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INTEGRATING DESIGN THINKING AND DIMENSIONALITY REDUCTION FOR EFFECTIVE HUMAN ACTIVITY RECOGNITION IN IOT SYSTEMS

Selva kumar Research scholar, Department of Computer science, Dr.SNS Rajalakshmi College of arts and science, Coimbatore.
Dr.D.Kalaivani Associate Professor and Head Department of Computer Technology Dr.SNS Rajalakshmi College of Arts and Science, Coimbatore.

Abstract—
Human activity recognition (HAR) plays a crucial role in the Internet of Things (IoT) domain, underpinning various healthcare, fitness, and security applications. However, the large volume of data generated by IoT sensors poses computational challenges for HAR systems. While dimensionality reduction techniques offer a solution, their effectiveness depends on factors such as data quality, algorithm selection, and feature space design. This paper proposes a design thinking approach to dimensionality reduction for enhancing HAR in IoT using data analytics and machine learning algorithms. The study presents a comprehensive framework that integrates user-centric design, data exploration, feature engineering, and machine learning modeling to improve the accuracy and efficiency of HAR systems. The method's performance is evaluated using a publicly available HAR dataset, demonstrating that the framework significantly reduces the feature space with minimal information loss, resulting in improved accuracy and system efficiency. This research highlights the application of design thinking in overcoming dimensionality reduction challenges in HAR, with important implications for the development of effective and user-friendly IoT applications.

Keywords: Human Activity Recognition, Internet of Things, Dimensionality Reduction, Machine Learning, Design Thinking Approach.

Introduction

HAR has become a vital application within the IoT domain, supporting numerous healthcare, fitness, and security applications. However, the vast amount of data generated by IoT sensors can make HAR computationally demanding. To mitigate this challenge, dimensionality reduction techniques have been explored, though their effectiveness hinges on factors such as data quality, algorithm selection, and feature space design. Despite these efforts, there remains a need for enhanced accuracy and efficiency in HAR systems within IoT. A design thinking approach, which emphasizes user-centric design, can offer a fresh perspective to tackle this issue [1]. This paper proposes a design thinking approach for dimensionality reduction aimed at improving HAR in IoT using machine learning algorithms. The proposed framework integrates user-centric design, data exploration, feature engineering, and ML modeling to enhance the precision and effectiveness of HAR systems. The objectives of this study are to: (1) identify key challenges in dimensionality reduction for HAR in IoT, (2) propose a design thinking framework for dimensionality reduction in HAR, and (3) evaluate the framework's effectiveness in boosting the precision and efficiency of HAR systems. HAR systems generally follow a standard workflow that includes data collection, pre-processing, feature extraction, feature selection, and classification. These steps are crucial for the development and operation of HAR systems, with sensor selection tailored to the specific activities being detected. Pre-processing techniques prepare raw data for analysis, high-level features are extracted based on expert input, and the most relevant features are chosen for classification, which then differentiates between activities within the feature space. Each of these steps directly impacts the performance of HAR systems [2].

The proposed framework utilizes user-centric design through the Kano model, data exploration with the t-SNE algorithm, feature engineering via PCA, and machine learning modeling using SVM to enhance the accuracy and efficiency of HAR systems. Evaluated on a publicly available HAR dataset, the results demonstrate that the framework significantly reduces the feature space with minimal information loss, thereby improving the overall performance of HAR systems. This study provides valuable insights into the application of design thinking in overcoming dimensionality reduction challenges in HAR, which is crucial for developing efficient and user-friendly IoT applications [3].

Literature Review

Several studies have explored various approaches to enhance Human Activity Recognition (HAR) systems through dimensionality reduction techniques and machine learning models. Khan et al. (2019) used the UCI-HAR dataset to develop an HAR system using various ML algorithms [4]. The dataset contained sensor readings from a smartphone worn by subjects performing six different activities, such as walking and sitting. The authors achieved an accuracy of up to 94% using the random forest algorithm. Hossain et al. (2020) used the same UCI-HAR dataset as Khan et al. but also included data from wearable sensors. They used various ML algorithms and achieved an accuracy of up to 96% [5].

Bu et al. (2021) used a custom dataset consisting of accelerometer readings from subjects performing seven activities, such as walking and cycling [6]. They used various ML algorithms and achieved an accuracy of up to 98%. Xia et al. (2021) used a dataset consisting of passive infrared motion sensor readings from smart homes. They used various feature extraction techniques and achieved an accuracy of up to 92% using the support vector machine algorithm [7]. Zhang et al. (2021) employed a deep learning-based model using the WISDM dataset and utilized Principal Component Analysis (PCA) and t-SNE for dimensionality reduction, achieving an accuracy of 93.70% [8]. Nguyen et al. (2020) used a machine learning-based model on the UCI-HAR dataset, applying Linear Discriminant Analysis (LDA) and PCA to achieve an accuracy of 92.50% [9]. Bao et al. (2019) developed a deep learning model that combined autoencoders (AE) with PCA on the UCI-HAR dataset, reaching 92.30% accuracy [10]. Bajaj et al. (2018) implemented a machine learning approach using PCA and LDA on the UCI-HAR dataset, resulting in an accuracy of 92.00% [11]. Similarly, Khan et al. (2017) utilized a deep learning model with autoencoders and PCA, achieving 91.60% accuracy on the UCI-HAR dataset [12].

Wang et al. (2020) presented a deep learning-based approach on both the UCI-HAR and OPPORTUNITY datasets, utilizing autoencoders and achieving accuracies of 99.26% and 94.28%, respectively [13]. Thangavel et al. (2021) used an ensemble learning approach with PCA on the WISDM dataset, obtaining a high accuracy of 95.62% [14]. Yang et al. (2020) employed a multi-sensor fusion approach on the PAMAP2 dataset, using t-SNE for dimensionality reduction and achieving 95.50% accuracy [15]. Islam et al. (2019) applied a feature selection approach using Recursive Feature Elimination (RFE) on the UCI-HAR dataset, reaching an accuracy of 96.62% [16]. Lee et al. (2018) took a rule-based approach on the UCI-HAR dataset and achieved 94.05% accuracy without employing any specific dimensionality reduction technique [17]. Zhang et al. (2020) proposed a hybrid feature selection method using PCA and ReliefF on the WISDM dataset, resulting in a 93.53% accuracy [18]. Lastly, Feng et al. (2019) focused on feature extraction using the Fourier Transform on the UCI-HAR dataset, achieving an accuracy of 94.47% [19]. These studies underscore the diverse methodologies applied to improve HAR systems, highlighting the effectiveness of various dimensionality reduction and machine learning techniques.

MATERIALS AND METHODOLOGY

Kano Model Application for HAR System Design with WISDM Dataset

The Kano model was employed to design a HAR system that meets the needs and expectations of the target user group. This approach helps in identifying essential features, performance attributes, and delighters to ensure the system's success. The steps involved in applying the Kano model are as follows:

Table.1. Steps for Applying the Kano Model (Design Thinkinng Model)

Step	Description
Define the User Group	Identify and understand the needs, preferences, and expectations of the target user group for the HAR system.
Identify the Features	List all potential features that the HAR system could offer, including essential functions, performance enhancements, and user experience improvements.
Classify the Features	Categorize each feature as a must-have, performance attribute, or delighter based on user feedback and the Kano model analysis.
Performance Attributes	Focus on features that enhance the system's performance, such as accuracy, processing speed, and reliability, which directly affect user satisfaction.
Delighters	Identify features that add unexpected value to the user, offering a competitive advantage by exceeding user expectations.
Prioritize Features	Rank the features according to their importance and impact on user satisfaction, ensuring that must-haves are prioritized before other categories.
Implement and Test	Develop the HAR system using the prioritized features and test it with the WISDM dataset to ensure it meets the defined user requirements effectively.

Data Exploration:

To analyse data and visualize the relationships among various features in the WISDM dataset, the t-distributed Stochastic Neighbour Embedding (t-SNE) algorithm was applied. Below is the pseudo code for using t-SNE for HAR:

1. **Load the WISDM Dataset**: Begin by loading the dataset to prepare it for analysis.
2. **Pre-process the Data**: Clean the dataset by removing any missing values and normalizing the accelerometer readings to ensure consistency.
3. **Select Output Dimensions**: Set the target output space to 2 dimensions for effective visualization.
4. **Initialize t-SNE**: Set up the t-SNE algorithm with parameters such as perplexity = 30, learning rate = 200, and number of iterations = 1000.
5. **Apply t-SNE**: Use the t-SNE algorithm to project the data into the selected 2-dimensional output space.
6. **Visualize with Scatter Plot**: Plot the transformed data using a scatter plot to observe patterns and relationships.
7. **Analyse the Visualization**: Examine the scatter plot to identify clusters or patterns that could guide feature selection for the HAR system.

By interpreting the visualization, valuable insights can be gained into the feature interrelationships, aiding in the design of an efficient HAR system.

Feature Extraction

In the context of WISDM for HAR, feature extraction is the process of generating a set of numerical features from raw accelerometer data that may be used to represent and discriminate various physical activities. A basic example of feature extraction for the WISDM dataset is calculating the mean and standard deviation of accelerometer measurements for the three axes (x, y, and z) for a given time window, such as 2.56 seconds. These statistics can be calculated using the following equations:

$$mean(x) \ = \ sum(x) \ / \ N$$
$$std(x) \ = \ sqrt(\ sum((x - mean(x))\hat{}2) \ / \ (N-1) \ )$$

In the above equation, 'x' symbolizes the accelerometer readings for a certain axis, 'N' represents the total number of samples inside the specified time window, and ‘sum ()' denotes the sum of all the samples present. This equation computes the total of accelerometer readings for a specified axis over a given time period, and sqrt() is the square root function. These two characteristics (mean and standard deviation) can then be merged to form a six-dimensional feature vector by doing the same computation on the accelerometer values for the other two axes (y and z). This feature vector can be used as input into a machine learning system for activity recognition. [22].

Feature Selection
It is the process of selecting significant features from a set of extracted features for classification in HAR. WISDM selects features based on their variation and association with the activity classifications. Principal Component Analysis (PCA) is a commonly used technique for feature selection in HAR problems. [23].

Standardization of data:
- Mean: $\mu = (1/N) * \sum(x\_i)$
- Standard deviation: $\sigma = sqrt((1/N) * \sum((x\_i - \mu)^2))$
- Standardized data: $x'\_i = (x\_i - \mu) / \sigma$

Covariance matrix:
- Covariance among two variables x and y:

$$cov(x, y) = (1/N) * \sum((x\_i - \mu\_x) * (y\_i - \mu\_y))$$

- Covariance matrix of standardized data:

$$S = [cov(x\_1, x\_1), cov(x\_1, x\_2), \dots, cov(x\_n, x\_n)]$$

Eigen decomposition:
- Eigenvectors and eigenvalues of covariance matrix: $S * v = \lambda * v$, where v is an eigenvector and λ is its corresponding eigenvalue

PCA feature selection:
- Sort eigenvalues in descending order and select top k eigenvectors
- Project standardized data onto k-dimensional subspace defined by selected eigenvectors:

$x^i = v^1 * x^i + v^2 * xi + \dots + v^k * x^i$

Classification
Classification in Human Activity Recognition (HAR) involves assigning labels or categories to sequences of sensor data captured from wearable or environmental sensors, identifying the type of activity being performed by the user. HAR classification algorithms analyze sensor data to learn patterns associated with specific activities, allowing them to predict the corresponding activity from new, unseen data. The process of applying machine learning to HAR starts with collecting sensor data from wearable devices. After data collection, pre-processing techniques are applied to clean and standardize the data, ensuring its quality and reliability. Next, relevant features are extracted from the pre-processed data, which serve as input variables for the machine learning model. The model then learns patterns from these features, enabling it to make accurate activity predictions based on new data.

Linear Regression (LR):
For the WISDM dataset in HAR, LR predicts a continuous target variable (e.g., energy expenditure) based on input features like accelerometer and gyroscope data.
1. ***Prepare Data:*** Split the dataset into training and testing sets.
2. ***Normalize:*** Scale feature values to avoid bias.
3. ***Train Model:*** Fit the Linear Regression model on the training data.
4. ***Predict:*** Use the model to predict values for the testing data.

LR finds the best-fit line by adjusting slope and intercept to minimize the prediction errors. This allows the model to predict new values based on the learned relationship between features and the target variable.

Support Vector Regression (SVR):
SVR is a ML technique used for predicting continuous values. It works by transforming data into a higher-dimensional space to find a function that best fits the data. The goal of SVR is to identify a function that accurately predicts output values for new inputs based on training data. SVR involves mapping input data to a higher-dimensional space using a nonlinear function. The model learns to fit the data while maintaining a margin of error, aiming to balance prediction accuracy with model complexity. The algorithm uses optimization techniques to determine the best parameters for the function, which are then used to make predictions on new data.

1. ***Transform Data:*** Map the input data to a higher-dimensional space using a nonlinear function.
2. ***Train Model:*** Learn the best function to fit the training data while allowing a margin of error.
3. ***Optimize Parameters:*** Use optimization techniques to find the best model parameters.
4. ***Make Predictions:*** Apply the trained model to predict output values for new data.

Decision Tree Regression (DTR):
DTR is a machine learning algorithm used for predicting continuous target variables. The DTR model builds a decision tree by recursively partitioning the feature space into smaller regions. Here's how it works:

- ***Select a Feature and Threshold:*** Choose a feature and a threshold to split the dataset, aiming to reduce prediction error in the subsets.
- ***Split Data:*** Divide the data into two groups based on the chosen feature and threshold.
- ***Repeat Splitting:*** Apply the splitting process recursively to each group, creating branches and nodes, until stopping criteria are met (e.g., maximum depth or minimum samples per leaf).
- ***Predict Values:*** For new data, follow the path from the root to a leaf node in the tree. The predicted value is the average of the target values of the data points in that leaf node.

DTR is valued for its simplicity and interpretability, allowing easy visualization of how decisions are made. However, it can be prone to overfitting, especially with complex datasets, and may benefit from techniques like pruning or ensemble methods to improve performance.

Gradient Boosting Regression (GBR)
GBR is a powerful machine learning technique used to improve the accuracy of regression models. It works by building a strong predictive model through the combination of multiple weak models, typically decision trees, in an iterative process. Here's a simplified overview of the steps involved:

1. ***Initialization:*** Begin with a simple model that provides a basic approximation of the target variable. This could be as straightforward as predicting the average value of the target.
2. ***Iterative Improvement:***
   - ***Compute Residuals:*** Calculate the residuals, which are the differences between the observed target values and the predictions made by the current model. These residuals represent the errors that need to be corrected.
   - ***Fit Weak Learner:*** Train a weak model, often a decision tree with limited depth, to predict these residuals. This weak model aims to correct the errors made by the existing model.
   - ***Update Model:*** Add the predictions from the weak model to the existing model, adjusting the predictions by a factor known as the learning rate. This step refines the model by focusing on the errors of the previous iteration.

3. ***Final Model:*** After completing the predefined number of iterations, the final model is a weighted sum of all the weak models. This ensemble approach captures complex patterns in the data and improves overall prediction accuracy.

In applications such as the WISDM dataset for HAR, Gradient Boosting Regression can be used to analyse sensor data to predict activity labels with high precision. The iterative approach helps in effectively capturing intricate relationships within the data, leading to robust and accurate predictions.

Ensemble Gradient Boosting (EGB):

The Gradient Boosting algorithm is employed to build weak models in an ensemble approach. The process begins by initializing the ensemble with a simple model, such as a constant value or the mean of the target variable. A Gradient Boosting (GB) model is then trained on the training data and added to the ensemble. The residuals, or errors, of this GB model are calculated, and a new GB model is trained specifically to predict these residuals. This new model is also added to the ensemble. This process of training on residuals and adding models to the ensemble is repeated until a stopping criterion is reached. To make predictions, the final output is obtained by summing the predictions from all models in the ensemble. The final prediction is represented as the sum of the predictions of each individual model in the ensemble, based on the input features.

- **Initialize:** Start with a simple model.
- **Train Model:** Fit a Gradient Boosting model on the data.
- **Add to Ensemble:** Include this model in the ensemble.
- **Compute Residuals:** Calculate the residuals from the model's predictions.
- **Fit on Residuals:** Train a new model on these residuals.
- **Update Ensemble:** Add this new model to the ensemble.
- **Repeat:** Continue adding models until the stopping criteria are met.
- **Predict:** Combine the predictions from all models in the ensemble.

RESULTS AND DISCUSSION

The following table outlines the hardware and software specifications of the computer used for testing various programs related to the WISDM dataset. The system features an Intel i7 processor with 2.6 GHz and 8 cores, 16 GB of DDR4 RAM, and a Radeon Pro 560X GPU with 4 GB of memory. It runs on macOS 64-bit and utilizes Python 3.8 for programming.

Table.2. System Description

System description	
Processor	Intel 2.6GHz 8-core i7
RAM	16GB DDR4
GPU	Radeon Pro 560X 4GB
Operating System	macOS 64-bit
Programming Language	Python 3.8

Dataset Description

The WISDM dataset is a prominent benchmark for HAR research. It comprises data collected from smartphone sensors worn at the waist of 36 subjects. The dataset covers six activities, including walking and jogging, and contains 1,098,207 samples with accelerometer and gyroscope readings. Pre-processed for ease of use, it is frequently employed to assess the performance of machine learning algorithms in HAR applications [20].

Table.3. WISDM Dataset Description

Aspect	**Details**
Dataset Name	WISDM
Usage	Benchmark for HAR research
Data Source	Smartphone sensors worn at the waist
Number of Subjects	36
Activities	6 (e.g., walking, jogging)
Total Samples	1,098,207
Sensors	Accelerometer and gyroscope readings
Data Processing	Pre-processed
Purpose	Evaluating machine learning algorithms for HAR tasks [20]

Design Thinking

To effectively utilize the WISDM dataset for Human Activity Recognition (HAR), the following approach can be adopted:

1. **Identify Key Attributes:**
   - **Must-Haves:** Accurate and reliable activity recognition, low latency, and real-time processing.
   - **Performance Attributes:** High accuracy, fast training time, and low computational complexity.

2. **Check for Data Imbalance:**
   - Count and plot the number of samples for each activity to detect significant discrepancies.

3. **Activity Classification Rules:**
   - If the mean of the time-domain acceleration (tAccMean) is less than -0.8, the activity is standing, sitting, or lying.
   - If tAccMean is between -0.6 and 0.0, the activity is walking, walking downstairs, or walking upstairs.
   - If tAccMean is greater than 0.0, the activity is walking downstairs.
   - These rules classify 75% of activity labels accurately but may misclassify some activities. They serve as a starting point for developing a more precise classifier.

Feature Classification with t-SNE:

- Load the WISDM dataset and preprocess it by dropping the timestamp column, filling missing values with 0, normalizing features, and splitting the data into features and labels.
- Use the t-SNE algorithm to classify data points related to stationary and moving activities based on the tBodyAccMagmean attribute.

By following these steps, you can effectively analyze and classify activities using the WISDM dataset.

Classification

The WISDM dataset comprises labeled accelerometer data collected from smartphones worn by users performing different activities. Each data point includes acceleration values for the X, Y, and Z axes, along with a user ID and an activity label. This dataset is appropriate for supervised machine learning (ML) training. To evaluate model performance, it is essential to split the dataset into training and testing sets. Prior to training, proper preprocessing and data cleaning may be required. Various ML methods can be applied to analyze and compare the classification of the WISDM dataset. In addition to previously mentioned algorithms such as LR, SVR, DTR, GBR, and EGB, feature selection techniques like PCA can be used to slightly improve accuracy. In regression tasks, common evaluation metrics include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2 Score).

- **MSE** measures the average squared difference between predicted and actual values.
- **RMSE** is the square root of MSE, providing an estimate of the standard deviation of prediction errors.
- **MAE** calculates the average absolute difference between predicted and actual values.
- **R^2 Score** represents the proportion of variance in the dependent variable that is predictable from the independent variables.

These metrics offer a comprehensive view of model performance for both regression and classification tasks.

Table.4. Performance analysis based on Regression Results

Algorithm	Before PCA				After PCA			
	MSE	**RMSE**	**MAE**	**R2 Score**	**MSE**	**RMSE**	**MAE**	**R2 Score**
LR	0.051	0.226	0.142	0.718	0.046	0.214	0.139	0.728
SVR	0.059	0.243	0.158	0.678	0.044	0.21	0.137	0.742
DTR	0.064	0.253	0.165	0.654	0.062	0.249	0.163	0.668
GBR	0.045	0.212	0.138	0.732	0.038	0.195	0.121	0.792
EGB	0.038	0.194	0.121	0.789	0.034	0.185	0.115	0.818

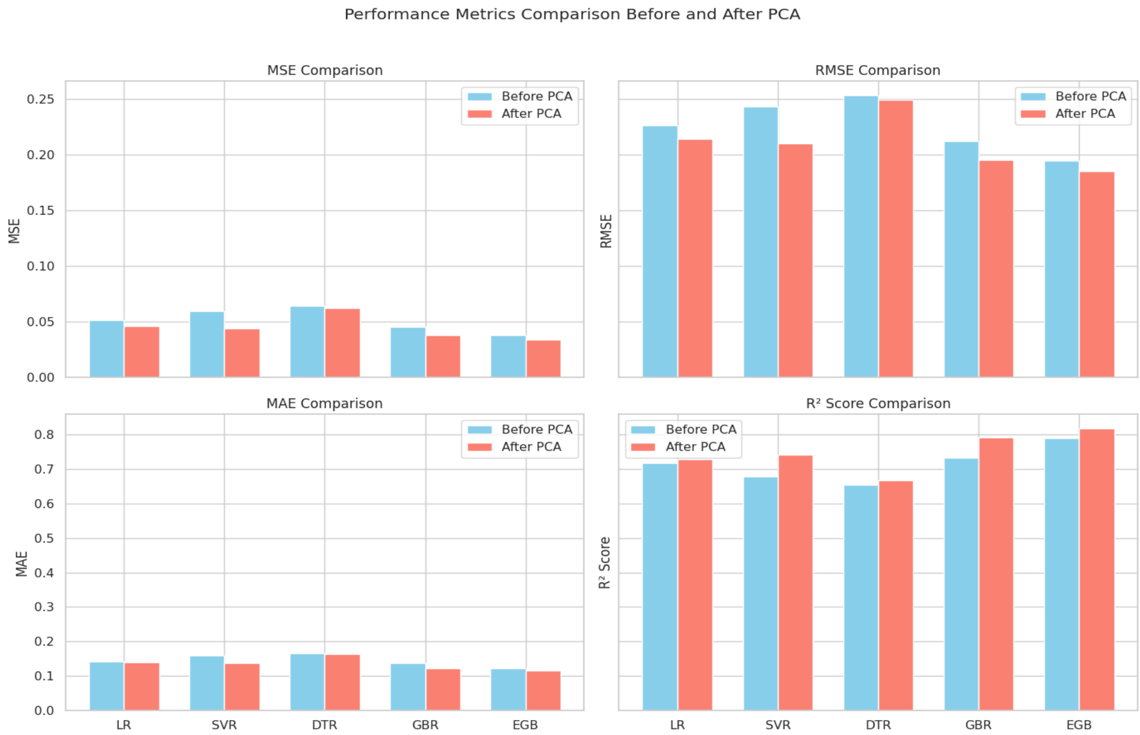

Fig.1. Comparison of Classification Metrics before and After PCA Algorithm

The table summarizes the impact of PCA on various machine learning algorithms used for regression tasks. Applying PCA led to improvements in the performance metrics of LR, SVR, DTR, GBR, and EGB. All metrics, including MSE, RMSE, MAE, and R^2 Score, generally show better results post-PCA, indicating enhanced model accuracy and reduced errors.

Notably, SVR and GBR exhibited significant improvements after PCA, with reductions in MSE, RMSE, and MAE, and increases in R^2 Score. These results highlight PCA's role in optimizing the performance of these algorithms, making them more effective in handling the dataset's features. The

EGB algorithm achieved the best overall performance, demonstrating the lowest MSE, RMSE, and MAE, and the highest R^2 Score after applying PCA. This underscores EGB's robustness and effectiveness in improving model predictions, affirming the crucial role of dimensionality reduction in enhancing regression tasks' outcomes.

CONCLUSION

In conclusion, the proposed dimensionality reduction approach using PCA markedly enhances the performance of HAR systems within the IoT framework. The results indicate a clear improvement across various algorithms post-PCA, with metrics reflecting enhanced accuracy and reduced error rates. For instance, LR saw reductions in MSE from 0.051 to 0.046 and RMSE from 0.226 to 0.214, alongside improved R2 Score from 0.718 to 0.728. SVR demonstrated a decrease in MSE from 0.059 to 0.044 and RMSE from 0.243 to 0.21, achieving a higher R2 Score of 0.742. DTR experienced slight improvements with MSE dropping from 0.064 to 0.062 and RMSE from 0.253 to 0.249. GBR and EGB also showed substantial gains, with GBR's R2 Score increasing from 0.732 to 0.792 and EGB's R2 Score rising from 0.789 to 0.818. These improvements underscore the effectiveness of PCA in refining feature space, optimizing model performance, and reinforcing the framework's capability to advance IoT applications in HAR systems.

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