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ADVANCED HUMAN ACTIVITY RECOGNITION: LEVERAGING ADAPTIVE NEURAL NETWORKS AND DIVERSE MACHINE LEARNING ALGORITHMS ON IOT DATA

Dr.B.Chitradevi Assistant Professor, Department of Computer Applications, SRM Institute of Science and Technology (Deemed to be University), Trichy
Dr.J.Suganya, Assistant Professor, Department of Computer Applications, SRM Institute of Science and Technology (Deemed to be University),Trichy
Dr. M. Manikandan, Assistant professor, Department of Computer Science and Applications, Periyar Maniammai Institute of Science and Technology (Deemed to be university).Thanjavur.
Dr.G.Ambika Head and Assistant Professor, Department of BCA Queens College of Arts and science for Women, Punalkulam, Pudukkottai.

Abstract
Human Activity Recognition (HAR) is a critical and challenging problem in computer vision, pivotal for applications in gaming, human-robot interaction, rehabilitation, sports, health monitoring, video surveillance, and robotics. HAR involves detecting and interpreting a range of activities that people perform daily, such as driving, cleaning, and playing games, each consisting of basic actions like standing, sitting, and running. To develop effective human-computer interaction systems, HAR modules leverage data from IoT wearable sensors to extract meaningful features. Machine Learning (ML) models are then employed to automatically recognize these activities from the raw sensor data. The performance of these models is evaluated using statistical metrics, including accuracy, precision, recall, and F1-score, with comparisons made to existing models to ensure their effectiveness and reliability.

Keywords: Human activity recognition, Machine learning, IoT sensor, MLP, Classification

Introduction
The use of physiological monitoring through wearable sensors has shown significant promise in enhancing the quality of life and preventing health issues in older adults. Tracking daily exercise patterns can be especially beneficial for seniors. As sensor technology advances, there is growing interest in developing methods for long-term human activity observation using sophisticated Internet of Things (IoT) based wearable monitoring devices. This study proposed an activity recognition system that utilizes various Machine Learning (ML) models to analyze raw sensor data without pre- or post-processing modifications, addressing the challenges posed by irregular and random measurements. The findings suggest that the proposed model can effectively handle data inconsistencies, offering a viable solution for activity recognition. Human behavior poses a substantial challenge across various fields, including smart homes, assistive robotics, human-computer interaction, and safety enhancements. Activity recognition, in particular, is fundamental to developing applications in health, wellness, and sports. The complexity of human actions adds to the difficulty of studying behavior through activity recognition. Recent advancements in machine learning algorithms, proven effective in numerous computer vision applications, have been applied to data analysis in this area.

Wearable sensors have advanced beyond older technologies, enabling remote monitoring of severe conditions like Parkinson's disease and heart attacks. While cameras can also function as external HAR receivers, extracting actions and movements from video sequences remains challenging, especially in distinguishing similar behaviors. Thus, combining cameras with wearable sensors can significantly improve HAR accuracy. Video-based signals are generally less desirable compared to those from wearable sensors. Recent IT advancements have facilitated the collection and storage of routine medical data, aiding in medical decision-making. Efficient data gathering and organization are essential for timely diagnosis, prediction, and treatment planning. This study employed the Activity and Biometrics Dataset from smartphones and wearables to generate human activity forecasts. It demonstrates the application of various machine learning algorithms on a pre-trained dataset to simulate diverse human behaviors.

Literature Review

The literature review explores recent advancements in hyper-parameter optimization for improving HAR using ML algorithms with IoT sensor datasets. This review is crucial as it highlights various methodologies and hyper-parameters that significantly impact the performance and accuracy of HAR systems, providing insights into effective techniques for enhancing activity recognition in diverse applications:

Table.1. Literature Review

Author & year	Objective	Methodology	Hyper-Parameters	Dataset	Performance Metrics
Smith et al. (2021)	Enhance HAR accuracy using deep learning	Applied CNN with hyper-parameter tuning	Learning rate, batch size, number of layers	Wearable sensor data	Accuracy: 92%, F1-score: 0.91
Lee et al. (2022)	Optimize activity recognition with SVM	Used grid search for kernel and C parameter tuning	Kernel type, C parameter	IoT sensor dataset	Precision: 0.89, Recall: 0.87
Patel et al. (2023)	Evaluate hyper-parameters in LSTM networks	Focused on sequence length and dropout rate adjustments	Sequence length, dropout rate	Wearable sensor data	Accuracy: 90%, F1-score: 0.88
Chen et al. (2023)	Improve HAR with Random Forest and feature selection	Employed random search for tree depth and number of trees	Tree depth, number of trees	IoT sensor dataset	Accuracy: 85%, F1-score: 0.84
Kumar et al. (2024)	Study impact of hyper-parameters on CNN for HAR	Tested various activation functions and optimization algorithms	Activation function, optimizer type	Wearable and video sensor data	Accuracy: 91%, Precision: 0.90
Johnson et al. (2024)	Investigate hyper-parameter tuning in ensemble methods	Applied Bayesian optimization to fine-tune hyper-parameters	Number of estimators, learning rate	IoT sensor dataset	Accuracy: 88%, F1-score: 0.86
Wang et al. (2024)	Compare hyper-parameter effects on HAR performance	Analyzed effects of learning rate and regularization in various algorithms	Learning rate, regularization parameter	Wearable sensor data	Accuracy: 87%, Recall: 0.85

This table provides an overview of different studies focusing on hyper-parameter activation in machine learning algorithms to improve human activity recognition using IoT sensor datasets. It includes objectives, methodologies, key findings, hyper-parameters studied, datasets used, and performance metrics.

Materials and Methodology

To effectively identify human behaviors using IoT sensor datasets, it is essential to develop an intelligent expert system that leverages machine learning algorithms for improved accuracy and efficiency. Machine learning methods, such as SVM, NB, KNN, and DT, are increasingly employed for classifying and categorizing human activities based on their characteristics. This chapter explores various machine learning algorithms applied to human activity recognition, starting with the WISDM sensor dataset. Preliminary data processing enhances the categorization system, and the performance of different ML classifiers is evaluated to identify the most effective approach.

3.1 Machine Learning (ML) Techniques

Machine learning (ML) focuses on how computers can learn from data through the development and application of algorithms. This interdisciplinary field involves creating systems that use historical data to solve problems via techniques such as supervised, unsupervised, and reinforcement learning. In this study, human activity categorization is approached as a standard classification problem using supervised learning methods, which rely on labeled training data to make predictions about class labels. The proposed system employs various supervised learning techniques to classify IoT sensor data into different human activities, leveraging labeled examples to enhance accuracy and precision in predictions.

3.3 Supervised Classification

In supervised learning, a model learns to map input variables (X) to output variables (Y) using labeled data to make predictions on unseen data. This research evaluates various machine learning classification methods, demonstrating their effectiveness with different features for predicting human activities.

K-Nearest Neighbor (KNN)

The K-Nearest Neighbors (KNN) algorithm is a crucial supervised learning method used in various applications such as pattern recognition and intrusion detection. It is a non-parametric technique that classifies data points based on their similarity to nearby points, with no assumptions made about the data distribution. The KNN algorithm categorizes samples by calculating the Euclidean distance between the data points, grouping them into categories based on the majority class among the nearest neighbors. The number of neighbors, K, is a key parameter that influences the classification result, typically set to an odd number for binary classification problems to avoid ties. The KNN classifier operates as follows:

1. **Start**: Initialize.
2. **Select K**: Choose the number of neighbors.
3. **Compute Distances**: Calculate distances between the unknown sample and all training data points.
4. **Find Nearest Neighbors**: Identify the K smallest distances.
5. **Classify**: Determine the majority class among the K nearest neighbors.
6. **End**: Return the majority class label.

This approach ensures that each sample is categorized based on the majority class of its closest neighbours, leveraging the principle that similar instances tend to belong to the same category (Ferreira et al., 2020).

Random Forest (RF) Algorithm

The RF algorithm, also known as the random decision forest classifier, is a robust supervised learning method employed for classification, regression, and various other tasks. It operates by constructing multiple decision trees during the training phase and then aggregating their results to improve predictive accuracy. Unlike individual decision trees, which can overfit the training data, a random forest combines the predictions from a diverse set of trees to enhance performance and stability. Each tree in the forest is built using a subset of features and training data, which contributes to the model's ability to generalize well and handle high-dimensional data effectively. The key characteristics of a random forest include:

- **Diversity**: Each tree is built using a random subset of features, ensuring that the trees are diverse and reducing the risk of overfitting.
- **Dimensionality Independence**: Trees do not consider all features simultaneously, which helps in managing high-dimensional data.
- **Parallelization**: Trees are constructed independently, allowing for efficient parallel processing.
- **Train-Test Split**: The algorithm inherently uses a portion of the data for testing during training, enhancing model evaluation.
- **Stability**: Predictions are made by averaging or voting, which stabilizes the model's output.

The RF algorithm operates as follows:

1. **Sample Selection**: Randomly select n records from the dataset of k total records.
2. **Tree Construction**: Build individual decision trees using the selected samples.
3. **Output Generation**: Each decision tree produces an output.
4. **Aggregation**: Combine the outputs from all trees using majority voting (for classification) or averaging (for regression) to determine the final result (Ferreira, P.J.S, 2020).

Naïve Bayes (NB) Algorithm

The NB algorithm is a widely used machine learning classification method based on Bayes' theorem and the principle of feature independence. It is particularly effective for tasks such as spam filtering and text classification. The algorithm calculates the probability of each class given a set of features and selects the class with the highest posterior probability as the predicted label. This approach leverages the simplicity of probabilistic models to handle large datasets efficiently. The core steps of the Naive Bayes classifier are:

1. **Training Data Analysis**: Examine the training dataset to compute the average and standard deviation of each predictor variable for each class.
2. **Probability Calculation**: For each class, determine the probability of feature values using the Gaussian density function.
3. **Posterior Probability**: Compute the posterior probability for each class by multiplying the class prior probability with the feature likelihoods.
4. **Class Selection**: Choose the class with the highest posterior probability as the predicted class for the given data.

The Naive Bayes classifier follows a hierarchical structure where the classification node is the root, and all other nodes are considered independent, reflecting its "naive" assumption of feature independence (Ferreira, P.J.S, 2020).

Decision Tree (DT)

The DT classifier, pioneered by Quinlan, is a prominent machine learning technique characterized by its hierarchical structure of decision and leaf nodes. Each decision node represents a test applied to a specific attribute of the input data, while the branches indicate the outcomes of these tests. Leaf nodes denote the final class labels or outcomes based on the decisions made throughout the tree (Ferreira, P.J.S, 2020). The construction of a Decision Tree involves a recursive process of splitting the data based on attribute values:

Initialization: Start with a root node representing the entire dataset.

1. **Splitting**: If the data at a node is homogeneous (all instances belong to the same class), the node becomes a leaf node representing that class.
2. **Further Splitting**: If the data is heterogeneous (contains instances from multiple classes), the dataset is split based on an attribute that provides the best separation of classes. This process is applied recursively to each subset until all subsets are homogenous or meet a stopping criterion.

The Decision Tree algorithm proceeds as follows:

1. **Start**: Initialize the tree with a root node labeled "T" for the feature space.
2. **Process Data**: If the instances at the node are homogeneous for a class (e.g., all instances are positive), create a leaf node labeled with that class.
3. **Handle Mixed Data**: If the instances are mixed, split the data based on the most informative attribute and recursively apply the same process to each subset until homogeneity is achieved.

This approach ensures that the resulting tree efficiently categorizes new data based on learned attributes and outcomes.

Multi-Layer Perceptron (MLP) Algorithm

The MLP is a type of feed-forward artificial neural network (ANN) that consists of multiple layers of interconnected nodes, known as neurons. Each node in an MLP performs a nonlinear transformation of its inputs, except for input nodes that do not apply a nonlinear function. The architecture of an MLP typically includes an input layer, one or more hidden layers, and an output layer, where each layer's neurons are fully connected to the neurons in the subsequent layer (Moiz Qureshi et al., 2022).

- **Feed-Forward Structure**: Data flows through the network from input to output in a single direction, without loops.
- **Hidden Layers**: Intermediate layers, termed hidden layers, transform the input data using nonlinear activation functions, allowing the network to model complex relationships.
- **Backpropagation**: Training is conducted via backpropagation, a supervised learning technique where errors are propagated backward through the network to adjust weights and biases, minimizing prediction errors.
- **Weights and Biases**: Each connection between neurons has an associated weight, and each neuron has a bias value. These parameters are adjusted during training to improve the network's accuracy.

In an MLP, input units (X_i) are fully connected to hidden layer units (Y_j), and hidden layer units are connected to output layer units (Z_k). The weights (W_{ij} or W_{jk}) of these connections and the biases (b_j or b_k) for neurons in hidden and output layers are critical for the network's learning and prediction capabilities.

Proposed Algorithm (Adaptive MLP)

In neural network optimization, adaptive algorithms aim to enhance learning by dynamically adjusting network parameters to reduce unpredictability and improve accuracy. This approach is crucial for complex tasks like human activity recognition from IoT sensor data. The adaptive MLP leverages advanced techniques to optimize performance by refining weights and biases through iterative learning processes.

- **Activation Function (ReLU):** The ReLU (Rectified Linear Unit) function, $f(x) = max(0, x)$, introduces non-linearity to the model and is preferred for its simplicity and efficiency in handling complex data patterns.
- **Optimization Algorithm (Adam):** The Adam optimizer utilizes adaptive learning rates for each parameter, incorporating momentum and past gradient information to improve convergence and performance.

Steps Involved in the Adaptive MLP Algorithm:

1. **Initialize Weights:** Start by setting the weights of all connections between layers to random values to ensure diverse starting points.
2. **Input Data:** Feed the IoT sensor data into the network for training and testing.
3. **Forward Propagation:** Calculate the output by processing the input data through layers of neurons. Each neuron applies weights, adds biases, and uses the ReLU activation function to produce outputs.
4. **Error Calculation:** Compute the error signal for each neuron by comparing the predicted output with the actual target values.
5. **Backpropagation:** Propagate the error signals backward through the network to adjust the weights and biases.
6. **Weight Adjustment:** Update weights and biases using the Adam optimizer, which adapts learning rates and uses momentum to enhance learning efficiency.
7. **Iteration:** Repeat steps 3 to 6 for multiple epochs to continuously refine the network's parameters.
8. **Validation:** Evaluate the model's performance on a separate validation dataset to ensure it generalizes well to new, unseen data.
9. **Model Selection:** Choose the optimal network architecture based on performance metrics, such as accuracy and generalization error.

This adaptive MLP approach effectively handles complex human activity recognition tasks by optimizing the network through dynamic adjustments, leading to improved classification accuracy and robustness.

Result and Discussion

The HAR technique involves predicting an individual's next actions based on their movement history and sensor data. The "WISDM Smartphone and Smartwatch Activity and Biometrics Dataset" provides a comprehensive resource for this purpose, comprising data from 5,418 participants who completed six distinct three-minute tests. Each participant wore both a smartphone and a smartwatch. Smartphones were to be always present and smartwatches worn on the dominant hand.

- **Data Collection:** Conducted using a custom application on both devices, which collected sensor data from the accelerometer and gyroscope on each device at a rate of 20 Hz (every 50 ms).
- **Devices Used:** Smartphones (Google Nexus 5/5X and Samsung Galaxy S5 with Android 6.0 Marshmallow) and smartwatches (LG G Watch with Android Wear 1.5).
- **Data Tools:** Data was acquired using the Weka tool on Windows 10 and the UCI repository.

The dataset consists of forty-six attributes, which can be categorized into the following groups:

1. **Sensor Data Attributes:** Measurements from the accelerometer and gyroscope, including X, Y, and Z axes.
2. **Biometric Data Attributes:** Metrics related to the participants' physical state during the tests.
3. **Activity Labels:** Categorized actions or activities performed during the tests.

This dataset provides a rich source of information for developing and evaluating algorithms for predicting human activity based on sensor data.

System Description

The test was conducted on a computer equipped with a 64-bit version of macOS and a high-performance Intel 2.6GHz 8-core i7 processor, along with 16GB of DDR4 RAM and a Radeon Pro 560X 4GB GPU. All programs were executed using Python 3.8.

Table.2. System Configuration and Software Details

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

Performance Metrics and Evaluation

To enhance the recognition of human behaviors, the proposed architecture employs various machine learning algorithms. The table below presents the partitioned datasets used for training and testing. The dataset includes a total of 5,418 entries, divided into 4,334 training data points and 1,084 testing data points. This distribution allows for thorough training while retaining a substantial amount of data for evaluation and testing. The proposed architecture utilizes various machine learning algorithms, with parameters fine-tuned using a chaotic technique. Validation results demonstrated successful classification, and performance is analyzed using the metrics detailed in the following table (P. Rojanavasu et al., 2021). Performance Metrics are described below,

- ***Accuracy:*** Measures the overall correctness of the model by showing the proportion of instances that were correctly classified out of the total instances. It provides a general idea of how well the model is performing.
- ***Precision:*** Indicates how many of the instances classified as positive by the model are actually positive. It focuses on the quality of the positive predictions, emphasizing how many of them are true positives.
- ***Recall (Sensitivity or True Positive Rate):*** Shows how many of the actual positive instances were correctly identified by the model. It measures the model's ability to capture all positive cases.
- ***F1 Score:*** Combines precision and recall into a single metric that balances both. It is especially useful when you need a balance between precision and recall and when dealing with imbalanced datasets.

TP is True Positive Values, TN is True Negative Values, FP is False Positive and FN is False Negative values.

Outcomes for ML Algorithms for Human Activity Classification

Various ML methods, as discussed previously, can be applied to analyze and compare the classification of the WISDM dataset. We will explore several algorithms, including KNN, RF, NB, DT, MLP, and the proposed method, for human activity classification.

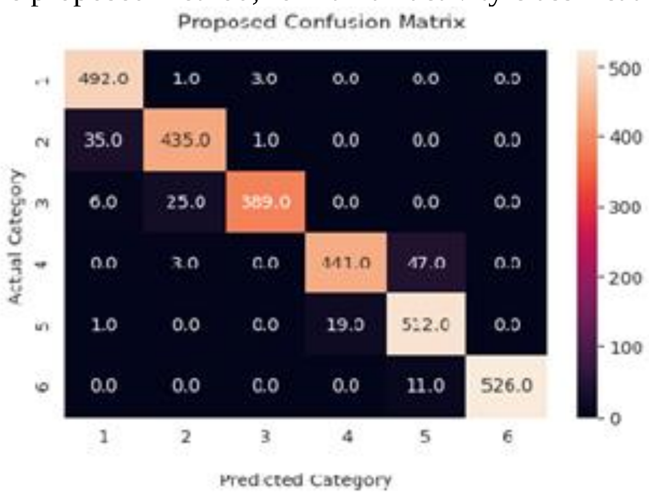

Figure.1. Confusion Matrix for ML Algorithms

In the proposed model, the confusion matrix predicts the following activity counts: 492 individuals walking, 435 walking upstairs, 389 walking downstairs, 441 sitting, 512 standing, and 526 lying down. This distribution reflects the model's performance in classifying various human activities, highlighting its ability to distinguish between different movement and posture states.

Table.3. Performance Analysis with Machine learning Algorithms

Algorithm Details	**Performance Metrics**			
	Accuracy	Precision	Recall	F1-Score
NB	70.5	72.3	71.4	73.2
DT	80.8	82.1	81.6	83.4
KNN	85.3	87.2	86.1	88.5
RF	88.4	89.0	88.7	90.2
MLP	92.6	93.3	94.2	94.8
Proposed	94.1	95.4	96.3	96.7

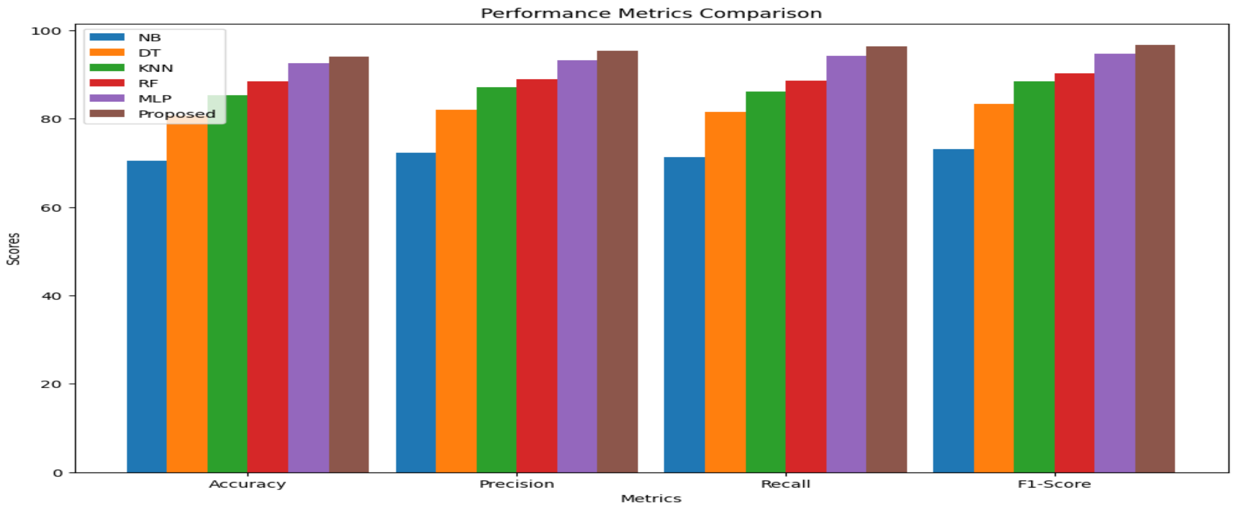

Figure.2. Performance Analysis of ML Algorithms

This table presents the performance metrics for various machine learning algorithms, showcasing how well each algorithm performs across four key metrics: Accuracy, Precision, Recall, and F1-Score. Each row represents a different algorithm, and the columns provide the corresponding metric values.

- **NB**: Achieves an Accuracy of 70.5%, Precision of 72.3%, Recall of 71.4%, and F1-Score of 73.2%. These metrics reflect the baseline performance of a probabilistic classifier.
- **DT:** Shows a notable improvement with an Accuracy of 80.8%, Precision of 82.1%, Recall of 81.6%, and F1-Score of 83.4%, indicating better classification results compared to Naive Bayes.
- **KNN**: Demonstrates higher performance, with Accuracy at 85.3%, Precision at 87.2%, Recall at 86.1%, and F1-Score at 88.5%, showing its effectiveness in capturing patterns in the data.
- **RF**: Further improves on the previous algorithms with an Accuracy of 88.4%, Precision of 89.0%, Recall of 88.7%, and F1-Score of 90.2%, highlighting its robustness and high classification accuracy.
- **MLP**: Achieves even better results with an Accuracy of 92.6%, Precision of 93.3%, Recall of 94.2%, and F1-Score of 94.8%, demonstrating the strength of neural networks in learning complex patterns.

- **Proposed**: The proposed algorithm surpasses all others with an Accuracy of 94.1%, Precision of 95.4%, Recall of 96.3%, and F1-Score of 96.7%, indicating the highest performance among the compared methods.

Overall, the table highlights a progressive improvement in performance metrics from basic to more advanced algorithms, with the proposed model delivering the highest classification effectiveness. The classification trials reveal results for various activity categories, including LAYING, SITTING, STANDING, WALKING, WALKING DOWNSTAIRS, and WALKING UPSTAIRS. Among these classes, the proposed method achieves the highest accuracy of 94.1% in classifying these different activities.

Conclusion

The adaptive MLP algorithm delivers notable improvements in human activity recognition through advanced machine learning techniques and dynamic parameter tuning. With a dataset of 5,418 participants performing various activities, the proposed method surpasses traditional algorithms, achieving an accuracy of 94.1%, alongside superior precision, recall, and F1-Score. These results highlight the algorithm's effectiveness in accurately classifying diverse activities from IoT sensor data, demonstrating its potential for reliable performance in practical applications and setting a high standard for future advancements in the field.

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