Punch Types and Range Estimation in Boxing Bouts using IMU Sensors

Saravanan Manoharan
Department of Applied Mechanics
Indian Institute of Technology Madras
Chennai, India
am21d010@smail.iitm.ac.in

John Warburton
Applied Sport and Exercise Science
Liverpool John Moores University
Liverpool, United Kingdom
john.warburton@inspireinstituteofsport.com

Ravi Hegde
Department of Electrical Engineering
Indian Institute of Technology
Gandhinagar, India
hegder@iitgn.ac.in

Ranganathan Srinivasan
Department of Chemical Engineering
Indian Institute of Technology Madras
Chennai, India
ranga@iitm.ac.in

Babji Srinivasan*
Department of Applied Mechanics
Indian Institute of Technology Madras
Chennai, India
babji.srinivasan@iitm.ac.in

2023 IEEE International Conference on Internet of Things and Intelligence Systems (IoTaIS) | 979-8-3503-1904-0/23/$31.00 ©2023 IEEE | DOI: 10.1109/IOTAIS60147.2023.10346074

***Abstract*— In the field of competitive boxing, performance is often evaluated by analyzing punch frequency and type, a process now enhanced by machine learning and Inertial Measurement Unit sensor data. Despite these advancements, punch range, a crucial factor influencing strategy and punch effectiveness, has been largely overlooked. To address this aspect, our work focuses on classifying punch types and ranges using various ML techniques trained on IoT sensors like IMU sensor data. We utilize spatiotemporal features, specifically power spectral density extracted from the four types of punch data, as input for the ML models. The models employed include Fine Decision Tree, Coarse Decision Tree, Linear Discriminant, Quadratic Discriminant, and Random Forest. In our comparative analysis of these ML models, we have found that the Random Forest classifier achieves the highest accuracy, accurately predicting punch types and their corresponding ranges with an impressive accuracy rate of 96.5%. This breakthrough in punch classification enables coaches and trainers to comprehensively assess a boxer's performance and design tailored training regimens for further improvement.**

Keywords— ***machine learning, punch classification, IMU sensor***

I. Introduction

In boxing analysis, key performance indicators (KPIs) such as punch accuracy, power, speed, defense efficiency, ring generalship, and Ring IQ are essential for objectively evaluating and understanding a boxer's performance. These indicators help identify strengths, weaknesses, and progress, enabling coaches, trainers, and analysts to make informed decisions for performance enhancement.

Punch classification in martial arts and combat sports is a fundamental aspect of training and performance evaluation [1]. By categorizing punches based on their execution, impact, and distance from the target, coaches, and athletes can analyze and improve their striking techniques. One crucial factor in effective punching is achieving the optimal position for engagement, where the athlete's weight is evenly balanced over both legs, facilitating powerful rotational movement. This requires precise footwork to move into the desired range, allowing boxers to capitalize on punching opportunities. The 'range' is a key element of strategy in boxing, dictating the type of punches that can be effectively deployed. It is often determined by the distance between the combatants, and hence the reach of the target. Punches are often classified into three main ranges: long-range, mid-range, and close-range [2,3] Long-range punches are thrown from a distance to control the fight's pace, often jabs, straights, or crosses. Mid-range punches, like hooks, uppercuts, and overhands, are used to create openings and close the gap. Close-range punches occur in close proximity, allowing for powerful strikes, such as body punches or clinch punches. While classifying punches into these ranges provides a general framework, it's important to note that individual techniques can overlap between ranges, showcasing the adaptability and versatility of skilled boxers. The most accomplished fighters can adeptly modify their punching strategies, employing a combination of long, mid, and close-range punches to gain an advantage over their opponents. Many tactical cues may be gleaned from a boxer's punch range. For instance, a boxer with a more extended punch range may strike their opponent farther away, making it harder for them to land their own blows.

Notably, there is a lack of extensive research explicitly addressing the classification of punches along with their corresponding ranges. Recognizing the importance of understanding these punching dynamics, our study aims to delve deeper into punch classification and their ranges by integrating machine learning techniques with IoT sensors like inertial measurement unit (IMU) sensor data. The insights derived from identifying specific punch characteristics can help in tailoring training regimes, enhancing both offensive and defensive techniques. Furthermore, they can be instrumental in deciphering an opponent's tactics, potentially predicting their next move based on recognized patterns.

A. Literature Review

The domain of punch classification in martial arts and combat sports has been an active area of research, with substantial focus placed on classifying different types of punches based on their execution, impact, and distance from the target. In competitive combat sports like boxing, analysis often focuses on specific punching combinations during the training camp. To facilitate this process, the automation of analyzing complex strike patterns is desirable, as traditional observational coding and notational analysis can be laborious [4]. Recent studies have demonstrated the potential of using 9DOF inertial sensors and machine learning models to accurately identify different types of punches in boxing [5]. However, the performance of these models can be influenced by factors such as sensor characteristics, sensor placement, features used, and the specific movement being classified. Furthermore, assessing the accuracy of boxing punch prediction in a combative context, such as sparring or competitive matches, holds promise in improving scoring decisions made by ringside judges [6]. In combat sports performance analysis, IMUs data are used to examine punch quality, classification, frequency, head punch, and technique characteristics [7]. These studies often employ machine learning-based data analysis and frequently position IMUs on the shins or wrists. Additionally, combining IMUs with visual systems has been found to be beneficial for training moves in martial arts and combat sports [8].

The current studies emphasize the significance of punch classification in combat sports, specifically categorizing punches based on execution, impact, and distance from the target. However, it is noteworthy that limited research has been found that specifically addresses the classification of punches with their corresponding ranges. This work aims to explore the classification of punches and their respective ranges by combining machine learning techniques with data from inertial measurement unit (IMU) sensors. This integration allows for a more comprehensive understanding of punch dynamics. By analyzing specific punch characteristics, we can optimize training routines, improve offensive and defensive techniques, and gain valuable insights into an opponent's strategies. Additionally, recognizing patterns in punch data may enable us to anticipate an opponent's next move, enhancing tactical decision-making.

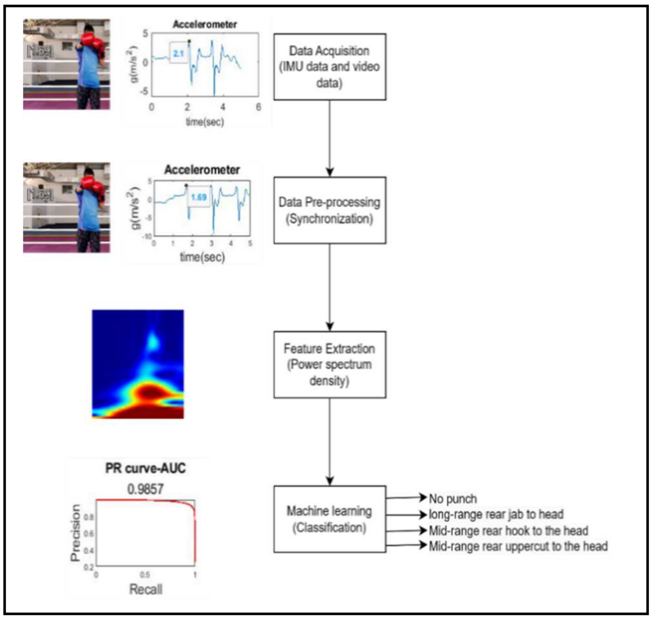

Figure 1. Flowchart of the proposed method

CoE for sports science and analytics for the funding, Indian Institute of Technology, Madras.

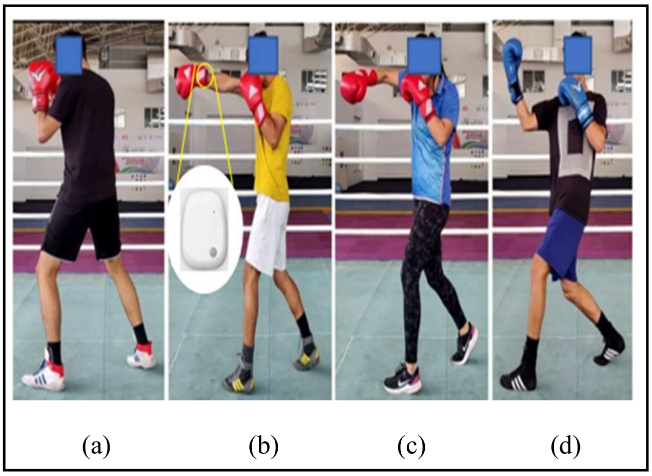

Figure 2. Punch types; (a) No punch (b) Long-range rear jab to head (c) Mid-range rear hook to head (d) Mid-range rear uppercut to head

II. EXPERIMENTAL STUDIES

Eight elite boxers (6 males and 2 females) from the Inspire Institute of Sports (IIS) in Karnataka, India participated in the study. All of them are international boxers and have been extensively trained by top coaches to reach their full potential. An Inertial Measurement Unit sensor (MetaMotion, Mbientlab, San Francisco) with 200 Hz sampling frequency, ±16 g accelerometer, ±2000 deg/s gyroscope, provides real-time data on an individual's movements and orientation. The device uses accelerometers and gyroscopes for precise tracking of motion and punch orientation, while its inbuilt Bluetooth capability enables real-time data transmission to other devices such as smartphones or computers.

The high-resolution and high-frequency data allowed for detailed analysis of the boxers' movements and provided valuable insights into their punching technique and make it ideal for wearable devices, sports equipment, and robotics. VelcroTM bands were used to secure the sensor underneath the boxing gloves on the left and right wrists. The flowchart of the proposed work is shown in Figure 1. A variety of supervised machine learning models were to be used to categorize the different punch types and their ranges using the technique, which was designed to collect IMU data and video data simultaneously. The data collection session consisted of the elite boxers performing a shadow boxing of 320 punches for each of the 14 different punches, such as long-range lead jab to head, long-range rear jab to head, long-range lead jab to body, long-range rear jab to body, long-range lead hook to head, long-range rear hook to head, mid-range lead hook to head, mid-range rear hook to head, mid-range lead steep hook to head, mid-range rear steep hook to head, mid-range lead hook to the body, mid-range rear hook to the body, mid-range lead uppercut to the head, mid-range rear uppercut to the head.

Initially, we have done four types of classification such as no punch, long-range rear jab to head, mid-range rear hook to head, and midrange rear uppercut to head as shown in Figure 2.

A. Data Pre-Processing and Feature Engineering

In our study, we conducted precise time synchronization of the IMU (Inertial Measurement Unit) data and the video data, ensuring accurate annotation and reliable ground truth information. Subsequently, we performed feature extraction on the IMU sensor data, specifically the accelerometer and gyroscope data from the x, y, and z axes as shown in Figures

3(a), 3(b) & 3(c), while Figures 4(a), 4(b) & 4(c) displays a corresponding spectrogram that visualizes the extracted features from all six axes. The feature extraction involved a time-frequency analysis of the IMU data, allowing us to extract spatio-temporal features such as power spectral density across various frequency bands (Fig. 4(a), 4(b), and 4(c)). Each axes in both the accelerometer and gyroscope comprised 258 frequency power values, representing features for each time value. These features are valuable for characterizing different types of punches, identifying patterns and trends, and ultimately improving performance. By analyzing the power spectral density, it becomes possible to identify specific frequency ranges associated with certain punch types, such as jabs, hooks, or uppercuts, along with their respective ranges.

This comprehensive approach of time-frequency analysis and feature extraction provides a profound understanding of the data, revealing the relationships between frequency components and punch characteristics. It plays a crucial role in accurately classifying and characterizing punches, enabling insights into patterns, trends, and variations in punch execution. Ultimately, these findings contribute to the development of effective training programs, technique refinement, and overall performance enhancement in martial arts and combat sports.

B. Supervised Machine Learning Model

In our study, multiple supervised machine learning models were chosen for their specific strengths concerning our data and research objectives. Fine and Coarse Decision Trees were chosen for their ability to capture complex patterns and avoid overfitting, respectively. Random Forest was used to handle high-dimensional spaces and large training samples, while LDA and QDA were chosen for their proficiency in handling linear and non-linear classes, respectively. Our dataset consists of IMU sensor data including accelerometer, and gyroscope. It was divided into training and testing sets. The training set consisted of 80% of the data, specifically including (N=250) number of punches from each category. The remaining 20% constituted the testing set, which comprised 50 punches from each category. These subsets were used to train and evaluate the different machine learning models, assessing their performance in accurately classifying the punches based on type and range. The ground truth, which is the actual or true labels of the data, was obtained by visually inspecting the recorded video. The accuracy of each technique was then compared to see which one performed best. The results of this study could be used to determine which machine learning technique is best suited for classifying the type and range of punches in similar datasets.

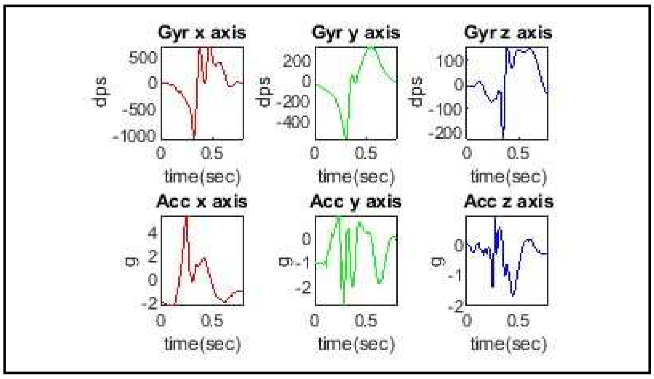

Figure 3(a). 6DOF plot of long-range rear jab to head

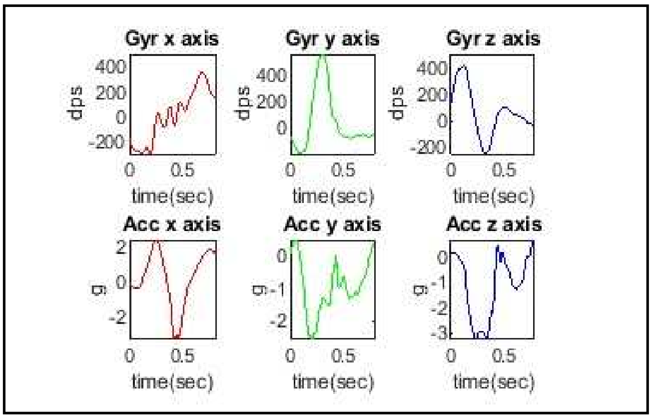

Figure 3(b). 6DOF plot of mid-range rear hook to head

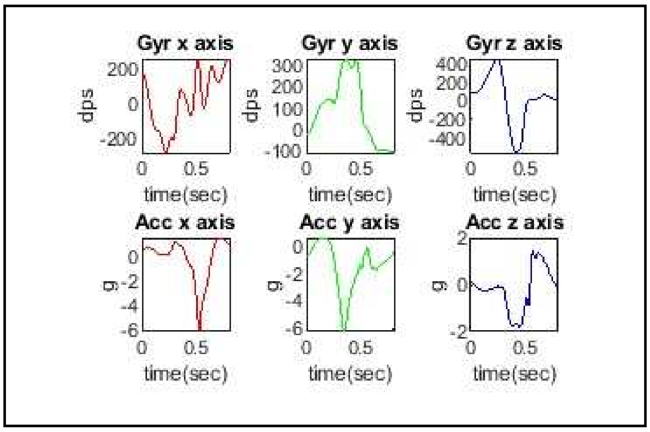

Figure 3(c). 6DOF plot of mid-range rear uppercut to head

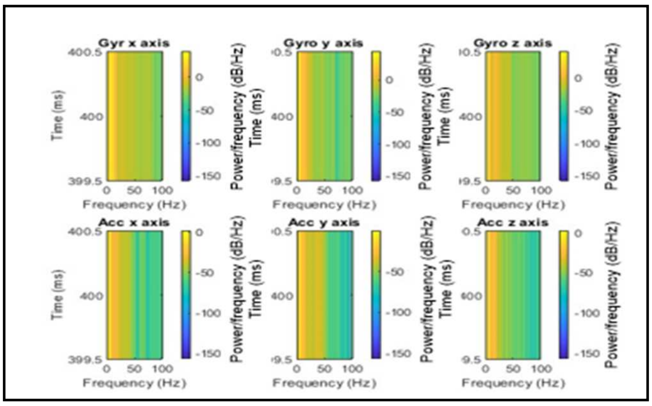

Figure 4(a). Spectrogram of long-range rear jab to head

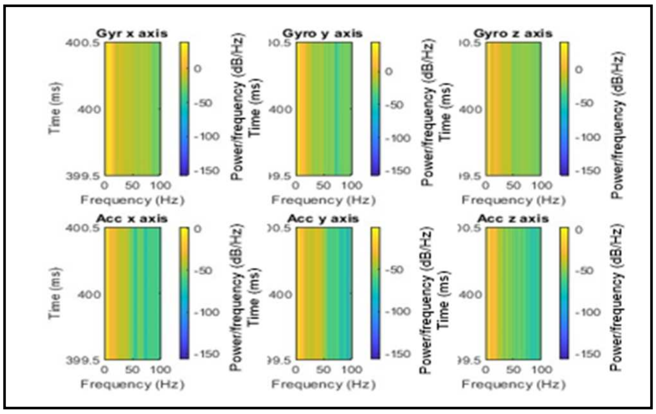

Figure 4(b). Spectrogram of mid-range rear hook to head

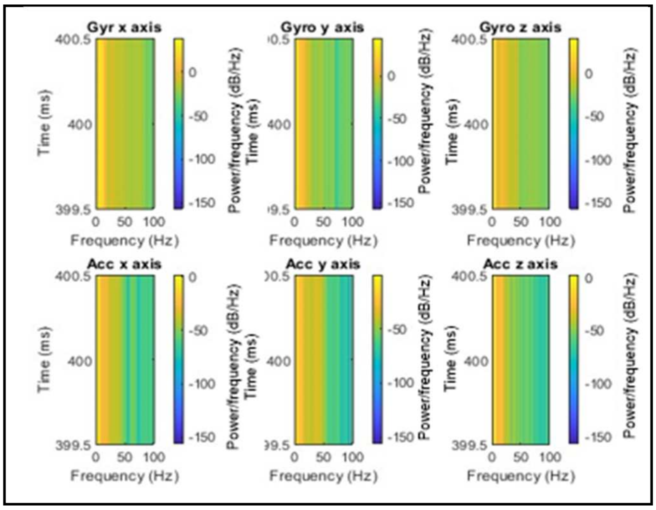

Figure 4(c). Spectrogram of mid-range rear uppercut to head

C. Performance metrics

In assessing the efficacy of our machine learning models for punch classification, we compare key metrics - accuracy, precision, recall, and F1-score - across models. The objective is to identify the model providing the optimal balance of these metrics for punch classification, with a careful consideration of the impacts of false positives and negatives via a confusion matrix. This strategy enables a succinct yet detailed comparison of model performance.

A confusion matrix is a table that is used to evaluate the performance of a classification model by comparing the predicted class with the actual class. The matrix is constructed with four values: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). These values can be used to calculate other accuracy metrics such as precision, recall, and F1 score.

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad (1)$$

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \quad (2)$$

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (3)$$

$$F1 - score = 2 * \frac{\text{precision} * \text{recall}}{precision + recall} \quad (4)$$

The accuracy metrics measures the overall performance of the model by calculating the ratio of correctly classified instances to the total number of instances. Precision indicates the model's ability to accurately predict positive instances, while recall measures its capability to correctly identify positive instances. The F1-score combines both precision and recall into a single metric, providing a balanced assessment of the model's performance. The formulae for these metrics are shown (Equations (1)–(4)).

The choice of metrics for punch classification hinges on its application. If used for boxer training or real-time feedback, precision is prioritized to ensure accurate advice. In contrast, for strategy analysis, maximizing recall is essential to capture as many punch instances as possible. Thus, the model choice should consider the trade-off between accuracy, precision, and recall, favoring precision for training and recall for strategy analysis.

III. RESULTS AND DISCUSSION

Initial results are demonstrated for classifying four different punch types and punch ranges such as no punch, long-range rear jab to the head, mid-range rear hook to the head, and mid-range rear uppercut to the head. The 50-count of each type of punch can be classified using a machine learning algorithm.

To evaluate the performance of the machine learning algorithms, several techniques are used and reported, including fine decision tree, coarse decision tree, linear discriminant, quadratic discriminant, and random forest. The accuracy of these techniques is measured using several metrics, including model accuracy, precision, recall, and F1-score, and these results are summarized in Table 1.

Table 1: Classification results from various machine learning algorithms

Model	Accuracy	Precision	Recall	F1-score
Fine Decision Tree	0.93	0.93	0.93	0.93
Coarse Decision Tree	0.60	0.60	0.74	0.66
Linear Discriminant	0.91	0.91	0.92	0.91
Quadratic Discriminant	0.65	0.65	0.78	0.71
Random Forest	0.96	0.96	0.96	0.96

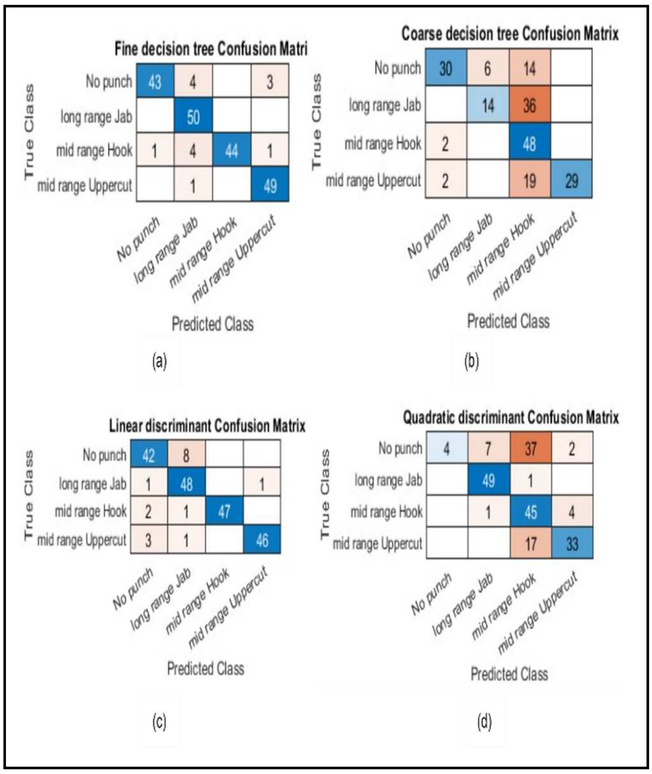

Figure 5. Confusion matrix of machine learning model; (a) Fine decision tree (b) Coarse decision tree (c) Linear discriminant (d) Quadratic discriminant

The results show that the Random forest, fine decision tree, and linear discriminant algorithms have the higher accuracy (>90%) among all the techniques used. The confusion matrix of the fine decision tree model showed that it performed well in classifying long-range jabs and mid-range uppercuts, which are critical punches in boxing (Fig. 5(a)). Conversely, the coarse decision tree is best suited for mid-range hook classification (Fig. 5(b)). Linear discriminant analysis (Fig. 5(c)) yielded accurate classification for most punches, with only a few instances of misclassification for all classes. This algorithm is a statistical technique used to find a linear combination of features that characterizes or separates two or more classes of objects or events. Its performance suggests that it can be an effective method for classifying different types of punches in boxing. Quadratic discriminant analysis (Fig. 5(d)) only accurately classified the long-range jab, with minimal misclassification. This algorithm is similar to linear discriminant analysis but allows for a quadratic decision boundary. The poor performance of this algorithm in classifying the other types of punches suggests that a linear decision boundary can be more appropriate for this task.

Finally, among all the algorithms used, the random forest algorithm exhibited the highest accuracy metrics, with overall model accuracy, precision, recall, and F1-score of 96.5%. Its exceptional accuracy implies that it can effectively classify different types of punches in boxing, making it a valuable tool for training and performance evaluation. The high precision signifies a large proportion of correctly classified punches among those predicted as positive. Similarly, the high recall, or sensitivity, indicates a significant proportion of accurately predicted punches with range instances among all actual positive instances. Furthermore, the high F1 score highlights the model's ability to achieve a balanced performance, combining precision and recall to provide a robust classification outcome. The confusion matrix of the random forest algorithm, shown in Fig. 6, reveals that all four punch types with their ranges are classified accurately, except for the no punch and rear hook punch, where there are a few instances of misclassification. We compared the statistical analysis such as mean, standard deviation, and variance of the misclassified no-punch category with the true categories of no-punch and hook data. The majority of the features showed a statistical match with the mid-range hook data category instead of the no-punch category. This is because a free preparatory motion for a punch was done by a boxer, so it was misclassified as a mid-range hook. The current dataset can be acquired as individual types of punches from different boxers but in a boxing bout where multiple punches are thrown. The future goal is to test the revealed algorithm in a full boxing bout.

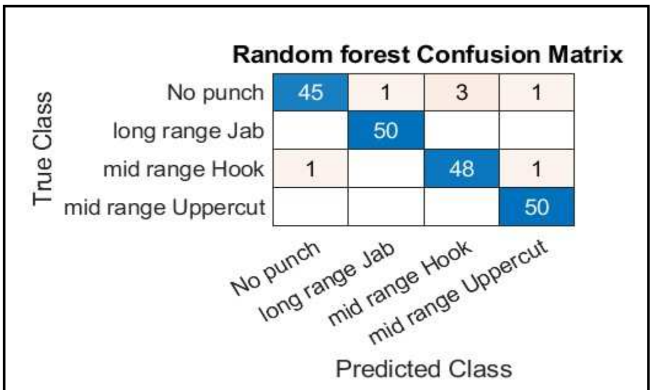

Figure 6. Confusion matrix of random forest model

IV. Conclusion

The current study aims to employ machine learning techniques to accurately classify the type and range of punches thrown by boxers, utilizing the data obtained from Inertial Measurement Unit (IMU) sensors. This classification process is vital for enhancing boxers' performance in various areas of their game, such as offense, defense, and overall control of the match. The study was conducted and the results were analyzed, which revealed that the random forest algorithm was found to be the most effective classification method, outperforming other methods that were evaluated. This is a significant finding, as it indicates that the random forest algorithm can be utilized to accurately classify the type and range of punches in boxing. Expanding the algorithm to cover all 14 types of punches and their ranges is a significant step towards providing comprehensive data and insights into boxers' performance. With this level of granularity, coaches can gain a better understanding of their athletes' strengths and weaknesses, and tailor training programs accordingly. Measuring punch force is another crucial aspect of the platform, as it provides a quantitative measure of the athlete's performance. By collecting punch force data in real-time, coaches can track progress and adjust training regimens to optimize performance. The IoT platform combines machine learning and IoT technology to provide real-time feedback to coaches and athletes. Machine learning algorithms process the data collected by IoT devices, providing insights and recommendations for improving performance. This technology revolutionizes boxing training and evaluation, providing coaches and athletes with valuable information that can inform training decisions, optimize performance, and reduce the risk of injury.

Acknowledgement

The Boxing Federation of the Inspire Institute of Sports (Ballary, Karnataka, India) administration, athletes, coaches, and leaders are all acknowledged for organizing the experiments and actively contributing to the study.

References

[1] Kasiri-Bidhendi, S., Fookes, C., Morgan, S., Martin, D. T., & Sridharan, S. (2015, September). Combat sports analytics: Boxing punch classification using overhead depthimagery. In 2015 IEEE International Conference on Image Processing (ICIP) (pp. 4545-4549). IEEE.

[2] Xing, Y., & Lin, J. (2022, October). Training Research based on Cloud Computing Mode to Improve the Application of Boxing Middle and Short Range Techniques in Actual Combat. In 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC) (pp. 640-643). IEEE.

[3] Beattie, K., & Ruddock, A. D. (2022). The role of strength on punch impact force in boxing. Journal of Strength and Conditioning Research, 36(10), 2957-2969.

[4] Attal, F.; Mohammed, S.; Dedabrishvili, M.; Chamroukhi, F.; Oukhellou, L.; Amirat, Y. Physical human activity recognition using wearable sensors. Sensors 2015, 15, 31314–31338.

[5] Hahn, A.G.; Helmer, R.J.N.; Kelly, T.; Partridge, K.; Krajewski, A.; Blanchonette, I.; Barker, J.; Bruch, H.; Brydon, M.; Hooke, N.; et al. Development of an automated scoring system for amateur boxing. Procedia Eng. 2010, 2, 3095–3101.

[6] Worsey MT, Espinosa HG, Shepherd JB, Thiel DV. A Systematic Review of Performance Analysis in Rowing Using Inertial Sensors. Electronics. 2019; 8(11):1304.

[7] Polak E, Kulasa J, VencesBrito A, Castro MA, Fernandes O. Motion analysissystems as optimization training tools in combat sports and martial arts. Revista de Artes Marciales Asiáticas. 10. 105–123.

[8] Worsey, M. T., Espinosa, H. G., Shepherd, J. B., & Thiel, D. V. (2020). An evaluation of wearable inertial sensor configuration and supervised machine learning models for automatic punch classification in boxing. IoT, 1(2), 360-381.

[9] Cust, E.E.; Sweeting, A.J.; Ball, K.; Robertson, S. Machine and deep learning for sport-specific movement recognition: A systematic review of model development and performance. J. Sports Sci. 2019, 37, 568–600.

[10] Soekarjo, K.M.W.; Orth, D.; Warmerdam, E. Automatic classification of strike techniques using limb trajectory data. In Proceedings of the 2018 Workshop on Machine Learning and Data Mining for Sports Analytics, Dublin, Ireland, 10 September 2018.

[11] Ashker, S.E. Technical and tactical aspects that differentiate winning and losing performances in boxing. Int. J. Perform. Anal. Sport 2011, 11, 356–364.

[12] McGrath, J.W.; Neville, J.; Stewart, T.; Cronin, J. Cricket fast bowling detection in a training setting using an inertial measurement unit and machine learning. J. Sports Sci. 2019, 37, 1220–1226.

[13] Khasanshin, I. (2021). Application of an artificial neural network to automate the measurement of kinematic characteristics of punches in boxing. Applied Sciences, 11(3), 1223.

[14] Wagner, T., Jäger, J., Wolff, V., & Fricke-Neuderth, K. A machine learning driven approach for multivariate timeseries classification of box punches using smartwatch accelerometer sensordata. In 2019 Innovations in Intelligent Systems and Applications Conference (ASYU) (pp. 1-6). IEEE.

[15] Brindha, J., & Nallavan, G. (2022, June). A Wearable Biometric Performance measurement System for Boxing-A SURVEY. In 2022 IEEE World Conference on Applied Intelligence and Computing (AIC) (pp. 536-540). IEEE.

[16] Wu, Q. (2022). Boxing speed and muscle scientific training. Revista Brasileira de Medicina do Esporte, 28, 82-84.

[17] Amerineni, R., Gupta, L., Steadman, N., Annauth, K., Burr, C., Wilson, S., ... & Vaidyanathan, R. (2021). Fusion Models for Generalized Classification of Multi-Axial Human Movement: Validation in Sport Performance. Sensors, 21(24), 8409.

[18] Stanley, E. (2020). Maximal punching performance in amateur boxing: An examination of biomechanical and physical performance-related characteristics.