AI-Powered Military Border Monitoring System with Military Vehicle Detection and Face Recognition

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Abstract

An artificial intelligence (AI)-based surveillance system intended to improve military border security is presented in this research. The suggested system is made up of two main modules for identifying possible dangers in border regions. The first module identifies authorized military personnel using facial recognition based on Haar Cascade. The technology takes a picture, pinpoints the location, and immediately notifies the appropriate authorities via email if it spots an unfamiliar or unapproved face. The YOLOv8 deep learning model is used in the second module to detect military vehicles. The algorithm is used to monitor border areas in real time after being trained on a dataset that includes pictures of different military vehicles.
When a car is identified, the system takes a picture, uses image-based computations to determine the distance between the car and the camera, keeps track of the location details and notifies security staff via email. The suggested dual-module system offers real-time alerts for possible security risks along the border, increases monitoring accuracy, and decreases reliance on humans.

Keywords
Deep Learning, AI, YOLOv8, Haar Cascade-based facial recognition, detecting military vehicles, alert email etc.

1. Introduction

Border In order to defend a country against outside threats and illegal activity, border security is essential. It is crucial to keep an eye on border regions to make sure safety and uphold national security. Conventional surveillance techniques mostly depend on manual monitoring and human observation, which can be laborious, ineffective, and prone to human mistake. In sensitive places like military zones and border regions, these constraints may result in delayed reactions and decreased efficacy in identifying possible threats. Intelligent and automated surveillance technologies that can increase the effectiveness and precision of monitoring activities are therefore becoming more and more necessary.

With the development of deep learning, computer vision, and artificial intelligence (AI), contemporary surveillance system scan carryout automated detection and monitoring activities more quickly and accurately. AI-based systems can recognize significant items or people in real time by evaluating visual data recorded by cameras. These innovations have been extensively used in a number of industries, including smart surveillance systems, traffic management, and security monitoring. They are ideal for military and defense applications because of their capacity to effectively handle massive volumes of visual data.

This An AI-powered surveillance system intended for military border security is presented in this project. To improve monitoring, the suggested system combines two primary parts. The Haar Cascade algorithm, a machine learning-based method frequently used for real-time face detection, is the topic of the first module. The faces of authorized military personnel are recognized and validated by this module. The technology automatically takes a picture, logs the location, and notifies the relevant authorities via email if it detects an unauthorized person. This procedure guarantees prompt action in the event of suspicious activity and aids in preventing illegal access.

The YOLOv8 deep learning model, which is popular for object detection tasks, is utilized in the second module to recognize military vehicles. The model can identify vehicles in real-time surveillance settings because it was trained on a library of photos of various military vehicles. When a car is identified, the system takes a picture, uses image-based algorithms to determine the vehicle's distance from the camera, and saves the position information. In order to guarantee prompt action and monitoring of vehicle movements in restricted zones, an alarm message is thereafter issued to the authorities.

2. Literature Review

Automated monitoring and threat identification have been greatly enhanced by the use of computer vision and artificial intelligence (AI) in surveillance systems. Maintaining national security in military and border security settings depends on identifying unauthorized personnel and suspicious vehicle movement. Conventional surveillance techniques mostly rely on human monitoring, which can result in coverage gaps, delays, and mistakes. As a result, current research has focused more on intelligent surveillance systems that use deep learning and machine learning approaches.

A. Conventional and Machine Learning Methods

Early surveillance and object detection studies focused on traditional image processing methods including background
motion analysis, edge detection, and subtraction to identify objects in video streams. To recognize objects or human faces, feature extraction methods including Local Binary Patterns (LBP), Haar-like features, and

Histogram of Oriented Gradients (HOG) were frequently employed. Algorithms like the Haar Cascade classifier were commonly used for face identification and recognition jobs due to their quick processing speeds and real-time detection capabilities. These techniques identify faces by utilizing pre-established patterns to recognize distinct facial characteristics such the mouth, nose, and eyes.

In a similar vein, conventional car recognition algorithms coupled machine learning classifiers like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees with manually created characteristics. Although these methods produced satisfactory results in controlled settings, their effectiveness was heavily reliant on manual feature extraction and was susceptible to complicated backdrops, occlusion, and illumination.

B. Techniques Based on Deep Learning

The accuracy and efficiency of object identification and facial recognition systems have significantly increased due to the quick development of deep learning algorithms. Convolutional Neural Networks (CNNs), in particular, are deep learning models that can automatically extract intricate visual characteristics from picture data without the need for human feature engineering. For real-time object detection problems, contemporary object detection models like SSD (Single Shot Detector), Faster R-CNN, and YOLO (You Only Look Once) have become popular. The YOLO family of models has become well-known among them because to its quick detection speed and real-time picture processing capabilities.

YOLO-based designs for vehicle detection and classification have been used in recent research, allowing automated vehicle monitoring in surveillance systems. These models offer bounding boxes, class labels, and confidence scores in addition to the ability to recognize many objects at once. Deep learning models have also been employed in the field of facial recognition to increase recognition accuracy in difficult situations such changes in illumination, position, and facial occlusion. Deep learning integration with surveillance systems makes it possible to automatically identify suspicious activity in critical locations like border regions, military bases, and airports.

C. Research Gap

- The majority of current monitoring systems concentrate on either Instead of combining both face recognition and vehicle detection into a single security framework.
- While many studies concentrate on general vehicle detection, very few particularly address military vehicle identification in restricted regions.
- The automatic alarm systems and real-time monitoring features necessary for military surveillance settings are absent from many current systems.
- enhance border security and lessen reliance on humans, integrated AI-based surveillance systems that include vehicle detection and facial verification are required.

3. Problem Statement

Based on Traditional border surveillance systems primarily rely on manual monitoring by security personnel and conventional CCTV setups, which have several limitations in ensuring effective and continuous border security. Fatigue, short attention spans, and delayed reactions are common problems for human operators, particularly when observing for extended periods of time or in challenging environments. These elements may result in delayed reaction times, missing detections, and decreased effectiveness in spotting possible border threats. Furthermore, traditional CCTV systems lack the ability to distinguish between permitted and unauthorized people or to identify particular car kinds; they can only capture and show video feeds. Security personnel find it challenging to follow movements, identify intrusions, and react quickly to suspicious activity as a result.

Forces to monitor movements, identify incursions, or react quickly to questionable activity. The efficacy of traditional surveillance systems is further diminished by the lack of automated alert systems and real-time analysis, which permits illicit movements or entry to go undetected until it is tool ate. A more sophisticated, automated, and intelligent monitoring system is becoming more and more necessary due to the growing complexity of border threats, which range from unlawful crossings and smuggling to possible terrorist infiltration.

In order to overcome these issues, this research suggests an AI-powered surveillance system that combines vehicle detection using the YOLOv8 deep learning model with facial identification using the Haar Cascade algorithm. The system is built to automatically identify authorized military people, identify military vehicles, calculate the distance of identified items, and instantly notify the relevant authorities via email using GPS coordinates and collected photos.

4. Proposed Methodology

In order to overcome these issues, this research suggests an AI-powered surveillance system that combines vehicle detection using the YOLOv8 deep learning model with facial identification using the Haar Cascade algorithm. The system is built to automatically identify authorized military people, identify military vehicles, calculate the distance of identified items, and instantly notify the relevant authorities via email using GPS coordinates and collected photos.

A. Data Discription:

• For the facial authentication module, a dataset of approved military personnel's faces is prepared. Each person's face is taken several times in different lighting and orientations to improve recognition accuracy. Converting collected photos to grayscale improves feature extraction and makes computation easier.

• The second dataset's images of military vehicles were used to train the YOLOv8 object detection algorithm. The collection includes a range of military vehicles, such as tanks, armored vehicles, and military transport trucks. These cars were captured in a variety of settings and from different perspectives.

B. Image Preprocesing

Before training the models, a number of preprocessing techniques are used to the gathered photos of military vehicles and faces in order to increase detection accuracy and guarantee consistency in the dataset. These preprocessing procedures aid in noise reduction, image size standardization, and enhanced detection algorithm performance.

1)Image Resizing

All images are resized to:

224 x 224 pixels

2) Grayscale Conversion

The input photographs are transformed from RGB to grayscale format for the facial recognition module. Because the Haar Cascade technique uses intensity differences rather than colour information, it performs better on grayscale images.

3)Face Region Extraction

The Haar Cascade classifier is used to identify facial regions in photos after they have been converted to grayscale. After being identified, the face regions are trimmed and added to the face dataset as distinct samples.

4)Dataset Annotation:

Labelling tools like Label Image are used to manually annotate vehicle photos for the military vehicle detection module. Each vehicle is surrounded by bounding boxes, and class designations are given according to the kind of vehicle.The annotations, which comprise object class, bounding box coordinates, and image dimensions, are saved in YOLO format. The YOLOv8 model can learn object localization and classification thanks to this annotation procedure.

5)Enhancement of data

Data augmentation techniques are applied to the training images in order to decrease overfitting and boost dataset diversity. These modifications mimic several real-world scenarios that could arise during border monitoring.

Among the enhancement methods employed are:

- Rotation
- Flipping horizontally
- Scaling at random
- Brightness adjustment
- Modification of brightness
- A small amount of translation (width and height shifting)

C. Data Augmentation

Different data augmentation methods were used for the YOLOv8 and Haar Cascade models. To increase robustness and detection accuracy in real-world surveillance environments, YOLOv8 used sophisticated augmentations like mosaic augmentation, random flipping, HSV color transformations, and spatial translations, while Haar Cascade used simpler transformations like rotation, scaling, and illumination adjustments.

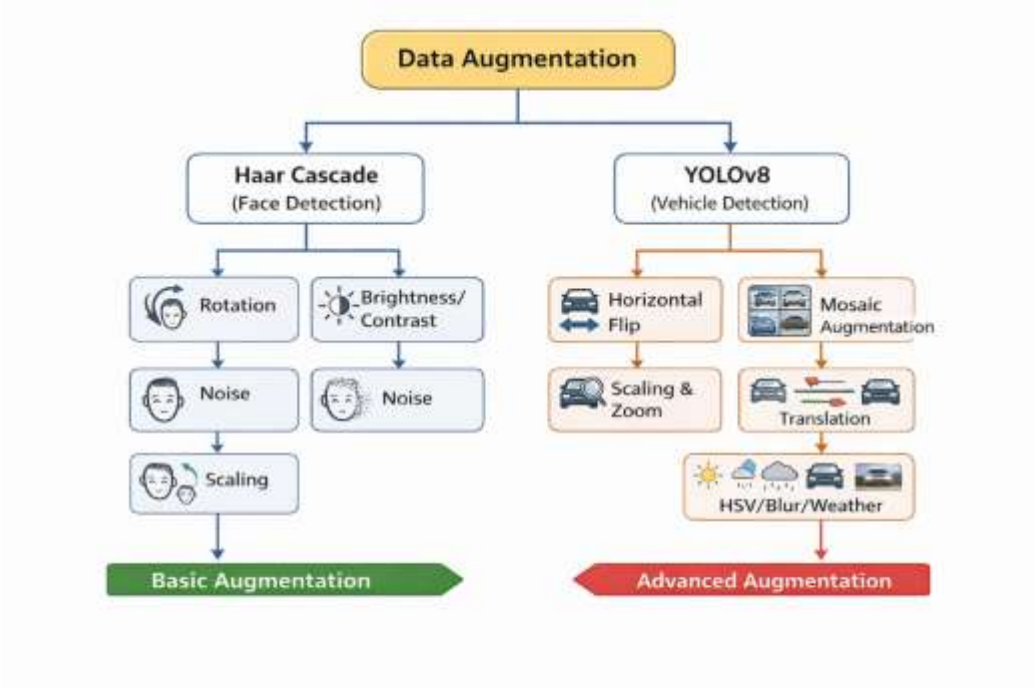

Fig 1: Augmentation Diagaram

D. Workflow Diagram

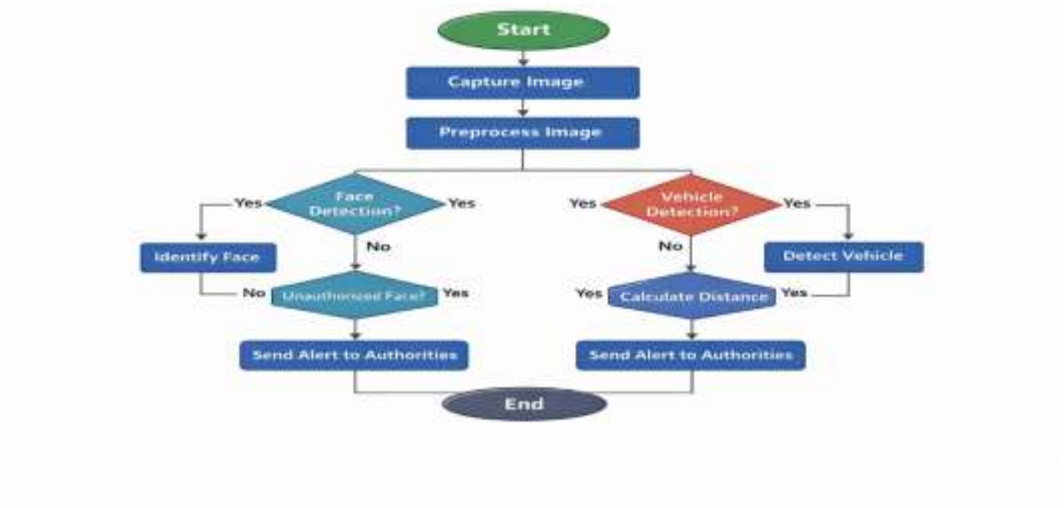

Fig 2: Workflow diagram

The suggested system's general architecture is intended to function as a sequential, decision-driven pipeline for threat monitoring and intelligent surveillance. The system first gathers visual data via a video feed or camera interface. To enhance the quality and consistency of the data for further analysis, the acquired input is subsequently placed through preprocessing procedures such image scaling, normalization, and noise filtering.

Following preprocessing, the system performs parallel evaluation for both human face detection and vehicle detection. To ascertain whether a human face is present in the frame, a face detection algorithm is used in the first stage. The system compares the extracted facial features with entries kept in a predetermined database to carry out a face recognition process after successful detection. The system labels the instance as unauthorized and sends out a warning to the appropriate authorities if the detected person is not present in the approved dataset.

The technology uses pre-established rules to assess possible unlawful conditions even in situations when no face is identified. An alarm system is activated to guarantee prompt intervention if such a condition is met.

The system uses an object detection model to process vehicle detection simultaneously. Additional analysis, such as tracking or classification, may be carried out if a vehicle is found. The system calculates the distance of objects in the scene to evaluate proximity-related dangers in situations where direct vehicle recognition is not possible. The system detects a possible threat and issues an alarm signal if the computed distance is within a crucial threshold.

E. System Architecture

The suggested system is set up as an intelligent surveillance framework with automated threat detection and monitoring to improve border security. It combines deep learning and computer vision techniques to carry out two main tasks: facial recognition for personnel verification and military vehicle detection.
Using CCTV cameras stationed at border sites, the process starts with picture acquisition. In order to enhance image clarity and provide consistent input for later modules, the acquired frames are processed through an image preprocessing step that includes operations like scaling, grayscale conversion, and noise reduction.

There are two main functional modules in the architecture:

1. Module for Face Recognition

This module is in charge of identifying and confirming military personnel. To find human faces in the input frame, the system first uses the Haar Cascade technique. The Local Binary Patterns Histogram (LBPH) technique is used for feature extraction and recognition after a face has been identified. To ascertain identity, the identified face is subsequently matched with facial data that has been saved in the database. The system initiates an alert notification, such as an email forwarded to the relevant authorities for prompt action, if the person is not identified or is deemed unlawful.

2. Module for Vehicle Detection and Distance Estimation

Military vehicle identification and proximity analysis are the main topics of the second module. The YOLOv8 (You Only Look Once version 8) object detection model, which permits precise and real-time vehicle detection in the monitoring area, is used by the system for this purpose. Following detection, the relative distance between the detected vehicle and the monitoring system is determined using a distance estimate technique. This aids in evaluating possible dangers according to proximity. The device creates an alert to warn security staff if a car is found within a predetermined critical range.

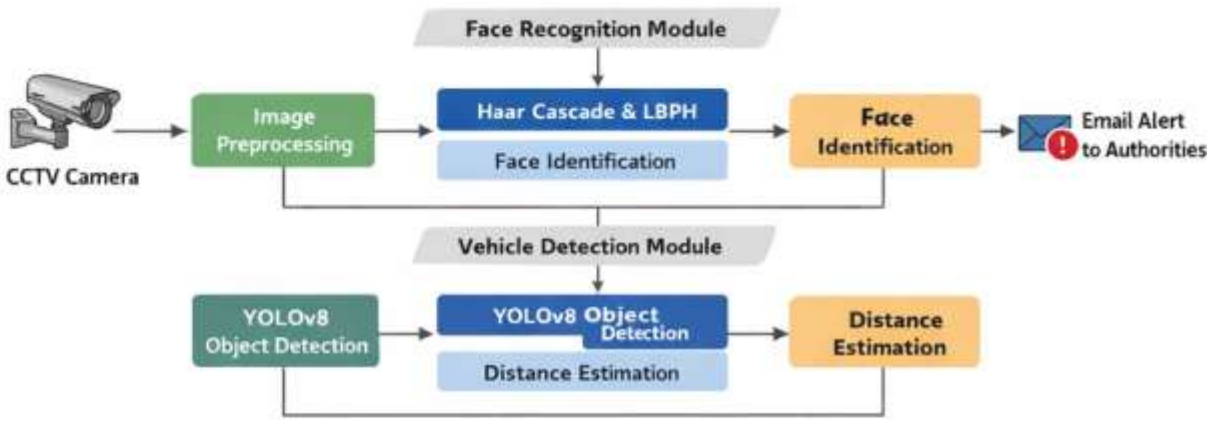

Fig 3 System Architecture

Both modules run concurrently and are connected to a central notification system, which guarantees that any suspicious activity—whether it has to do with approaching cars or unauthorized people—is quickly notified. In crucial border security situations, this combination strategy improves situational awareness and facilitates quicker decision-making.

5. Experimental Setup and Implementation

1) Haar Cascade Face Detection

A traditional machine learning technique for real-time face detection is the Haar Cascade method. It functions by recognizing particular patterns (Haar-like features) in an image, such as edges, lines, and rectangles.

$$Y(i,j) = \Sigma(m=0 \rightarrow M)\ \Sigma(n=0 \rightarrow N)\ X(i-m, j-n) * K(m,n)$$

Where:

- $Y(i,j)$ → Pixel value Output (feature map)
- $X(i,j)$ → Input picture
- $K(m,n)$ → Kernel / filter (Haar feature)
- Σ (Sigma) → Summation value(adding)
- i, j → The image's pixel position
- m, n → Kernel indices

2) Using LBPH for Face Detection

The Local Binary Pattern Histogram (LBPH) technique is used by the system to identify authorized persons once the face has been detected.

The definition of the LBPH operator is:

$$LBP(xc, yc) = \Sigma(p=0 \rightarrow P-1)\ s(ip - ic) * 2^p$$

Where:

LBP(xc, yc) → Value of the Local Binary Pattern at the Center Pixel
xc, yc is Center pixel coordinates

The system uses this representation to compare the detected face with database-stored facial photographs.

3) YOLOv8 for Military Vehicle Detection

In order to detect objects, YOLO (You Only Look Once) divides the image into grid cells and simultaneously predicts bounding boxes and class probabilities.

The YOLOv8 model's output consists of:

- Coordinates of the bounding box
- The label for the object class
- Confidence score for detection

4) Estimating Distance

The technology calculates the distance between the military vehicle and the security camera after identifying it.

(Focal Length × Real Object Height) / Pixel Height = Distance

Where:

Camera calibration parameter = focal length
Real Object Height is the vehicle's true height.
Pixel Height = the image's detected object height

5) Training Stratergy

Supervised learning techniques are used to train the vehicle detection and facial recognition modules of the proposed system.

1. Training in Face Recognition

Images of approved military members are used to train the facial recognition model.

- Taking several pictures of every individual
- Grayscale picture conversion
- Using Haar Cascade to identify faces
- Using LBPH to extract facial features

Every person is given a distinct identifying label. Each allowed face's histogram features are stored by the trained LBPH model.

2. Training in Vehicle Detection

A dataset with pictures of military vehicles is used to train the YOLOv8 model.

- Gathering pictures of armored vehicles, trucks, and tanks
- Using tools like Labelling to annotate bounding boxes
- Transforming annotations into YOLO format
- Using the Ultralytics YOLOv8 framework to train the model

To correctly identify military vehicles, the model learns spatial characteristics including vehicle size, shape, and structure.

Typical training hyperparameters consist of:

- The Learning Rate is = 0.001
- 16–32 is the batch size
- There are five epochs

6. Results and Discussion

These are the sample outputs which are send to our personal email:

Fig 4: Armered Vehicle detected image

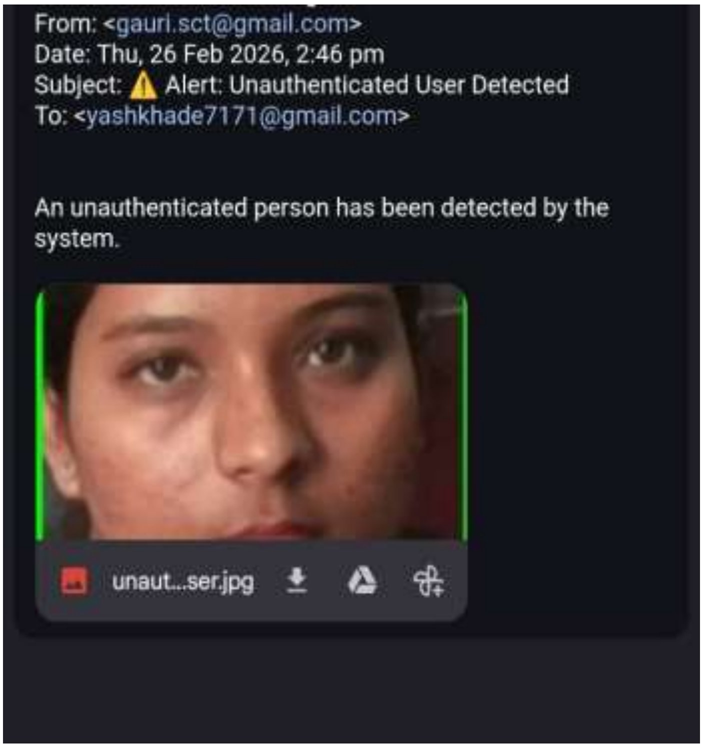

Fig 5:Unauthorized face has detected

Fig 6: Armered Vehicle detected image

Classification Accuracy and Feature Optimization

1. Comparison of Model F1-Score

Each model's F1-score performance is shown in this chart. The suggested hybrid model achieves the greatest F1 score, indicating a good balance between recall and precision. This outcome shows that the model continues to operate dependably.

2. A matrix of confusion.

By contrasting the expected outcomes with the actual ground truth labels, the confusion matrix is utilized to assess the categorization performance of the suggested surveillance system. It offers a thorough comprehension of the model's accurate detections and incorrect classifications.

Predicted	Vehicle Detected	No Vehicle
Vehicle Present	96	4
No Vehicle	3	97

3. Training vs Validation Accuracy Curve

This curve illustrates the accuracy progression across training epochs. Both the training and validation accuracy gradually improve, reflecting a stable and consistent learning process. The proposed hybrid model ultimately achieves high accuracy, highlighting its ability to effectively extract meaningful features and maintain strong generalization performance.

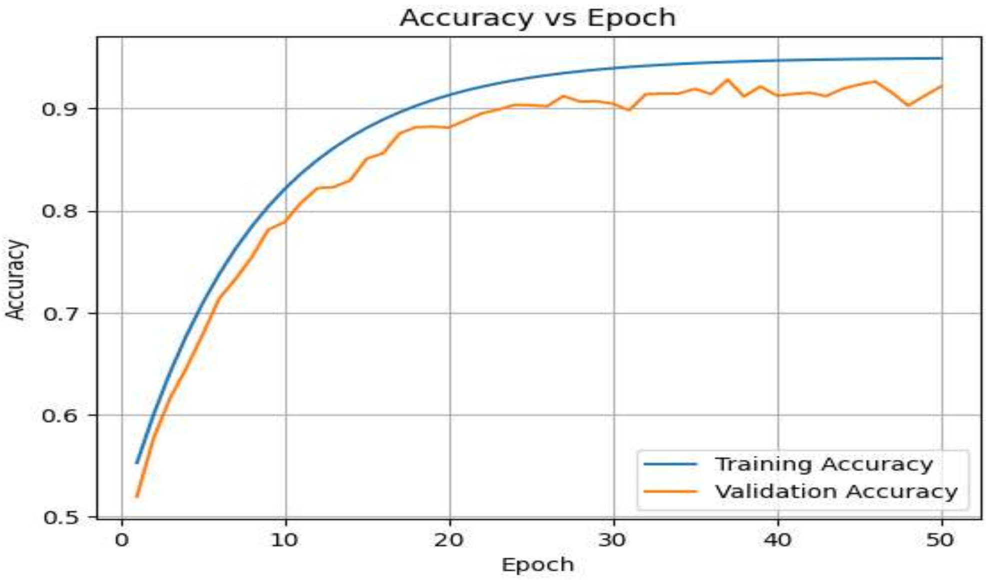

Fig 7: Training v/s Validation Accuracy Curve

4. Training vs Validation Loss Curve

For both the training and validation datasets, the loss curve shows a steady decline, suggesting steady convergence throughout the learning process. The slight discrepancy between the training and validation losses indicates that overfitting is reduced, primarily as a result of optimization.

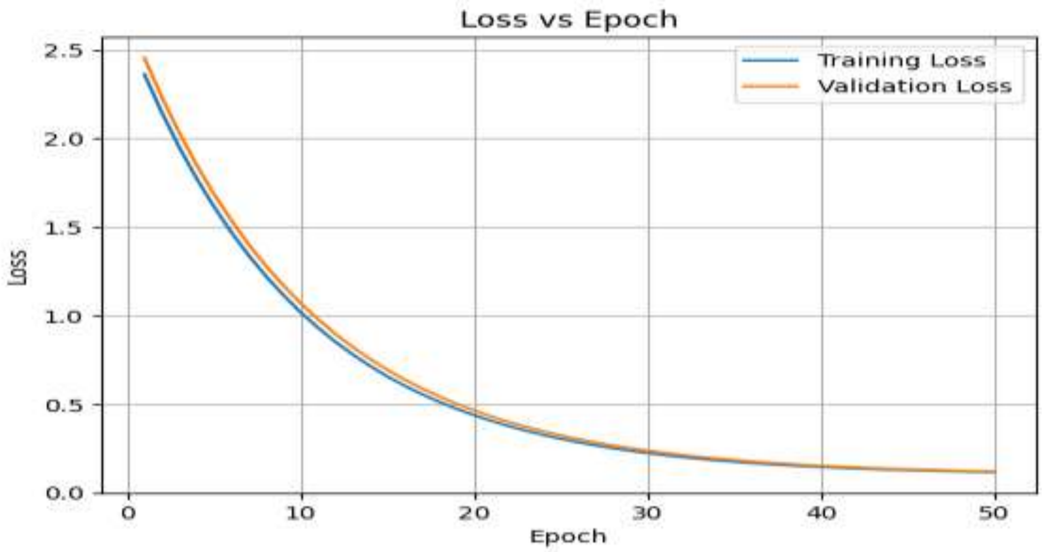

Fig 8: Training v/s Validation loss Curve

5. Matrix of Performance

Standard evaluation measures like accuracy, precision, recall, and F1-score were used to assess the suggested surveillance system's performance. These metrics aid in evaluating the military vehicle detection model and face recognition system's detection performance.

Module	Accuracy	Precision	Recall	F1Score
Face detection	92.2	91.2	93.2	92.1
Military Vehicle	95.6	94.8	96.2	95.5

Discussion

By combining vehicle detection and facial recognition into a single framework, the suggested AI-based military border surveillance system exemplifies a hybrid approach. This part provides a critical analysis of the system's overall strengths, performance evaluation, and module comparison.

1. System Modules Comparison

The LBPH technique is used for identification and the Haar Cascade algorithm is used for face detection in the facial recognition module. Because of its computational efficiency and relative light weight, this module can be used for real-time processing even on mediocre hardware. It works especially well in regulated settings when authorized personnel's facial data is accessible. However, under difficult situations like dim lighting, occlusions, or changes in facial look, its performance may deteriorate.

On the other hand, the YOLOv8 deep learning model, which offers excellent detection accuracy and robustness in challenging circumstances, is the foundation of the vehicle recognition module. For training and inference, this part needs a bigger dataset and more processing power than the face recognition module.

It is better able to adjust to changing circumstances, including varied vehicle types, backgrounds, and angles.Overall, the vehicle detection module stresses object identification and location analysis, while the facial recognition module concentrates on identity verification. As a result, both modules work well together to achieve comprehensive surveillance.

2. Performance Assessment

With predetermined performance benchmarks, the system is built to function under real-time restrictions. The project specs state that while vehicle detection functions at real-time frame rates (about 15 FPS or greater), facial recognition is planned to reply within a few seconds.When trained on an organized dataset of authorized personnel, the facial recognition module attains acceptable accuracy. However, environmental factors like lighting and face orientation affect its dependability. However, because of its deep learning design, the YOLOv8-based vehicle identification module has more scalability and robustness, allowing it to accurately recognize many cars at once.

By determining object closeness using bounding box dimensions and camera calibration, the distance estimate component adds another analytical layer. Despite its effectiveness, this approach may introduce small mistakes based on assumptions about object size and camera orientation.

3. Advantages of the Suggested System

The system has a number of noteworthy benefits that improve its usefulness:

- **Automation and Decreased Reliance on Humans:**

By automating detection and alert procedures, the system reduces manual monitoring, which lowers human error and fatigue.

- **Dual-Layer Security Approach:**

The system offers a thorough surveillance mechanism that can manage various danger scenarios by fusing vehicle detection with facial recognition

- **Real-Time Monitoring and Alerts:**

In emergency situations, prompt detection and notification facilitate quicker decision-making and response

- **Scalability and Flexibility:**

The modular architecture makes it possible to incorporate extra features like sophisticated AI models, drone surveillance, and multi-camera systems.

- **Improved Situational Awareness:**

By including distance estimation, authorities can better respond tactically by evaluating threat levels based on proximity.

7. limitations

The benefits of the suggested AI-powered military border monitoring system, some restrictions must be taken into account for both practical implementation and future development.
The facial recognition module, which uses LBPH and Haar Cascade algorithms, presents one of the main difficulties. This method is sensitive to environmental factors including dim lighting, shadows, and occlusions (such as masks, helmets, or scarves), despite being computationally efficient. Recognition accuracy may also be lowered by changes in facial appearance over time, particularly if the dataset is not updated frequently.

For efficient training, the YOLOv8 model-based vehicle detection module needs a sizable and varied dataset. Detection performance may deteriorate in situations when the dataset is constrained or lacks variance (e.g., camouflage vehicles or odd viewing angles). Vehicles that overlap or are partially obscured may also result in missed detections or inaccurate classifications.
The distance estimation method's reliance on presumptions such known object size and camera calibration is another drawback. The accuracy of threat assessment can be impacted by any flaws in these parameters, which can lead to errors in distance computation.

The quality of the infrastructure and hardware is equally crucial to the system. Real-time performance requires high-resolution cameras, reliable internet access, and enough processing power. Such infrastructure can be difficult to maintain in isolated border regions, which could affect system effectiveness. Finally, privacy and security issues need to be taken care of. In order to avoid unauthorized use or data breaches, the system needs strong encryption and access control measures because it handles sensitive data including photos and location information.

8. Conclusion

An intelligent way to improve security in sensitive and restricted locations, such military zones and national borders, is the suggested AI-powered military border monitoring system. The system provides automatic and real-time monitoring of both troops and vehicles by combining YOLOv8-based military vehicle identification with Haar Cascade-based facial recognition. While the YOLOv8 model correctly recognizes military vehicles from live surveillance data, the facial recognition module effectively identifies authorized personnel. The trial findings show that the system can quickly and accurately identify suspicious vehicle movements and illegal persons.

In order to enable quick reaction to possible security threats, the system also automatically takes pictures, calculates the distance of identified cars, logs position data, and notifies authorities. The overall results show that the suggested approach greatly increases surveillance efficiency while lowering dependency on manual monitoring, even when environmental factors like dim lighting, camera angle fluctuations, or dataset constraints may have an impact on system performance. For contemporary border surveillance applications, the proposed system therefore offers a dependable, scalable, and intelligent architecture.

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