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An Accurate Classification for Human Sport Activity Recognition from Sensor Data Using Hybrid Machine Learning Models

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ABSTRACT

The significance of human sports activities recognition (HSAR) in many computing applications, including sports analytics, smart surroundings, and healthcare monitoring is huge. The current use of vision sensors for HSAR is a difficult task due to the intricate movements involved in sports and fitness workouts, as well as fluctuations in illumination conditions. Therefore, a comprehensive review of machine learning algorithms (such as XGBoost, Random Forest (RF), Decision Trees (DT), and K-Nearest Neighbors (KNN)) and their usage for human sports activities classification based on sensor data called ML-HSAR is presented in this article. A dataset containing 19 different human activities gathered from 8 different people through different types of sensors was used for this work; the dataset contains activities like sitting and standing, as well as other activities that require serious movements, such as running, cycling, and playing basketball. This study primarily aims to determine the performance of the considered ML models in accurately classifying these activities found in the dataset. The training of the algorithms and the subsequent evaluation were done on the segmented sensor data, effectively leveraging the dataset's temporal aspect. In addition to the presented results for each of these algorithms, the limitations of each algorithm and their strengths in handling the complexities involved in HSAR were also presented. The contribution of this analysis is towards the understanding of the most appropriate ML models for HSAR tasks; it also offers valuable insights for future research and practical applications.

1. Introduction

Machine learning (ML) and image processing researchers have shown interest in investigating advanced video analysis, specifically for security reasons. Human sports activity recognition (HAR) strives toward automatic tracking and identification of various human postures and sporting movements from still images or real-time recordings [1, 2]. HSAR systems can be used in many areas, including smart homes, crime prevention, healthcare monitoring, sports support, and security surveillance. Numerous recording devices (installed) is required in public places for these applications, such as stadiums, public gardens, etc. to capture the required number of videos [3].

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Automatic systems are critically needed for video content analysis because it takes a long time and money for human eyes to analyze these recordings. The primary objective of these video-detecting systems is to autonomously recognize and comprehend interesting occurrences inside certain sequences. As a result, rather than focusing on entire settings, these HSAR applications primarily concentrate on the subjects' typical social behavior [4].

People's behaviors in many scenarios can be detected and classified into two main groups using automated systems; the groups include activities that are usual and activities that are unclear or suspicious (out-of-character). For instance, visual monitoring devices (sensor data or video analysis) are used in interactive systems, sports analytics, and healthcare monitoring to examine patient's usual and unusual behavior. Automatic detection of desperate situations triggers alarms to draw the attention of medical personnel. Violence cam detectors can prompt quick responses in the context of crime prevention, such as the prompt deployment of security personnel in response to suspected fights, domestic violence, and violent strikes [5]. In HAR, smart home implementation aims to increase home security for people by continuously monitoring and assessing their behavior. Players can also use HAR-based sports assistance systems to assess and critically monitor their indoor workout routines, fitness levels, and interactions. A human operator is required in traditional security surveillance systems to supervise and handle a number of video cameras, but this process is costly and prone to error. On the other hand, HSAR has significant promise for effectively managing surveillance systems at reduced costs, with more precision and requiring fewer human interventions. The HSAR technology generates intelligent virtual worlds that benefit humans in numerous ways [6].

Four fundamental modules, preprocessing, posture tracking and estimation, cue extraction, and recognition, make up the majority of earlier HSAR systems [7]. The pre-processing module removes extraneous information, such as noise or distortion, and focuses incoming data, such as video or signal, on the intended region of interest. Salient area detection is used by the posture estimation and tracking module to identify observably important human areas and to track important body parts that are represented by labels or masks in a series of frames [8]. During the phase of human action recognition, the Cues extraction module facilitates the portrayal of a human silhouette by utilizing ideal measurement units. In the identification module, distinctions between various postures are finally noted, and incoming data sequences are used to train and test a classifier engine to identify activity classes. Several popular machine-learning techniques are used in different ways to improve HSAR systems. Even though researchers have put in a great deal of work, HSAR still faces many difficulties [9]. These difficulties include uneven human movement, variations in human height and shape in images, dynamic backgrounds, lighting issues, feature selection techniques, the articulated nature of the body, and different scales of normalization [10]. Hence, this work proposed a new model utilizing four machine learning models to make it easier to classify human sports activities in real-time using sensor data. This capability is especially valuable for applications that demand prompt and immediate activity recognition, including healthcare monitoring, sports analytics, and interactive systems.

The objectives of this paper are to propose an HSAR model that can classify different human sports activities from sensors using several ML algorithms. Thus, a set of steps must be involved to achieve that, starting by acquiring a suitable dataset, into finally generating the classification results and evaluating the chosen models. Therefore, the contributions of the study can be summed as follows:

i. The development of these ML models facilitates a thorough assessment and comparison of their performance in classifying the 19 different classes of human sports activities. This evaluation aids in understanding the advantages and weaknesses of the selected models to identify the most optimal approach for achieving accurate classification.

ii. The used dataset is large considering the total number of samples, and it is also diverse in terms of the different human activities that it contains (19 different classes exist within the dataset). The dataset also contains data gathered in varying lighting conditions and environment, thereby improving its diversity.

iii. The implementation and refining of these ML models aided in obtaining higher accuracy rates in human HAR classification.

iv. Real-time HSAR classification based on sensor data was facilitated by the advancement of these ML models. This is a significant capability for applications where prompt and immediate activity recognition is required, such as in healthcare monitoring, interactive systems, and sports analytics.

2. Literature Review

Deep learning (DL)-based models have performed well in several fields of study, including HAR [11, 12]. Many CNN-based models have also been developed recently, in addition to those based on RNN, and other DL approaches. However, the recognition accuracy of CNN models has been superior with great promise. The Temporal CNN framework, for instance, is a type of temporal model that employs a hierarchy of temporal convolutions. It was used in the study by Nair *et al.,* [13] to learn long-term relationships from variable-length sequence data. Another study strived to address the problems of multimodal sensor fusion and normalization by developing a CNN-based method for sensor fusion [14]. Several CNN models were employed by Ronao *et al.,* [15] to increase the HAR recognition accuracy. In the work by [16], the use of an ensemble of CNN models to achieve better performance than the individual models were proposed.

RNN is another DL technique that has been extensively used for HAR owing to its unique ability to learn spatial data sequences. LSTM-based networks, for instance, are more appropriate for wearable/inertial sensor-based HAR owing to their ability to learn long-term relationships from any data sequence. Das *et al.,* [16] combined LSTM and shallow RNN to create a lightweight model for activity recognition. The spatiotemporal characteristics for human activities classification were learned by the authors in [17] using LSTM-based models. Different authors have achieved different levels of increase in recognition accuracy using numerous hybrid models, such as CNN-RNN [18], CNN-LSTM [18], LSTM-CNN [19], and CNN-GRU hybridization [20].

Scholars have paid attention recently to the encoding of time-series data as images using DL based techniques, especially CNN because this technique allows the learning of visual structures and patterns and enables visual recognition and classification. Time series data are mostly encoded as images using the Markov Transition Field (MTF) and Grammian Anular Field (GAF) models as first presented in the study by [21]. The classification of the single GAF and MTF images, as well as the compound GSF-MTF images, was achieved using Tiled CNNs. As per Souza *et al.,* [22], it is believed that different time series features may be contained in the frequency domain, however, they may not be seen in the temporal domain; hence, they considered the usage of recurrence plots as a different graphical representation for the classification of time series data. A method for the extraction of texture features from that graphical representation for use in time series data classification was also developed [23] suggested a similar method). Authors in [24] discovered a different kind of feature in the image representation of time series data that is not found in 1D sensor data. They visualized the recurrent nature of a route through phase space by first presenting a 2D texture image of the sensor signal using recurrence plot. Then, various feature levels were extracted from the texture images using a CNN model.

A two-stage strategy was proposed by Zhang *et al.,* [25] as solution to the problem of dissimilarities in the distinctive sequence length and region scale. In the study, sensor data encoding was first performed using enhanced recurrence plots called Multi-scale Signed Recurrence Plots (MS-RP) followed by the application of ResNet and fully convolutional networks for the image processing step. Hur *et al.,* [26] introduced Iss2Image, a novel encoding method for the transformation of inertial sensor signal into an image with minimal distortion. Real-valued sensor readings were split by Iss2Image into three sections: integers, the first two decimal places, and the next two decimal places. A three-channel image was then encoded from the separated data. Daniel et al. suggested another encoding method that was comparable in [27]. The suggested INIM framework employed a residual network that has been trained on the ImageNet dataset [28] to recognize activity after initially encoding the signal of the sensor into 3D RGB images. A unique technique for encoding time series data into two-channel GAF images was presented by Qin *et al.,* [29]) through the unification of global and local time series features. Then, they demonstrated a fusion ResNet framework that discovered the angular velocity and acceleration feature correspondences in the generated GAF image pixels; a similar proposal was also made by the authors [30]. In contrast to earlier research, they employed four distinct activity image types and multimodally processed each one by convolving it through two spatial domain filters: the high-boost filter and the Prewitt filter. The deep features from many modalities were extracted using ResNet-18, and they were then fused using canonical correlation-based fusion. Ultimately, activity recognition was accomplished using a multi-class SVM. The concept of employing the Fast Fourier Transform (FFT) to convert a 1D signal into a 2D signal is realized by the authors in [31]. The spectrogram is a frequency-domain image that shows the signal's composition over time across many frequencies. It is used as an input for a three-layered CNN model that extracts and classifies features. Sensor signals were encoded into spectrograms using Short-Time Fourier Transformation (STFT) by Lawal and Bano [32]. Another study suggested a condensed two-stream CNN-like VGG-Net architecture for activity and location identification [33].

Enhancement of the overall accuracy of models in activity recognition via selection of the pertinent features using different FS-based strategies has been recommended [34]. In the study by San and Tiglao [35] a HAR model based on sensor fusion in smartphones was suggested feature ranking was achieved using a filter-based technique. An improved HAR approach was developed by Fan and Gao [36] using the Bee Swarm Optimization (BSO) with a deep Q network. In the work by Dewi and Chen [37], four classifiers (RF, SVM, KNN, and LDA) were compared on HAR datasets and RF achieved the best accuracy. Daily activity recognition using a position-based FS approach for body sensors was proposed [38]; the system's overall accuracy was assessed using a classifier, filter-based and correlation-based optimization approaches to ensure feature set reduction. Several academics have studied the application of GA, one of the most popular and old metaheuristic algorithms, in a variety of fields, including feature selection, image steganography, medical diagnostics, stock price prediction, image segmentation, and contrast enhancement. To determine an individual's fitness. Saitoh [39] presented a GA-based method for image contrast improvement that measured the strength of the spatial edges present in the image. By analyzing the grey levels of the input-output relationships, the original grey image was transformed into an image with enhanced contrast, and GA was utilized to search for a solution in global space.

The authors in [40] adjusted the image's intensity information to provide an effective method of improving image contrast using a fuzzy intensification operator and GA; this increased the visibility information of an image.

It is clear from the discussion above that numerous scholars have attempted to categorize human activities by examining images of those activities. The task of identifying human activities from sensor data has always been fascinating and difficult. Certain movements, like walking and running, are easily identifiable, still, there are a few sophisticated behaviors that are challenging to categorize. The creation of an effective activity recognition model has the potential to advance multiple sectors, including sports, health, and psychological understanding. For this reason, the creation of capable HAR models was greatly aided by machine learning and deep learning-based techniques. ML-based methods not only reduce processing time but also dramatically improve classification accuracy during the process.

3. Proposed Method

The objective of the proposed ML-HSAR model is to be able to classify different human sports activities from sensors through the use of several ML algorithms. Thus, a set of steps must be involved to achieve that, starting by acquiring a suitable dataset, into finally generating the classification results and evaluating the chosen models. The developed system's workflow is depicted in Figure 1.

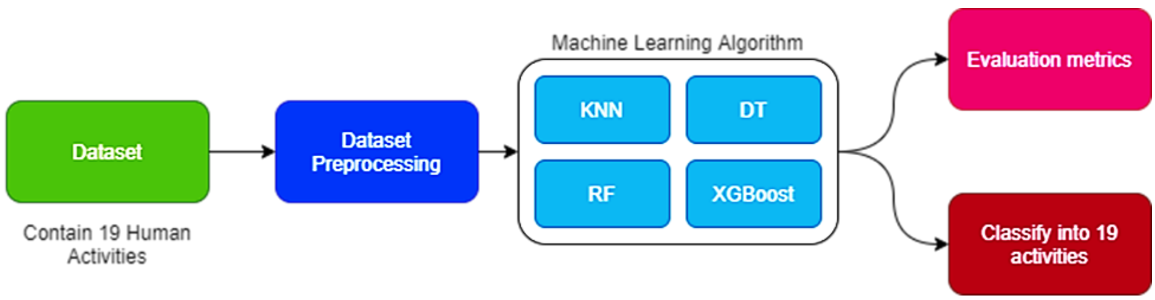

Fig. 1. Workflow of the proposed classification system

Initially, a suitable dataset containing 19 different classes of human sports activities is acquired. The choice of the dataset is essential since it is the cornerstone upon which the ML models will be trained and based on their results. The chosen dataset must have a suitable size in terms of the number of instances that it contains, as well as being diverse so that the ML models can learn details about several human activities, such that when presented with a random activity, the ML model can recognize it. After the dataset is acquired based on the mentioned criteria, data pre-processing must take place. Data pre-processing is a set of procedures to get the data ready to be used for training depending on the characteristics of the dataset and the requirements of the ML models to be used. After pre-processing, the data are fed into 4 different ML models, namely Decision Tree DT, XGBoost, K-NN, and RF. These ML models use the pre-processed data to learn patterns that identify each of the human activities, in what is referred to as a training stage. After training, the models are presented with new data "testing dataset" where they must classify each instance into one of the classes based on the learned data. The results obtained by each of the ML models in the testing stage are evaluated based on several metrics that determine how well each model performs in the task of classifying human activities.

3.1 Dataset

To achieve the task of training and testing ML models on human activities, a dataset comprising different human activities is selected. Thus, the chosen dataset offers an extensive examination of human activity recognition [8]. The dataset is diverse such that it provides 19 different types of human activities that range from sedentary, and slightly active, to more active movements. These human activities were recorded from 8 different individuals whose ages range between 20 and 30 years old. Each activity has been recorded in 5 minutes, whereas the dataset is comprised of 5-second increments of each activity, making up 480 segments for each activity and subject. The diversity of the activities is presented by the fact that they rely on daily postures and dynamic movement and include daily routine activities such as walking, going up and down the stairs, sitting, running on a treadmill, and even more rigorous activities such as playing basketball and many other similar activities.

The activities present in the dataset are shown in Figure 2, where each type of activity is assigned a label, such as Jumping = A18, moving in elevator = A8, etc. In addition, the number of samples for each of the labeled activities is shown, such that each type or class of activity included 500 samples.

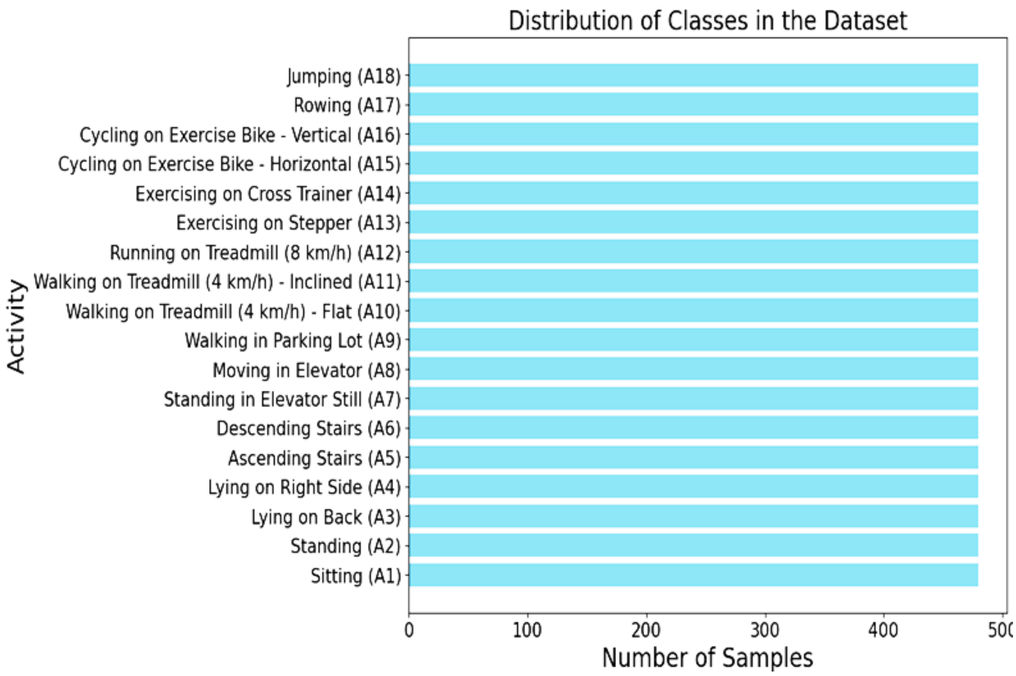

Fig. 2. The activities present in the dataset, alongside their respective number of samples

The dataset was captured through calibrated sensor units located in 5 regions of the body: right arm, right leg, torso, left arm, and left leg. Since the dataset is acquired from sensors, it comprises data of 25 Hz sampling frequency. The sensor units are also diverse in the type of sensors, where each unit contains the following sensors: gyroscopes, magnetometers, and accelerometers in three spatial dimensions.

Gyroscopes [41] are sensors that measure angular velocity or rotation. They provide information about the rate at which an object or device is rotating around a particular axis. Magnetometers are sensors that detect and measure magnetic fields. They are utilized to determine the strength and orientation of magnetic fields in the surrounding environment. Accelerometers are sensors that measure acceleration or changes in velocity. They detect the rate of change of motion along multiple axes.

The structure of the dataset consists of 45 columns and 125 rows in each of the 5-second segments, such that sensor type and unit are the basis for grouping. The description of the dataset and its structure is presented in Table 1.

Table 1
Description of levels within the dataset and its structure

Level	Description
Activities (a)	19 different activities (A1 to A19) are denoted by a distinct folder for each (a01, a02, …, a19).
Subjects (p)	8 different subjects are selected to perform each of the 19 activities, where each of them is denoted by a subfolder included in the activity folder (p1, p2, …, p8).
Segments (s)	Each subject provides data that is separated into 60 segments, where a text file within the subject subfolder is dedicated for each (s01, s02, …, s60).
Units	5 units were used for the collection of data; they were placed on the Right Arm (RA), Right Leg (RL), Torso (T), Left Arm (LA), and Left Leg (LL).
Sensors	Each unit comprises 9 sensors (x,y,z accelerometers, x,y,z gyroscopes, x,y,z magnetometers) for data collection.
Data Structure	Each text file contains 45 columns, representing the data collected from 9 sensors across 5 units. There are 125 rows in each file, corresponding to a 5-second duration with a sampling rate of 25 Hz. Each column contains 125 samples of data collected from one sensor of one unit. Each row also contains data from all 45 sensor axes at specific sampling conditions (values are comma-separated).

This implies that the acquired dataset is not large just in terms of the number of samples contained, but also in the type of considered activities. The dataset also contains recordings from different environments (indoor and outdoor spaces) to ensure a proper depiction of human activity scenarios.

3.2 Dataset Pre-Processing

Data preprocessing is performed before training ML models to ensure that the data is fit to be used by each of the employed ML models. The quality of images is improved after a pre-processing step as the distortions are removed and features are improved. With this process, the model can accurately use these features to perform classification tasks. Pre-processing also ensure that significant features are identified through analysis and aids in finding the relationships between them. Data pre-processing, as earlier stated, is comprised of techniques like data scaling, data augmentation, and data normalization. The employed pre-processing methods in this work are data normalization, followed by label encoding, and lastly data splitting into training and testing sets.

As per Singh and Birmohan [42], data normalization involves the process of data value transformation into values in the range of 0 and 1; it is mostly done to ensure that the learning process is not dominated by any single feature due to differing scales. Data normalization also encourages convergence and positively influences model’s performance. The Min-Max strategy [43] (Eq. (1)) was adopted in this work for the data normalization process.

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where X is the original feature values, X_{min} is the minimum value of X, X_{max} is the maximum value of X.

In this work, label encoding was used for the conversion of the categorical or textual labels into numerical forms [44]. In this technique, each distinct label is assigned a unique integer value. In this paper, the primary goal of using label encoding is to convert categorical data into a format that the ML algorithms can comprehend and process, as these algorithms generally operate with numerical data. In this research, scikit-learn's LabelEncoder [45] was utilized to assign a unique integer to each activity label.

To make the most use of the utilized dataset, it is divided into a training dataset used to train the models and a testing dataset used to test the classifications of the models. The training dataset is used by the model to acquire and learn the patterns and features within each activity such that the model becomes able to recognize said activity by analyzing the patterns in the new data. On the other hand, the testing dataset is a group of new data not previously seen by the model, which requires classifications. Usually, a common practice is to divide the dataset into 80 % training data, and 20 % testing data, which was the case in this study. This split ratio guarantees that the data are enough for effective model training and robust evaluation on an independent dataset.

3.3 Machine Learning Models

While machine learning models share common principles such as learning from data and making predictions, they can differ significantly in their approach, complexity, interpretability, and performance characteristics. In this study, 4 different machine learning algorithms are implemented which are XGBoost, DT, RF, and KNN; these 4 algorithms are described in the following sub-sections.

KNN is categorized as a non-parametric algorithm, which implies that it does not assume any specific data distribution [46]. It is easy to comprehend and implement, and can handle both numerical and categorical features. As a simple powerful ML technique, KN is mostly used for classification and regression tasks. It allocates a class label to a test example during classification tasks, in consideration of the majority vote of its K nearest neighbors. If K, for instance, is set to 5 and the majority of the closest neighbors belong to class A, KNN will assign the test example to class A.

Random Forest (RF) is an ML model known for its ability to handle extensive datasets, high-dimensional features, and data with missing values or noise [47]. RF avoids the issue of overfitting and provides insights into the relevance of different features. RF can improve prediction performance by merging the outputs of numerous decision trees; hence, RF is considered an ensemble of decision trees, where each tree requires a random subset of the training data and another set of features to be trained. Throughout training, each tree autonomously learns from the data and can produce an independent prediction. Thus, the Random Forest algorithm ultimately reaches the results by combining the predictions of all the trees, through voting in the case of classification, or averaging in the case of regression.

Besides, Decision Trees are highly efficient in classifying data and comparatively straightforward to train [48]. Nevertheless, they can be sensitive to data noise and become challenging to interpret when the tree structure becomes overly complex. The Decision Tree algorithm is a machine learning technique that creates a model in the shape of a tree to aid in decision-making processes. Data partitioning is based on various features, resulting in a hierarchical structure of decision nodes. Each internal node in the tree relates to a feature while each branch is considered a possible outcome associated with that feature. The leaves, or terminal nodes of the tree represent the final prediction.

Also, XGBoost framework iteratively constructs an ensemble of weak prediction models, usually DT, merge their predictions to arrive at a more precise model [49]. In this model, each subsequent model is trained to correct the problems associated with the preceding models. The objective is to reduce the overall prediction discrepancy. In the XGBoost model, a distinctive regularization approach called "gradient boosting with trees" is employed; the model employs the gradient descent optimization algorithm for loss function minimization, making it capable of managing intricate relationships and capturing non-linear data patterns.

3.4 Evaluation Metrics and Tools

The considered metrics for the evaluation of the proposed ML-HSAR model for performance in this work are recall, precision, accuracy, f1-score, and confusion matrix [50-52]. With these metrics, it is easy to understand the overall performance of the models, as well as their capacity to classify instances that belong to each class accurately.

Recall is calculated to determine the ability of the model to correctly generate true positives out of the total number of true positives and false negatives; it is also called sensitivity or Hit rate, and computed as follows:

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (2)$$

Precision is a way of determining the ability of a model to generate true positive instances out of the total number of positives (TP + FP). Another notation for Precision is "Positive Predictive Value". It is possible to calculate the precision value through the following equation:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (3)$$

The F1-score metric is based on both recall and precision, which uses both values to determine the effectiveness of the evaluated model in capturing relevant instances while minimizing misclassifications. F1-score value becomes a critical evaluation metric in the cases of imbalanced data specifically. To calculate the F1-score value, the following equation is used:

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Furthermore, one of the metrics that is most frequently chosen to evaluate the effectiveness of a machine-learning model is accuracy. The percentage of correctly classified instances relative to all instances is known as accuracy. Consequently, as indicated by the following equation, it is calculated by dividing the total number of accurate forecasts by the entire number of predictions.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad (5)$$

4. Results

In this study, the aim is to implement machine learning models that are capable of classifying the human sports activities picked up by sensors into labeled activities such as jumping, running on a treadmill, walking, moving in an elevator, walking on a treadmill, cycling, playing basketball and many others from a specific dataset. Essentially, after training the ML models, namely KNN, DT, RF, and XGBoost, the models are tested and their performances are monitored and assessed to come up with a conclusion on how these models perform in this specific task, and how they compared to each other in terms of results.

According to these described four metrics, it is possible to assess the performance of the used machine learning models individually as depicted in Figures 3, 4, 5, and 6. However, an additional method can be used to visualize exactly which classes were correctly classified and in case of misclassification, which class was specifically misclassified and what was the predicted classification for that class. This method is termed Confusion Matrix [53], which is a visual representation in the form of a 19×19 grid in this case, since there are 19 different classes in this study.

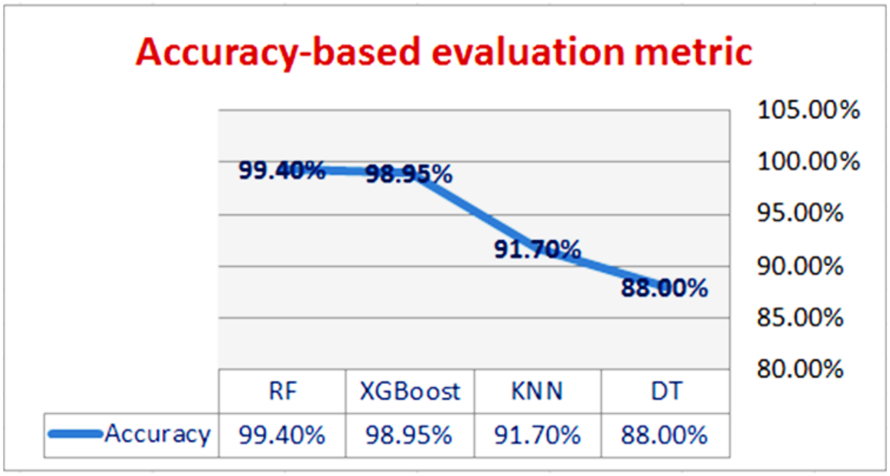

Fig. 3. The accuracy metric of the proposed ML-HSAR model for classifying the human sport activities

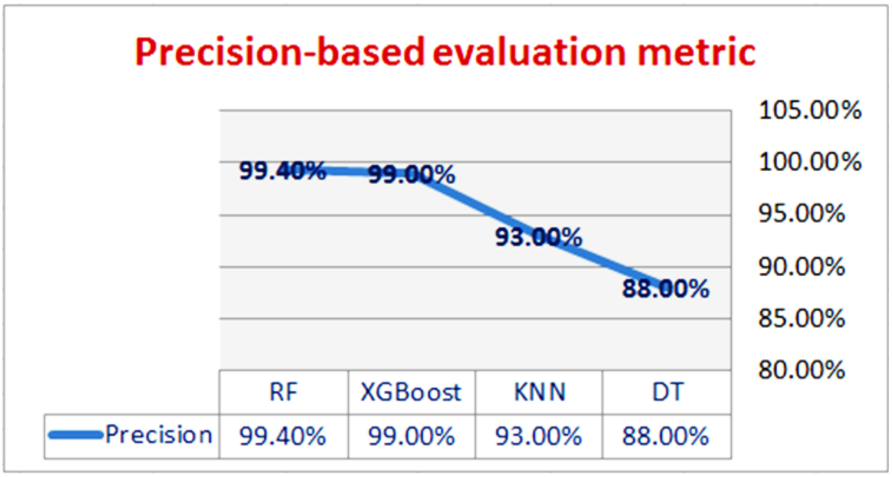

Fig. 4. The precision metric of the proposed ML-HSAR model for classifying human sport activities

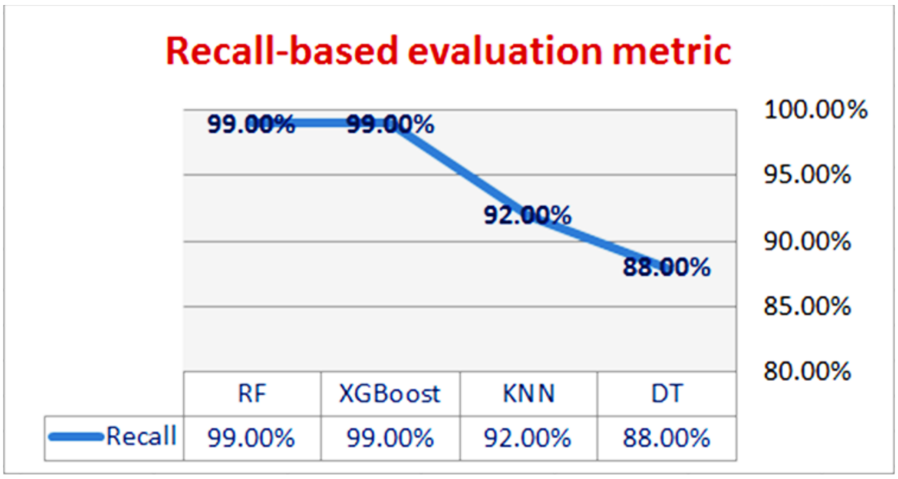

Fig. 5. The recall metric of the proposed ML-HSAR model for classifying the human sport activities

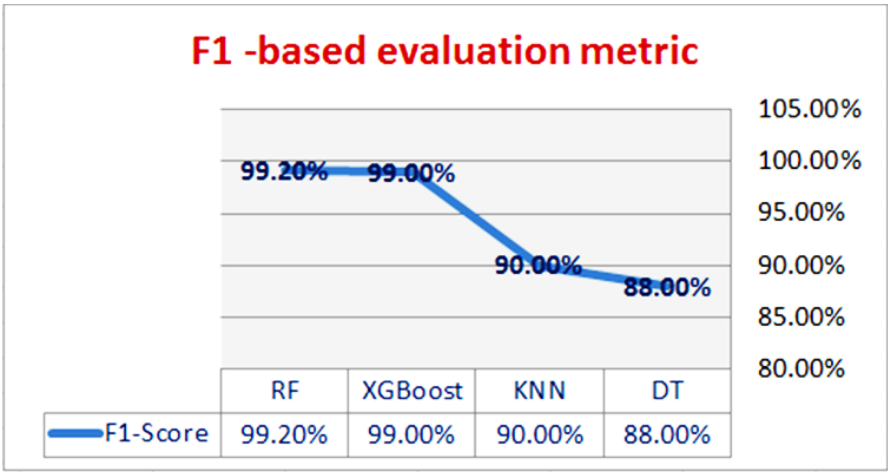

Fig. 6. The F1 metric of the proposed ML-HSAR model for classifying the human sport activities

Starting with the DT model, which was the lowest-scoring model in terms of all the evaluation metrics, the model achieved an 88 % accuracy value, accompanied by a similar value (88 %) for each recall, precision, and F1-score. These results reflect on the fact that DT is susceptible to overfitting, which is evident in the model's performance, despite being easy to interpret and a reliable method for understanding how the decision-making process takes place. However, the model's performance can be improved by fine-tuning hyper-parameters and implementing pruning techniques.

Figure 7 shows the confusion matrix achieved by the DT model. The figure shows that the model performed well while achieving high values along the diagonal, where it accurately assigned instances to their appropriate classes. The confusion matrix of the DT model indicates that it successfully identified the underlying patterns in the data and provided precise predictions for each class. In specific details, the confusion matrix of DT shows a few misclassifications in the A7 and A8 classes mostly. In addition, the A19 class showed numerous misclassifications, where 1 instance was misclassified as A1, 5 as A5, 7 as A8, 6 as A9, 2 as A10, 6 as A11, 5 as A12, 4 as A13, 8 as A14, 3 as A16, 6 as A18, and only 53 instances were correctly classified as A19.

The KNN model achieved better results compared to the DT model in terms of recall, precision, F1 score, as well as accuracy. Specifically, the model achieved 91.7 % accuracy, with a high precision value of 93 %, a high recall value of 92 %, and a slightly lower F1-score value of 90 %. These values indicate that the model is capable of minimizing false positives (high precision) and capturing all relevant instances. In general, the KNN model demonstrates strong performance across multiple classes, with slight variations in precision and recall, indicating its suitability for the specific dataset.

These results are also reflected in the confusion matrix of the KNN model, shown in Figure 8. The confusion matrix of KNN shows that it performs well diagonally and that it has some misclassifications in the A8 class, where 48 instances were classified as A7, and the remaining 39 instances were correctly classified as A8. Similar to DT, the KNN model also showed numerous misclassifications in the A19 class. In the A19 class, only 18 instances were correctly classified, whereas 20 were misclassified as A2, 22 as A7, 12 as A8, and 23 as A13. On the other hand, many classes such as A4, A5, and A6 as well as other classes were perfectly classified each time by the KNN model.

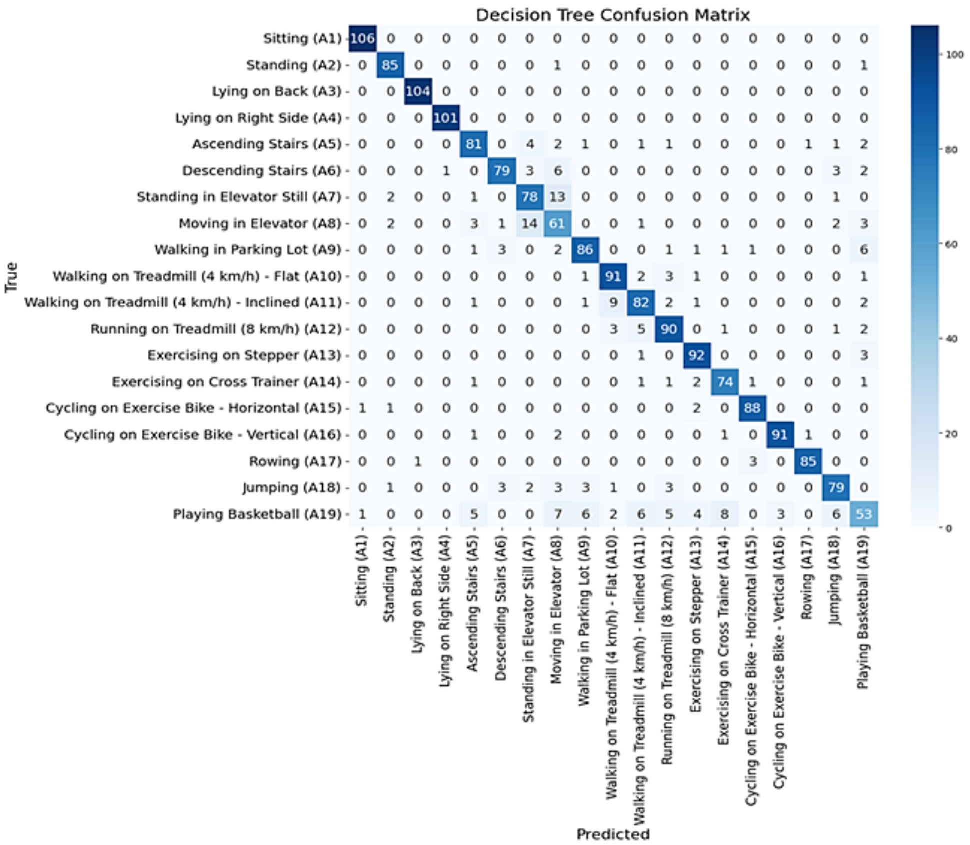

Fig. 7. Confusion matrix achieved by DT model

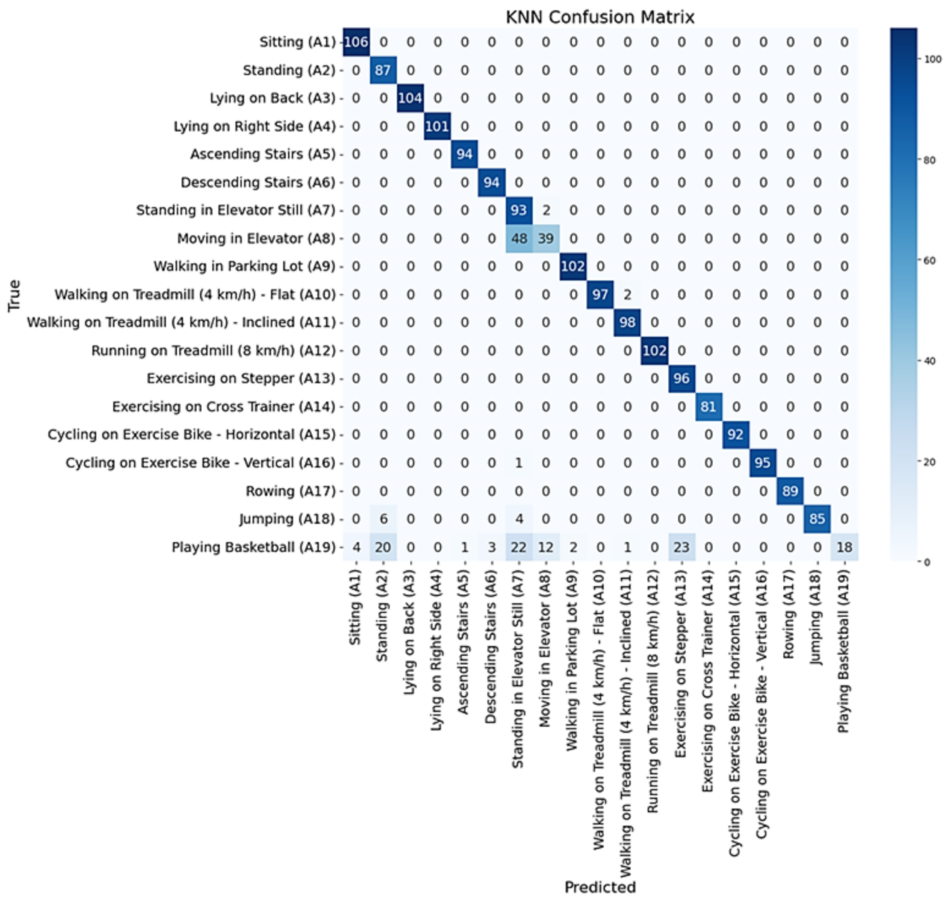

Fig. 8. Confusion matrix of the KNN model

XGBoost model still performed better than the KNN model in terms of all the evaluation metrics. The highest score achieved by the XGBoost model was the accuracy score which was 98.95 %. The other 3 metrics were the same for KNN scoring 99 % in recall, precision, and F1-score. The exceptional performance of the XGBoost model can be attributed to its capacity to handle intricate relationships within the data, coupled with efficient tree-boosting techniques. The model consistently achieves outstanding scores in a majority of metrics, demonstrating its robustness and effectiveness.

Furthermore, the XGBoost confusion matrix proves its exceptional performance in the different classes, where only a few misclassifications took place in classes such as A8 (5 misclassifications) and A19 (5 misclassifications). Thus, in comparison between DT, KNN, and XGBoost, it is clear that XGBoost classifies the A19 class with the highest accuracy over the other 2 models; these results are depicted in Figure 9.

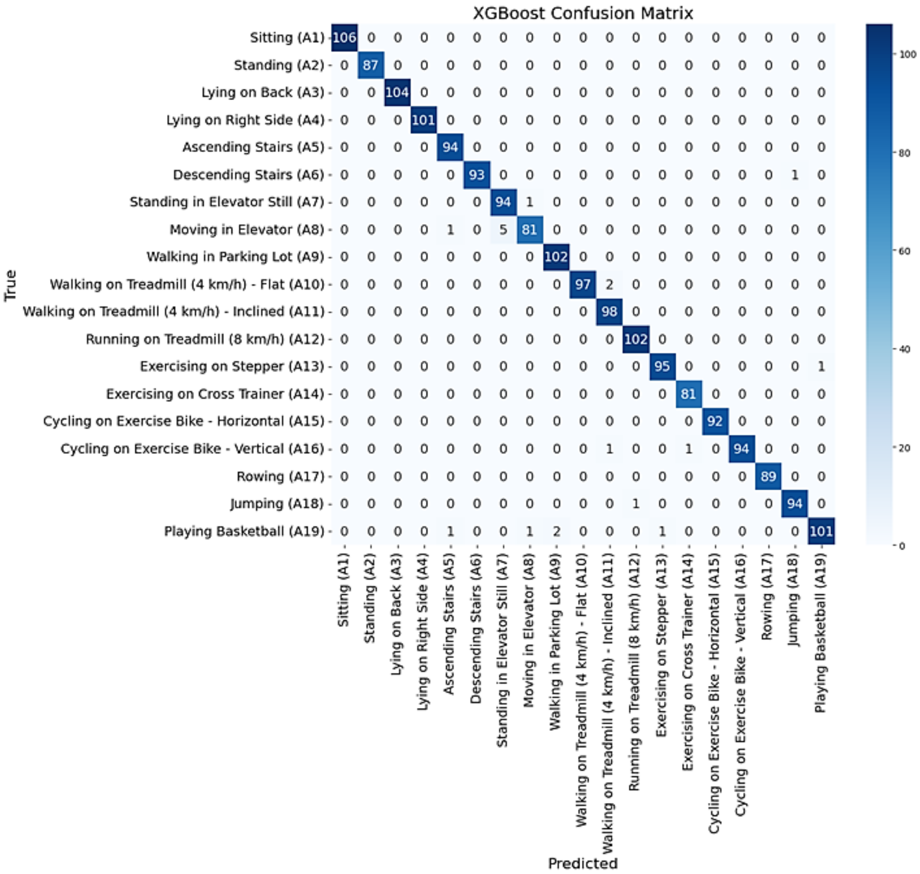

Fig. 9. Confusion matrix of XGBoost model

Lastly, the best-performing machine learning model in this study was the Random Forest model which was able to achieve the highest accuracy, recall, precision, and f1-score. Random Forest achieved almost perfect accuracy in classifying activities which was 99.4 %. Similarly, 99.4 % value was achieved as precision, 99 % value was achieved as recall, and 99.2 % value was achieved as F1-score. These results demonstrate the power of ensemble learning models in classification tasks. Random Forest excels in addressing high-dimensional data and preserving accuracy even when confronted with missing data. Its superiority over alternative algorithms is evident in terms of both overall accuracy and metrics specific to individual classes.

The outstanding superior results of the RF model are also presented by its confusion matrix shown in Figure 10. The confusion matrix of RF shows that the only classes with misclassifications are A7, A8, A18, and A19. The A7 class showed only 3 misclassifications, A8 only 5 misclassifications, A18 only 2 misclassifications, and A19 only 1 misclassification. These results show that the Random Forest model was almost perfectly able to classify the A19 class, which was problematic for the rest of the algorithms. Additionally, RF perfectly classified all the remaining 15 classes. The model's resilience was enhanced by the combination of numerous decision trees.

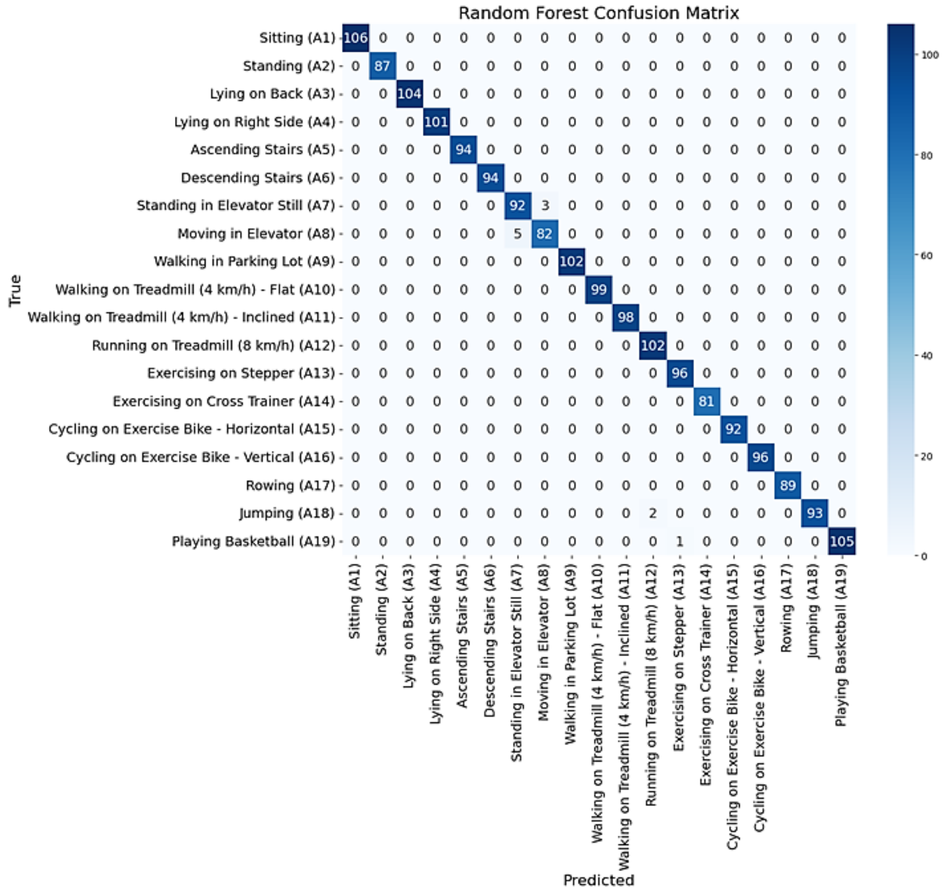

Fig. 10. Confusion matrix of Random Forest model

In addition, the classifier's performance as its discrimination threshold changed was graphically displayed using ‘Area Under the ROC Curve,’ or "AUC." Plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold levels creates the ROC curve. The two-dimensional area under the curve, extending from (0, 0) to (1, 1), is quantified by the area under the ROC curve (AUC).

The True Positive Rate (TPR) designates sensitivity or recall, and it is a representation of how many actual positives are identified correctly. On the other hand, the False Positive Rate (FPR) represents the probability of a false alarm by quantifying how many true negatives are identified as positives.

As depicted in Figure 11, the AUC of the XGboost algorithm achieved a 1.0 value on several occasions, which indicates that this model was able to classify these classes without errors; the classes upon which XGBoost scored perfectly are: ‘Running on Treadmill (8 km/h)’, Cycling on Exercise Bike - Horizontal’, ’Lying on Back’, Rowing’, ‘Sitting’, ‘Lying on Right Side’, Cycling on Exercise Bike - Vertical’, and ‘Standing’. On the other hand, XGBoost performed well with some errors in some classes such as ‘Walking on Treadmill (4 km/h) - Inclined’, ‘Standing in Elevator Still’, Walking on Treadmill (4 km/h) - Flat’, ‘Playing Basketball’, ‘Walking in Parking Lot’, ‘Jumping’, Ascending Stairs’, Exercising on Stepper’, Moving in Elevator’, and ‘Descending Stairs’ where the AUC was near 1.0.

Similarly, as depicted in Figure 12, the KNN algorithm was capable of perfectly classifying many classes by achieving a 1.0 AUC value, such as in the case of 'Running on Treadmill (8 km/h)', Cycling on Exercise Bike - Vertical', Exercising on Cross Trainer', 'Lying on Back', 'Rowing', 'Walking in Parking Lot', Cycling on Exercise Bike - Horizontal', and 'Lying on Right Side'.

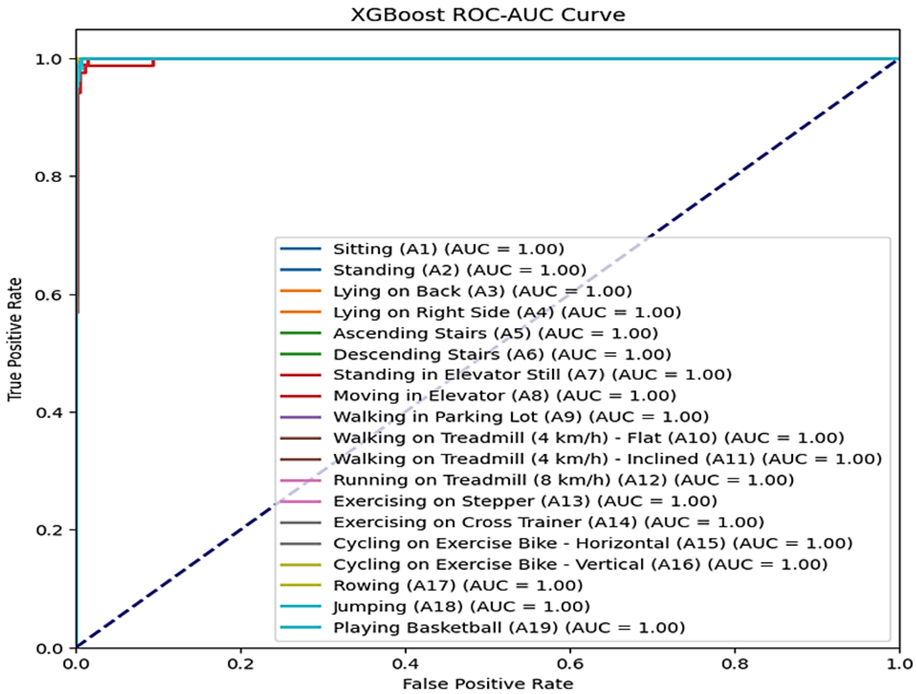

Fig. 11. XGboost ROC-AUC curve

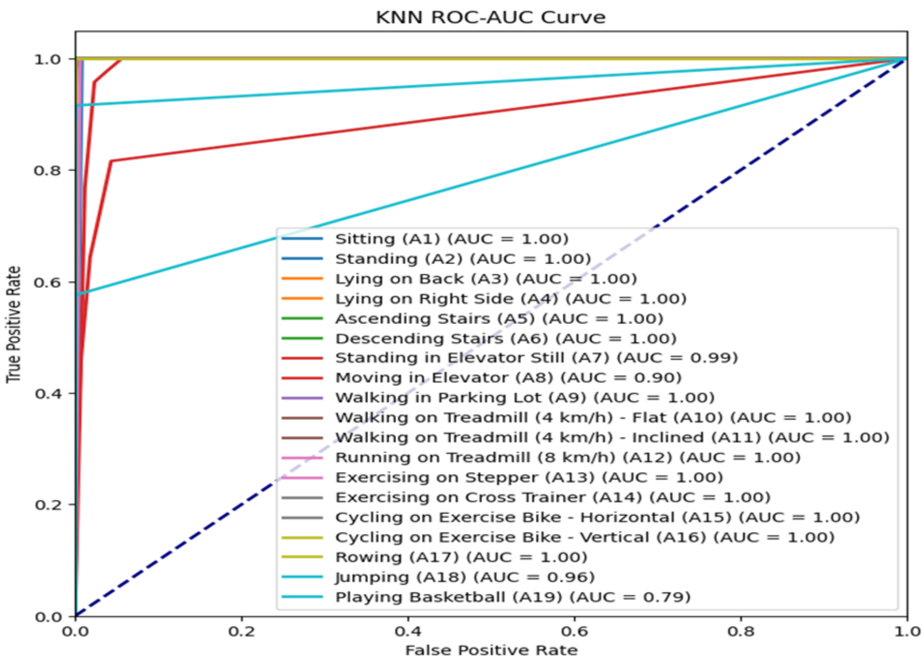

Fig. 12. KNN ROC-AUC curve

In other classes, AUC was nearly 1.0, which indicates that KNN also performed well in classifying the following classes with minimal errors: 'Ascending Stairs', 'Walking on Treadmill (4 km/h) - Inclined', 'Moving in Elevator', 'Standing', 'Exercising on Stepper', 'Sitting', 'Jumping', 'Standing in Elevator Still', 'Descending Stairs', and 'Walking on Treadmill (4 km/h) - Flat'. On the other hand, KNN did not reach a high AUC for the 'playing basketball' class, since the AUC was only 0.7877, which indicates some errors in classifying this class.

Figure 13 shows that the Decision Tree model only managed an AUC equaling 1.0 for two classes: 'Lying on Right Side', and 'Lying on Back', which indicates the perfect capability of classifying these classes without any errors. On the other hand, DT achieved AUC between 0.74 and 0.99 for each of the following classes: 'Ascending Stairs', 'Exercising on Stepper', 'Cycling on Exercise Bike - Horizontal', 'Descending Stairs', 'Rowing', 'Exercising on Cross Trainer', 'Standing', 'Playing Basketball', 'Walking on Treadmill (4 km/h) - Inclined', 'Walking in Parking Lot', 'Standing in Elevator Still', 'Jumping', 'Running on Treadmill (8 km/h)', 'Moving in Elevator', 'Sitting', 'Cycling on Exercise Bike - Vertical', and 'Walking on Treadmill (4 km/h) - Flat'.

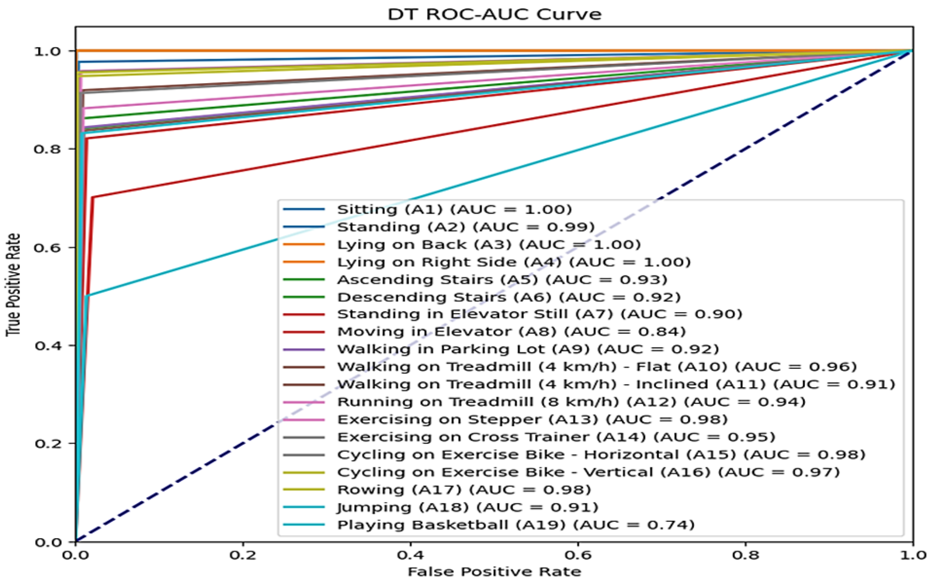

Fig. 13. DT ROC-AUC curve

Figure 14 shows that the AUC of the Random Forest algorithm was 1.0 in several classes, indicating classifying them perfectly without any errors. These classes are 'Exercising on Cross Trainer', 'Jumping', 'Walking on Treadmill (4 km/h) - Flat', 'Standing', 'Rowing', 'Running on Treadmill (8 km/h)', 'Sitting', 'Descending Stairs', 'Cycling on Exercise Bike - Vertical', 'Lying on Right Side', 'Exercising on Stepper', 'Ascending Stairs', 'Walking on Treadmill (4 km/h) - Inclined', 'Walking in Parking Lot', 'Lying on Back', and 'Cycling on Exercise Bike - Horizontal'. On the other hand, the RF model was incapable of classifying other classes with perfect precision, where the AUC reached near 1.0 but not exactly 1.0. The 3 classes that were not perfectly classified by RF are 'Playing Basketball', 'Moving in Elevator', and 'Standing in Elevator Still'.

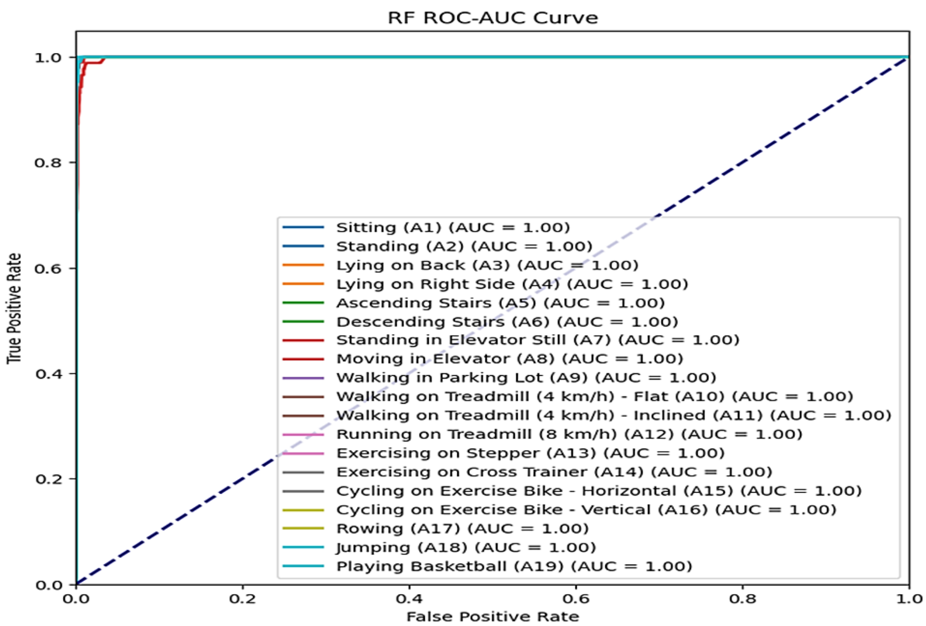

Fig. 14. RF ROC-AUC curve

4.1 Research Benchmarking

In this study, the performance of the utilized XGBoost, DT, RF, and KNN were evaluated based on metrics like accuracy, F1-score, precision, and recall. The 4 ML models achieved high accuracies and scored well in the other metrics in the task of classifying human sports activities. The problem of human activity classification using similar algorithms, datasets, and approaches has been reported; however, the comparison of the achieved performance of the proposed ML-HSAR model to those achieved by earlier models is important.

Earlier, an innovative hybrid network structure was proposed by Koşar and Barshan (2023) that merges LSTM and 2D CNN branches for human activities identification using wearable motion sensors and DL techniques; the LSTM analyzed the raw signals while the 2D CNN processed the spectrograms. Later, the extracted features using CNN and LSTM were combined via concatenation to improve activity recognition accuracy. At last, the model reached 95.66 % and 92.95 % accuracies on the tested datasets [54].

Yurtman [55] also strived towards achieving activity recognition that cannot be influenced by the orientation or position of wearable sensors. The reported classification results were SVM (90.8 %), ANN (90.9 %), RF (88.5 %), KNN (87.4 %), and LDC (89.8 %) [55]. Table 2 presents the achieved results of the benchmarked models, in comparison to the results of the proposed approach.

Table 2 shows that the proposed ML-HSAR models, specifically XGBoost and RF models, demonstrated remarkably higher accuracy, surpassing the performance reported in these similar studies.

Table 2
Comparison of the accuracy of the propose algorithms and other models

Model	Accuracy (%)
Proposed KNN	91.70
Proposed DT	88.00
Proposed RF	99.40
Proposed XGBoost	98.96
CNN-LSTM dataset 1 [54]	95.66
CNN-LSTM (dataset 2) [54]	92.95
SVM [55]	90.80
ANN [55]	90.90
KNN [55]	87.40
LDC [55]	89.80
RF [55]	88.50

5. Conclusions

Sport Activity Recognition (SAR) involves the automated identification and classification of various sports activities or movements using sensor data or video analysis. It encompasses the recognition of activities like running, walking, cycling, swimming, basketball, soccer, and weightlifting. SAR systems commonly utilize machine learning methods to train models on extensive datasets that contain labeled instances of different sports activities. In this study, a dataset containing 19 different types of human activities was used to train 4 machine learning algorithms, namely KNN, RF, XGBoosting, and DT to learn and identify these activities. After the dataset was acquired, pre-processing was performed, and 80 % of the pre-processed data was used for training. On the other hand, after training, 20 % of the pre-processed data was used to assess the performance of the 4 ML models. Upon testing, it was evident that the ML algorithm with the optimal performance in terms of achieving the highest accuracy was RF with an accuracy of 99.4 % in identifying the 19 different activity classes. In addition, the proposed Random Forest model achieved better than other algorithms found in the literature.

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