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RESEARCH ARTICLE

Machine Learning-Based Classification of Badminton Strokes Using IMU-Integrated Racket

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ABSTRACT - Badminton, a fast-paced racket sport, demands precision, power, and strategic execution. While previous research has explored using inertial measurement units (IMUs) for stroke classification, this study presents an integration of sensor-embedded rackets with IMUs to provide a more accurate and automated approach. The collected motion data was processed and classified using machine learning models such as logistic regression, k-nearest neighbors (k-NN), and support vector machines (SVM). Of these, k-NN achieved the highest accuracy at 75 percent, with backhand strokes showing better classification precision. However, challenges in classifying forehand strokes suggest a need for further refinement in feature extraction. The study contributes a framework for improving stroke classification accuracy in badminton and offers insights into optimizing ML-driven motion analysis for more precise performance assessment in badminton.

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1.0 INTRODUCTION

Badminton, a sport with a rich history across continents, is known for its fast-paced gameplay involving rackets and shuttlecocks. Recognized as one of the fastest racket sports in the world, it combines precision, power, and strategy. Its global prominence began as a demonstration sport at the 1972 Munich Olympics, later becoming a medal event at the 1992 Barcelona Games [1]. Today, badminton is played at all levels, from casual recreational matches to professional tournaments worldwide. Malaysia has long been a powerhouse in badminton, producing exceptional players like Datuk Lee Chong Wei, who held the world number one ranking for several years and earned multiple Olympic medals. Rising stars such as Lee Zii Jia, the 2022 Badminton Asia Champion, and the doubles team of Aaron Chia and Soh Wooi Yik, recent world champions, continue to uphold the nation's legacy. Badminton remains a vital part of Malaysia's sports culture, inspiring athletes to compete at the highest levels [2].

In badminton, mastering strokes is essential for success. Strokes are the fundamental techniques that drive gameplay, requiring players to execute movements with precision and adaptability. Recognizing and analyzing strokes helps athletes refine their techniques, improve their strengths, and address weaknesses [3]. Coaches depend on stroke analysis to design targeted training programs and develop effective game strategies [4]. However, traditional methods for stroke recognition rely heavily on manual observation, which is time-consuming, prone to human error, and inconsistent—making it less suitable for high-performance training [5].

Machine learning (ML) has opened new possibilities in sports analytics by efficiently processing complex data and identifying patterns. In badminton, ML automates stroke recognition, enabling faster, more accurate analysis. Using data from sensors like accelerometers and gyroscopes, ML models detect even minor variations in strokes and adapt to different playing styles and skill levels, benefiting players at all levels [6]. In Malaysia, where badminton is a cultural and competitive priority, adopting ML-based systems is key to staying competitive globally. Unlike video analysis, which has limitations like inconsistent angles and subjective interpretation, ML combined with sensor technology offers real-time, precise feedback, aligning with modern, data-driven sports science [7].

This study aims to improve stroke recognition by integrating sensor technology and ML. Sensors in racket handles will collect data on stroke motion and force, which ML algorithms will process for real-time, accurate classification. Various ML models, including decision trees, support vector machines, and neural networks, will be tested for accuracy, efficiency, and adaptability across players of different skill levels. While results are pending, this research is expected to set new standards in badminton performance analytics.

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The expected outcomes include a reliable stroke classification system offering detailed feedback on stroke mechanics, transforming training by enabling data-driven adjustments. Beyond badminton, the research could advance sports engineering and showcase ML's potential in performance analysis. By improving stroke recognition, the study aims to enhance training and support Malaysia's badminton success, while advancing technology in sports and paving the way for future innovations in athletic performance analysis.

2.0 RELATED WORKS

Wang et al. (2019) designed a deep convolutional neural network (CNN) model incorporating an adaptive feature extraction mechanism to track ten primary badminton strokes. Their approach achieved an impressive accuracy of 98.65 percent, outperforming traditional stroke classification models and highlighting the effectiveness of deep learning in sports training applications [8].

Lin et al. (2020) developed an intelligent racket system that combined voiceprint-based algorithms with machine learning techniques for stroke detection. Their system demonstrated over 96 percent accuracy with personalized models and around 84 percent accuracy when using generalized models, underscoring the benefits of player-specific adaptation in stroke recognition [9].

Xia et al. (2020) introduced a hybrid clustering methodology for distinguishing between three badminton strokes—serve, drive, and smash—using a wristband-based sensor system. By employing a support vector machine (SVM) classifier, their approach achieved 76 percent accuracy, reinforcing the potential of wearable sensor technology in real-world sports training scenarios [10].

Lin et al. (2020) engineered a smart racket equipped with an acoustic sensor and an inertial measurement unit (IMU) for recognizing and documenting badminton strokes. Data were transmitted via Bluetooth to a smartphone, where a voiceprint-based algorithm identified hitting events with over 99.9 percent accuracy, surpassing commercial alternatives. Stroke classification via machine learning yielded 96.5 percent accuracy for personalized models and 84 percent for generalized models [7].

Peralta et al. (2022) examined badminton stroke classification by integrating accelerometer and gyroscope data. Their study applied data augmentation and transfer learning, achieving 93.35 percent accuracy using gyroscope-based deep learning models, demonstrating their efficacy in stroke recognition [11].

Mekruksavanich et al. (2022) leveraged deep residual networks on IMU sensor data for badminton action recognition and player assessment. Their method achieved 98.00 percent accuracy in activity classification and 98.56 percent in player evaluation, underscoring the reliability of deep learning models in analyzing complex actions during matches [12].

Toshniwal et al. (2022) employed computer vision and machine learning techniques to evaluate player swings against an ideal swing database. Their system achieved 90.84 percent accuracy in recognizing and assessing badminton swings, providing valuable insights for improving player performance [5].

Liu (2022) conducted research on badminton stroke classification using support vector machines (SVM) and convolutional neural networks (CNN). Their findings indicated that acceleration and velocity data captured during play effectively identified stroke events such as drive, lift, and block, with CNN outperforming both SVM and random forest models in sensor-based recognition [13].

Yip et al. (2022) developed a badminton smash classification system utilizing deep learning-based video analysis. The study compared the performance of ResNet-18, GoogleNet, and VGG-16 models, with ResNet-18 achieving superior accuracy of 97.51 percent during training and 98.86 percent in testing using Jupyter software. Meanwhile, GoogleNet reached its highest accuracy of 83.04 percent in training and 97.20 percent in testing using Jetson Nano hardware [14].

Ghazali et al. (2022) classified badminton strokes using inertial sensors and machine learning algorithms. Data collected from ten players underwent preprocessing and feature extraction, followed by classification using Decision Tree, kNN, and SVM models. Among these, Cubic SVM exhibited the highest accuracy at 83.4 percent, proving its efficiency in sports activity recognition [6].

Ghosh et al. (2022) presented DeCoach, a deep learning framework designed to assess badminton players by analyzing both their stroke execution and body posture. Using Inertial Measurement Units (IMUs), the system tracks the movements of both upper and lower limbs. A CNN classifier achieved 89.09 percent accuracy in stroke classification, while a deep regressor predicted player performance with an R^2 score of 88.84 percent. The results showed that professional players outperformed intermediates and novices, with success rates of 86.11 percent and 76.38 percent, compared to 58.33 percent and 30.55 percent, respectively [15].

Isa et al. (2024) introduced a deep learning-based system for real-time badminton stroke classification, eliminating reliance on manual annotation methods. Video data captured from off-court angles were processed using OpenCV and MediaPipe for feature extraction, with three models—Simple Dense Neural Network (SDNN), Recurrent Neural Network (RNN), and RNN with Gated Recurrent Unit (GRU)—evaluated. Using an 80:20 training-validation split across 300 stroke videos per class, the study provided valuable insights for optimizing player strategies [16].

Seong et al. (2024) addressed the scarcity of comprehensive badminton action datasets by compiling a multi-sensor dataset focused on forehand clear and backhand drive strokes. Data collected from 25 players of varying skill levels included 7,763 swing instances with eye tracking, body tracking, muscle signals, foot pressure, video recordings, and expert annotations. A proof-of-concept machine learning model validated the dataset’s relevance, highlighting its significance for advancing badminton training and biomechanics research [17].

3.0 METHODOLOGY

This chapter outlines the methodology for badminton activity recognition, combining multi-sensor data and machine learning classification. It details the process flow, model selection, and evaluation. Data will be collected from a IMU-embedded racket, pre-processed, and classified using ML models, with performance analysis after testing.

3.1 Data Collection

The system architecture, illustrated in Fig. 1, integrates a sensor-based measurement system within the badminton racket handle. This setup comprises an Arduino Nano 33 BLE Sense Rev2 microcontroller, a force sensor, and a microSD card module. Sensor data from badminton stroke events are collected and stored as .csv files on the microSD card for further analysis. The Arduino Nano 33 BLE Sense Rev2 features a 9-axis inertial measurement unit (IMU), which includes an accelerometer, gyroscope, and magnetometer, enabling six degrees of freedom (DOF) motion tracking. This satisfies the requirement for precise motion analysis by measuring acceleration, angular velocity, and magnetic field strength.

Figure 1. Racket with integrated measurement electronics.

Sensor data were processed in Python using Jupyter Notebook, with Pandas for manipulation, NumPy for numerical operations, and SciPy for signal processing. Visualization was done with Matplotlib and Seaborn, streamlining the workflow for machine learning classification.

A semi-professional badminton racket was used to balance accessibility and performance. The system identifies five strokes—smash, forehand drive, forehand clear, backhand drive, and backhand clear—performed by beginner players, with 100 repetitions per stroke to create a robust dataset for model training. Data were collected from the IMU (accelerometer and gyroscope), capturing racket orientation and angular velocity for comprehensive motion analysis and feature extraction.

3.2 Data Preprocessing

This process segments individual strokes from continuous motion data, like Player 2's Backhand Clear shown in Fig. 2. Gyroscopic signal peaks indicate stroke events, with rest periods removed. A fixed 9-frame window was chosen for peak detection and windowing, based on exploratory data analysis (EDA). Despite challenges like overlapping peaks and missed strokes, the approach effectively captured stroke events, with start and end frames, and class labels recorded. Player IDs were also stored for future analysis. Hand-engineered features will be added for improved classification.

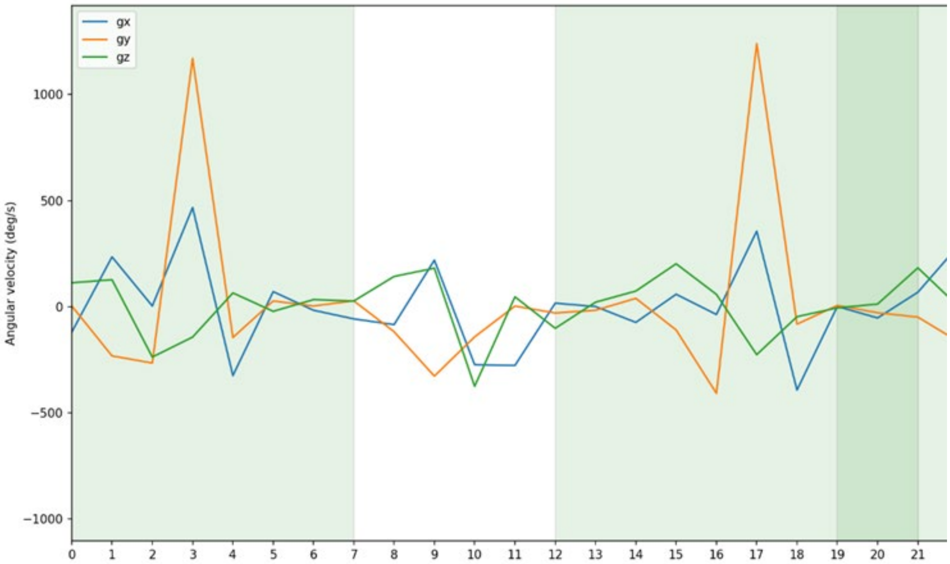

Figure 2. Example of Player 2's Backhand Clear stroke data segmentation.

3.3 Feature Selection

After processing data from the accelerometer and gyroscope, several features were added to enrich the dataset. These include statistical measures like kurtosis, range, magnitude, minimum, maximum, average, and skewness, which provide insights into the distribution and characteristics of the data. These features improve dataset comprehensiveness, enabling deeper analysis and enhancing classification accuracy.

3.4 Data Splitting

Data splitting separates the dataset into 80 percent training and 20 percent testing to evaluate model performance and prevent overfitting, ensuring a balanced approach for development and assessment.

3.5 Machine Learning Models

This work explored three machine learning models for classifying stroke events based on processed data, including:

- Logistic regression is a supervised model used for classification, outputting probabilities between 0 and 1 via the Sigmoid function. It classifies data based on a threshold value.
- k-Nearest Neighbors (k-NN) classifies data by comparing its similarity to existing data points, assuming similar points belong to the same category. It is a non-parametric "lazy learner" that stores the dataset and classifies new data at the time of testing.
- Linear Support Vector Machine (SVM) fits a hyperplane to divide the data, classifying new points based on which side of the hyperplane they fall.

MODEL EVALUATION

In this work, a multi-class classification approach is used to distinguish between different types of badminton strokes: Backhand Clear, Backhand Drive, Forehand Clear, Forehand Drive, and Forehand Smash. The performance of the machine learning models is evaluated using a confusion matrix (see Table 1), which helps identify how well the model predicts each stroke.

Table 1. Multi-Class Confusion Matrix

		Predicted Stroke				
		Backhand Clear	**Backhand Drive**	**Forehand Clear**	**Forehand Drive**	**Forehand Smash**
True Stroke	**Backhand Clear**	TP	FP	FP	FP	FP
	Backhand Drive	FN	TP	FP	FP	FP
	Forehand Clear	FN	FN	TP	FP	FP
	Forehand Drive	FN	FN	FN	TP	FP
	Forehand Smash	FN	FN	FN	FN	TP

A confusion matrix is a square matrix where each row represents the true class, and each column represents the predicted class. The diagonal elements of the matrix rep-resent True Positives (TP), where the model correctly predicts the stroke type. False Positives (FP) occur when the model incorrectly predicts a stroke type, while False Negatives (FN) represent cases where the model fails to predict the correct stroke type. True Negatives (TN) refer to instances where the model correctly predicts the absence of a particular stroke.

This matrix provides a comprehensive view of the model's performance, allowing for the calculation of precision, recall, and F1-score for each stroke. These metrics offer insights into the model's accuracy in classifying strokes and help identify areas for improvement in the classification process.

Recall (or sensitivity, true positive rate) measures the percentage of correctly detected positive predictions out of all actual positive instances. It is calculated using true positives (TP) and false negatives (FN) from the confusion matrix:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{1}$$

Recall is crucial in domains where missing positive examples can have significant consequences, helping to minimize false negatives.

Precision (or positive predictive value) evaluates the accuracy of positive predictions, reflecting the proportion of correct positive predictions relative to the total predicted positives. It is calculated as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

Precision is especially important when the cost of false positives is high or when high accuracy in positive predictions is required.

F1-Score combines precision and recall into a single metric, offering a balanced evaluation by accounting for both false positives and false negatives. It is particularly useful in managing unbalanced datasets:

$$\text{F1 Score} = 2 \times \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precison} + \text{Recall}}\right) \tag{3}$$

The F1-score enables informed decisions when both types of classification errors need to be minimized.

Accuracy measures the proportion of correct predictions (both positive and negative) out of the total instances. While accuracy is a common performance metric, it can be misleading in cases of imbalanced datasets. Considering precision, recall, and F1-score in conjunction with accuracy provides a more comprehensive understanding of the model's performance.

4.0 RESULTS AND DISCUSSION

4.1 Logistic Regression

The logistic regression (LR) model achieved an overall accuracy of 67 percent in classifying badminton strokes, with varying performance across stroke types, as shown in Table 2. The Backhand Drive demonstrated the best results with an F1-score of 0.88 (precision: 0.85, recall: 0.92), while the Backhand Clear also performed well, achieving an F1-score of 0.76. These results suggest that the model effectively distinguishes backhand strokes due to their unique features.

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Table 2. Classification Results for Badminton Strokes Using LR model.

Stroke	Precision	Recall	F1-Score
Backhand Clear	0.78	0.74	0.76
Backhand Drive	0.85	0.92	0.88
Forehand Clear	0.56	0.67	0.61
Forehand Drive	0.77	0.61	0.68
Forehand Smash	0.37	0.37	0.37
Model Accuracy		0.67	

The confusion matrix shows good performance for backhand strokes, but forehand strokes, especially Forehand Smash, are often misclassified. The LR model's linear decision boundaries struggle with the non-linear nature of the data, and class imbalances affect underrepresented strokes. To improve, addressing class imbalances and exploring more complex models like ensemble methods or deep learning may help capture the data's complexity.

In summary, the LR model performs well for backhand strokes but struggles with forehand strokes. Future efforts should focus on better feature representation, handling class imbalances, and exploring more advanced models.

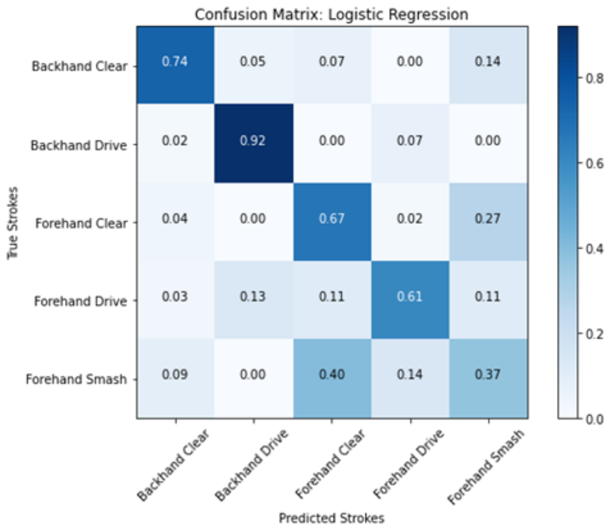

Figure 3. Confusion matrix of LR model in classifying badminton strokes.

4.2 k-NN

The k-Nearest Neighbors (k-NN) classifier achieved an overall accuracy of 75 percent in classifying five badminton strokes: Backhand Clear, Backhand Drive, Forehand Clear, Forehand Drive, and Forehand Smash. The confusion matrix (Fig. 4) and de-tailed classification metrics (Table 3) highlight the model's performance across these stroke categories

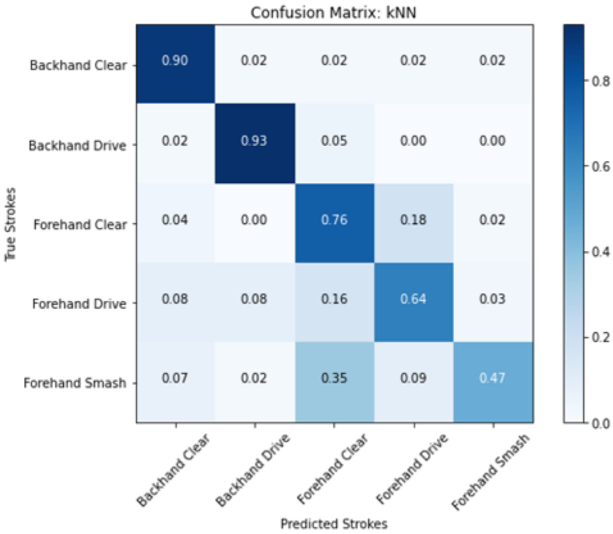

Figure 4. Confusion matrix of k-NN model in classifying badminton strokes.

Table 3. Classification Results for Badminton Strokes Using k-NN model.

Stroke	Precision	Recall	F1-Score
Backhand Clear	0.78	0.90	0.84
Backhand Drive	0.89	0.93	0.91
Forehand Clear	0.57	0.76	0.66
Forehand Drive	0.74	0.64	0.68
Forehand Smash	0.83	0.47	0.43
Model Accuracy		**0.75**	

The k-NN model demonstrated strong classification performance for Backhand Drive, with a precision of 0.89, recall of 0.93, and F1-score of 0.91. Backhand Clear also performed well, achieving a recall of 0.90 and an F1-score of 0.84. These results indicate that the model can reliably identify these strokes, likely due to distinct mo-tion characteristics that differentiate them from others.

In contrast, the classification of Forehand Smash proved to be the most challenging. It achieved a recall of only 0.47 and an F1-score of 0.43, indicating significant mis-classification with other strokes, particularly Forehand Drive. This is evident in the confusion matrix, where 35 percent of Forehand Smash instances were misclassified as Forehand Drive. Such overlaps may arise due to similarities in motion patterns between these two strokes, particularly when executed with similar power or trajecto-ry.

Forehand Clear also exhibited moderate performance, with a recall of 0.76 and an F1-score of 0.66. This suggests that while the model can identify most Forehand Clears, there remains some ambiguity, as indicated by misclassifications spread across other strokes. Forehand Drive, although achieving a precision of 0.74, strug-gled with recall (0.64), highlighting difficulties in consistently recognizing this stroke.

The results highlight the strengths of k-NN in distinguishing strokes with distinct kine-matic profiles, such as Backhand Drive and Backhand Clear. However, strokes with overlapping characteristics, such as Forehand Smash and Forehand Drive, require further attention. The relatively low performance for Forehand Smash could stem from inadequate feature separation in the input data or inherent similarities in execu-tion styles.

Moreover, the confusion matrix suggests potential feature overlap between Forehand Clear and Forehand Drive, which further underscores the need for enhanced feature engineering or dimensionality reduction techniques to improve class separability. Techniques such as principal component analysis (PCA) or the inclusion of time-series features might address this limitation.

4.3 SVM

The Support Vector Machine (SVM) classifier achieved an overall accuracy of 75 percent in classifying badminton strokes. Table 4 provides the classification metrics, while Fig. 5 illustrates the confusion matrix, highlighting strengths and weaknesses in stroke classification.

Table 4. Classification Results for Badminton Strokes Using SVM model.

Stroke	Precision	Recall	F1-Score
Backhand Clear	0.72	0.81	0.76
Backhand Drive	0.84	0.98	0.91
Forehand Clear	0.85	0.43	0.57
Forehand Drive	0.77	0.79	0.78
Forehand Smash	0.58	0.70	0.63
Model Accuracy		**0.75**	

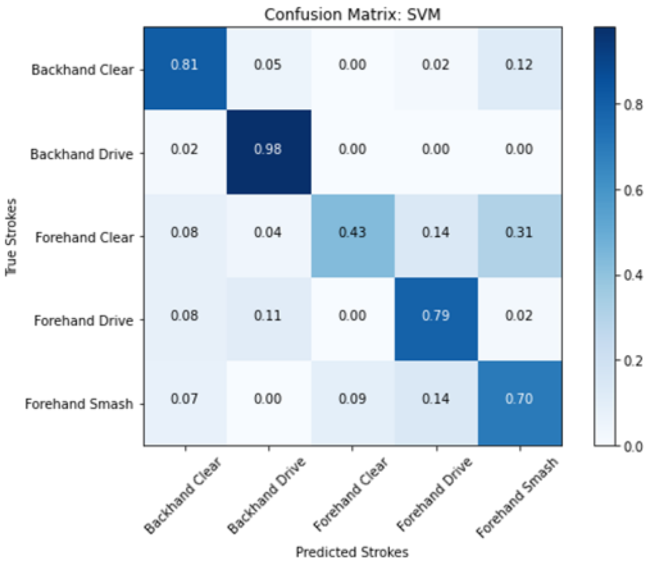

Figure 5. Confusion matrix of SVM model in classifying badminton strokes.

The SVM model excelled in recognizing Backhand Drive, achieving near-perfect recall (0.98) and an F1-score of 0.91. This indicates the model's ability to consistently identify this stroke, with minimal misclassification. Similarly, Backhand Clear showed strong results, with a recall of 0.81 and an F1-score of 0.76, despite a 12 per-cent misclassification rate as Forehand Smash.

For Forehand Clear, performance was less satisfactory, with a recall of only 0.43 and significant misclassifications into Forehand Drive (14 percent) and Forehand Smash (31 percent). These misclassifications suggest overlapping features between these strokes, particularly in execution speed or angle. Forehand Smash, while achieving a recall of 0.70, also suffered from misclassification, with 14 percent of instances incor-rectly labeled as Forehand Drive.

Forehand Drive demonstrated balanced metrics (recall 0.79, F1-score 0.78), though 11 percent of its instances were misclassified as Forehand Smash, reflecting moderate ambiguity between these strokes.

The confusion matrix shows the SVM model excels at distinguishing Backhand Drive and Backhand Clear but struggles with overlapping strokes like Forehand Clear and Forehand Smash. Misclassification patterns suggest improvements through feature engineering, such as including temporal, angular velocity, or biomechanical features.

Notably, Forehand Clear misclassified as Forehand Smash (31 percent) highlights the need for better differentiation in motion data. Similarly, Forehand Smash's overlap with Forehand Drive points to execution speed or trajectory similarities the model cannot resolve. While SVM shows promise, it requires more advanced models, en-semble approaches, and a larger dataset for better accuracy and stroke differentia-tion.

4.4 Performance Comparison between Models

This section compares the classification performance of the Logistic Regression, k-NN, and SVM models. The key metrics for comparison include precision, recall, F1-score, and overall accuracy.

Table 5. Performance Comparison of Classification Models

Model	Accuracy (%)	Best Stroke	Worst Stroke
Logistic Regression	67	Backhand Drive (F1: 0.88)	Forehand Smash (F1: 0.37)
k-NN	75	Backhand Drive (F1: 0.91)	Forehand Smash (F1: 0.43)
SVM	75	Backhand Drive (F1: 0.91)	Forehand Clear (F1: 0.57)

The results in Table 5 indicates that k-NN and SVM performed similarly, achieving 75% accuracy, while Logistic Regression lagged behind at 67%. Across all models, Backhand Drive was the most accurately classified stroke, while Forehand Smash consistently exhibited the lowest performance. The misclassification of forehand strokes suggests the need for advanced feature selection and deep learning techniques to improve class separability. Future work should consider ensemble methods or hybrid models to enhance recognition accuracy further.

5.0 CONCLUSION

This study evaluated machine learning (ML) models for badminton stroke recogni-tion using sensor data from an IMU-embedded racket. The k-NN and SVM models achieved the best performance, both with 75% accuracy, outperforming Logistic Regression 67%. The k-NN model excelled in classifying Backhand Drive, while Forehand strokes, particularly Forehand Smash, were misclassified across all models. These challenges underscore the need for improved feature engineering and more advanced models.

Overall, the study highlights the potential of ML in automating stroke analysis and providing valuable feedback for player training. Future research should focus on refining feature selection, exploring deep learning, and expanding the dataset to im-prove classification accuracy and model adaptability.

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