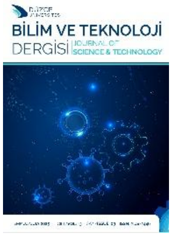
Düzce University Journal of Science & Technology, 13 (2025) 1385-1405



Düzce University
Journal of Science & Technology

Research Article

Integration of Sensor and Biometric Data in Shooting Training: An Efficient and Goal-Oriented Approach through an Intelligent Decision Support System

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DOI: 10.29130/dubited.1716947

ABSTRACT

Shooting training presents significant challenges in terms of efficiency due to high costs, time constraints, and the limitations of manual assessment processes. Furthermore, objectively evaluating trainees' performance is often difficult, which in turn slows down the learning process. In this study, a sensor-based system integrated into both the firearm and the target was developed to enhance training efficiency and reduce costs. Accelerometer (ACC) and gyroscope (GYRO) sensors precisely measure the dynamic movements of the firearm, capturing critical data such as recoil, vibration, directional changes, and angular velocity in real time. Additionally, the sensor-equipped target system instantly detects the accuracy of each shot and provides immediate feedback regarding hits or misses. The proposed system not only monitors firearm movements but also incorporates biometric data to deliver a more comprehensive performance analysis. Heart rate, a key biometric factor that directly influences shooting performance, is monitored and analyzed in real time. This allows instructors to provide more informed and effective feedback by considering not only mechanical errors but also the psychological and physiological states of the trainees. Moreover, the importance of features extracted from the collected data was evaluated using the Random Forest algorithm. It was observed that heart rate accounts for approximately 28% of the variance in the dataset. Finally, a predictive model was developed using the Support Vector Machines (SVM) algorithm, achieving an accuracy rate of 74% in shot prediction.

Keywords: *Shooting training, biometric data, decision support systems, machine learning, support vector machines*

Atış Eğitiminde Sensörlerin ve Biometrik Verilerin Entegrasyonu: Akıllı Bir Karar Destek Sistemi

ÖZ

Atış eğitimi, yüksek maliyetler, zaman kısıtlamaları ve manuel değerlendirme süreçlerinin sınırlılıkları nedeniyle verimlilik açısından önemli zorluklar sunar. Dahası, kursiyerlerin performansını objektif olarak değerlendirmek genellikle zordur, bu da öğrenme sürecini yavaşlatır. Bu çalışmada, eğitim verimliliğini artırmak ve maliyetleri düşürmek amacıyla hem ateşli silah hem de hedefe entegre edilmiş sensör tabanlı bir sistem geliştirilmiştir. İvmeölçer (ACC) ve jiroskop (GYRO) sensörleri, ateşli silahın dinamik hareketlerini hassas bir şekilde ölçerek geri tepme, titreşim, yön değişiklikleri ve açısal hız gibi kritik verileri gerçek zamanlı olarak yakalar. Ek olarak, sensör donanımlı hedef sistemi her atışın doğruluğunu anında tespit eder ve vuruş veya ıskalar hakkında anında geri bildirim sağlar. Önerilen sistem, sadece ateşli silah hareketlerini izlemekle kalmaz, aynı zamanda daha kapsamlı bir performans analizi sunmak için biyometrik verileri de içerir. Atış performansını doğrudan etkileyen

Received: 10/06/2025, Revised: 13/07/2025, Accepted: 14/07/2025

önemli bir biyometrik faktör olan kalp atış hızı, gerçek zamanlı olarak izlenir ve analiz edilir. Bu, eğitmenlerin sadece mekanik hataları değil, aynı zamanda kursiyerlerin psikolojik ve fizyolojik durumlarını da dikkate alarak daha bilinçli ve etkili geri bildirimler sunmalarını sağlar. Ayrıca, toplanan verilerden çıkarılan özelliklerin önemi Random Forest algoritması kullanılarak değerlendirilmiştir. Kalp atış hızının veri kümesindeki varyansın yaklaşık %28'ini oluşturduğu gözlemlenmiştir. Son olarak, Destek Vektör Makineleri (SVM) algoritması kullanılarak atış tahmininde %74'lük bir doğruluk oranına ulaşan bir tahmin modeli geliştirilmiştir.

Anahtar Kelimeler: *Atış eğitimi, biyometrik veriler, karar destek sistemleri, makine öğrenimi, destek vektör makineleri*

I. INTRODUCTION

Shooting training plays a crucial role in the security sector, particularly within military and law enforcement agencies, as well as in shooting sports. High-precision shooting not only requires successfully hitting the target but also demands safe and professional firearm handling. Accordingly, effective shooting training serves as the foundation for accurate targeting and safe firearm use. However, traditional training methods have several disadvantages, including time inefficiencies, high costs, and limited practice opportunities [1]. Due to extensive ammunition consumption and the limited availability of professional instructors, trainees may not always have sufficient opportunities to practice during the training process, which further increases the overall cost of training. Additionally, since these methods offer a restricted number of trial attempts, the contribution of mistakes to the learning process remains limited [2].

At this point, technology-assisted shooting training is becoming increasingly important. Particularly through sensor technologies and biometric data analysis, trainees can achieve higher efficiency in a shorter period [3]. Technology-supported training not only saves time for trainees but also helps training institutions reduce costs associated with shooting ranges, instructors, and equipment. This enables organizations to optimize their training processes while simultaneously improving shooting accuracy [4].

Technology has become a critical tool in shooting training and the enhancement of athletes' performance. High-precision sensors and cameras analyze athletes' movements and biomechanical structures in detail, improving their motor coordination and reaction times. Wearable devices help identify potential injury risks, allowing for the implementation of preventive measures. These technologies not only enable coaches and athletes to make training processes more efficient but also facilitate the creation of personalized training plans through data analysis, leading to faster development. Additionally, the collection and analysis of in-game data allow for informed and accurate decision-making regarding athletes' performance. Technological advancements also enhance the design of sports equipment, making training processes more effective and efficient [5].

Shooting training is not limited to safe firearm handling; it also involves the development of professional skills. Shooting is a sport that integrates body control, strong mental focus, and accurate decision-making abilities. Particularly in precision shooting, an athlete's mental concentration and strategic thinking skills play a crucial role alongside physical capabilities. Success in competitive shooting relies on the perfect synchronization of these skills to accurately hit small targets. Therefore, as part of shooting training, enhancing these abilities enables athletes to achieve greater success [6].

In particular, the development of accuracy and precision among athletes enhances the value of each shot made during training. Additionally, shooting training helps athletes use firearms safely and responsibly, reinforcing not only their technical skills but also a strong culture of safety. A well-structured shooting training program is of critical importance for both beginners and experienced shooters alike [7].

Today, sensor-based training and biometric data have become essential tools for enhancing performance in shooting training. These technologies provide shooters with real-time feedback, enabling more accurate and efficient outcomes at every stage of the training process. Sensors measure variables such as acceleration, rotation, velocity, and heart rate, offering far more detailed and precise insights than traditional observations. Furthermore, through IoT technologies, this data can be analyzed to personalize training programs. The integration of such technologies in both military and civilian domains facilitates a faster and more effective learning process, significantly improving shooters' performance [1].

In response to the limitations of traditional shooting training—such as subjectivity, high costs, and limited feedback—this study proposes an integrated system combining firearm and target-based sensor data with real-time biometric monitoring. The central hypothesis is that a machine learning–based decision support system utilizing both physical and physiological parameters can enhance training effectiveness by enabling objective performance evaluations and personalized feedback. To test this, accelerometer and gyroscope data from the firearm, along with heart rate measurements from wearable devices, were collected and analyzed. The model developed using Support Vector Machines (SVM) achieved a shot accuracy prediction rate of 74%, and Random Forest analysis revealed that biometric data (especially heart rate) accounted for 28% of performance variance. These findings demonstrate the potential of the proposed system to revolutionize shooting training by providing data-driven, adaptive instruction mechanisms.

II. LITERATURE REVIEW

Wearable technologies have become a significant tool for movement tracking and analysis in various fields, particularly in health and sports. Accelerometer-based motion detectors enable the monitoring of physical activity, while the use of sensor data in sports that require high precision and coordination, such as shooting, necessitates more specialized approaches. One such specialized approach is biofeedback.

Biofeedback is a technique aimed at teaching individuals to consciously control their physiological processes (such as heart rate, muscle tension, brain waves) by providing real-time information about these processes. In shooting sports, biofeedback is a promising method, particularly for stress management and performance optimization. Heart rate variability (HRV) is a commonly used parameter in biofeedback studies. HRV reflects the balance between the sympathetic and parasympathetic branches of the autonomic nervous system and provides valuable insights into athletes' both physical and psychological states [8].

One of the pioneering studies examining the effects of heart rate variability biofeedback (HRV-BF) on shooting performance investigated the impact of a 12-week HRV-BF training program on shooting athletes. In this study, positive changes were observed in the experimental group, including a reduction in anxiety levels, improvement in shooting accuracy, and an increase in HRV parameters (particularly high-frequency HRV). These findings suggest that HRV-BF training may improve the balance of the autonomic nervous system, helping athletes remain calmer and more focused in stressful situations [9] .

Similar results were obtained in another 12-week study conducted with 15 shooting athletes. In this study, athletes who underwent HRV-BF training showed improvements in HRV values, a reduction in negative emotional states, and enhanced shooting performance. The researchers indicated that biofeedback training helped restore emotional balance by improving the autonomic nervous system's balance, and that these improvements contributed to better shooting performance [10].

Biofeedback not only focuses on HRV but also aims to regulate arousal levels. A study examining the effects of arousal regulation practice on performance in skilled shooters highlighted the importance of biofeedback-assisted training. In this study, the experimental group received arousal regulation training with biofeedback, while the control group underwent standard training. The shooters in the experimental group scored significantly higher in the final test and shooting transfer test compared to the control group, while also exhibiting lower arousal levels during shooting. These results are explained within the framework of the Feedback Theory, where the suppression of the sympathetic system and the activation of the parasympathetic system contribute to these improvements [11].

However, it should also be noted that not all types of biofeedback may be equally effective under every condition. A study examining the effects of wearable and mobile technology-assisted tactical breathing with heart rate biofeedback presents an interesting finding. Thirty-nine participants performed a shooting task in a controlled shooting range while practicing breathing techniques guided by biofeedback. While biofeedback intervention was effective in reducing stress, it did not lead to significant improvements in shooting performance. The researchers interpreted this result as indicating the need for a more comprehensive evaluation of different shooting levels and individual differences. This highlights the necessity for the personalization and adaptation of biofeedback applications to different contexts [12].

One study aimed at understanding the specific mechanisms through which biofeedback affects shooting performance investigated the effects of real-time biomechanical feedback in elite rifle shooters. The biofeedback group received personalized auditory feedback to improve posture and barrel stability, while the control group received no feedback. Significant improvements were observed in performance measures (e.g., shooting scores) in the biofeedback group, while no differences were found between the groups in stability measures (e.g., barrel sway). This finding suggests that biofeedback may improve certain aspects of the shooter's decision-making process and shooting technique, but it may not equally affect all biomechanical parameters [7].

While the foundations of biofeedback and its initial applications in shooting sports have shown promising results, researchers are deepening studies in this field by utilizing more advanced technologies and methods.

One of the studies conducted in this direction developed an enhanced real-time biofeedback application for precision shooting training. The use of technological tools in shooting training, which is critical in security sectors, has the potential to improve efficiency. In this study, an application measuring handgun movements was developed, and shooting accuracy was evaluated using sensor signals (particularly hand movements during the aiming phase). Experiments with 32 subjects showed that real-time feedback and coaching advice scenarios were effective in minimizing shooting errors. The researchers indicated that this application could provide time, resource, and cost savings for professional shooters and security personnel [3].

Another study that examines the role of sensor technologies in shooting training in more detail developed a sensor device that measures handgun movements during precision shooting. This device uses an Inertial Measurement Unit (IMU) sensor, which includes micro-electromechanical systems (MEMS), to collect data from an accelerometer, gyroscope, and magnetometer. These data were used to analyze movement variability during the aiming, firing, and post-firing stages of the shot. The aim of the study was to provide real-time biofeedback to the shooter, detect faulty shots, and reduce training time. It was determined that sensor data had a significant impact on shooting accuracy and success. The researchers predict that future analyses with larger datasets could increase accuracy and further improve biofeedback parameters. This study demonstrates that sensor technologies can be used in shooting training not only to provide feedback but also to objectively measure performance [4].

A study examining the effects of different types of feedback on shooting performance divided novice shooters who underwent a 12-week intensive shooting training into four groups: a control group, a group receiving only outcome knowledge (KR), a group receiving both outcome and process knowledge (KR+KP), and a group receiving visual feedback (FB-II) in addition to the others. While all training groups improved their performance in moving target shooting, the results showed that KR alone and KR+KP together were effective, but visual feedback did not provide additional benefits. This finding suggests that the type and content of feedback should be carefully evaluated for their impact on the learning process and performance [13].

The integration of advanced technologies into shooting training is not limited to sensors and biofeedback. A study that developed a coaching system aimed at improving the performance of Air Rifle/Pistol shooters utilized artificial intelligence and fuzzy logic algorithms. This system collects data by tracking the shooters' arm movements, weapon sight movements, and trigger times, and analyzes these data using infrared technology, camera systems, and video processing techniques. Artificial intelligence and fuzzy logic provide coaches with analysis and decision support regarding athlete performance, aiming to enhance the accuracy of aiming and improve performance at an Olympic level [6].

Machine learning is another powerful tool increasingly used to analyze and improve shooting performance. A study that developed a machine learning-based accuracy prediction model to enhance the effectiveness of precision shooting training and reduce costs employed the Random Forest (RF) algorithm. This model processes accelerometer, gyroscope, and magnetometer data to detect hand movement, aiming, and trigger errors, evaluating shooting performance based on angular velocity and angle signals. The model, validated with experimental data, successfully minimized shooting errors with an accuracy rate of 91.27%. The researchers noted that by providing real-time and terminal feedback, shooters could make immediate improvements, thus accelerating the training process [2].

A study demonstrating the potential of machine learning techniques in the military field used Random Forest and AdaBoost classifiers to correct shooting errors and predict shooter performance. In experiments conducted with real-time military data, an accuracy of 96.8% was achieved in error model recognition and 69% accuracy in performance prediction. This study highlights that while traditional methods are time-consuming and prone to errors, machine learning techniques can provide more efficient and reliable results [14].

The positive effects of biofeedback, sensor technologies, and machine learning on shooting performance raise the applicability of these approaches in more challenging and high-stress environments, such as military training and operations. One important study examined the performance, deadly force decision-making, and team interactions of expert and novice shooters using psychophysiological metrics and biofeedback. Researchers evaluated participants' psychophysiological profiles using EEG (electroencephalography) and EKG (electrocardiography) data, aiming to accelerate learning processes through closed-loop biofeedback. It was observed that expert shooters could better control their physiological states (e.g., heart rate, brain activity) during tasks compared to novice shooters. Furthermore, the performance of novice shooters was enhanced through the use of an Adaptive Psychophysiological Training System (APPT). In combat scenarios, expert shooters exhibited lower stress levels and higher attention levels compared to novices. Team neurodynamics analyses revealed that team interactions optimized performance. This comprehensive study demonstrates that psychophysiological data analysis can make significant contributions to shooting training and operational performance [15].

In situations that require specialized skills, such as marksmanship, detecting and correcting performance errors is critically important. One study investigating this topic explored the role of cognitive processes in detecting performance errors in sniping. Thirteen pistol shooters (with varying skill levels) performed 60 rounds of live shooting, and their abilities to detect performance errors were evaluated. It was found that less skilled shooters, particularly under closed sight conditions, struggled to anticipate performance errors, whereas experienced shooters were able to detect errors more successfully by utilizing more complex information sources (such as weapon recoil, sounds, and body sensations). This study shows that as skill level increases, the ability to detect errors also improves, and this ability is closely linked to cognitive structures such as attention, perception, and memory [16].

Shooting training is a critical process for improving athletes' performance and ensuring their safety. During this process, instructor-based decision support systems help instructors make more accurate and informed decisions by providing sensor data and real-time analysis. These systems enable instructors to provide immediate feedback to athletes, contributing to the development of their technical skills. By utilizing artificial intelligence and data analytics, instructors can offer strategic recommendations and make the training process more efficient [17]. Another study emphasizes the importance of developing skills such as visual perception, attention, and situational awareness in police officer training. In shooting training, instructors play a critical role by analyzing sensor data and providing athletes with correct and immediate feedback. In this context, instructor-based decision support systems can assist instructors in making more informed and effective decisions, thereby improving the efficiency of the training process. These systems can optimize the training process by providing real-time data to instructors and help athletes improve their performance more quickly and effectively [18].

In order to provide a clearer overview of the literature comparison, Table1 presents a comparative summary.

Table 1. *Literature Comparison*

Study	Method / Technology	Participants	Key Findings	Contribution
Effects of HRV Biofeedback on Shooting Performance [9]	HRV Biofeedback (12 weeks)	Shooters	Anxiety decreased, HRV increased, shot accuracy improved	Demonstrates the impact of autonomic nervous system balance on performance
Relationship between Emotional State and Performance with HRV Biofeedback [10]	HRV Biofeedback (12 weeks)	15 Athletes	Negative emotions reduced; HRV and accuracy increased	Highlights psychological balance as a key factor for performance
Regulation of Arousal Level via Biofeedback [11]	Biofeedback + Arousal Control	Experimental vs Control Group	Experimental group showed better scores and lower arousal	Parasympathetic activation supports improved performance
Tactical Breathing Exercises Combined with HR Biofeedback [12]	Breathing Control + Mobile Biofeedback	39 Participants	Stress levels decreased, but shooting accuracy did not improve	Suggests need for individualized biofeedback protocols
Real-Time Posture and Barrel Stabilization Feedback [13]	Auditory Biomechanical Biofeedback	Elite Shooters	Scores improved, but stability unaffected	Technical skill enhancement with some biomechanical limitations
Hand Movement Sensor-Based Feedback Application [14]	IMU-Based Hand Movement Analysis	32 Individuals	Real-time feedback reduced errors	Accelerated training process and reduced costs
Shot Accuracy Analysis Using IMU Sensors [15]	IMU (Accelerometer, Gyroscope, Magnetometer)	Not specified	Identified errors in aiming, shooting, and follow-through	Provided objective measurement of performance

Study	Method / Technology	Participants	Key Findings	Contribution
Effects of Different Feedback Types [16]	Knowledge of Results (KR), Knowledge of Performance (KP), Visual Feedback	4 Groups, 12 weeks	KR and KP were effective; visual feedback was ineffective	Feedback content is critical for training efficacy
AI-Supported Coaching System [17]	AI + Fuzzy Logic + Image Processing	Air Rifle/Pistol Shooters	Improved shot accuracy and analysis	Provided decision support to coaches
Shot Accuracy Prediction Model Based on Random Forest [18]	RF, IMU Data (Angle, Speed)	Experimental Validation	Achieved 91.27% accuracy in hit prediction	Accelerated learning with real-time feedback
Military Shooting Error Prediction Using RF and AdaBoost [19]	Machine Learning Algorithms, Real Military Data	Military Users	96.8% error detection rate, 69% success prediction	Faster and more reliable than traditional training
Psychophysiological Training System (APPT) [20]	EEG, ECG, Closed-Loop Biofeedback	Expert vs Novice Shooters	Experts excelled in stress control; novices improved with APPT	Enhanced team dynamics and attention performance
Cognitive Process Analysis of Error Detection [21]	Actual Shooting (60 shots), Cognitive Analysis	13 Shooters	Experienced shooters detected errors better	Increased experience enhances perceptual awareness
Instructor-Supported Decision-Making System [22]	Sensor Data + Decision Support System	Not specified	Real-time feedback led to technical improvements	Made coaching decisions data-driven
Visual Attention and Environmental Awareness in Police Training [23]	Instructor-Based Analysis System	Police Cadets	Sensor-supported feedback improved decision quality	Improved visual attention and decision-making performance

A. CONTRIBUTIONS TO THE LITERATURE

A.1. Comprehensive Motion Analysis and Efficiency Enhancement through Multi-Sensor Fusion

In the current literature, shooting training systems often focus on collecting data from a single sensor type (e.g., accelerometer) or from a single point (e.g., the firearm), which limits the holistic analysis of shooting performance. This study develops a more precise and detailed model of firearm movement by simultaneously collecting data from accelerometer and gyroscope sensors. Additionally, for the first time, this multi-sensor fusion approach, which simultaneously tracks both firearm and target movements, makes a unique contribution to the literature by evaluating the variables originating from both the firearm and target together. This approach has the potential to enhance the efficiency of shooting training, reduce training time, and lower costs.

A.2. Accelerated Learning through Automated and Objective Feedback from the Target

In traditional shooting training, accuracy detection is typically a subjective and time-consuming process based on manual observation. This study overcomes this limitation by providing automatic, objective, and instant feedback on shot accuracy through a sensor placed on the target. The digital data from the target sensor (hit/miss) offers more precise and reliable information compared to manual methods in the literature, thereby enhancing training efficiency. As a result, shooters can identify their mistakes more quickly, make necessary corrections faster, and accelerate the learning curve.

A.3. Holistic Performance Assessment and Stress Management through Biometric Data Integration

Most studies in the literature focus solely on mechanical movements in shooting performance, often overlooking the impact of the shooter's physiological condition. This study, for the first time, integrates heart rate (HR) data with firearm and target sensor data. This multidimensional approach enables a comprehensive examination of the relationships between shooting performance and physiological condition, making a significant contribution to the literature. This integration may help shooters improve their stress management skills, maintain high performance even under challenging conditions, and reduce potential injury risks.

A.4. Overcoming the Limitations of Traditional Instructor Observation

Existing studies in the literature typically rely on traditional shooting training methodologies, where instructors evaluate athlete performance based on subjective observations and experience. This approach can lead to erroneous or incomplete feedback due to the natural limitations of human perception. This study addresses these limitations through the integration of instructor-based decision support systems. Using sensor technologies and real-time data analysis, the biomechanical and physiological parameters of athletes during shooting are measured and analyzed objectively. These parameters include critical performance indicators such as firearm grip stability, cardiovascular responses (heart rate variability, blood pressure), and neuromuscular activity. The collected data enables instructors to provide real-time and accurate feedback, allowing for the objective and scientific evaluation of athlete performance. This enhances the effectiveness and efficiency of shooting training, maximizing the performance potential of athletes.

III. MATERIALS AND METHODS

A. DATASET

This study was conducted within the framework of a proof-of-concept model, aiming to provide an initial validation of the proposed system. Accordingly, a pilot implementation was carried out with a limited number of participants, involving three volunteers. Among the participants, two were male and one was female, with ages ranging from 38 to 41.

All participants had basic-level experience in shooting and were involved solely in the data collection and preliminary evaluation phases of the system. Informed consent was obtained from each participant, and all personal data were handled in accordance with ethical principles and confidentiality standards.

This small-scale implementation served to assess the technical feasibility of the system and the functionality of the data collection processes. It represents a preliminary step toward more comprehensive and large-scale future studies.

As this study constitutes a proof-of-concept aimed at evaluating the fundamental functionality of the developed system, it was conducted with a limited number of participants selected through purposive sampling. The participants were chosen from among volunteers with basic-level shooting experience. This selection strategy was employed to ensure the reliable collection of sensor data, assess the technical adequacy of the system, and establish a foundational basis for more extensive future research.

Rather than aiming for statistical generalization, this small-scale sample focuses on testing the system's feasibility, the operability of data collection processes, and overall technical integrity. In this way, the potential of the system for future advanced research and development efforts can be observed in a concrete manner.

B. PROPOSED SYSTEM ARCHITECTURE

B. 1. Shooting Data Acquisition Module

The system architecture used in this study, as shown in Figure 1, consists of four main components: the system that collects shooting data, the target system, the user biometric data collection system, and the data collection and visualization system.

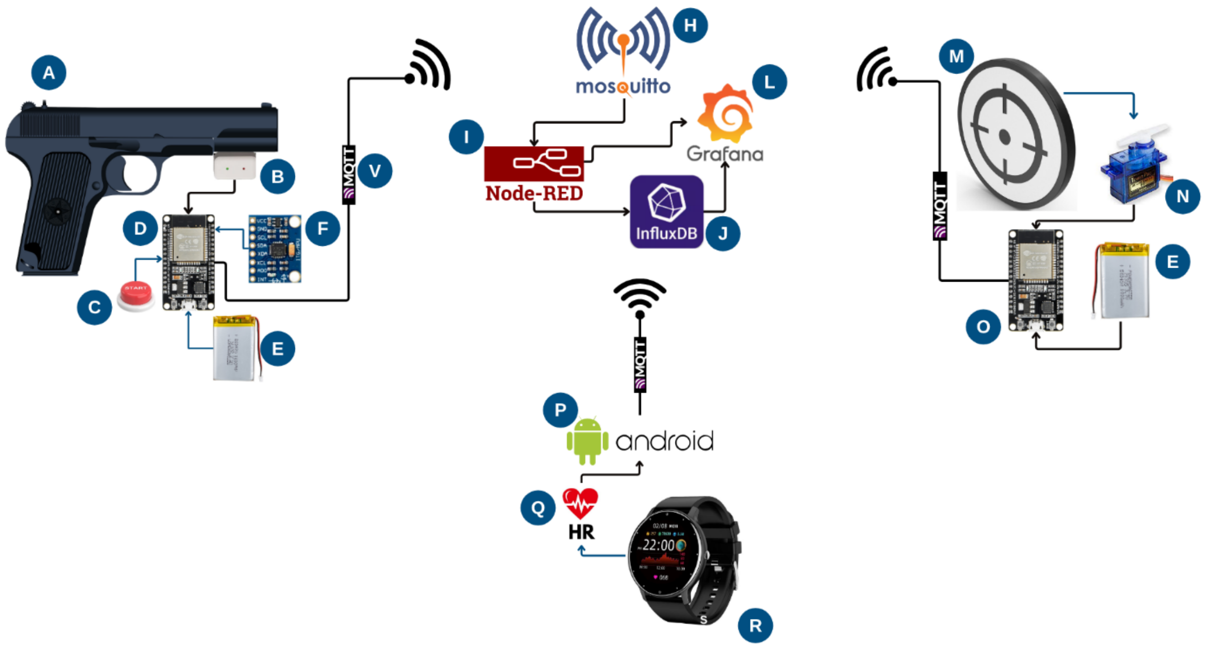

Figure 1. *Multi-Component Shooting Analysis System Architecture.*

The system that collects shooting data consists of two main modules: the firearm (A) that collects data during the shot and the IoT data collection unit (B) mounted on it. This unit provides the system's electrical infrastructure with the ESP32 microcontroller (D), the MPU 6050 sensor (F), and a lithium-ion battery (E). When the user presses the Start button (C), a 4-second time window is initiated. During this period, the ESP32 microcontroller collects data from the sensor module integrated into the firearm at 1 ms intervals, creating a detailed data record of the shooting process. During this process, parameters such as the start and end times of the shot, motion data from the accelerometer and gyroscope sensors, shot count, and angular velocity are measured accurately. Once the time period is completed, the collected data is processed and securely transferred to the central server or cloud system via wireless communication (MQTT) (V) technology. This enables the movement data at the moment of the shot to be analyzed quickly and reliably.

B. 2. Shooting Data Acquisition Module

The target system has a structure that includes the evaluation of shots and a feedback mechanism. The system consists of key components such as the target board (M), a physical platform that analyzes shooting accuracy, and the servo motor (N), which performs specific movements after a shot. The servo motor is used to return the target board to its starting position after the shot is completed, providing feedback such as "Successful Shot" in case of a successful shot, and evaluating the shooter's performance. The ESP32 Microcontroller (O), which takes control of the system, manages the movements of the servo motor while transmitting the collected data to the central server via the MQTT protocol. Additionally, the necessary energy for the system's portability and independent operation is provided by the Lithium-Ion Battery (E).

B. 3. Biometric Data Collection System

The user biometric data collection system consists of a structure aimed at recording the shooter’s physiological and motion data to correlate with shooting performance. The Android application (P) receives the biometric data obtained from the user's smartwatch (S) and transmits it to the central server via the MQTT protocol. The smartwatch measures critical biometric parameters such as heart rate (HR) (Q) during the shot, analyzing the user's physical and mental condition. These data are correlated with shooting performance, enabling comprehensive evaluations.

B. 4. Data Processing and Visualization Platform

The data collected by the system is analyzed through the data collection and visualization system, providing meaningful feedback to users. This process involves the centralized collection, processing, storage, and visualization of the data. The MQTT server functions as a central communication point by collecting data from the firearm, smartwatch, and target board. The Mosquitto Broker (H), operating with the MQTT protocol, directs incoming messages to the relevant clients, organizing the data flow. The collected data is processed via Node-RED (I), converted into appropriate formats, and integrated with other system components. For long-term storage and detailed analysis of the data, the InfluxDB database (J) is used, where shooting data is stored in a time-series format, allowing for analytical investigations. Finally, the Grafana (L) platform visualizes the data stored in InfluxDB, providing dynamic charts and detailed reports through which users can assess their shooting performance. Through this structure, the data is not only collected but also systematically analyzed, making significant contributions to user performance evaluations and system optimization processes.

B. 5. System Communication Architecture

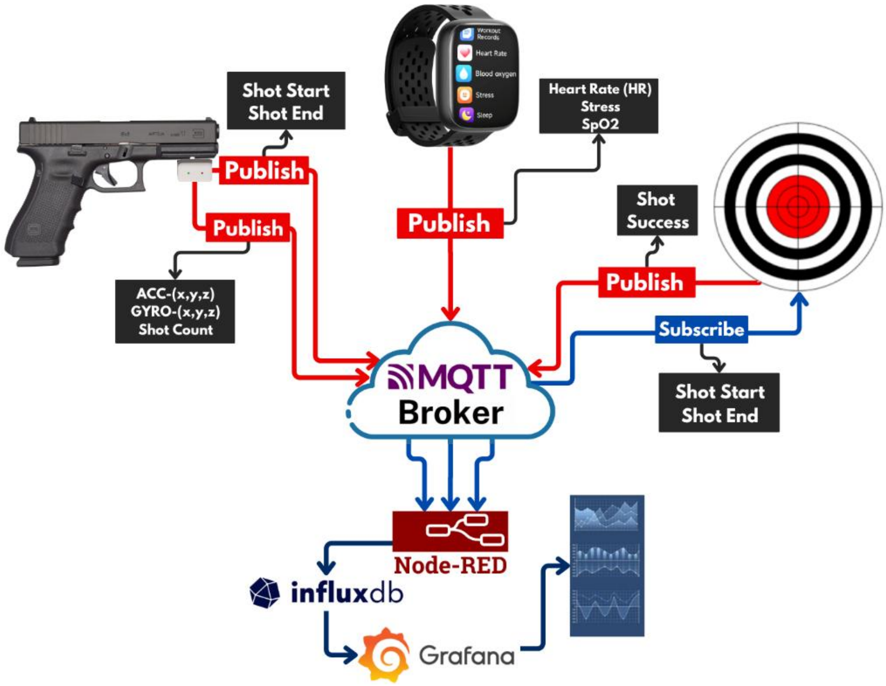

Figure 2. *Multi-Component Shooting Analysis System Communication Architecture.*

Figure 2 illustrates the data flow diagram of the shooting data collection and analysis system. The MQTT Broker serves as the central communication layer, managing the data flow between the firearm, smartwatch, and target system. The sensors on the firearm transmit the collected data to the MQTT Broker using the Publish method. Similarly, the smartwatch collects its data and transmits it via the same method. The target system uses the Subscribe method to receive shot start and end information, while it sends feedback data, such as the success of the shot, to the MQTT Broker using the Publish method, sharing it with the relevant components. This structure ensures that the data flow is managed in a reliable and efficient manner in both directions.

All data transmitted to the system is processed by the Node-RED platform and converted into appropriate formats for different data types, then integrated into the central database. InfluxDB, as a time-series database, stores shooting motion data and biometric measurements chronologically, providing a structured data repository for long-term analyses. During the data visualization process, the Grafana platform is used to present the data stored in InfluxDB in the form of dynamic charts, time-series analyses, and interactive dashboards. In this way, while the data flow between system components is ensured in real-time, comprehensive analyses of shooting performance and biometric feedback processes are optimized.

IV. DATA ANALYSIS AND MACHINE LEARNING

In this section, the time-dependent variation of sensor data obtained during shooting is examined, analyzing how the accelerometer and gyroscope sensors reflect the dynamics of the firearm's movement and how the biometric sensors influence changes in the shooter's physiological condition. The analysis evaluates the relationships between the firearm's recoil, rotation, and linear movements, and the shooter's heart rate. In this way, the mechanical and biological effects occurring at the moment of the shot are considered from a holistic perspective. The findings obtained are presented below, accompanied by visualized graphs.

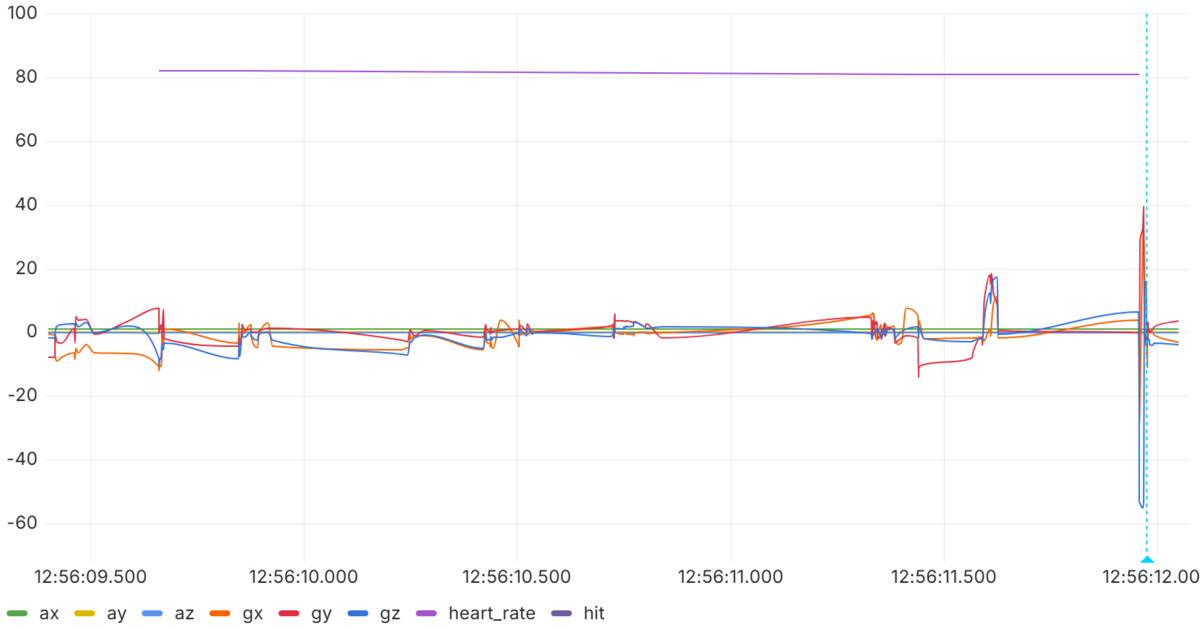

Figure 3. *General Variation of Sensor Data During Firearm Shooting*

Figure 3 presents a comprehensive time-series visualization of data collected from multiple sensors during a firearm discharge. The graph includes data from the accelerometer (ax, ay, az – representing linear acceleration along the X, Y, and Z axes) and the gyroscope (gx, gy, gz – representing angular velocity along the X, Y, and Z axes). Additionally, physiological data derived from a biometric sensor monitoring the shooter's state (heart_rate) is also displayed.

At the moment of firing, specifically at 12:56:12, a significant increase is observed in the gyroscope readings. The peak detected in the gy axis indicates a sudden rotational motion of the firearm, which may have contributed to a loss of control during the shot. Similarly, the accelerometer data reveals a sharp rise in the ay value, suggesting a concentration of linear motion dynamics along the Y-axis. This indicates that the recoil force was predominantly exerted in this direction. The variations in the ax and az axes reflect the vibrations and the reactive forces generated during the shot.

Biometric data are also visually represented on the graph. The shot accuracy is evaluated through a target-integrated sensor system, and its output is illustrated with a turquoise dashed line, indicating whether the shot was successful. These multimodal sensor data, when analyzed through the visualizations, provide a multidimensional perspective on the shooter's performance.

In the subsequent phases of the study, the collected data were subjected to various analytical methods. A feature importance map was generated, and predictive modeling was conducted using machine learning algorithms. Data preprocessing included feature engineering, model development, correlation analysis, and descriptive statistical analysis.

The dataset, composed of sensor data streams, was statistically characterized to identify the fundamental attributes of each variable. The variables examined included accelerometer readings (ax, ay, az), gyroscope data (gx, gy, gz), and biometric signals (heart_rate). All variables were normalized using Z-score normalization, and the standardized dataset was used for analysis, the summary of which is presented in Table 2.

Table 2. *Descriptive Statistical Results of the Dataset*

	ax_z	ay_z	az_z	gx_z	gy_z	gz_z	heart_rate_z	hit
count	2000	2000	2000	2000	2000	2000	2000	2000
mean	2.47E-16	-2.42E-17	0	-4.9E-18	-1.1E-17	-3.2E-18	4.49E-15	0.5
std	1	1	1	1	1	1	1	0.5
min	-13.214	-1.41E+01	-10.55	-9.710	-13.542	-12.550	-4.269	0
0,25	0.028	-3.53E-02	-0.12	-0.124	-0.097	-0.063	-0.541	0
0,5	0.080	1.68E-02	-0.04	-0.009	-0.013	-0.002	0.083	0.5
0,75	0.120	6.51E-02	0.04	0.094	0.069	0.061	0.5	1
max	10.625	10.019	9.50	14.031	9.776	14.749	6.036	1

The accelerometer components ax_z, ay_z, and az_z represent motion along the X, Y, and Z axes, respectively. These variables have been transformed to standard normal distribution, resulting in mean values very close to zero and standard deviations of 1.0. However, when considering minimum and maximum values, it is evident that the signals exhibit significant fluctuations at certain time points. For instance, the ax_z variable has a minimum value of -13.21 and a maximum of +10.62, indicating the occurrence of sudden and rapid changes in acceleration due to the user's arm movements during shooting.

Similarly, the gyroscopic variables gx_z, gy_z, and gz_z were also standardized, yet the wide variation inherent in the raw data has been preserved. Notably, gx_z exhibits extreme values ranging from -9.71 to +14.03, reflecting significant rotational dynamics of the weapon during the firing moment.

The most remarkable component of the dataset is the heart rate (heart_rate_z). While it has been normalized to a mean of zero and a standard deviation of one, its minimum and maximum values are -4.28 and +6.04, respectively. This distribution implies a high level of physiological or emotional response during shooting, pointing to significant variations in stress levels, which may directly impact shooting accuracy.

Although the heart rate variable exhibits lower variance compared to motion-based variables, it plays a decisive role in classification performance. This suggests that the user’s psychophysiological state—such as stress and heart rate—has a direct influence on shot success, while accelerometer and gyroscope data serve as complementary, yet secondary, sources of predictive information. This analysis highlights that shooting performance is not solely determined by mechanical or physical motion, but is also significantly affected by emotional and biological factors. The findings contribute both to human-computer interaction (HCI) literature and to the development of affective decision support systems.
To determine which variables play a more critical role in the decision-making mechanism for predicting shot success based on sensor data, a feature importance analysis was conducted using the Random Forest model—a widely used, interpretable classification algorithm.

Random Forest is an ensemble learning method rooted in statistical learning theory, consisting of multiple decision trees [19]. It builds each tree by randomly sampling the training data (bootstrap sampling) and constructs independent decision trees on each subset [20]. Final predictions are made using majority voting (for classification) or averaging (for regression). This method enhances generalization performance by preventing overfitting [21]. Additionally, Random Forest is capable of capturing complex interactions between variables and can compute feature importance scores, typically based on metrics such as Gini gain or information gain [22].

As illustrated in Figure 4, feature importance scores were calculated based on the frequency and decisiveness with which each variable was used in the decision trees. The results yielded one of the most significant findings of this study: the heart rate (heart_rate_z) variable was ranked first, with an importance score of 28%, indicating that psychophysiological response is a critical predictor of shooting performance.

In contrast, motion-based variables—accelerometer (a* variables) and gyroscope (g* variables) contributed with importance levels ranging between 6% and 23%. For instance, the gy variable accounted for only 9% of the importance. This supports the conclusion that while hand, arm, and wrist movements provide supporting input to the classification process, the most decisive factor is the internal physiological state of the user.

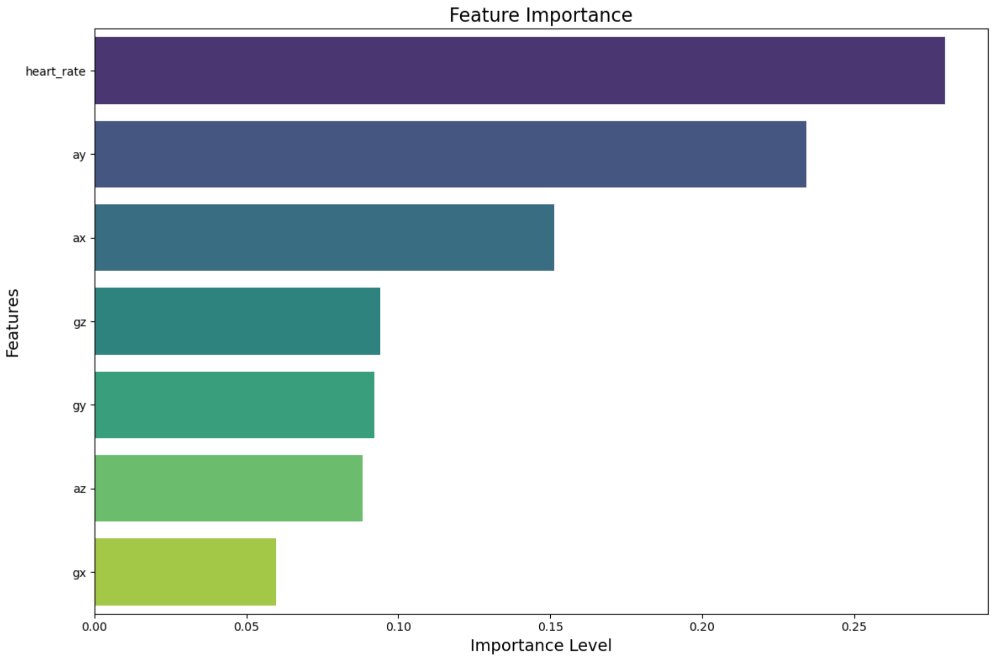

Figure 4. *Feature Importance Scores of Sensor Variables.*

The results obtained demonstrate that the Random Forest algorithm provides high performance in both accuracy and interpretability, attributed to its strong modeling capacity. This analysis indicates that shooting accuracy is not solely determined by motor skills, but is also closely linked to intrinsic physiological and psychological parameters.

Following this stage, the study proceeded with the development of predictive models using SVM and Logistic Regression (LR). These models were selected over more computationally intensive alternatives due to the requirement that the final system be operable on resource-constrained edge computing devices.

As summarized in Table 3, hyperparameter tuning for both SVM and LR models was performed using GridSearch and 5-fold cross-validation. For the SVM model, the optimal parameters were identified as: cost parameter (C) set to 100, gamma set to 'auto', and the kernel type as Radial Basis Function (RBF). These choices allowed the model to construct flexible non-linear decision boundaries, which are suitable for handling complex patterns in the biometric and motion sensor data. In contrast, the LR model used a maximum iteration value of 1000 to ensure convergence during training, especially given the potential multicollinearity in the feature space. The consistent use of 5-fold cross-validation for both models ensured a reliable performance estimation while mitigating overfitting. These hyperparameter configurations played a crucial role in balancing model complexity and generalization performance.

Table 3. *Hyperparameters Optimized via GridSearch and K-Fold Cross-Validation Values Used in Machine Learning Algorithms*

Algorithm		**P1**	**P2**	**P3**	**P4**
SVM	Parameter	K-fold	C	Gamma	Kernel
	Value	5	100	auto	Rbf
LR	Parameter	K-fold	maxiter		
	Value	5	1000		

SVM are a powerful machine learning algorithm used to construct linear or non-linear decision boundaries in classification problems, with the primary goal of determining the hyperplane that best separates two classes by maximizing the margin between them [23]. SVM was developed based on Statistical Learning Theory by Vapnik and colleagues [24], SVM utilizes support vectors for optimal separation and incorporates kernel functions to handle non-linear cases by mapping data into a higher-dimensional space [25].Commonly used kernel functions such as the Radial Basis Function (RBF) and Polynomial kernels enhance SVM's flexibility [26], making it highly effective across various applications in engineering, bioinformatics, and other domains [27], and suitable for tasks like classification, regression, and clustering [28].

Table 4. *Classification Report of the SVM Model*

	precision	**recall**	**f1-score**	**support**
0	0.80	0.71	0.75	324
1	0.70	0.79	0.74	276
accuracy			0.74	600
macro avg	0.75	0.75	0.74	600
weighted avg	0.75	0.74	0.74	600

As shown in Table 4, the SVM model, implemented using the Radial Basis Function (RBF) kernel, achieved an overall accuracy of 74%, indicating a reasonable classification performance. The model showed a slightly better precision for the non-hit class (0.80 for hit = 0) compared to the hit class (0.70 for hit = 1), whereas the recall was higher for the hit class (0.79) than for the non-hit class (0.71). This indicates that the model is more likely to correctly identify hit cases when they occur (high recall), but it tends to misclassify some non-hit cases as hits (lower precision). The F1-scores for both classes are balanced (0.74–0.75), suggesting that the classifier maintains a consistent trade-off between precision and recall. The macro and weighted averages being nearly identical also reflect a balanced performance across the two classes without significant bias toward any particular outcome. These results suggest that while the model is effective, future enhancements could involve more complex features or ensemble approaches to improve discriminatory power.

The presence of non-linear relationships between physiological signals and accelerometer/gyroscope data appears to limit the maximum performance achievable with the RBF kernel. The confusion matrix and the ROC curve associated with the model are presented in Figure 5 and Figure 6, respectively. Subsequently, a LR model was also evaluated.

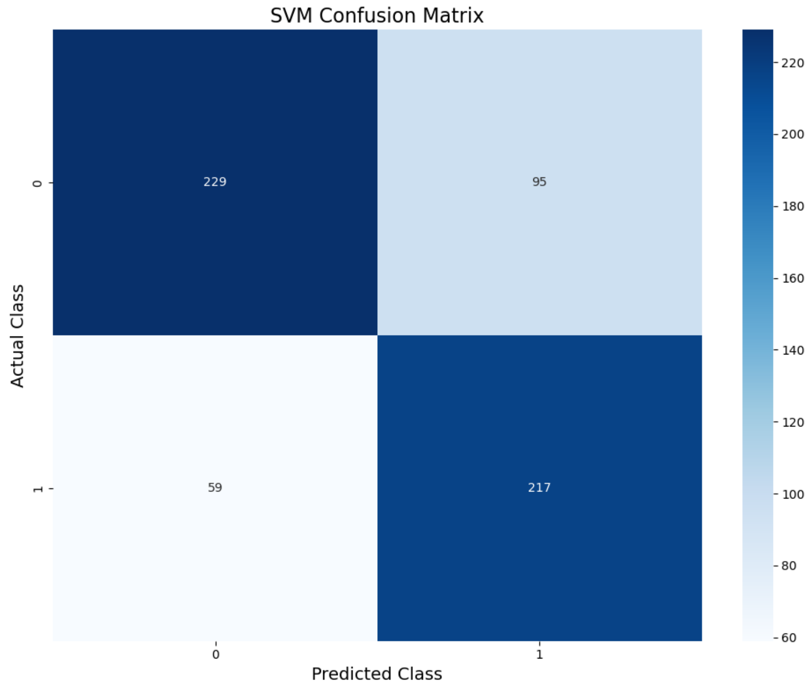

Figure 5. *Confusion Matrix for the SVM Model*

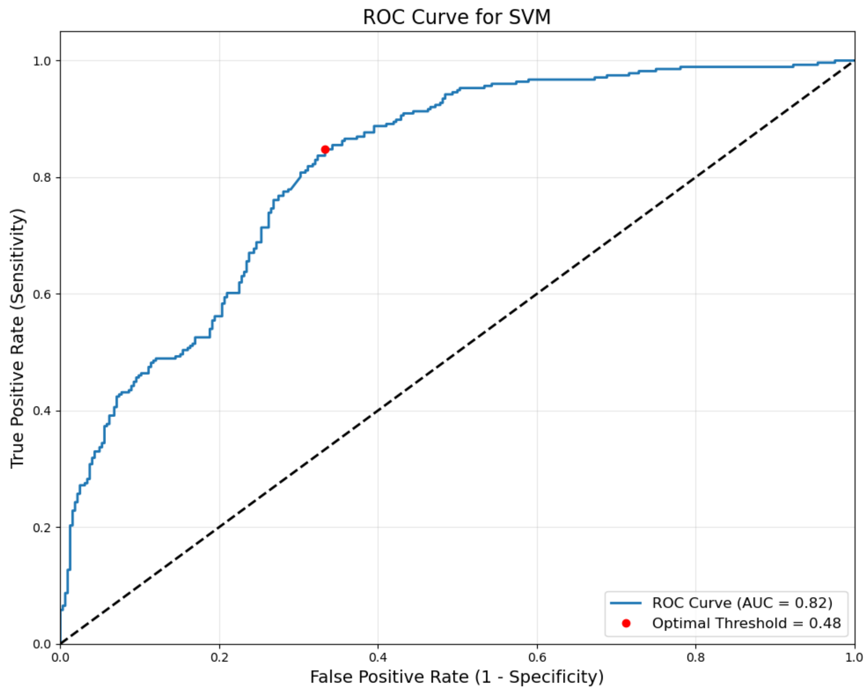

Figure 6. *ROC Curve for the SVM Model*

LR is a classical classification algorithm that estimates the probability of class membership using the logistic (sigmoid) function, which maps outputs to a range between 0 and 1 for probability-based decisions [29]. It constructs a linear decision boundary and can be enhanced with regularization techniques to handle high-dimensional datasets effectively [30]. Its main advantages lie in its interpretability, computational efficiency, and wide applicability across domains [31].

As presented in Table 5, the LR model yielded a classification accuracy of 54%, indicating poor overall performance. Notably, the model failed to identify any instances of the hit = 1 class, with both precision and recall values equal to 0. In contrast, the model perfectly recalled all instances of the hit = 0 class (recall = 1.00), but with a modest precision of 0.54, leading to an F1-score of 0.70 for this class. The macro-averaged F1-score was only 0.35, highlighting a significant class imbalance in predictive capability. These findings suggest that the linear decision boundaries of LR are insufficient to capture the complex patterns in the dataset, particularly for the hit = 1 class.

Table 5. *Classification Report for the LR Model*

	precision	**recall**	**f1-score**	**support**
0	0.54	1	0.70	324
1	0	0	0	276
accuracy			0.54	600
macro avg	0.27	0.50	0.35	600
weighted avg	0.29	0.54	0.38	600

Considering these outcomes, the performance of both the SVM and LR models appears to be limited. This suggests that the features within the dataset exhibit non-linear and interactive structures, which can only be effectively captured by more flexible models. The confusion matrix and ROC curve for the LR model are presented in Figure 7 and Figure 8, respectively.

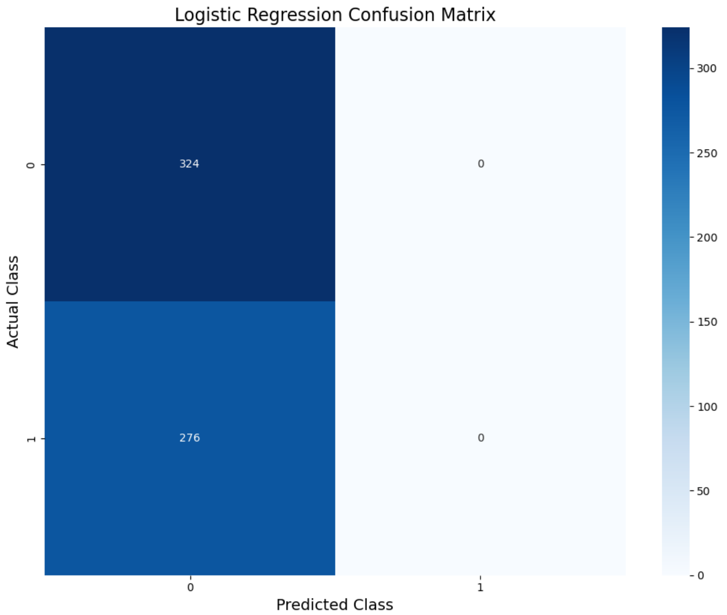

Figure 7. *Confusion Matrix for the LR Model*

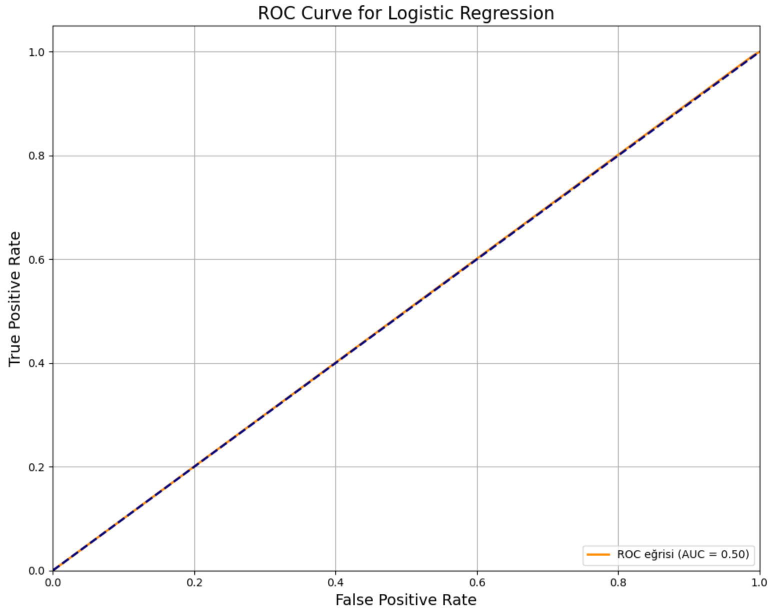

Figure 8. *ROC Curve for the LR Model*

V. CONCLUSION AND SUGGESTIONS

A. LIMITATIONS OF THE STUDY

Although the data collection and transmission processes were handled separately in this study, the use of higher-quality sensors and microcontrollers during the data acquisition phase could minimize potential data losses. In particular, replacing the heart rate sensor embedded in a smartwatch with a more sensitive and reliable sensor is expected to improve the accuracy and stability of the collected data.

Furthermore, it has been observed that an alternative design could be developed to reduce the impact of recoil during firing on the data collection nodes placed on both the target and the weapon. Such a design would enhance the stability and reliability of the sensor data. It is also anticipated that collecting a broader dataset from diverse users would increase the variability of the dataset and improve the generalizability of the developed system.

B. CONCLUSION

This study proposes an innovative system architecture that supports instructors' decision-making processes in shooting training through a data-driven approach. The developed instructor-based decision support system enables more scientific and precise analysis at every stage of shooting training by integrating sensor data and biometric measurements.

The proposed system provides real-time visualization of both the movement dynamics during shooting and the shooter's physiological responses, allowing instructors to perform more detailed assessments. In this way, instructors can evaluate not only the shooter's hit rates, but also critical performance factors such as breath control, hand tremor, and stress level, enabling more informed feedback. Moreover, thanks to automated target analysis and visualization techniques, errors can be detected immediately, thereby accelerating the training process and enabling the development of personalized improvement strategies.

The system not only enhances shooting accuracy, but also improves the efficiency of training processes while reducing costs. In the future, this infrastructure can be further enhanced through AI-powered data analysis, providing an innovative transformation in shooting training. This would offer a more effective, efficient, and scientifically grounded learning experience for both instructors and shooters.

Compared to existing models in the literature, the proposed machine learning approach exhibits enhanced predictive performance, primarily due to the integration of biometric data. Notably, incorporating heart rate as a key feature significantly boosted the model's accuracy, highlighting the value of a multimodal data fusion strategy—an aspect that has received limited attention in prior studies.

In addition, the developed machine learning model can predict shooting success in advance, allowing training programs to be optimized accordingly. Finally, considering the influence of heart rate on shooting performance, it can be concluded that this study offers a novel perspective on marksmanship training.

Despite offering valuable initial insights, this study is subject to certain limitations inherent in its proof-of-concept design. The participant pool was small, and although testing was conducted in a real shooting range, all participants had only basic training. This limits the extent to which the findings can be generalized to broader or more diverse populations. To enhance the validity and applicability of the proposed system, future research should incorporate larger sample sizes and more heterogeneous participant profiles.

Article Information

Acknowledgments: The authors would like to express their sincere thanks to the editor and the anonymous reviewers for their helpful comments and suggestions. This research was not supported by any external funding.

A patent application has been filed for the method presented in this study (Application No: 2025/009525, Filing Date: 11.07.2025).

Author's Contributions: The author was solely responsible for the conceptualization, methodology, data curation, formal analysis, writing (original draft and revisions), and final approval of the manuscript.

Artificial Intelligence Statement: The language of this article was reviewed using artificial intelligence technologies to enhance clarity and coherence.

Conflict of Interest Disclosure: No potential conflict of interest was declared by authors.

Plagiarism Statement: This article was scanned by the plagiarism program.

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