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Research Article

Comparative Analysis of Human Activity Recognition for Karate Skills Using IMU Raw Data and Derived Body Joint Angles

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ABSTRACT

Human Activity Recognition (HAR) is a machine learning (ML) application that plays a vital role in various fields such as medicine and sports. Recent advancements have made HAR a well-established field. HAR can be performed using imagery or sensory data; this study focuses on sensory data generated by the Inertial Measurement Units (IMUs). HAR typically requires data from at least one sensor. However, raw sensor data from two sensors—specifically raw sensors placed on two joint body joints- are needed to calculate a joint's three-axis angles. To our knowledge, no evidence in the literature compares the performance of HAR models trained on raw sensory data versus those trained on body joint angles in sports science. In this study, we aim to bridge this research gap by studying the difference in training on both data types in the karate sport as a case study. The current work includes two comprehensive four karate skills datasets: one consisting of raw sensory data and the other comprising calculated body joint angles derived from the raw data. The datasets were collected from professional karate players performing four distinct skills. We proposed a normalization algorithm to address the different numbers of readings per player performing the same karate skill. Next, several ML models were trained on the normalized versions of both datasets to determine which dataset contains more easily predictable patterns. The results indicate that the body joint angles dataset exhibited significantly higher accuracy than the raw sensory dataset. Moreover, the proposed normalization algorithm demonstrated promising results across all models and effectively mitigated the overfitting issue in both datasets.

Keywords: Biomechanics of Bodies (BoB), Features extraction, Human Activity Recognition (HAR), Inertial Measurement Unit (IMU), Machine learning (ML), and Wearable sensors.

I. INTRODUCTION

HAR describes the ability to recognize people's different activities, such as sitting, standing, walking, running, eating, sleeping, and more. Recently, HAR has gained more interest in some fields, such as intelligent systems, healthcare, and sports science [1-4]. Recent studies in literature have employed IMUs and motion capture systems to track human motion during individual activities [5-7]. While multi-camera-based motion capture systems can be used for human activity data collection, they require large-scale, complicated, and costly measuring environments. By contrast, IMUs consist of accelerometers, gyroscopes, and magnetic trackers that capture data across nine axes, three for each sensor, two approaches are commonly used to store data for HAR models from IMU sensors: the non-sliding window-based [8] and the sliding-window-based methods [9]. The non-sliding window-based method treats each sensor reading as a separate feature. In contrast, the sliding-window-based method involves sliding a window over a sequence of consecutive sensor readings, with each window position generating new features for training the predictive model. The window size is defined by the number of samples it contains.

Sikder et al [8]. developed a non-sliding window-based method to create the KU-HAR dataset, which consists of data from 90 participants engaging in 18 activities. They collected accelerometer and gyroscope (Accel-Gyro) sensor data and organized them using a non-sliding window technique. They then trained a random forest (RF) algorithm on this dataset, achieving an accuracy of 89.67%. In contrast, Grzeszick et al. [10] used the sliding window technique to collect data from three workers in two warehouses using IMUs placed at their wrists and torso. They then used a conventional Neural Network (CNN) model to recognize human activities based on the extracted features from the sliding windows.

Sports activity analysis is an important application of HAR models. Jaehyun Lee et al. [11] aimed to construct a self-coaching system suited for squat exercises. Thus, they built a public-domain HAR dataset based on the data gathered from 39 participants. They utilized a deep learning CNN-LSTM and the RF models to be trained on the collected dataset. They used one or a combination of two or five IMUs to train the collected dataset. The accuracy with five IMUs using the RF model was 75.4%; the accuracy using the CNN-LSTM model was 91.7%. Training on the data from a single IMU placed on the right thigh produced the lowest results, with 58.7% accuracy for the RF model and 80.9% for the CNN- LSTM model. Rafael Kuperman et al. [12] built a football activity recognition system. They used five IMUs placed on each of 11 male soccer players in different body joints such as the pelvis, right thigh, etc. A combination of CNN layers followed by recurrent (bidirectional) LSTM layers was employed to train and evaluate the dataset, which consists of five football-related activities. Their proposed model achieved an accuracy of 98.3%.
The shortcomings of recent research motivated the current study. These shortcomings are two-fold. First, recent studies have not applied deep learning or ML algorithms to recognize and evaluate performance on a real dataset of karate sports. Second, recent studies did not use body joint angle readings; instead, they depended on the accelerometer and gyroscope sensor (raw sensor) dataset. In this context, we proposed utilizing a karate dataset of four skills captured with the help of a set of 17 IMUs [13] to generate two datasets; one includes raw sensor readings, and the other includes the body joint angles. Then, we proposed utilizing the non-sliding window technique to extract the features of these datasets. Next, a set of ML models was trained on these two datasets to predict karate skills. Moreover, we proposed analyzing the performance gap of the HAR predictive models on the accuracy rate for the sensor readings and body joint angles datasets in recognizing karate skills. The proposed datasets and source code are publicly available on a GitHub repository[1]. The main contributions of this study are as follows: 1) We proposed framing the problem of recognizing four different karate skills as a HAR problem on two datasets: raw sensor and body joint angles. In this context, appropriate real-life datasets were utilized to achieve this goal. 2) We proposed a non-sliding window technique to extract the required features for training the proposed predictive HAR models. 3) To our knowledge, this is the first work to compare the performance of HAR models trained on two different karate datasets.

II. RELATED WORK

In [14] the authors introduced a framework for the intricate analysis of motion kinematics. This study relied on dynamic time wrapping and a hidden Markov classifier to compare the captured motion with the action templates. The Gesture Description Language segmentation module divides the motion samples recorded from the incoming motion capture (MoCap) system. The actions associated with kicking were defined solely based on attributes related to using legs. The attributes considered for kicking actions included the speed, the body joint, the body joint angles, and the force exerted by the legs. By analyzing these attributes, the framework could accurately identify and classify different kicking motions. The recognition rate of 0.92 indicated that the framework was highly effective in accurately recognizing and categorizing kicking actions based on leg-related attributes. The comparison and analysis of the MoCap measurements obtained from athletes have been addressed in [14, 15]. In [14] the authors deployed a signal comparison technique based on the Dynamic Time Warping (DTW) algorithm to evaluate the efficacy of commonly performed karate kicks executed by athletes. As a result, DTW is used to evaluate the singular action using distances and alignments on pre-processed MoCap data to define the repetition degree. However, nonlinear temporal displacements of action phases and spatial variations in trajectories can impact this repetition level. In }[15], the authors produced a visual representation to generate the kinematic analysis. The dataset was acquired by recording the movements of two proficient black-belt practitioners (i.e., 560 recordings) using IMUs. A comprehensive analysis is conducted to compute the accuracy of the proposed algorithm by comparing similarities and differences with ground-truth data. The proposed study indicates that Algorithm 1 performs optimally when applied to activities of shorter duration, typically ranging from 2 to 4 seconds, and the actions are all classified correctly. However, this work is limited by its inability to yield favorable outcomes for extended physical activity and its reliance on a small sample of athletes to document proficient motions. The KUMITRON is an artificial intelligence system mainly designed to analyze real-time sensor data, aiming to deliver individualized feedback and recommendations to individuals engaged in karate [16]. This system employs a combination of a sensor and a drone camera to track the physical exertion of karate practitioners during kumite, which refers to the combat aspect of karate sport. By capturing data on factors such as speed, power, and reaction time, the KUMITRON system can provide valuable insights into the players' performance. The amalgamation of computer vision and ML algorithms enables the system to explore the adversary's motions and offer recommendations on proactively predicting and preventing them with efficacy. The KUMITRON system revolutionizes the practice of karate, enabling practitioners to refine their techniques and augment their combat skills. In [17], the authors introduced a novel dataset named MS-KARD, which incorporates several vision perspectives and sensor data from accelerometers and gyroscopes. The dataset was specifically proposed to improve the identification of movements characterized by comparable spatial trajectories, making it a significant resource for research on human action recognition. It has 2,814,930 frames and 5,623,734 sensor data samples, encompassing 23 distinct karate movements. Notably, the data is captured using three IMUs and 2 RGB cameras. An ensemble-based approach, known as KarateNet, employs deep learning methods trained on the vision and sensor streams of MS-KARD to achieve precise classification for movements. A cross-sectional study was conducted, and it included a sample of 20 male karate players and 20 male swimmers aged between 20 and 50. The players performed four standing postural control tasks of varying difficulty [18]. This study employs functional and behavioral tests that aim to assess accurately the extent of balance impairment. This implies that the practice of karate may have potential benefits as a pre-habilitation strategy that potentially contributes to the mitigation of age-related deterioration in balance control. The results emphasize the particularity of exercise training principles and the potential of karate as a means of pre-habilitation in mitigating age-related deteriorations in balance control. The authors in [19] have proposed a three-dimensional arm GUI to illustrate the Choku-zuki punches, considered basic karate punches. The participants can practice these punches using wireless communication technology, which facilitates the instantaneous monitoring and analysis of the rotational motion and fluctuating angular velocity of punches. The 3D image produced is subjected to a comparative analysis alongside a precise reference and a consistent punching pattern obtained from karate masters. This allows the participants to receive real-time feedback on their punching technique and make necessary adjustments. The accuracy of the proposed system is evaluated by conducting different tests on a sample of 10 female and male karate practitioners against 10 male and female newbies. Nevertheless, various problems arise for inexperienced individuals regarding manipulating their hands, specifically concerning rotation and fluctuations in angular velocity, which need more investigation. In [20], the authors aimed to study the application of linear acceleration sensors in the automatic recognition of punches in the context of karate. The acceleration of different karate punches is analyzed through the use of IMUs fixed to the wrists of athletes. Significant features are extracted, and convolutional neural network approaches are used to calculate the punches' statistical characteristics. In addition, the study incorporated the inclusion of movement devoid of punches as a measurable variable. The proposed model has evidenced an accuracy of 96% for the five punch categories tested, indicating its effectiveness in accurately calculating the punches' statistical characteristics.

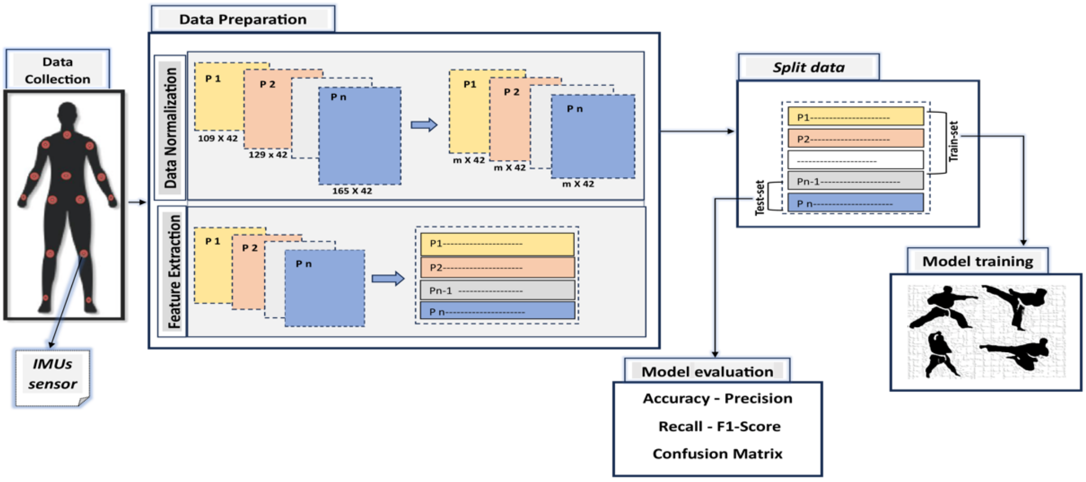

Figure 1. The block diagram of the proposed karate skills HAR method.

III. THE PROPOSED METHOD

A. *Overview*

Error! Reference source not found., illustrates the overall proposed methodology for this work. A specific dataset containing four karate skills was used to collect and process data for karate sport. Algorithm 1 was proposed for data processing purposes to ensure consistent data size during model training. The normalized data were then subjected to feature extraction by storing the data of each file after normalization as a row. A set of ML models were trained on the pre-processed dataset and evaluated. Finally, accuracy, precision, recall, and F1-score evaluation metrics were computed using the micro average to validate the model's performance.

B. The proposed dataset

We utilized an open-source dataset related to karate sports (Fathalla et al., 2023) The goal of the suggested system was recording and evaluating professional skills of the karate trainees on four karate skills in different skill levels: Gedan Barai, Oi-zuki, Jodan Age–uke and Soto–uke executed by 3-4 players. Initially, a dataset was collected based on three axes X, Y, Z, including 17 sensors Accelerometer and gyroscope placements spanning various body parts: the hip, legs, feet, shoulders, arms, hands, head, and spine. Information from these IMU sensors was interpreted using Axis Neuron software that was used to establish the motion position and direction of movement; thus, this enabled the monitoring of the movement and recording of performance in a calc file 178 files for four activities in total. After that, biomechanical analysis was performed with the BoB software method, where joint angles were extracted from the IMUs sensors. It focuses on 14 specific body joints, including the ankles, knees, hips, wrists, elbows, shoulders, lumbar, and neck areas, each described by three distinct joint angles across enumerated locations. Furthermore. Figure 2 shows the raw sensor data readings from an IMU sensor placed on the spinal region as the player performed the Gedan Barai exercise, while Figure 3 displays the data represented in body joint angles. In summary, it is worth noting that the first dataset was based on the readings of the accelerometer and gyroscope axes, while the second was based on body joint angles between bones. Furthermore, Table 1, Figure 2, and Figure 3 emphasize the difficulty of the prediction in accelerometer-gyroscope axis reading compared to the body joint angles dataset.

Algorithm 1. Data Normalization

```
Input:
    min_readings: the minimum number of readings required
    readings_per_file: the current number of readings per file
while readings_per_file > min_readings do
    readings_to_drop ← readings_per_file − min_readings
    if readings_to_drop > 0 then
        interval_size ← readings_per_file/readings_to_drop
```

```
5:        indices_to_drop ← [ ]
6:        item ← interval_Size/2
7:        for iteration = 1, 2, . . . , readings_to_drop do
8:            indices_to_drop[iteration] ← item
9:            item+ ← interval_Size
10:       end for
11:       for i = length(indices_to_drop) down to 1 do
12:           remove element at index indices_to_drop[i] from readings_list
13:       end for
14:   end if
15: end while
```

C. The proposed system

The dataset used in the study consists of 178 performances: raw sensor readings or the body joint angles. The number of performances for each activity varies, with 53 performances gathered by four players in Gedan Barai, 49 performances gathered by four players in Oi-zuki, 39 performances gathered by three players in Age-uke, and 37 performances gathered by three players in Soto-uke. This observation can be made because of the varying number of rows of each dataset file due to the start and end variation of the timestamp of the activity for each participant. This simply means each participant takes a different time to perform the same exercise, such as taking 1.5 seconds compared to another person taking 1.4 seconds to complete it. These discrepancies in timings further lead to differences in the number of rows of each file, which might affect the precision of the model. So, more preprocessing techniques are needed to make the time intervals uniform so that the data will be consistent and reliable. Thus, we propose Algorithm 1 with two inputs, namely, 1) the minimum number of readings required and 2) the current number of readings per file. In general, Algorithm 1 removes extra readings from each file in a dataset to have the same number of readings in each file for better accuracy in ML models that will be trained on this data. In Algorithm 1 line 1 checks if the current number of readings per file is greater than or equal to the minimum required readings. If the check result is true, line 2 calculates the number of readings to drop, which is the difference between the current number of readings per file and the minimum required readings. Lines 3 to 13 start by checking if the number of readings to drop is greater than zero, Algorithm 1calculates the interval size, which represents the number of divided intervals for each file. Then, Algorithm 1 instantiates an empty list called indices to drop. It instantiates the variable item as half the interval size. Lines 7 - 10 contain a for loop that iterates the number of readings to drop. On each iteration, Algorithm 1 appends the current value of the item to indices to drop and increments it by the interval size. Finally, lines 11-13 represent another loop cycling through the indices to drop readings in reverse order. Each iteration removes the corresponding element from the readings list.

Table 1. The mean, standard deviation (STD), maximum, and minimum readings for body joint angles, including right shoulder (INT/EXT) angles, left leg (INT/EXT) angles, and spinal (front/back) angles, along with raw x-axis readings from the right shoulder, left leg, and spinal regions.

Activity	**IMUs Placement**	**Body Joint Angles (°)**				**Accel Axis Readings(M/s^2)**			
		Mean	STD	Max	Min	Mean	STD	Max	Min
Gedan-Barai	Right Shoulder	-18.69	16.46	17.29	-51.84	0.72	1.21	5.90	-5.42
	Left Leg	-0.97	1.38	1.596	-5.815	-0.36	1.03	2.80	-7.37
	Spine	11.07	11.43	33.20	-1.166	-0.05	0.65	2.29	-2.44
Oi-zuki	Right Shoulder	-22.46	20.54	6.546	- 63.94	0.67	0.72	2.96	-3.97
	Left Leg	3.77	2.66	8.620	-1.57	-0.35	0.75	1.89	-2.49
	Spine	11.33	11.81	33.33	-3.21	0.19	0.61	2.66	-2.08
Soto-uke	Right Shoulder	-3.98	8.82	7.65	- 26.29	0.68	0.75	3.35	-1.18
	Left Leg	-3.98	4.92	2.96	-	-0.44	0.87	2.15	-4.03

					9.688				
	Spine	22.98	8.56	39.46	13.04	0.15	0.74	3.09	-1.79
Age-uke	Right Shoulder	-46.04	34.55	4.99	- 84.86	0.75	0.56	2.25	-0.89
	Left Leg	-5.56	4.75	2.99	-12.84	-0.45	0.95	2.64	-2.92
	Spine	20.71	8.50	37.59	10.45	0.19	0.75	3.73	-2.47

IV. RESULTS

A. Experiment using unnormalized data

We want to find out the relative accuracy of two datasets-one based on the raw sensor data and the other on the body joint angles data-within an unnormalized scale. Then at the beginning, Pandas library was used to read each file and store the contents of it as a row. Owing to the fact that there was a difference in file sizes, we treated missing values by dropping them. So reducing the size of the overall dataset might impact model performance. We then split our data into 80% (142 sub-samples) to train our models and the remaining 20% (36 sub-samples) for testing. Afterwards, we tried several ML algorithms to train and evaluate our models. For the raw sensor readings, the K-NN algorithm showed a training accuracy of 95.77% and a testing accuracy of 91.66%, while in SVM, it showed a perfect training accuracy of 100% with a testing accuracy of 91.66%. DT showed a training accuracy of 99.29% with a testing accuracy of 80.55%. At last, the RF algorithm provided a training accuracy of 100% and a test accuracy of 91.66%. Besides, for the body joint angle, the K-NN algorithm provided 96.47% for training and 91.6% for testing. Then, the training and test accuracy for the SVM algorithm is 100% and 97.22%, respectively. The DT algorithm showed a training accuracy of 100% and testing accuracy of 97.2%, while the RF algorithm perfectly reached an accuracy of 100% for both training and testing.

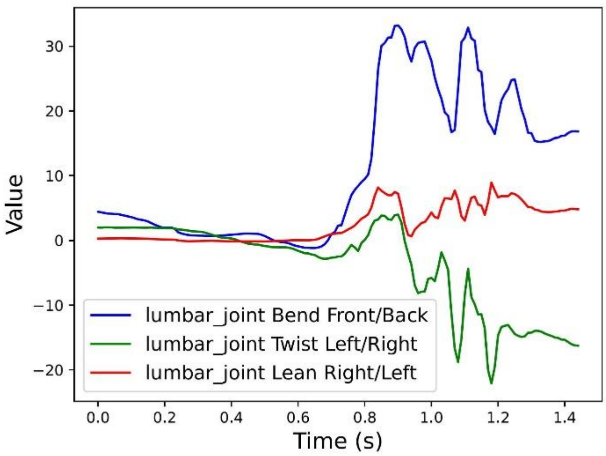

Figure 1. spine reading over time along three of body joint angles.

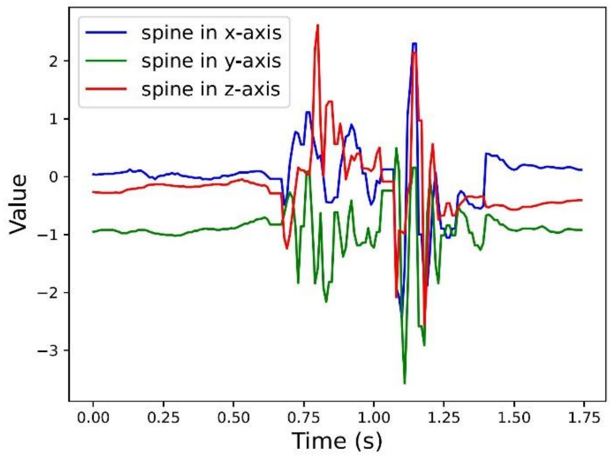

Figure 2. spine reading over time along three accele-motere axis readings.

B. Experiment using normalized data

We aim to evaluate the performance of our model by normalizing two datasets to address discrepancies in file sizes. In this, algorithm 1 is used to standardize all data files to a consistent format, reducing data loss; after that, we chose 80% for training and used the rest of the data as testing data. Employing ML algorithms, we assessed our model's performance on raw sensor readings and body joint angles datasets. Using the raw sensor readings dataset, the K-NN algorithm achieved 95.77% for training accuracy versus 86.11% for test accuracy. Correspondingly, for SVM, perfect training accuracy, 100%, and a test accuracy of 94.44%. In the same direction, the DT algorithm had a perfect fit training accuracy of 99.29% and a test accuracy of 100%. Similarly, RF algorithms were also able to achieve perfect classification accuracy for both training and test sets, scoring 100% on both. In the body joint angles dataset, the K-NN algorithm reached a training accuracy of 97.81% and a testing accuracy of 94.28%. the SVM, DT, and RF reached 100% for training and testing accuracy. In summary, the results show that our normalization algorithm significantly improves performance in the raw sensors and the body joint angles datasets. Also, decreasing over-fitting problem. Some of our models, such as RF, reached 100 accuracy, which is rarely seen in machine learning. However, we are not alone in this result; Hao Wu et al. [21] also reported 100% accuracy on a different HAR dataset for non-sport applications.

Table 2. Proposed models' performance through 10-fold cross-validation using a normalized sensor's axis reading dataset.

Classifier	Accuracy	Precision	Recall	F1-score
KNN	94.93% ± 3.90%	95.82% ± 3.49%	94.93% ± 3.90%	94.93% ± 3.93%
SVM	89.87% ± 7.02%	93.01% ± 4.84%	89.87% ± 7.02%	89.77% ± 7.28%
DT	95.98% ± 4.56%	96.89% ± 3.40%	95.98% ± 4.56%	95.88% ± 4.71%
RF	98.86% ± 2.29%	99.11% ± 1.77%	98.86% ± 2.29%	98.88% ± 2.25%

Table 3. Models' performance through 10-fold cross-validation using a normalized body joint angle.

Classifier	Accuracy	Precision	Recall	F1-score
KNN	96.57% ± 3.75%	97.50% ± 2.58%	96.57% ± 3.75%	96.55% ± 3.83%
SVM	97.06% ± 2.94%	97.72% ± 2.30%	97.06 %± 2.94%	97.09% ± 2.91%
DT	98.86%± 2.29%	99.07% ± 1.86%	98.86% ± 2.29	98.84% ± 2.32%
RF	100.00% ± 0.00%	100.00% ± 0.00%	100.00% ± 0.00 %	100.00% ± 0.00%

V. DISCUSSION

To validate the performance of proposed ML models, we have applied a validation method called k-fold cross-validation. The validation method is a statistical approach used to estimate the performance or accuracy of ML models. K-fold cross-validation is one of the strategies used to improve upon the holdout method. Predefined numbers of folds or partitions divide this data and carry on separate analysis in each fold. The last step is the computation of the mean and the standard deviation of the estimated total error. Table 2 and Table 3 presents the variation in performances of raw sensors and the body joint angles datasets using a proposed models with 10-fold cross validation technique. Although the model underwent several trainings and evaluations with different folds acting as the validation sets and the rest as training sets, Table 3 shows that the body joint angle dataset is a lot better in terms of accuracy for SVM algorithms. For KNN, DT, there existed a moderate amount of improvement whereas for the RF model, very slight improvement compared to that of the raw sensor dataset. Note that the highest average standard deviation of the body joint angle dataset does not exceed 0.0375, whereas in the raw sensor dataset this value is as high as 0.0702. This may indicate that accuracy measures in the body joint angle dataset are less varied compared to those of the raw sensor dataset and point to the higher consistency of model performance.

Figure 3 and Figure 5 present a heatmap visualization of the Gedan Barai activity for a single player, illustrating the correlation between sensors and joints on the shoulder, spine, and foot in both the raw sensor data and the angle dataset. In comparison to Figure 3, which depicts the raw sensor data, Figure 5 shows more distinct color variations. This is due to the correlation values in heatmap Figure 3 being closer to zero, indicating weak relations, while heatmap Figure 5 displays correlations near +1 or -1, signifying stronger connections between joints in the body joint angle dataset.

This superiority can be reasoned with the fact that body joint data gives unique readings for each activity, hence making it much easier for any model to predict activities as compared to axis data shown in Additionally, in Table 1 the angle data displays a notable distinction, with readings showing a more pronounced variation compared to the data from raw sensors. This variability enhances the accuracy of exercises performed using angle data. In a summary, the normalized body joint angles deliver high accuracy across all models. In contrast, the raw sensor data achieves high accuracy in certain models, with KNN showing the lowest accuracy at 86.11%.

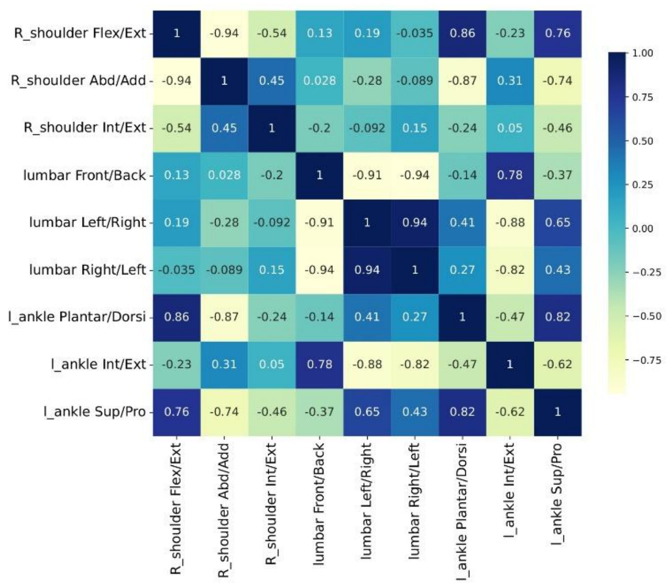

Figure 3. Heatmaps to depict the relation between the right shoulder, spine, and left foot cross both datasets Accelemotere axis readings.

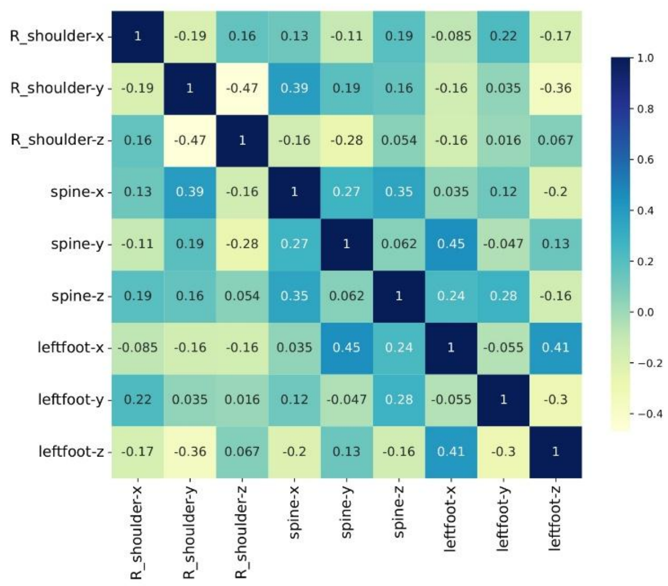

Figure 4. Heatmaps to depict the relation between the right shoulder, spine, and left foot across body joint angle readings.

VI. CONCLUSION

This paper addresses karate skill recognition from IMU data as a HAR problem, focusing on four main activities: Gedan Barai, Oi-zuki, Jodan Age-uke, and Soto–uke based on a dataset from the literature. We developed a normalization algorithm and compared two datasets: raw sensor data from 17 body-placed sensors and derived body joint angles for 14 specific joints. Four basic ML models evaluated performance using a non-sliding window technique. Our normalization algorithm improved results in both datasets by reducing overfitting. Body joint angles consistently outperformed raw sensor data, as confirmed by 10-fold cross-validation (average standard deviations: 0.0375 vs 0.0702). This study advances the development of a robust coaching assistant for karate analysis across skill levels and an intelligent arbitration system, potentially reducing costs and eliminating the need for human referees. Future research will explore advanced ML and deep learning models, expand the range of karate skills analyzed, and extend the methodology to other combat sports, broadening the application of this HAR approach.

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