Evaluating Sensor Placement and Feature Importance for Hurling Movement Classification

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Abstract: Human Activity Recognition (HAR) involves recognising and classifying human activities from data collected by sensors through machine learning (ML) techniques. The assessment of athletic movement via HAR has benefited sport performance analysis by identifying technical and tactical performance indicators. Hurling is a dynamic stick and ball invasion team sport that involves high-impact movements. Sensor placement and feature selection in HAR tasks impact the classification accuracy of the ML model during testing and training. This study aims to determine the optimal inertial measuring unit (IMU) sensor placement for recognizing hurling movements and to identify the most important features for accurate classification. Time-domain and frequency-domain features of accelerometer data were computed and were used to train and test three classification models: Support Vector Machine (SVM), Random Forest (RF) and k-Nearest Neighbour (k-NN). A RF model achieved the highest mean accuracy in the recognition of four hurling specific movements, for sensors located at the forearm (86%) and the thigh (84%). Features extracted from the z-axis, specifically zero crossing rate (ZCR), standard deviation (STD), and root mean square (RMS) were most discriminative in classifying hurling sport movements with a RF model using a forearm-mounted IMU.

1 INTRODUCTION

Hurling is a stick and ball team sport that is predominantly played in Ireland and involves high intensity, intermittent activity (Mullane et al., 2018). The sport involves a multitude of advanced technical skills and requires the proficient use of a stick (Hurl) to control and strike a ball (sliotar) at high velocities (Leddy et al., 2023). Hurling encompasses a broad range of skills and physiological considerations such as explosive power, striking a ball in the air, jumping, and sprinting (Collins et al., 2022). Successful performance outcomes in hurling match-play are linked with an understanding and knowledge of physical and physiological demands (Keane et al., 2021). Activity monitoring of team sports leads to increased knowledge of physical and physiological in-game demands and assists in performance profiling, training prescription and reduces the likelihood of injury (Ribeiro et al., 2020). The increased desire to understand sports motion has led to motivated research in sports activity recognition which has examined the frequency, intensity, duration, and type of activity performed during competitive and training events (Pfeiffer et al., 2023; Ren et al., 2016).

Monitoring and automatic recognition of physical activities is often referred to as a human activity recognition (HAR) task (Bulling et al., 2014). HAR is a challenging time-series task that has been used in team sports such as Australian football (Cust et al., 2021), field hockey (Shahar et al., 2020) and cricket

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(McGrath et al., 2021) to detect and identify actions of athletes. HAR in sports applications has been shown to be beneficial for measuring training volume (Hendry et al., 2020), player performance evaluation and assessing biomechanical factors of sports movement (McDevitt et al., 2022; Roslan & Ahmad, 2020). The continuous and coupled developments in technology and artificial intelligence (AI) over the past two decades has enabled sports activity recognition that is robust, accurate and increasingly automated (Chmait, & Westerbeek, 2021). An inertial measuring unit (IMU) is a sensor system that combines a gyroscope, accelerometer and often a magnetometer for measurements of angular velocity, acceleration, and orientation, and are commonly used as data inputs for classification of human movement (Kranzinger et al., 2023). A review of wearable technology in sport reported that IMU and its subcomponent accelerometer were the main keywords featured in 2568 research articles which were indexed in the Social Sciences Citation Index (SSCI) or the Science Citation Index Expanded (SCI-E) (Seçkin et al., 2023). Tri-axial accelerometers are particularly suited to activity recognition due to their ability to measure acceleration proportional to external force allowing for measurements of dynamic movements reflecting changes in activity intensity and frequency (Twomey et al., 2018).

The HAR framework is depicted in Figure 1. Typically, the following steps are involved: data acquisition, data preprocessing (signal processing and segmentation techniques), feature extraction, classification through AI techniques and performance evaluation (Bento et al., 2022). The application of AI in the form of a machine learning (ML) or deep learning (DL) model for classification of activities and an associated performance evaluation of said model is an integral component of the HAR framework (Kulsoom et al., 2022). Studies have shown that each step of the ML modelling process are iterative, and classification accuracy depends on the specific characteristics of the movement being analysed (Gil-Martín et al., 2020).

Traditional supervised ML models such as Support Vector Machine (SVM), Random Forest (RF) and k-nearest neighbour (k-NN) have been extensively employed for activity recognition tasks based on accelerometer data (Slim et al., 2019) and in the classification of human motion data based on IMUs in sports (Kranzinger et al., 2023). SVM is widely reported in the literature for the classification of spatiotemporal features into activity categories in sensor-based sport activity recognition (Cust et al., 2021). Naïve bayes (NB), Decision Tree (DT) and Convolutional Neural Networks are also commonly applied ML models in the HAR research area (Pajak et al., 2022). The k-NN algorithm has demonstrated strong performance in the classification of human activities (Mohsen et al., 2022). A weighted k-NN model achieved 82.5 ± 4.75% accuracy in the prediction and classification of performance indicators attributed to the shooting score in archery (Muazu Musa et al., 2019). In HAR research, it is common to apply several ML models to determine the best fit for the recognition and classification of the activities (Preatoni et al., 2020), as the classification performance of the ML model will be dependent upon the characteristics of the dataset under investigation.

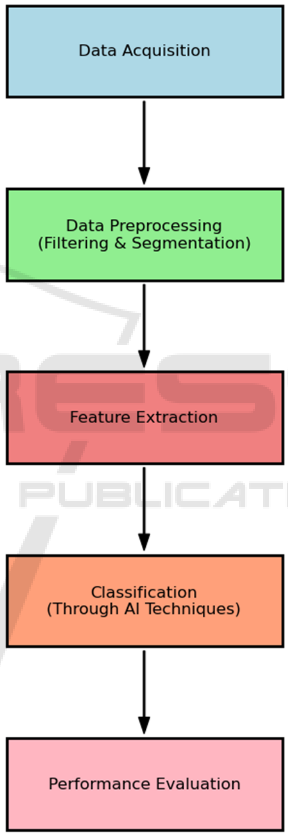

Figure 1: Sports Activity Recognition Framework.

The data pre-processing is the second step in sport activity recognition where the data is filtered and segmented to define activity boundaries through techniques such as overlapping windows. The statistical and mathematical features are then extracted from each window to prepare for use with ML models. Feature extraction captures the relevant information required to differentiate activities represented by the sensor signals during sports movement. Feature premutation refers to the assessment of the impact of feature relevance on a model's performance on given datasets (Vallance et al., 2020). For HAR tasks from IMU data, features are typically extracted from the time-domain and frequency-domain (Gomaa & Kamas, 2023; Rosati et al., 2018). Features extracted from the time domain reveal statistical information about the signal and are the most utilised method in HAR tasks (Rosati et al., 2018). Studies have shown that time-domain features may be sufficient to classify an activity class (Chong et al., 2021). Frequency-domain features reveal information about the signal's periodicity, such as underlying oscillations which is beneficial in the recognition of activities with distinct periodic patterns (Dehkordi et al., 2020). To obtain high performance accuracy, the input features must be representative of the movement being analyzed. The selection of appropriate features has been of interest in HAR research (Allik et al., 2019; Bennasar et al., 2022). Studies have found that the number of features (Brzostowski and Szwach, 2018) in addition to the type of features (McGrath et al., 2021) have an influence on the classification performance of ML models in sport activity recognition tasks.

Performance evaluation metrics are quantitative methods used at the end of the HAR pipeline to determine the effectiveness of the classification model. Performance is generally assessed using accuracy, which is a measure of the number of correct predictions divided by the total number of predictions and is derived from a confusion matrix (Ward et al., 2011). Accuracy may be over predicted when the classes in a dataset are imbalanced, or if there is insufficient information on the instances of false positives and false negatives. Precision and recall are metrics which can be used to supplement accuracy when evaluating a model's classification performance. Precision focuses on minimizing false positives, while recall aims on minimizing false negatives (Ward et al., 2011). The classification accuracy is highly dependent on the incoming data, and as such the sensor location should correspond with the movement being analyzed. For example, ankle-mounted IMUs produced high accuracy of 80-83%, in the in-situ classification of Australian football kick types (Cust et al., 2021). An investigation into the optimal sensor placement for badminton found that a sensor placed on the bottom of the rackets grip provided the best recognition accuracy when examining stroke types (Steels et al., 2020). Other studies investigating the influence of sensor location on the recognition of complex movements found that a combination of sensors achieved the highest performance of 96.7% accuracy (Shahar et al., 2020) and 97.6% (Preatoni et al., 2020) respectively. The placement of sensors at varying body segments and sensor combinations should be explored to determine classification accuracy for optimised sport activity recognition (Xia & Sugiura, 2021).

Extensive research has been conducted on the use of accelerometer data and ML techniques for accurate sport activity recognition and classification (Cust et al., 2019; Pfeiffer et al., 2023). However, to the best of current knowledge, the investigation of HAR to classify hurling movements has not yet been conducted. This study aims to determine the optimal IMU sensor placement for recognizing hurling movements and to identify the most important features for accurate classification using three ML models; SVM, RF, k-NN.

2 METHODS

2.1 Data Collection

A total of four hurling specific sport activities were performed for 1-min each, over an 8-min period, with 1-min intervals of rest between each activity type. Five hurling players (age 22.0 ± 5.61 years; height 178.4 ± 5.64 cm; body mass 83.6 ± 17.73 kg) with an average training age (Myer at al., 2013) of 16.8±4.09 years participated in this study. The activities included (1) jab lift, (2) overhead catch, (3) soloing, and (4) striking. A description of these activities is detailed in Table 1 below. Ethical approval was obtained from the South East Technological University Research Ethics Committee (Ethical approval code: 332).

The dataset analysed in this study was a primary dataset collected utilising the Xsens Motion Visualization and Navigation (MVN) link inertial measuring system (Movella Technologies B.V., Enschede, Netherlands). The Xsens MVN link is a 3D motion capture system which consists of 17 IMUs that are wired and tightly affixed to body segments in a Lycra suit. The data used in this study was accelerometer derived data obtained from the IMUs located at the forearm, and right upper leg, which will be referred to hereafter as 'thigh'. The forearm sensor is positioned on the dorsal (posterior) side of the forearm, just above the wrist joint. The thigh sensor is positioned a few centimetres above the mid-thigh, or on the iliotibial band on the external side of the leg (Movella, 2022). The 23 segments of the kinematic model are defined according to the international Society of Biomechanics (ISB) recommendations, and detailed sensor placement information can be found in the MVN user manual (Movella, 2024).

The accelerometer range for Xsens MVN link system is MTx: ± 160 m/s2 (16 g) MTw: ±160m/s2 (16g) (Movella, 2024). The movements were simultaneously recorded by a Panasonic HX-WA20 camera with a resolution rate of 1920px *X* 1080px and a frame rate of 30fps. The cameras, which were mounted on stationary tripods, were used to establish ground truth. All statistical and visual analysis were conducted in a Python environment (Python, 3.8.12).

Table 1: Hurling Activities Description.

Activity	Description
Jab Lift	Player slides the hurl under the ball and scoops it into the hand in one swift action.
Overhead catch	Player positions themselves under the flight path of the sliotar, anticipating its descent. The player then jumps into the air off one leg, bending the opposite leg, and the ball is caught with a cupped hand.
Soloing	Player balances the sliotar on top of the hurl as they take steps. The hurl is held out in front of the player.
Striking	Player positions their dominant hand at the top of the handle and their non-dominant hand further down the handle. The hurl is swung above the head until it meets contact with the sliotar, where it is struck.

2.2 Data Preprocessing

IMU sensors measuring dynamic movements may be susceptible to noise and drift in the signals due to magnetic disturbances and offset errors owing to the participants' unintentional shaking or movement. These movements may present as slight and potentially repetitive fluctuations which distort the signal, affecting the quality of the movement data captured and the classification performance of the associated machine learning model (de Cheveigné & Nelken, 2019). Correspondingly, the application of lowpass filtering is an integral component of the activity recognition framework following on from data acquisition (Hsu et al., 2018). The purpose of a filter is to remove interference noise, miscellaneous signal fluctuations, and low-frequency components (Yin et al., 2021). A low pass filter only allows lower signal frequencies that are below its cutoff frequency to pass through, while attenuating all signals above the cut off frequency, effectively extracting the useful components of the signal relating to physical activity which lie within a specific frequency range (Shouran & Elgamli, 2020). Fridolfsson et al. (2019) suggested that accelerations related to human movements are typically found between 1 and 10 Hz. The comparison between filtered and unfiltered accelerometer data (x, y, z axes) recorded from the forearm mounted IMU of a participant during 60 seconds of striking is displayed in Figure 2.

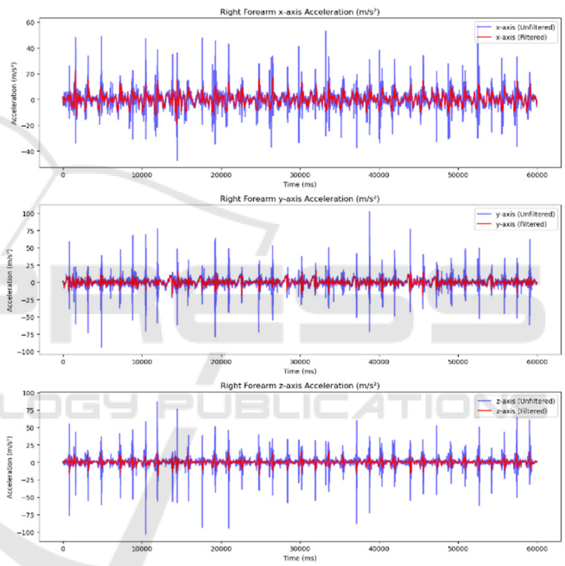

Figure 2: Comparison of Unfiltered (blue line) and Filtered (red line) Acceleration Data for Striking Movement obtained by the Forearm IMU sensor.

In this study, a low-pass 4th order Butterworth filter with a cut-off frequency of 10 Hz using a second-order filter two times to the time series was implemented to smooth the signal by attenuating frequencies higher than 10 Hz. A fourth-order Butterworth filter is commonly used in biomechanical applications (Crenna et al., 2021) and in motion recognition (Liu et al., 2022). Additionally, a moving average filter with a window size of 5 samples was applied to smooth the data. Once the data has been filtered, it is segmented into overlapping windows to facilitate feature extraction and model training (Cero Dinarević et al., 2019). The optimal window size and overlap depends on the specific characteristics and application of the dataset. Bonomi et al. (2009) found that reducing the segment size decreased the machine learning classification accuracy for physical activity recognition. Conversely, Brzostowski and Szwach (2018) reported that increasing the window size to 80 samples improved the classification performance of k-NN and Logistic Regression for classification of stroke type in tennis.

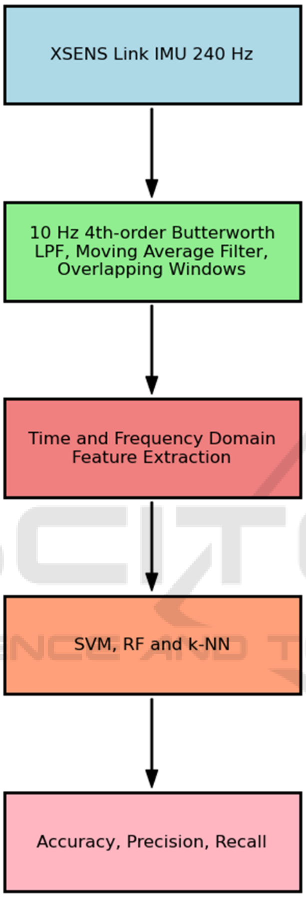

Figure 3: Sport Activity Recognition Framework applied in this research.

For this study, a sliding window approach of 2.5s with a 50% overlap was applied. The 2.5s window size demonstrates the most accurate detection performance for common sports activity for supervised machine learning models (Ghazali et al., 2018). The features were extracted from each window segment in both the time domain and frequency domain for the x, y, and z axes. The extracted features are detailed as follows: mean, standard deviation (SD), root mean square (RMS), skewness, kurtosis, zero crossing rate (ZCR), dominant frequency, and total power. These features have been widely adopted in previous studies examining accelerometer-based activity recognition (Gomaa & Khamis, 2023). The time-domain features in this study are simple features extracted through basic statistical analysis providing characteristics of the signal over time and are highly effective in discriminating activities from accelerometer signal (Erdaş et al., 2016). Simple statistical features have shown outstanding classification accuracy in differentiating static and dynamic activities (Coelho et al., 2022). Frequency-domain features are extracted through spectral analysis and compliment time-domain features (Erdaş et al., 2016) for robust feature representation (Nguyen et al., 2021). The hurling activities examined in this research exhibit a combination of rotational and linear movements with varying intensities and as such, features with high discriminative abilities are required to accurately recognise and classify different activities. For example, striking movements often involve rapid, intense movements leading to greater variability and distinct skewness and kurtosis values compared to more uniform activities. Additionally, frequency domain features reveal underlying oscillations and energy distributions in the data. Activities such as jogging (soloing) and jumping (Overhead catch) have indicative frequency components that can be detected through these features.

The train/test split of the data was 80/20%, where 80% of the data was used to train the machine learning models (SVM, RF, and k-NN), and the remaining 20% was used for performance evaluation. In this study, a 5-fold cross validation was implemented. K-Fold cross validation involves randomly partitioning the data in k-equal subsets, training the data on k-1 subset, and using a different fold for testing (Dehghani et al., 2019). This process is repeated k times and when the k iterations are completed, performance metrics such as accuracy, precision and recall are calculated by averaging the results of all k folds. The sport activity recognition framework implemented in this study is shown in Figure 3.

3 RESULTS AND DISCUSSION

Each of the five participants performed each activity for 1 minute, which corresponds to 240 s at a sampling frequency of 240 Hz/s. For each activity, 14400 samples were collected per axis, resulting in 172800 samples per participant across all three axes. The data was segmented into fixed sized windows of 2.5 s with a 50% overlap this translates to 600 samples per window with an overlap of 300 samples, this segmentation yielded 940 windows per sensor. Each window was processed to extract various time-domain and frequency-domain features. Three supervised classification models, specifically SVM, RF and k-NN were compared to determine the best performance in terms of mean accuracy (A), mean precision (P), and mean recall (R), these results are displayed in Table 2. Figure 4 presents the confusion matrices, while Tables 3 and 4 provide a detailed breakdown of the TPs, TNs, FPs, and FNs for our classification models using the forearm and thigh sensors. Permutation feature importance with a cut-off threshold of 0.05 was conducted to determine the importance of different features across the time and frequency domain for each of the sensor locations in predicting the hurling activity classes.

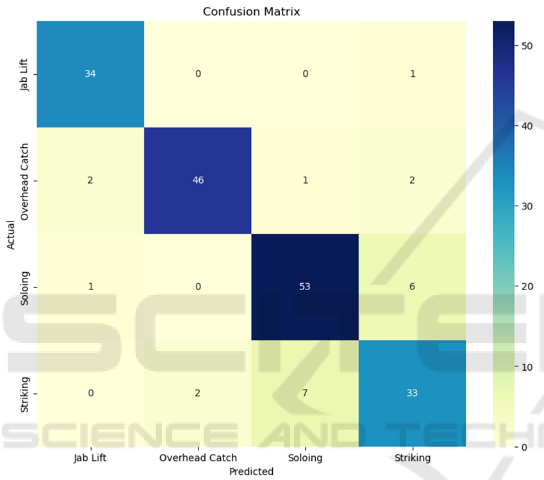

Figure 4: The confusion matrix for Random Forest model using the forearm sensor for the detection of four Hurling sport specific activities.

Table 2: Performance metrics of SVM, RF, and k-NN Models for the recognition and classification of four hurling specific activities (A = mean accuracy, P = mean precision, and R = mean recall. These metrics summarise the model performance).

Sensor Location	Model	Mean A	Mean P	Mean R
Forearm	SVM	0.848	0.850	0.848
	RF	0.863	0.866	0.864
	k-NN	0.741	0.743	0.740
Thigh	SVM	0.815	0.816	0.814
	RF	0.842	0.845	0.844
	k-NN	0.659	0.657	0.657

The confusion matrices from the RF model for the forearm sensor and thigh sensor are displayed in Figure 4 and Figure 5, respectively. The high values on the diagonal (correctly classified instances) suggest that the RF model is performing favourably for the classification of hurling activities from both sensor locations.

The analysis of two sensor locations revealed the RF model as the best-performing classifier with mean accuracy of 86% for the forearm, and 84% for the thigh respectively.

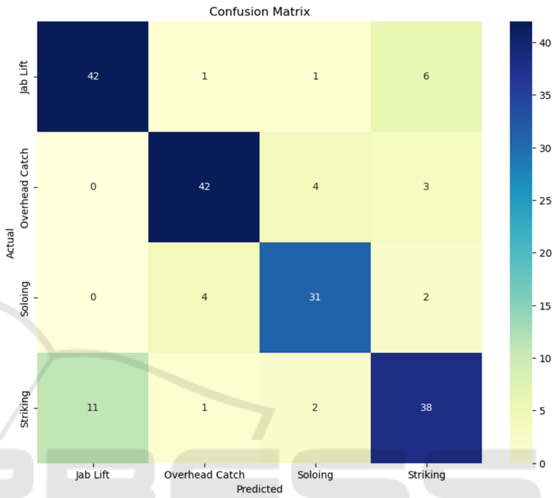

Figure 5: The confusion matrix for Random Forest model using the thigh sensor for the detection of four Hurling sport specific activities.

Table 3: Mean True Positives (TPs), True Negatives (TNs), False Positives (FPs) and False Negatives (FNs) for SVM, RF and k-NN classifiers on Forearm Sensor Data.

Model	Class	Mean TPs	Mean TNs	Mean FPs	Mean FNs
SVM	0	42.4 ± 6.46	136.0 ± 5.96	5.0 ± 2.0	4.6 ± 1.35
	1	43.2 ± 3.65	137.4 ± 4.07	3.6 ± 3.2	3.8 ± 1.93
	2	39.4 ± 7.00	133.2 ± 7.93	7.8 ± 1.16	7.6 ± 2.87
	3	34.6 ± 3.84	129.0 ± 6.29	12.0 ± 3.82	12.4 ± 2.80
RF	0	43.4 ± 5.12	136.4 ± 6.97	4.6 ± 1.01	3.6 ± 1.85
	1	41.4 ± 4.49	138.2 ± 2.71	2.8 ± 2.22	5.6 ± 2.41
	2	40.2 ± 6.67	135.0 ± 7.18	6.0 ± 1.89	6.8 ± 2.56
	3	37.4 ± 2.05	128.8 ± 6.01	12.2 ± 2.99	6.6 ± 2.57
k-NN	0	40.0 ± 4.09	133.6 ± 4.84	7.4 ± 3.38	7.0 ± 2.09

Table 4: Mean True Positives (TPs), True Negatives (TNs), False Positives (FPs) and False Negatives (FNs) for SVM, RF and k-NN classifiers on Forearm Sensor Data.(cont.)

	1	36.6 ± 5.78	133.2 ± 4.53	7.8 ± 1.46	10.4 ± 3.32
	2	37.4 ± 7.14	121.2 ± 9.62	19.8 ± 5.15	9.6 ± 2.65
	3	25.4 ± 3.97	127.4 ± 6.77	13.6 ± 3.44	21.6 ± 3.26

Table 3 and 4 summarize the TP (True Positives), TN (True Negatives), FP (False Positives), and FN (False Negatives) values for each classifier across both forearm (Table 3) and thigh sensors (Table 4). TP are the number of positive cases correctly identified as positive; the activity is classified accurately. TN are the number of negative cases correctly identified as negative; the activity is classified accurately. FP are the number of negative cases incorrectly identified as positive; the activity is misclassified. FN are the number of positive cases incorrectly identified as negative; the activity is misclassified. (Bennasar et al., 2022). For both sensor locations, SVM and RF models showed a decline in performance as denoted by a decrease in TPs and TNs, and an increase in FPs and FNs, particularly in class 3. However, both SVM and RF present as generally reliable with high mean TPs and TNs values throughout. RF was revealed as the better-performing classifier, showing notable performance with the forearm sensor. In contrast, the k-NN model had a significant drop in performance across both sensor locations with higher FPs and FNs lower TPs and TNs.

Table 5: Mean True Positives (TPs), True Negatives (TNs), False Positives (FPs) and False Negatives (FNs) for SVM, RF and k-NN classifiers on Thigh Sensor Data.

Model	Class	Mean TPs	Mean TNs	Mean FPs	Mean FNs
SVM	0	38.6 ± 2.24	134.2 ± 3.81	6.8 ± 2.63	8.4 ± 1.35
	1	39.2 ± 5.6	130.8 ± 3.54	10.2 ± 1.93	7.8 ± 2.03
	2	39.0 ± 7.42	135.4 ± 7.86	5.6 ± 2.72	8.0 ± 2.09
	3	36.6 ± 6.49	129.0 ± 7.12	12.0 ± 2.75	10.4 ± 2.57
RF	0	40.2 ± 2.92	135.4 ± 4.33	6.0 ± 2.09	6.8 ± 1.72
	1	42.6 ± 3.92	130.0 ± 2.52	11.0 ± 4.60	4.4 ± 2.93
	2	39.8 ± 5.91	137.6 ± 6.46	3.4 ± 3.07	7.2 ± 2.71
	3	35.8 ± 4.99	131.8 ± 6.24	9.2 ± 3.12	11.2 ± 2.31
k-NN	0	35.6 ± 3.07	125.0 ± 5.32	16.0 ± 2.52	11.4 ± 3.07
	1	31.8 ± 3.12	119.6 ± 3.72	21.4 ± 4.63	15.2 ± 2.78
	2	32.6 ± 6.56	130.0 ± 7.89	11.0 ± 3.40	14.4 ± 4.96
	3	24.0 ± 7.66	125.4 ± 6.18	15.6 ± 2.05	23.0 ± 2.96

The importance of features based on their impact on predictive performance of a RF model was calculated for each of the sensor locations through permutation feature importance, as displayed in Figure 5 and Figure 6. The features that demonstrated the greatest importance for the forearm mounted IMU with the RF classifier were ZCR, STD, and RMS in the z-axis, whereas total power from the x-axis, and mean from the y axis were of little predictive power. The most important features for the thigh mounted IMU were STD from the y axis, mean from the z-axis, and RMS from the y-axis. Features extracted from the x-axis, specifically RMS and total power were of least predictive power. Time-domain features, such as std, mean and rms are particularly effective for capturing the magnitude and variability of lower body accelerations in activities such as jumping (overhead catch) and jogging (soloing). Frequency domain features, such as dominant frequency, are particularly relevant for activities characterised by complex and rhythmic motions, which are common in striking activities. These features help in identifying activities with prominent rhythmic components.

This study shows that the RF model achieved the highest performance as denoted by the mean accuracy, precision and recall in both sensor locations. This result is synonymous with the work of Hölzemann & Van Laerhoven (2018) who examined the performance of ML models for classification of basketball activities, reporting that a RF model achieved the greatest mean accuracy of 87.5% outperforming a k-NN model. Similarly, a RF outperformed a k-NN and SVM models for the classification of human daily activities, and in these experiments, the highest accuracies of a RF model were achieved when the classifier was fed with time-domain features only (Erdaş et al., 2016) and a combination of time-domain and frequency-domain features (Nurwulan & Selamaj, 2020).

Random Forests are ensemble methods that combine multiple random decision trees (in this study the model consisted of 100 decision trees), each tree is trained on a random subset of the data (Breiman, 2001). Thus, the random sampling and aggregation of predictions results in a classifier that is scalable, efficient and robust to overfitting, enabling it to capture a broad range of patterns and characteristics from complex sporting activities. RF identifies the most relevant features, and research has shown that features extracted from the z-axis are of most importance (Casale et al., 2019).

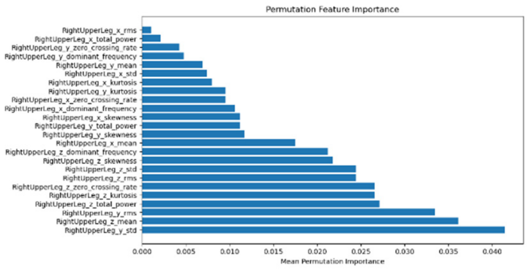

Figure 6: Permutation Feature Importance of Thigh Mounted IMU Features for Random Forest Classifier in Classifying four Hurling Movements.

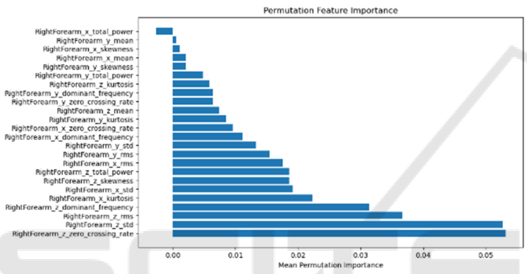

Figure 7: Permutation Feature Importance of Forearm Mounted IMU Features for Random Forest Classifier in Classifying four Hurling Movements.

A novel activity recognition system which combined nonparametric weighted feature extraction (NWFE), principal component analysis (PCA) and least squared support vector machine (LS-SVM) was introduced by Hsu et al. (2018) for the recognition of 10 daily human activities and 11 sport activities and reported an overall correct classification rate (CCR) of between 98.33 – 99.55%. Research in HAR is underpinned by the "No Free Lunch" theorem which explains that there is no universal best fit algorithm (Wolpert, & Macready, 1997). This is particularly evident in HAR research whereby differences are evident in data collection specifications, data pre-processing techniques, machine learning modelling and evaluation. As aforementioned, every step of the HAR pipeline is iterative and should be considered in alignment with the characteristics of the movement being analysed.

The optimal sensor placement has been of significant interest in HAR research (Davoudi et al., 2021; Steels et al., 2020). In this study, it was demonstrated that a single IMU mounted at the right forearm coupled with a RF model achieved a marginally higher accuracy compared to a thigh mounted IMU sensor for the recognition and classification of hurling activities. Shahar et al. (2020) examined the influence of sensor combination and location for activity recognition in field hockey and reported that a left wrist mounted sensor achieved 86.2% accuracy with a cubic SVM compared to other single sensor locations (waist, right wrist, and chest). However, the highest accuracy (96.7%) in these experiments was achieved when all 4 sensor locations were combined.

By combining several sensors from varying body segments, the classification performance of an ML model may be improved (Davoudi et al., 2021), but there are drawbacks including labour intensive post-processing and increased computational load. Moreover, considering the importance of ecological validity in sport science, HAR research should take place, where possible, in the athletes' natural sporting environment. Using multiple sensors in these training and competitive environments may prove to be cumbersome for athletes, and in such scenarios a single body-mounted sensor may be more practical.

Permutation feature importance is a technique used to determine the importance of different features in a predictive model. It works by randomly shuffling the value of each feature and measuring the resultant decrease in the model's performance, such as prediction accuracy and area under the curve (AUC) (Vallance et al., 2020). The larger the drop in ML performance, the more important that feature is. The analysis of feature importance in this study highlighted that simple time-domain features, particularly those extracted from the z-axis, were generally most relevant. Other research on significant features for HAR using tri-axial accelerometers reported that simple time domain features were of most significance (Bennasar et al., 2022). A comparison of two feature sets for HAR, showed that a feature set comprised exclusively of time-domain features achieved a performance of 96.7% compared to a more complex feature set, containing both time-domain and frequency-domain derived features which obtained a slightly higher performance of 97.1% (Rosati et al., 2018). The previous research suggest that time-domain features can be highly effective for HAR tasks, but the addition of frequency domain features can reveal underlying patterns and oscillations in the data and contribute to the accurate classification of complex sports movements (Dehkordi et al., 2020; Tran et al., 2014).

4 CONCLUSION

In this study, a sports activity recognition framework is proposed for the classification of four hurling sport specific movements. Accelerometer data were collected from IMUs mounted on the forearm and thigh of five hurling athletes. The performance of SVM, RF and k-NN models for the recognition and classification of Hurling activities was assessed for each sensor location. Additionally, the most relevant features for activity classification were examined though permutation feature importance. According to the study results, the RF achieved the best result in both cases represented by a mean accuracy of 86% for the forearm sensor, and 84% for the thigh sensor, respectively. The analysis revealed that time-domain features extracted from the y-axis and z-axis were of most importance for the thigh sensor in their contribution to the RF model's predictive power. Similarly, for the forearm sensor, time-domain features extracted from the z-axis were most important, specifically ZCR.

This study demonstrates that dynamic field sports involving non-cyclical movements, such as hurling, are amenable to human activity recognition research. Traditional machine learning models, namely SVM, RF and k-NN showed favourable results, as demonstrated by mean accuracies between 74% - 86% for the forearm sensor location, and 65% - 84% for the thigh sensor location. Future research in this field may consider combining features from different sensor locations for increased event detection and model generalisability in future scenarios. But if one sensor is preferred, a sensor mounted at the forearm for recognition and classification of hurling activities is recommended.

The limited sample size of 5 participants reflects the specific inclusion criteria for hurling players and the availability of participants at the time of testing. The small sample size may affect the generalisability and interpretation of the findings. However, given that this is the first research examining activity recognition in the sport of hurling, this research is exploratory in nature and provides valuable insights. Moreover, the methodology outlined in this research did not include hyperparameter tuning for the selected models. As a result, this may have affected the generalisability and accuracy of the models. Future research may consider hyperparameter tuning techniques such as Grid Search or Bayesian Optimization to enhance the performance and generalisability of SVM, k-NN, and RF models.

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