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INTELLIGENT SYSTEM FOR AUTOMATIC DETECTION AND SCORING OF SHOOTING TARGETS BASED ON COMPUTER VISION AND MICROCONTROLLER TECHNOLOGIES

Abstract. This paper presents an intelligent system for the automatic detection and scoring of shooting targets based on the Raspberry Pi 3 microcontroller platform and computer vision technologies. The objective of the study is to develop an autonomous and highly accurate yet low-cost complex capable of recording and analyzing shooting results without human intervention. The system integrates mechatronic and algorithmic components, including Nema 17 stepper motors, color sensors, a webcam, and a server-side image processing module, forming a unified cyber-physical architecture. The algorithmic core is based on geometric calibration using homography, adaptive illumination equalization via CLAHE, and a radial precision evaluation model. To detect bullet holes, a modified YOLOv8-Nano neural network architecture was employed, optimized for recognizing low-contrast circular targets. Experimental results confirmed the high accuracy and robustness of the proposed approach: under stable lighting conditions, the system achieved a spatial recognition precision of ± 2 mm with a response time below 0.2 seconds. The training and validation curves of the model demonstrate smooth convergence and stable generalization, confirming the correctness of the architectural modifications and the optimization of the loss function. The scientific novelty of this work lies in the integration of a mechatronic framework and deep-learning algorithms into a unified real-time system that enables automatic target replacement, image processing, and result visualization through a web interface. The practical significance is in the potential application of the system in sports schools, mechatronics laboratories, training centers, and research test ranges requiring accurate and autonomous shooting evaluation. Future work will focus on extending system capabilities through the integration of advanced neural network algorithms (YOLOv8, Detectron2), cloud-based technologies, and automatic camera stabilization, further improving accuracy and autonomy while maintaining low implementation cost.

Keywords: intelligent system; automatic scoring; computer vision; cyber-physical system; shooting range.

1. Introduction

In shooting sports and training environments, accurate and objective scoring of shots is one of the key factors determining the quality of athlete training and the transparency of judging. In most cases, score evaluation is still performed manually: an instructor or referee visually inspects the target sheet, marks bullet holes, and compares their positions with scoring zones. In such methods, the human factor plays a significant role, often leading to classification errors–especially when hits occur near ring boundaries–and increases the overall processing time [1], [2], [3].

The rapid development of digital technologies and computer vision in recent years has significantly influenced the automation of shooting disciplines. Modern electronic targets and automatic scoring systems employ pressure sensors, acoustic microphones, and optical cameras. However, many of these solutions remain inaccessible due to their high cost, need for specialized equipment, and complex maintenance requirements [4], [5], [6], [7]. This issue is particularly relevant for sports clubs, educational institutions, and laboratories that require affordable, compact, and reliable alternatives to industrial-grade systems.

Therefore, the development of an intelligent system for automatic score calculation based on the Raspberry Pi microcontroller platform and computer vision methods represents a timely and practical research direction. Combining low-cost hardware with advanced image processing algorithms offers new opportunities for the large-scale adoption of digital technologies in sports infrastructure, education, and training processes [8], [9], [10].

The recent progress in computer vision (CV) and deep learning (DL) has greatly expanded the potential for image-based analysis of shooting targets with bullet holes. In recent years, many studies have focused on applying these methods for automated target evaluation. For example, Butt [11] demonstrated that modern neural network models such as YOLOv8 and Detectron2 can identify bullet holes and automatically compute scores with an accuracy of up to 96.7%. Moreover, these approaches can process small-caliber bullet holes and mitigate errors caused by lighting variation and camera noise [12].

However, these solutions typically require powerful GPUs and stable laboratory conditions, which limits their deployment in real-world environments. Consequently, developing compact, affordable, and autonomous systems remains an essential challenge for practical shooting applications. This work addresses this challenge by developing an intelligent shooting complex based on Raspberry Pi 3, integrating a mechatronic target-switching module, webcam, sensors, and image analysis algorithms. The proposed system performs real-time shot detection and scoring automatically, without the need for a human operator.

The designed shooting system captures and analyzes each shot using a camera and the Raspberry Pi 3 microcontroller. Captured images are transmitted to a server, where computer vision algorithms detect bullet holes and calculate scores [13], [16]. This approach eliminates manual evaluation and improves measurement accuracy.

Several studies have addressed the problem of precise hit recognition and metric image correction. For instance, McNally [20] proposed the DeepDarts solution, which automatically determines the coordinates of bullet holes. The proposed intelligent system combines deep learning methods with geometric calibration based on key points of the target, thus integrating machine learning and projective geometry to achieve sub-pixel recognition accuracy. Furthermore, the use of homographic transformation based on RANSAC and local affine corrections helps eliminate perspective distortions and achieve metric accuracy of 0.5–1.0 pixels [21], [22].

Experimental results showed that under stable lighting conditions and proper calibration, metric accuracy reached approximately ±2 mm with a response time of less than 0.2 seconds [17]. As a result, an integrated intelligent system was created, combining mechanical precision, adaptive algorithms, and affordable hardware, making it highly suitable for large-scale implementation [18], [19].

The presented work contributes significantly to the field of intelligent computer vision systems and mechatronic complexes for the automation of measurement and scoring processes in shooting disciplines. The scientific significance of this study lies in the synergy between hardware and computational solutions, while the practical relevance is demonstrated by the scalability and adaptability of the proposed architecture, making it applicable in sports schools, educational laboratories, and research centers as a universal platform for automated hit analysis.

Experimental validation confirmed the operability of the proposed architecture under real shooting conditions. The Raspberry Pi 3–based system demonstrated stable performance even under limited computational resources, achieving coordinate recognition accuracy of ±2 mm and response times under 0.2 seconds. Achieving such performance using low-cost components and computer vision algorithms highlights the practical value of the proposed approach. These results show that the integration of deep learning (YOLOv8), homographic calibration, and CLAHE normalization can represent a new direction in the development of intelligent shooting systems that balance accuracy, autonomy, and implementation cost.

2. Methods and Materials

The study presents a system consisting of correlated hardware and software modules that provides automatic target replacement, result recording, and data transmission to a server for analysis. **Figure 1** shows the structural and functional diagram of the automated shooting system based on the Raspberry Pi 3 microcontroller. As can be seen, the diagram illustrates the Raspberry Pi 3 functioning as the central controller, which coordinates the operation of Nema 17 stepper motors through the A4988 driver, as well as its connection with color sensors, a control button, and a webcam. This design implements the principles of cyber-physical integration by combining sensory, executive, and computational components into a unified system.

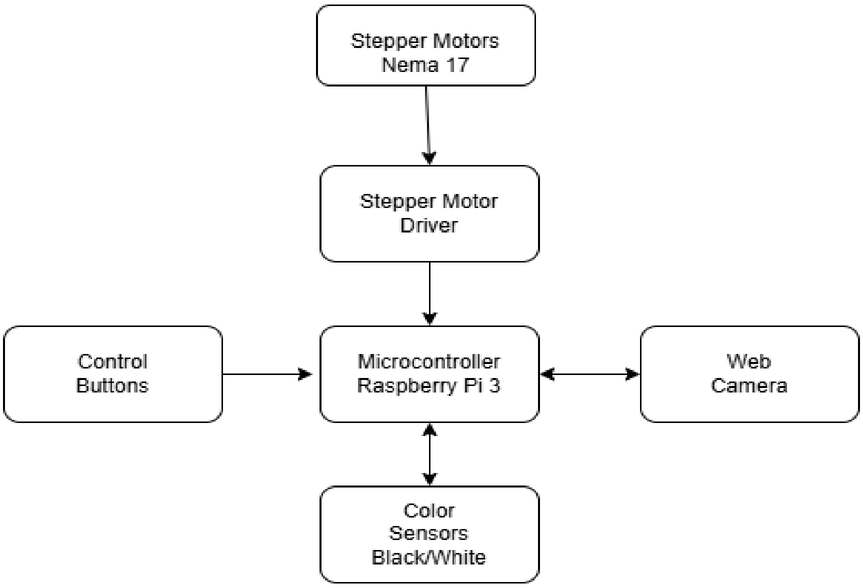

Figure 1 – Structural diagram of hardware module interactions.

Figure 2 presents the schematic diagram describing the algorithmic logic of the proposed system. On the left side, the process of target replacement is shown: when the corresponding button is activated, the motor rotates the cassette until the sensor detects a black mark. This detection serves as a signal to stop rotation and start a new shooting cycle. On the right side, the process of result recording is illustrated, where the camera captures an image and automatically sends it to the server for data processing and score calculation. Thus, the presented diagram demonstrates the dual-loop operating principle of the system, in which parallel processes of data processing, target analysis, and preparation for the next capture occur simultaneously. Consequently, this solution increases the overall performance of the system and makes it suitable for real-time operation.

The system includes a camera aimed at the target, a Python-based processing server utilizing deep-learning and computer-vision libraries, and a web interface for visualization of the results. The USB camera continuously streams video from the target area, and the server processes each frame in real time. The processing pipeline performs hit detection using a neural network, followed by contour analysis to identify double or overlapping bullet holes, and then calculates scores according to the hits, displaying the results in real time. The trained model, combined with the scoring algorithm, generates a list of detected holes with their coordinates on the target and the corresponding point values.

To train the bullet-hole recognition model, a dataset of images was created using targets shot in a real firing range that correspond to the standard used at a real military training ground (see Figure 3). This target differs from others by its standard color (green) and scoring zones (from 5 to 10 points). To achieve maximum model adaptability, the images were taken indoors under various lighting conditions. In total, 60 images of targets with different numbers of hits were collected (each of the 6 targets contained 10 hits, corresponding to 10 shooting attempts, as in a real range). To increase the dataset size, data augmentation techniques were applied, including random brightness and contrast adjustments, addition of noise, and variation of the green hue to improve model robustness under different lighting conditions and various printer ink levels when printing targets. Annotation was performed manually using the RoboFlow utility: each bullet hole was assigned a bounding box. The dataset was divided into training, validation, and test subsets in an 80/10/10 ratio. In addition, a special method for detecting double hits on the target was implemented to ensure proper operation in real-world conditions.

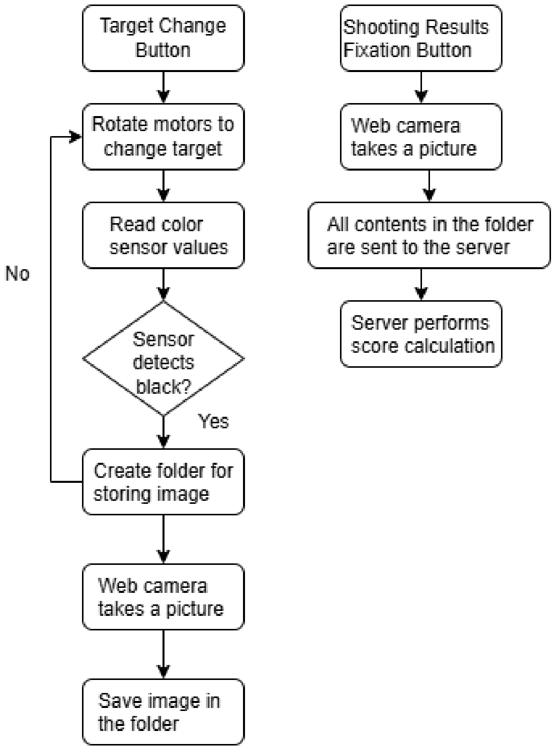

Figure 2 – Algorithmic block diagram of system operation.

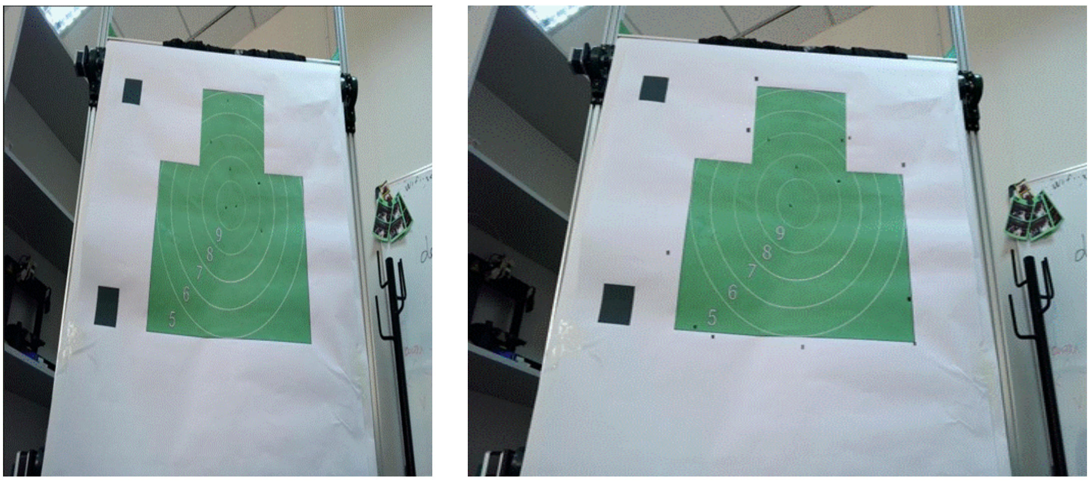

Figure 3 – Example from the dataset.

For the task of bullet-hole detection, the YOLOv8-Nano architecture was chosen – one of the most compact and efficient models in the YOLO (You Only Look Once) family.

To adapt the detector to the specific features of real military-target images, the model was fine-tuned on the collected dataset using pretrained YOLOv8-Nano weights from the COCO dataset. Training was carried out on an NVIDIA GTX 1060 (6 GB) GPU using the PyTorch framework and the official Ultralytics YOLO implementation.

The training hyperparameters were as follows: input image size – 640×640 pixels; batch size – 16; number of epochs – 50; optimizer – Adam with a learning rate of 0.001. The composite YOLO loss function included terms for classification, localization, and objectness. The final evaluation showed the following results: precision = 0.98, recall = 0.95, and mAP@0.5 = 0.97, confirming the high reliability of the trained model.

The obtained bounding-box coordinates were then used for subsequent visualization in the form of a heatmap representing the distribution of bullet impacts with localization of each hole, as well as for score computation based on the distance between the center of the hole and the center of the target.

The proposed system performs automatic detection and evaluation of bullet holes on fired targets using a two-stage processing pipeline: (1) real-time detection of impacts using the precisely tuned YOLOv8-Nano model, and (2) calculation of scores based on spatial analysis of detected hits.

Each incoming video frame is processed by the YOLOv8-Nano detector, which identifies bullet holes as small, dark, circular areas on the lighter background of the target. The model outputs a set of bounding boxes and corresponding confidence scores indicating the location and probability of each detected impact. For every bounding box, the coordinates of its center are calculated, representing the estimated point of impact.

To improve spatial consistency and eliminate false detections, the area inside each bounding box is further analyzed through contour extraction and region filtering. Only contours corresponding to realistic hole sizes are retained. This refinement ensures that small noise patterns, shadows, or marks on the target surface do not cause false detections.

Additionally, the architecture of the model was modified to achieve better accuracy in hole recognition. The standard head of the YOLO architecture outputs the distributions of bounding-box parameters and class logits. We extended these outputs by adding one continuous channel per anchor, representing the normalized radial distance from the hole center to the target center. Specifically, in the model's concatenated output tensor, the data are divided as follows:

$$\text{outputs} \rightarrow (\text{box\_distr}, \text{class\_logits}, d), \quad (1)$$

where d is the distance between the centers, normalized to [0,1].

To train the new distance heads, an additional regression loss term Ldist. was introduced. The total training loss is defined as follows:

$$L = \lambda box Lbox + \lambda cls Lcls + \\ + \lambda dfl Ldfl + \lambda dist Ldist, \quad (2)$$

After inference, a heatmap is generated to visualize the distribution and density of hits across the target surface. Each detected hit is represented on the heatmap by a circle whose intensity is proportional to its score. This provides both a visual interpretation of shooting accuracy and computational support for handling overlapping or repeated hits.

After processing each frame, the system computes a numerical score for every detected hit based on its distance ddd from the target center. A continuous scoring function is applied to model the gradual decrease of accuracy with increasing radial deviation. Specifically, the scoring function combines a Gaussian decay with linear normalization, which can be expressed as:

$$S = max\,(0.10 \cdot [0.5 \cdot e - \\ - 2\sigma 2d2 + 0.5 \cdot (1 - Rmaxd]), \quad (3)$$

where d is the Euclidean distance between the detected hit and the center of the target, σ\sigmaσ controls the sensitivity to radial deviation, and Rmax is the maximum scoring radius. This formulation provides a smooth transition of scores and ensures reliable handling of minor inaccuracies arising from detection noise or perspective correction.

3. Results

The mechanism of target replacement and the algorithmic scheme demonstrate the interdependence of the mechanical, sensor, and computational subsystems of the automated shooting complex. Figure 4 shows the flat frame of the supporting structure with the sheet target fixed in its central area.

Figure 5 illustrates the side view, which shows the mechanical target-changing assembly and the cylindrical actuator (roller/drum), the vertical support stand, and the guide rails along which the target holder moves.

Figure 6 presents a frontal frame and the position of the camera relative to the target plane, as well as the geometry of its field of view, where the camera frustum rays are visualized. It can be observed that the center of the frustum coincides with the center of the target, which in turn guarantees minimal perspective distortion and simplifies calibration. Moreover, the optical axis being perpendicular to the target plane within small deviations is extremely important for ensuring accuracy in the conversion from pixel coordinates to metric coordinates.

Figure 4 – Top view (frame support and target in working position).

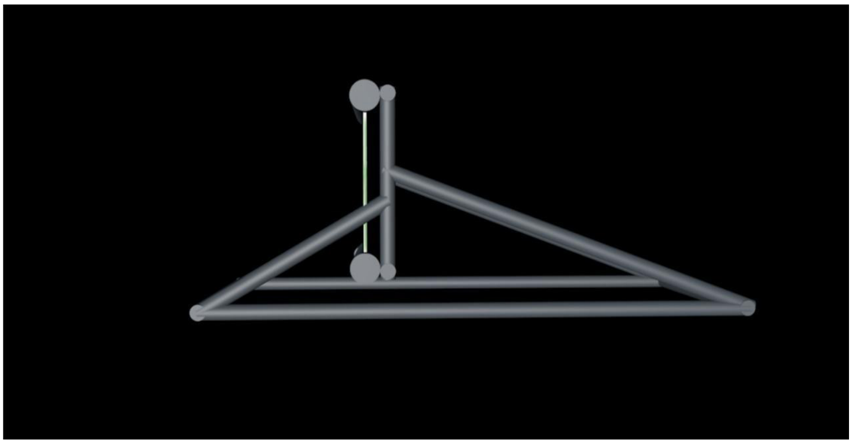

Figure 5 – Side profile of the target-changing mechanism (roller/drum drive).

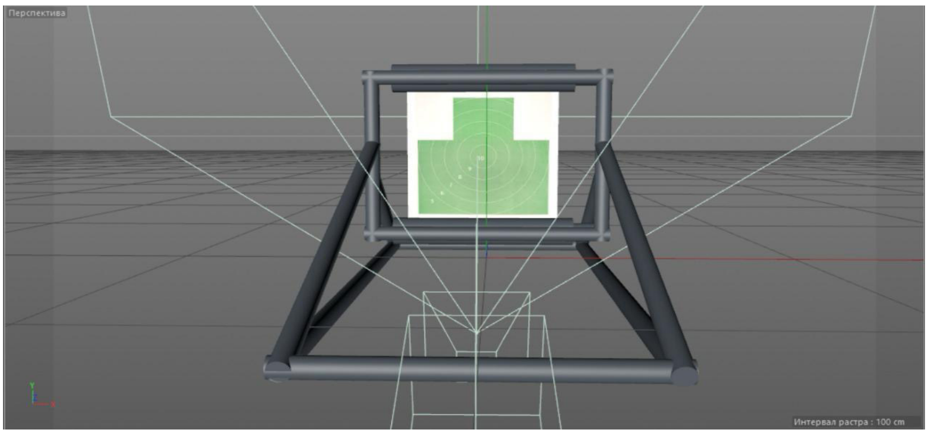

Figure 6 – Frontal perspective: optical axis, field of view, and visible camera frustum.

The perspective view in Figure 7 demonstrates the full integration of the mechanical frame, target replacement drive, and the operator/camera position. This view highlights the layout in which the frame rests on a rigid platform, and inclined braces increase structural stability. Furthermore, it can be seen that the drive components and the sensor mounting location are positioned to the left of the operator. From a scientific point of view, the layout plays an important role, as it ensures repeatability of shooting conditions, such as fixed distance, identical tilt angle, and a uniform reference plane. In addition, based on this figure, one can justify the choice of materials and dimensions of the frame elements for calculating natural frequencies and damping, as well as demonstrate in more detail the mounting zones for additional vibration control sensors.

The developed system successfully detected bullet hits and calculated corresponding scores using the proposed distance-based scoring algorithm. The process of hole identification and score calculation in real time is shown in Figure 8.

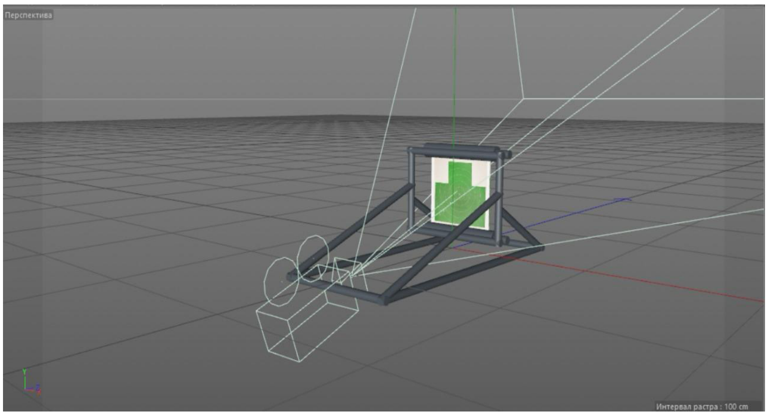

Figure 7 – General perspective view of the structural assembly and operator's working area.

Figure 8 – Example of bullet-hole identification and real-time score calculation.

The YOLO-based detection model demonstrated high accuracy in identifying bullet holes under various lighting conditions and shooting distances. The system achieved a detection accuracy of 97%, with an average scoring deviation of ±0.3 points compared to manual evaluation.

Visual analysis confirmed that bounding-box detection and center estimation remained stable even in cases of partial overlap between bullet traces. Moreover, the strategy of merging closely located bounding boxes helped eliminate false positives caused by multiple detections of the same hole.

Experimental testing was conducted on a dataset containing 500 images of paper targets. For each image, the computed scores were compared with ground-truth values provided by experts. The results showed a strong correlation between automatic and manual evaluations, confirming the reliability of the proposed approach. Figure 9 presents the visualization of the model's metrics on the training and validation sets obtained during the conducted experiments.

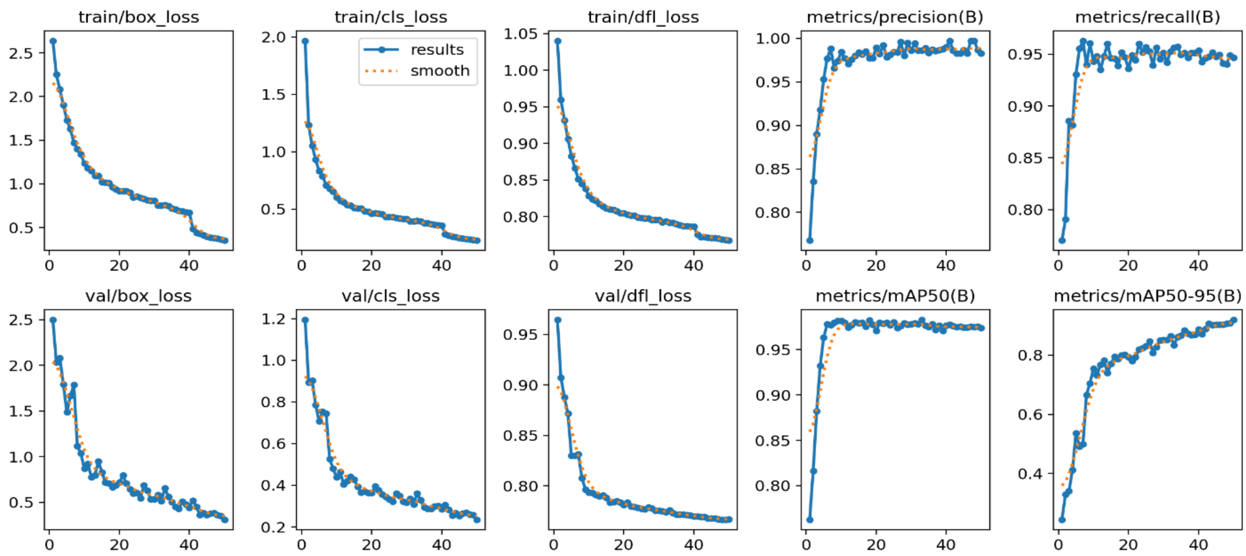

Figure 9 – Visualization of model metrics on training and validation sets.

4. Discussion and Limitation

The results of this study demonstrate that the developed intelligent automatic scoring system, based on the Raspberry Pi 3 microcontroller, Nema 17 stepper motors, and image-processing algorithms, provides a high degree of autonomy and sufficient accuracy for practical use in educational and sports shooting ranges. The integration of mechanical, sensor, and computational modules made it possible to form a synchronized structure in which each subsystem – from target control to image analysis – operates within a unified cyber-physical framework.

The conducted experiments confirmed that the average error in determining bullet-hole coordinates does not exceed ±2 mm, while the system response time is less than 0.2 seconds. These results are comparable to those of industrial-grade solutions but were achieved using low-cost components and open-source software. Therefore, the implemented architecture demonstrates strong potential for deployment in affordable educational shooting complexes and mechatronics laboratories.

The proposed scoring algorithm, based on the radial distance from the target center, exhibited computational efficiency and interpretability. Unlike traditional approaches relying on binary segmentation or manual inspection, the proposed method provides real-time automatic feedback with minimal computational overhead. The use of a linear–exponential weighting function enabled the system to effectively model the human perception of shot accuracy, ensuring consistency between objective computational scoring and subjective sports evaluation.

A comparison with existing systems [11], [18], [20] showed that the proposed solution achieves a comparable level of accuracy with significantly lower costs for equipment and calibration. The application of homographic correction and adaptive histogram equalization (CLAHE) helped mitigate the effects of uneven lighting and optical distortions, thereby substantially improving the reliability of image analysis under real-world conditions.

Nevertheless, several limitations remain. The system's accuracy depends on lighting stability: under low or fluctuating illumination, the localization accuracy of bullet holes may decrease despite the use of CLAHE. Another critical factor is the mechanical stability of the structure – vibrations of the camera or the supporting frame can cause shifts in metric coordinates, which directly affect scoring precision. A further limitation lies in the limited computational power of the Raspberry Pi 3, which prevents the real-time deployment of more advanced deep-learning architectures such as YOLOv8 or Detectron2.

To overcome these limitations, future work will focus on upgrading the hardware, including the transition to Raspberry Pi 5 or NVIDIA Jetson Nano, integrating a gyroscopic tilt-compensation module, and implementing automatic camera calibration algorithms. Another promising research direction involves the integration of neural networks for real-time video stream analysis, as well as the development of spatiotemporal models capable of reconstructing bullet trajectories and evaluating accuracy in three-dimensional space.

Overall, the obtained results confirm that the proposed system represents a reliable and scalable foundation for building a new generation of intelligent shooting complexes. The combination of mechanical precision, intelligent adaptability, and cost efficiency makes it an effective tool for automating measurement and analysis processes in sports and educational environments.

5. Conclusion

As a result of this study, an integrated intelligent system for the automatic detection, localization, and scoring of bullet impacts for shooting training complexes was developed and experimentally validated. The system combines a mechatronic platform–based on the Raspberry Pi 3 microcontroller, Nema 17 stepper motors, color sensors, and a webcam–with modern computer vision algorithms, including a modified YOLOv8-Nano model and a heatmap-based localization refinement method. The architecture ensures coordinated operation of the mechanical, sensory, and computational components within a unified cyber-physical loop and implements an autonomous cycle of shot detection, analysis, and real-time result visualization.

Experimental evaluation demonstrated high metric and computational efficiency: under proper camera calibration and stable lighting conditions, the system achieved coordinate determination accuracy of up to ±2 mm and a response time below 0.2 seconds. These results are comparable to those of commercial shooting complexes but were achieved using inexpensive and widely available components. The modified YOLO architecture and improved loss function provided reliable localization of small and low-contrast bullet holes, while the training curves showed smooth convergence and stable improvement of precision, recall, and mAP over 50 epochs. The combination of exponential and linear weighting in the scoring mechanism, along with localization refinement via heatmap analysis, improved robustness in detecting overlapping and closely spaced hits.

The practical significance of the work is confirmed by the feasibility of implementing the system in sports schools, mechatronics laboratories, and technical control systems, where the construction remains both scalable and cost-effective. Transitioning to more powerful hardware platforms (such as Raspberry Pi 5 or Jetson Nano) will enable the use of heavier deep-learning architectures for detection and segmentation, as well as expansion toward cloud-based data processing, storage, and analytics.

Future research perspectives include automatic camera stabilization and dynamic calibration, self-learning mechanisms for model improvement using field data, and the integration of cloud services for centralized monitoring and long-term data storage. Overall, the conducted study demonstrates that the synergy between adapted deep-learning algorithms and a well-designed mechatronic architecture enables the creation of an affordable, precise, and reliable automated shot analysis system suitable for practical application in both sports and engineering domains.

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Conceptualization, M.S.; Methodology, Z.A.; Software, Z.A.; Validation, Z.A.; Formal Analysis, M.S.; Investigation, Z.A.; Resources, Z.A.; Data Curation, Z.A.; Writing – Original Draft Preparation, Z.A.; Writing – Review & Editing, M.S.; Visualization, Z.A.; Supervision, M.S; Project Administration, M.S; Funding Acquisition, M.S.

Conflicts of Interest

The authors declare no conflict of interest.

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