the Softmax function, a crucial part of the LGBM. The number of boosting stages, or 'n_estimators', is kept at its default value, enabling the model to dynamically determine the optimal number of stages for effective error minimization. To balance model performance and avoid overfitting, the maximum depth of each tree is specified by the 'max_depth' parameter, which is set to its default value.

IV. EXPERIMENTAL ANALYSIS AND RESULTS

The dataset used in our experiment consists of data from 7 different classes collected from 2 sensors: an Accelerometer and a gyroscope using wristwatches. We used different models. The classes include walking, sitting, standing, Biking, stairs-up, stairs-down, and null. Various machine learning models were trained on the dataset, which contains 3,540,962 rows and 10 columns using active learning approaches. Data encoding was used after the dataset underwent preprocessing. Uncertainty sampling was used in the active learning strategy, where samples were chosen according to expected probabilities. A typical 75%-25% split was used to divide the dataset into training and test sets. RF, XGBoost, KNN, DT, GB, and LGBM are the six machine learning models used with active learning. The models were trained iteratively in 3 iterations, with samples for labeling chosen each time via uncertainty sampling. We used the classifier's default hyperparameters, which varied accordingly. The objective of this procedure was to evaluate the effect of active learning on model performance for various methods.

A. PERFORMANCE METRICS

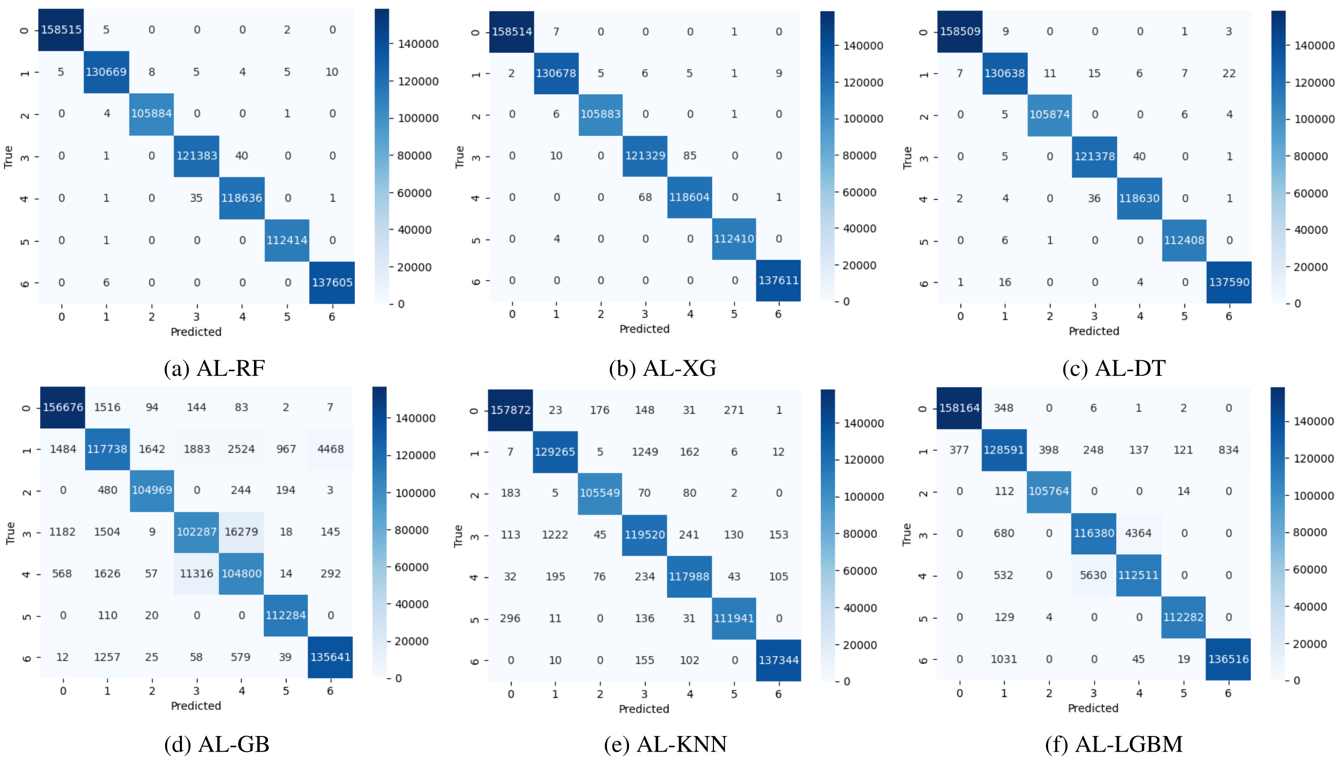
Performance metrics are critical indicators that measure how well machine learning algorithms work. They enable comparison and the choice of the best algorithms for particular tasks by providing numerical insights into how well a model is performing. Metrics for measuring categorization include accuracy, precision, recall, and F1 score. These indicators direct model improvement, assisting with ongoing machine learning solution improvement and guaranteeing alignment with expected results. The performance of the models was evaluated on the accuracy, precision, recall, F1-Score and confusion matrix. Confusion Matrix provides a clear overview of the model's ability to classify instances.

B. EXPERIMENTAL RESULTS

The trained models are evaluated by the true positive, true negative, false positive and false negative in the confusion matrix and Receiver Operating Characteristics (ROC) curves, as seen in Figure 3 and Figure 5. The target column consists of 7 classes *stand, null, sit, walk, stairup, stairdown and bike,* referred to in the confusion matrix as 0, 1, 2, 3, 4, 5, and 6, respectively. We used accuracy and F1-score in the classification tasks to identify instances. Our study used accuracy to assess how well our models performed over the 7 classes, producing a range of accuracy and F1-score values shown in Table 2 and Table 3.

1) RESUTS ON ACCELEROMETER DATA

An accelerometer is a sensor that measures the rate at which an object's velocity changes over time. It can track velocity changes across various dimensions, including the x, y, and z axes. Accelerometers are used in smartphones and wearable technology to provide functions like screen rotation, step counting, and gesture recognition. Accelerometers gather



(a) AL-RF (b) AL-XG (c) AL-DT

(d) AL-GB (e) AL-KNN (f) AL-LGBM

FIGURE 3. Confusion matrix of machine learning classifiers on accelerometer data.

TABLE 2. Evaluation results on accelerometer data.

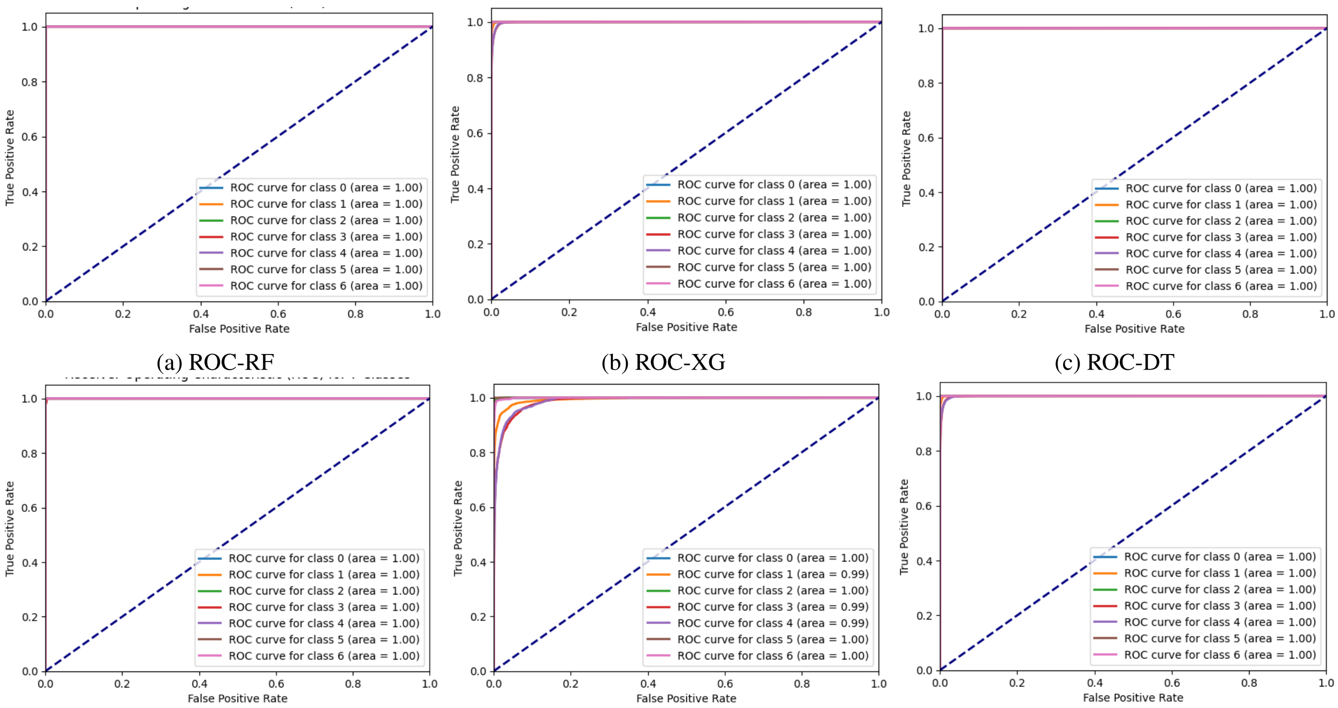
Iterations	Model	Accuracy	F1-Score
Iteration 1	Random Forest	99.98%	99.98%
	XGboost	98.26%	98.26%
	KNN	99.35%	99.35%
	Decision Tree	99.97%	99.97%
	Gradient Boosting	94.26%	94.24%
	LGBM	98.30%	98.30%
Iteration 2	Random Forest	99.98%	99.98%
	XGboost	98.26%	98.26%
	KNN	99.35%	99.35%
	Decision Tree	99.97%	99.97%
	Gradient Boosting	94.26%	94.24%
	LGBM	98.30%	98.30%
Iteration 3	Random Forest	99.98%	99.98%
	XGboost	98.26%	98.26%
	KNN	99.35%	99.35%
	Decision Tree	99.97%	99.97%
	Gradient Boosting	94.26%	94.24%
	LGBM	98.30%	98.30%

vital information for analyzing motion, keeping track of physical activity, and improving user experiences in contemporary technology by detecting the acceleration of an object or device. Table 2 provides the results on accelerometer data. We applied 6 models on the Watch accelerometer dataset, providing high accuracy and F1-Score rates of 99.98% and 99.98% on RF. Meanwhile, XGBoost and DT, KNN, GB, and LGBM gave us the accuracy of 98.26%, 99.97%, 99.35%, 94.26%, and 98.30%.

Confusion Matrix in Figure 3 describes the class classification that provides insight into the model performance and shows how well the models perform on the dataset. The confusion rate of models like RF, XGBoost, DT and KNN is pretty high, showing that these models provided a higher accuracy rate; meanwhile, GB and LGBM's confusion rate is low, indicating that they are less likely to provide higher predictions. There were a few misclassifications between class 3 (walk) and class 4 (stairup); since these human behaviors are the same, this misclassification may have shown some misleading values. In Figure 4, ROC curves explain model performance at various classification levels for data collected through an accelerometer. For instance, the ROC curve for RF, Figure 4a, showed strong performance for all classes, with no exceptions, leaving no room for development. The presented model's ROC curves present the performance at all classification thresholds. It helps to identify the weak classes the model is trained on, but we did not have many weak classes.

2) RESULTS ON GYROSCOPE DATA

Cutting-edge technology that precisely detects users' motions is the gyroscope smartwatch sensor. It uses advanced gyroscopic technology to measure rotational motion and angular velocity, giving precise information on physical activity. This sensor conveniently connects to smartwatches and provides real-time input on activity levels, workouts, distance, positions and sleep habits. Because of its accuracy, users can receive personalized fitness insights to decide what is best for their health and well-being. Table 3 provides the results on gyroscope data. We applied six models on the Watch gyroscope dataset, and RF and DT gave us high



(a) ROC-RF (b) ROC-XG (c) ROC-DT

(d) ROC-KNN (e) ROC-GB (f) ROC-LGBM

FIGURE 4. ROC of machine learning classifiers on accelerometer data.

TABLE 3. Evaluation results on gyroscope data.

Iterations	Model	Accuracy	F1-Score
Iteration 1	Random Forest	99.99%	99.99%
	XGboost	98.14%	98.14%
	KNN	99.26%	99.26%
	Decision Tree	99.98%	99.98%
	Gradient Boosting	94.79%	94.76%
	LGBM	98.18%	98.18%
Iteration 2	Random Forest	99.99%	99.99%
	XGboost	98.14%	98.14%
	KNN	99.26%	99.26%
	Decision Tree	99.99%	99.99%
	Gradient Boosting	94.79%	94.76%
	LGBM	98.18%	98.18%
Iteration 3	Random Forest	99.98%	99.98%
	XGboost	98.14%	98.14%
	KNN	99.26%	99.26%
	Decision Tree	99.99%	99.99%
	Gradient Boosting	94.79%	94.76%
	LGBM	98.18%	98.18%

accuracy and F1-Score rates of 99.99% and 99.99%. The other models, XGBoost, KNN, GB, and LGBM, provide an accuracy of around 98.26%, 99.35%, 94.79%, and 98.30%, respectively.

Figure 5 describes the classification insight into the model performance; it also shows how well the models perform on the gyroscope dataset. The confusion rate of models like RF, XGBoost, GB, DT, and KNN is higher than others. There were a few misclassifications between class 3 (walk) and class 4 (stairup); since these human behaviors are the same, this misclassification may have shown some misleading values. In Figure 6, ROC curves explain model performance at various classification levels for data collected through a gyroscope. For example, the ROC curve for RF in Figure 6a demonstrated excellent performance for every class, showing little to no space for improvement. Similarly, we can see results in the ROC of other models. ROC helps to identify the weak classes the model is trained on, but in our case, we did not have many weak classes.

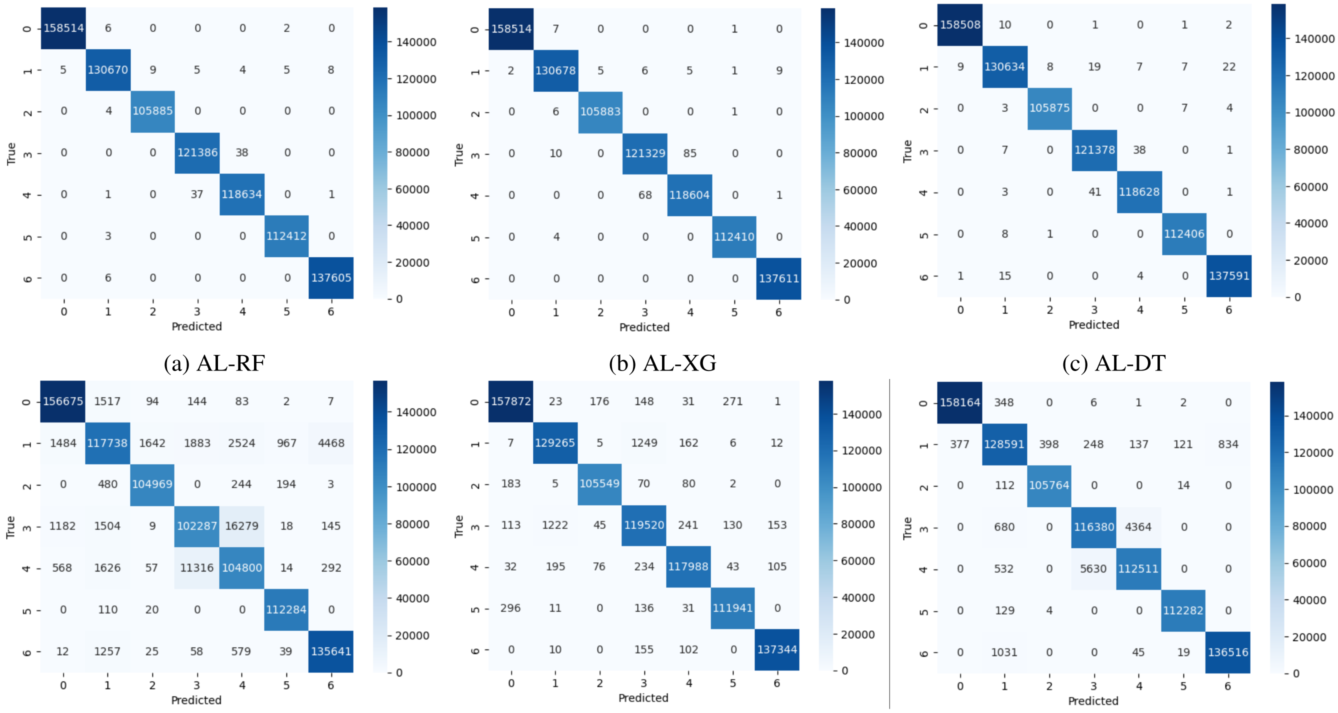
TABLE 4. Performance comparison with DeepTransHHAR [12].

Reference	F1-Score
[12]	94.25%
AL-RF	99.99%

Table 4 compares our approach with the latest baseline research studies DeepTransHHAR [12]. Due to our active learning approach, we achieved higher results, up to 99.99% on our trained RF and DT model, a total increase of 5.74% from the baseline approach. This proves that active learning proves to be a better approach than the currently available approaches.

C. DISCUSSION

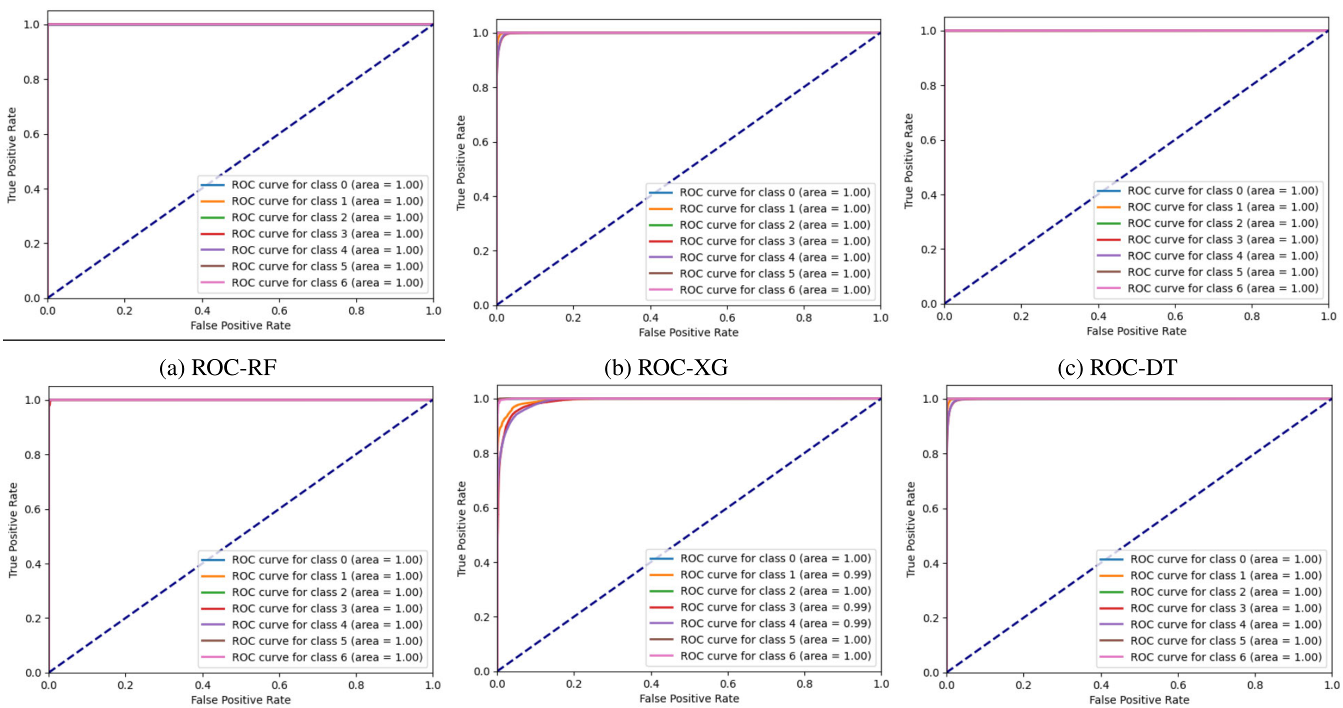
Using a Watch accelerometer and gyroscope dataset, the effectiveness of six different models was assessed: RF, XGBoost, DT, KNN, GB, and LGBM. ROC curves, accuracy, F1-score, and a confusion matrix were used to base the evaluation. The models' performance was evaluated using accuracy for each of the seven classes. Several models showed decent accuracy, including XGBoost, KNN, GB, and LGBM, which ranged from 94.26% to 99.26%. With RF and



(a) AL-RF (b) AL-XG (c) AL-DT

(d) AL-GB (e) AL-KNN (f) AL-LGBM

FIGURE 5. Confusion matrix of machine learning classifiers on gyroscope data.



(a) ROC-RF (b) ROC-XG (c) ROC-DT

(d) ROC-KNN (e) ROC-GB (f) ROC-LGBM

FIGURE 6. ROC of machine learning classifiers on gyroscope data.

DT in particular, the active learning approach demonstrated good efficacy, obtaining the best accuracy of 99.99% and an F1-score of 99.99%. Our active learning approach to human activity recognition differentiates us from other methods that rely on SVMs, deep learning algorithms, and neural networks. This work focuses on utilizing data from wearable sensors to make better predictions and improve the gap left behind. This is crucial due to the unique challenges posed by wearable sensors, such as the diverse range of human actions and real-world situations, making our method invaluable for practical applications.

V. CONCLUSION AND FUTURE SCOPE

This paper proposed an active learning approach to identify human behavior from the data collected through an accelerometer and gyroscope on the HHAR dataset. It gave much better results than the baseline approach, with an increase of 5.74% F1-score gain. We reviewed several research studies on human activity recognition to get insights and potential benefits for our investigation. We applied various machine-learning models with an active learning approach to the HHAR. The highest results achieved were 99.99% from RF and DT on the gyroscope dataset and 99.98% with RF on the accelerometer dataset. The other models on the gyroscope, including XGBoost, KNN, GB, and LGBM, provided an accuracy of 98.14%, 99.26%, 94.79% and 98.18%, and F1-score of 98.14%, 99.26%, 94.76% and 98.18% respectively. Meanwhile, on the accelerometer, other models, including DT, XGBoost, KNN, GB, and LGBM, provided an accuracy of 99.97%, 98.26%, 99.35%, 94.26 and 98.30%, and F1-score of 99.97%, 98.26%, 99.35%, 94.24% and 98.30% respectively. The results imply that our approach can generate the most accurate results. In the future, we intend to fuse multiple datasets into one to provide a generalized model to predict activities. Further, we intend to collect data from more sensors.

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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 but are not limited to computer forensics, machine learning, criminal profiling, software watermarking, intelligent systems, and data privacy protection.

SHTWAI ALSUBAI received the bachelor's degree in information systems from King Saud University, Saudi Arabia, in 2008, the master's degree in computer science from California Lutheran University (CLU), USA, in 2011, and the Ph.D. degree from The University of Sheffield, U.K., in 2018. He is currently an Assistant Professor of computer science at Prince Sattam bin Abdulaziz University. His current research interests include XML, XML query processing, XML query optimization, machine learning, and natural language processing.

MUHAMMAD IBRAR UL HAQUE (Senior Member, IEEE) received the B.E. degree in electronic engineering from the NED University, Dawood College of Engineering and Technology, Karachi, Pakistan, in 1992, and the M.S. and Ph.D. degrees in electronic engineering from the Sir Syed University of Engineering and Technology (SSUET), Karachi, in 2007 and 2017, respectively. From June 1994 to August 2000, he worked as a Senior Engineer at International Office Products Private Ltd., Karachi. From August, 2000 to December 2002, he served as the Instructor at Pakistan Navy, PNS Karsaz, Karachi. Since December 2002, he has been working as a faculty member at SSUET and since March 2017, he has been working as an Associate Professor at Electrical Engineering Department, SSUET. Since June 2020, he also holds the charge of Acting Chairman of Electrical Engineering Department, SSUET Karachi, Pakistan. He is involved in management of the department and also teaching BS and MS Electrical/ Electronic/ Telecommunication Engineering students. Has more than 28 years of field and teaching experience. He is Professional Engineer (P.E.) and member of Pakistan Engineering Council (PEC), The Institution of Electrical and Electronics Engineers Pakistan (IEEEP) and The Institution of Engineers Pakistan (IEP). He is ExCOM Member of IEEE Karachi Section, Vice Chair of IEEE Power & Energy Society (PES) Karachi and Faculty Advisor of IEEE Power and Energy Society (PES) student branch chapter at SSUET. His research areas are Digital Signal Processing, Image Processing and Optical Communication. He has published number of research papers in national and international journals and conferences. He served as reviewer in various journal and conference papers. He is also member of various statutory bodies, research cluster of the department and Guidance & Evaluation committee (GEC) member of Ph.D. Scholars.

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.

AHMAD ALMADHOR (Member, IEEE) 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, then a Lecturer, from 2011 to 2012, with Aljouf University, Aljouf. Then, he became a Senior Graduate Assistant and a Tutor Advisor with the University of Denver, in 2013 and 2019. He is currently an Assistant Professor of CEN and the Vice Dean of the Computer and Information Science College, Jouf University, Saudi Arabia. His research interests include AI, blockchain, networks, smart and microgrid cyber security, integration, image processing, video surveillance systems, PV, EV, machine, and deep learning. His awards and honors include the 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 the 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 also a Lecturer in computer science with the University of Tabuk. His research interests include technology-enhanced learning, image processing, virtual and augmented reality, motion capture, and education applications.

IRYNA IVANOCHKO is currently with the Department of Economics and Finance, Faculty of Management, Comenius University Bratislava. In addition to pedagogy, she is also engaged in scientific and publishing activities. She has written several university textbooks, contributions at domestic and foreign conferences, and magazine articles. Her research interests include but is not limited to artificial intelligence and management sciences.