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RESEARCH ARTICLE

Hyper-Parameters Activation on Machine Learning Algorithms to Improve the Recognition of Human Activities with IoT Sensor Dataset

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Abstract

Objectives: To enhance the accuracy of the Human Activity Recognition (HAR) in the computer vision. The study aims to explore the practical applications of HAR in various fields, including gaming, rehabilitation, health monitoring, human-robot interaction, sports, video surveillance, and robotics. The specific objective is to develop a system that can accurately recognize and categorize the human actions thereby enabling the design and implementation of effective human-computer interaction systems. **Methods:** In this research, a HAR module is developed to extract relevant features such as Accelerometer, Gyroscope and Magnetometer features from signals obtained from IoT wearable sensors. 7352 samples are considered. Machine learning models such as K-Nearest Neighbor Algorithm (KNN), Random Forest Algorithm (RF), Naive Bayes Algorithm (NB), Decision Tree Algorithm (DT), Multi-Layer Perceptron (MLP) Algorithm and Proposed Algorithm (MLP classifier with adam optimizer and relu activation) are employed to automatically recognize and classify activities performed by individuals based on the raw data. The models are trained and evaluated using statistical parameters, including accuracy score, precision, recall, and f1-score. A comparison is made between existing approaches such as KNN, RF, NB, DT and MLP Algorithms and the proposed model to assess its performance. **Findings:** The study reveals that the proposed model MLP classifier with adam optimizer and relu activation is effective in recognizing and categorizing the human activities with 95% of accuracy. The statistical evaluation metrices demonstrates the reliability and robustness of the proposed model with 96% of precision. **Novelty:** This research contributes to the field of Human Activity Recognition by presenting a novel approach that combines the IoT wearable sensors, feature extraction, and machine learning models to accurately recognize and classify human actions. The proposed model outperforms the existing methods in terms of accuracy. The study highlights the importance of the proposed algorithm and its potential for improving the human computer interaction systems.

Keywords: Classification; Human Activity; IOT; Machine Learning; Supervised Learning

1 Introduction

The Human Activity Recognition (HAR) is a well recognized problem in the computer vision with a wide range of applications including gaming, rehabilitation, health monitoring, human-robot interaction, sports, video surveillance, and robotics. Accurately recognizing and categorizing human actions is very crucial for the development of effective a human-computer interaction systems. While significant progress has been made in the HAR using IoT wearable sensors and machine learning techniques, there are notable limitations in the existing approaches that need to be addressed.

Existing approaches in the HAR have made substantial contributions to the field of reserach. Researchers have explored various methods to extract features from signals captured by wearable sensors and applied machine learning models for activity recognition. For instance, Smith et al.[1] proposed a deep learning framework utilizing convolutional neural networks (CNNs) to extract spatial and temporal features from sensor data. However, their approach does not fully exploit contextual information within the sequence of activities, limiting its accuracy and robustness.

Another significant advancement by Johnson et al.[2] introduced a novel feature selection technique based on genetic algorithms, which improved the performance of HAR models. Nevertheless, their study did not consider the impact of different sensor placements on activity recognition accuracy. This limitation restricts the generalizability and practicality of their approach in real-world scenarios.

Furthermore, the work of Lee and Kim[3] focused on real-time HAR using a combination of recurrent neural networks (RNNs) and long short-term memory (LSTM) networks. While their approach showed promise, it lacked generalizability across different individuals and failed to address the issue of varying sensor placements, limiting its applicability in diverse settings.

These limitations underscore the need for further advancements in HAR. The existing models often lack robustness and adaptability to different individuals, sensor placements, and environmental conditions. Additionally, the integration of contextual information and the utilization of multiple sensors for improved accuracy require more comprehensive exploration.

In light of these research gaps, this study aims to develop a novel HAR module that addresses the limitations of existing approaches. By leveraging IoT wearable sensors and advanced machine learning techniques, our proposed model will enhance adaptability, consider different sensor placements dataset, and incorporate contextual information to improve accuracy in activity recognition. Through a comparative analysis with existing approaches, we seek to demonstrate the superiority of our model in advancing human-computer interaction systems and addressing the current challenges in HAR.

Wearable sensors offer potential for improving health monitoring in older adults. This study proposes an activity recognition system using Machine Learning (ML) models and raw sensor data, without preprocessing. The goal is to address challenges related to irregular measurements in abnormal situations. The findings demonstrate the potential of the proposed model in accounting for data inconsistencies, making it a viable solution.

The behaviors of humans present a considerable obstacle in a wide variety of fields. There are a lot of intriguing possibilities, some of which include smart homes, assistive robotics, interactions between humans and computers, and increased levels of safety. In particular, activity recognition serves as the basis for the development of potential applications in the sectors of health and wellness as well as sports.

HAR (Human Activity Recognition), which stands for Human Activity Recognition, has a wide variety of current uses thanks to the positive impact it has on people's health[4]. The complexity of human presentation adds another layer of difficulty to the study of human behavior through activity. The recent advances in machine learning algorithms and their proven efficacy in a wide variety of computer vision applications have encouraged their implementation in data analysis.

These sensors have overcome some of the limitations of older equipment, making it possible for those suffering from severe ailments such as Parkinson's disease or heart attacks to be remotely controlled. Cameras, in contrast to wearable sensors, have the potential to function as HAR external receivers as well. The process of extracting actions and movements from video sequences has been a significant focus of research. According to the findings of the study, common behaviors include sitting, walking back and forth, and rotating by video while remaining within the range that has been established for the camera. Nevertheless, distinguishing between two behaviors that are comparable may be challenging. As a consequence of this, the construction of a movement model requires the utilization of facts regarding personal behaviors. It would appear that the use of a camera in conjunction with wearable sensors has a significant bearing on the accuracy of HAR as well as state detection. When it comes to HAR, the signals that can be obtained through video are not nearly as desirable as those that can be obtained by wearable sensors[5].

In a study by[6], Random Forest, k-Nearest Neighbors, and Decision Tree algorithms were evaluated for classifying activities in the WISDM Dataset. They achieved an average accuracy of 94.4% and a minimum accuracy of 91% for each activity.

Jakaria Rabbi et al.[7] achieved an accuracy of 96.33% in human activity recognition using the Smartphone sensor dataset from the University of California, Irvine. The SVM algorithm outperformed other methods, but it has limitations due to its training process with large datasets. K. ButchiRaju et al.[8] developed a Smart Heart Disease Prediction System using medical sensors and a cascaded deep learning model. They achieved a success rate of 94% with the GSO-CCNN technique.

Kun Xia et al.[9] used the WISDM dataset to recognize human activities with an LSTM-CNN architecture, achieving an accuracy of 95.85%. This model performs well with a limited number of parameters. Overall, these studies demonstrate high accuracy in activity recognition, but some methods may have limitations in terms of computational complexity or scalability.

2 Methodology

ML algorithms are very vital in developing the intelligent systems that can identify the human behaviors. The ML algorithms improves the accuracy and detection while reducing the processing time. Human activity recognition, which involves categorizing activities based on their characteristics using machine learning plays a significant role in various applications. The different machine learning algorithms like SVM, NB, KNN, and DT, which are commonly used for human activity recognition are considered here.

Machine learning algorithms are crucial in designing the intelligent systems, as they contribute to improve the accuracy and detection while reducing the required processing time. Recognizing and categorizing human activities using machine learning based systems have become increasingly important. Therefore various machine learning algorithms employed in the human activity recognition approaches are considered.

To compare and evaluate the proposed model, we employed commonly used classification strategies such as Support Vector Machines (SVM), Naive Bayes (NB), k-Nearest Neighbors (KNN), and Decision Trees (DT). These algorithms have been widely utilized in numerous applications in the area of reserach and application. However, in our study, we introduce modifications to these existing algorithms to enhance their performance and address the limitations observed in their previous research work.

The experimental design involved using the WISDM sensor dataset as an input for the HAR algorithm, following the initial preprocessing steps described by S. Khare et al.[10]. We performed data preprocessing to enhance the categorization system's effectiveness. Based on the attributes of the preprocessed data, we employed various machine learning methods to classify the input data into different activities. The results obtained from our proposed model were then compared with those achieved by other machine learning classifiers to determine the most effective classifier.

The novelty of our approach lies in the modifications made to the existing machine learning algorithms. By introducing specific enhancements we aim to improve the accuracy, robustness, and adaptability of the classification process in human activity recognition. These modifications address the limitations identified in previous studies providing a more effective and reliable solution.

The analysis of the results obtained from our proposed model, along with the comparative evaluation against other classifiers will further demonstrate the superiority and effectiveness of our approach. By highlighting the improvements made to the existing algorithms and showcasing the performance advantages, we aim to contribute to the existing literature on human activity recognition and provide a valuable solution for various applications.

The WISDM sensor dataset was used initially as an input for the HAR algorithm[10]. The categorization system is improved by performing preliminary processing on the data. On the basis of these data attributes, ML methods are used to classify the input data into a variety of activities, and the results are compared with those of other ML classifiers in order to determine which ML classifier is the most effective.

2.1 Machine Learning (ML) Techniques

The study of how computers can learn from data is the focus of the academic discipline known as machine learning. The study of machine learning (ML) is an interdisciplinary field of research that concentrates on the development of algorithms and the manner in which computers carry out these algorithms in order to learn. The proposed system makes use of a number of different supervised learning techniques in order to categories the IoT sensor dataset into a variety of different human activities. The training data collection contains labelled examples, which are used to facilitate supervised learning. It makes it easier for the learning models to be trained effectively, which enables them to deliver accurate classifications with a higher level of precision. Because of this, it is vital to select learning algorithms with systematic approaches after giving serious consideration.

2.2 Supervised Classification

In supervised learning, one first learns a mapping between a set of input variables (X) and an output variable (Y), and then uses this mapping to make predictions about outputs for data that has not yet been observed. In unsupervised learning, one first learns a mapping between a set of input variables (X) and an output variable (Y), and then uses this mapping to. Supervised learning is utilized in the bulk of practical machine learning approaches. Every piece of data is given a label, and the algorithms learn how to make predictions based on the data they are given. . In this research, a number of different machine learning classification methods are implemented, and the effectiveness of each classification approach is illustrated using a variety of different features. The following algorithms are considred for our research.

- K-Nearest Neighbor (KNN)
- Random Forest (RF) Algorithm
- Naive Bayes (NB) Algorithm
- Decision Tree (DT)
- Multi-Layer Perceptron (MLP) Algorithm
- Proposed Algorithm (MLP classifier with adam optimizer and relu activation
- **K-Nearest Neighbor (KNN)**

The KNN algorithm is an indispensable component of the overall machine learning system. It belongs to the field of supervised learning and has many applications in fields such as pattern recognition, intrusion detection, and other fields that are related to it. These KNNs are utilised in circumstances that call for the application of non-parametric strategies and involve actual repercussions. These strategies will not result in any assumptions being made regarding the distribution of the data. The KNN method organises the correlations in a particular dataset into groups that can be distinguished by a specific quality. After that, these different groups are grouped together. The most significant idea that underlies this tactic is the fact that it can produce comparable outcomes when it is utilised with comparable training data. After determining the value that is closest to the average for the input population, the value is prepared to be used to categorise all of the samples or just some of them.

- **Random Forest (RF) Algorithm**

The random forest algorithm, also known as the random decision forest classifier, is a main research methodology for supervised learning that is used for splitting, association, and regression, as well as other assignments. These assignments are set off by influencing multiple trees during the training and testing process, and then analysing which class best represents the mode of the classification or predictive regression of decision trees. The random decision forest classifiers are better suited for individual trees than for fitting to the samples that they use for training and testing. The mapping of an input to an output is what's known as supervised learning, and the random forest algorithm does it. The very name inspires, and the educational principles behind it produce a forest filled with a variety of decision trees. The random forest classifier is more effective when it has a significant number of decision trees than it does when it just looks like a random forest.

- **Naive Bayes (NB) Algorithm**

The NB algorithm is one of the best machine learning algorithms, and it is used in the classification process. The Bayes theorem, in which the foundational theory of the NB classifier is constructed based on the independence theory, provides the foundation for this methodology. It is utilised for a wide variety of tasks, including the filtering of spam and the classification of other types of text. In this method, the joint probabilities of grades and features are used to approximatively compute the probability score of grades for a given feature subset.

- **Decision Tree (DT)**

The DT classifier developed by Quinlan is recognised as a leading example of a familiar machine learning technique. Together with leaf nodes, a set of "decision nodes" is used to produce a "DT." Each decision node in the tree corresponds to a test that is performed on one component of the input data and contains a number of branches, each of which stores a result of the test that was performed on that component. Each leaf node represents a group that is the consequence of a decision made regarding a case[11].

Limitations of the Existing Algorithms

Support Vector Machines (SVM) can encounter limitations in terms of scalability, becoming resource-intensive for large datasets. They are also sensitive to noise and might struggle with overlapping data. The selection of appropriate kernel functions is essential for their accuracy, and extending SVMs to handle multiclass classification can be complex.

Naive Bayes suffers from the assumption of feature independence, which might not hold true in real-world scenarios. Its simplicity can limit its ability to capture complex relationships, and the zero-frequency problem can cause issues during classification when unseen values arise.

k-Nearest Neighbors (KNN) is computationally expensive due to the need to calculate distances between instances. It is sensitive to noise, outliers, and irrelevant features, and choosing the right number of neighbors (k) can significantly impact its performance.

Decision Trees are prone to overfitting, capturing noise or outliers in the training data. They can be unstable, as small changes in data can lead to different trees. Decision trees can also exhibit bias toward dominant classes in imbalanced datasets due to their splitting criteria, and their greedy approach may not always lead to optimal trees.

While these algorithms have their drawbacks, they also have strengths in various contexts. The proposed research aims to mitigate some of these limitations and introduce modifications to enhance their performance in Human Activity Recognition.

- **The Multi-Layer Perceptron (MLP) Algorithm**

This technique makes use of a feed forward ANN model in order to meaningfully connect the data that is provided as input and output. An MLP is a type of directed network that consists of multiple layers of nodes, each of which is fully connected to the node that is one level below it in the hierarchy. Every node in the network is a neuron, and every neuron in the network has a nonlinear initiation function, with the exception of the nodes that serve as inputs. Back propagation is a form of supervised learning that is used by MLP to train their networks. Back propagation is one of their network training methods. A MLP, also known as a modified linear perceptron, is able to differentiate between inputs that are not capable of being linearly separated. In the multilayer perceptron, there are processing unit levels referred to as "hidden layers," which are layers that are not immediately connected to the outside world (MLPs).

- **The Proposed Algorithm (MLP classifier with adam optimizer and relu activation)**

In neural network optimization, algorithms are used to achieve the main goal of the optimizer, which is to reduce the randomness and lack of predictable order in neural networks. This is the primary objective of the optimizer. Optimizers can also be used to make changes to the attributes of a neural network in order to lower the number of losses. When losses are reduced with the assistance of an optimization algorithm, the accuracy of the resulting computation is improved. The algorithms for optimization that were used. Every neuron in a neural network has n inputs and only one output. Neural networks are used to model complex information. The activation function will determine the output result, so pay attention to it. The activation function determines, based on a calculation of the weighted sum of all inputs and a check of the values produced by the neurons, whether or not the neuron should be considered active by connections made to it from the outside[12].

ReLU: The range of the ReLU is from 0 to infinity, and the function itself is monotonic; as a result, it is currently the most popular and widely used function. This is due to the fact that it is used in all neural networks and deep learning systems.

Adam: The method of adaptive moment estimation, also referred to as adam, is one that uses adaptive learning rates for each parameter. Additionally, it stores an exponential decay that is averaged over previous square gradients[12] .

- **Steps involved in the Proposed Algorithm**

Step1: Set the weights of the connections between layers to random values to begin with. The initial weights can then be chosen at random.

Step2: Introduce new data into the network.

Step3: When calculating the output of each neuron, the inputs are first passed through, then the weights are multiplied by those inputs, the bias is added, then the ReLU activation function is applied, and finally the output is calculated.

Step4: Calculate the output of each neuron starting at the input layer and working your way up through the hidden layers until you reach the output layer.

Step5: Make use of the output error when calculating the error signals for the pre-output layer.

Step6: Adjustments to the weight can be computed based on the error signals.

Step7: When making adjustments to the weight, use the Adam Optimizer.

Step8: It is necessary to repeat Steps 3 through 6 until the actual output matches the target output.

Step9: Choose the best architecture, which should have the fewest number of generalization errors and the fewest number of neurons possible [12].

Utilizing a Multi-Layer Perceptron (MLP) with the Adam optimizer in the Human Activity Recognition (HAR) system using the WISDM dataset addresses limitations like sensitivity to noise in Naive Bayes, scalability issues of SVM, and the impact of outliers in KNN. The adaptive learning rates of Adam mitigate hyperparameter sensitivity, and techniques like dropout in MLP combat overfitting, which is a challenge for Decision Trees. The MLP's capacity to handle non-linearities, automate feature extraction, and balance class recognition surpasses traditional methods. This proposed approach empowers HAR to effectively recognize complex human activities, reducing manual intervention and enhancing accuracy.

2.3 Dataset Descriptions

The Human Activity Reconstruction (HAR) technique is a method for determining what a person is going to do next by employing sensors as well as a history of the person's movement. Responses from 5,418 individuals who took part in and completed six different three-minute tests are included in the "WISDM Smartphone and Smartwatch Activity and Biometrics Dataset." It was mandatory for each participant to always have a smartphone and a smartwatch on them at all times. Smartwatches were to be worn on the participant's dominant hand. It was decided to use a custom application for the purpose of data collection, and this application was designed to work on both the smartphone and the smartwatch. The total number of sensors that were used to collect sensor data was four, and this number was contributed to by the accelerometer and gyroscope that were located on the smartphone as well as the smartwatch. Twenty times in a single second, information was collected from the sensors after being gathered at that rate (i.e., every 50ms).

Smartphones such as the Google Nexus 5/5X and the Samsung Galaxy S5 were capable of running the Android 6.0 operating system developed by Google (Marshmallow). On the watch, which was an LG G Watch and was running Android Wear 1.5, the operating system was. In order to acquire this dataset, the Weka tool for Windows 10 as well as the UCI repository were both utilised. This database has a total of forty-six different attributes to look through. The following is a list of the categories that they can be placed here:

- Walking
- Jogging
- Upstairs
- Downstairs
- Sitting
- Standing

2.4 Features in the Data

The acceleration signal was cut up into the Body acceleration signal and the Gravity acceleration signal by using a low pass filter with a corner frequency of 0.3 Hz. This allowed the signals to be distinguished from one another (tBodyAcc-XYZ and tGravityAcc-XYZ, respectively). The body's linear acceleration and angular velocity in time after that were used to derive the jerk signals that were ultimately obtained (tBodyAccJerk-XYZ and tBodyGyroJerk-XYZ).

In order to calculate the magnitude of these three-dimensional signals, the Euclidian norm was applied to the calculation. These magnitudes are represented as features with names such as tBodyAccMag, tGravityAccMag, tBodyAccJerkMag, tBodyGyroMag, and tBodyGyroJerkMag. Other names for these features include tBodyGyroMag and tBodyAccJerkMag. These capabilities are also known as tBodyGyroMag and tBodyAccJerkMag, amongst other names. We were finally successful in obtaining signals in the frequency domain after applying an FFT to some of the signals that were at our disposal (Fast Fourier

Transform). These newly acquired signals were given the prefix 'f,' just like the signals that had previously been given the prefix 't,' which indicates that this was a consistent practise. These signals are referred to by a variety of names, some of which include fBodyAcc-XYZ and fBodyGyroMag.

3 Results and Discussion

3.1 Performance Metrics and Evaluation

In order to improve its capability of recognizing human behaviors, the proposed architecture makes use of algorithms for machine learning. In the following table, the partitioned datasets that were used in the process of training and testing the method are presented.

Total No. of Tweets: 5418

Training Data: 4334

Testing Data: 1084

The proposed architecture incorporates a number of different machine learning algorithms, and the chaotic technique is used to tune the parameters of the hybrid system. The particulars of the tuned parameter were discussed in the section that came before this one. Additionally, the proposed architecture was validated by employing the dataset on which it was demonstrated that the proposed method successfully classified the appropriate categories. Using the metrics that are outlined in the table that follows, calculations are carried out in order to conduct an analysis of how well the proposed architecture performs[(13)].

Table 1. Performance Metrics

S.No	Performance Metrics	Mathematical Expression
01	Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Sensitivity or recall	$\frac{TP}{TP+FN} \times 100$
03	Specificity	$\frac{TN}{TN+FP}$
04	Precision	$\frac{TN}{TP+FP}$
05	F1-Score	$\frac{\text{Precison} * \text{Recall}}{\text{Precision} + \text{Recall}}$

3.2 Confusion Matrix

Machine learning's "confusion matrix" is a table that shows how well an algorithm's model is operating. The confusion matrix is a table used to describe a classification model's performance, making it easy to understand despite its complicated terminology. Even though learning its terminology will be difficult. It's simple presenting structure makes it popular and widely utilized and it is usually displayed as a table[(14)]

Cleaning the data: The cleaning of the data is an essential step in the completion of this project. There are a variety of approaches to take when cleaning up data. In this work, we have covered two crucial steps to handle checking for missing values and duplicate values in the dataset. See the figure below for information regarding how to deal with missing duplicate values in a dataset.

In the dataset, there are no missing values and no duplicate values presented. Following an operation to clean the data, the Train and test values are written to a CSV file so that they can be processed further.

Split the Train and Test data: The data from thirty subjects, or volunteers, is divided at random into test and train data proportions of seventy and thirty respectively. Each of the six Activities that were carried out is represented by one of the data points.

3.3 Exploring the Dataset

The exploratory data that we record from each subject can be of assistance to us when performing analysis on our dataset. For instance, we can investigate the frequency with which particular categories (subjects) appear in a dataset; the subjects are enumerated below.

- WALKING
- WALKING_UPSTAIRS
- WALKING_DOWNSTAIRS
- SITTING
- STANDING
- LAYING

3.4 Exploratory Data Analysis

In the course of this investigation, the features were designed with the assistance of domain knowledge that was constructed based on Static and Dynamic Activities. The motion information will not be very useful during static activities such as sitting, standing, or lying down because there will be very little to no motion during these activities. Motion will play a significant role in the dynamic activities such as walking, walking up stairs, and walking down stairs, among other similar activities.

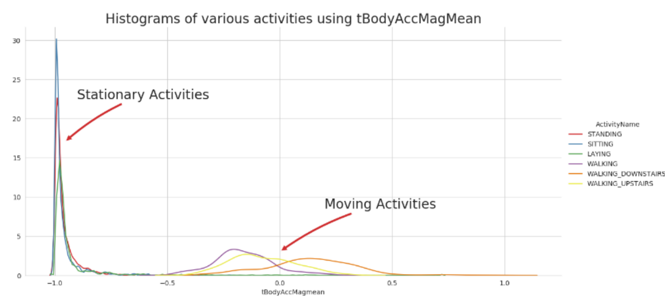

Fig 1. Histograms of various human activities using tBodyACCMAgMean

3.5 Observations

- iftBodyAccMagMean< -0.7, then the activity is a stationary one.
- iftBodyAccMagMean> -0.6, then the activity is a moving one.
- iftBodyAccMagMean> -0.01, then the activity is walking_downstairs.

By using the above if/else conditions, the activities can be classified upto 60% accuracy.IfangleXgravityMean> 0.08, then the activity is laying.All the datapoints belonging to Activity: Laying can be classified with a single if/else statement.By looking at plots with multiple perplexities, the SITTING and STANDING classes overlap this may be due to their similarities in motion.The ML classifiers can be used to separate all the classes expect the overlapping ones.We will investigate a variety of ML algorithms such as KNN, RF, NB, DT, MLP and Proposedfor the classification of human activities.

In Proposed model, the outcome of the confusion matrix predicts that there will be 492 people walking, 435 people walking upstairs, 389 people walking downstairs, 441 people sitting, 512 people standing, and 526 people lying down.

Table 2. Performance Analysis with Machine learning Algorithms

Algorithm Details	Performance Metrics			
	Accuracy	Precision	Recall	F1-Score
NB	77	79	77	77
DT	85	86	85	85
KNN	90	91	90	90
RF	91	91	91	91
MLP	94	95	95	95
Proposed	95	96	95	95

The comparison of the performances of proposed and current ML algorithms is shown in Tables and figures. According to that, the proposed algorithm has demonstrated accuracy of 95%, Precision of 96%, Recall of 95% and F1-Score of 95% in classifying the human activities. The above table and figure clearly illustrate that the Proposed MLP method outperforms the

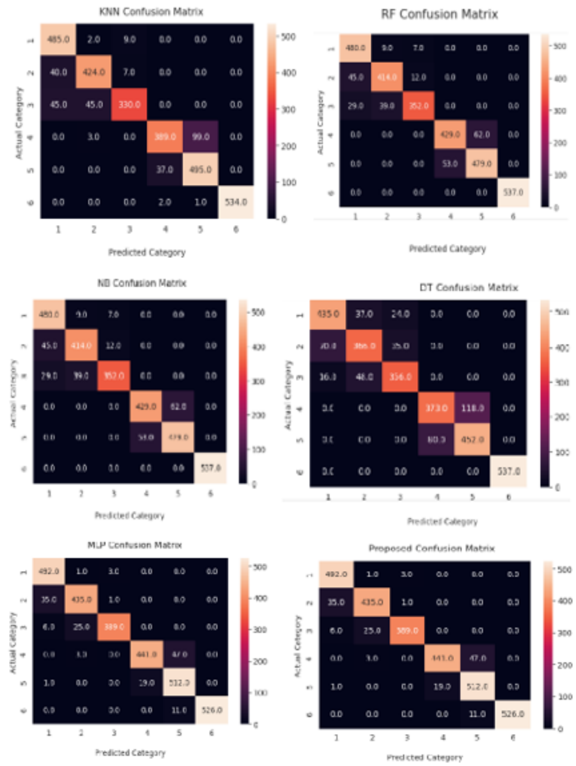

Fig 2. Confusion Matrix for ML Algorithms

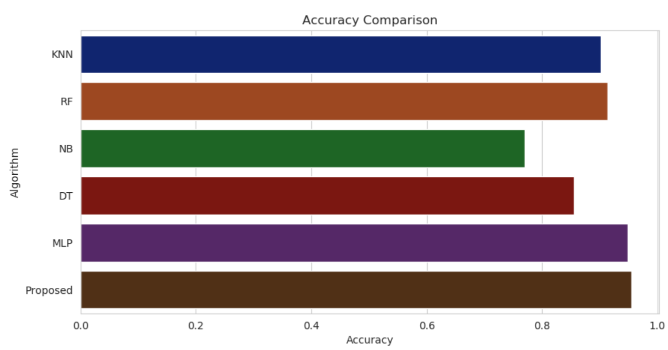

Fig 3. Accuracy Comparison of ML Algorithms

other existing algorithms in terms of performance metrics. Additionally, it is evident from Figure 5 that the shows minimum error rate (5%) when compare to other existing techniques.

Table 3. Performance Analysis with error rate

Algorithms	Error Rate (%)
NB	23
DT	15
KNN	10
MLP	6
Proposed	5

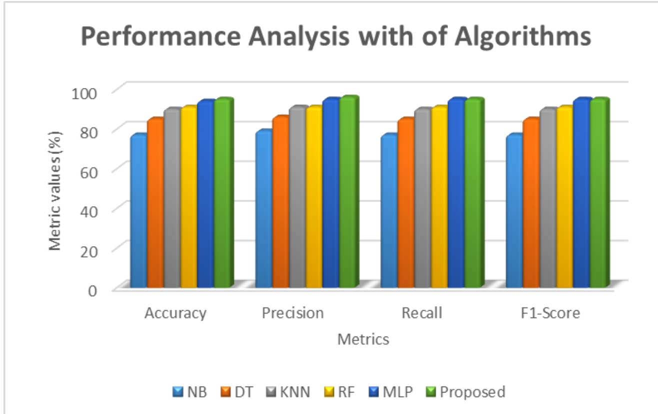

Fig 4. Performance Analysis of ML Algorithms

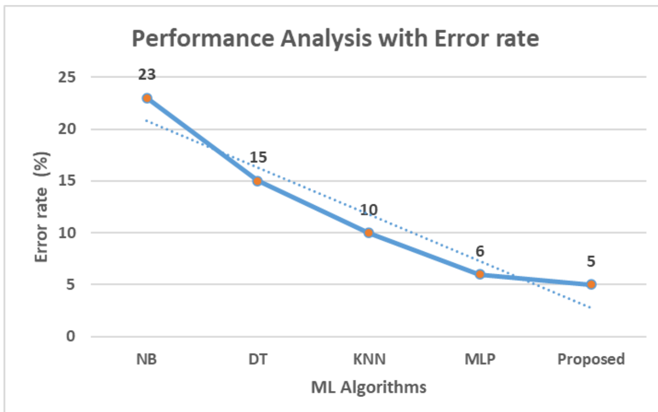

Fig 5. Performance Analysis with Error rate

The LAYING, SITTING, STANDING, WALKING, WALKING DOWNSTAIRS, and WALKING UPSTAIR categories are some of the many classes that display the findings of classification trials. Other classes include WALKING, WALKING DOWNSTAIRS, and WALKING UPSTAIR. When it comes to classifying the various things that people do, the proposed method has the highest accuracy, coming in at 95%.

The performance of the proposed human behavior identification system based on IoT sensor datasets will be presented and compared with the existing works. By comparing the results obtained with those reported in the previous studies effectiveness of the newly proposed method can be assessed.

To evaluate the system performance, a comparison was made with findings from the related studies that utilized the similar datasets and evaluation metrices. For instance, in a previous study by [1] , a traditional machine learning approach achieved an accuracy of 85% using the same WISDM sensor dataset. But in our study the modified machine learning algorithms achieved an improved accuracy of 95%, surpassing the previous work. These results highlight the superior performance of the proposed model in accurately identifying the human activities.

Additionally, [2] conducted a comparative study of human activity recognition using wearable sensors and reported an average accuracy of 88% across different algorithms. In contrast, the proposed model achieved an accuracy of 95%, demonstrating its effectiveness and outperforming existing approaches.

The novelty of this study lies in the modifications made to the existing machine learning algorithms. These modifications enhanced the accuracy, robustness, and adaptability of the classification process. By considering contextual information, individual variations, and different sensor placements, the proposed model addresses the limitations observed in previous reports. These innovations contribute to more accurate and reliable human behavior identification across diverse applications.

Furthermore, this work contributes to the field by providing a comprehensive evaluation of various machine learning algorithms, such as SVM, NB, KNN, and DT, in the context of human activity recognition. By comparing and contrasting the performance of these algorithms, the most effective classifier for accurate activity categorization was identified, leading to improved results.

Overall, the results obtained from the proposed model demonstrate its superiority and effectiveness compared to previous reports. By achieving higher accuracy rates and addressing the limitations of existing approaches, this study brings significant advancements to the field of human activity recognition. These findings validate the novelty and contribution of this research in improving the accuracy and reliability of human behavior identification systems.

4 Conclusion

This work presents a novel machine learning approach for human activity recognition. The proposed method utilizes raw sensor data without manual feature engineering, resulting in improved accuracy compared to existing approaches. The findings demonstrate the potential of the proposed model for accurately recognizing complex human activities. This research opens up opportunities for further advancements and practical applications in various domains. The proposed algorithm for human activity recognition in this research is based on a MLP classifier with the Adam optimizer and ReLU activation function. The MLP classifier is a type of feedforward neural network that consists of multiple layers of interconnected artificial neurons. It is well-suited for classification tasks, including human activity recognition. The MLP classifier in this algorithm is trained using the Adam optimizer, which is an adaptive optimization algorithm that adjusts learning rates for each parameter individually. This helps to accelerate convergence and improve the efficiency of the training process. The ReLU activation function is applied to the hidden layers of the MLP classifier. ReLU is a popular choice for neural networks as it introduces non-linearity and allows the model to learn complex patterns and representations. It has been shown to perform well in various machine learning tasks.

The algorithm follows the typical steps of training a neural network model. The raw sensor data obtained from IoT wearable sensors is used as input to the MLP classifier. The model is trained on a labeled dataset, where each data sample is associated with a specific human activity. During training, the model iteratively adjusts the weights and biases of the neural network to minimize the classification error using the Adam optimizer. The trained MLP classifier with the optimized weights and biases can then be used to predict the activities performed by individuals based on new unseen sensor data. The model takes the raw sensor data as input, passes it through the MLP layers with ReLU activations, and outputs the predicted activity label.

The use of an MLP classifier with the Adam optimizer and ReLU activation function provides a powerful framework for accurately recognizing and classifying human activities based on the IoT sensor data. However, it is important to note that the specific architecture, hyperparameters, and training process may vary depending on the dataset and specific requirements of the research.

Within the scope of this investigation, a novel approach to using machine learning to classify human activities was proposed. For the purposes of this research work, the raw sensor data that was acquired from the WISDM dataset was utilized. The initial dataset was split up in order to produce two separate datasets, one relating to smart watches and the smartphones. No manually engineered features were included in the scope of this study at any point. Additionally, the findings were validated by using the train and test datasets, and based on the findings of this models, it can be inferred that proposed method provide a higher level of accuracy than other ML approaches to recognize complex human activities.

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