Journal of Applied Informatics and Computing (JAIC)
Vol.9, No.6, December 2025, pp. 3669~3680
e-ISSN: 2548-6861

Real-Time Arrow Detection and Scoring on Archery Targets Using YOLOv8 with Euclidean Distance-Based Zone Estimation

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Article Info

Article history:

Received 2025-09-08
Revised 2025-10-23
Accepted 2025-11-08

Keyword:

Computer Vision,
Euclidean Distance,
Archery,
CNN,
YOLO v8.

ABSTRACT

The current study aims to create an automated scoring system for archery target board using computer vision technologies. As archery has develop from a traditional practice to a competitive activity, the scoring procedures have become a crucial element. While the current manual scoring procedures are fallible and can be challenging for organizers. This study offers a solution to this issue by using YOLO v8 (You Only Look Once) architecture for real- time arrow recognition and scoring. The development process consists of dataset collecting, picture pre-processing, model training and implementation using 2 photos of the target boards with arrows. The computer processes the scores by calculating the distance from the center of the arrow to the selected scoring zones using Euclidean distance. System testing established a baseline accuracy of 67%. While users noted the system's processing efficiency (speed), this accuracy level highlights significant room for improvement. The results demonstrate the potential for applying computer vision to automate the archery scoring system, while simultaneously emphasizing the critical need for advanced model performance enhancements. This study serves as a preliminary step in exploring automated sport technology, expected to contribute to future refinements of the archery scoring system.

I. INTRODUCTION

Archery, an ancient practice that dates back thousands of years, originally used as a weapon in combat, hunting and warfare across various cultures [1]. This skill has grown from a survival skill into competitive sport which is in the modern practice, this sport adheres to international standards proposed by World Archery Federation (WA or FITA) where archers are required to shoot arrows at targets composed of concentric circles, each with varying point values[2]. In Indonesia, this sport is gaining popularity as the establishments of the Indonesian Archery Association (PERPANI) in 1953 [3][4].

As the archery continues to grow, understanding the factors that contribute to an athlete's success is crucial. Success in archery requires a combination of physical fitness, technical proficiency, mental focus, and tactical awareness [5]. To effectively evaluate an athlete's performance over time, point detectors can be employed, facilitating in-depth comparison and enhancing accuracy and strategy [6],[7]. However, the current manual scoring process can lead to fatigue for the organizers and increase the possibility of errors or inaccuracies [8]. Moreover, direct observation of arrow shots by judges poses a risk of accident and is also subject to bias [9]. At the amateur and junior competition levels, judges and coaches manually record the scores of archers. They use binoculars or approach the target board to accurately verify and document the precise position of the arrows [10].

To address these challenges, the current research aims to develop an automated scoring system that employs computer vision technology to accurately recognize the precise position of arrows and automatically calculate the scores [11]. This system is expected to improve the objectivity of assessments, reduce the risk of accidents, and meet the practical needs of archers and judges in the field.

Previous studies have proposed various approaches to scoring in target sports such as archery and shooting. For instance [12], suggested using image processing for an automatic scoring system in archery. However, the model has limitations including the motion effects of arrows upon impact, which can lead to inaccuracies in detecting arrowhead locations since the testing has been limited to laboratory conditions. The model also relies on high-quality images means that if there is variation in lighting and camera angles can significantly affect the performance. Furthermore, the geometric assumption made about the target shapes may not hold in real-world scenarios which leading to an inaccurate score. Last, the sample size was limited, therefore may not represent diverse archery practice and cause the generalization in the result. In the same vein [13], developed an automatic scoring system for shooting sport. Despite its innovation in scoring the shooting sport, the model has significant limitation such as false positive detection, high image quality requirements, lighting challenges. There is still a margin of error that could affect scoring precision.

Despite these advancement in automatic scoring system for target sports, significant limitation remain that hinder their practical application in real-world archery competition. The previous study mentioned earlier highlight issues in scoring the target sport. Therefore, there is a clear need for further research to develop a more robust and adaptable automatic scoring system that effectively addresses the challenges, ensuring accuracy and reliability in various competition environments. The current study introduces an innovative application of computer vision technology aimed at facilitating automatic and more accurate assessment in archery. It is expected that this system will significantly benefit the development of the sport both in Indonesia and globally.

In conclusion, the development of archery from traditional sport to a competitive modern sport highlights the critical need to adjust to new situations, especially when it comes to scoring. The proposed computer vision-based automated scoring systems is a major step forward in overcoming the drawbacks of both the current automated systems and human approaches. This study contributes to the development of archery by investigating the potential of an automated scoring system. The research provides a foundation for future technologies aimed at assisting competitors, referees, and fans in Indonesia and beyond.

II. METHOD

This section describes the methodology, including data acquisition, augmentation, CNN model development, and system implementation for automatic archery target scoring.

A. Data Collection

The type of data used in this research consists of images of archery target boards with arrows already embedded, as shown in Figure 1. The collected image data will be used to train the computer vision system as training and testing data. Of the 100% data, 70% is allocated for training data and 30% for testing data [14].

Figure 1. Sample image data used [15]

In addition to direct data collection, this research also utilizes image data augmentation by applying transformations to images. Several transformations are applied to the training data, such as rescaling (normalization), horizontal flip, rotation range (random rotation), height shift range (random vertical shift), and fill mode (pixel filling method).

B. Computer Vision System Development

The development of an automatic scoring system for archery target boards utilizes computer vision technology. In the implementation of computer vision, the system requires a model that serves as a rule to recognize objects captured by the system. The model needs to be trained using a model training algorithm. One of the algorithms used for model training is Convolutional Neural Network (CNN) [16], [17].The CNN model development design can be seen in Figure 2.

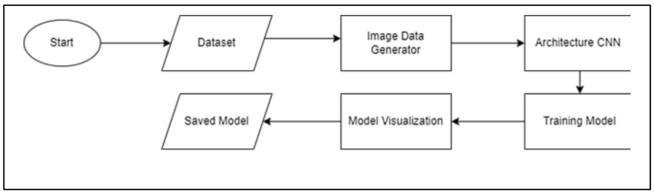

Figure 2. CNN model development design

The following is the explanation of the processes involved in model development [18]. Based on Figure 2, Dataset collection step involves collecting data that will be used to train and test the CNN model. The dataset may consist of images that are used to create object recognition patterns. Image Data Generator is a class from the Keras API that is very useful for image data processing. This generator will load images from the provided dataset and can apply various transformations such as rotation, shift, zoom, and normalization of the images to help enrich the dataset and prepare it for training. After all data were prepared, the training using CNN architecture will started. This step involves creating a CNN architecture that will be used for a specific task. The architecture consists of multiple convolution layers, pooling layers, and fully connected layers that contribute to feature extraction and classification. This research proposed the YOLO (You Only Look Once) architecture developed by [19] as CNN architecture.

As an evolution of YOLOv5, Glenn Jocher's YOLOv8 introduces several significant modifications to enhance performance. A key architectural change involves replacing the C3 module with the more efficient C2f module, which simplifies the CSP bottleneck by using two convolutions instead of three. Furthermore, the model's head is now decoupled, allowing it to handle classification and detection tasks independently. The training process has also been refined, substituting the previous IOU matching with a loss function based on positive and negative sample matching. Ultimately, this redesigned network structure leads to notable improvements in both detection speed and accuracy. Yolov8 architecture shown in figure 3.

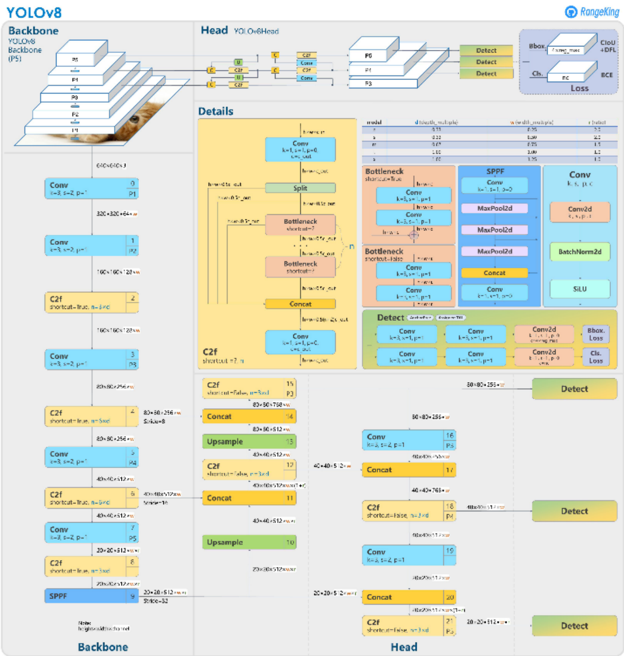

Figure 3. Yolov8 Architecture[20]

C. System Design

The working principle of the automatic scoring system for archery target boards is divided into software and hardware operations. The working principle of the software is illustrated in the form of a diagram which can be seen in Figure 4.

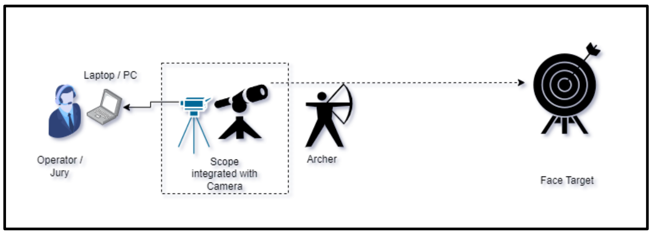

Figure 4. diagram of the system's working principle

This research develops a computer vision-based system to automatically calculate archery scores by using hardware for data collection and testing. A scope integrated with a webcam camera is connected to a PC or laptop to capture the image of the target board when the arrow hits the target. Then the camera sends the image for processing [21]. The dataset consists of 200 images of target boards with arrows, which were used to train the system using CNN algorithms on high-performance hardware via Google Colab. Once developed, the system detects the tip of the dart on the target board, applying a skew technique for image transformation due to the camera angle [22]. The tests involved archers shooting at targets, with scores calculated automatically by the system and manually as reference data (ground truth), including evaluation of camera distance, lighting, and target conditions. The system evaluation used confusion matrix to measure accuracy, comparing automatic and manual calculations to score true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), with precision measuring the accuracy of the system in calculating scores [23].

$$Precision = \frac{TP}{(TP+FP)} \quad (1)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (2)$$

$$F-measure = \frac{2\ x\ Precision\ x\ Recall}{(Precision+Recall)} \quad (3)$$

$$Accuracy = \frac{(TP+TN)}{(TP+FN+TN+FP)} \quad (4)$$

TP indicates the number of correctly identified shooting actions, while TN reflects the number of correctly classified non-shooting actions. FP occurs when the system incorrectly identifies a non-shooting action as shooting, while FN occurs when the system fails to detect an actual shooting action.

Precision measures the proportion of correct shooting detections, while recall indicates the extent to which the system successfully detects all shooting actions. Since precision and recall often have an inverse relationship, the F-measure, which is the harmonic mean of the two, is used to provide a balanced assessment. In addition, accuracy is calculated to determine the extent to which the system is able to correctly distinguish between shooting and non-shooting actions.

III. Results And Discussion

This section presents the experimental results and analysis, covering dataset preparation, model training and testing, as well as system evaluation against manual scoring.

A. Dataset Collection

During the dataset collection phase, the author built a camera sensor to capture images of the archery target board with arrows. The Archery Student Activity Unit (UKM Panahan) of Politeknik Negeri Pontianak provided support as an expert in the sport. Initial experiments placed the sensor at a distance of 3 meters from the target, but this posed a risk of sensor damage due to arrows. To solve this issue, the author used a scope, which is commonly used in archery, mounted on a tripod to assist the camera sensor. The first experiment used a smartphone camera, but the resulting images were large and took up a lot of memory. As a result, another experiment was conducted using a webcam sensor mounted on the scope, as shown in Figure 5.

Figure 5. Capture results from the smartphone camera sensor

Images produced by webcam are smaller in size, thereby saving storage capacity, and the image quality is sufficient for training data. Magnification of the scope increases the sharpness of the image, resulting in better results. The image captured using the webcam camera sensor and an example of the image data that has been collected can be seen in Figure 6.

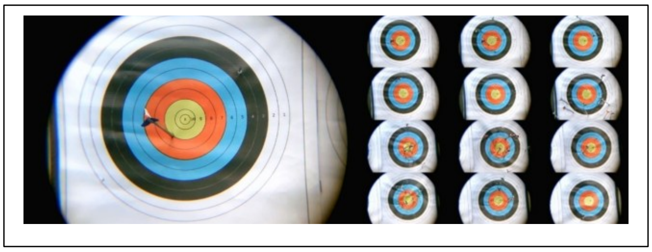

Figure 6. Image data captured by the webcam camera sensor and Sample training image data

At this stage, a total of 200 primary training images have been collected for model training and testing, which will go through pre-processing including cleaning unnecessary images and performing annotations. Image annotations label the dataset, providing ground truth for the training data, thus enabling the object detection algorithm to recognize the tip of the arrow stuck in the target board. The annotation process, which is performed individually for each image using the labelling library, involves creating a bounding box around the target object, as illustrated in Figure 7.

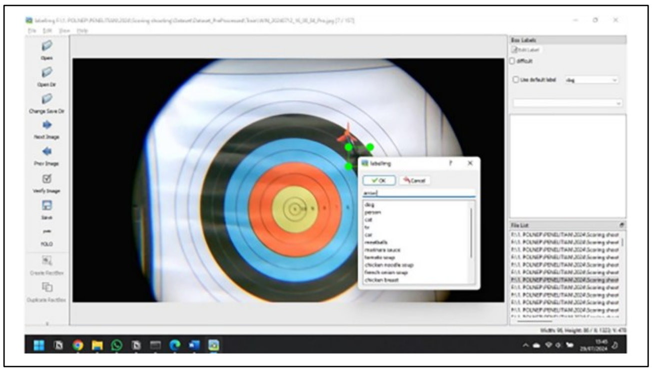

Figure 7. Labeling (Annotation) Process of Training Images

Annotation in this study is performed using Labelling, by assigning one label, i.e. 'arrow,' to each bounding box, resulting in a 'txt' file containing the label index and pixel position as ground truth for training. In addition to the primary data collected, this study was supplemented with secondary data sourced from Kaggle. The gathered images consist of archery target faces with arrows lodged in them. A total of 650 images were collected and annotated, which, when combined with the secondary data, resulted in a total dataset of 850 images. The dataset is divided into a training set (approximately 680 images) and a validation set (approximately 170 images) in a ratio of 80:20. The training folder includes "images" for training images and "labels" for annotation files containing bounding box coordinates and object class. The validation folder has a similar structure and is used to evaluate the performance of the model without updating the weights, helping in assessing the generalization ability of the model and preventing overfitting.

B. Development of an Automatic Scoring System Based on Computer Vision

The calculation is done through several stages that have been proposed as follows:

1. Training preparation

After data acquisition, the next step is to prepare training images using the CNN algorithm, specifically the YOLO (You Only Look Once) architecture developed by [19]. The YOLO algorithm includes several key hyperparameters that have a significant effect on model performance during training and inference, so careful tuning is required to obtain optimal results [22][24][25]. The hyperparameters include: Learning Rate (lr) Controls the weight update after each step; Batch Size Number of samples in one iteration of weight update; Epochs Total number of processing cycles of the dataset; Anchor Boxes Preset dimensions for detecting objects of various sizes; Image Size (imgsz) Adjusted image resolution during training; Momentum Used in optimizations such as SGD to accelerate convergence; Weight Decay (wd) Prevents overfitting by penalizing large weights; Confidence Threshold Minimum confidence for bounding box predictions; IoU Threshold (Intersection over Union) Used in non-max suppression to determine overlapping predictions; Optimizer Updates model weights based on gradient. Understanding these hyperparameters is critical to optimizing the YOLO model to effectively perform object detection in the archery scoring system.

2. Image pre-processing

To enhance the model's robustness and prevent overfitting, a series from the Albumentation library were applied probabilistically to the training images. Each transformation was selected to simulate realistic variations found in the data acquisition process. All augmentation parameter and value describe in table 1. A Gaussian blur was applied with a 1% probability using a random kernel size of 3, 5, or 7. This simulates variations in camera focus and improves the model's performance on images with low sharpness. A median filter was applied with a 1% probability using a random kernel size of 3, 5, or 7. This technique helps the model become invariant to high-frequency noise, such as sensor artefacts or "salt-and-pepper" noise. Images were converted to grayscale with a 1% probability. The purpose of this augmentation is to force the model to learn shape- and texture-based features rather than relying exclusively on colour information. CLAHE (Contrast Limited Adaptive Histogram Equalization) was applied with a 1% probability. Using an 8x8 tile grid and a contrast clip limit randomly selected from [1.0, 4.0], this technique normalizes lighting conditions and enhances local texture details, making the model more robust to variations in illumination and exposure.

TABEL I
AUGMENTATION PARAMETER AND VALUE

Transformation	Parameter	Value	Justification
Blur	p	0.01	Applies the augmentation with a 1% probability.
	blur_limit	(3, 7)	Simulates minor camera focus issues with a small, standard kernel size.
MedianBlur	p	0.01	Applies the augmentation with a 1% probability.
	blur_limit	(3, 7)	Reduces high-frequency sensor noise using a common kernel size range.
ToGray	p	0.01	Forces the model to learn color-invariant features like shape and texture.
CLAHE	p	0.01	Applies the augmentation with a 1% probability.
	clip_limit	(1.0, 4.0)	Prevents noise over-amplification while enhancing local contrast.
	tile_grid_size	(8, 8)	A standard grid size for balancing local detail enhancement and computation.

3. Training Model

The model training process was conducted using Google Colab, equipped with specifications that included Python version 3.10.12, the library torch-2.3.1+cu121 CUDA, an NVIDIA L4 GPU with 22,700 MiB, 12 CPUs, 53.0 GB of RAM, and 78.2 GB of storage. Training was carried out for a total of 100 epochs, with 100 iterations for each epoch. The output of this training is a model designed for predicting the position of arrowheads.

4. Model Evaluation

The evaluation of training performance is visualized through graphs that assess the success of the training process, as shown in Figure 7. The key metrics used include loss, mean Average Precision (mAP), Precision, and Recall, which are tracked over the entire training epoch. The train/box_loss graph shows a significant decrease in bounding box loss in the early stages of training, indicating an improvement in object location prediction accuracy. The train/cls_loss graph shows a decrease in classification loss, reflecting an improvement in the model's ability to classify objects. The train/dfl_loss graph shows an increased focus on more challenging predictions. The metrics/recall(B) graph shows an increase in the recall value, indicating the model is getting better at detecting all the objects.

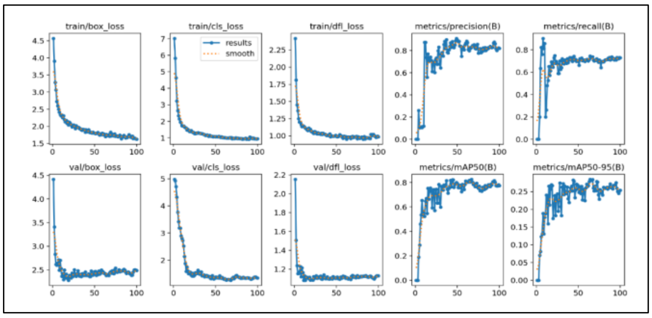

Figure 8. Results of the training process evaluation.

Validation metrics, such as val/cls_loss and val/dfl_loss, also show decreases, indicating improved classification and handling of difficult examples. The metrics/mAP50(B) graph reflects increasing mAP at a 50% threshold, signifying better detection accuracy, while the metrics/mAP50-95(B) graph indicates strong performance across various thresholds. Overall, the evaluation shows that the model is well-trained, with decreasing loss and increasing performance metrics, highlighting its effectiveness in recognizing and classifying objects within images.

5. Testing model

The trained model was then tested by inputting images from both the training dataset and external sources. The prediction results from the trained model using training images are shown in Figure 9.

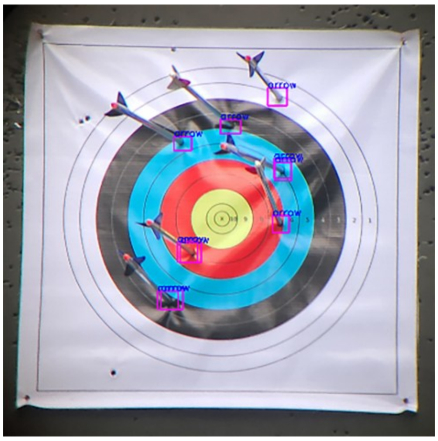

Figure 9. Arrow Detection Results

Figure 9 illustrates the detection of arrows embedded in the target board, with several arrows successfully identified by the trained model. The arrows that hit the target are marked with bounding boxes indicating their tips. The latest model achieved an accuracy of 78% in detecting arrows. This performance can be improved by readjusting the hyperparameters during training.

C. *Creation of Guiding Circles on the Face Target*

According to the latest regulations of the World Archery Federation (formerly known as FITA), archery targets have a design consisting of concentric circles with standardized sizes and values. The archery target structure consists of 10 concentric circles, each with a different color and value, where smaller circles are inside larger circles. Scores on the target range from 1 to 10, with the innermost circle getting the highest score, which is 10 [26]. Standard targets used in international archery competitions have diameters of 122 cm, 80 cm, 60 cm, and 40 cm, depending on the competition category and shooting distance. Details of the circle sizes for targets, according to FITA standards, are shown in Figure 10.

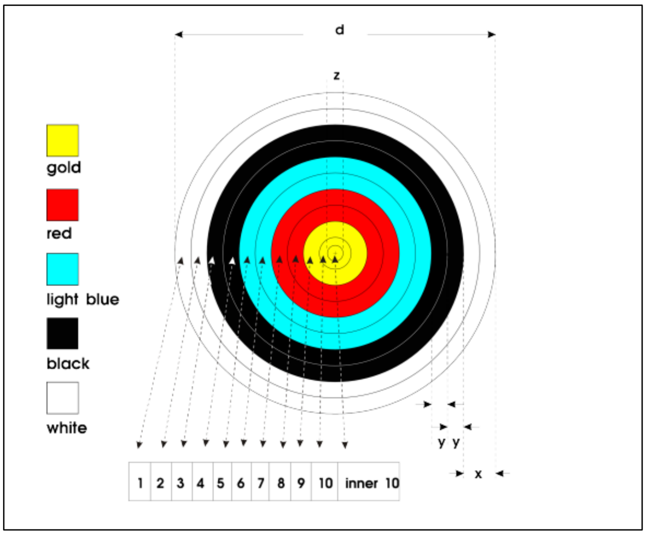

Figure 10. Circle Pattern of the Target Board According to FITA Rules [27]

The sizes of each circle vary according to the size of the target board used, as presented in Table 2.

TABEL 2
SCORING ZONES 1 TO 10 ON THE FACE TARGET

D	x	Y	Z
Diameter of Target	Color Zone	Scoring Zone	Diameter Inside 1
(cm)	(cm)	(cm)	(cm)
122	12,2	6,1	6,1
80	8	4	4
60	6	3	3
40	4	2	2

The target face is divided into color zones for scoring (Table 1) yellow for scores 10 and 9, red for 8 and 7, blue for 6 and 5, black for 4 and 3, and white for 2 and 1. The center "X" ring scores 10 and serves as a tie-breaker. The diameter of each scoring zone is determined by the equation 5.

$$D(x) = \frac{d.x}{10} \quad (5)$$

where d is the total diameter and x represents the scoring zone. The radius for each zone is calculated using Equation 6 to create 20 layers providing a framework for the scoring zones.

$$r(x) = \frac{d.x}{20} \quad (6)$$

These guide circles appear in the camera sensor output and assist in aligning the camera's position, including distance and zoom. When the camera is activated, the guide circles should align with the face target to ensure that the positions of the arrows can be recognized. The center point of the virtual guide circles is defined by Equation 7.

$$C(xy) = \left(\frac{Width}{2}\frac{Height}{2}\right) \quad (7)$$

The center point of the circle, C(x,y)C(x,y)C(x,y), is determined by dividing the height and width by 2 to find the midpoint of the frame. The results of creating these virtual guide circles applied to the camera sensor are shown in Figure 11. The score prediction automatically proceeds in three key phases: the calculation of the arrow center, the computation of the distance to the target center, and the conversion of the distance into the corresponding score.

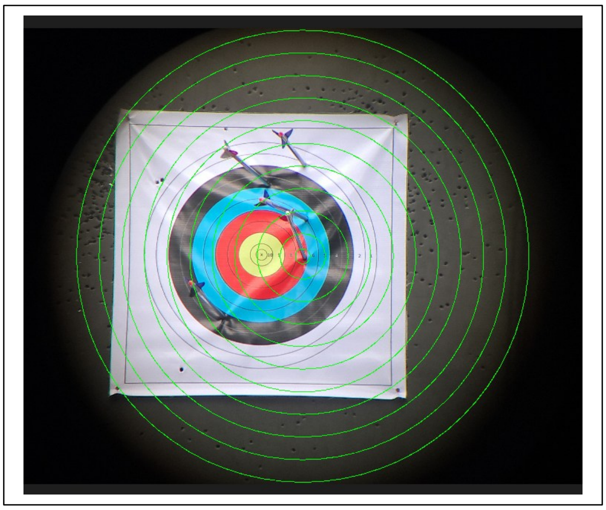

Figure 11. Virtual guide circles of the face target.

The arrow center calculation is achieved through the model's bounding box coordinates, as outlined in equation 8:

$$Cbox(x,y) = \left(\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2}\right) \tag{8}$$

1. Euclidean distance for zone estimation

The primary objective of the system is to operate in real-time. The system architecture divides the task into two phases: (1) Detection, handled by YOLOv8 to find the `(x, y)` coordinates of the arrow, and (2) Scoring, to calculate the score based on those coordinates. Euclidean Distance is the optimal choice because of some reason. Firstly is efficiency, Euclidean distance is a fundamental mathematical operation. This operation has a negligible computational cost and can be executed in microseconds on modern CPUs. In a context where the YOLOv8 inference already consumes the majority of the frame processing time budget, adding a lightweight post-processing step is essential. Secondly is Direct Relevance to Scoring Rules. The archery scoring system is inherently based on radial distance. A score is determined only by the distance between the arrow's impact point and the target's center. Euclidean Distance directly computes the single scalar value (distance) that maps directly to these scoring rules. In this case, Euclidean distance formula is utilized in the measurement of the distance between two centers as defined by:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{9}$$

This distance is then converted into a score based on FITA regulations, where scores range from 1 to 10 depending on the proximity of the arrow to the center of the target. The conversion formula dynamically adjusts based on the camera sensor size and the predefined radius threshold for each scoring zone. Measurement results of distance C(x,y), with Cbox(x,y) are illustrated in Figure 12.

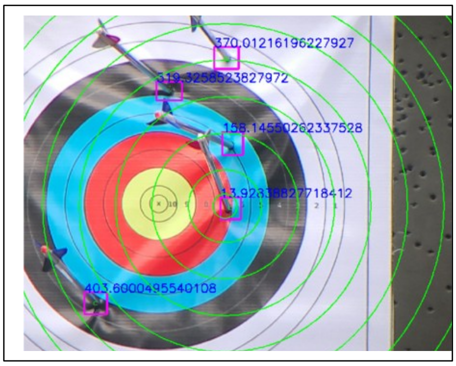

Figure 12. Measurement results of distance *C(x,y)* with *Cbox(x,y).*

Evaluation of automated scoring systems involves several testing phases to assess the accuracy and reliability of the system in detecting and recording shot results [28], [29]. Ten archers each shot ten arrows, for a total of 100 shots, where the scores from the system were compared to the manual scoring of the judges. The system was calibrated with the camera sensor positioned 15 meters from the target. The results of detection and automatic score prediction are illustrated in Figure 13 and summary of the test results can be seen in Table 3.

TABEL 3.
RECAP OF TEST RESULT

Number of Not Detected (TT)	Number Detected	Number of Correct Score Predictions	Total Shots
9	91	67	100

As in the test results (Table 3), it shows an accuracy of 67% for the automated scoring system, with a detection error of 33%. The error is caused by factors such as lighting conditions and the proximity of the arrow to the scoring zone as shown in Figure 13. Overall, the system performed adequately but requires improvement to increase accuracy and reliability.

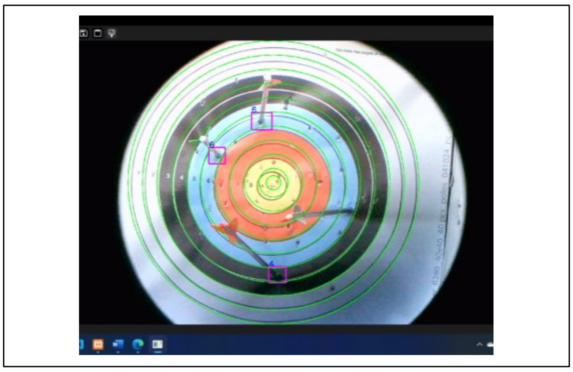

Figure 13. Results of detection and automatic score prediction

During training and competition, the automated scoring system's performance was inconsistent, successfully detecting arrows but also exhibiting detection failures in certain case.

2. Limitation of the system

Errors arose when arrows were in positions not covered in the training data or when two arrows overlapped. So in the sport of archery, a stable shooting position is very important to obtain high shot accuracy [28]. Calibration challenges with the guide lines led to significant score prediction errors due to small movements in the scope. The system also struggled in poor lighting conditions, especially towards dusk. In addition, misalignment of the centers of the labeled arrows contributed to incorrect score predictions, especially at the target borders. Improvements to image labeling, calibration, and performance in low-light conditions could improve the accuracy of the system.

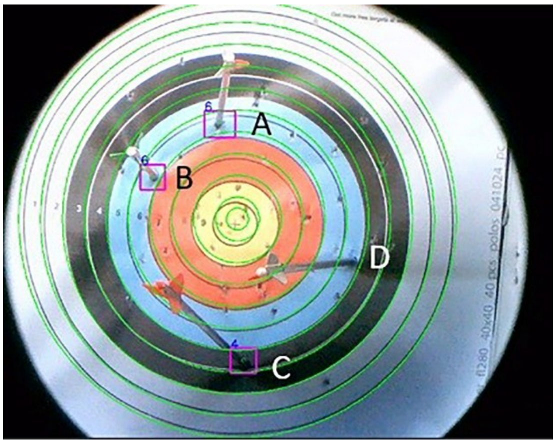

Figure 14. Arrow Detection Error: Arrow Not Detected

The accuracy of the proposed system is lower compared to previous studies, especially in assessments using color features, while only a few studies, including this research, use coordinate-based methods as presented in Table 4.

TABLE 4.
COMPARISON WITH OTHER SCORE CALCULATION METHODS

No	Reference	Score Measurement Method	Accuracy	Precision	Error
1	Proposed Method	Measuring the radius between the center point of the face target guide lines and the arrow object using Euclidean distance.	67 %	-	33 %
2	(Parag, 2017) [15]	*Face target* color-based approach	86 %	-	-
3	(Zin et al., 2013b) [29]	color and shape features	100 %	-	-
4	(Ma & Madden, 2023) [8]	colour masking	-	40 %	-
5	(Rudzinski & Luckner, 2013b) [13]	Prewitt edge detection and the Hough transformation	99%	-	0,05 %
6	(Ligutan et al., 2019)[30]	based on color classification in HSV color space.	96.67%	-	-
7	(A. J. Callaway & Broomfield, 2012) [21]	a measure of straight-line distance from the centre of the target (Pythagorean distance).	>97 %	-	2%
8	(Ogasawara et al., 2021) [31]	The box color represents the movement used as the basis for feature extraction. The green plot indicates the actual shooting time, while the red plot shows the time detected by the trained shot detector.	95%	97 %	-
9	(Butt et al., 2023) [32]	The trained models were then assessed on the test dataset, and their performance was compared using matrices like mAP50, mAP50-90, precision, and recall. The results showed that YOLOv8 models can detect multiple objects with good confidence scores.	96,5 %	-	-
10	(McNally et al., 2021) [33]	Develop a deep convolutional neural network around this idea and use it to predict dart locations and dartboard calibration points within an overall pipeline for automatic dart scoring, which we call DeepDarts	84%	94, 7%	

The dataset collection phase of this research highlights the innovative approach taken to capture images of archery targets while ensuring the safety of the camera sensor. In line with this, [34] agreed that ensuring the safety of camera sensors is a critical aspect of the dataset collection phase. The innovative approach likely includes strategic placement of cameras to avoid direct hits from arrows, thereby protecting the equipment while still capturing high-quality images of the targets. This consideration is essential in practical applications where equipment damage could lead to increased costs and downtime.

Building on this innovative approach, the study further enhanced the data collection process by transitioning from a smartphone camera to a webcam. The study successfully reduced the chance of arrow damage, a frequent concern in archery, by using a sight fixed on a tripod. The switch from a smartphone camera to a webcam enhanced the quality of the photos taken while simultaneously reducing the image size and saving storage space [35]. This decision underscores the importance of selecting appropriate hardware for specific applications, particularly in fields like computer vision where image quality can significantly impact model performance [36]. The collection of 850 training images, along with the rigorous annotation process, lays a solid foundation for developing a robust object detection model. With the successful collection and annotation of training images, the research naturally progressed to the development of an automatic scoring system utilizing advances computer vision techniques.

The basis of this ground-breaking scoring system is the deployment of effective, advanced machine- learning techniques, with a particular emphasis on the YOLO (You Only Look Once) architecture. The YOLO architecture is an effective scoring tool that necessitates careful tuning of many parameters to reach peak performance. The development of an automatic scoring system based on computer vision represents a significant advancement in archery scoring methodologies [37]. The work uses the YOLO architecture, which is an innovative technique noted for its efficiency in real-time object recognition as its baseline [32]. Adjusting hyperparameters such as learning rate, batch size, and confidence thresholds is crucial for optimizing model performance, and the details of this part of the work illustrate the importance of understanding machine learning principles in depth. The performance of the trained model is shown to be dependent on these parameters, so they must be set correctly if one wants to achieve a goal [38]. The training method was conducted on Google Colab, using powerful hardware which is also indication of the considerable effort and practical concern that must be managed during deep learning experiments.

The performance metrics of the model showcase both its strengths and its areas that need improving. They highlight the iterative quality of machine learning, in which the critical role of data-based insights cannot be emphasized enough when it comes to honing a model's accuracy [39][40], [40]. The visualization of training performance through various metrics provides valuable insights into the model's learning process. The graphs depicting loss, mean Average Precision (mAP), precision, and recall serve as indicators of the model's ability to accurately detect and classify arrows. The observed decrease in loss values and the increase in recall suggest that the model is effectively learning to identify the target objects. However, the achieved accuracy of 78% indicates room for improvement, particularly through hyperparameter adjustments and potentially expanding the dataset. This finding aligns with common challenges in machine learning, where achieving high accuracy often requires iterative refinement and extensive experimentation [40].

By following set regulations and applying a methodical approach to scoring zone design, this research not only strengthens the technical capabilities of the scoring system but also ensures its practical usefulness in competitive archery. The creation of guiding circles on the target face, in accordance with World Archery Federation regulations, adds a layer of sophistication to the scoring system. By establishing a clear framework for scoring zones, the research not only adheres to established standards but also enhances the usability of the system in competitive settings. The mathematical equations used to determine the dimensions of the scoring zones demonstrate a methodical approach to integrating theoretical principles with practical applications [41]. This aspect of the research highlights the importance of aligning technological advancements with existing regulations to ensure acceptance and effectiveness in real-world scenarios [42].

In conclusion, this research presents a comprehensive approach to developing an automated archery scoring system through the integration of computer vision techniques. The careful collection and annotation of a training dataset, combined with the application of advanced algorithms like YOLO, showcase the potential for technology to enhance traditional sports. The findings underscore the importance of continuous improvement and adaptation in machine learning applications, as well as the necessity of aligning technological solutions with established standards in the sport. Future work could focus on refining the model's accuracy and exploring additional features, such as real-time scoring feedback, to further enhance the user experience in archery competitions. Feedback from users was positive, as the system simplified score recording and reduced human error in stressful competitions. Improvements needed include improving accuracy in low-light conditions through image quality enhancement and adding a manual confirmation feature for cases that fall within the boundaries of the scoring zone. In addition, automating target circle detection can reduce calibration time and improve system efficiency.

3. Participant Feedback

Participants were requested to provide feedback on various aspects, including usability, and comfort during system operation within a competition context. This evaluation aimed to obtain a clearer understanding of the system's effectiveness in supporting user requirements, the intuitiveness of its interface, and whether its features could be operated easily without disrupting the participants' concentration during the competition. The feedback obtained from the archers and judges will serve as a basis for subsequent improvements and further development to ensure the system delivers an optimal user experience.

Following the direct trial, a questionnaire was administered to the archers and judges to be completed based on their respective experiences. The questionnaire was segmented into several categories: Respondent Profile, Usability, User Interface, Comfort During System Use, Feedback and Suggestions, and Overall Satisfaction. The questions and the results of the user testing for the Respondent Profile category are available at https://s.id/n6bsP .

4. Usability Evaluation

Regarding usability, the majority of respondents (54.5%) rated the system as "Fairly Easy" to operate, while 36.4% rated it "Easy." A significant finding, however, was that 90.9% of respondents (a combination of "Yes, a little help was needed" and "Yes, significant help was needed") required guidance during their first use. This indicates the need for a clearer initial tutorial or onboarding process. Nevertheless, following the initial setup, the core process of viewing post-shot scores was deemed "Fairly Intuitive" by 63.6% of respondents and "Intuitive" by 27.3%.

5. User Interface (UI) Evaluation

The user interface (UI) received a positive visual response. The majority (54.5%) found the display "Attractive," and 27.3% found it "Very Attractive." Information presented on the screen was also considered easy to understand, with 36.4% rating it "Very Easy to Understand" and 36.4% "Fairly Easy to Understand." Design aspects such as text and icon size were generally well-regarded, evenly split between "Fairly Good" (45.5%) and "Comfortable" (45.5%).

6. Comfort and Efficiency Evaluation

In the context of competition use, the system demonstrated a positive impact. Most respondents (a combination of "Helpful" and "Very Helpful") felt the system assisted in accelerating the scoring process. A crucial finding was that 100% of respondents stated the system "Did Not Disturb" or "Did Not Disturb at All" their concentration while shooting, a critical factor in the sport of archery. The general comfort level of using the system was rated "Comfortable" (36.4%) and "Fairly Comfortable" (36.4%). The system was also perceived as capable of increasing scoring efficiency, with 45.5% of respondents rating it "Fairly Efficient."

7. Feedback and Suggestions for Development

Respondents provided constructive qualitative feedback for future improvements. The primary themes that emerged were the need for enhanced score detection accuracy and processing speed. Specific suggestions included:

a) Improving score-reading accuracy, especially in handling overlapping holes from previous arrows.
b) Reducing the *delay* between image capture and score display to achieve a more *real-time* performance.
c) Adding an automatic calibration feature to simplify the initial setup process.
d) Implementing automatic detection for various *target face* types (e.g., standard circular targets and *horsebow* targets).

8. Overall Satisfaction

Overall, satisfaction levels with the system were positively distributed. Respondents were evenly split between "Satisfied" (36.4%) and "Fairly Satisfied" (36.4%), with an additional 27.3% feeling "Very Satisfied." As a key indicator of system acceptance, 63.6% of respondents stated, "Yes, I would recommend" this system for use in archery competitions. This indicates the system's strong potential for wider adoption following iterative improvements based on the user feedback received.

9. Processing Time Performance Testing

To validate the real-time performance of the arrow detection and scoring system, an evaluation was conducted using video footage. This test aimed to quantify the total latency required by the system to process a single video frame, spanning from initial capture to the display of detection results. The total processing time for each frame was measured by summing three primary components recorded in the test logs :

a) Preprocess Time: The time required to prepare the video frame (e.g., resizing, normalization) before it can be fed into the detection model.
b) Inference Time: The core time required by the YOLOv8 model to perform object detection (arrow) on the processed frame.
c) Postprocess Time: The time required to process the raw output from the model (e.g., non-max suppression, score calculation) into user-readable information.

This test analysed a total of 205 frames from the test video to obtain a comprehensive overview of the system's performance. Based on the analysis of 205 processed frames , the following processing time statistics were obtained on table 4.

TABLE 4
PROCESSING TIME STATISTICS

Metric	Average Time (ms)
Average Preprocess Time	4.52 ms
Average Inference Time	138.11 ms
Average Postprocess Time	2.42 ms
Average Total Time per Frame	**145.05 ms**

The analysis results indicate that the average total processing time required for the system to detect and score a single video frame is 145.05 milliseconds (ms). The largest component of this processing time is the inference time (138.11 ms), which is characteristic of the computational load of a deep learning model. The pre-process and postprocess times contributed minimally, at only 4.52 ms and 2.42 ms, respectively.

IV. CONCLUSION

This research successfully developed an automated scoring system for archery using computer vision technology called YOLO v8 architecture for real-time arrow detection and scoring. The study highlights the transition of archery from a traditional practice to a competitive sport, emphasizing the critical need for accurate and efficient scoring methods. Using a dataset of 850 images of target boards with arrows, the system was able to calculate score based on the Euclidean distance from the arrow's center to predefines scoring zones, achieving an accuracy of 67%. The selection of Euclidean Distance is not a compromise on robustness. Rather, it is a deliberate design decision for efficiency and task specificity. It directly, quickly, and cheaply solves the core problem of distance-based zone estimation, which is essential for achieving the system's overall real-time performance target.

User feedback indicated appreciation for the system's efficiency and reliability, underscoring its potential to enhance the scoring process in archery competitions. While the accuracy achieved is lower than some previous studies, this research introduces a novel approach that lays the groundwork for future improvements. The findings suggest that further refinements in model performance, particularly in low-light conditions and image quality, are necessary to enhance accuracy and reliability.

The average latency of 145.05 ms (or 0.145 seconds) demonstrates that the system operates effectively in a real-time scenario. From the user's perspective , a delay of 0.145 seconds between the physical event and the score display is indistinguishable from an instantaneous response.

Overall, this study contributes to the advancement of automated sports technology, offering a promising solution to the challenges faced in traditional scoring methods. Future work should focus on optimizing the model, expanding the dataset, and exploring additional features, such as real-time scoring feedback, to further improve the user experience in archery competitions. This research also emphasizes the importance of aligning technological advancements with established standards in the sport, ensuring that the automated scoring system is not only effective but also accepted in competitive environments. The integration of guiding circles based on FITA regulations enhances the usability of the system, providing a structured framework for scoring that adheres to international norms.

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