YOLOv8-Based Firearm Detection for Real-Time Video Surveillance Applications

Rexhep Mustafovski, Tomislav Shuminoski, *Member, IEEE*, and Aleksandar Risteski, *Senior Member, IEEE*

***Abstract*—Real-time firearms detection is key for ensuring safety in public spaces and security-sensitive environments. In this paper, we present a computer vision approach using the YOLOv8 object detection model to identify whether an individual is carrying a firearm. The model's architecture allows for rapid and accurate detection, making it suitable for real-time applications. A custom dataset of images was used for training and validation, with preprocessing techniques applied to enhance model generalization. The proposed system was evaluated on key performance metrics, achieving high precision and recall in detecting both exposed and partially concealed firearms. The ability to operate in real-time offers a promising solution for improving security measures in various contexts. Future work will focus on refining the system to reduce false positives and expanding the dataset to include a broader range of scenarios.**

***Index Terms*—AI, Computer Vision, Firearms Detection, YOLOv8**

I. INTRODUCTION

In military operations, distinguishing between combatants and non-combatants is a critical task that can have significant operational and ethical implications. Identifying whether an individual is carrying a firearm or not is one of the primary means of differentiating armed combatants from unarmed civilians in conflict zones. However, manual identification can be highly error-prone, especially in dynamic environments with large crowds or concealed weapons. Misidentification can lead to catastrophic consequences, including civilian casualties, operational setbacks, and violations of international humanitarian law. Automated systems leveraging computer vision and deep learning have the potential to significantly enhance situational awareness and support rapid, data-driven decision-making in such environments [1].

Rexhep Mustafovski is with the Faculty of Electrical Engineering and Information Technologies, University "St. Cyril and Methodius" – Skopje, Skopje, Republic of North Macedonia
(e-mail: redzep.mustafovski@ugd.edu.mk)
Tomislav Shuminoski (Member IEEE) is with the Faculty of Electrical Engineering and Information Technologies, University "St. Cyril and Methodius" – Skopje, Skopje, Republic of North Macedonia
(e-mail: tomish@feit.ukim.edu.mk)
Aleksandar Risteski (Senior Member IEEE) is with the Faculty of Electrical Engineering and Information Technologies, University "St. Cyril and Methodius" – Skopje, Skopje, Republic of North Macedonia
(e-mail: acerist@feit.ukim.edu.mk)

Object detection models, in particular, have demonstrated remarkable success in identifying various types of objects within images or video streams in real-time. Among these models, the You Only Look Once (YOLO) family of detectors has gained prominence due to its ability to balance detection speed and accuracy, making it highly suitable for military applications where split-second decisions are required. Despite advances in deep learning, the task of firearm detection in military zones remains a challenging problem. Factors such as poor visibility, cluttered backgrounds, and the concealment of weapons can hinder the performance of existing models. Moreover, there is a limited amount of research focused specifically on real-time firearm detection in combat scenarios, particularly in distinguishing combatants from non-combatants [2]. The objective of this research is to address these gaps by developing a YOLOv8-based system capable of recognizing firearms with high accuracy, providing military personnel with a reliable tool for decision-making in high-stakes environments.

Recent conflicts and asymmetric warfare scenarios have highlighted the need for precise identification systems capable of minimizing collateral damage. While artificial intelligence (AI) and deep learning have demonstrated strong performance in tasks such as surveillance, target recognition, and situational awareness, the application of these techniques specifically for distinguishing combatants from non-combatants based on firearm presence remains limited.

Existing studies often rely on constrained datasets or do not address real-time performance in complex operational environments characterized by occlusions, dynamic movement, and heterogeneous backgrounds. This limitation represents a significant research gap in the deployment of reliable detection systems in military contexts.

The YOLO series of object detection models is well-known for its speed and accuracy in detecting various objects, including vehicles, weapons, and even specific behaviors.
YOLOv8, a widely adopted version of the YOLO family, builds on these strengths by providing an optimized architecture that balances detection speed and accuracy, making it suitable for real-time object detection applications.

This makes it particularly suitable for military applications, where delays in detection can have severe consequences. Unlike earlier versions, YOLOv8 incorporates innovations that improve detection in cluttered environments, allowing for more reliable recognition of partially concealed or obscured firearms.

DOI: 10.36244/ICJ.2026.2.9

These improvements are particularly important in urban and densely populated environments, where civilians and combatants are often in close proximity [3].

The proposed system leverages a custom dataset designed to reflect real-world operational conditions in military environments, including variations in lighting, crowd density, and the presence of non-combatant objects such as bags or tools. The system is evaluated using multiple performance metrics, with the objective of providing a reliable decision-support tool for military personnel, enhancing operational effectiveness while supporting compliance with international humanitarian law [1–7].

The objective of this study is to develop and evaluate a YOLOv8-based object detection system capable of accurately identifying firearms in real-time under diverse environmental conditions. The proposed approach focuses on improving detection performance and supporting decision-making processes in security and surveillance scenarios. Although this work does not introduce a new detection architecture, its contribution lies in the application and evaluation of a YOLOv8-based system for firearm detection in operationally relevant scenarios, supported by a curated dataset and system-level integration.

The main research question addressed in this study is whether a YOLOv8-based detection system can achieve reliable and accurate firearm detection in real-time under diverse and challenging environmental conditions.

II. LITERATURE REVIEW

Recent studies in object detection have demonstrated significant improvements in both accuracy and computational efficiency, particularly with the adoption of deep learning–based models. Early approaches to object detection were often computationally expensive and time-consuming; however, the introduction of pre-trained convolutional neural networks and optimized architectures has enabled faster and more accurate detection in real-time applications [7–10].

In the context of military and security applications, firearm detection plays a critical role in enhancing situational awareness and reducing risks to both civilian and military personnel. Several studies have explored the use of deep learning techniques for weapon detection, aiming to improve decision-making processes in complex operational environments [11–14]. However, many of these approaches are limited by constrained datasets or lack robustness under varying environmental conditions.

The YOLO (You Only Look Once) family of models has become a dominant approach in real-time object detection due to its ability to achieve a favorable balance between speed and accuracy. YOLOv8, a widely adopted version of this family, introduces architectural improvements that enhance multi-scale feature extraction and detection performance across objects of different sizes [7]. Despite these advancements, challenges remain in detecting small or partially occluded objects in cluttered environments [15–19]. Although newer YOLO variants (e.g., YOLOv9–YOLOv12) have been introduced, YOLOv8 was selected in this study due to its stability, strong community support, and well-documented implementation. Additionally, YOLOv8 provides a favorable balance between detection accuracy and computational efficiency, making it suitable for real-time firearm detection applications.

Several extensions of YOLO-based models have been proposed to address these challenges. For example, the integration of Context Attention Blocks (CAB) has been shown to improve the detection of small objects by leveraging multi-scale feature representations, leading to significant improvements in mean Average Precision (mAP) without increasing computational complexity [8].

In addition, YOLOv8 has been successfully applied in various real-time applications beyond security, including assistive technologies for visually impaired individuals and intelligent traffic monitoring systems. The integration of YOLOv8 with tracking algorithms such as DeepSORT enables robust multi-object detection and tracking in complex environments, even under conditions of occlusion and object overlap [7,8].

Despite these advances, there remains a limited number of studies specifically addressing real-time firearm detection in realistic military scenarios characterized by dynamic conditions, heterogeneous backgrounds, and operational constraints. This gap highlights the need for robust and efficient detection systems tailored to such environments.

The integration of deep learning with advanced sensing technologies presents significant potential for improving firearm detection systems. By leveraging these technologies, it is possible to develop more reliable, accurate, and data-driven solutions that enhance both operational effectiveness and the protection of critical infrastructure [16–20].

III. SYSTEM MODEL AND ALGORITHM

The proposed framework aims to detect small arms and distinguish combatants from non-combatants based on images or video received from compatible streaming devices. Based on the detection results, appropriate actions are triggered. Figure 1 illustrates the overall methodology of the proposed system.

The system consists of several key components: (i) data acquisition module, (ii) small arms dataset, (iii) YOLOv8-based detection module, (iv) decision-making module, (v) feedback and model improvement module, and (vi) system interface. Each component contributes to enabling real-time firearm detection and classification of individuals as combatants or non-combatants.

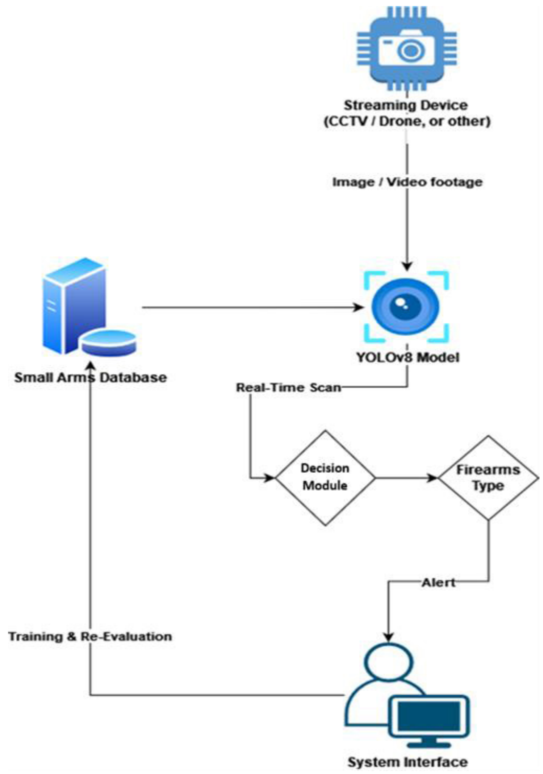


Fig. 1. Diagram overview of the proposed model framework

A. Data Acquisition Module: The system receives input from compatible streaming devices such as CCTV cameras, drones, or other real-time video sources. These devices continuously transmit image or video frames to the processing system for analysis. In this context, a compatible streaming device refers to any device capable of capturing and transmitting real-time video data using standard communication protocols (e.g., RTSP, HTTP, or UDP) and supported video formats.

The device should provide sufficient image resolution (e.g., minimum 720p) and frame rate (e.g., at least 15–30 frames per second) to enable reliable object detection. Examples of compatible devices include CCTV cameras, unmanned aerial vehicles (UAVs), body-worn cameras, and other IP-based video streaming systems.

B. Dataset Construction: A small arms dataset is constructed using verified images of various firearm types, including pistols, rifles, and other small arms.

The images are collected from publicly available and local sources, ensuring diversity in environmental conditions and object appearance.

C. Detection Module (YOLOv8): The YOLOv8 model is trained on the constructed dataset to perform real-time object detection. The model processes incoming frames and identifies the presence of firearms with high accuracy while maintaining real-time performance.

D. Decision-Making Module: Based on the detection results, the system classifies individuals as combatants or non-combatants. If a firearm is detected, predefined actions are triggered, including alert generation and classification outputs.

E. Feedback and Model Improvement: False positives and undetected firearms identified by human operators are collected and fed back into the dataset. This feedback loop enables continuous improvement of the model through retraining and refinement.

F. System Interface: The processed results are displayed through a system interface, providing visual feedback and alerts to the user. This interface supports real-time monitoring and decision-making.

The main contributions of the proposed system are summarized as follows:

1. Design of a real-time firearm detection system based on YOLOv8 for operational environments.
2. Development of a structured dataset for small arms detection under diverse conditions.
3. Implementation of an automated decision-support mechanism for distinguishing combatants from non-combatants.
4. Integration of a feedback mechanism for continuous model improvement through retraining.
5. Deployment-ready architecture compatible with various streaming devices, including CCTV and UAV systems.
6. Applicability of the system in both military and civilian security scenarios.

A. YOLOv8 Model Development and Training Process

To train, validate, and evaluate the proposed model, a customized dataset was constructed. The finalized dataset consists of 3184 annotated images of small arms, including pistols, rifles, and other weapon types. The images were collected from publicly available datasets and Google Images, as summarized in Table I.

TABLE I
DISTRIBUTION OF THE SMALL ARMS DATASET

Dataset Type	Size & Type	Source
Pistol and Knife Dataset	1000 images	Andalusian Research Institute in Data Science and Computational Intelligence
Automatic Weapons Dataset (RPG, Shotgun, SMG, Sniper)	714 images	Snehil Sanyal Weapon Public Dataset
Pistol and Automatic Rifle Dataset	1470 images	A.N.M Jubear Weapons in CCTV Public Dataset

The dataset includes a diverse range of small arms captured in various environments, including day and night conditions, forests, deserts, and urban settings. While the dataset includes diverse weapon types and environmental conditions, the representation of partially occluded objects remains limited. This reflects real-world data availability constraints and highlights an important direction for future dataset expansion.

The images also vary in object characteristics such as size, shape, and color, as illustrated in Figure 2.

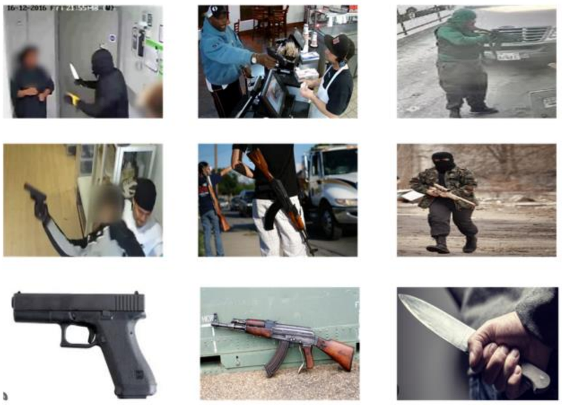


Fig. 2. Example of the images within the complete dataset

In order to successfully adopt and train the dataset in YOLOv8 the dataset itself was assigned labels and the annotating bounding boxes. The value of the annotating box coordinate in each image is then normalized between 0-1 as seen in Figure 3.

Fig. 3. Annotating small arms by class (Knife Class)

This process was carried out using Roboflow, which makes it possible to annotate and make data labels in the desired format. Furthermore, the dataset is carefully divided into three mutually exclusive subsets: training (70%), validation (20%), and test (10%). The training set is used to optimize the model parameters, while the validation set is used for hyperparameter tuning and monitoring the training process. The test set is strictly held out and is not used during training or model selection, ensuring an unbiased evaluation of the model's performance on previously unseen data. Table II presents the class-wise distribution of the dataset, comprising a total of 3184 images.

TABLE II
DATASET ORGANIZED BY CLASSES

Class	Images
All	3184
Pistol	850
Knife	420
Automatic Rifle	700
Shotgun	500
SMG	500
RPG	214

First and foremost, in the model training process we fine-tune the YOLOv8m model which is already pre-trained on the COCO data set. Furthermore, Transfer learning was used to train on the unified dataset. Moreover, various augmentation processes such as HSV, color spacing, mosaic, and image scaling were applied. The model was trained using fine-tuned hyperparameters, including the SGD optimizer, a learning rate of 0.01, and a weight decay of 0.0005, with a batch size of 32. The training process was monitored over multiple epochs, as illustrated in the learning curves presented in Figures 4 and 5.

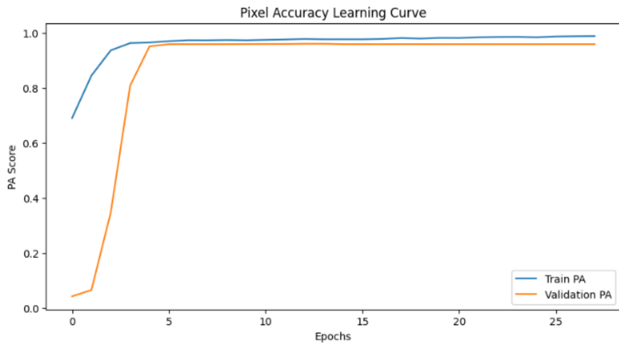
TABLE III
YOLOV8 MODEL TRAINING SUMMARY

Parameter	Value	Description
Model Variant	YOLOv8m	Medium-scale YOLOv8 model
Total Images	2373	Number of training images
Instances	4776	Total labeled objects
Precision (Box(P))	0.938	Bounding box precision
Recall (R)	0.733	Detection recall
mAP@0.5	0.911	Mean Average Precision (IoU = 0.5)
mAP@0.5:0.95	0.569	Mean AP across multiple IoU thresholds

The setup was chosen as it proved very effective in building similar models in previous works related to computer vision target identification [4]. The model was built using Google Collaboratory resources to process the dataset. All performance metrics reported in this study, including precision, recall, and mean Average Precision (mAP), are computed exclusively on the held-out test set. The following results are obtained from evaluation on the held-out test dataset. Care was taken to ensure that no overlapping images or frames were present across the training, validation, and test subsets in order to avoid data leakage. All images were manually verified and annotated to ensure dataset quality and consistency for training and evaluation.

IV. RESULTS AND DISCUSSION

The following results are obtained from evaluation on a strictly held-out test dataset. The training process is illustrated through the learning curves shown in Figures 4 and 5. The accuracy values shown in Figure 4 represent the proportion of correctly classified instances on the validation dataset during training and are presented to illustrate the convergence behavior of the model. The training accuracy increases steadily and stabilizes at a high value, while the validation accuracy follows a similar trend, indicating good generalization capability. Similarly, the training and validation loss decrease and converge, suggesting that the model effectively learns without significant overfitting.



. Fig. 4 Training and Validation Accuracy Curve

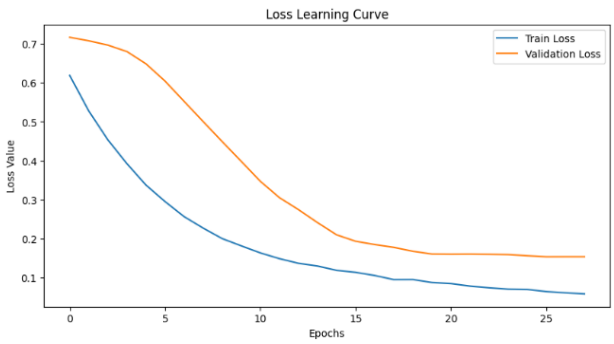


Fig. 5 Learning Loss Curve

To evaluate the performance of the proposed system, the trained model was tested across different scenarios using a confidence threshold of 0.4.

When evaluated on the held-out test dataset, the model achieved an average accuracy of 0.91, reflecting a high proportion of correctly classified instances.

The confusion matrix presented in Figure 6 demonstrates that the model is capable of correctly classifying the majority of samples. Additionally, qualitative results show that the model successfully detects and classifies firearms in various conditions.

TARGET / OUTPUT	Pistol	Knife	Automatic Rifle	Shotgun	SMG	RPG	SUM
Pistol	830 26.07%	15 0.47%	0 0.00%	0 0.00%	5 0.16%	0 0.00%	850 97.65% 2.35%
Knife	10 0.31%	410 12.88%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	420 97.62% 2.38%
Automatic Rifle	0 0.00%	0 0.00%	640 20.10%	10 0.31%	50 1.57%	0 0.00%	700 91.43% 8.57%
Shotgun	0 0.00%	0 0.00%	80 2.51%	400 12.56%	20 0.63%	0 0.00%	500 80.00% 20.00%
SMG	20 0.63%	0 0.00%	50 1.57%	5 0.16%	425 13.35%	0 0.00%	500 85.00% 15.00%
RPG	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	214 6.72%	214 100.00% 0.00%
SUM	860 96.51% 3.49%	425 96.47% 3.53%	770 83.12% 16.88%	415 96.39% 3.61%	500 85.00% 15.00%	214 100.00% 0.00%	2919 / 3184 91.68% 8.32%

Fig. 6. Confusion matrix for classes

Precision, recall, and F1-score were used as primary evaluation metrics. For example, the precision for pistols reaches 0.9765, indicating that approximately 97.65% of detected pistols are correctly classified.

The recall for shotguns is 0.9639, showing that the model successfully identifies most of the actual instances present in the dataset.

The F1-score further confirms balanced performance across classes, with high values observed for pistols (0.9708) and knives (0.9704).

The macro and weighted F1-scores, at 0.9227 and 0.9170 respectively, demonstrate strong overall model performance, with the weighted score accounting for class imbalance in the dataset.

TABLE IV
CLASSIFICATION PERFORMANCE METRICS OF THE PROPOSED MODEL

Class / Metric	Value 1	Value 2
Pistol	Precision: 0.9765	Recall: 0.9651
	F1-score: 0.9708	
Knife	Precision: 0.9762	Recall: 0.9647
	F1-score: 0.9704	
Automatic Rifle	Precision: 0.9143	Recall: 0.8312
	F1-score: 0.8707	
Shotgun	Precision: 0.8000	Recall: 0.9639
	F1-score: 0.8743	
SMG	Precision: 0.8500	Recall: 0.8500
	F1-score: 0.8500	
RPG	Precision: 1.0000	Recall: 1.0000
	F1-score: 1.0000	
Overall Accuracy	0.9168	
Misclassification Rate	0.0832	
Macro F1-score	0.9227	
Weighted F1-score	0.9170	

The obtained results confirm that the proposed YOLOv8-based approach is capable of achieving high detection accuracy across multiple weapon classes, supporting its suitability for real-time deployment in security and surveillance scenarios. These findings support the hypothesis that a YOLOv8-based model can provide reliable detection performance under diverse operational conditions.

However, the model exhibits certain limitations. In some cases, objects such as wallets or other visually similar items may be incorrectly classified as firearms, leading to false positives. These issues are more pronounced at greater distances or under low-quality imaging conditions, where object details are less distinguishable.

Additionally, the detection of small or partially occluded objects remains a challenge, particularly when such cases are underrepresented in the training dataset.

The limited representation of occluded and small objects in the dataset contributes to reduced detection performance in such scenarios, indicating the need for targeted data augmentation and dataset expansion.

Environmental factors such as poor lighting or adverse weather conditions can also impact detection performance.

Fig. 7. Example of predicted output in testing on publicly available CCTV footage

Despite these limitations, the results demonstrate that the proposed system provides a reliable foundation for real-time firearm detection, with potential for further improvement through larger datasets and extended training.

V. Experimental Setup and Real-Time Performance

The proposed system was implemented using a cloud-based environment with GPU acceleration. Specifically, the model was trained and evaluated using an NVIDIA Tesla T4 GPU available through Google Colaboratory. The YOLOv8m model variant was selected due to its balance between detection accuracy and computational efficiency.

The input frames were resized to 640×640 pixels, and standard preprocessing steps were applied, including color space conversion (BGR to RGB) and pixel normalization.
During inference, the system achieved an average processing speed of approximately 20–30 frames per second (FPS) under GPU acceleration, corresponding to a latency of approximately 33–50 ms per frame. This enables near real-time processing of video streams.

The actual performance may vary depending on the computational resources and deployment environment, particularly when processing multiple concurrent video streams.

VI. Conclusion

The implementation of a YOLOv8-based system for real-time firearm detection demonstrates promising potential for improving situational awareness and supporting decision-making in dynamic environments such as crowded scenes or operational settings involving potential threats. The model achieves high detection accuracy across multiple weapon classes, indicating its effectiveness in identifying small arms under varying conditions.

The results highlight that YOLOv8 provides a favorable balance between detection accuracy and computational efficiency, enabling near real-time performance when deployed on suitable hardware. This makes the approach applicable to a range of security and surveillance scenarios, including military operations, public safety, and critical infrastructure protection.

However, the experimental results also indicate that detection performance may degrade under challenging conditions, particularly in cases involving partial occlusion, low image quality, or visually complex backgrounds. While the model is capable of detecting many instances under such conditions, its robustness is limited when objects are heavily obscured or insufficiently represented in the training dataset.

These findings suggest that further improvements can be achieved through the use of larger and more diverse datasets, as well as enhancements in model architecture and training strategies. In particular, future work should focus on improving detection performance under occlusion and other adverse conditions through targeted dataset augmentation and specialized model adaptations.

Overall, the proposed approach provides a solid foundation for real-time firearm detection systems, with practical applicability in both military and civilian domains.

Acknowledgment

The author would like to express sincere gratitude to **PhD. Tomislav Shuminoski**, mentor, and **PhD. Aleksandar Risteski**, advisor, for their continuous academic guidance, professional support, and constructive feedback throughout the author's PhD studies. Their expertise, dedication, and encouragement have been instrumental in the author's academic development and in progressing toward the completion of the doctoral research.

References

[1] J. C. Scharre, *Army of None: Autonomous Weapons and the Future of War.* New York, NY, USA: W. W. Norton & Company, 2018. DOI: 10.1080/15027570.2019.1637555

[2] M. E. Feickert and A. F. Sadowski, *Artificial Intelligence and National Security*. Congressional Research Service, Washington, DC, USA, Rep., 2021.

[3] Ultralytics, "YOLOv8: A state-of-the-art, real-time object detection model," Ultralytics Documentation, 2023. [Online]. Available: https://docs.ultralytics.com

[4] A. Petrovski, M. Radovanović, and A. Behlić, "Application of drones with artificial intelligence for military purposes," in *Proc. 10th Int. Sci. Conf. Defensive Technologies (OTEH)*, Belgrade, Serbia, 2022, pp. 92–100.

[5] J. Huang *et al*., "Speed/accuracy trade-offs for modern convolutional object detectors," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2017, pp. 7310–7311. DOI: 10.48550/arXiv.1611.10012

[6] G. Cheng, P. Zhou, and J. Han, "Learning to predict layout-to-image conditional convolutions for semantic image synthesis," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2019, pp. 8779–8788. DOI: 10.48550/arXiv.1910.06809

[7] A. Yadav, P. K. Chaturvedi, and S. Rani, "Object detection and tracking using YOLOv8 and DeepSORT," in *Advancements in Communication and Systems*, 2023, pp. 81–90. DOI: 10.56155/978-81-955020-7-3-7

[8] M. Talib, A. H. Y. Al-Noori, and J. Suad, "YOLOv8-CAB: Improved YOLOv8 for real-time object detection," *Karbala Int. J. Mod. Sci.*, vol. 10, no. 1, Art. no. 5, 2024. DOI: 10.33640/2405-609X.3339

[9] C. Zhang, F. Kang, and Y. Wang, "An improved apple object detection method based on lightweight YOLOv4 in complex backgrounds," *Remote Sens.*, vol. 14, Art. no. 3896, 2022. DOI: 10.3390/rs14174150

[10] C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao, "YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2023, pp. 7464–7475. DOI: 10.1109/CVPR52729.2023.00721

[11] M. Maktab, M. Razaak, and P. Remagnino, "Enhanced single-shot small object detector for aerial imagery using super-resolution feature fusion and deconvolution," *Sensors*, vol. 22, no. 12, Art. no. 4562, 2022. DOI: 10.3390/s22124339

[12] L. Deng, H. Li, H. Liu, J. Gu, and L. Deng, "A lightweight YOLOv3 algorithm used for safety helmet detection," *Sci. Rep.*, vol. 12, Art. no. 1125, 2022. DOI: 10.1038/s41598-022-15272-w

[13] L. Ali *et al*., "Development of YOLOv5-based real-time smart monitoring system for increasing lab safety awareness in educational institutions," *Sensors*, vol. 22, no. 15, Art. no. 5555, 2022. DOI: 10.3390/s22228820

[14] H. Liu, F. Sun, J. Gu, and L. Deng, "SF-YOLOv5: A lightweight small object detection algorithm based on improved feature fusion mode," *Sensors*, vol. 22, no. 18, Art. no. 6789, 2022. DOI: 10.3390/s22155817

[15] P. Yong, S. Li, K. Wang, and Y. Zhu, "A real-time detection algorithm based on Nanodet for pavement cracks by incorporating attention mechanism," in *Proc. 8th Int. Conf. Hydraulic and Civil Engineering*, Xi'an, China, 2022, pp. 1245–1250. https://ui.adsabs.harvard.edu/link_gateway/2022ichc.conf...70Y/ DOI: 10.1109/ICHCE57331.2022.10042517

[16] S. Mitra, N. Reddy, I. Tal, and M. Bendechache, "Towards an optimized vehicle detection algorithm for multi-object tracking in traffic surveillance," in *Proc. 29th AIAI Irish Conf. Artif. Intell. Cogn. Sci. (AICS)*, 2021.

[17] Y. R. S. Kumar, T. Nivethetha, P. Priyadharshini, and U. Jayachandiran, "Smart glasses for visually impaired people with facial recognition," in *Proc. Int. Conf. Commun., Comput. Internet Things (IC3IoT)*, Chennai, India, 2022, pp. 1–4.
DOI: 10.1109/IC3IOT53935.2022.9768012

[18] A. Ghosh *et al.*, "Assistive technology for visually impaired using TensorFlow object detection in Raspberry Pi and Coral USB accelerator," in *Proc. IEEE Region 10 Symp. (TENSYMP)*, Dhaka, Bangladesh, 2020, pp. 186–189.
DOI: 10.1109/TENSYMP50017.2020.9230630

[19] P. Boobalan, S. Bhuvanikha, M. Sivapriya, and R. Sivakumar, "Object detection with voice guidance to assist visually impaired using YOLOv7," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 11, no. 2, pp. 1500–1505, 2023. DOI: 10.22214/ijraset.2023.50182

[20] M. Bianchini, M. Simic, A. Ghosh, and R. N. Shaw, *Machine Learning for Robotics Applications*. Singapore: Springer, 2022.
DOI: 10.1007/978-981-16-0598-7

Rexhep Mustafovski was born in Viterbo, Rome, Italy in 1999. He received the M.Sc. degree in electrical engineering and information technologies from Ss. Cyril and Methodius University in Skopje, Skopje, North Macedonia. He is an officer and a dedicated Teaching and Research Assistant in the Department for Cybersecurity and Digital Forensics at the Military Academy "General Mihailo Apostolski" - Skopje. His research interests include military communication systems and platforms, UAV communication systems, cyber resilience, radar systems, and the integration of artificial intelligence and computer vision techniques. He has authored and co-authored over 35 scientific papers published in various international journals and conferences. He presented the scientific paper "MobileSecureComm: A Next-Generation Tactical Communication Platform for Land, Sea and Air Operations" at the 32nd International Conference on Systems, Signals and Image Processing (IWSSIP 2025), held in Skopje in June 2025, with the paper subsequently published in IEEE Xplore.

Aleksandar Risteski received the B.Sc. (1996), M.Sc. (2000), and Ph.D. (2004) degrees in telecommunications from Ss. Cyril and Methodius University in Skopje, Skopje, North Macedonia.
He is currently a Professor and Vice- Dean for Research and International Cooperation at the Faculty of Electrical Engineering and Information Technologies at the same university. He has held internships at the IBM T. J. Watson Research Center, Yorktown Heights, NY, USA, where he worked on modeling and optimization of high-speed fiber links. His research interests include optical communications, secure communications, coding theory, and cybersecurity. He has authored and co-authored over 50 journal and conference papers, published widely, including in IEEE Xplore.
Dr. Risteski is a Senior Member of the IEEE and has been an independent member of the Board of Directors of Macedonian Telecom.

Tomislav Shuminoski received the B.Sc. (2008), M.Sc. (2010), and Ph.D. (2016) degrees in electrical engineering and information technologies from the Faculty of Electrical Engineering and Information Technologies, Ss. Cyril and Methodius University in Skopje, Skopje, North Macedonia.
He is currently an Associate Professor at the Institute of Telecommunications within the same faculty. His research focuses on areas such as wireless and mobile multimedia networks, cyber security, and quantum communications and computations. He has published work in international journals and conferences.
Dr. Shuminoski has been a member of the IEEE since 2006.