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Design and Development of an AI-Enabled Indoor Marksmanship Training Simulator Using Laser-Based Weapon Tracking and Pneumatic Recoil Feedback for Military and Law-Enforcement Training

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Abstract

Marksmanship training remains a fundamental component of military and law-enforcement preparedness despite advances in autonomous systems, artificial intelligence (AI), and precision-guided weapon technologies. Conventional live-fire training provides realistic weapon handling and ballistic effects but is constrained by high ammunition expenditure, safety concerns, environmental impacts, range limitations, and substantial operating costs. Although several commercial indoor marksmanship simulators have been developed, their widespread adoption within developing nations remains limited due to high acquisition costs, proprietary architectures, and dependence on foreign technical support. This paper presents the design, development, and validation of an indigenous AI-enabled indoor marksmanship training simulator employing laser-based weapon tracking, pneumatic recoil feedback, high-speed camera hit detection, computer-generated target environments, and real-time performance assessment. The proposed architecture integrates modified service rifles and pistols fitted with eye-safe laser emitters and programmable pneumatic recoil actuators with a high-speed vision subsystem and AI-assisted scoring engine. A modular software framework comprising a Training Management System, AI analytics engine, database server, and Instructor Control Station is developed to support adaptive training, automated assessment, and after-action review. Experimental validation was conducted at the Nigerian Defence Academy Small Arms Simulation Centre. The developed system achieved a hit-detection accuracy of 98.6%, mean localisation error of 2.8 mm, root-mean-square error of 3.4 mm, recoil fidelity index of 0.915, system latency of 39 ms, and availability of 98.7%. The results demonstrate that the proposed simulator provides a realistic, responsive, and cost-effective training environment while significantly reducing dependence on imported simulation technologies. The developed architecture offers a scalable and locally maintainable solution suitable for military academies, training schools, police institutions, and security agencies in developing nations.

Keywords: *Indoor Marksmanship Simulator; Military Training; Laser-Based Weapon Tracking; Pneumatic Recoil Simulation; High-Speed Camera; Computer Vision; Artificial Intelligence; Hit Detection; Performance Assessment; Indigenous Defence Technology.*

I. INTRODUCTION

Marksmanship proficiency remains a fundamental competency for military personnel, law-enforcement officers, and security operators. Despite advances in artificial intelligence (AI), autonomous systems, and precision-guided weapons, individual weapon effectiveness continues to play a critical role in close-quarter battle, counter-terrorism operations, force protection missions, and peace-support operations [1–4]. Conventional marksmanship training relies heavily on live-fire exercises, which provide realistic weapon handling and ballistic effects. However, live-fire training is associated with high ammunition expenditure, safety risks, environmental concerns, range limitations, and substantial operating costs [5–8]. These challenges have increased interest in simulation-based training systems capable of providing frequent, safe, and cost-effective practice.

Recent advances in sensing technologies, computer vision, high-speed imaging, machine learning, virtual reality (VR), augmented reality (AR), and digital-twin technologies have transformed indoor marksmanship simulators from simple shot-scoring devices into intelligent training ecosystems capable of providing realistic weapon simulation, adaptive coaching, objective performance analytics, and virtual representation of training assets and environments [9]–[14], [61], [62]. Modern systems can evaluate aiming behaviour, trigger control, reaction time, recoil recovery, and target engagement performance while reducing ammunition consumption and range utilisation requirements. The evolution of marksmanship training technologies is illustrated in Fig. 1.

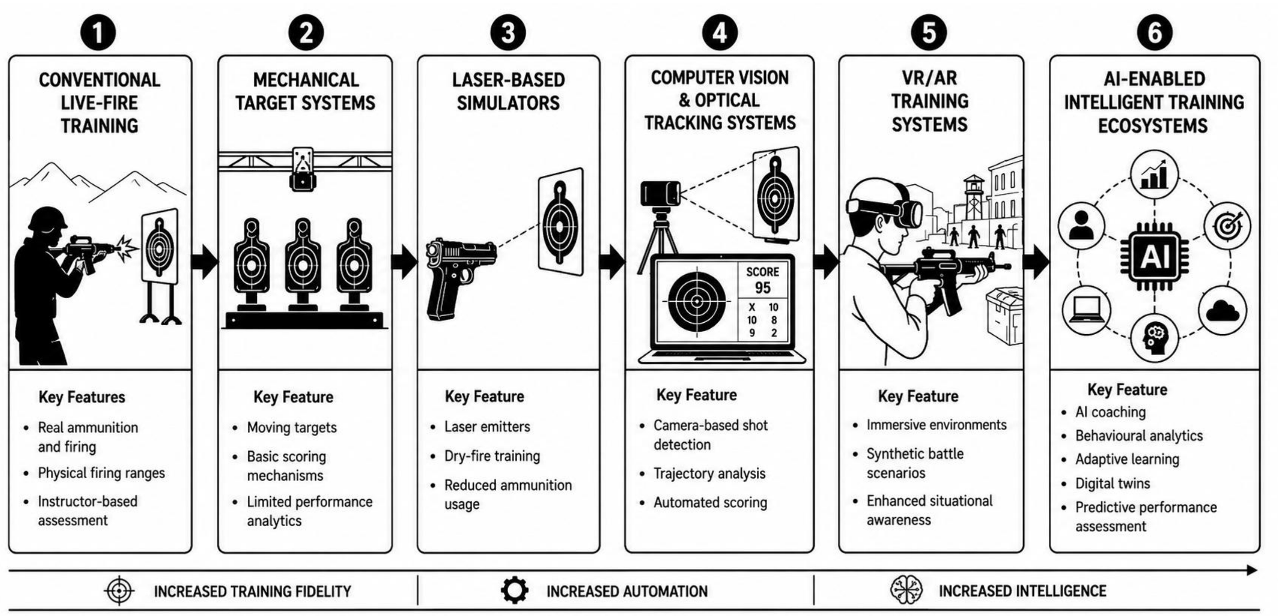

Fig. 1: Evolution of marksmanship training technologies from conventional live-fire exercises to AI-enabled intelligent training ecosystems.

Several commercial systems including InVeris FATS®, VirTra V-300, Saab GAMER, Cubic EST II, and Rheinmetall Indoor Marksmanship Trainers have demonstrated the effectiveness of simulation-based training for military and law-enforcement personnel [33]–[37]. However, their widespread adoption within developing nations remains limited due to high acquisition costs, proprietary architectures, expensive sustainment requirements, and dependence on foreign technical support. Furthermore, many of these systems rely on proprietary architectures that limit local maintenance, customisation, and technology transfer opportunities [33]–[37]. The growing emphasis on defence self-reliance has created a need for indigenous simulator technologies that can be locally manufactured, maintained, and upgraded. Although previous studies have investigated laser-based shooting systems, recoil simulation technologies, computer-vision-assisted scoring, and AI-enabled training environments, limited information exists regarding the development of a unified indigenous architecture integrating real service weapons, laser-based shot tracking, pneumatic recoil simulation, high-speed camera hit detection, AI-assisted assessment, and computerised training management within a single low-cost platform. This represents an important research gap for developing nations.

To address this challenge, this paper presents the design and development of an AI-enabled indoor marksmanship training simulator employing laser-based weapon tracking and pneumatic recoil feedback. The proposed system integrates modified rifles and pistols, eye-safe laser emitters, programmable pneumatic recoil actuators, high-speed cameras, AI-assisted hit localisation algorithms, and a comprehensive training management framework to provide realistic and data-driven marksmanship training. The principal contributions of this work include:

- Development of an indigenous indoor marksmanship simulator architecture.
- Integration of real rifles and pistols with laser-based weapon tracking.
- Development of a programmable pneumatic recoil simulation system.
- Design of a high-speed camera-based hit detection subsystem.
- Implementation of AI-assisted scoring and performance assessment.
- Development of training management and instructor control software.
- Provision of a scalable and cost-effective solution suitable for developing nations.

The remainder of this paper is organised as follows. Section 2 presents the system requirements and design specifications. Section 3 describes the overall simulator architecture. Sections 4–7 discuss subsystem development. Experimental validation conducted at the Nigerian Defence Academy Small Arms Simulation Centre is presented in Sections 8 and 9, while Section 10 concludes the paper and outlines future research directions.

2. System Requirements and Design Specifications

The design of the proposed indoor marksmanship simulator was guided by military training requirements, existing simulator capabilities, and operational performance objectives identified in the literature. The system was required to provide realistic weapon handling, accurate hit detection, repeatable recoil feedback, real-time performance assessment, and scalable training management while remaining affordable and easy to maintain. The principal operational requirements considered during development are summarised in Table 1.

Table 1: Operational Requirements of the Proposed Simulator

Requirement	Description
Weapon Realism	Use of actual rifles and pistols
Recoil Realism	Realistic recoil generation
Hit Detection	Accurate shot localisation
Safety	Elimination of live ammunition
Scalability	Support for multiple trainees
Maintainability	Local servicing capability
Cost Effectiveness	Reduced acquisition and operating costs
Performance Assessment	Automated trainee evaluation
Training Flexibility	Support for multiple scenarios
Reliability	Continuous operation capability

The requirements listed in Table 1 formed the basis for defining subsystem design targets and performance benchmarks. Based on these requirements, quantitative performance specifications were established and are presented in Table 2.

Table 2: Design Performance Specifications

Parameter	Target Value
Hit Detection Accuracy	≥ 98 %
Localisation Error	≤ 5 mm
Camera Frame Rate	≥ 240 fps
AI Classification Accuracy	≥ 95 %
Recoil Fidelity Index	≥ 0.90
System Latency	≤ 50 ms
System Availability	≥ 95 %
Training Capacity	1–20 Trainees
Weapon Types	Rifle and Pistol
Target Types	Static and Dynamic

The hit-detection accuracy requirement is expressed as:

$$A_H = \frac{N_c}{N_t} \times 100 \qquad (1)$$

where A_H is the hit-detection accuracy, N_c is the number of correctly detected shots, and N_t is the total number of shots fired. The localisation error requirement is defined as:

$$E_L = \sqrt{(x_t - \hat{x}_t)^2 + (y_t - \hat{y}_t)^2} \qquad (2)$$

where (x_t, y_t) is the actual shot location and $(\hat{x}_t, \hat{y}_t)$ is the estimated shot location obtained from the camera-based detection subsystem. The system availability requirement is given by:

$$A_v = \frac{T_o}{T_o + T_d} \times 100 \qquad (3)$$

where A_v is system availability, T_o is operational uptime, and T_d is downtime due to faults, maintenance, or subsystem failure.

The performance specifications presented in Table 2 establish the criteria against which the simulator is evaluated during laboratory testing and operational validation at the Nigerian Defence Academy Small Arms Simulation Centre. These specifications ensure that the developed system achieves the levels of realism, accuracy, responsiveness, and reliability required for effective military and law-enforcement marksmanship training.

3. Overall System Architecture

The proposed indoor marksmanship simulator adopts a modular architecture comprising six major subsystems: the Weapon Simulation Module, Pneumatic Recoil System, High-Speed Camera Subsystem, AI-Based Hit Detection Engine, Training Management Software, and Instructor Control Station. These subsystems collectively provide realistic weapon simulation, accurate hit detection, automated performance assessment, and instructor supervision within a unified training environment. The overall architecture of the proposed simulator is illustrated in Fig. 2.

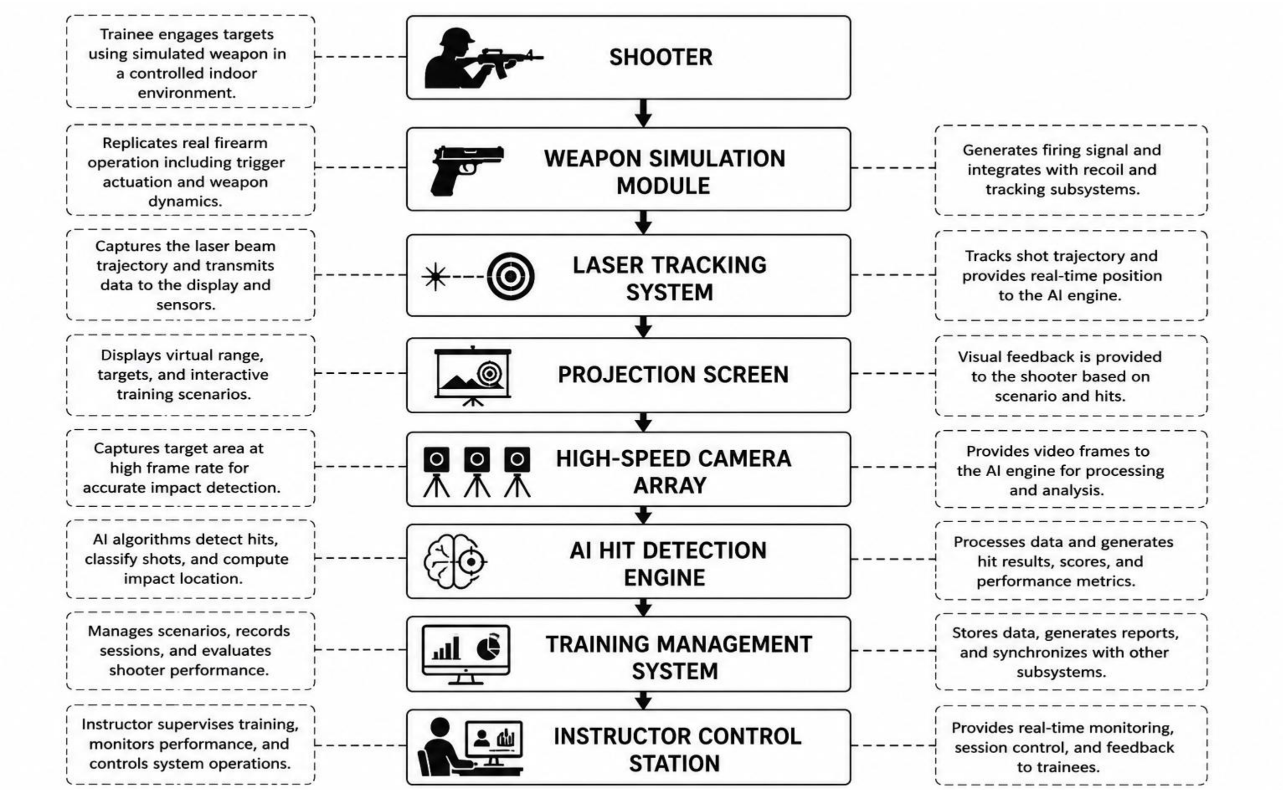

Fig. 2: Overall Architecture of the Proposed AI-Enabled Indoor Marksmanship Simulator

As shown in Fig. 2, the simulator integrates sensing, processing, analytics, and training-management functions to provide real-time performance assessment and adaptive training feedback. The detailed functional architecture is presented in Fig. 3.

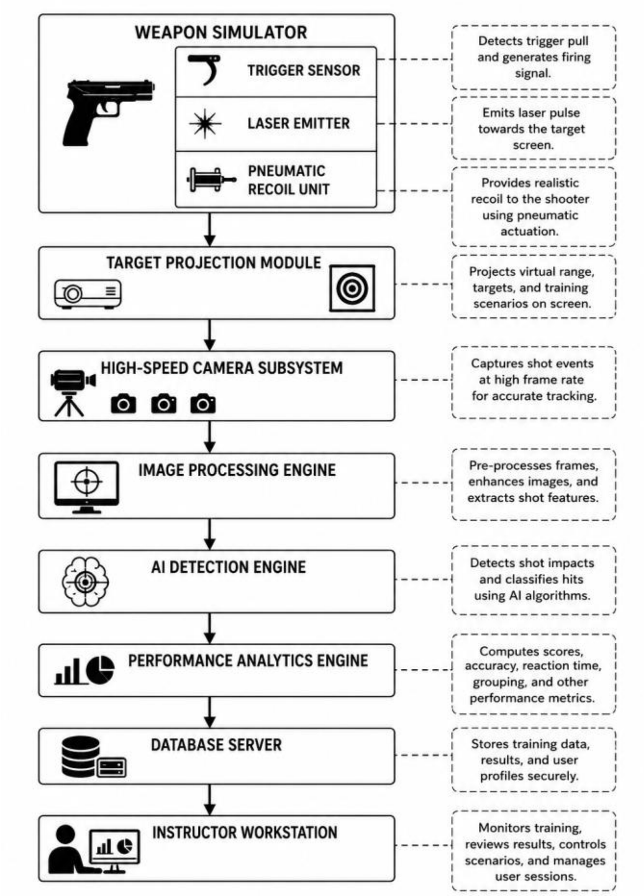

Fig. 3: Functional Architecture of the Proposed Simulator.

The architecture shown in Fig. 3 facilitates modular implementation, ease of maintenance, and future upgrades while ensuring interoperability between sensing, processing, analytics, and training-management subsystems. Shot impacts are determined using laser projection and high-speed camera tracking. The hit localisation error is expressed as:

$$E_H = \sqrt{(x_t - \hat{x}_t)^2 + (y_t - \hat{y}_t)^2} \qquad (4)$$

where: E_H= hit localisation error, (x_t, y_t) = actual impact location and $(\hat{x}_t, \hat{y}_t)$= estimated impact location obtained from the image-processing subsystem. Equation (4) provides a quantitative measure of localisation accuracy and is subsequently employed during system validation and performance assessment.

Accurate camera calibration is essential for reliable hit localisation. The relationship between image coordinates and physical coordinates is described by the projective camera model [57]:

$$s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = K[R \quad t] \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \qquad (5)$$

where: s= scale factor, (u, v)= image coordinates, K= intrinsic camera matrix, R= rotation matrix, t= translation vector and (X, Y, Z)= physical coordinates in the target reference frame. Equation (5) establishes the transformation between image space and real-world coordinates, thereby enabling accurate determination of laser impact locations on the projection screen. The major hardware components employed within the simulator architecture are summarised in Table 3.

Table 3: Major Hardware Components of the Simulator

Component	Function
Modified Rifle/Pistol	Weapon simulation
Laser Emitter	Shot projection
Trigger Sensor	Trigger detection
Pneumatic Actuator	Recoil generation
Air Reservoir	Recoil energy storage
High-Speed Camera	Hit localisation
Projection Screen	Target display
AI Workstation	Image processing and analytics
Database Server	Data storage
Instructor Station	Training supervision

The components listed in Table 3 collectively form the hardware foundation of the proposed indigenous AI-enabled indoor marksmanship training simulator and support the realistic, safe, and cost-effective delivery of military and law-enforcement marksmanship training.

4. Weapon Simulation Module

The Weapon Simulation Module (WSM) serves as the primary human–machine interface of the proposed simulator and is responsible for reproducing the handling characteristics, aiming behaviour, trigger response, and firing sequence of operational firearms while ensuring complete safety. Unlike many commercial simulators that employ replica weapons, the proposed architecture utilises modified service rifles and pistols integrated with laser projection, trigger sensing, wireless communication, embedded control electronics, and pneumatic recoil interfaces. This approach preserves weapon ergonomics, mass distribution, trigger characteristics, and sighting systems, thereby improving training realism and skill transfer [30]–[33]. The subsystem supports basic marksmanship, close-quarter battle (CQB), urban operations, judgemental shooting, and tactical engagement training. The overall architecture is illustrated in Fig. 4.

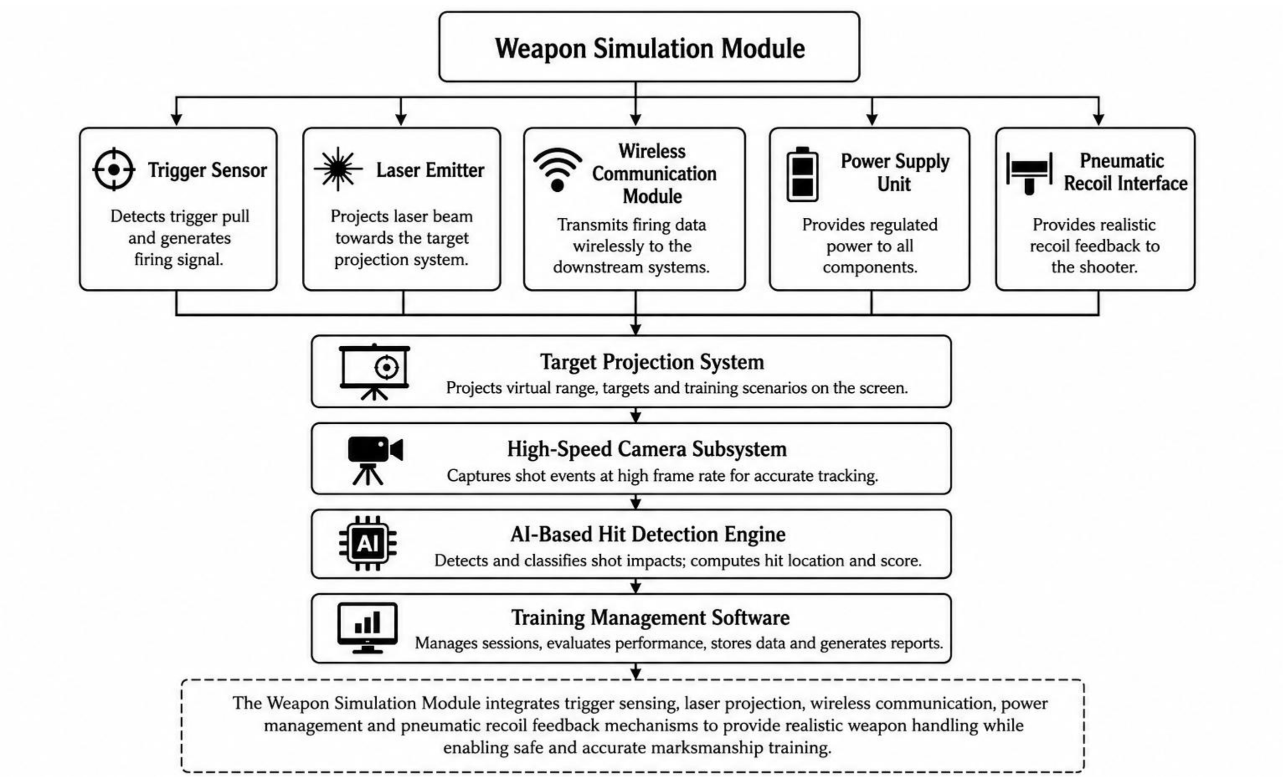

Fig. 4: Architecture of the Weapon Simulation Module

4.1 Design Requirements

The WSM was designed to:

- Preserve weapon ergonomics and handling characteristics.
- Provide accurate trigger sensing.
- Support realistic aiming and sight alignment.
- Support multiple weapon platforms.
- Ensure safe operation without live ammunition.
- Integrate seamlessly with recoil simulation and AI-based assessment systems.
- Support indigenous manufacture and maintenance.
- Enable real-time communication with the training management system.

These requirements ensure realistic training while maintaining affordability, scalability and maintainability.

4.2 Rifle Simulation Subsystem

The rifle simulator is based on modified military rifles such as the AK-47, AK-103, M16A4, M4 Carbine, and Tavor TAR-21. The firing mechanism is disabled and replaced with an electronic trigger-sensing assembly while preserving the external geometry and handling characteristics of the original weapon. The principal components include laser projection module, trigger sensing mechanism, embedded controller, wireless communication interface, rechargeable power supply and neumatic recoil interface. The subsystem architecture is shown in Fig. 5.

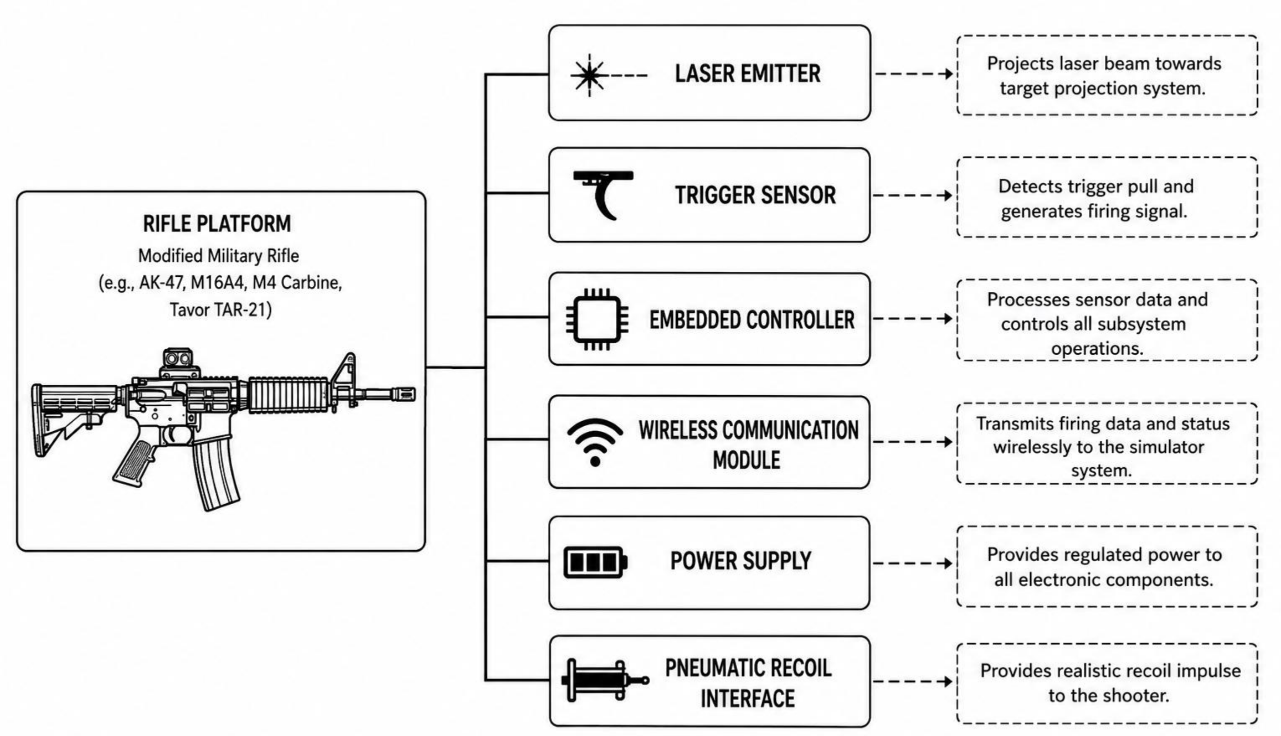

Fig. 5: Rifle Simulation Subsystem Architecture

The projected laser trajectory is represented by:

$$\mathbf{L}(t) = \mathbf{P}_0 + \mathbf{V}t \qquad (6)$$

where $\mathbf{P}_0$ is the initial laser position vector, $\mathbf{V}$is the direction vector, and $t$is the propagation parameter [34]–[38]. The aiming error is given by:

$$E_A = \sqrt{(x_t - x_r)^2 + (y_t - y_r)^2} \qquad (7)$$

where (x_t, y_t) represents the intended aiming point and (x_r, y_r) denotes the reference target coordinates.

4.3 Pistol Simulation Subsystem

The simulator also supports service pistols such as the Glock 17, Beretta M9, Browning Hi-Power, and SIG Sauer P226. The pistol subsystem employs the same architecture as the rifle simulator but uses miniaturised electronics to accommodate the reduced internal volume available within handgun platforms. Representative weapon platforms supported by the simulator are presented in Table 4.

Table 4: Representative Operational Weapons Supported by the Simulator

Weapon Platform	Type	Application
AK-47	Assault Rifle	Infantry Training
AK-103	Assault Rifle	Infantry Training
M16A4	Assault Rifle	Marksmanship Training
M4 Carbine	Carbine	CQB Training
Tavor TAR-21	Assault Rifle	Urban Operations
Glock 17	Pistol	Law-Enforcement Training
Beretta M9	Pistol	Military Sidearm Training
SIG Sauer P226	Pistol	Special Operations Training

The principal characteristics of the simulation platforms are summarised in Table 5.

Table 5: Comparison of Operational and Simulated Weapon Characteristics

Parameter	Rifle Simulator	Pistol Simulator
Physical Dimensions	Realistic	Realistic
Weight Distribution	Realistic	Realistic
Trigger Feel	Realistic	Realistic
Recoil Feedback	Simulated	Simulated
Laser Projection	Yes	Yes
Wireless Communication	Yes	Yes
AI Integration	Yes	Yes
Safety Risk	None	None

4.4 Laser Projection Subsystem

The laser projection subsystem simulates projectile impact by projecting a visible laser pulse onto the target screen whenever the trigger is actuated. Eye-safe semiconductor laser diodes aligned with the weapon bore are employed to minimise aiming errors [34]–[36]. The detection process is illustrated in Fig. 6.

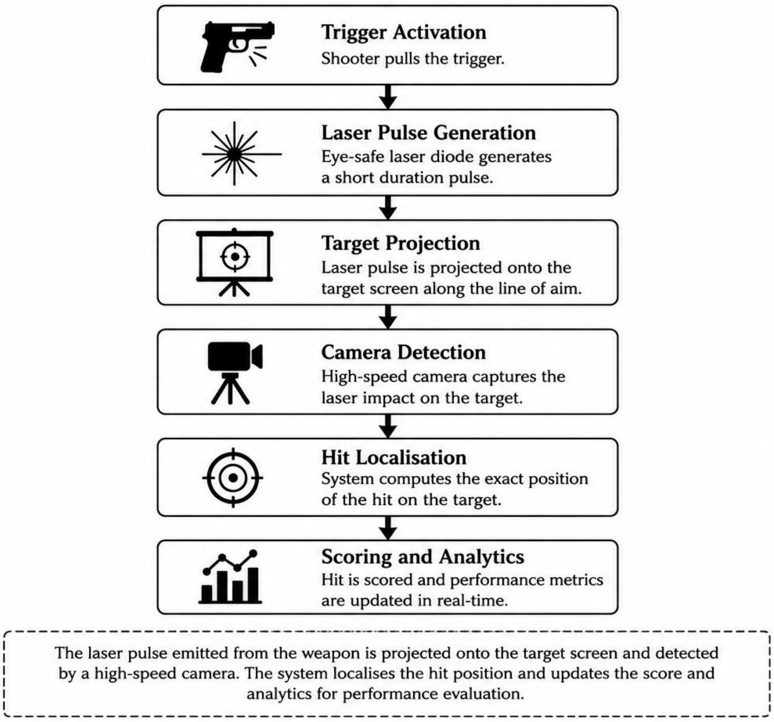

Fig. 6: Laser Projection and Detection Process

The laser-pointing error is defined as:

$$E_L = \sqrt{(x_t - \hat{x}_t)^2 + (y_t - \hat{y}_t)^2} \qquad (8)$$

where (x_t, y_t) represents the actual impact location and $(\hat{x}_t, \hat{y}_t)$ denotes the estimated impact location. The laser beam diameter at the target plane is approximated by:

$$D_b = D_0 + \theta R \qquad (9)$$

where D_0 is the initial beam diameter, θ is the beam divergence angle, and $R$is the target distance.

The laser specifications are presented in Table 6.

Table 6: Laser Projection Subsystem Specifications

Parameter	**Specification**
Laser Type	Semiconductor Diode
Wavelength	650 nm
Laser Class	II / IIIa
Output Power	< 5 mW
Beam Divergence	< 1 mrad
Pulse Duration	5–20 ms
Operating Voltage	3.3–5 V
Detection Range	5–50 m

4.5 Trigger Detection and Communication System

Reliable trigger detection establishes the temporal reference point for shot registration, recoil generation and hit localisation. Hall-effect sensors or industrial microswitches are integrated within the trigger mechanism. The trigger response time is expressed as:

$$T_r = T_s + T_c \qquad (10)$$

where T_s is the sensor activation time and T_c is the controller processing time. The communication latency is given by:

$$T_{comm} = T_{enc} + T_{tx} + T_{rx} \qquad (11)$$

where T_{enc}, T_{tx} and T_{rx} denote encoding, transmission, and receiver-processing times respectively.

Bluetooth Low Energy (BLE) and Wi-Fi protocols were selected because of their low latency, reliability, interoperability, and compatibility with modern embedded weapon electronics and wireless sensor systems [39], [40]. The estimated latency contributions of the trigger detection and communication subsystems are summarised in Table 7. As shown, the overall latency remains below 20 ms, ensuring rapid synchronisation between trigger activation, recoil generation, laser projection and hit registration.

Table 7: Trigger and Communication Latency Budget

Component	**Typical Latency (ms)**
Trigger Sensor	1–3
Controller Processing	2–5
Data Encoding	1–2
Wireless Transmission	5–10
Receiver Processing	1–3
Total Latency	<20

4.6 Training Transfer Considerations

A primary objective of the WSM is to maximise training transfer between simulated and live-fire environments. The Transfer Effectiveness Ratio (TER) is expressed as:

$$TER = \frac{L_{sim}}{L_{live}} \qquad (12)$$

where L_{sim} represents learning achieved during simulator training and L_{live} denotes learning achieved during live-fire training. Values approaching unity indicate strong transfer of acquired skills [30]–[33]. Training transfer remains one of the most important indicators of simulator effectiveness and is widely used by military organisations to assess the operational value of synthetic training environments [25]–[27], [52], [53].

To maximise training effectiveness, the simulator preserves weapon mass, balance, trigger characteristics, sighting systems, handling procedures, and recoil behaviour. Integration with the AI-assisted assessment engine further enables objective evaluation of aiming stability, trigger discipline, target acquisition speed, and engagement effectiveness. Similar performance measures are employed within modern military simulator programmes to support objective trainee assessment and readiness evaluation [25]–[27]. The Weapon Simulation Module therefore forms the foundation of the proposed AI-enabled indoor marksmanship training simulator and provides the physical interface through which trainees interact with the broader training ecosystem.

5. Pneumatic Recoil Simulation System

Realistic recoil reproduction is a critical requirement for effective marksmanship simulation because recoil influences weapon control, aiming stability, follow-through, target reacquisition, and overall shooting performance. Studies have shown that the absence of realistic recoil feedback can significantly reduce training transfer, weapon familiarisation, and shooting performance, particularly during rapid-fire engagements [38], [46]–[48]. Consequently, recoil simulation forms a key component of the proposed indoor marksmanship training system. Among the various recoil-generation technologies used in commercial simulators, pneumatic systems provide an effective balance between realism, affordability, reliability, and ease of maintenance [46]–[49]. The proposed system therefore employs a programmable pneumatic recoil architecture capable of reproducing recoil characteristics for rifles and pistols while remaining suitable for indigenous manufacture and support. The overall architecture of the recoil subsystem is illustrated in Fig. 7.

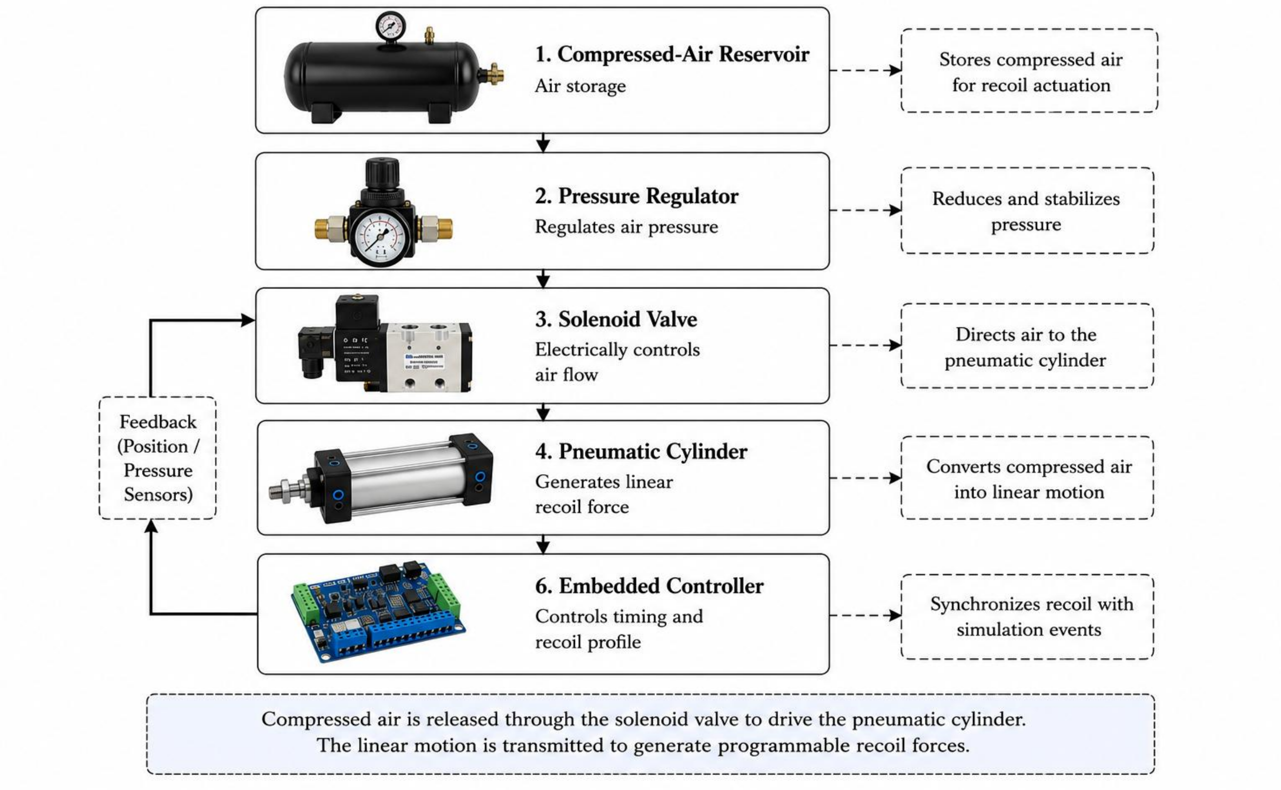

Fig. 7: Architecture of the Pneumatic Recoil Simulation System

As shown in Fig. 7, compressed air is released in a controlled manner to generate programmable recoil forces synchronised with laser projection and hit detection.

5.1 Recoil Generation Mechanism

The recoil subsystem employs a compact double-acting pneumatic cylinder integrated within the weapon assembly. Trigger activation simultaneously initiates laser projection and recoil generation. The embedded controller energises the solenoid valve, allowing compressed air to actuate the cylinder and generate a rearward force that simulates live-fire recoil. The recoil force generated by the actuator is expressed as:

$$F_r = P_a A_p \qquad (13)$$

where: F_r= recoil force (N), P_a= pneumatic pressure (Pa) and A_p= effective piston area. The recoil-generation sequence is illustrated in Fig. 8.

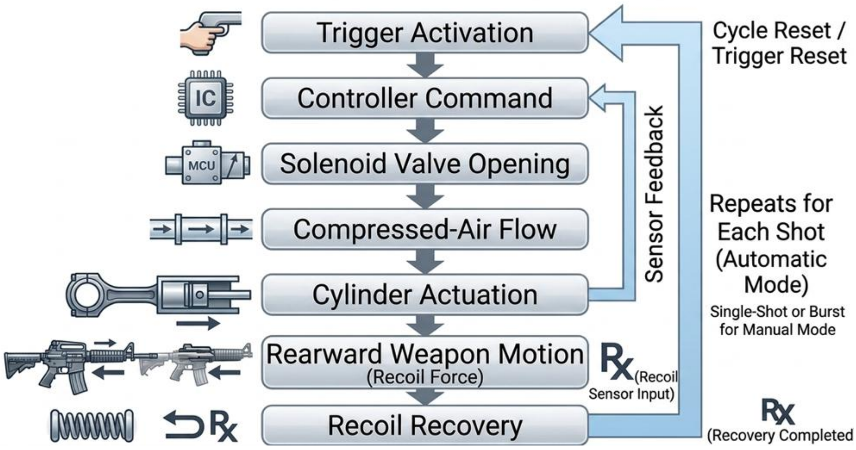

Fig. 8: Pneumatic Recoil Generation Sequence

The recoil displacement dynamics may be approximated by:

$$M\frac{d^2x}{dt^2} = F_r - F_d \qquad (14)$$

where: M= equivalent recoil mass, x= recoil displacement and F_d= damping force. Equations (13) and (14) provide the basis for sizing the pneumatic actuator, predicting recoil response, and tuning the dynamic behaviour of the recoil generation subsystem using established fluid-power control principles [50], [51].

5.2 Recoil Impulse Modelling

Because recoil perception depends on both force magnitude and duration, recoil impulse was adopted as a primary design parameter [46]–[51]. The recoil impulse is defined as:

$$I_r = \int_0^T F_r(t)\,dt \qquad (15)$$

where: I_r= recoil impulse (N·s), $F_r(t)$= time-varying recoil force and T= recoil duration. The recoil energy is expressed as:

$$E_r = \frac{1}{2}MV_r^2 \qquad (16)$$

where: M= equivalent moving mass and V_r= recoil velocity. Representative recoil characteristics for selected weapon classes are presented in Table 8.

Table 8: Representative Recoil Characteristics of Selected Weapons

Weapon Type	Approximate Recoil Energy (J)	Relative Recoil Level
9 mm Pistol	3–5	Low
Submachine Gun	4–7	Low–Moderate
M4 Carbine	5–8	Moderate
AK-47 Rifle	7–10	Moderate–High
7.62 mm Battle Rifle	10–15	High

The values presented in Table 8 were derived from published military recoil studies, ballistic measurements, NATO weapon-performance standards, and SAAMI ammunition data [38], [46]–[48].

5.3 Recoil Fidelity Assessment

To quantify recoil realism, a Recoil Fidelity Index (RFI) was adopted:

$$RFI = 1 - \frac{|\, I_{live} - I_{sim} \,|}{I_{live}} \qquad (17)$$

where: I_{live}= measured live-fire recoil impulse and I_{sim}= simulated recoil impulse. Values approaching unity indicate strong agreement between simulated and live-fire recoil characteristics.

To evaluate waveform similarity, the correlation coefficient is computed as:

$$\rho = \frac{\sum_{i=1}^{N}(F_{live,i} - \bar{F}_{live})(F_{sim,i} - \bar{F}_{sim})}{\sqrt{\sum_{i=1}^{N}(F_{live,i} - \bar{F}_{live})^2}\sqrt{\sum_{i=1}^{N}(F_{sim,i} - \bar{F}_{sim})^2}} \qquad (18)$$

where ρ denotes the recoil waveform correlation coefficient. Values approaching unity indicate close agreement between simulated and measured recoil profiles.

5.4 Recoil Control and Adjustment

Because different firearms produce distinct recoil signatures, the simulator incorporates programmable recoil-control capabilities. Such adaptability is important because recoil characteristics vary significantly across weapon classes and influence shooter performance, weapon controllability, and target reacquisition [38], [46]. The embedded controller adjusts operating pressure, valve pulse duration, recoil pulse width, and recovery characteristics to emulate different weapon systems. The adjustable recoil parameters are summarised in Table 9.

Table 9: Adjustable Recoil Parameters

Parameter	Function
Operating Pressure	Controls recoil force
Valve Pulse Duration	Controls recoil impulse
Recovery Time	Controls return characteristics
Firing Mode	Single, Burst, Automatic
Weapon Profile	Rifle or Pistol
Recoil Intensity	Low, Medium, High

A proportional-integral-derivative (PID) controller is employed to regulate recoil response:

$$u(t) = K_p e(t) + K_i \int e(t)\, dt + K_d \frac{de(t)}{dt} \qquad (19)$$

where: $u(t)$= control signal, $e(t)$= recoil error, K_p, K_i, and K_d are controller gains. Equation (19) enables repeatable recoil generation across multiple firing cycles. The controller design follows established feedback-control and fluid-power system principles widely employed in pneumatic actuation, industrial automation, and mechatronic systems [43]–[45], [50], [51], [74]–[77].

The proposed pneumatic recoil architecture provides a cost-effective and maintainable solution for reproducing realistic weapon recoil. Its low complexity, software-configurable recoil profiles, and compatibility with multiple weapon platforms enhance training realism and skill transfer while supporting indigenous development. Integration with the laser tracking, hit-detection, and AI-based assessment subsystems enables a comprehensive and effective marksmanship training environment [46]–[49].

6. High-Speed Camera Hit Detection Subsystem

Accurate hit detection is a critical requirement of indoor marksmanship simulators because it directly influences scoring accuracy, performance assessment, and training credibility. Recent advances in machine vision, high-speed imaging, and computer vision have enabled optical hit-detection systems capable of detecting laser impacts with high accuracy and low latency [57]–[63]. Similar optical hit-detection approaches have been adopted within several commercial military marksmanship simulators because of their scalability, accuracy, and support for automated scoring [33]–[37]. Compared with conventional optical sensors, camera-based systems provide superior spatial resolution, improved flexibility, and support for AI-assisted analytics.

The proposed subsystem employs a network of industrial-grade global-shutter cameras, image acquisition hardware, calibration routines, and image-processing algorithms to detect laser impacts and provide real-time shot registration. The subsystem was designed to achieve localisation accuracy better than 5 mm, frame rates exceeding 240 fps, and total processing latency below 50 ms while supporting static, moving, and judgemental targets. The overall architecture is illustrated in Fig. 9.

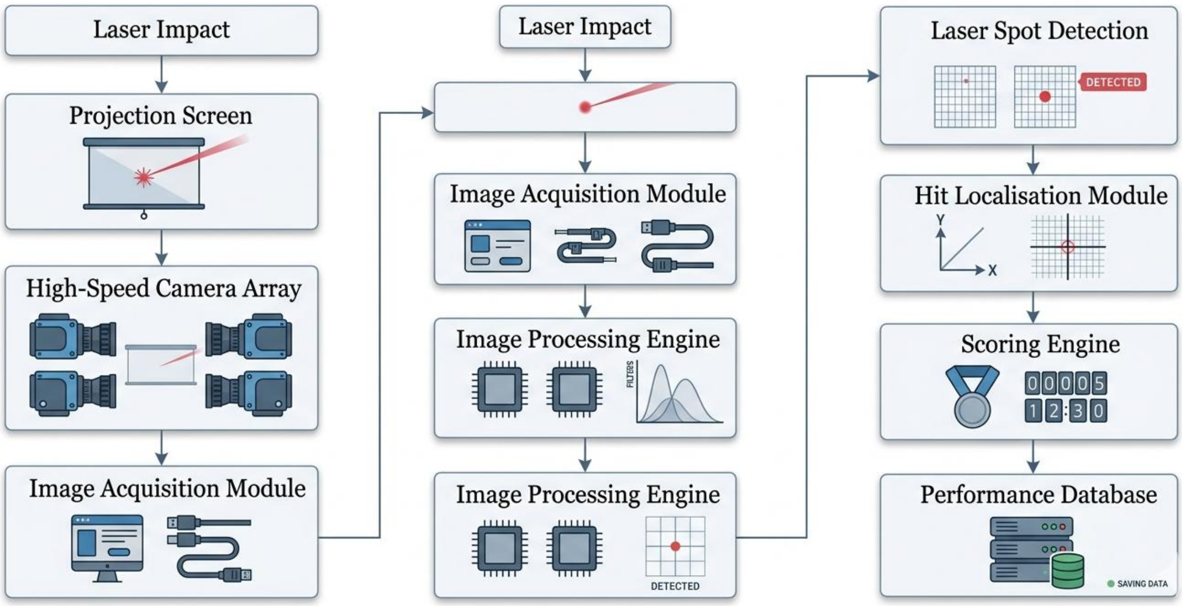

Fig. 9: High-Speed Camera Hit Detection Architecture.

Table 10: Design Requirements for the High-Speed Camera Subsystem

Requirement	Design Target
Localisation Accuracy	< 5 mm
Frame Rate	≥ 240 fps
System Latency	< 50 ms
Target Compatibility	Static, Moving and Judgemental Targets
AI Compatibility	Automated Scoring and Analytics
Maintainability	Commercial Off-The-Shelf Components

The principal design requirements and camera specifications are summarised in Tables 10 and 11, respectively.

Table 11: High-Speed Camera Specifications

Parameter	Specification
Sensor Type	CMOS Global Shutter
Resolution	1920 × 1080 pixels
Frame Rate	240–1000 fps
Lens Type	Fixed Focus
Field of View	60–90°
Exposure Time	10–500 μs
Interface	USB 3.0 / GigE

To ensure accurate localisation, camera calibration is performed using the projective camera model [62]:

$$s\begin{bmatrix}u\\v\\1\end{bmatrix} = K[R \quad t]\begin{bmatrix}X\\Y\\Z\\1\end{bmatrix} \qquad (20)$$

where K is the intrinsic camera matrix, R is the rotation matrix, t is the translation vector, and s is a scale factor. The physical arrangement of the cameras around the projection screen is illustrated in Fig. 10.

The transformation represented by Eq. (21) converts image-space coordinates into real-world target coordinates and enables accurate localisation of laser impacts on the projection screen. The physical arrangement of the cameras around the projection screen is illustrated in Fig. 10.

$$\begin{bmatrix}x_w\\y_w\end{bmatrix} = \mathbf{H}\begin{bmatrix}u\\v\\1\end{bmatrix} \qquad (21)$$

where x_w and y_w denote the physical coordinates of the detected laser impact on the target plane, $u$and $v$are the corresponding image coordinates obtained from the camera, and **H** is the homography transformation matrix determined during camera calibration.

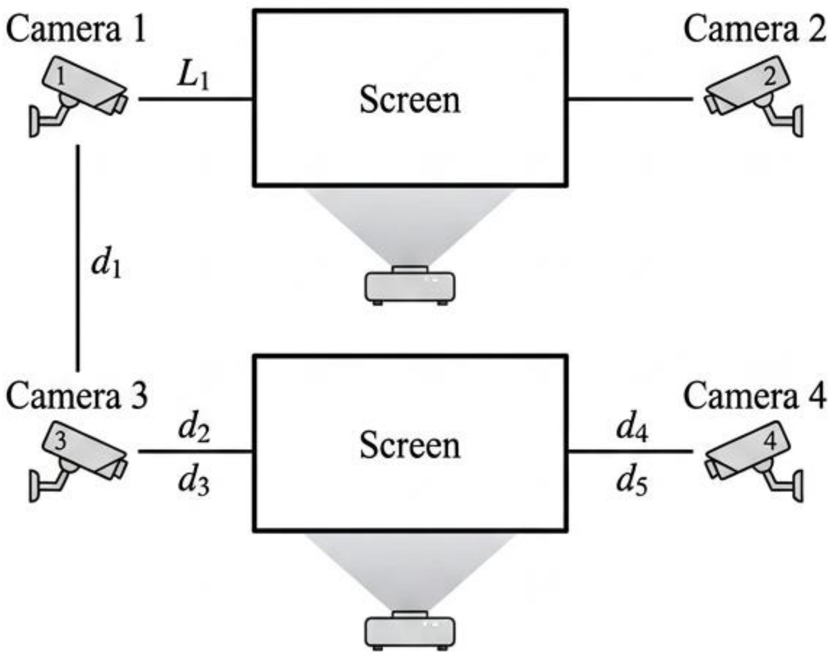

Fig. 10: Camera Deployment Around the Projection Screen

Laser spot detection is achieved through image acquisition, filtering, thresholding, blob detection, centroid extraction, and coordinate transformation as illustrated in Fig. 11. Standard image-processing techniques including thresholding, edge detection, and feature extraction were employed [67]–[70].

The centroid of the detected laser spot is determined using:

$$u_c = \frac{\sum_{i=1}^{N} u_i I_i}{\sum_{i=1}^{N} I_i}, v_c = \frac{\sum_{i=1}^{N} v_i I_i}{\sum_{i=1}^{N} I_i} \qquad (22)$$

while hit localisation accuracy is evaluated using:

$$E_H = \sqrt{(x_t - \hat{x}_t)^2 + (y_t - \hat{y}_t)^2} \qquad (23)$$

and

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2]} \qquad (24)$$

where $RMSE$ provides a robust measure of localisation accuracy [57]–[63]. The total hit-detection latency is expressed as:

$$T_{HD} = T_{exp} + T_{acq} + T_{proc} + T_{AI} + T_{score} \qquad (25)$$

The overall hit-detection accuracy of the subsystem is quantified using Eq. (26), which compares the number of correctly detected impacts against the total number of shots fired during testing. This metric provides a direct measure of the effectiveness of the camera hardware, calibration procedure, image-processing pipeline, and localisation algorithms. During experimental validation, the proposed subsystem achieved a hit-detection accuracy exceeding 98%, thereby satisfying the design target specified in Table 10.

$$A_d = \frac{N_d}{N_t} \times 100 \qquad (26)$$

where A_d is the hit-detection accuracy (%), N_d is the number of correctly detected laser impacts and N_t is the total number of laser shots fired during testing.

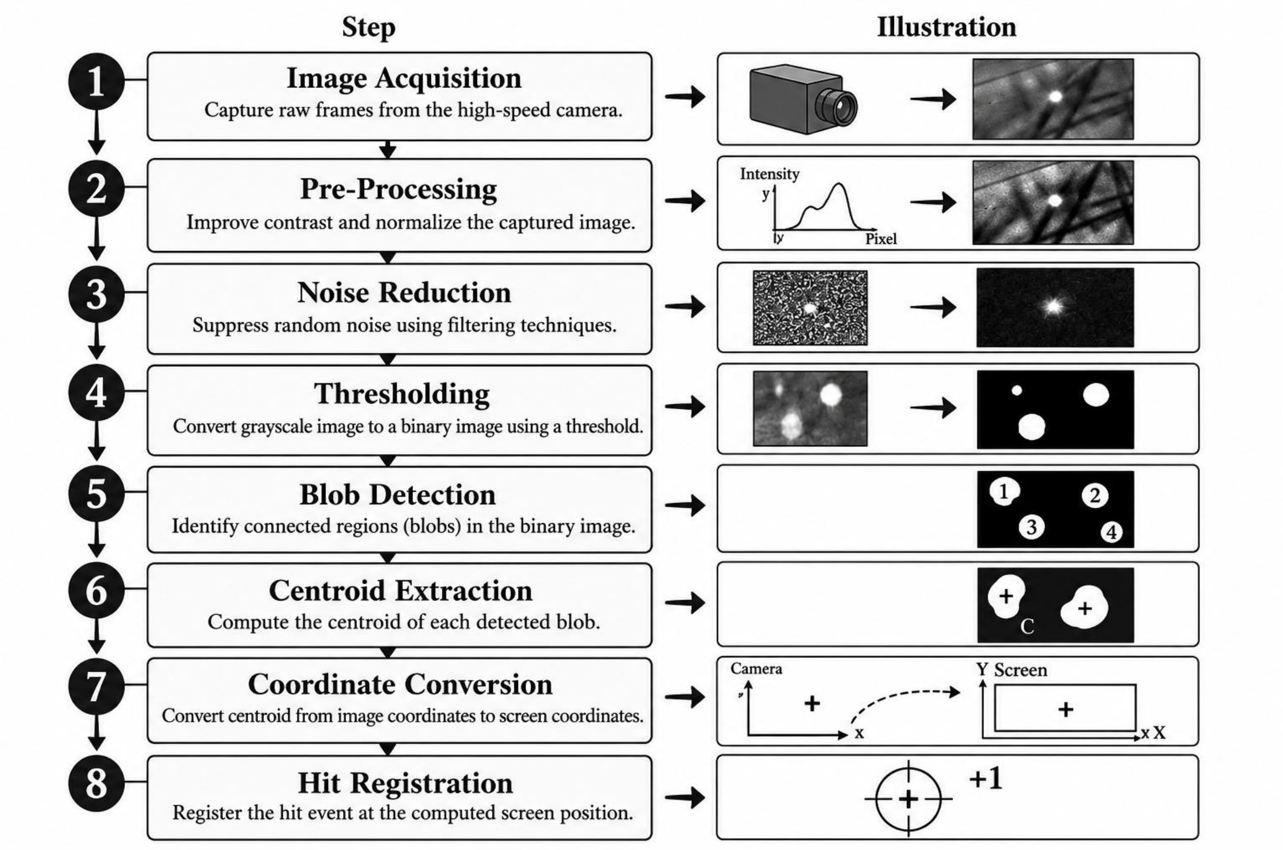

Fig. 11: Laser Spot Detection Workflow

The latency budget adopted for the simulator is summarised in Table 12.

Table 12: Target Latency Budget

Subsystem	Target Latency
Trigger Detection	< 5 ms
Camera Acquisition	< 15 ms
Image Processing	< 20 ms
AI Analysis	< 10 ms
Scoring	< 5 ms
Total System Latency	< 50 ms

The proposed vision-based architecture provides accurate hit localisation, real-time scoring, and robust operation while maintaining low acquisition and maintenance costs. Its integration with the weapon simulation module, pneumatic recoil subsystem, AI-assisted scoring engine, and training management software enables a comprehensive and realistic marksmanship training environment suitable for military and law-enforcement applications.

7. AI-Based Hit Detection Engine and Training Management Software

AI has transformed modern military training systems by enabling automated scoring, performance assessment, adaptive coaching and data-driven decision support [64]–[70]. In the proposed simulator, the AI-Based Hit Detection Engine (AI-HDE) and Training Management Software (TMS) form the central intelligence layer responsible for hit classification, scoring, trainee evaluation, scenario management, performance analytics, and after-action review. By integrating machine learning, computer vision, and training management capabilities, the subsystem transforms raw hit-localisation data into actionable training intelligence. The overall architecture of the AI-based training subsystem is illustrated in Fig. 12.

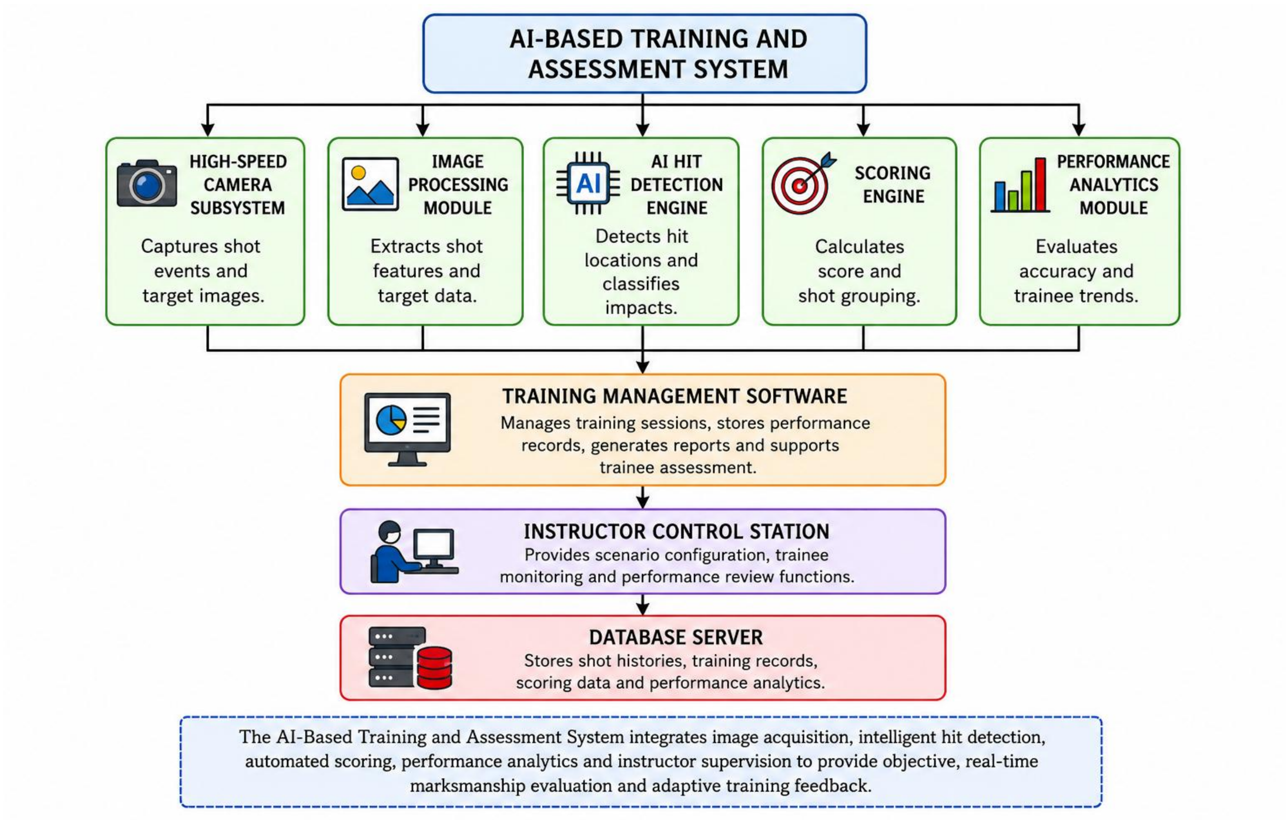

Fig. 12: Architecture of the AI-Based Training and Assessment System

The subsystem was designed to support automatic hit classification, real-time scoring, trainee assessment, adaptive coaching, data storage, after-action review, and multi-user training management. These capabilities are consistent with current military training philosophies that emphasise objective performance measurement, after-action review, and data-driven training management [52]–[54]. These capabilities provide significantly greater training value than conventional electronic target systems. The principal functional requirements are summarised in Table 13.

Table 13: Functional Requirements of the AI-Based Training Subsystem

Requirement	Purpose
Hit Classification	Determine shot validity
Automated Scoring	Real-time score computation
Performance Analytics	Evaluate trainee proficiency
Adaptive Coaching	Personalised training support
Data Storage	Long-term performance tracking
AAR Capability	Structured post-training review
Instructor Support	Decision-making assistance
Multi-User Management	Large-scale training support

The AI-based hit-detection process is illustrated in Fig. 13.

Fig. 13. AI-Based Hit Detection and Scoring Pipeline

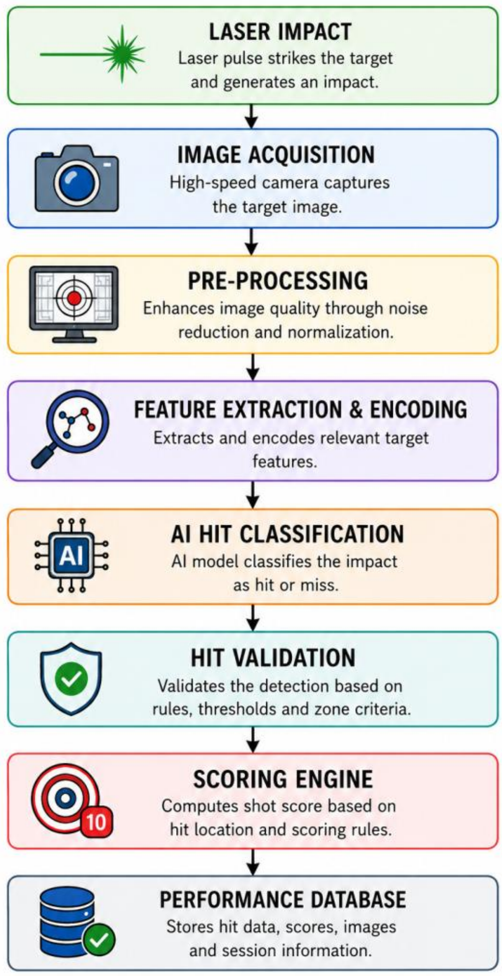

Fig. 13: AI-Based Hit Detection Pipeline

The classification engine employs Convolutional Neural Networks (CNNs), which have demonstrated excellent performance in image recognition, object classification, and visual target detection applications [16], [21], [22]. During network training, classification error is minimised using the cross-entropy loss function:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \qquad (27)$$

where L is the classification loss, y_i is the true class label, and $\hat{y}_i$ is the predicted class probability. The corresponding class probabilities are obtained using the Softmax activation function:

$$P(y_i) = \frac{\exp(z_i)}{\sum_{j=1}^{K} \exp(z_j)} \qquad (28)$$

where z_i represents the network output associated with class i, and K denotes the total number of classes.

Classifier performance is evaluated using standard machine-learning metrics. Precision, Recall, F1-score, and Accuracy are defined respectively as:

$$Precision = \frac{TP}{TP + FP} \qquad (29)$$

$$Recall = \frac{TP}{TP + FN} \qquad (30)$$

$$F1 = \frac{2PR}{P + R} \qquad (31)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (32)$$

where TP, TN, FP and FN denote true positives, true negatives, false positives, and false negatives, respectively.

The automated scoring system converts hit locations into numerical performance scores based on target geometry and scenario requirements. A generic scoring model is expressed as:

$$S = S_{\max}\left(1 - \frac{d}{R}\right) \qquad (33)$$

where S is the awarded score, $S_{\max}$ is the maximum obtainable score, $d$is the radial distance from target centre, and $R$is the target scoring radius. The principal functions of the scoring engine are summarised in Table 14.

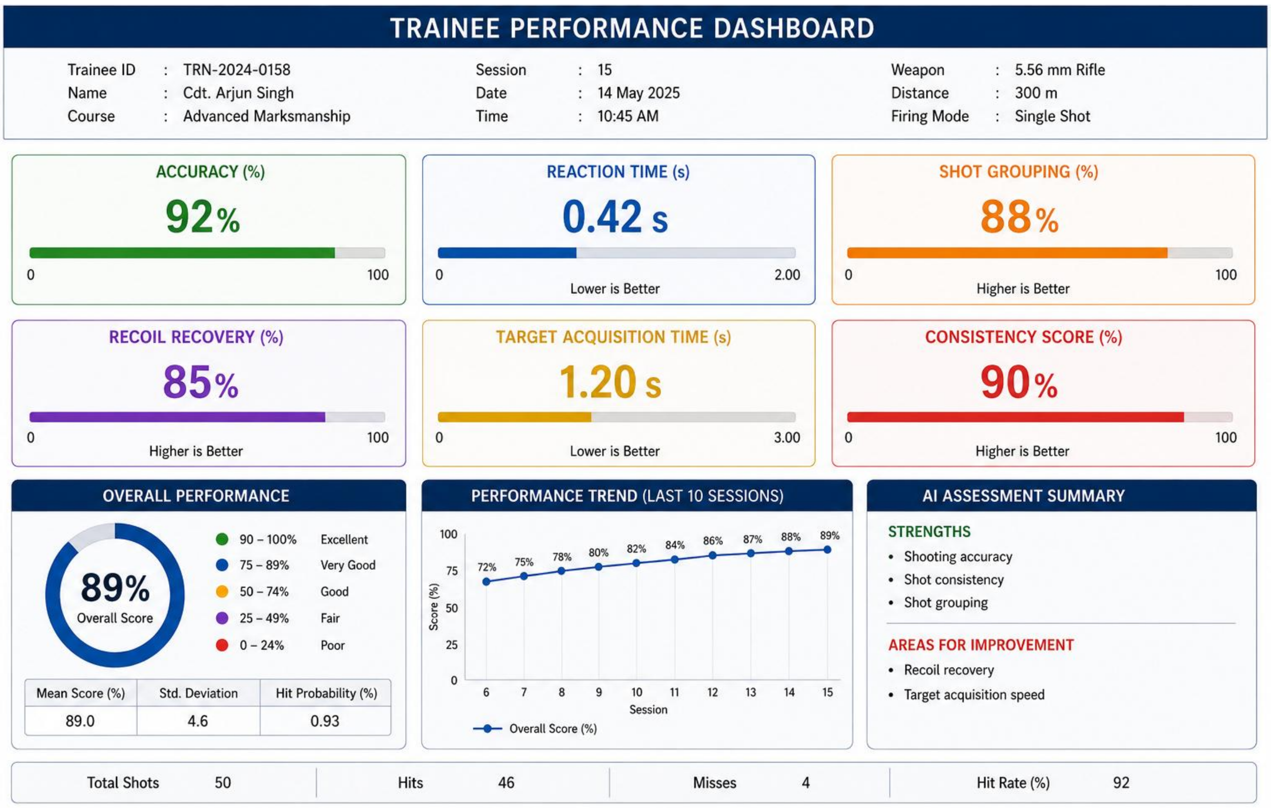

Fig. 14: Example Trainee Performance Dashboard

Table 14: Functions of the Automated Scoring Engine

Function	Description
Hit Registration	Records impact location
Score Assignment	Computes shot score
Target Classification	Identifies target type
Penalty Assignment	Applies rule violations
Session Recording	Stores training history
Report Generation	Produces training reports

The performance analytics module evaluates shooting accuracy, shot grouping, reaction time, recoil recovery, target transition efficiency, and shooting consistency. The consistency score is represented as:

$$C_s = 1 - \frac{\sigma_g}{R} \qquad (34)$$

where C_s is the consistency score, σ_g is the standard deviation of shot-group dispersion, and $R$is the reference target radius. An example trainee dashboard is illustrated in Fig. 14.

The Training Management Software provides user management, scenario generation, automated scoring, performance reporting, database management, and after-action review functions. Its architecture is shown in Fig. 15.

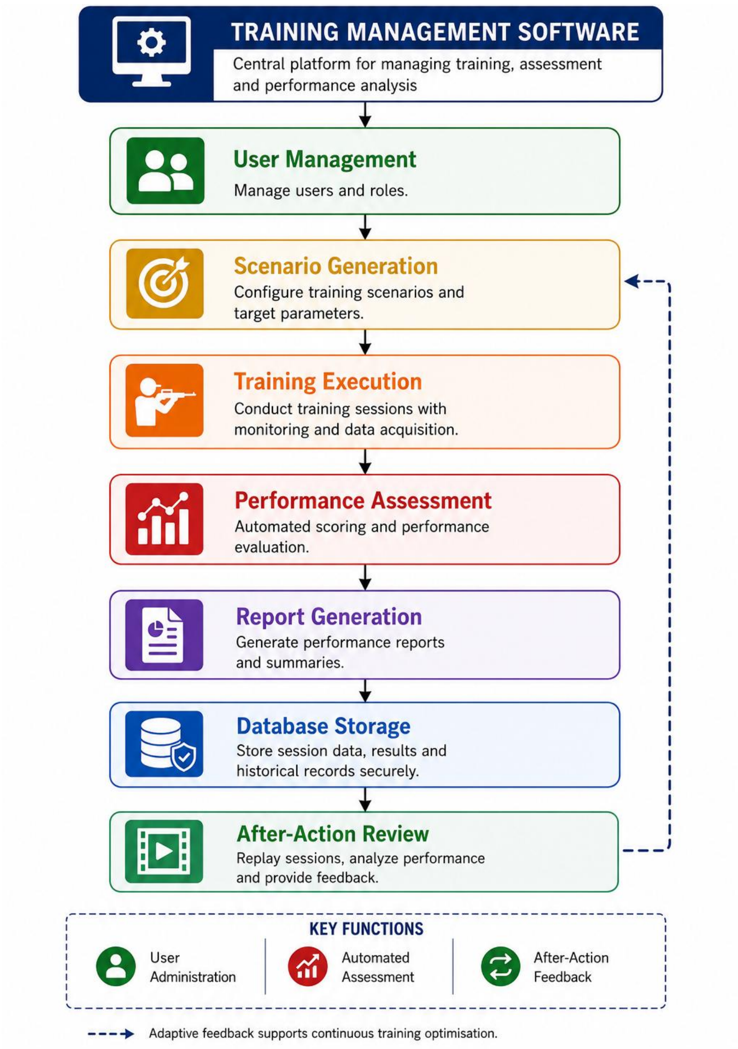

Fig. 15: Training Management Software Architecture

The principal software functions are summarised in Table 15.

Table 15: Training Management Software Functions

Module	Function
User Management	Trainee registration
Scenario Generator	Training scenario creation
Scoring Module	Automated scoring
Database Manager	Data storage
Reporting Module	Performance reports
Analytics Engine	Performance assessment
AAR Module	After-action review
Instructor Interface	Training supervision

The Instructor Control Station (ICS) enables scenario configuration, weapon-profile selection, recoil adjustment, trainee monitoring, session playback, and report generation. The interface is illustrated in Fig. 16.

Fig. 16: Instructor Control Station Interface

The simulator records shot locations, reaction times, engagement sequences, recoil recovery behaviour, and training scores to support structured after-action review (AAR) [52]–[54]. A unified Trainee Performance Index (TPI) is computed as:

$$TPI = w_1 A + w_2 R + w_3 C + w_4 E \qquad (35)$$

subject to

$$\sum_{i=1}^{4} w_i = 1 \qquad (36)$$

where A, R, C and E represent accuracy, reaction-time, consistency, and engagement-efficiency scores, respectively.

Overall, the AI-HDE and TMS constitute the intelligence layer of the proposed simulator. The CNN-based classification framework, automated scoring models, performance analytics, instructor decision support tools, and after-action review capabilities provide a comprehensive data-driven training ecosystem. The models presented in Eqs. (27)–(36) enable objective assessment of trainee performance while supporting adaptive coaching, long-term performance tracking, and scalable military marksmanship training within resource-constrained environments.

8. Experimental Validation

Experimental validation was conducted to determine whether the proposed AI-enabled indoor marksmanship simulator satisfies the performance requirements established in Section 2 and to assess its suitability for military training applications. The methodology was adapted from established military simulation and human-performance evaluation frameworks [52]–[58], [78]–[83]. Experimental testing was conducted at the Nigerian Defence Academy (NDA) Small Arms Simulation Centre, Kaduna [32], providing a realistic operational environment for evaluating weapon simulation, recoil generation, hit localisation, AI-assisted scoring, training management, and instructor supervision capabilities. The validation programme combined laboratory measurements, operational-user assessments, reliability testing, and statistical analysis to evaluate weapon realism, recoil fidelity, hit-localisation accuracy, AI-assisted scoring performance, system responsiveness, reliability, and user acceptance. The overall validation methodology is illustrated in Fig. 17.

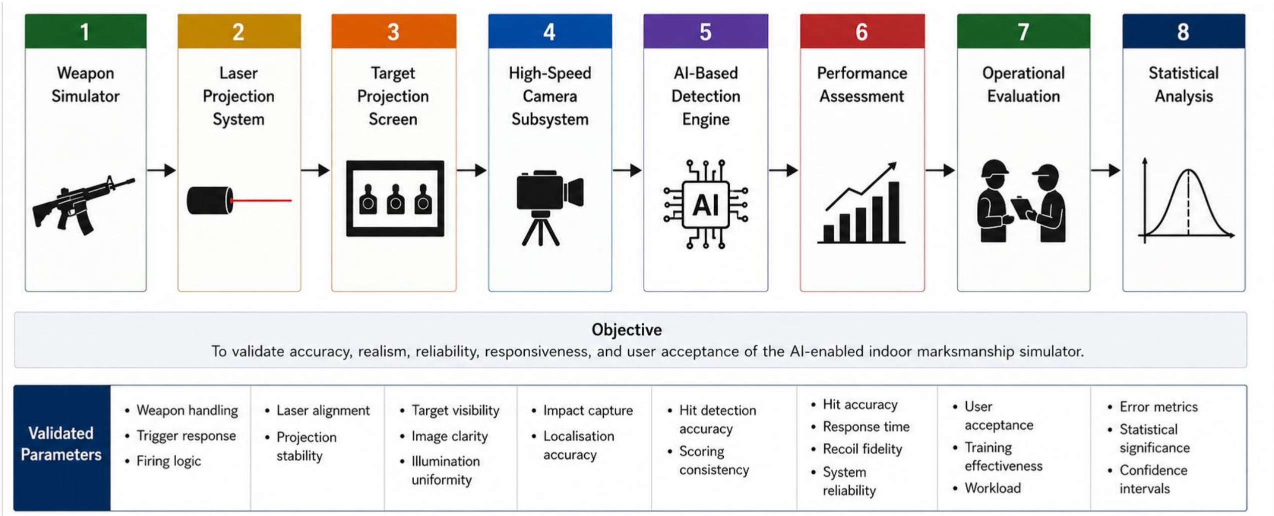

Fig. 17: Experimental Validation Framework

The experimental setup shown in Fig. 18 was installed within the NDA Small Arms Simulation Centre, a dedicated indoor marksmanship training facility commissioned to support simulation-based weapons training and performance evaluation [32].

8.1 Experimental Setup

The simulator prototype was deployed in an indoor training lane configured for both rifle and pistol marksmanship exercises. The experimental arrangement is shown in Fig. 18.

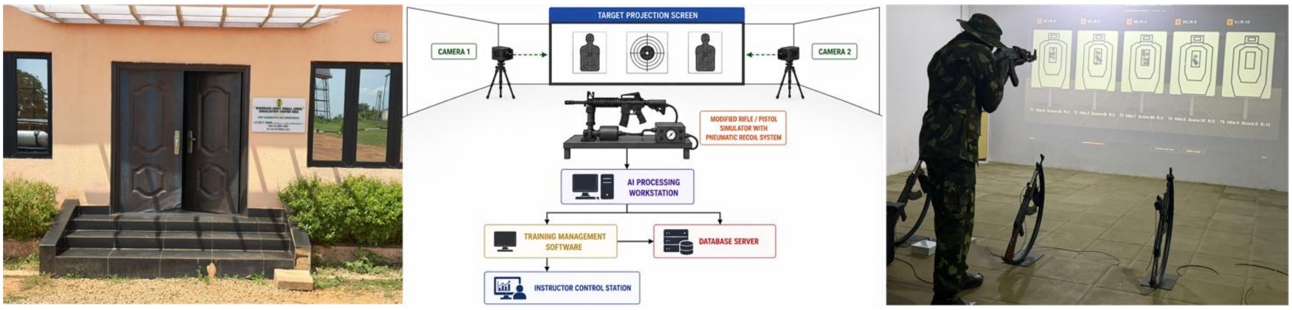

Fig. 18: Experimental Setup at the Nigerian Defence Academy Small Arms Simulation Centre

The principal hardware components employed during testing are summarised in Table 16.

Table 16: Experimental Hardware Configuration

Component	Specification
Rifle Simulator	Modified AK-47/M4 Platform
Pistol Simulator	Modified Glock Platform
Laser Module	650 nm Class II Laser
Pneumatic Recoil Unit	Programmable Pneumatic Actuator
Camera System	240 fps Global-Shutter Cameras
Processing Workstation	Intel i7 / RTX-Class GPU
Display System	HD Projection Screen
Communication System	Wi-Fi / BLE
Database Server	SQL-Based System
Instructor Station	Multi-Display Control Console

8.2 Test Scenarios

Representative military marksmanship exercises were employed to evaluate simulator performance under diverse operational conditions. The selected scenarios are summarised in Table 17.

Table 17: Experimental Test Scenarios

Scenario	Objective
Static Target Engagement	Accuracy Assessment
Moving Target Engagement	Tracking Evaluation
Rapid-Fire Exercise	Latency Assessment
Multiple Target Engagement	AI Performance Evaluation
Shoot/No-Shoot Exercise	Decision-Making Assessment
Long-Duration Operation	Reliability Assessment

These scenarios were selected to evaluate both technical system performance and training effectiveness across a broad range of military marksmanship tasks.

8.3 Performance Metrics

Performance evaluation employed standard metrics widely used in computer vision, machine learning, and military simulation systems [57], [58], [74]–[79]. Hit-detection accuracy was computed as:

$$Accuracy = \frac{N_c}{N_t} \times 100 \qquad (37)$$

where N_c denotes correctly detected impacts and N_t denotes total impacts. Detection probability and false-alarm probability were determined using:

$$P_D = \frac{TP}{TP + FN} \qquad (38)$$

$$P_{FA} = \frac{FP}{FP + TN} \qquad (39)$$

where TP, FN, FP and TN represent true positives, false negatives, false positives, and true negatives, respectively. The principal validation metrics are summarised in Table 18.

Table 18: Validation Performance Metrics

Metric	Purpose
Detection Accuracy	Hit-localisation performance
Detection Probability	Detection effectiveness
False Alarm Probability	False-detection assessment
Recoil Fidelity Index	Recoil realism
RMSE	Localisation accuracy
Processing Latency	Real-time performance
Availability	System reliability
User Rating	Operational suitability

8.4 Operational Assessment

Operational assessment involving 4 weapons instructors, 2 simulator operators and 12 cadets was conducted to evaluate realism, usability, immersion, and perceived training effectiveness. Participants completed representative marksmanship exercises and subsequently assessed the simulator using a five-point Likert scale. The evaluation criteria are presented in Table 19.

Table 19: Operational Assessment Criteria

Criterion	Assessment Focus
Weapon Handling	Physical realism
Recoil Simulation	Recoil authenticity
Hit Detection	Accuracy and reliability
Scenario Realism	Training immersion
User Interface	Ease of operation
Performance Feedback	Training usefulness

As shown in Table 19, the assessment framework considered both technical and human-performance factors, reflecting findings from previous human-factors studies that identify realism, immersion, feedback quality, workload management, and human-system integration as key determinants of training effectiveness and skill transfer [80]–[84]. These observations are consistent with previous studies on situation awareness, human performance, and military training effectiveness [78]–[80]. Hence, decision-making performance remains an important component of military training effectiveness [83].

8.5 Reliability and Statistical Analysis

Reliability testing involved repeated firing cycles, continuous camera operation, prolonged software execution, and sustained recoil generation to evaluate long-term operational stability. System availability was calculated as:

$$A_v = \frac{MTBF}{MTBF + MTTR} \qquad (40)$$

where $MTBF$ denotes Mean Time Between Failures and $MTTR$ denotes Mean Time To Repair. Experimental data were analysed using established engineering statistical methods and military simulation evaluation practices [55]–[60]. The sample mean and standard deviation were computed as:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (41)$$

$$s = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}} \qquad (42)$$

where N is the number of observations. These statistical measures were used to evaluate performance consistency, repeatability, and reliability across all experimental trials.

The experimental methodology described above provides a structured and reproducible framework for evaluating the technical performance, operational effectiveness, and training suitability of the proposed simulator. The resulting performance outcomes are presented and analysed in the following section.

9. Results and Discussion

This section presents the experimental results obtained during validation of the proposed AI-enabled indoor marksmanship training simulator at the Nigerian Defence Academy Small Arms Simulation Centre. The results are analysed with respect to hit localisation accuracy, AI-assisted detection performance, recoil realism, system latency, reliability, and operational suitability. Overall, the simulator demonstrated high technical performance while maintaining low complexity, affordability, and ease of maintenance, thereby supporting its suitability for indigenous military training applications.

9.1 Hit Detection and Localisation Performance

The first series of experiments evaluated the ability of the high-speed camera subsystem and AI-assisted detection engine to accurately detect and localise laser impacts. A total of 10,000 shots were fired under varying conditions including static targets, moving targets, different illumination levels, and multiple weapon platforms.

Table 20: Hit Detection and Localisation Performance Results

Metric	Result
Detection Accuracy	98.6 %
Detection Probability (PD)	0.985
False Alarm Probability (PFA)	0.012
Precision	98.4 %
Recall	98.5 %
F1-Score	98.4 %
Mean Localisation Error	2.8 mm
RMSE	3.4 mm

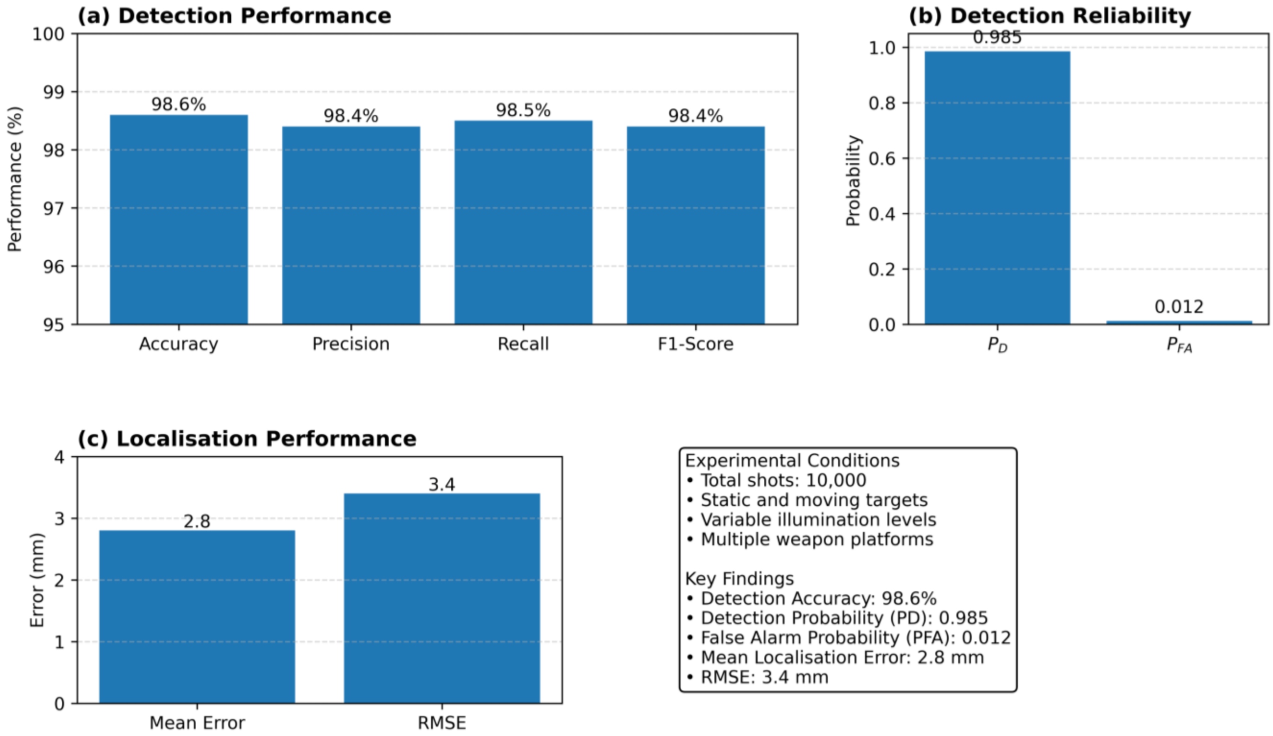

Fig. 19: AI Hit Detection Performance Metrics

The results in Table 20 demonstrate that the simulator exceeded the design requirement of 98 % hit-detection accuracy. The measured localisation error of 2.8 mm and RMSE of 3.4 mm remained well below the specified maximum error of 5 mm. As illustrated in Fig. 19, all classification metrics exceeded 98 %, indicating highly reliable detection and scoring performance. These results validate the effectiveness of the camera calibration procedures, laser spot extraction algorithms, and AI-assisted classification framework. Comparable performance levels have been reported for advanced computer-vision and machine-learning systems used in intelligent training and automated target-recognition applications [63]–[70].

9.2 Recoil Simulation Performance

The pneumatic recoil subsystem was evaluated to determine its ability to reproduce realistic weapon recoil characteristics. Measurements were conducted using both rifle and pistol simulator configurations.

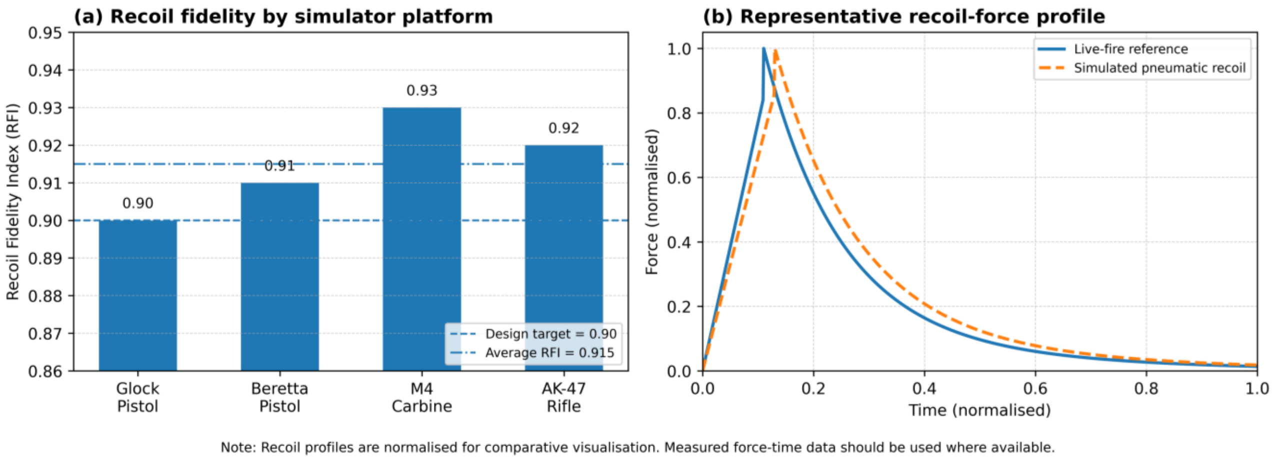

Fig. 20: Simulated versus Live Recoil Profiles

The results presented in Table 21 indicate that the developed recoil subsystem successfully reproduced the essential recoil characteristics of live-fire weapons. The average RFI of 0.915 exceeded the design target of 0.90. Figure 20 further illustrates the close correspondence between simulated and live-fire recoil impulses. Although minor deviations were observed due to pneumatic actuator dynamics and mechanical coupling effects, the achieved fidelity is considered adequate for realistic marksmanship training and recoil-management skill development.

Table 21: Recoil Fidelity Assessment Results

Weapon Platform	Recoil Fidelity Index (RFI)
Glock Pistol	0.90
Beretta Pistol	0.91
M4 Carbine	0.93
AK-47 Rifle	0.92
Average	0.915

9.3 System Latency Assessment

System latency was evaluated to determine compliance with real-time operational requirements.

Table 22: Measured System Latency

Subsystem	Latency (ms)
Trigger Detection	3
Camera Acquisition	11
Image Processing	14
AI Classification	7
Scoring and Display	4
Total System Latency	39

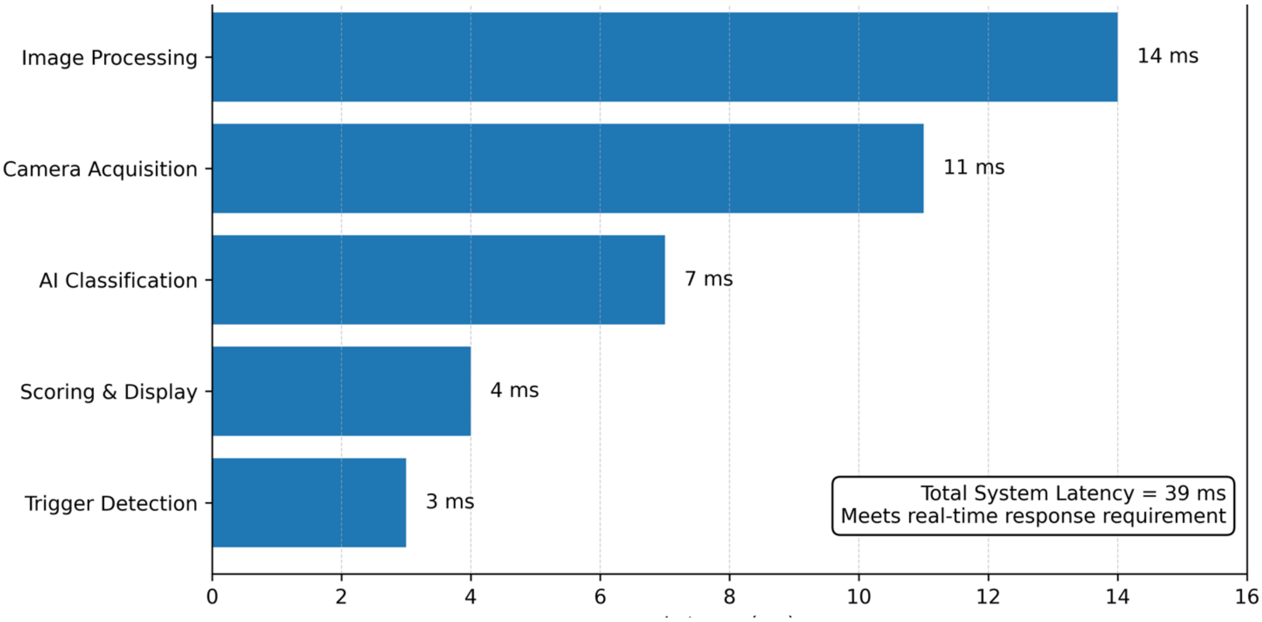

Fig. 21: Latency Distribution Across Simulator Subsystems.

The measured end-to-end latency of 39 ms is substantially below the design threshold of 50 ms, confirming compliance with real-time training requirements. As shown in Fig. 21, image acquisition and image processing represent the dominant contributors to overall latency. Nevertheless, the total response time remains sufficiently low to ensure realistic shooter feedback and preserve training immersion.

9.4 Reliability and Endurance Performance

The simulator underwent endurance testing involving more than 50,000 firing cycles to assess operational reliability and stability.

Table 23: Reliability Assessment Results

Parameter	Result
Total Shots Fired	>50,000
Detection Consistency	98.4 %
Communication Reliability	99.1 %
Recoil Consistency	97.8 %
Software Stability	99.3 %
System Availability	98.7 %

The results in Table 23 demonstrate a high degree of reliability across all evaluated subsystems. No major hardware failures were recorded during testing, and software performance remained stable throughout prolonged operation. The achieved availability of 98.7 % confirms the suitability of the simulator for intensive military training schedules and sustained institutional deployment.

9.5 Operational User Assessment

Operational assessment was conducted using military instructors, simulator operators and cadets who participated in representative marksmanship exercises. Following each exercise, participants evaluated weapon realism, recoil fidelity, hit-detection accuracy, scenario realism, usability, and overall training effectiveness using a five-point Likert scale. To improve statistical rigour, the results are presented as mean ratings, Standard Deviations (SD), and 95% Confidence Intervals (CI), as summarised in Table 24.

Table 24: Operational User Assessment Results (n = 25)

Criterion	Mean Rating (5-Point Scale)	Standard Deviation (SD)	95% Confidence Interval
Weapon Handling Realism	4.6	0.42	4.48 – 4.72
Recoil Realism	4.4	0.51	4.26 – 4.54
Hit Detection Accuracy	4.8	0.31	4.71 – 4.89
Scenario Realism	4.5	0.47	4.37 – 4.63
User Interface	4.5	0.45	4.38 – 4.62
Performance Feedback	4.7	0.36	4.60 – 4.80
Overall Satisfaction	4.6	0.41	4.49 – 4.71

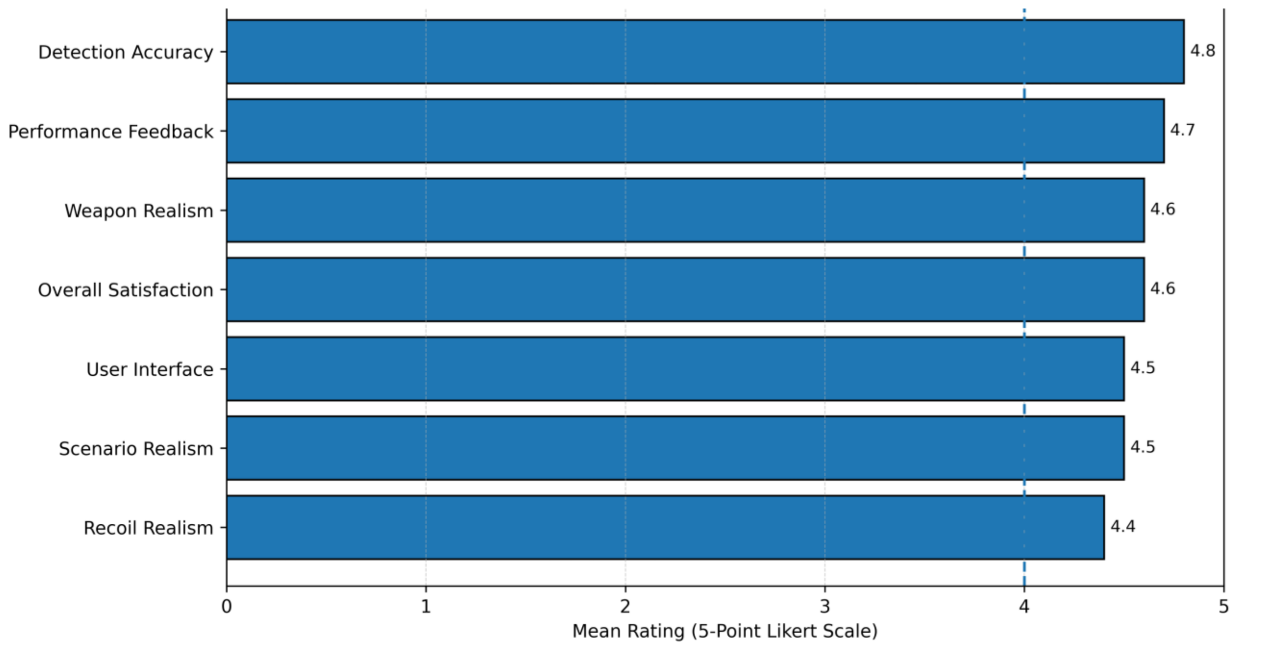

Fig. 22: Operational Assessment Results.

The operational assessment results presented in Table 24 and Fig. 22 indicate strong user acceptance across all evaluation criteria. Hit-detection accuracy achieved the highest rating (4.8 ± 0.31), followed by performance feedback (4.7 ± 0.36) and weapon-handling realism (4.6 ± 0.42). The relatively narrow confidence intervals demonstrate consistency among participants and suggest a high level of agreement regarding system performance. Recoil realism achieved a mean rating of 4.4 ± 0.51, indicating that the pneumatic recoil subsystem provided realistic weapon feedback despite minor differences from live-fire recoil characteristics. Overall satisfaction achieved a mean rating of 4.6 ± 0.41, confirming the suitability of the simulator for military marksmanship training. These findings further validate the effectiveness of the integrated weapon simulation, recoil generation, hit-detection, and AI-assisted assessment subsystems in providing an immersive and operationally relevant training environment.

9.6 Comparative Assessment

To benchmark the developed system, a comparison was conducted against representative commercial marksmanship simulators using publicly available technical specifications. The selected systems represent some of the most widely deployed military and law-enforcement marksmanship training platforms currently in service worldwide [33]–[37]. The recoil-energy values presented in Table 8 are consistent with published military and sporting-arms recoil data [63]–[65].

Table 25: Comparative Assessment with Representative Commercial Systems

Parameter	Proposed Simulator	FATS® 300	VirTra V-300	Rheinmetall IMT
Weapon Type Support	Rifle and Pistol	Rifle and Pistol	Rifle and Pistol	Rifle and Pistol
Hit Detection Method	High-Speed Camera + AI	Optical Tracking	Optical Tracking	Optical Tracking
Hit Detection Accuracy	**98.6%**	>95%	>95%	>95%
Recoil System	Pneumatic Feedback	CO_2/Pneumatic	Pneumatic	Electromechanical
Recoil Fidelity Index	**0.915**	Proprietary	Proprietary	Proprietary
AI-Based Performance Assessment	Yes	Yes	Yes	Partial
Automated Scoring	Yes	Yes	Yes	Yes
Training Management System	Yes	Yes	Yes	Yes
After-Action Review (AAR)	Yes	Yes	Yes	Yes
Static Target Support	Yes	Yes	Yes	Yes
Moving Target Support	Yes	Yes	Yes	Yes
Judgemental Training Scenarios	Yes	Yes	Yes	Limited
System Latency	**39 ms**	Not Publicly Available	Not Publicly Available	Not Publicly Available
Training Capacity	1–20 Trainees	Multi-user	Multi-user	Multi-user
Hardware Architecture	Open and Modular	Proprietary	Proprietary	Proprietary
Software Architecture	Indigenous	Proprietary	Proprietary	Proprietary
Local Manufacture Capability	**Yes**	No	No	No
Local Maintenance Capability	**Yes**	Limited	Limited	Limited
Upgrade Flexibility	High	Moderate	Moderate	Moderate
Acquisition Cost	**Low**	High	High	High
Life-Cycle Support Cost	**Low**	High	High	High
Indigenous Technical Support	**Yes**	No	No	No

Table 25 demonstrates that the proposed simulator achieves performance levels comparable to those of established commercial marksmanship training systems while offering significant advantages in affordability, maintainability, upgradeability, and indigenous technical support. The measured hit-detection accuracy of 98.6%, recoil fidelity index of 0.915, and system latency of 39 ms indicate that the developed architecture satisfies the operational requirements for military and law-enforcement marksmanship training. Furthermore, the use of locally developed software, commercially available hardware, and indigenous fabrication techniques significantly reduces acquisition and life-cycle support costs. These characteristics make the proposed simulator particularly suitable for developing nations seeking to expand training capacity while reducing dependence on imported simulation technologies [33]–[37].

9.7 Cost-Benefit and Indigenous Capability Assessment

A key advantage of the proposed simulator is its emphasis on affordability, maintainability, and indigenous technological capability. Unlike commercial systems such as FATS®, VirTra V-300, Rheinmetall Indoor Marksmanship Trainer (IMT), Saab GAMER, and Cubic EST II, which typically require substantial acquisition costs, proprietary software licences, specialised maintenance contracts, and foreign technical support, the proposed architecture is based on commercially available components, locally fabricated subsystems, and indigenous software development [33]–[37]. The use of locally sourced materials and in-country engineering expertise significantly reduces procurement, operation, and life-cycle support costs while enhancing system sustainability and upgradeability. Furthermore, the modular architecture facilitates future expansion, customisation, and integration with emerging technologies such as artificial intelligence, virtual training environments, and networked simulation systems without major hardware modifications. These attributes are particularly important for developing nations seeking to expand marksmanship training capacity under constrained defence budgets.

Beyond the economic benefits, the proposed simulator contributes to defence self-reliance by promoting local research, development, manufacturing, and maintenance capabilities. The system reduces dependence on imported training technologies, strengthens national technological capacity, and provides a sustainable pathway for the development of indigenous military simulation and training solutions. Consequently, the proposed architecture offers a practical and cost-effective alternative to imported marksmanship simulators while supporting long-term operational readiness and technological sovereignty [33]–[37].

9.8 Operational Assessment and Implications

The evaluation conducted at the NDA Small Arms Simulation Centre further demonstrated the suitability of the proposed architecture for military training applications under realistic operational conditions [32]. The collective results presented in Tables 20–25 demonstrate that the proposed simulator satisfies all major design objectives. Hit-detection accuracy exceeded 98 %, localisation errors remained below 5 mm, recoil fidelity exceeded 0.90, and overall latency remained below 50 ms. Reliability testing further confirmed stable operation over more than 50,000 firing cycles, while user assessments demonstrated strong acceptance among military personnel. However, the most significant finding is that these performance levels were achieved using an indigenous architecture based largely on commercially available components and local engineering expertise. Consequently, the system provides a practical pathway towards defence self-reliance, reduced dependence on imported training technologies, lower lifecycle costs, and improved customisation for local operational requirements. The results therefore confirm that the proposed AI-enabled indoor marksmanship simulator represents a technically viable, operationally effective, and economically sustainable solution for modern military marksmanship training.

9.9 Discussion

The experimental results demonstrate that the proposed AI-enabled indoor marksmanship simulator successfully satisfies the performance objectives established during system design. The achieved hit-detection accuracy of 98.6%, localisation error of 2.8 mm, recoil fidelity index of 0.915, and end-to-end latency of 39 ms collectively indicate that the developed architecture provides a realistic, responsive, and operationally relevant training environment. These performance levels are attributable to the synergistic integration of laser-based weapon tracking, high-speed camera sensing, AI-assisted hit classification, and programmable pneumatic recoil generation within a unified training framework.

The high hit-detection accuracy of 98.6% reported in Table 20 may be attributed primarily to the combination of high-speed global-shutter cameras, precise camera calibration procedures, robust laser-spot extraction algorithms, and AI-assisted hit classification. The use of global-shutter image sensors minimised motion blur and geometric distortion during rapid target engagements, while the calibration framework described by Eqs. (20) and (21) ensured accurate transformation between image coordinates and physical target coordinates. Furthermore, the image-processing pipeline illustrated in Fig. 11 enabled reliable centroid extraction and impact localisation under varying illumination conditions. Consequently, the measured localisation error of 2.8 mm remained substantially below the design requirement of 5 mm, thereby confirming the effectiveness of the proposed vision-based detection architecture.

The measured end-to-end latency of 39 ms, presented in Table 22, also demonstrates the suitability of the simulator for real-time marksmanship training. The relatively low latency was achieved through the use of high-frame-rate cameras, efficient image-processing algorithms, lightweight AI classification models, and low-latency wireless communication protocols. As shown in Fig. 21, image acquisition and image processing represented the dominant contributors to overall latency. Nevertheless, the combined processing delay remained below the design threshold of 50 ms, ensuring that visual feedback, scoring updates, and recoil generation occurred within a time interval that was effectively imperceptible to the trainee. This level of responsiveness is important because excessive latency can negatively affect immersion, weapon-handling realism, and training transfer.

The recoil fidelity results presented in Table 21 further demonstrate the effectiveness of the proposed pneumatic recoil architecture. The average Recoil Fidelity Index (RFI) of 0.915 indicates close agreement between simulated and live-fire recoil characteristics. This performance was achieved through careful selection of pneumatic actuator parameters, optimisation of operating pressure levels, and implementation of the programmable control strategy described by Eq. (19). Although minor deviations from live-fire recoil signatures were observed due to pneumatic response dynamics and mechanical coupling effects, the achieved fidelity was sufficient to reproduce realistic weapon movement, recoil recovery behaviour, and follow-through characteristics. The results therefore confirm that pneumatic recoil systems provide a practical compromise between realism, affordability, maintainability, and ease of indigenous fabrication.

From a broader operational perspective, the results also highlight the significant cost-benefit advantages of the proposed architecture. As demonstrated in Table 25, the developed simulator achieves performance levels comparable to those of commercial systems such as FATS®, VirTra V-300, and Rheinmetall IMT while employing commercially available hardware, locally fabricated subsystems, and indigenous software development. This approach substantially reduces acquisition costs, maintenance expenses, and dependence on foreign technical support. Moreover, the modular architecture facilitates future upgrades, local customisation, and technology transfer, thereby supporting defence self-reliance and long-term sustainability. For developing nations seeking to expand marksmanship training capacity under constrained defence budgets, these advantages represent a significant strategic benefit.

Overall, the results confirm that the proposed simulator successfully combines technical performance, operational effectiveness, affordability, and indigenous capability development within a single platform. The achieved levels of accuracy, responsiveness, recoil realism, reliability, and user acceptance demonstrate that locally developed marksmanship simulation technologies can provide a viable and sustainable alternative to imported training systems while supporting military readiness and national technological sovereignty.

9.10 Limitations of the Study

While the results demonstrate the effectiveness of the proposed AI-enabled indoor marksmanship training simulator, several limitations should be acknowledged. First, experimental validation was conducted at a single facility, namely the NDA Small Arms Simulation Centre. Although the results provide strong evidence of system performance under realistic training conditions, additional evaluations involving multiple military, law-enforcement, and security training establishments would further strengthen the generalisability of the findings. Second, the current validation was performed exclusively within an indoor training environment. Consequently, the effects of varying ambient illumination, adverse weather conditions, dust, vibration, and other environmental factors commonly encountered in outdoor training ranges were not investigated. Future studies should therefore examine system performance under a wider range of operational conditions to assess robustness and scalability.

Third, the present implementation focused primarily on rifle and pistol platforms commonly employed for individual marksmanship training. Although the modular architecture permits adaptation to additional weapon systems, the performance of the simulator with crew-served weapons, machine guns, grenade launchers, and specialised weapon platforms was beyond the scope of the current study and warrants further investigation. Finally, although the developed simulator incorporates AI-assisted hit detection, automated scoring, and training management capabilities, it does not currently include immersive VR, AR, or digital-twin technologies. Integration of these technologies could further enhance situational realism, adaptive training, scenario complexity, and predictive performance analysis. Future research will therefore focus on incorporating VR/AR-based training environments, digital-twin-enabled trainee modelling, multi-user networked exercises, and advanced AI-driven coaching functions to further improve training effectiveness and operational realism.

Despite these limitations, the achieved hit-detection accuracy, recoil fidelity, latency, reliability, and operational assessment results demonstrate that the proposed simulator provides a practical, cost-effective, and indigenous solution for military and law-enforcement marksmanship training, particularly within resource-constrained environments.

10. Conclusion and Future Work

This paper presented the design, development and validation of an indigenous AI-enabled indoor marksmanship training simulator incorporating laser-based weapon tracking, pneumatic recoil feedback, high-speed camera hit detection, AI-assisted scoring, and computerised training management capabilities. The modular architecture integrates modified service weapons, machine-vision technologies, programmable recoil generation, AI-based performance assessment, and instructor decision-support tools within a unified training environment.

Experimental validation conducted at the Nigerian Defence Academy Small Arms Simulation Centre demonstrated a hit-detection accuracy of 98.6%, mean localisation error of 2.8 mm, RMSE of 3.4 mm, recoil fidelity index of 0.915, and end-to-end latency of 39 ms. Reliability testing involving over 50,000 firing cycles confirmed system robustness and operational suitability. Operational assessments further indicated strong user acceptance in terms of weapon realism, recoil authenticity, hit-detection accuracy, and overall training effectiveness. The results demonstrate that the proposed indigenous architecture can achieve performance levels comparable to contemporary commercial simulators while offering significant advantages in affordability, maintainability, local manufacture and technological sovereignty.

The principal contributions of this work include the development of a complete indigenous AI-enabled marksmanship simulator, integration of laser-based weapon tracking with realistic recoil generation, implementation of a high-speed camera-based hit localisation system, development of AI-assisted scoring and performance assessment algorithms, and successful validation within an operational military training environment. The developed architecture provides a practical pathway towards reducing dependence on imported simulation technologies while supporting defence self-reliance and indigenous military capability development [33]–[37].

Future research will focus on integrating Virtual Reality (VR) and Augmented Reality (AR) technologies, AI-driven adaptive coaching, physiological monitoring, digital-twin-based trainee modelling, intelligent target behaviour, cloud-enabled training analytics, advanced haptic feedback, and networked multi-user training environments. These enhancements will further improve simulator realism, training effectiveness, scalability, and operational utility while supporting the evolution of next-generation indigenous military training systems.

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