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Early Warning System for Firearm Detection on University Campuses Using Computer Vision

Freddy Tapia León[1*], José Danilo Collahuazo[2], Paola Cristina Farinango[3], Cesar Chiliquinga[4], Luis Tello-Oquendo[5], and Johanna Rivera[6]

[1*]Department of Computer Science, University of the Armed Forces ESPE, Sangolquí, Ecuador.
fmtapia@espe.edu.ec, https://orcid.org/0000-0001-9591-3563

[2]Department of Computer Science, University of the Armed Forces ESPE, Sangolquí, Ecuador.
jdcollahuazo1@espe.edu.ec, https://orcid.org/0000-0003-3655-2942

[3]Department of Computer Science, University of the Armed Forces ESPE, Sangolquí, Ecuador.
pcfarinango@espe.edu.ec, https://orcid.org/0000-0002-1889-3703

[4]Department of Computer Science, University of the Armed Forces ESPE, Sangolquí, Ecuador.
cichiliquinga@espe.edu.ec, https://orcid.org/0009-0002-1382-0537

[5]College of Engineering, Universidad Nacional de Chimborazo, Riobamba, Ecuador.
luis.tello@unach.edu.ec, https://orcid.org/0000-0002-5274-666X

[6]College of Engineering, Universidad Nacional de Chimborazo, Riobamba, Ecuador.
jarivera.fie@unach.edu.ec, https://orcid.org/0009-0004-2838-6651

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Abstract

Firearm violence in educational settings represents a critical challenge to institutional security globally. This study proposes an innovative system for early detection of firearms using advanced computer vision techniques, convolutional neural networks (CNN), and computational intelligence in educational institutions. The main objective was to develop a deep learning model based on CNN architectures capable of identifying and alerting the presence of weapons in real time, improving traditional security protocols. The methodology implemented a systematic approach comprising three fundamental stages: data collection, model training, and experimental validation. For model training, a set of 9,000 rigorously labeled images processed using the Roboflow tool was used. The YOLOv5 algorithm, implemented in Google Colab, allows training a detection model with high-precision parameters. The system was integrated directly with the security camera infrastructure of the university campus. Experimental results demonstrated remarkable efficiency: 99% accuracy, 93% detection rate and 97% overall performance. The system can continuously monitor spaces, triggering instant alerts upon identification of potential threats, with a processing capacity that significantly exceeds traditional human monitoring. The findings suggest that machine vision is a promising strategy for strengthening preventive security in educational institutions. Future research will focus on optimizing the model's adaptability to diverse environments and environmental conditions, potentially expanding its implementation to different types of institutions.

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*Corresponding author: Department of Computer Science, University of the Armed Forces ESPE, Sangolquí, Ecuador.

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1 Introduction

In Ecuador, the Comprehensive Security Law establishes specific regulations for gun control in educational environments. For the past two years, the country has been facing a security crisis with an increase in organized crime-related offenses, making it the second most violent country in South America, according to surveys. Supreme Decree 3757, which establishes the "LAW ON WEAPONS, MISSIONS, EXPLOSIVES, AND ACCESSORIES" in Ecuador, contains provisions to regulate arms control, including the acquisition, possession, carrying, registration, and control of firearms, ammunition, and explosives (Hakami et al., 2025).

The crisis in Ecuador's penitentiary system and the lack of control have allowed criminal gangs to take over prisons, which has led to a sharp increase in violence both inside and outside these centers (Reuters, 2024; de América, 2024). This situation led former president Guillermo Lasso to decree a new state of emergency in the country's prisons (Primicias, 2025). Furthermore, his decision to authorize the possession and carrying of weapons in a country with high rates of violence has sparked intense debate in Ecuadorian society, with experts warning of the dangers associated (Mundo, 2023).

Several Ecuadorian universities reject the decision to allow the carrying of weapons for personal defense, arguing that it would increase violence and would mainly affect the most vulnerable sectors (Comercio, 2023). In this context, cameras and closed-circuit surveillance systems are revolutionizing security by leveraging technology to safeguard both areas and individuals. The ability of these systems to identify weapons and employ advanced machine vision techniques is a central argument in favor of their effectiveness (Burhan et al., 2023; Biswas & Tiwari, 2024).

We rely on several innovative projects as a reference for the development of the gun detection system (Prabu & Sudhakar, 2024). Scientists at the University of Granada have developed an algorithm based on artificial intelligence that automatically detects when a subject in a video pulls out a gun, achieving an accuracy of over 96.5% (Olmos et al., 2018). Christian Olivo has carried out a project focused on the detection of weapons in videos using deep learning techniques (Olivo et al., 2025). In addition, the DISARM project, funded by the State Research Agency, focuses on the automatic detection of armed individuals and aggressive behavior in video surveillance environments (Carretero, 2023).

In high-security locations, such as educational institutions, early detection of suspicious objects is critical to prevent incidents and protect people. Customizing and tuning convolutional neural network models in real time is key to achieving optimal efficiency in detection (Gali et al., 2022; Jayaraman & Kumar, 2024). According to a DINAPEN report, since 2019, there have been 26 cases of extortion and possession of firearms inside schools in Ecuador (Ecuavisa, 2023), as detailed in table 1.

Table 1: Weapons-related apprehensions and arrests per year in educational settings in Ecuador (Ecuavisa, 2023)

Year	Apprehended	Arrested
2019	7	-
2020	1	-
2021	1	-
2022	13	-
April 2023	2	2

In addition, according to data from the Monitoring Room of the National Directorate of Risk Management of the Ministry of Education reported in table 2, from 2019 to date, three cases have been reported in which firearms were found among the belongings of students (Ecuavisa, 2023).

Table 2: Cases of gun possession in educational settings in Ecuador by year and month (ecuavisa, 2023)

Year	**Month**	**Location**	**Weapons**	**Extortion**
2019	December	Zone 3: Cotopaxi, Chimborazo, Tungurahua, Pastaza	1	-
2020	January	Zone 8: Guayaquil, Durán, Samborondón	-	-
2020	March	Zone 2: Pichincha, Napo, Orellana	1	-
2022	November	Zone 5: Santa Elena, Guayas, Bolívar, Los Ríos, Galápagos	1	1
2022	November	Zone 4: Manabí, Santo Domingo	1	1
2022	November	Zone 8: Guayaquil, Durán, Samborondón	1	-
2023	November	Zone 8: Guayaquil, Durán, Samborondón	-	-
2023	January	Zone 8: Guayaquil, Durán, Samborondón	4	4
2023	February	Zone 8: Guayaquil, Durán, Samborondón	1	-

The persistent insecurity in Ecuador, characterized by violence and the increasing use of weapons, represents a challenge for the whole of society (Mella, 2023). The University of the Armed Forces ESPE, in its role as an educational environment, faces various challenges related to security on its campus. The prison crisis, the state of emergency, the increase in armed violence in educational environments, and the approval of the use of firearms for self-defense raise critical issues for the security of the university community.

To effectively address these challenges, the creation of an early warning system on the campus of the University of the Armed Forces ESPE, supported by advanced technologies such as YOLOv5 and Roboflow, has been proposed. The increase in violence and the increasingly easy access to firearms pose a real and constant threat to community safety, which makes the search for innovative and rapid solutions a priority (Schcolnik-Elias et al., 2023).

This study focused on the development of an early warning system for weapons detection designed to strengthen security at the University of the Armed Forces ESPE. The combination of technologies with the warning system will provide a flexible response to potential threats that will contribute to increasing the security of the university.

Extensive testing and thorough validation are conducted to ensure that the system works correctly and efficiently, which enhances student safety. In addition, this project becomes a model for other educational institutions to see how they can leverage advanced technologies to improve their own security systems.

Methodology and Data Collection

The choice of the Scrum methodology is based on its collaborative approach and its ability to adapt during development through short sprints, which improves communication, speeds up decision-making, and fosters innovation (Torras, 2015). When building the weapon detection model, data collection consisted of using public galleries such as Google and Kaggle. The dataset used in this model is very important to determine the final model that will be embedded in the security cameras of the main campus of the University of the Armed Forces ESPE.

Model Development and Construction

This section details the development process of the early warning system to detect firearms. Figure 1 illustrates this process.

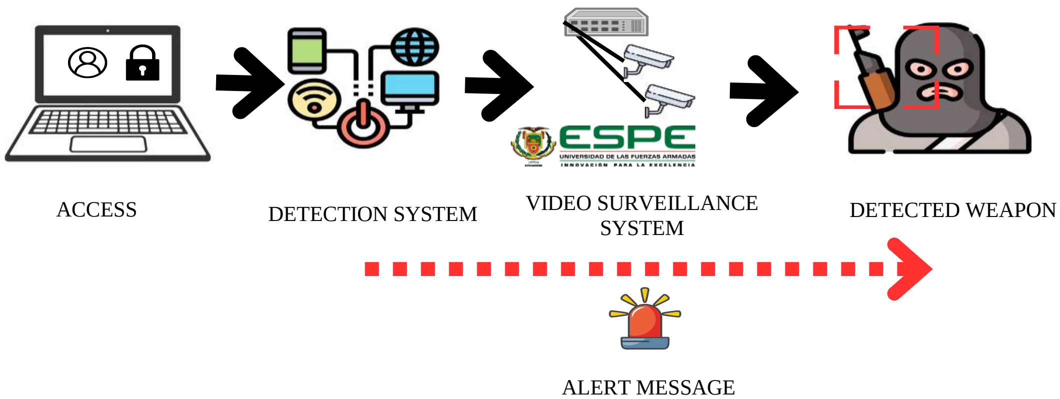

Figure 1: Structure of the detection and alert system

The study was structured in two main phases: first, the construction of a deep learning model and, secondly, the application of this model in the form of a desktop application. The convolutional network model was developed from 4084 images of weapons that were tagged using Roboflow. After, data augmentation policies were used to increase the set to 9212 images. This model built on the base of YOLOv5 was trained on Google Colab, where it provided an incredible result: 99% accuracy and 93% detection for the chosen class, and the overall performance was 97%. The evaluation results show that the proposed method has a sensitivity of 95%, high accuracy, and an F1 score of 0.91.

Construction of the Convolutional Network Model

In this initial phase, the process of building the deep learning model, fundamental for the development of the weapons detection system on the campus of the University of the Armed Forces ESPE, is described. The methodology, tools, and settings used to understand its creation and relevance are detailed.

Stages of the Convolutional Network Model Architecture

The architecture is organized in defined phases, as illustrated in figure 2, allowing a clear and orderly understanding of the process.

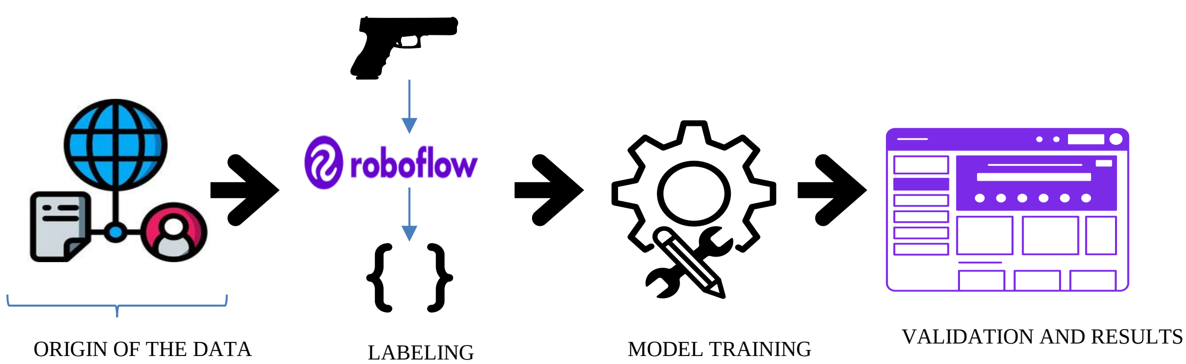

Figure 2: Convolutional network model architecture

Origin of the data: In this phase, firearm images are collected and organized from public repositories to create a representative dataset. The process includes

1) Download 1084 images from the web.

2) Compilation of 1500 images from Kaggle.

3) Acquisition of another 1500 images from Kaggle.

In total, 4084 high-quality images are obtained.

Tagged: In this stage of the project, the dataset images are carefully labeled by hand using the Roboflow tool. Weapons are marked and framed with a purple box, as illustrated in figure 2. This step is crucial, as it ensures the system is trained with precise data, enhancing its ability to detect objects with greater accuracy and efficiency. Proper identification of these items plays a vital role in ensuring the model functions as intended.

Data Augmentation: We train the model with different methods to increase its efficiency and accuracy using Roboflow image enhancement techniques (Rajendran et al., 2025). In this case, we rotate the images 90 degrees in any direction and flip them horizontally. Unfortunately, different elements have reduced the completeness of the dataset we store, forcing us to work hard to substantially increase the size of the dataset from 4,084 images to 9,212 (almost double) and thus to increase the training data as well. But having a large dataset is crucial to training our model to learn object recognition in different conditions. By exposing the system to several variations of an identical image, the model learns more about the appearance of objects under different angles and orientations. The diversity of the dataset ensures that the model is better adapted to real-world environments, where it has instances with different lighting, position, etc.

Division of Dataset: To validate the learning model, we divided the data into training, validation, and test sets (Solawetz, 2020a). We allocated 80% for training and 10% for validation and testing, respectively. We blend and distribute data to ensure reliability in performance (Solawetz, 2020b).

Model Training: The model training was performed in Google Colab, using the YOLOv5 dataset provided by Roboflow. The necessary parameters were manually configured in a workbook, taking advantage of the platform capabilities to ensure efficient training tailored to the project requirements, as observed in figure 3.

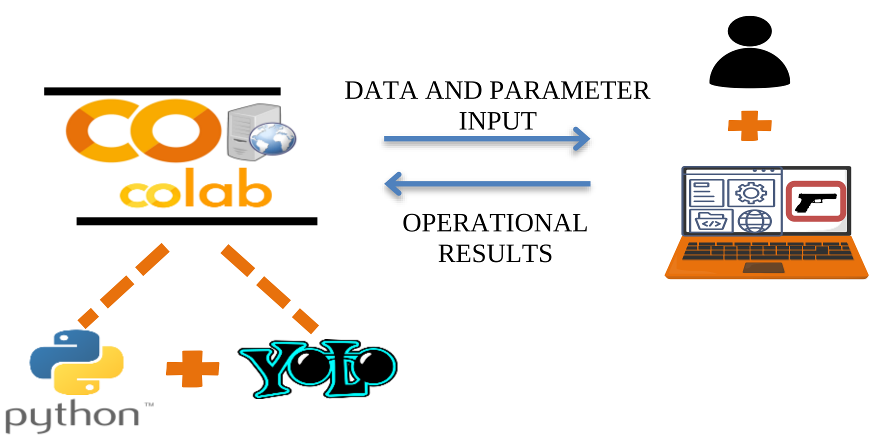

Figure 3: Model training infrastructure diagram

To start training the YOLOv5 model in Google Colab, the working environment is configured by cloning the YOLOv5 repository and installing the necessary dependencies, including Roboflow for data processing. The configuration code is shown in Code 1. Roboflow provides an access code to link the ". ArmasV3" workspace, essential for the next step: model training. Once YOLOv5 is linked to the Roboflow access code, model training begins, using specific parameters to achieve optimal results. This model achieved an accuracy of 99%, a detection rate of 93%, and a performance of 97%.

In the code depicted in listing 1, it is described how to clone the YOLOv5 repository and configure the necessary dependencies for its execution.

Listing 1: Importing Yolov5 libraries and their requirements

```
# Clone YOLOv5 and install dependencies
!git clone https://github.com/ultralytics/yolov5  # clone repo
%cd yolov5
%pip install -qr requirements.txt  # install dependencies
%pip install -q roboflow

import torch
import os
from IPython.display import Image, clear_output  # to display images

print(f"Setup complete. Using torch {torch.__version__} "
f"({torch.cuda.get_device_properties(0).name if torch.cuda.is_available()
else 'CPU'})")
```

Model information: YOLOv5 (version 7.0-278); Python: 3.10.12; PyTorch: 2.1.0 with CUDA 12.1 support; GPU NVIDIA Tesla T4 (15 GB VRAM); Input Resolution: (1, 3, 416, 416), i.e., 1 image, 3 channels (RGB), 416x416 pixels.

2 Model Evaluation

In the following, we provide deployment-related performance metrics related to the total time it takes for the model to process a single image from the moment it receives it to when it delivers the final detection results. Each component (speed, inference, Non-Maximum Suppression (NMS) per image at shape [1, 3, 416, 416]) represents a stage in the weapon detection pipeline.

The time needed to prepare the image before inference, named speed, is 0.3ms; this includes resizing the image to 416x416. The time it takes for the model to process a new input (image) and produce a prediction or result (weapon detection), named inference, is 7.4ms; specifically, the hardware is a Testa T4 GPU with CUDA then a low inference time is synonymous with a fast and efficient model. The post-processing step to filter and refine the detections, eliminating duplicate or overlapping detections, keeping only the most reliable ones, named NMS is 2.7ms per image at shape (1, 3, 416, 416); it means that these times are for processing a single image at a time, also that the input image has a size of 416x416, with 3 color channels (RGB) and a batch size of 1 (one single image).

Computing the total time per image: Pre-processing (speed) is 0.3ms, model inference is 7.4ms, NMS is 2.7ms; total time per image = 0.3ms + 7.4ms + 2.7ms = 10.4ms. A total time of 10.4ms per image means that the model can process approximately 96 frames per second (1000ms/10.4ms = 96 FPS). This means that the YOLOv5 model on the Tesla T4 GPU can process approximately 96 frames per second (FPS).

3 Model Analysis

Figure 4 illustrates the confusion matrix used to evaluate a convolutional neural network model in the firearms detection project at the University of the Armed Forces ESPE. Key metrics for analyzing the effectiveness of the model include

- **Accuracy:** Evaluates the accuracy of positive predictions, i.e., how accurate the model predictions are;
- **Sensitivity or Recall:** Measures the ability of the model to correctly identify positive cases. A high value indicates effectiveness in capturing elements of the specific class;
- **F1 Scoring:** It combines accuracy and sensitivity to assess overall weapon detection effectiveness, providing a balance between the two metrics;
- **PR Curve:** Analyzes the model's ability to distinguish between positive and negative classes using confidence thresholds.

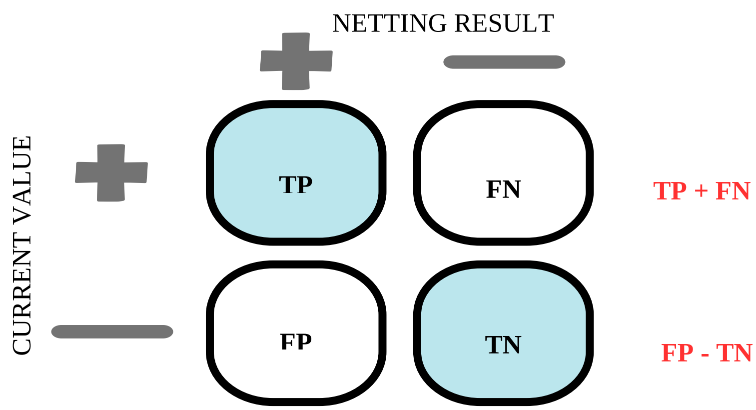

Figure 4: Confusion matrix

The dataset was divided into training and testing, and the model was evaluated with various metrics to balance the classification.

Accuracy: The model achieves an accuracy of 99% after the tenth epoch in a training of 100 epochs, as depicted in figure 5. This indicates high accuracy in firearms prediction, crucial for the early warning system.

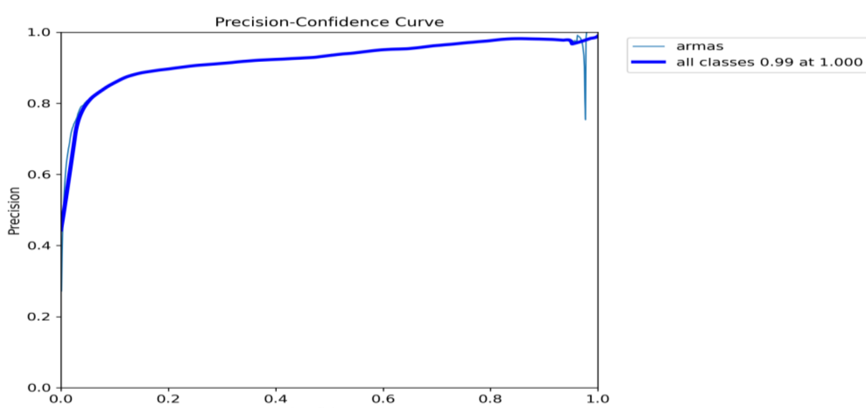

Figure 5: Accuracy evaluation of the object detection model

Sensitivity or Recall: The model achieves a recall of 95%, indicating excellent performance in firearms identification, as depicted in figure 6.

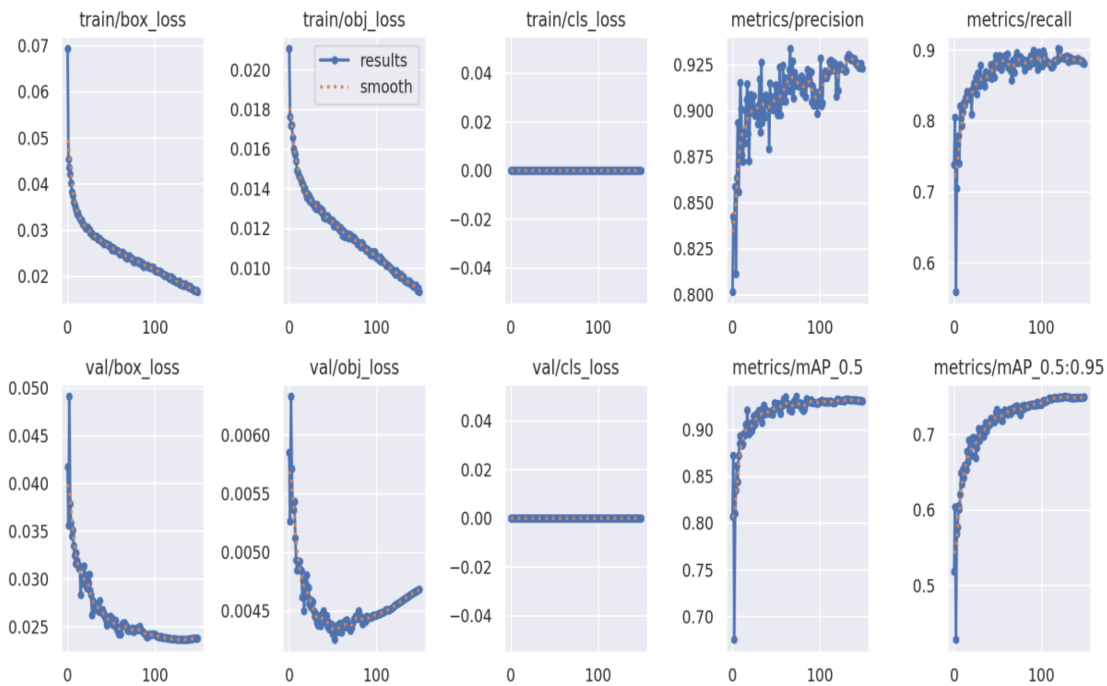

Figure 6: Sensitivity evaluation of the object detection model

Figure 7 illustrates the recall-confidence curve; as obs3rved, it achieves 0.91, showing a good balance between accuracy and sensitivity.

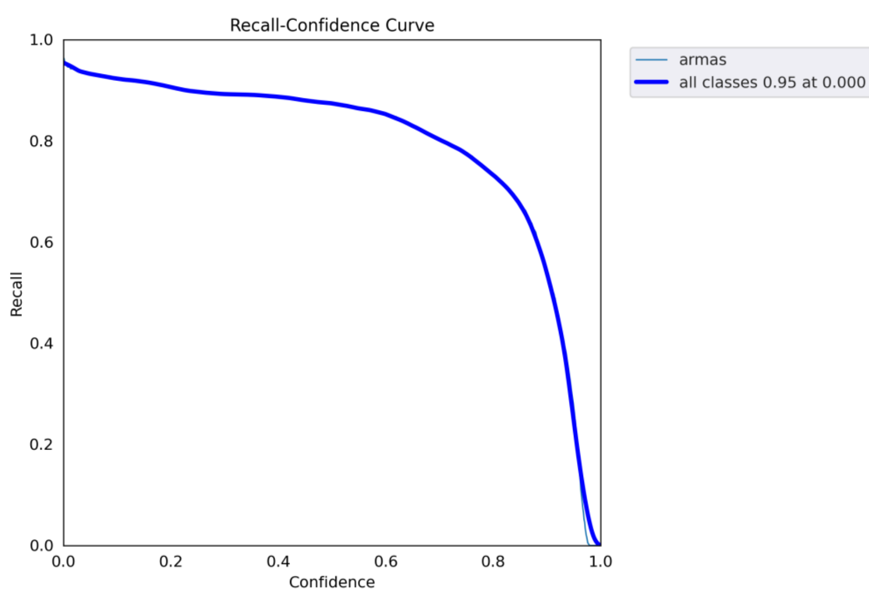

Figure 7: Optimal confidence value of the object detection model

Based on the results, the confusion matrix illustrated in figure 8 indicates that the model achieved a true positive (TP) rate of 0.90, a false positive (FP) rate of 0.10, a false negative (FN) rate of 1.00, and a true negative (TN) rate of 0. Although the model demonstrates strong performance in identifying positive cases, the presence of both false positives and false negatives reveals areas that require improvement. To gain a more comprehensive understanding of these errors, it is important to consider class-specific metrics such as precision, recall, and the F1 score, as they provide a more detailed and balanced evaluation of the model's performance. These findings suggest the need for further adjustments to enhance the model's discriminative capacity and overall effectiveness.

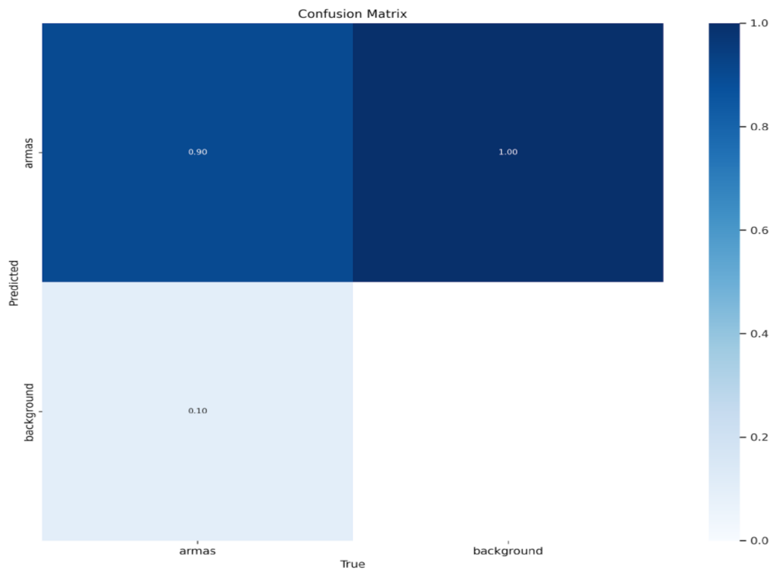

Figure 8: Confusion matrix of the object detection model

4 Implementation of the Trained Model

The software was designed with separate modules for ease of development, maintenance, and scalability. The diagram of the training model in figure 9 illustrates the implementation and adjustment of the detection system, successfully integrating it into the video surveillance system. The results were validated to precisely meet the specific requirements of the project, ensuring its effectiveness and continuous adaptability.

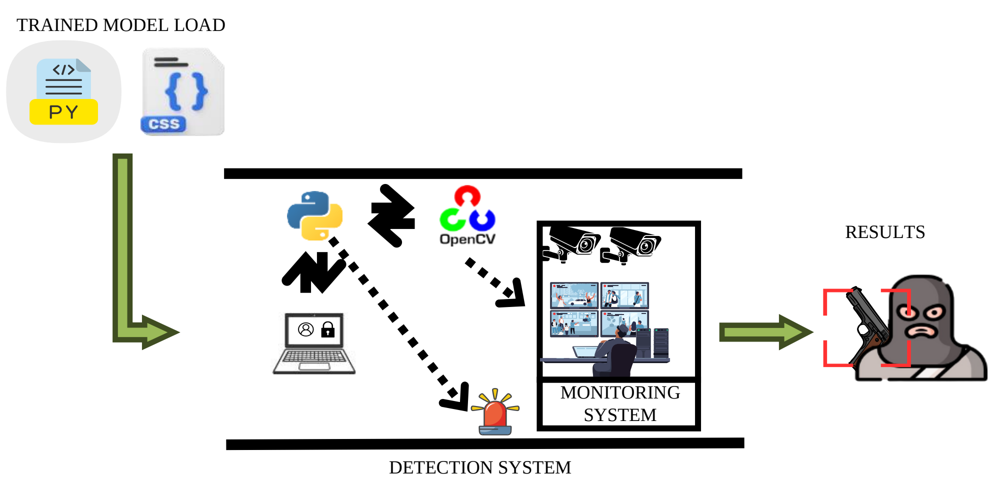

Figure 9: Trained model implementation diagram

Interface Result: Figure 10 displays real-time detection with greater than 93% confidence. Immediate activation of audio and visual alerts for effective response to detected threats.

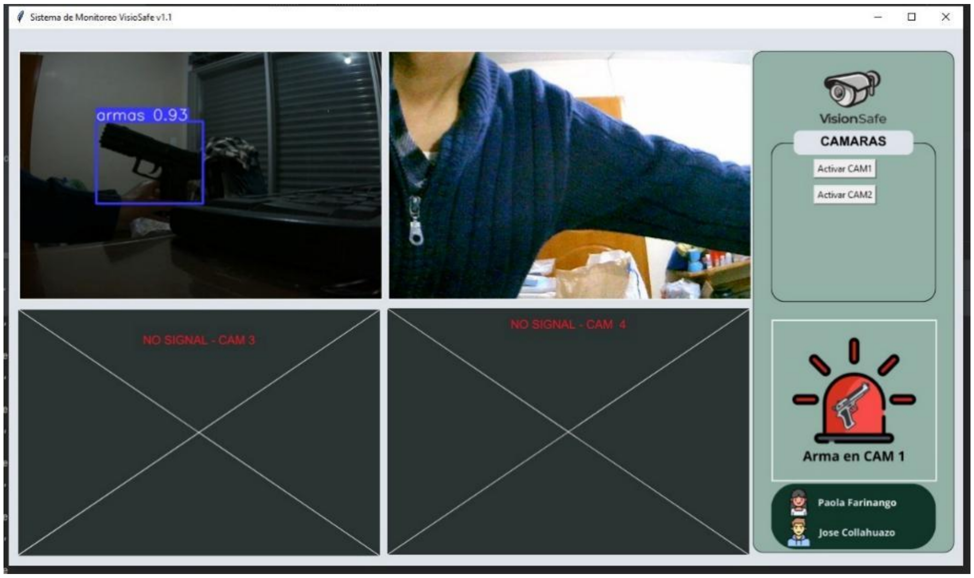

Figure 10: Real-time object detection - CAM 1

Use of video surveillance system: The HIKVISION video surveillance system enables accurate detection of moving objects to ensure site security. The access interface with credentials is depicted in figure 11.

Figure 11: Hikvision video surveillance system login

At the end of development, our system adopts layered architecture with three key components for its operation, as depicted in figure 12.

- Data Layer: it handles creating and adjusting the model by collecting and loading data, taking advantage of computational resources in Google Colab;
- Application Layer: it develops the user interface and combines the trained model for object detection, issuing alerts upon object recognition;
- User Layer: it evaluates system performance in a real environment.

Synchronization between these layers ensures an efficient and adaptable system.

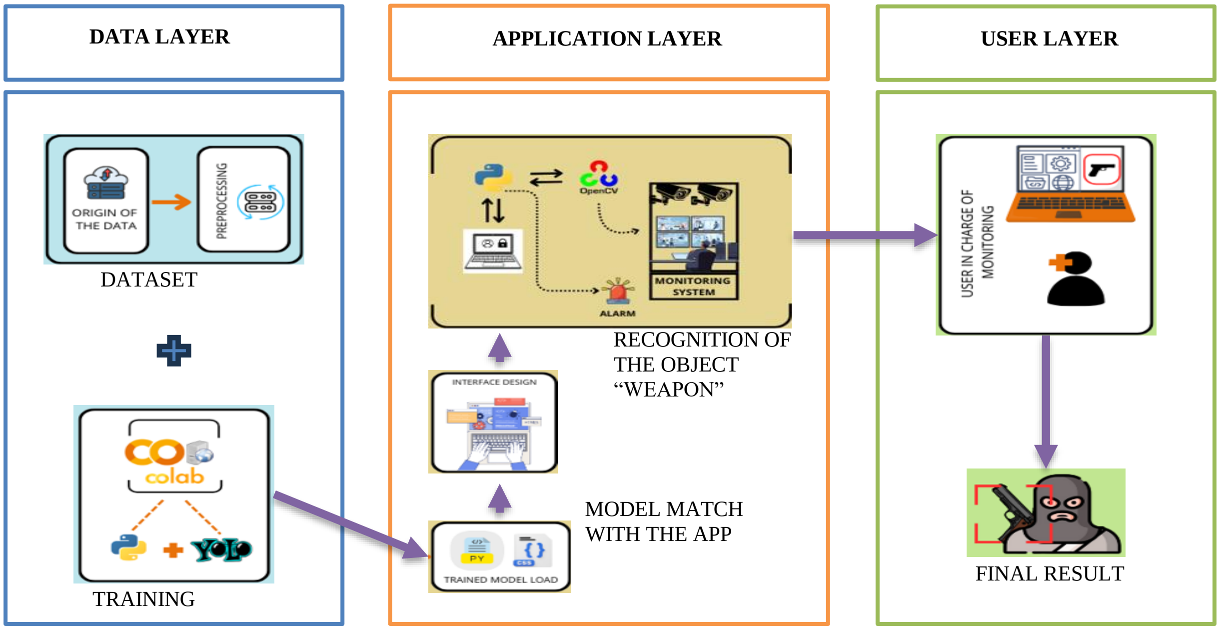

Figure 12: General architecture

Results

Security cameras, commonly located in crowded areas, present challenges in real-time monitoring due to the large number of elements in each video frame. Surveillance personnel, sometimes distracted, can compromise security. This work seeks to improve surveillance on the campus of the University of the Armed Forces ESPE through a Deep Learning model that detects firearms, as illustrated in figure 13.

Figure 13: Detection system operation

Interface: The system in operation is shown in figure 14, where the firearm is detected and delimited and emits visual and audible alerts in the lower right corner to facilitate monitoring. Detection accuracy varies by camera: camera 1 is 71% accurate due to its resolution whereas camera 2 is as high as 95%.

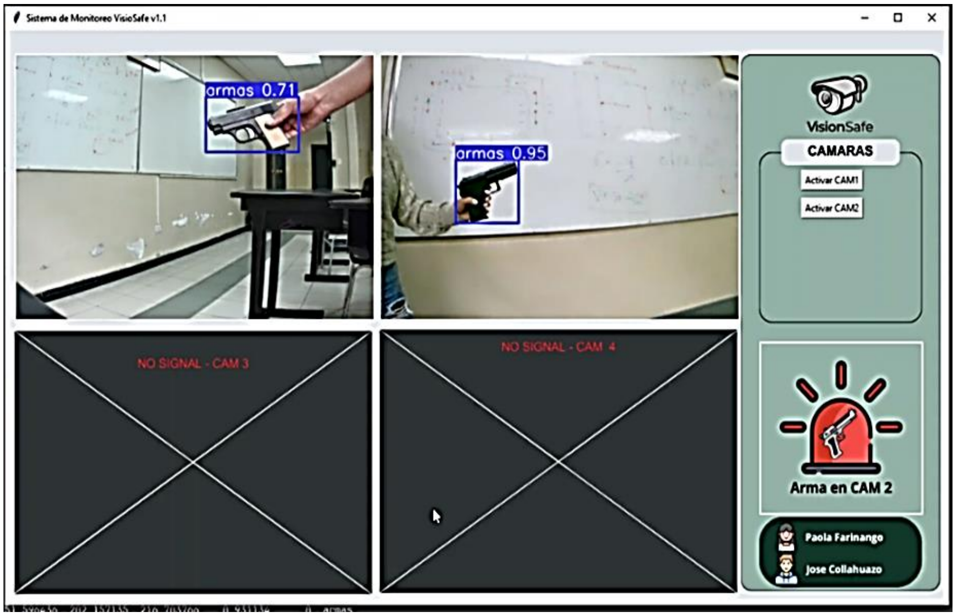

Figure 14: Simultaneous weapon detection in two cameras

In another context, it is noticeable how the system detects the firearm with 94% accuracy, adjusting to the surrounding conditions as illustrated in figure 15.

Figure 15: Weapon detection with close proximity

In another environment, after implementing our model in HIKVISION's video surveillance system, a test was conducted that demonstrated an accuracy of 95 percent. The quality of video resolution and transmission is crucial for effective detection, as is the system's ability to adapt to changes in lighting, as depicted in figure 16.

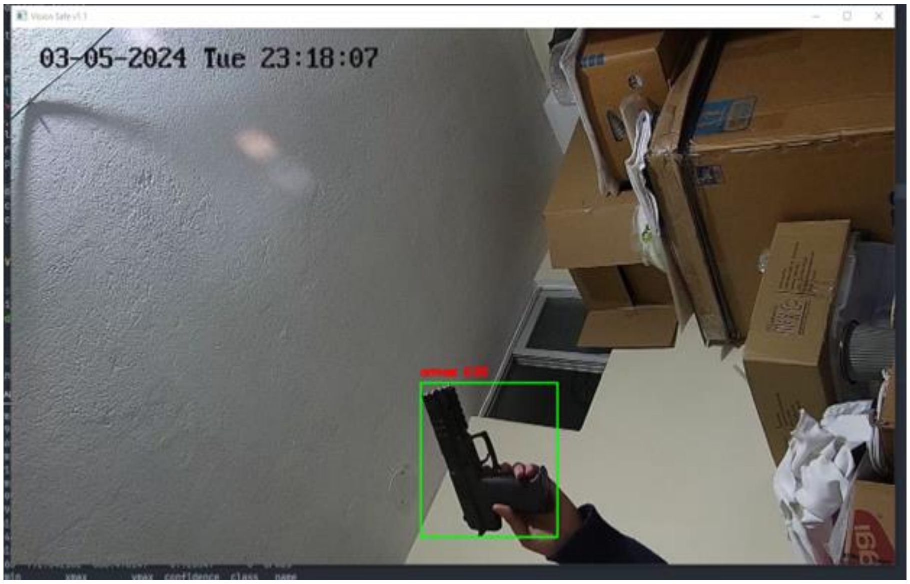

Figure 16: Deep learning model implementation - hikvision video surveillance system

Conclusions

The development of a weapons' detection system at the University of the Armed Forces ESPE has been a decisive step in strengthening campus security. The project has proven to be highly effective in improving security, using the Scrum methodology to develop and deploy a deep learning model based on YOLOv5. This model has achieved an outstanding accuracy of 99%, a detection rate of 93%, and an overall performance of 97%. To achieve these results, the team undertook the collection and preparation of an extensive image dataset, labeling and data augmentation, and training of the model in Google Colab.

Once integrated into the HIKVISION video surveillance system, the model will enable continuous and accurate surveillance, providing audio and visual alerts for rapid response to potential threats. The system will be designed to adjust to various lighting conditions and video quality, thus ensuring reliable detection of weapons under any circumstances; in a scenario with limited light, the detection was 93% and with more illumination, the detection was 95%. This project not only aims to optimize security in real time but also highlights how advanced technologies can evolve and adapt to meet today's security challenges.

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Ethical Considerations and Privacy Implications

The use of the detection system must be strictly limited to security purposes, avoiding its use for unauthorized surveillance. To achieve this, clear protocols must be established, transparency in data handling ensured, and strict access controls implemented. The collection and processing of video data must comply with data protection regulations and respect individuals' privacy and anonymity whenever possible.

Additionally, it is necessary to prevent biases in the machine learning model by using diverse and representative datasets, thereby minimizing false positives or negatives that could lead to discrimination or unequal treatment.

In conclusion, the responsible and transparent implementation of the system is key to respecting individual rights and maintaining trust within the academic community.

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Authors Biography

Freddy Tapia León was born in Quito on May 14, 1977. He is a Doctor of Computer and telecommunications engineering. He currently works as a professor and the research coordinator in the Department of Computer Science at the University of the Armed Forces (ESPE), where he spearheads various academic and scientific initiatives. He also provides professional advice and services at different universities in Ecuador, actively contributing to the training and development of the educational and technological sectors. In recent years, he has collaborated directly with MBTU (Miami Business Technological University), strengthening academic exchange and international cooperation. He is distinguished by his participation in multidisciplinary research projects and his integration into networks and research groups at the national and international levels. His work has been published in several scientific journals, and he has advanced knowledge in his field of specialization. With an innovative vision and a firm commitment to education and research, Freddy continues to promote technological and academic development, contributing to the growth of the scientific sector.

José Danilo Collahuazo Information Technology Engineer with a strong passion for networks and cybersecurity. Among his achievements, he stands out for securing third place at the 2024 Multidisciplinary International Congress on Science and Technology (CIT). Additionally, he holds solid certifications in cybersecurity, including Cisco's CyberOps and Fortinet's Professional Network Security. Currently, he works as a Specialist in the Security Operations Center (SOC and CSIRT), focusing on implementing robust technological solutions in cybersecurity.

Paola Cristina Farinango Medina is an Information Technology Engineer from the Armed Forces University ESPE, Ecuador. She currently works at DWConsulware, specializing in data analysis. Her research interests focus on data analysis, artificial intelligence, and information security. She has been recognized for her research performance in the Outstanding Undergraduate Research Student category and holds certifications in cybersecurity, cloud security fundamentals, project management, and agile methodologies. She enjoys taking on new challenges that enhance her personal and professional development.

Cesar Chiliquinga is an Ecuadorian professional with academic training and extensive experience in the field of engineering and technology. His career combines technical knowledge with teaching and research skills. Throughout his career, he demonstrated a strong commitment to higher education, actively participating as a university lecturer and collaborator in various academic and technological projects. He has worked on initiatives related to software development, cybersecurity, data analysis, and digital tools. Additionally, He maintains a focus on collaborative work, pedagogical innovation, and the training of honest and highly skilled professionals. Recognized for his professional ethics and competencies in teaching, technological development, and educational management, contributing to the academic and scientific development of the country, projecting efforts towards a regional and global impact.

Luis Tello-Oquendo received the electronic and computer engineering degree (Hons.) from Escuela Superior Politécnica de Chimborazo (ESPOCH), Ecuador, in 2010, the M.Sc. degree in telecommunication technologies, systems, and networks, and the Ph.D. degree (Cum Laude) in telecommunications from Universitat Politécnica de Valencia (UPV), Spain, in 2013 and 2018, respectively. From 2013 to 2018 he was Graduate Research Assistant with the Broadband Internetworking Research Group, UPV. From 2016 to 2017 he was a Research Scholar with the Broadband Wireless Networking Laboratory, Georgia Institute of Technology, Atlanta, GA, USA. He is currently an Associate Professor with the Universidad Nacional de Chimborazo. His research interests include MTC, wireless SDN, 5G and beyond cellular systems, IoT, machine learning. He is a member of the IEEE and ACM. He received the Best Academic Record Award from the Escuela Técnica Superior de Ingenieros de Telecomunicación, UPV, in 2013, the Extraordinary Doctoral Thesis Award from the Escuela de Doctorado, UPV, in 2019, and the Best Researcher Award from the Ecuadorian Corporation for the Development of Research and the Academy (CEDIA), in 2021.

Johanna Rivera is an Engineer in Electronics and Telecommunications, graduated from the National University of Chimborazo, Ecuador. She is currently pursuing a master's degree in project management and direction in Spain. He has experience in research projects and has collaborated with the National University of Chimborazo in technical and academic support processes. His work has focused on logistical assistance, editorial coordination, and the writing of scientific and technical articles in various sectors.