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A real-time tennis level evaluation and strokes classification system based on the Internet of Things

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A B S T R A C T

In this study a single wearable inertial measurement unit (IMU) and machine learning methodologies were used to conduct player level evaluation and classification five prototype tennis strokes in real-time. The International Tennis Number (ITN) test was used to verify the accuracy of this IoT system in evaluating participant level. We conducted the ITN test on thirty-six participants and conducted one-way ANOVA on the ITN test results using IBM SPSS 26. The IMU in this study contained a tri-axis accelerometer (± 16 g) and tri-axis gyroscope (± 2000° /s) worn on the participants' wrist connected to a wireless low-energy Bluetooth smart-phone with data sent to the computer terminal by cloud storage. Data processing including preprocessing, segmentation, feature extraction, dimensionality reduction and classification using Support Vector Machines (SVM), K-nearest neighbor (K-NN) and Naive Bayes (NB) algorithms. One-way ANOVA analysis predicting participants' ITN level and ITN field test scores yielded $p < 0.001$ at the three different skill levels tested. SVM (MinMax), SVM (Standardiser) and SVM (MaxAbsScaler) classified unique tennis strokes precision and recall factors at the three different skill levels reliably yielded in f1-scores above 0.90 for serve, forehand and backhand, with f1-scores for forehand and backhand volley scores falling below that. The results of this study suggest using a single six-axial 50 Hz IMU in combination with SVM and SVM + PCA represents a significant step towards a more reliable wearable tennis stroke performance and skill level real-time evaluation and feedback technology.

1. Introduction

Optimal performance in tennis can be aided by a number of things including general fitness and real-time feedback from coaches and/or IoT based software that guides players towards the use of maximally efficient tennis strokes. Therefore, real-time evaluation, quantification and monitoring of tennis technical movements are extremely important.

; IoT, Internet of Things; IMU, inertial measurement unit; ITN, International Tennis Number; SVM, Support Vector Machines; K-NN, K-nearest neighbor; NB, Naive Bayes; ITF, International Tennis Federation; PCA, Principal Component Analysis.

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Inertial sensors have been used for sport related analysis and performance enhancement studies in conjunction with or as an alternative to video in many sports for 20 years [1]. Due to the development of micro-electro-mechanical system (MEMS) technology and the reduction of inertial sensor size and cost, IMU have been widely used in the sports field. Camomilla et al. (2018) performed a search of titles, abstracts and keywords of studies using accelerometer, gyroscopes and/or magnetometer to analyze sport motor-tasks performed by athletes which revealed 286 research studies using those technologies [2].

In a study on badminton, Wang et al. (2018) recruited twelve male subjects each wearing a single wireless wearable sensing device (WSD) on their wrist, connected to a mobile APP by Bluetooth and machine processing to recognize three different types of badminton strokes and classify the skill levels of participants [3]. Four elite, sub-elite and amateur tennis players were identified using four machine learning algorithms. That study established a reasonably reliable IoT framework for badminton stroke analysis and skill level evaluation.

Currently most researchers in this field utilize arrays of wearable sensor devices, which increase the complexity and practicality of data processing and analysis, especially when combined with high acquisition frequencies most of which are 100 Hz or even 1000 Hz [4–12]. For instance, Xinyu Liu (2020) used four wearable devices (560 Hz) worn by each of seven participants to classify different tennis strokes, though he only achieved an accuracy of 79% [8]. Kenichirou Fuji et al. (2011) used twelve accelerometers (237.5 Hz) located on the wrists, elbows, shoulders, waist, knees and ankles of six experienced and five inexperienced male college students [12]. In addition, their participant and unique stroke technique type sample sizes were small, which makes it impossible to accurately establish a reliable, versatile prototype tennis stroke performance analysis and level evaluation system [6, 7, 10–19]. Though stroke and player level evaluation accuracies have improved over the past 20 years none can monitor players' stroke performance in real time [12, 13, 20–25].

There have been many tennis related studies using IMU to recognize and classify tennis strokes [4–25, 27–31]. Connaghan et al. (2011) at Dublin City University and Tyndall National Institute in Cork were the first to utilize a single IMU containing accelerometers ($\pm$ 3 g) , magnetometers and/or gyroscopes for tennis stroke recognition and classification [4]. David Whiteside et al. (2016) recruited eleven male and eight female players each wearing single nine-axis (tri-axial accelerometer, gyroscopes and magnetometer) 500 Hz IMU worn on the wrist for data collection. Six machine learning methods were used to classify nine unique prototype tennis strokes. He recorded accuracies averaging 93.2% [5]. However, the sensor used in their study had nine-axis and acquisition frequency as high as 500 Hz producing large data volume which increased the data processing workloads. In contrast, in this study we used a six-axial 50 Hz IMU to reduce computation load thus making real-time feedback feasible.

For the past three decades machine learning has been one of the fastest growing areas in computer science and is a component of artificial intelligence. At present, it has been applied in many fields such as facial recognition, data mining, efficient processing and so on [26]. Many researchers have applied IMU combined with machine learning methods for recognition and classification of most prototype tennis stroke techniques [5–19, 27–31]. Carefully selected machine learning algorithms are able to process sensor data very rapidly offering the possibility of monitoring tennis strokes in real time as part of an integrated IoT system.

This study was designed to measure the accuracy of a platform that recognizes the five most commonly used tennis stroke types within the three skill levels of participants tested offering players and coach real-time feedback with higher accuracies than previous studies. In this study, a) we significantly reduced computation load by selecting the relatively low acquisition frequency of 50 Hz, b) utilized only one low charge IMU worn on the wrist of the participants' dominant arm, and c) used a Bluetooth connection from the IMU to a smart-phone with data then sent to a computer terminal via cloud stroage. This was almost instantaneously followed by high speed data processing via machine learning algorithm(s).

2. Methods

2.1. Participants

Thirty-six right-handed male tennis players (mean age= 25.03 years, SD = 3.32), including elite ($N = 12$), sub-elite ($N = 12$) and amateurs ($N = 12$) participated in this study. They were selected by convenience sampling from a larger pool of university student volunteers. The experimental procedure was reviewed and approved by the Ethics Committee (2020114H). Participants volunteered to participate in this experiment and signed written informed consent forms prior to the experiment. The participants' demographic information is shown in Table 1.

2.2. ITN test

The ITN test is the international standard for tennis skill levels assessment launched at the International Tennis Federation (ITF) AGM in Rio de Janeiro in September 2003 (www.internationaltennisnumber.com). The test was carried out in accordance with

Table 1
The participants' demographic information.

Skill level	Age (year)	Height (m)	Weight (kg)	Training experience (years)
Elite	24.42±2.54	1.83±0.07	79.58±8.80	13.58±3.42
Sub-elite	25.33±1.44	1.79±0.06	71.17±6.25	5.71±1.32
Amateurs	25.33±5.09	1.78±0.07	72.17±6.87	1.75±0.54

requirements of the ITF. Prior to the ITN test, participants warmed up for 20 min under the guidance of a professional tennis coach, who additionally administered ITN tests to study participants.

The ITN field test of the ITF is composed of five tasks, Groundstroke Depth Assessment, Groundstroke Accuracy Assessment, Volley Depth Assessment, Serve Assessment and Mobility Assessment. Each task is scored and the sum of the scores determines ITN ranking with 10 being beginner level skill and 1 the highest score in the elite professional group. One-way ANOVA of ITN test results were calculated using IBM SPSS 26. Test participants were assigned to level groups based on ITN test scores. ITN test scores were also used to ascertain the accuracy of this study's participant skill level algorithm-based analysis thus serving as a measure of intertest reliability.

2.3. IoT system

Fig. 1 illustrates the design of the IoT system used in this study. Tennis stroke data collected by participants' single IMU was then processed using machine learning for the purpose of creating an IoT system that can reliably differentiate and classify three different tennis skill levels and five unique tennis strokes.

2.3.1. Data collection

Detailed specifications of the wireless IMUs used in this study were provided by Wang et al. [3]. Principal components of the IMU BMI160 (3 mm x 2.5 mm x 0.83 mm) manufactured by Bosch Sensortec (Reutlingen, Germany) include a tri-axial accelerometer (±16 g) and a tri-axial gyroscope (2000°/s), a Bluetooth wireless communication microprocessor module, radio transceiver, baseband processor, a coin cell battery and a switch.

Fig. 2 shows the IMU device (50 Hz) affixed to the participants' wrist. The X, Y, Z axis of the IMU relative to the forearm is also shown in Fig. 2. According to the principle of kinetic chain large motor-set tennis movements begin in the legs with the power sequentially transferred through hips, trunk and back, then passes to the shoulders, upper arm, elbow and wrist before the final segments, the hand, racket and ball [32].

After the ITN test, participants put the IMU bearing watch strap on the wrist of their dominant arm. The IMU were connected to an Android smartphone by wireless Bluetooth technology. The ball feeding procedure used during data collection was in accordance with the ITN test standard. The specific stroke order for all participants was: forehand, backhand (one-handed backhand or two-handed backhand), forehand volley, backhand volley, serve (serve in deuce court and advantage court). Thirty strokes were collected for each stroke type. Valid ball strike data was recorded manually and mistaken ball data marked. After each set of strokes, participants rested until they achieved a Rate of Perceived Exertion (RPE) level 8 before the next set of strokes [33]. In cases where the participant felt uncomfortable the rest interval was extended.

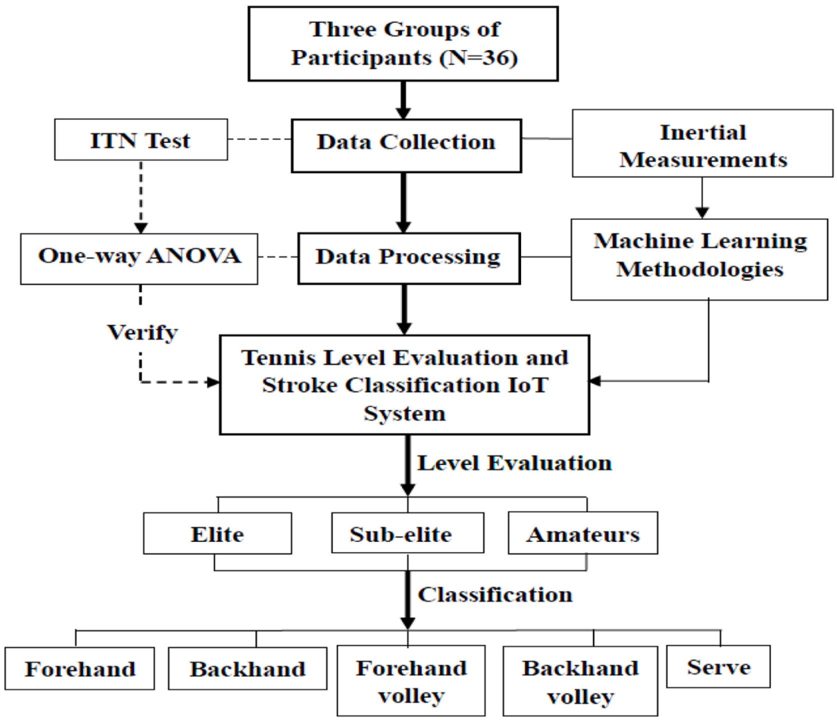

Fig. 1. Tennis level evaluation and stroke classification IoT system.

Fig. 2. Position of IMU on participants' wrist.

2.3.2. Data processing

We collected 5400 data sets from 36 participants (12 elite, 12 sub-elite and 12 amateurs), including 30 effective strokes from each of five different strokes. The tri-axial acceleration and tri-axial angular velocity data collected by the wearable device was transmitted to the computer terminal through cloud storage for real-time data processing. As shown in Fig 3, data processing included: pre-processing, segmentation, feature extraction, dimensionality reduction and classification [3,34].

The methods of data preprocessing, segmentation and feature extraction are exactly the same as those used in [34]. To reduce complex stochastic error from raw data, preprocessing including cleansing, noise reduction, and filtering are required. Data cleansing involves supplying default values in cases of missing data and reconciling inconsistent data through macro-integration. Gaussian filtering acts as a low pass filter which smooths the signal but allows only lower frequencies to pass through it.

The Principal Component Analysis (PCA) was used to reduce the dimensionality of high-dimensional data to the dimensions required by the SVMs tested in this study [3]. Relevant information in the data was extracted. Computational load was reduced by lowering the IMU transmission frequency to 50 Hz and using PCA for data preprocessing due to its performance superiority .

In the process of classification, we first labelled the five types of tennis strokes (forehand, backhand, forehand volley backhand volley and serve) at three different skill levels. Then, SVM supervised machine learning identified model labels for each category and categorized the new datasets. The K-NN algorithm finds the k records closest to the new data from the training set and then decides the types of new data according to their main classifications. NB methods are a set of supervised learning algorithms based on application of Bayes' theorem with a "naive" independence assumption. SVM, NB and K-NN algorithms were extracted from the Scikit-Learn official website (https://scikit-learn.org/stable/).

Five different SVM classifiers, SVM (MinMax), SVM (Standardiser), SVM (Normalizer), SVM (MaxAbsScaler) and SVM (RobustScaler) were used and compared in testing the IoT system. K-NN and NB algorithms are used to compare the accuracy of classified tennis strokes with SVM classifiers [34]. Data from half the participants was used to construct the model with the remainder used to verify the trained set model. Optimal model parameters were selected to obtain the classifier model. We used the trained classifier to classify the test samples. Following that we compared the output prediction results with the real situation as captured on video, and finally calculated the classification accuracy of the classifier.

In order to find optimal model of the SVM classifier, we first randomly selected C and gamma parameters. The selectable parameter C ranges from 1 to 50,000; gamma range is from 0.00001 to 0.05, and the kernel function selects the default Radial Basis Function (RBF). To avoid the overfitting problem 10-fold cross validation was used during data training and appropriate parameters were established using the best fit SVM classifiers.

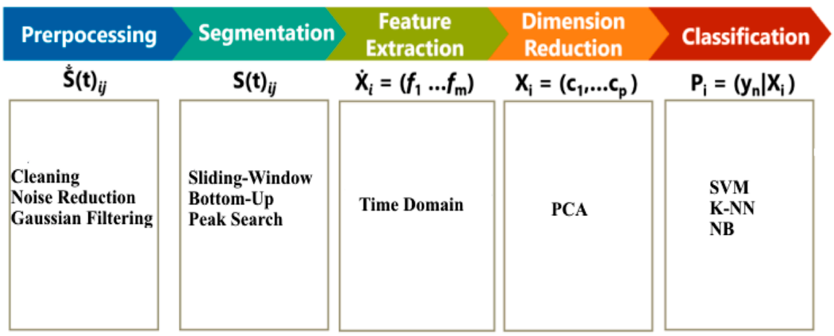

Fig. 3. data processing flow.

3. Results

3.1. ITN test

3.1.1. ITN level

Fig. 4 shows there was a significant difference between groups in ITN level as determined by one-way ANOVA (F (2,33) = 658.913, $p < 0.001$). A Tukey post hoc test revealed that the obtained ITN level of the elite group (1.083 ± 0.289) was significantly higher than sub-elite (2.912 ± 0.289, $p < 0.001$) and amateur groups (7.583 ± 0.669, $p < 0.001$). There was also a significant difference between the sub-elite and amateur groups ($p < 0.001$).

3.1.2. ITN field test

Groundstroke Depth Assessment including power factor (ten alternate forehand and backhand ground strokes): There were significant differences between ITN level groups on Groundstroke Depth Assessment scores as determined by one-way ANOVA (F (2,33) = 46.294, $p < 0.001$). A Tukey post hoc test revealed the Groundstroke Depth Assessment scores were significantly higher in the elite (78.000 ± 8.944) than sub-elite (59.667 ± 8.283, $p < 0.001$) and amateur groups (38.167 ± 12.670, $p < 0.001$).

Volley Depth Assessment including power exertion factor (eight alternate forehand and backhand volleys): Significant differences were found between the three level groups as measured by Volley Depth Assessment scores and analyzed by one-way ANOVA (F (2,33) = 185.964, $p < 0.001$). A Tukey post hoc test revealed the Volley Depth Assessment scores for the elite group (61.000 ± 7.006) were significantly higher than scores obtained from the sub-elite (39.917 ± 5.900, $p < 0.001$) and amateurs (16.750 ± 3.306, $p < 0.001$). There was also a significant difference between the sub-elite and amateurs' groups ($p < 0.001$).

Groundstroke Accuracy Assessment including power exertion factor (six alternate forehand and backhand strokes down the line and six alternate forehand and backhand cross court strokes): There were significant differences between level groups on Groundstroke Accuracy Assessment scores as determined by one-way ANOVA (F (2,33) = 74.567, $p < 0.001$). A Tukey post hoc test revealed the Groundstroke Accuracy Assessment scores were significantly higher in elite (75.917 ± 6.302) compared to sub-elite (67.750 ± 8.335, $p < 0.001$) and amateurs (35.250 ± 10.687, $p < 0.001$). There was also a significant difference between the sub-elite and amateurs' groups ($p < 0.001$).

Serve Assessment including a power exertion factor during tennis serves (twelve total serves with three serves in each target area): There were significant differences between level groups on Serve Assessment score as determined by one-way ANOVA (F (2,33) = 158.641, $p < 0.001$). A Tukey post hoc test revealed the Serve Assessment scores of the elite (100.083 ± 5.728) were significantly higher than sub-elite (90.250 ± 6.341, $p < 0.001$) and amateurs (32.083 ± 15.306, $p < 0.001$). There was also a significant difference between the sub-elite and amateurs' groups ($p < 0.001$).

There were also significant differences in the Mobility Assessment Scores between groups as measured by one-way ANOVA (F (2,33) = 22.559, $p < 0.001$). A Tukey post hoc test revealed the Mobility assessment scores were significantly higher in elite (69.750 ± 7.724) than sub-elite (57.000 ± 7.385, $p < 0.001$) and amateurs (45.083 ± 11.341, $p < 0.001$). There was also a significant difference between sub-elite and amateurs' groups ($p < 0.001$).(Fig. 5)

3.2. Example sensor data

Fig. 6 shows sample sensor data of five common tennis stroke types from the elite player group. Significant differences between the five tennis stroke types in acceleration and angular velocity can be seen in the raw data. The raw data shows a clearly identified peak in three axes produced by each unique stroke.(Fig. 6)

3.3. Tennis strokes recognition and classification

3.3.1. Different SVM classifiers

Tables 2 – 6 illustrate the classification results of different stroke types at three different motor skill levels: SVM (MinMax), SVM (Standardiser), SVM (Normalizer), SVM (MaxAbsScaler) and SVM (RobustScaler).

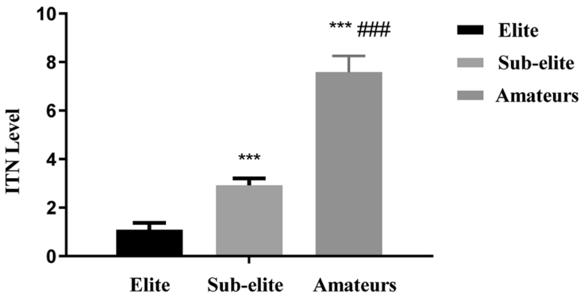

Fig. 4. ITN level in three motor skill levels.*** Compared to elite groups p < 0.001; ### Compared to sub-elite groups p < 0.001.

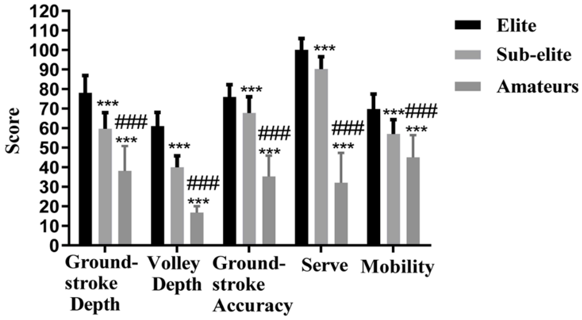

Fig. 5. ITN sub-scores in three motor skill levels.*** Compared to elite groups $p < 0.001$; ### Compared to sub-elite groups $p < 0.001$.

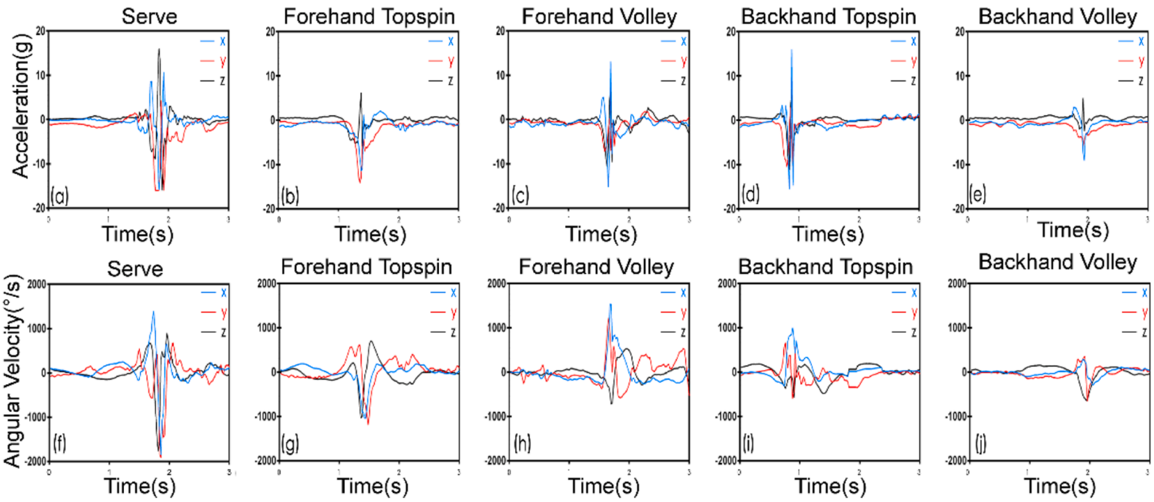

Fig. 6. Example of MEMS sensor raw data recorded from one participant in the elite player group.

Table II shows the results of SVM (MinMax) classification of the five common tennis stroke types performed by participants in each of the three different levels tested yielding an average precision, recall and f1-score of 88%. Results from the serve, forehand and backhand in the elite group yielded precision accuracies of 92% and above, but forehand volley and backhand volley classification accuracies were only 75% and 80% respectively. Classification accuracies of sub-elite players strokes paralleled elite, however were

Table 2
SVM (MinMax) accuracy of classification of precision and recall factors at three motor skill levels.

Motor skill level & movement	Precision	Recall	f1-score
Elite			
Serve	0.98	0.97	0.98
Forehand	0.9	0.94	0.92
Backhand	0.98	0.97	0.97
Forehand volley	0.7	0.81	0.75
Backhand volley	0.79	0.82	0.8
Sub-elite			
Serve	0.96	0.97	0.97
Forehand	0.9	0.86	0.88
Backhand	0.94	0.96	0.95
Forehand volley	0.69	0.63	0.66
Backhand volley	0.72	0.77	0.75
Amateurs			
Serve	0.98	0.98	0.98
Forehand	0.89	0.92	0.91
Backhand	0.95	0.94	0.94
Forehand volley	0.89	0.81	0.85
Backhand volley	0.91	0.84	0.88
Average	0.88	0.88	0.88

slightly lower. The accuracy of classification of the five stroke types by amateurs were all above 80%. The lower classification precision results from forehand volley and backhand volley in all three levels of participants tested led to an overall much lower average.

Table 3 shows the results of the SVM (Standardizer) classification of the five common tennis stroke types by players at the three skill levels tested which found the average precision, recall and f1-scores to be 90%. Averaged scores from the serve, forehand and backhand strokes by participants in the three levels tested were at or above 93%, but as with SVM (MinMax), the forehand volley and backhand volley classification precision scores were reliably lower, 89% and below.

Table 4 shows the results of the SVM (Normalizer) classification of the five common tennis stroke types at the three different levels tested yielded an average precision, recall and f1-score of 77%. Using SVM (Normalizer) for classification of the five tennis strokes, only the serve yielded results of 91% and above at all three skill levels tested. The precision of classification of the other stroke types was reliably lower. With an average classification precision of only 77%, SVM (Normalizer) was found to be relatively unreliable for stroke movement component analysis at all three skill levels tested.

Table 5 shows the results of SVM (MaxAbsScaler) classification of the five common tennis stroke types at the three different skill levels tested yielding an average precision, recall and f1-score of 89%. As with use of SVM (MinMax) and SVM (Standardizer) the classification precision of serve, forehand and backhand strokes was found to be quite high, 90% and above, with forehand volley and backhand volley classification precision average scores falling considerably below that.

Table 6 shows results of the classification precision of the five tennis stokes at the three levels tested with average precision of 85%, recall 86% and an f1-score of 85%. The pattern of results was similar in SVM (MinMax), SVM (Standardizer) and SVM (MaxAbsScaler) with the classification precision of serve, forehand and backhand at all three levels tested above 92%. The classification precision of forehand and backhand volley strokes fell at or below 80%.

3.3.2. *Data processing normalization*

Table 7 shows the accuracies obtained from the application of the five types of SVM classifiers: SVM (MinMaxScaler), SVM (StandardScaler), SVM (Normalizer), SVM (MaxAbsScaler) and SVM (RobustScaler) used to test obtained data. This study's comparison of different SVM algorithms shows that SVM (StandardScaler), SVM (MinMaxScaler) and SVM (MaxAbsScaler) classifiers obtained superior accuracies (90%, 88% and 89%, respectively), with SVM (RobustScaler) yielding intermediate results of 85% and SVM (Normalizer) yielding the lowest accuracies with an average of only 77%.

3.3.3. *SVM algorithm compared with other algorithms*

The results of machine processing of the test data by SVM (raw) + PCA algorithm yielded a combined average precision, recall and f1-score of 86%. The results from the serve, forehand and backhand data at all three levels yielded precision averages above 85%. Forehand volley and backhand volley strokes yielded results under 85% in all three skill levels of participants consistent with the trained SVM algorithms cited above.

The K-NN algorithm classified the five tennis stroke types within each of the three difference skill levels with an average precision of 47%, recall of 46% and f1-score of 46%.

The NB algorithm classified the five tennis stroke types at the three difference levels with an average precision of 64%, recall of 65% and f1-score of 63%. NB algorithm yielded low precision results for four of the five tennis stroke types at all three skill levels. The one stroke type exception was serves performed by elite and amateur participants. NB yielded the lowest average classification precision results compared to all machine learning algorithms tested in this study.

3.3.4. *Comparison of different classifiers*

Table 8 shows results from untrained (raw) SVM, K-NN and NB algorithm classifiers. Looking at the data it can be seen that SVM+PCA was the best classifier of data collected in this study. In regards to finding the optimal estimator for our data we tested k values ranging from 1 to 15 and found the greatest accuracies when $k = 7$. Tests of two other algorithms also fell far below that of combined PCA+SVM. (Table 8)

4. Discussion

This study has at least two advantages over most current related studies, a) use of a single IMU and b) lower sampling frequency of 50 Hz to collect data and categorize five basic tennis strokes. At present, most researchers attempting to classify tennis strokes using wearable devices use multiple IMUs worn on the left and right ankles, knees, shoulders, elbows and shoes, as well as waist, torso, pelvis, and chest to collect data needed for reliable recognition of even one prototype tennis stroke [5–12]. Application of those studies' methodologies during practical training is also problematic due to complexity and large data volume using multiple wearable devices.

The tennis stroke classification results found in this study suggest: a) SVM (StandardScaler), SVM (MinMaxScaler), SVM (MaxAbsScaler), SVM (RobustScaler) and SVM+PCA algorithms yielded reliable results with average precisions calculated at 90%, 88%, 89%, 85% and 86% respectively, b) SVM (Normalizer), K-NN and NB algorithms on the other hand demonstrated average precisions of 77%, 47% and 64% respectively and c) the algorithms' recognition and classification of tennis forehand and backhand volley strokes yielded relatively lower classification precision, recall and f1-scores, especially the forehand volley compared to the other strokes tested.

In similar studies, Liu identified unique tennis strokes utilizing four wearable devices (560 Hz) with SVM algorithms obtaining an overall average accuracy of only 79% [8]. Research by Ó Conaire et al. identified three types of unique tennis strokes using six

Table 3
SVM (Standardizer) accuracy of classification of precision and recall factors at three motor skill levels.

Motor skill level & movement	Precision	Recall	f1-score
Elite			
Serve	0.97	0.97	0.97
Forehand	0.94	0.95	0.95
Backhand	0.97	0.96	0.97
Forehand volley	0.73	0.79	0.76
Backhand volley	0.85	0.83	0.84
Sub-elite			
Serve	0.97	0.98	0.97
Forehand	0.94	0.95	0.95
Backhand	0.97	0.96	0.97
Forehand volley	0.73	0.79	0.76
Backhand volley	0.85	0.83	0.84
Amateurs			
Serve	0.98	0.98	0.98
Forehand	0.93	0.95	0.94
Backhand	0.96	0.94	0.95
Forehand volley	0.87	0.84	0.85
Backhand volley	0.92	0.86	0.89
Average	0.9	0.9	0.9

Table 4
SVM (Normalizer) accuracy of classification of precision and recall factors at three motor skill levels.

Motor skill level & movement	Precision	Recall	f1-score
Elite			
Serve	0.92	0.94	0.93
Forehand	0.71	0.86	0.78
Backhand	0.85	0.84	0.84
Forehand volley	0.56	0.73	0.63
Backhand volley	0.78	0.81	0.8
Sub-elite			
Serve	0.91	0.93	0.92
Forehand	0.78	0.69	0.73
Backhand	0.78	0.79	0.78
Forehand volley	0.52	0.48	0.5
Backhand volley	0.69	0.78	0.74
Amateurs			
Serve	0.91	0.91	0.91
Forehand	0.81	0.81	0.81
Backhand	0.9	0.77	0.83
Forehand volley	0.76	0.62	0.68
Backhand volley	0.72	0.64	0.68
Average	0.77	0.77	0.77

wearable devices with an average accuracy of 93.44% [11]. The sensor's high acquisition frequency increases data processing time, and multiple sensors are not suitable for practical training and competition environments.

In this study one-way ANOVA results of ITN test showed there were significant differences between participants skill levels consistant with ITN level test scores, and the ITN field test scores between elite and sub-elite and amateur groups ($P < 0.001$). The elite group's ITN level and field test scores were significantly higher than sub-elite and amateur groups, and sub-elite scores significantly higher than the amateur group. Significant differences in skill levels between the three groups validated the IoT system's recognition and classification results.

Compared with Wang et al. (2018) [3], this study increased the number of participants as a larger sample size provides more accurate mean values and more easily identifies outliers enhancing measures of validity and reliability. Secondly, we chose a more standard way to distinguish the motor performance level of the athletes, that is, the motor performance level evaluation obtained by both competition performance and ITN scores, thereby adding an extra measure of inter-test reliability. Third, we used a lower bandwidth data transmission system to speed processing and fourth improved the algorithm to process the data. Based on the above reported results it appears we may have developed a more efficient and accurate system platform than previously reported in related literature that can provide real time data and evaluation. This study tentatively validates an IoT based platform that can distinguish between four of the five major tennis strokes at three skill levels with very high accuracies. Based on initial results, this platform provides a uniquely reliable and practical real-time level test and stroke quality feedback resource for coaches and athletes during daily sports training.

In future studies, we will apply this system to further verify the stroke performance of tennis players in actual tennis matches,

Table 5
SVM (MaxAbsScaler) accuracy of classification of precision and recall factors at three motor skill levels.

Motor skill level & movement	Precision	Recall	f1-score
Elite			
Serve	0.97	0.97	0.97
Forehand	0.9	0.96	0.93
Backhand	0.96	0.96	0.96
Forehand volley	0.72	0.79	0.75
Backhand volley	0.82	0.85	0.83
Sub-elite			
Serve	0.97	0.97	0.97
Forehand	0.94	0.87	0.9
Backhand	0.93	0.96	0.95
Forehand volley	0.73	0.69	0.71
Backhand volley	0.76	0.82	0.79
Amateurs			
Serve	0.98	0.98	0.98
Forehand	0.92	0.96	0.93
Backhand	0.96	0.94	0.95
Forehand volley	0.92	0.84	0.88
Backhand volley	0.93	0.85	0.89
Average	0.89	0.89	0.89

Table 6
SVM (RobustScaler) accuracy of classification of precision and recall factors at three motor skill levels.

Motor skill level & movement	Precision	Recall	f1-score
Elite			
Serve	0.97	0.97	0.97
Forehand	0.92	0.96	0.94
Backhand	0.96	0.94	0.95
Forehand volley	0.64	0.72	0.67
Backhand volley	0.78	0.79	0.78
Sub-elite			
Serve	0.97	0.97	0.97
Forehand	0.95	0.89	0.92
Backhand	0.92	0.95	0.93
Forehand volley	0.6	0.57	0.58
Backhand volley	0.71	0.7	0.7
Amateurs			
Serve	0.98	0.98	0.98
Forehand	0.94	0.95	0.95
Backhand	0.95	0.93	0.94
Forehand volley	0.69	0.75	0.72
Backhand volley	0.84	0.76	0.8
Average	0.85	0.86	0.85

Table 7
Tennis movement classification accuracy of different algorithms.

Classification algorithm	Parameters	Accuracy
SVM (MinMaxScaler)	C = 1000.0, gamma = 0.1	88%
SVM (StandardScaler)	C = 1000.0, gamma = 0.01	90%
SVM (Normalizer)	C = 1000.0, gamma = 0.1	77%
SVM (MaxAbsScaler)	C = 10,000.0, gamma = 10	89%
SVM (RobustScaler)	C = 1000.0, gamma = 0.005	85%

Table 8
Tennis strokes classification accuracy of different algorithms.

Classification algorithms	Parameters	Accuracy
SVM (raw)+PCA	C = 10.0, gamma = 0.1	86%
K-NN	$K = 7$	47%
NB	N. A	64%

including the distinction between winning points and unforced errors. In addition, we hope to diversify our participant sample base by including women and left-handed players. Finally, we plan to study more tennis stroke types so as to continuously improve this system.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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