Detection of Bullet Holes for Target Board in Malaysia Military (ATM) Shooting Exam Application

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Abstract

This study focuses on designing and developing a bullet hole detection system for target boards in the Malaysia Army (ATM) shooting exercise environment. The deep learning algorithm is based on YOLO models, utilizing Raspberry Pi and IoT via Blynk for remote monitoring. The prototype includes a Raspberry Pi 4b, HQ Camera Module Lens, 35mm Telephoto Lens, and tripod stand, all at an affordable cost. The study demonstrates that the bullet hole detection system is accurate and effective for ATM shooting exams, meeting SDG 3, SDG 9, SDG 11, and SDG 12 goals.

Keywords: Bullet Hole Detection, Military Shooting Exams, Internet of Things (IoT), Machine Learning, YOLOv8

1. Introduction

The Malaysian Military (ATM) shooting exam assesses shooter proficiency by scoring shots on target boards under various conditions. Traditionally, this process has relied on manual review, requiring examiners to inspect target boards and tally scores after each session. This method is prone to human error, inconsistency, and delays. This project proposes a detection system to automate bullet hole identification and scoring to address these limitations [1].

Current automated systems, such as electronic target surfaces and photoelectric technologies, have limitations like high power consumption and reduced mobility. Advances in image processing now allow for reliable and real-time bullet hole detection. Using Raspberry Pi 4b, this project leverages YOLO models for object detection and image processing. Bullet holes are detected and processed in real-time, with data transmitted wirelessly to a dashboard for visualization.

By transmitting target board images with bullet hole locations over wired or wireless connections to a distant computer or display device, the bullet hole detection system significantly improves the convenience of the reviewing process. This enables examiners to assess target boards from a secure and comfortable location. For instance, [1] [2] described a system that transmitted target board images to a smartphone using image processing and wireless connectivity, allowing examiners to review data remotely.

The proposed prototype offers prompt and comprehensive feedback by presenting the overall bullet hole locations on a dashboard. It displays information such as the distribution of bullet holes across scoring zones, the holes' size and position, and the shots' precision and consistency. Additionally, the system provides advice and recommendations to enhance shooting performance, enabling shooters to track and evaluate their marksmanship improvements. Detection systems like these have been shown to deliver graphical or numerical feedback on display monitors, assisting shooters in identifying their strengths and weaknesses [3].

The technology analyses target board pictures using powerful algorithms, delivering precise, real-time feedback and decreasing scoring fluctuation. Using Raspberry Pi technology and YOLO deep learning models, the system provides efficient, accurate, and dependable detection. The study aims to develop a prototype integrating hardware like cameras and dashboards, evaluate the system's detection accuracy, and analyse AI's ability to recognize bullet holes and assign graphical representations based on shot locations. This innovation not only enhances objectivity and efficiency but also promotes fairness in the ATM shooting exam, ultimately modernizing military training processes [4].

2. Methodology and Experimental Setup

This project was designed to detect the bullet holes for the target board in the Malaysia Military (ATM) shooting exam application. Currently, the project has been improved to work better. Using Raspberry Pi 4 Model B to run several motors and sensors as shown in Table 1. The new design will smooth out feeding by image processing.

Table 1. System Components.

Components	Quantity
Raspberry Pi 4 Model B	1
Raspberry Pi High-Quality Camera Module Lens	1
Raspberry Pi 35mm Telephoto Lens (C Mount)	1
Tripod Stand	1
USB B Type Cable	1
1KG 1.75mm ABS Filament (Black)	1

The system is activated when the detection system is initialized, with the Raspberry Pi hardware booting up and preparing for operation. The Raspberry Pi establishes communication with the Blynk app, which serves to visualize the entire system for the user.

Once the system is configured, the YOLOv8 model is loaded, and the camera starts broadcasting. The system continually collects photos of the target board, either every second or based on human input. If a target is identified, the system determines whether a target board is visible in the picture [5] [6].

Collecting the dataset was the first step in the project. the researcher Handling this work, by setting up a good environment for data collection and creating the troughs using a 3D printer. To get a large enough number of images as shown in Table 2, pictures of the troughs were shot empty, partially empty, and full.

A total of 1069 images were collected via the internet and using the camera on the iPhone 12 Pro Max with an image size of 3024 × 4032. The breakdown number of images for each class is shown in Table 2. The images of objects were captured with conditions such as lighting variations and reused target boards with stickers and captured images of the target boards from various distances.

Table 2. Number of Images for Each Class.

Sources	Number of Images
Dashboards	332
Cars	274
Wood	134
Glass	164
Walls	165
Total	1069

The images of the object were captured with different orientations and angles. This can enhance the generalization of the model to understand the structure and appearance of the object so that it can identify the object with a different viewpoint and orientation in the real world. Table 3 shows the example images of the three classes for this research.

Table 3. Sample Images of the troughs after annotation.

	Sample images with different angels
Bluet Hols.	
Military scoring board	

Once the images are gathered, the images are imported into Roboflow for data annotations, data pre-processing, and data augmentation. The dataset first undergoes the data annotation process whereby the object in the image is labeled. Then, data pre-processing methods were used to reduce the size of the image to 640 × 640 and auto-orient the annotation when there were changes to the image. The size of the dataset is 550 images only. Increasing the size of the training dataset can increase the performance of a deep-learning model. However, a large dataset requires time to capture images, label images, and prepare the dataset. Therefore, data augmentation techniques are used to artificially increase the size of the dataset by creating a modified version of the existing dataset. The dataset size for each class after data augmentation. The size of the dataset after data augmentation is 8453 images. Lastly, the dataset was split into the train set, validation set, and test set with a train:val: test ratio of 87:13:0 to be 792:117:0 of images. The dataset is converted into YOLOv8 PyTorch format for use in the training process [6] [7].

3. Results and Discussion

3.1. *Prototype*

The prototype was created using the items listed above, and Fig. 1 depicts the physical prototype. Provides an overview of the full prototype, including the Raspberry Pi, camera, and tripod, as well as the 3D-printed enclosure built for protection and stability. The 3D-printed shell secures the Raspberry Pi and camera module, protecting it from the elements and making it simple to install on the tripod. The tripod improves the stability and placement precision of the camera, which is critical for collecting exact photos of the target board. The finished prototype flawlessly incorporates all components, exhibiting the capability and potential of the bullet hole detecting system.

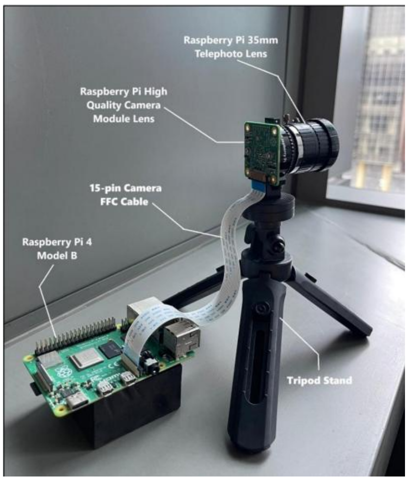

Fig. 1. Robot Farm.

The training results for the YOLOv8n model, illustrated in Fig. 2, show significant improvements in performance metrics. The train/box loss graph indicates a steady decrease from around 0.8 to 0.2 over 100 epochs, signifying enhanced accuracy in predicting trough locations. The train/classification loss reduced substantially from approximately 2.0 to nearly 0.0, highlighting the model's effectiveness in distinguishing between empty, partially empty, and full troughs, leading to high classification accuracy. Additionally, the train/distribution focal loss (DFL) decreased from about 1.3 to below 1.0, reflecting the model's increased precision in locating the troughs. Validation metrics, including Val/box loss and Val/classification loss, also improved, suggesting that the model generalizes well to new data, minimizing overfitting. Precision and recall metrics provide further insights, with high precision close to 1.0 indicating a low false positive rate and recall values approaching 1.0 demonstrating effective capture of all relevant trough statuses. The mean Average Precision at IoU=0.50 (mAP50) and mAP50-95 remained high, with mAP50 near 1.0 and mAP50-95 stabilizing around 0.9, confirming the model's robustness and accuracy across various detection challenges.

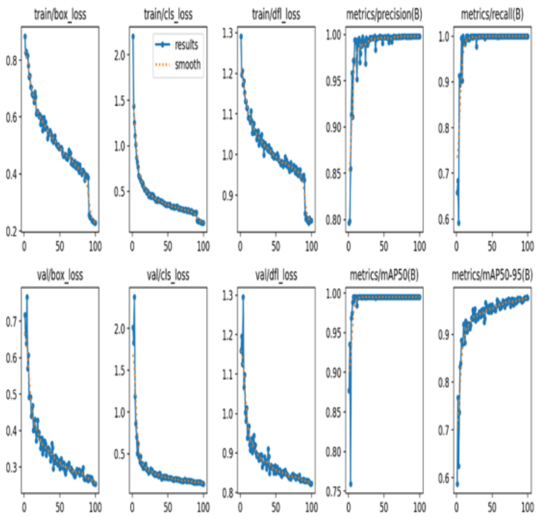

Fig. 2. Training and Validation Metrics for YOLOv8n Model on Trough Status Classification.

The comparison between YOLOv5 and YOLOv8, as illustrated in Fig. 3 and Fig. 4, highlights significant differences in their performance for bullet-hole detection. YOLOv5 achieves high precision (85.1%) and recall (80%), with a True Positive (TP) rate of 0.80 for bullet holes and a False Positive (FP) rate of 0.14. Its mean Average Precision (mAP) scores are moderate, with mAP@50 at 42.3% and mAP@50:95 at 29% or visualization.

In contrast, YOLOv8 demonstrates improved overall detection capabilities. It maintains similar precision (86%) and recall (80%) but achieves slightly reduced FP rates (0.13 for bullet holes) and higher mAP scores, with mAP@50 at 44.1% and mAP@50:95 at 32%. The normalized confusion matrix of YOLOv8 reflects better differentiation of bullet-holes, fewer misclassifications, and enhanced true positive rates.

As shown in the figure, YOLOv8's advancements make it the superior model for bullet-hole detection, with better learning, generalization, and performance across varying IoU thresholds compared to YOLOv5.

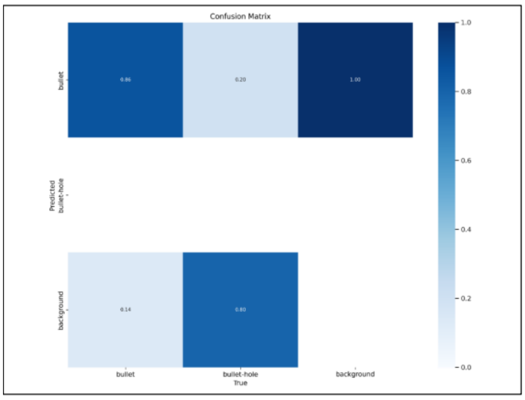

Fig. 3. Yolov5 Confusion Matrix of the trained model.

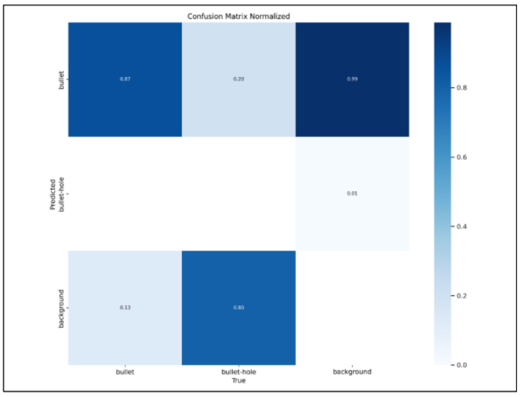

Fig. 4. Yolov8 Confusion Matrix Normalized of the trained model.

Fig. 5 shows the setup from the military base, which was crucial for gathering real-world data and insights necessary for developing and refining the detection of bullet holes system. The primary goal of the site visit was to collect high-quality images of target boards used in actual military shooting exercises. These images are vital for training the YOLOv8 model to accurately detect bullet holes. Additionally, the visit allowed for an environmental assessment, and an understanding of the conditions under which the shooting exercises take place. Observations included lighting variations, weather conditions, and the distances between shooters and target boards, which were essential for designing a strong system.

During the site visit, significant observations about traditional methods were made. In the traditional setup, around 120 participants undergo shooting exams over three days. This method not only leads to considerable bullet wastage but also poses safety risks as personnel are required to collect data from the target boards, sometimes while gunfire is ongoing. The manual collection and scoring of targets are time-consuming and prone to errors, impacting the efficiency and safety of the examination

Fig. 5. An example picture of the setup from the military base.

process. Furthermore, the site visit provided an opportunity to validate the prototype system in a real-world setting. This involved setting up the Raspberry Pi with a high-quality camera module and testing its functionality in capturing and processing images of the target boards. Direct interaction with military personnel also facilitated valuable feedback on the system's usability and accuracy, helping to identify areas for improvement to ensure the system meets practical needs. Fig. 6 shows the example system logbook of bullet holes detected. The system logbook can be used to track the current and past events of the system. In this example, 4 bullets were detected.

```
Shell
Speed: 44.2ms preprocess, 6270.9ms inference, 2.8ms postprocess per image at shape (1, 3, 608, 800)

0: 608x800 4 bullets, 6251.8ms
Speed: 62.6ms preprocess, 6251.8ms inference, 2.9ms postprocess per image at shape (1, 3, 608, 800)

0: 608x800 3 bullets, 6086.6ms
Speed: 45.4ms preprocess, 6086.6ms inference, 2.7ms postprocess per image at shape (1, 3, 608, 800)

0: 608x800 4 bullets, 6188.6ms
Speed: 66.6ms preprocess, 6188.6ms inference, 2.8ms postprocess per image at shape (1, 3, 608, 800)

0: 608x800 5 bullets, 6432.1ms
Speed: 54.8ms preprocess, 6432.1ms inference, 2.9ms postprocess per image at shape (1, 3, 608, 800)
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Fig. 6. Bullet holes system logbook.

Fig. 7 shows that although the YOLOv8 can detect bullet holes on the dashboard, it is not mature enough to detect all bullet holes consistently, and some may still be missed. Additionally, due to limitations in the Blynk app, the view of the live stream results is not stable. This instability can affect the reliability of real-time detection and needs to be addressed in future improvements. Enhancing the YOLOv8 model's accuracy and resolving the live stream issues in the Blynk app will be crucial steps in refining the system for practical use.

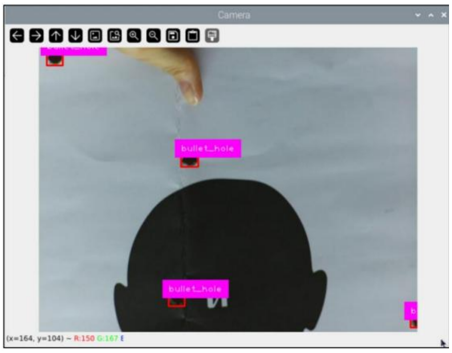

Fig. 7. Bullet holes system logbook.

The system leverages the Blynk app to visualize and manage the bullet-hole detection process, providing an interactive platform for user input and output. However, the app presents certain limitations, particularly in handling video live streaming. The quality and stability of the live video stream depend heavily on the available internet bandwidth. In environments with limited or unstable connections, the stream may experience lags, buffering, or dropped frames, potentially causing delays and inaccuracies in real-time monitoring. These challenges highlight the importance of considering network stability in deploying such systems.

4. Discussion

The project developed an automated system to monitor and manage goat feeding troughs, effectively addressing traditional method issues. Integrating a YOLOv8 model with hardware such as the Raspberry Pi 4, ultrasonic sensors, and a camera module accurately identified troughs statuses (bullet holes), significantly reducing the need for manual checks through image processing and machine learning. Key steps included collecting and enhancing a large set of trough images, using a deep learning model for object detection, and implementing real-time monitoring with the Blynk app, resulting in timely alerts for farmers. The model demonstrated high precision, recall, and F1 scores, with confusion matrices confirming accurate classification and performance curves indicating reliability. The project's success, driven by careful planning, effective methodology, and advanced technology, reduces farmers' workload, enhances resource management and goat care, and sets the stage for further innovations in automated farming, illustrating the potential of AI and IoT to improve military shooting exams.

5. Conclusion

In conclusion, the project successfully developed a bullet-hole detection system that addresses the limitations of traditional manual review methods, which often suffer from human error, subjectivity, and inconsistencies. Utilizing advanced technologies such as YOLOv8 for object detection, image processing algorithms, IoT integration via the Blynk app, and the Raspberry Pi platform, the system delivers high accuracy and real-time feedback. This enhances the fairness and efficiency of shooting exams and improves military training programs by providing instant feedback, allowing shooters to adjust and refine their skills more effectively.

The system also offers significant economic and safety benefits, reducing ammunition wastage, operational costs, and the risks associated with manual scoring near active shooting ranges. By automating data collection, it minimizes the need for human intervention, improving safety and sustainability.

Additionally, the project aligns with several United Nations Sustainable Development Goals (SDGs). It contributes to SDG 3 (Good Health and Well-being) by enhancing safety in shooting activities, SDG 9 (Industry, Innovation, and Infrastructure) by leveraging advanced technologies, SDG 11 (Sustainable Cities and Communities) through improved safety and resource efficiency, and SDG 12 (Responsible Consumption and Production) by reducing ammunition waste. With ongoing refinements and validation, the system is poised for broader application in military and sports contexts, emphasizing sustainability, scalability, and minimal environmental impact.

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Authors Introduction

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