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A Result-Oriented Review of Artificial Intelligence Assisted Shooting Training Simulators and Laser-Based Marksmanship Technologies

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Abstract
Effective marksmanship development depends on repetitive practice, immediate feedback, and stable training conditions. Although live-fire exercises remain the benchmark for realism, they are often constrained by ammunition cost, infrastructure requirements, safety regulations, and limited training access [3], [7], [8]. These constraints have accelerated the development of simulation-based training platforms, particularly laser-assisted systems supported by computer vision and artificial intelligence. Laser-based shooting simulators integrated with artificial intelligence, computer vision, and digital performance analytics have emerged as promising alternatives for safe, scalable, and accessible skill development [31], [32], [33]. However, a significant portion of existing literature emphasizes hardware or software architecture while giving comparatively less attention to measurable training outcomes. This review presents a result-oriented analysis of AI and computer vision based laser marksmanship training systems with emphasis on practical performance factors such as detection reliability, scoring repeatability, environmental sensitivity, grouping interpretation, and feedback utility. The study synthesizes existing research on laser simulators, vision-based shot recognition, AI-assisted training analytics, and immersive training interfaces, while also discussing common result-level limitations observed in practical deployment environments. The review highlights that future intelligent shooting training systems should be evaluated not only by technical sophistication, but by their ability to deliver stable, interpretable, and instructionally useful results under realistic operating conditions.
Keywords: *Marksmanship training, Laser shooting simulator, Artificial intelligence, Computer vision, Result-oriented review, Shot detection, Performance analytics*

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I. Introduction

Marksmanship is a performance-sensitive skill that depends on repeated motor refinement, visual alignment, and consistent execution under controlled conditions. Whether in military, cadet, law-enforcement, or competitive shooting contexts, improvement in shooting accuracy is rarely achieved through isolated practice; rather, it depends on repeated exposure to measurable performance feedback [7], [9]. For this reason, effective training environments must not only allow repetition, but also provide interpretable information about shot quality, grouping behavior, and consistency.

Conventional live-fire training remains the most direct method of firearms instruction. It enables realistic recoil exposure, weapon handling, and real target engagement. However, access to live-fire training is often restricted by cost, safety protocols, ammunition availability, supervision requirements, and infrastructure limitations [3], [8]. These constraints are especially significant in decentralized or resource-constrained training environments where repeated practice opportunities are limited.

To address these barriers, simulation-based alternatives have become increasingly important. Laser-based shooting simulators, computer vision-assisted scoring systems, and AI-supported performance analytics offer a safer and more accessible route for repetitive skill development [3], [4], [12], [18]. Such systems can support dry-fire training, track impact points, analyze shot spread, and provide immediate feedback without the recurring burden of live ammunition. Recent work has also shown that simulation-assisted training can positively influence live-fire performance when appropriately designed and validated [31], [35].

Although research in this area has expanded considerably, much of the existing literature remains technology-oriented, focusing on sensing methods, simulation interfaces, or architecture design [1], [2], [6]. In practical training contexts, however, the more meaningful question is not simply how a simulator is built, but how effectively it performs as a training tool.

This distinction motivates the present review. Rather than classifying systems only by technical design, this paper evaluates them from a result-oriented perspective. Specifically, it examines how intelligent marksmanship training systems perform in terms of detection dependability, scoring consistency, environmental robustness, training relevance, and feedback value. By shifting the focus from architecture to outcomes, this review aims to provide a more practically useful framework for assessing modern shooting simulation systems.

II. Novelty and Scope of the Review

The distinguishing feature of this review is its emphasis on training outcomes rather than technical categorization. Existing reviews and technical studies on shooting simulators often describe hardware configurations, immersive interfaces, or detection techniques [1], [3], [6]. While such approaches are valuable, they do not always provide sufficient insight into whether a system is reliable enough to support real skill development.

This paper addresses that gap by reviewing intelligent marksmanship training systems according to performance-oriented questions, including:

- Under what conditions do these systems produce dependable results?
- Which system-level factors most strongly affect shot detection quality?
- How robust are current systems to environmental disturbances?
- What kinds of feedback are most useful for training improvement?

The review includes laser-assisted dry-fire systems, computer vision based target analysis, AI-driven training analytics, and immersive training platforms such as VR and AR. Importantly, the discussion is framed to remain implementation-neutral, focusing on generalized performance principles and reported behavior in existing systems rather than unpublished design-specific methods.

Unlike conventional review papers that primarily organize technologies by category, this paper emphasizes result reliability, real-world usability, and performance consistency. This makes the review more relevant for practical training environments, particularly those where low-cost, portable, and repeatable systems are needed.

III. Traditional Firearms Training and Its Limitations

Traditional firearms training is generally performed through live-fire exercises in specialized ranges under controlled supervision [7]. Such training remains the most realistic method of preparing shooters for actual firing conditions. It helps develop recoil management, weapon familiarity, timing, and decision-making under realistic engagement conditions. However, despite its realism, live-fire training presents multiple limitations that affect training continuity and accessibility.

One of the most significant limitations is cost dependency. Ammunition consumption, target materials, range usage, and firearm maintenance all contribute to recurring expenditure [3], [7]. As a result, repeated training is often restricted, especially in institutional or cadet environments where training budgets are limited.

Another major limitation is safety. Live ammunition requires careful supervision, dedicated space, and strict procedural control. This can reduce flexibility and make beginner training more difficult to conduct frequently [8].

In addition, firearms training is often infrastructure-dependent. Access to dedicated ranges may not be feasible in many educational, cadet, or semi-urban environments. When training depends on distant or limited facilities, practice frequency is naturally reduced.

Low training frequency ultimately affects muscle memory development, consistency, and confidence. Because marksmanship is a skill that improves through repetition, irregular access to practice can significantly slow performance development.

These limitations have motivated the growth of safe, low-cost, and repeatable alternatives such as laser-assisted and computer vision based simulation systems [3], [4], [8].

IV. Evolution of Shooting Simulation Technologies

Shooting simulation technologies have evolved significantly over time, moving from simple dry-fire aids to intelligent platforms capable of scoring, analysis, and adaptive feedback [9], [10]. Modern systems can broadly be understood through four technological directions: laser-based simulators, camera-assisted scoring systems, VR-based training environments, and AR-supported practice platforms.

Laser-based systems represent one of the most practical forms of simulation. In these systems, a laser pulse replaces the projectile event and is detected optically at the target surface [3], [33]. This allows repeated, safe, and low-cost practice while preserving the basic shooting interaction.

Camera-based and optical systems extended this concept further by enabling automatic shot recognition and digital scoring [4], [12], [18]. These systems use imaging hardware and processing techniques to detect the shot event, estimate impact location, and convert it into interpretable feedback.

Virtual reality systems introduced a more immersive layer to shooting simulation by creating dynamic digital environments that support tactical or scenario-based training [1], [6], [31]. These systems are particularly useful where situational awareness and reaction timing are important.

Augmented reality systems take a hybrid approach by overlaying digital information onto the real world, allowing trainees to interact with physical environments enhanced by virtual targets or analytical elements [2].

Although these technologies differ in complexity and training purpose, their practical usefulness depends less on appearance or novelty and more on whether they deliver dependable and useful results.

V. Literature Review

Recent literature reflects growing interest in intelligent marksmanship training systems across military, law-enforcement, sports, and simulation research domains. Earlier work focused primarily on replicating firing mechanics and basic shot scoring, whereas more recent studies increasingly incorporate AI, motion analysis, visual computing, and immersive training interfaces [1], [3], [14], [17].

Girardi et al. proposed a virtual reality simulator for military shooting training and demonstrated the value of immersive environments for scenario realism and tactical engagement [1]. Similarly, Kim et al. investigated VR-assisted rifle training and reported measurable benefits in reaction and accuracy-oriented performance under simulator-based practice [6]. These studies suggest that immersive systems can contribute meaningfully to skill development, though they typically require more specialized hardware and infrastructure.

Laser-based simulation systems have remained especially relevant for practical and low-cost training. Soetedjo and Nurcahyo developed a laser pointer shooting simulator that highlighted the feasibility of safe, repeatable indoor practice without live ammunition [3]. Later work on embedded laser spot recognition further demonstrated that low-cost optical detection remains highly viable for simulation-based training [33].

Sun investigated image-capturing methods for firearms training simulators and emphasized the role of vision-assisted shot localization in practical scoring systems [4]. Similarly, Rudziński and Luckner showed that low-cost computer vision based scoring approaches can provide useful alternatives to expensive professional systems [34].

In parallel, computer vision literature has provided important foundational methods such as brightness thresholding, contour extraction, localization, coordinate transformation, and image-based pattern recognition [12], [13], [16], [18], [26]. AI and machine learning research has further contributed techniques for behavioral analysis, grouping interpretation, predictive trend analysis, and training-oriented feedback generation [14], [15], [17], [28], [29], [30].

Recent literature has also strengthened the case for result-oriented simulator validation. Lee et al. demonstrated that virtual reality based rifle training can contribute to measurable improvement in live-fire shooting performance, reinforcing the practical value of structured simulator-assisted practice [31]. Similarly, Huffman et al. reviewed the relationship between simulator performance and live-fire outcomes, emphasizing the need for stronger validation frameworks in marksmanship simulation research [35]. More broadly, recent systematic reviews in sports analytics confirm that AI-based performance analysis is increasingly effective when paired with interpretable and validated evaluation methods [32], [36].

Despite these advances, much of the literature remains primarily focused on:

- architecture,
- sensing pipelines,
- simulation realism,
- or proof-of-concept implementation.

Relatively fewer studies examine these systems according to result-oriented criteria such as:

- detection reliability,
- false detection resistance,
- environmental robustness,
- grouping stability,
- and training relevance.

This gap justifies the need for a review that emphasizes performance outcomes rather than only system categories.

VI. Why Result-Oriented Evaluation Matters

A technically sophisticated simulator is not automatically an effective training system. In applied training settings, usefulness is determined less by the novelty of the underlying hardware and more by the quality, consistency, and interpretability of the outputs it produces.

From a trainee's perspective, the value of a shooting simulator depends on whether it can answer practical questions such as:

- Was the shot recognized correctly?
- Can the score be trusted?
- Is the system usable in ordinary environments?
- Does the output help improve future performance?

These questions are especially relevant in low-cost and portable systems, where training value depends heavily on operational reliability rather than premium hardware [3], [4]. A system that misses valid shots, produces unstable scoring, or reacts poorly to environmental changes may still appear technologically interesting, but its instructional value is limited.

A result-oriented evaluation framework therefore provides a more realistic basis for comparing training systems. It shifts attention away from isolated technical features and toward the actual conditions under which performance improvement becomes possible.

VII. Result-Oriented Performance Metrics in Marksmanship Simulators

A meaningful review of shooting simulators requires clearly defined performance parameters. In result-oriented evaluation, the primary concern is not whether a system merely functions, but whether it functions reliably enough to support learning.

One of the most important parameters is shot detection accuracy, which refers to whether a valid shot is recognized at the correct location on the target [4], [12], [18]. A system that inconsistently detects shots cannot be trusted for performance analysis.

Closely related is shot detection stability. Even if a simulator can detect isolated shots, it must also maintain consistent behavior across repeated attempts and across different target regions. This is particularly important for grouping drills and progressive skill evaluation.

Another essential metric is scoring reliability. Once a shot is detected, its position must be mapped accurately enough to produce consistent and meaningful scoring output [12], [13]. Scoring inconsistency can mislead trainees and reduce the usefulness of repeated practice.

Response time also plays an important role in training effectiveness. Systems that provide immediate or near-immediate feedback are more useful for reinforcing correct technique and supporting self-correction [6], [14].

Grouping consistency analysis is especially relevant in marksmanship because tightly clustered shots often indicate strong shooter control, even when the group is slightly offset from center [7], [28]. Therefore, the ability to interpret grouping is often more valuable than isolated shot scoring alone.

Other important metrics include:

- environmental robustness
- false positive resistance
- feedback usefulness
- and session-wise performance interpretability

Together, these factors provide a more realistic framework for judging whether a simulator contributes meaningfully to training improvement.

VIII. Laser-Based Training Systems from a Results Perspective

Laser-based shooting simulators are among the most practical and accessible forms of simulation-based firearms training [3]. Their primary strength lies in their ability to replace projectile-based training with a safe optical event while preserving the essential interaction of aiming and trigger activation.

From a result-oriented perspective, laser systems are especially valuable because they enable:

- high repetition,
- safe dry-fire training,
- low recurring cost,
- and convenient indoor deployment.

These features make them particularly suitable for cadet training, early-stage shooter development, and low-resource environments.

However, the quality of results produced by laser systems depends strongly on how well the projected laser event can be captured and interpreted. This means that laser-based training effectiveness is not determined solely by the presence of a laser emitter, but by the interaction between:

- target surface behavior,
- ambient light,
- capture sensitivity,
- and scoring interpretation [4], [12], [18].

When these factors are favorable, laser systems can support meaningful training in:

- aim stabilization,
- trigger discipline,
- grouping drills,
- and repetition-based skill refinement [3], [7].

Thus, laser-assisted systems remain one of the strongest foundations for result-oriented marksmanship training, especially where affordability and portability are critical.

IX. Computer Vision in Result-Oriented Shot Detection

Computer vision plays a central role in transforming a projected shot event into measurable training data. In camera-assisted laser shooting systems, the target area is visually monitored and processed to identify where the shot event occurred [12], [18].

One common approach is brightness thresholding, where the system identifies sudden high-intensity points relative to the background [12]. This is particularly effective when the laser spot produces a clear brightness contrast against the target surface.

Another useful method is localized spot detection, often achieved through region or blob-based analysis. These methods help estimate the center of the detected laser event for shot localization [18]. Embedded-camera laser recognition has already been shown to be feasible for simulator applications, particularly when the detection problem is framed as a localized brightness event rather than a full-scene object recognition task [33].

Once the event is localized, coordinate mapping is used to translate the detected point into target-relative position and score region [12], [13]. Similarly, low-cost image-based target scoring methods have demonstrated that reliable result generation is possible without dependence on specialized industrial scoring hardware [34].

Additional operations such as contour cleanup, filtering, and noise suppression may be used to improve recognition stability [18], [26]. However, from a result-oriented perspective, the key issue is not only algorithm design, but whether the laser event remains visually distinguishable under real conditions.

This means that successful computer vision in marksmanship training depends heavily on:

- contrast quality,
- surface reflectivity,
- lighting stability,
- and resistance to non-shot brightness disturbances.

X. Artificial Intelligence in Performance Evaluation

Artificial intelligence extends the value of shooting simulators by transforming raw shot coordinates into interpretable performance intelligence [14], [15]. Rather than treating each shot as an isolated event, AI enables systems to detect patterns across multiple shots and multiple sessions.

One major contribution of AI is in shot grouping analysis, where clustering behavior can be examined to assess consistency, spread, and likely performance tendencies [17], [28], [29]. This helps shift training away from single-shot thinking and toward repeatable shooting quality.

AI also supports behavioral pattern recognition. For example, a repeated directional drift in shot placement may indicate a recurring mechanical or aiming issue. Over time, such trends can be used to generate more meaningful and personalized training feedback [14], [15].

This broader trend is consistent with recent systematic reviews showing that AI is increasingly effective in performance-oriented sports analysis when combined with meaningful evaluation metrics and interpretable outputs [32], [36].

Another valuable function of AI is longitudinal performance tracking, where multiple training sessions are compared to identify whether the shooter is improving, plateauing, or showing unstable behavior [28], [29].

The most useful AI systems in marksmanship training are therefore not those that simply "look advanced," but those that help trainees understand:

- what they are doing consistently,
- where they are drifting,
- and how their performance is changing over time.

XI. Virtual and Augmented Reality Systems in Performance Training

Virtual and augmented reality systems have broadened the scope of shooting simulators by enabling more immersive and interactive training environments [1], [2], [6]. These systems are especially useful in scenarios where realism, tactical movement, or environmental complexity are important.

VR systems are particularly effective for:

- situational awareness training,
- dynamic target engagement,
- decision-based shooting,

- and stress-linked scenario simulation [1], [6], [31].

AR systems, on the other hand, can overlay digital targets or instructions onto real environments, helping bridge the gap between physical shooting posture and digital training enhancement [2].

From a result-oriented perspective, these systems offer strong value in:

- tactical realism,
- engagement variety,
- and training immersion.

However, they also present limitations. Many immersive systems require:

- expensive hardware,
- dedicated setup,
- controlled calibration,
- and greater technical support [1], [6].

As a result, while VR and AR are highly valuable for advanced or scenario-based training, they may be less practical than low-cost laser and camera systems for frequent decentralized skill practice.

XII. Practical Result-Oriented Observations from Reported Testing Conditions

A meaningful evaluation of shooting simulators must account for how such systems behave outside idealized laboratory settings. In practical use, detection quality is often influenced by the interaction between the projected laser event, the target surface, surrounding illumination, and the sensitivity of the visual capture system. These factors can significantly affect whether a valid shot is reliably recognized, weakly represented, or incorrectly interpreted.

Across low-cost camera-assisted and optical shooting systems discussed in literature and practical demonstrations, a consistent pattern is often observed: environmental compatibility can be just as important as algorithmic sophistication [3], [4], [33], [34]. In other words, the same class of simulator may appear highly reliable under one set of conditions and unstable under another, even when the underlying detection principle remains unchanged.

This result-oriented perspective is especially important for low-cost training systems, where deployment conditions are rarely standardized. Therefore, practical operating conditions should not be treated as secondary implementation details; they are central to understanding the real usability of intelligent shooting simulators.

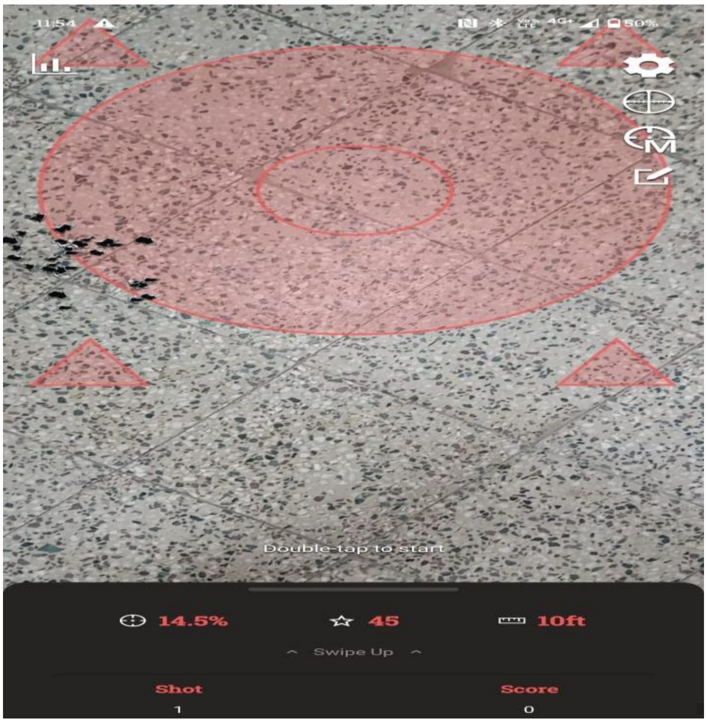

Fig. 1. Representative environmental conditions commonly affecting result quality in camera-assisted laser training systems.

Source: Author-prepared illustrative example.

XIII. Surface-Dependent Detection Performance

Target surface properties can significantly influence the quality of optical shot detection in laser-assisted training systems. In many reported vision-based approaches, result reliability depends not only on the emitted laser event, but also on how effectively the target surface reflects or suppresses the projected light.

13.1 Performance on Light Matte Targets

Light-colored matte targets generally provide favorable conditions for optical shot detection because they reflect sufficient laser intensity while minimizing visual ambiguity. Under such conditions, the projected laser event is more likely to appear as a distinct and isolated brightness region, improving localization reliability [12], [18], [33].

13.2 Performance Degradation on Dark Absorptive Regions

Dark target regions, particularly heavily inked or low-reflectance areas, may reduce detection performance because they absorb a larger portion of the projected light. As a result, the visible signature of the laser event may become weaker and less consistently detectable.

This issue is especially relevant in target-centered training contexts where central scoring regions are critical to performance interpretation.

13.3 Reflective and Glossy Surface Interference

Reflective or glossy surfaces introduce a different challenge. Rather than suppressing the projected signal, they may create glare or persistent highlights that visually compete with true shot events. In brightness-sensitive detection systems, this may reduce localization confidence or increase the likelihood of false event interpretation.

Taken together, these observations suggest that surface behavior should be considered a primary performance factor in the practical evaluation of vision-assisted marksmanship systems.

Fig. 2. Illustrative comparison of target surface characteristics influencing shot detection behavior.

Source: Author-prepared illustrative example.

XIV. Environmental Conditions and Result Quality

Environmental conditions can strongly affect the reliability of optical shot detection systems, particularly in low-cost or portable training setups. Even when the detection principle remains unchanged, variations in ambient lighting and background characteristics may alter result consistency.

14.1 Stable Indoor Conditions

Controlled indoor environments generally provide the most repeatable operating conditions for shot detection. Stable illumination reduces unintended brightness fluctuations and allows transient laser events to remain more visually distinguishable.

14.2 Uncontrolled Brightness Conditions

Performance may degrade in highly illuminated or open-area environments where natural light, glare, or moving brightness patterns create competing visual signals. Under such conditions, some systems may become more vulnerable to false positives or unstable sensitivity behavior [12], [18], [33].

14.3 Background Complexity and Contrast Dominance

Interestingly, visually complex backgrounds do not always result in failure. In some cases, patterned or textured surfaces may remain usable if the projected laser event still produces a sufficiently dominant contrast signature. This suggests that contrast dominance may, in some scenarios, be more important than background simplicity alone.

These findings reinforce the idea that result reliability is closely tied to **e**nvironmental compatibility, and therefore simulator evaluation should include realistic operating conditions rather than only idealized demonstrations.

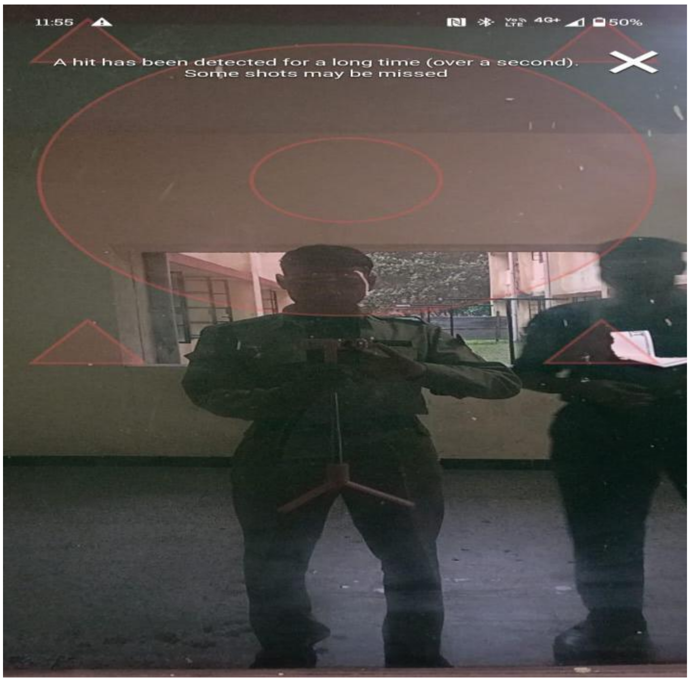

Fig. 3. Illustrative environmental conditions affecting detection stability in optical shooting simulators.
Source: Author-prepared illustrative example.

XV. Detection Reliability and False Positives

A result-oriented shooting simulator must not only detect valid shot events, but also minimize the misclassification of non-shot visual disturbances. In practical use, false positives can significantly reduce trust in the scoring output and limit instructional value.

One commonly discussed challenge in vision-assisted detection systems is the presence of persistent brightness artifacts. When a reflective point or visual highlight remains visible for an extended duration, some systems may interpret it as a valid or repeated event rather than a transient shot occurrence.

Another challenge arises from environmental light fluctuations. Minor changes in brightness, reflections, or moving shadows may trigger false detections in systems that are highly sensitive to intensity changes [12], [18]. Such errors become especially problematic in uncontrolled or mixed-light environments.

For this reason, reliable simulator performance requires a careful balance between:

- sufficient sensitivity to capture valid shot events,
- and sufficient robustness to reject environmental noise.

This balance remains one of the most important practical challenges in result-oriented simulator design.

XVI. Result Interpretation Through Shot Grouping and Accuracy Trends

One of the most valuable capabilities of intelligent marksmanship training systems is their ability to convert raw shot events into interpretable performance patterns [14], [28]. This is what allows such systems to support learning rather than merely display impact points.

A tightly clustered shot group is commonly interpreted as an indicator of:

- stable aim,
- repeatable trigger action,
- and consistent shooter control [7], [28].

Even when the grouping is not perfectly centered, clustering behavior can still provide useful evidence of repeatability. In such cases, the training need may relate more to directional correction than to general instability.

Likewise, a consistently offset shot cluster may suggest a recurring mechanical or alignment-related tendency. This makes grouping interpretation especially useful in training environments where repeated patterns are more informative than isolated score values.

Another important benefit is session-wise trend analysis. When grouping and placement are reviewed across multiple practice sessions, it becomes easier to evaluate whether performance is improving, stabilizing, drifting, or remaining inconsistent [14], [15], [29].

For this reason, result-oriented systems are often most effective when they help users interpret patterns of consistency and deviation, rather than only individual shot scores.

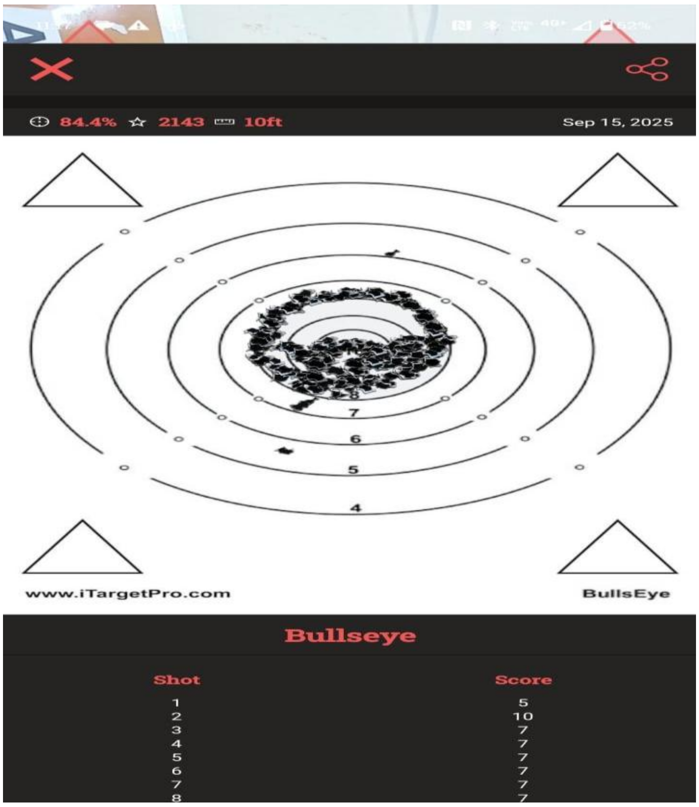

Fig. 4. Example of grouped shot visualization used for interpreting consistency and directional deviation.
Source: Author-prepared illustrative example.

XVII. Research Gaps

Despite substantial progress in intelligent shooting training systems, several important research gaps remain.

One major gap is the lack of standardized result validation. Many systems are described in technical or architectural terms but are not evaluated through repeated, performance-based, and environmentally varied testing procedures [35].

Another significant limitation is weak environmental adaptability. A large number of reported systems remain vulnerable to:

- bright ambient light,
- reflective surfaces,
- dark target regions,
- or visually unstable backgrounds [12], [18], [33].

There is also a shortage of work focused specifically on low-cost result optimization. While many commercial or advanced systems emphasize realism or feature richness, fewer studies focus on maximizing training reliability in portable and resource-accessible configurations [3], [33], [34].

Additionally, although AI is increasingly discussed, many systems still provide limited corrective interpretation. Raw score outputs remain common, while deeper performance explanation and adaptive feedback are still underdeveloped [14], [15].

Finally, a persistent portability versus precision trade-off remains visible across many practical systems. Solutions designed for ease of deployment may still struggle with calibration stability, environmental tolerance, or result consistency.

These gaps indicate that future research should move beyond proof-of-concept demonstrations toward validated, repeatable, and instructionally useful performance systems.

XVIII. Future Research Directions

Future research in intelligent marksmanship simulation should focus not only on technical advancement, but on result robustness and instructional value.

One promising direction is adaptive environmental compensation, where systems automatically adjust to changes in lighting, background brightness, and surface behavior [12], [18]. This would improve reliability in real training environments.

Another important area is surface-aware detection, especially for dark or absorptive target zones that currently reduce shot visibility. Better compensation for such conditions could improve scoring fairness and center-zone detection consistency.

AI-driven corrective coaching is also expected to become increasingly important. Rather than only showing scores, future systems should help trainees understand *why* their patterns are occurring and *how* to improve them [14], [15], [30].

Sensor fusion is another strong research direction. Combining vision-based systems with inertial or motion sensing could improve analysis of posture, stability, and trigger behavior. Recent work using inertial measurement units (IMUs) has shown promise for differentiating posture and stability patterns between novice and expert shooters, suggesting strong potential for multimodal training analytics [37].

Another useful direction is the development of multi-user analytics and instructor dashboard**s**, which would make simulator systems more useful for organized training programs and team-level performance tracking. Emerging visualization-focused research further suggests that multi-layered performance dashboards may improve how trainees interpret aiming behavior and consistency across sessions [38].

Ultimately, the most impactful future systems will be those that maximize training effectiveness effectiveness while maintaining affordability, portability, and result reliability.

XIX. Conclusion

This review examined AI and computer vision based laser marksmanship training systems from a result-oriented perspective, emphasizing the practical factors that determine whether such systems function effectively as training tools. Rather than evaluating simulators only by their sensing methods or interface design, the review focused on the quality of the outcomes they produce—specifically detection dependability, scoring repeatability, environmental tolerance, and instructional usefulness.

The present analysis suggests that laser-assisted and vision-based systems remain among the most promising approaches approaches for safe and accessible marksmanship training, particularly in settings where cost, portability, and repeatability are critical [3], [4], [12], [18]. At the same time, the review also shows that practical performance is strongly shaped by surface characteristics, lighting conditions, and the system's resistance to visual noise.

Artificial intelligence further increases the value of such systems by enabling grouping interpretation, pattern recognition, and training-oriented performance feedback [14], [15], [28]. However, for future systems to be truly impactful, research must move beyond feature-rich design toward validated, robust, and outcome-centered performance.

In this sense, the future of intelligent shooting simulation lies not only in smarter technology, but in building systems that consistently produce reliable results that trainees can learn from.

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