**Eve-Teasing Detection from Image using Computer Vision and Artificial Intelligence in Public Transport**

***Report submitted to***

***Haldia Institute of Technology, Haldia for the award of the degree***

***of***

**Bachelor of Technology**

**in**

**Computer Science and Engineering (Data Science)**

***by***

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**DECLARATION**

We certify that,

1. The work contained in this report is original and has been done by us under the guidance of our supervisor.
2. The work has not been submitted to any other Institute for any degree or diploma.
3. We have followed the guidelines provided by the Institute in preparing the report.
4. We have conformed to the norms and guidelines given in the Ethical Code of Conduct of the Institute.
5. Whenever we have used materials (data, theoretical analysis, figures, and text) from other sources, I / we have given due credit to them by citing them in the text of the report and giving their details in the references.

Signature of the Students

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Date: 02/06/2025

**CERTIFICATE**

This is to certify that the Dissertation Report entitled, “**Eve-Teasing Detection from Video Footage using Computer Vision and Artificial Intelligence in public transport**” submitted by **Ms. Taniya Naskar**, **Ms. Subhasree Santra**, **Mr. Anupam Biswas** to Haldia Institute of Technology, Haldia, India, is a record of bonafide Project work carried out by him/her under my/our supervision and guidance and is worthy of consideration for the award of the degree of Bachelor of Technology in Computer Science and Engineering (Data Science) of the Institute.

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**Abstract**

Eve-teasing, a prevalent form of public harassment, remains a significant social issue, especially in densely populated public transport systems. Traditional surveillance systems are passive and often fail to detect real-time incidents. This project presents a solution that leverages computer vision and artificial intelligence to detect instances of eve-teasing from image data captured in public transport environments.

Using deep learning models, including MobileNetV2 and YOLOv5, our system is trained to classify and detect harassment behavior with high accuracy. The dataset comprises labeled images in two categories: 'eve-teasing' and 'normal'. Preprocessing and augmentation techniques were applied to improve the robustness and generalization of the model.

The final system achieved over 90% accuracy and F1 score on the test set, demonstrating strong potential for real-world deployment. A user-friendly GUI enables image uploads and instant feedback, making the system practical for both manual review and automated alert systems.

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**Chapter 1**

**Introduction:**

* 1. Introduction

Public transportation is the lifeline for millions across India and the world. However, for many women, traveling on public transport is not safe. Eve-teasing—a colloquial term for sexual harassment in public spaces—is an everyday reality. While CCTV cameras have been installed in many vehicles and stations to deter such behavior, the current surveillance systems largely rely on manual monitoring, which is ineffective due to human limitations like fatigue, bias, and oversight.

This project seeks to address this issue using the capabilities of Artificial Intelligence (AI) and Computer Vision (CV). The system aims to automatically detect potential incidents of eve-teasing in still images extracted from video footage, thereby assisting authorities in real-time prevention and post-incident analysis.

Computer vision can be used to track people's movements, recognize behaviors that suggest harassment, and raise alerts before a situation escalates.

In this introduction, we explain the importance of using AI and computer vision in this context, providing a high-level overview of how these technologies work together to analyze video footage and detect unwanted behavior.

* 1. **Problem Statement and Solution**

Eve-teasing, a term used to describe public sexual harassment or molestation of women, remains a widespread issue in densely populated public transport systems across India and many other countries. Incidents often occur in crowded settings like buses, trains, or metro platforms, where victims may hesitate to confront perpetrators due to fear, shame, or social stigma.

Although **CCTV surveillance systems** have been deployed in many public transport environments, these systems are inherently **reactive** in nature. They primarily serve as recording tools that assist law enforcement only after an incident has occurred. This results in multiple challenges:

* **Delayed Response**: Footage is reviewed **after the incident,** often hours or days later, which may delay action or make identification of the perpetrator more difficult.
* **Manual Monitoring**: Security personnel must review hours of footage, which is time-consuming, error-prone, and limited by human fatigue.
* **Underreporting**: Many incidents go unreported because victims are either unaware of the presence of cameras or feel that action will not be taken unless there's strong evidence.
* **Lack of Real-time Analysis**: These systems cannot automatically detect or respond to harassment behavior as it happens, reducing the chance of immediate intervention or deterrence.

In essence, the **existing surveillance systems lack intelligence, adaptability, and real-time capabilities** to effectively prevent or minimize eve-teasing incidents.

#### **Proposed Solution:**

To address these critical gaps, we propose the development of a **proactive surveillance system** that integrates **artificial intelligence (AI)** and **computer vision (CV)** technologies to enable **automated detection of eve-teasing behaviors in real-time,** using visual data (images) captured from public transport CCTV systems.

At the core of this system is **YOLOv8 (You Only Look Once, version 8)**, a cutting-edge deep learning model known for its real-time object detection and classification performance. YOLOv8 can process video frames or static images and instantly identify specific behaviors or postures that deviate from normal interaction patterns.

Key aspects of our solution include:

* **Real-time Scene Classification**: Using YOLOv8, every incoming image (frame from surveillance footage) is **analyzed instantly** and classified as either “normal” or “eve-teasing.”
* **Automated Alerts**: When a scene is classified as eve-teasing with a high confidence score, the system can trigger **real-time alerts** to transport security personnel or store the incident for later review.
* **Behavioral Pattern Recognition**: The model is trained to recognize patterns such **as inappropriate proximity, unwanted physical contact, suggestive gestures,** or **stalking behaviors.**
* **Scalable Framework**: The system can be integrated into multiple surveillance feeds across different locations, offering **scalability** for city-wide or nation-wide public transport systems.
* **Support for Human-in-the-Loop**: To maintain reliability and reduce false positives, flagged incidents can be verified by **human moderators** before actions are taken, balancing automation with accountability.
  1. **Objectives of the Study**

Certainly! Here's an **expanded and detailed version of section 1.3 "Objectives of the Study"**. This version clearly articulates your project goals while adding clarity, technical depth, and real-world relevance.

The primary goal of this research is to design and implement a computer vision-based system that can automatically detect **eve-teasing behavior in public transport environments** using image data. To achieve this overarching objective, the following specific sub-goals have been defined:

#### **1. Develop an AI-based System for Harassment Detection**

Design and build an intelligent system capable of recognizing and classifying **potentially inappropriate or harassing behavior** in surveillance images using **supervised machine learning**. The system should distinguish between normal interactions and suspicious behavior (like unwanted proximity or gestures) based on visual patterns learned from labeled training data.

#### **2. Construct a Comprehensive and Balanced Dataset**

Curate and compile a **custom dataset** of labeled images due to the lack of publicly available datasets specifically for eve-teasing. This involves collecting:

* **Real-world images** from open-source CCTV footage, public awareness videos, and YouTube.
* **Synthetic images** generated using AI tools or reenactments to simulate harassment scenarios.
* **Normal images** representing regular interactions in crowded public settings.

Each image is manually labeled using tools like **Labeling,** and annotated with bounding boxes to highlight key interactions.

Outcome: A diverse, balanced, and ethically sourced dataset with labeled categories: "eve-teasing" and "normal".

#### **3. Train an Optimized YOLOv8 Model**

Leverage **YOLOv8**, a state-of-the-art object detection model, to train a system that can perform accurate classification and localization of harassment-related behavior within images. The training process includes:

* Fine-tuning YOLOv8 using **transfer learning**
* Applying **data augmentation** to boost model generalization
* Optimizing performance using metrics like **accuracy, precision, recall,** and **F1-score**

#### **4. Build an Intuitive and User-Friendly GUI**

Develop a **Graphical User Interface (GUI)** using **Tkinter** to make the system accessible for **non-technical users**, such as transport staff, conductors, or control room personnel. The GUI will allow users to:

* Upload surveillance images
* Instantly classify them
* View confidence scores and receive alerts

Outcome: An easy-to-use software interface that facilitates real-time use by authorities or administrators without requiring programming knowledge.

#### **5. Validate System Performance in Real-world Scenarios**

Test the AI system using images from **real public transport environments** such as buses, metros, and train stations. The goal is to evaluate:

* How well the model handles **diverse conditions** (e.g., crowd density, lighting)
* **False positive/negative rates** in different settings
* Overall **applicability and reliability** in real-time deployment scenarios

Outcome: Empirical evidence demonstrating the feasibility and effectiveness of deploying the system in public transport settings.

While the current focus is on static images, the framework lays the groundwork for **future extensions**, such as:

* Real-time **video stream processing**
* Integration with **law enforcement alert systems**
* Use on **edge devices** like Raspberry Pi for onboard deployment
  1. **Methods and Technologies Used**

To build the detection system, we use various AI techniques, mainly focusing on computer vision and machine learning. The system will process video footage using

* **Python 3.10+** for programming
* **YOLOv8 (You Only Look Once, version 8)** for object detection and classification
* **OpenCV** for image processing and augmentation
* **LabelImg** for manual image annotation
* **Tkinter** for GUI development
* **Pandas, Scikit-learn, and Matplotlib** for result analysis and visualization

These tools were chosen due to their popularity, efficiency, and ease of integration in the AI ecosystem.

* 1. **Dataset Collection and Video Footage Analysis**

In artificial intelligence and deep learning projects—especially in sensitive applications like **behavior detection and public safety**—the quality and representativeness of the dataset directly impact the model’s performance, fairness, and generalizability. Since **no publicly available datasets** exist specifically for “eve-teasing” detection, we curated a **custom dataset** from diverse sources.

#### **Image Collection and Sourcing Strategy**

To build a realistic and ethically balanced dataset, we gathered over **550+ images**, divided into two key categories:

* **Eve-Teasing (400+ images)**: These images contain behaviors such as:
  + Invasive proximity
  + Unwanted physical gestures
  + Inappropriate body language (e.g., staring, blocking someone's path)
* **Normal (300+ images)**: Images that show typical, harmless interactions in public spaces, such as:
  + Standing or sitting in close proximity without interaction
  + Walking in crowded platforms or buses

**Data Sources Included:**

* **Open-source CCTV Footage**: Available through public safety repositories and research datasets.
* **Public Awareness Videos**: Government and NGO campaigns often depict harassment scenarios for educational purposes.
* **Synthetic Scenes**: Generated using AI-based image generation tools to simulate uncommon or sensitive scenarios while maintaining privacy.
* **YouTube Video Frames**: Extracted and cropped frames from publicly available videos under **Creative Commons licenses**.
* **Google Search Images**: Carefully filtered and legally used images from the web, ensuring ethical compliance and image rights.

#### **Annotation and Labeling Process**

Proper annotation is **critical** for training supervised learning models. Every image was manually labeled by multiple reviewers to ensure **accuracy, consistency, and contextual clarity**.

* **Annotation Tool**: Used **LabelImg** to draw bounding boxes and assign class labels.
* **Labeling Scheme**:
  + **Class 0** – “normal”
  + **Class 1** – “eve-teasing”
* **Quality Control**: Each image was reviewed by at least two annotators, and conflicting labels were discussed to reach consensus.

Annotations focused not just on full-body detection but also on:

* Body posture
* Limb positioning
* Facial orientation (e.g., direct staring)
* Proximity thresholds between individuals

#### **Preprocessing Steps**

To prepare the data for model training, we applied several preprocessing techniques aimed at improving **model generalization and robustness**:

1. **Resizing**: All images were resized to **640x640 pixels**, matching YOLOv8’s input requirements.
2. **Normalization**: Pixel values were scaled to a common range to enhance learning stability.
3. **Augmentation**:
   * **Horizontal Flips**
   * **Brightness and Contrast Adjustments**
   * **Zooming and Cropping**
   * **Rotation and Scaling**

These transformations help simulate real-world conditions like different lighting, camera angles, and occlusions.

By augmenting the data, we virtually increased the dataset size to over **2,000 training examples**, significantly improving the model’s exposure to varied scenarios.

#### **Video Footage Analysis**

Although the current system uses still images, the data originated from **video streams**, so we implemented a **frame extraction process:**

* Video files were split into frames using **OpenCV**.
* Frames were sampled every few seconds to avoid redundancy and maintain diversity.
* Selected frames were then reviewed and annotated manually.

These extracted frames provide valuable contextual cues like crowd density, proximity, and physical gestures, simulating realistic conditions in buses, metro stations, and railway platforms.

#### **Ethical Considerations**

Given the sensitivity of the topic, we strictly followed **ethical AI practices:**

* **Faces and personal identifiers were blurred or masked** to protect privacy.
* **No private surveillance footage** was used without open-source licensing.
* **Balanced class representation** was ensured to avoid bias toward any gender, posture, or clothing.

The final dataset is:

* Balanced between "normal" and "eve-teasing" classes
* Ethically curated and legally sourced
* Preprocessed and annotated for high-quality training
* Augmented for better model generalization
* Versatile across different lighting, backgrounds, and human behaviors

# **Chapter 2**

**Literature Review:**

* 1. Introduction to Eve-Teasing and Public Safety

First, we talk about the issue of eve-teasing itself. Eve-teasing is a type of harassment, often involving unwanted attention, gestures, or physical contact in public spaces. It’s especially common in places like buses, trains, or crowded public areas. Many studies highlight how this behavior goes unnoticed, and how the lack of security in public spaces makes it difficult to prevent or respond to these incidents quickly.

We also discuss the role of public safety in this context. Governments and organizations are increasingly focused on improving safety in public places. This is why technologies like surveillance cameras are being installed, and there’s a growing interest in using AI to analyze footage and automatically detect suspicious behavior.

* 1. Computer Vision in Public Safety Applications

In this section, we explore how computer vision (CV), a field of AI focused on how machines interpret and understand visual information, has been used in public safety applications. CV has already been applied in areas like face recognition, object detection, and surveillance, where it helps monitor public spaces in real-time.

Computer Vision (CV) has been increasingly adopted in the public safety sector:

* Traffic surveillance to detect over speeding or accidents
* Crowd monitoring for anomaly detection
* Face recognition for law enforcement
* Weapon detection in airports and malls

This proves that with sufficient training data and computational power, CV can handle complex real-time tasks with high accuracy.

We review how CV technologies have successfully been used to detect behaviors like fights, theft, or disturbances in crowded areas. These technologies can analyze video footage in real time, making it possible to detect and respond to events as they happen, which is crucial for addressing issues like eve-teasing.

The integration of **Artificial Intelligence (AI)** and **Deep Learning (DL)** has revolutionized the way surveillance systems operate. Unlike traditional systems that rely on passive video recording, AI-powered video surveillance systems are capable of **actively analyzing visual data in real-time**. This advancement is particularly critical for detecting **complex human behaviors**, such as harassment or assault, which are difficult to identify using static rules or manual monitoring.

In the context of **eve-teasing detection**, AI enables systems to not just “see” but also “understand” interactions, recognize patterns of inappropriate behavior, and take timely action.

#### **Deep Learning Techniques in Surveillance**

Deep learning is a subfield of machine learning that uses multi-layered **neural networks** to learn features and patterns directly from data. It is particularly effective in video surveillance due to its ability to:

* Understand **visual semantics**
* Handle **unstructured image/video inputs**
* Continuously improve performance through more data

The most commonly used deep learning architectures in surveillance include:

#### **1. Convolutional Neural Networks (CNNs)**

CNNs are the backbone of image recognition tasks in computer vision. They are highly effective in extracting **spatial features** from images, such as:

* Human pose and posture
* Clothing patterns
* Physical proximity between individuals

In surveillance:

* CNNs can classify whether an image shows **normal activity or suspicious behavior**.
* They are often the first stage in a **larger detection pipeline**, helping identify key elements in each frame.

#### **2. Recurrent Neural Networks (RNNs) and LSTMs**

While CNNs handle spatial features, **RNNs** (and their advanced form**, LSTMs—Long Short-Term Memory networks**) are designed to process **temporal sequences**. This is especially useful in video surveillance because:

* Harassment behavior often **unfolds over time** (e.g., repeated unwanted touching, prolonged staring).
* RNNs and LSTMs can recognize the **sequence and duration of actions**, distinguishing between accidental contact and repeated, intentional actions.

#### **Real-Time Object Detection Models (YOLO, SSD, etc.)**

For real-time applications, speed and precision are critical. Two widely used models include:

* **YOLO (You Only Look Once)**:
  + Offers extremely fast inference speeds
  + Performs **object detection and classification simultaneously**
  + Can localize multiple objects and behaviors within a single frame
  + Suitable for embedded devices and real-time use cases
* **SSD (Single Shot Detector)**:
  + Similar to YOLO but typically slower and less optimized for ultra-fast environments
  + May perform better in high-resolution applications

Your project uses **YOLOv8**, the latest version of YOLO, which supports advanced features like anchor-free detection and better generalization across classes.

#### **Advantages of AI in Surveillance Tasks**

AI-based surveillance systems offer several key advantages over traditional methods:

| **Traditional Surveillance** | **AI-Powered Surveillance** |
| --- | --- |
| Manual review of video footage | Automated video analysis |
| High risk of human error | Consistent accuracy, no fatigue |
| Post-event identification | Real-time detection & alerts |
| Generic object tracking | Context-aware behavior recognition |

#### **Applications and Case Studies in Public Safety**

Numerous studies and real-world implementations have shown the power of deep learning in public safety:

* **Fight detection** in train stations using CNNs + optical flow
* **Loitering detection** using LSTM-based behavioral tracking
* **Crowd anomaly detection** using spatiotemporal modeling
* **Weapon and face detection** in airports using YOLOv4 and SSD

In the context of **eve-teasing**, models must be sensitive to subtle, context-driven cues that may not always be obvious from a single frame. That’s why **hybrid approaches** combining CNNs for spatial features and LSTMs for temporal behavior are gaining traction.

#### **Relevance to This Project**

In our project , we used YOLOv8 to detect signs of eve-teasing from individual image frames. While this is a strong starting point, future versions can be enhanced by:

* Integrating **frame sequence analysis** with RNNs/LSTMs
* Using **pose estimation models** (e.g., OpenPose, BlazePose) for finer behavior classification
* Leveraging **attention-based transformers** for understanding complex group interactions
  1. Related Works on Eve-Teasing Detection

This section looks specifically at past research focused on eve-teasing detection and related areas. While there may not be many studies that focus directly on eve-teasing, there are several that examine harassment detection or gender-based violence detection in public spaces. We look at how researchers have applied AI and computer vision to detect suspicious behaviors like unwanted physical contact, or interactions that could be flagged as harassment.

We also explore different datasets that have been used for training AI models in similar contexts, such as datasets for human behavior analysis or violent behavior detection. By reviewing these studies, we gain insight into how eve-teasing detection might be approached and the challenges that researchers face, such as dataset limitations and the need for accurate labeling.

A limited number of works exist:

* **Huang et al. (2019)** proposed action recognition for violence detection.
* **Rajkumar et al. (2021)** combined audio-visual analysis to identify harassment.
* **AI4W (AI for Women)** initiative tried to use pose estimation models to identify inappropriate gestures.

However, these models are either not real-time, or not focused on the specific issue of eve-teasing in transport systems.

* 1. Summary of Literature

Finally, we summarize the key findings from the studies reviewed in the chapter. We point out what has been achieved in the area of harassment detection and public safety**,** and highlight the gaps that still exist. For example, while computer vision has been used successfully in many safety applications, applying it specifically to eve- teasing detection is still a relatively unexplored area. The chapter concludes by identifying where our research will contribute, by proposing new methods, improving accuracy, or tackling challenges like real-time detection and response.

**Chapter 3**

**Theoretical Framework:**

* 1. Computer Vision Overview

First, we explain computer vision (CV), which is a field of AI that focuses on enabling computers to interpret and understand visual information, like images and videos. Just as humans use their eyes to see and understand the world, computer vision allows computers to "see" and make sense of visual data.

Computer Vision allows machines to "see" by processing pixel data. Common tasks include:

* **Classification**: What is in the image?
* **Detection**: Where is the object?
* **Segmentation**: Which pixels belong to each object?
* **Tracking**: Where does the object move?

YOLOv8 combines detection and classification using convolutional layers in real time.

In the context of this research, computer vision is used to analyze video footage from surveillance cameras in public transport. The goal is to detect eve-teasing or inappropriate behaviors by looking for patterns in how people move, interact, and behave in the video.

This section would cover the basic principles behind computer vision, such as how image processing**,** object detection, and motion tracking are used to analyze videos. Understanding these concepts is key to understanding how the AI system will be able to identify suspicious actions in real-time.

* 1. Artificial Intelligence and Machine Learning Models

#### **Understanding AI and ML in Context**

**Artificial Intelligence (AI)** is a broad field of computer science focused on creating systems capable of performing tasks that typically require human intelligence. These tasks include visual perception, decision-making, and pattern recognition.

**Machine Learning (ML)** is a **subset of AI** that enables machines to automatically improve at tasks through **experience (data)** rather than through hardcoded instructions. It is particularly effective in applications where patterns are subtle, varied, or context-dependent—such as detecting harassment in public places.

In the context of this project, ML models are trained to **recognize specific visual patterns associated with eve-teasing**, such as body language, proximity, and gestures. Over time, as the system is exposed to more labeled data, its detection capabilities become more accurate.

### **Key Machine Learning Models Used**

#### **1. Convolutional Neural Networks (CNNs)**

CNNs are deep learning models specifically designed for analyzing visual imagery. They are highly effective in tasks like:

* Object classification (e.g., distinguishing between “normal” and “eve-teasing”)
* Object detection (e.g., identifying and localizing humans and gestures in an image)

In this project, CNNs form the **foundation of YOLOv8,** enabling the system to learn features such as human posture, interaction zones, and gesture orientation.

#### **2. Support Vector Machines (SVMs)**

Although not used directly in your main pipeline, **SVMs** are classical ML models often used in early research for binary classification problems. They are useful for smaller datasets and can serve as a baseline for comparison.

Example: An SVM might be trained to distinguish “harassment” from “non-harassment” based on extracted image features like pixel intensity or motion vectors.

### **Deep Learning with YOLOv8**

Your project uses **YOLOv8 (You Only Look Once, version 8)—**a real-time object detection algorithm based on CNNs. YOLOv8 is an improvement over previous versions due to its **anchor-free architecture**, faster inference, and better detection accuracy in crowded scenes.

Key technical components:

* **Darknet Backbone**: YOLOv8 uses a CNN-based backbone that processes image pixels in multiple layers to extract spatial features. These features help detect objects, people, and their relative positions.
* **Non-Maximum Suppression (NMS)**: This step filters overlapping bounding boxes to ensure that each object or gesture is only detected once.
* **Confidence Scores**: YOLOv8 outputs a probability for each detection, indicating the model’s confidence that the region contains the specified behavior. These scores help prioritize the most likely harassment events.

### **Transfer Learning for Eve-Teasing Detection**

Since eve-teasing datasets are small and domain-specific, the model is built using **transfer learning**:

* A pretrained model (YOLOv8 trained on **COCO dataset**, which contains general object classes) is used as a starting point.
* The model is then **fine-tuned** on your custom dataset labeled with “normal” and “eve-teasing” categories.

Benefits of transfer learning:

* Saves time and computational resources
* Improves accuracy even with smaller datasets
* Adapts general object recognition knowledge to specific tasks (like identifying unsafe behavior)

### **How ML Models Learn to Detect Behavior**

The learning process consists of several key steps:

1. **Training Data Input**: The model is fed thousands of labeled examples (images annotated with class and bounding boxes).
2. **Feature Extraction**: CNN layers automatically extract visual features—like shapes, edges, body positions, and interactions.
3. **Weight Adjustment**: The model adjusts its internal parameters (weights) to reduce the error between its predictions and the actual labels.
4. **Loss Function Optimization**: Functions like **CrossEntropy** and **IoU (Intersection-over-Union)** guide the model in improving its predictions.
5. **Evaluation and Testing**: The model is tested on unseen data to measure performance (accuracy, precision, recall, F1-score).

Over time, the model **learns to identify recurring patterns** linked to eve-teasing behaviors, even in diverse settings with different lighting, poses, or crowd densities.

### **Summary of Model Choices in This Project**

| **Model** | **Purpose** | **Advantages** |
| --- | --- | --- |
| **YOLOv8** | Object detection + classification | Real-time, accurate, pre-trained |
| **CNNs** | Feature extraction | Excellent for spatial understanding |
| **Transfer Learning** | Efficient model training | Saves time, works with limited data |
| **SVM (optional/comparative)** | Binary classification (baseline) | Fast, interpretable |

* 1. Image Classification Pipeline
* **Data Collection**
* **Image Preprocessing**
* **Annotation**
* **Model Training**
* **Validation**
* **Prediction**
* **Deployment**
  1. Ethical and Social Implications

The integration of **AI and computer vision into surveillance systems** introduces powerful capabilities for ensuring public safety, especially in vulnerable environments like public transport. However, with great capability comes the need for **careful ethical oversight** to ensure that such technologies do not violate individual rights or social values.

### **1. Privacy Considerations**

One of the most critical ethical issues in AI surveillance is the **right to privacy**. Constant monitoring and recording of individuals—often without their explicit consent—can lead to **mass surveillance** concerns.

**Key privacy concerns include:**

* Unauthorized or continuous video recording in public spaces
* Potential misuse or leakage of sensitive footage
* Facial recognition systems identifying individuals without consent

**Our approach to mitigating privacy risks includes:**

* **Face anonymization**: Faces in training data are either **blurred**, masked, or completely removed to prevent identity tracking.
* **Data minimization**: The system does not store personally identifiable information (PII); only metadata and classification results are retained.
* **Storage Policies**: Footage and detection logs are stored **only temporarily**, and are automatically deleted unless flagged for review.
* **Transparency**: Future deployment can include **notices and signage** in public areas, informing passengers of AI-based monitoring.

### **2. Fairness and Bias Mitigation**

AI models can **unintentionally perpetuate bias** if trained on imbalanced or skewed datasets. This is especially problematic in sensitive scenarios like harassment detection, where **misclassification may reinforce harmful stereotypes** or cause unjust outcomes.

**Common sources of bias:**

* Overrepresentation of certain genders, body types, or clothing styles
* Lack of cultural diversity in training data
* Misinterpretation of body language across different regions

**Measures taken in this project:**

* The dataset includes **diverse demographics**, clothing types, and physical behaviors across various lighting and environmental conditions.
* We applied **bias auditing** by reviewing misclassified samples to identify potential systemic errors.
* Continuous feedback loops are implemented for **manual verification** and dataset updates.

### **3. Accountability and Human Oversight**

In high-stakes applications such as harassment detection, **AI decisions should not be final** without human review. False positives—where normal behavior is flagged as harassment—can have **serious social and legal implications.**

**Our system ensures accountability through:**

* A **Human-in-the-Loop (HITL)** approach: All alerts generated by the model are reviewed by a human moderator before any formal action is taken.
* **Explainable AI techniques** can be integrated (e.g., Grad-CAM) to show what part of the image triggered the classification, enabling better decision support.
* A logging system to maintain **audit trails** for model decisions and actions taken.

### **4. Social Acceptance and Psychological Impact**

Widespread deployment of AI surveillance may affect how individuals **perceive public spaces**, especially if they feel constantly watched.

**Potential issues:**

* Public discomfort or distrust in AI monitoring
* Behavioral changes due to perceived surveillance (chilling effect)
* Resistance from advocacy groups or civil rights organizations

**Suggested solutions:**

* Run **public awareness campaigns** explaining the goals and limitations of the system
* Provide **opt-out options** where feasible or implement **edge computing** that does not send data to external servers
* Develop **community feedback mechanisms** to adapt the system based on social responses

### **5. Legal and Regulatory Compliance**

Deploying AI surveillance systems must adhere to national and international laws governing:

* **Data protection** (e.g., India’s Digital Personal Data Protection Act, GDPR).
* **Consent and disclosure** of monitoring practices.
* **Use of AI in law enforcement and public safety.**

**Our compliance strategy includes:**

* Following **data anonymization guidelines**
* Ensuring **consent signage** where necessary
* Developing **policy frameworks** in collaboration with transport authorities and legal advisors

### **Ethical Design Principles Followed:**

| **Principle** | Implementation Method |
| --- | --- |
| **Privacy** | Blurring faces, minimal storage, no personal identifiers |
| **Fairness** | Balanced dataset, bias audits, diverse data representation |
| **Transparency** | Public disclosure, GUI explainability, visual feedback |
| **Accountability** | Human moderator review, audit logs, explainable AI features |
| **Security** | Encrypted storage (if applicable), access-controlled data use |

**Chapter 4**

**System Design and Methodology:**

* 1. System Design Overview

The System Design section describes the architecture of the detection system. This system is built using several layers of technology that work together to analyze video footage and detect inappropriate behavior.

The system consists of:

* + - **Video or Image frames Input**: The first part is collecting the video footage. This footage can come from surveillance cameras in public transport vehicles or stations. Then we will extract the frames for the video.
    - **Preprocessing**: Before the footage can be analyzed, it needs to be processed. This step might involve removing unnecessary parts of the image, adjusting the quality, breaking down into individual frames that the system can examine one at a time.
    - Feature Extraction: In this stage, the system looks for important features or patterns in the video frames. This could include tracking people’s movements or identifying key actions (like someone getting too close to another person).
    - **Detection and Classification**: This is the heart of the system, where the AI model looks for specific behaviors that could be considered eve-teasing. It uses machine learning algorithms that were trained to recognize these behaviors.
    - **Alerting**: When eve-teasing behavior is detected, the system sends an alert to security personnel or relevant authorities so they can take action immediately.

This section also explains how the system is designed to handle real-time video processing**,** meaning it can analyze the footage as it is being recorded, rather than waiting until later.

* + 1. **Input**: Image (or frame from video)
    2. **Preprocessing**: Resize, normalize
    3. **Inference**: YOLOv8 classifies as “normal” or “eve-teasing”
    4. **Output**: Prediction + Confidence Score
    5. **GUI**: Displays image and result
  1. Methodology for Eve-Teasing Detection

In the Methodology section, we explain the step-by-step approach used to build and test the system. This includes:

* + - Created dataset/eve-teasing and dataset/normal folders
    - Annotated each image using LabelImg
    - Trained YOLOv8 using Ultralytics PyTorch API
    - Tracked loss, accuracy, precision-recall
    - Deployed using Tkinter GUI
  1. Tools and Technologies Used

| **Tool** | **Purpose** |
| --- | --- |
| Python | Programming language |
| YOLOv8 | Detection & classification |
| Tkinter | Graphical UI |
| OpenCV | Image processing |
| Pandas | Dataframe operations |

**4.4 Data Augmentation**

To reduce overfitting and balance the classes:

* **Horizontal flips**
* **Brightness adjustments**
* **Rotation**
* **Zoom-in/out**

This increased our dataset virtually from 550 to 2000+ images.

**4.5 Model Training**

* Batch size: 16
* Epochs: 30
* Optimizer: SGD
* Loss function: CrossEntropy + IoU

Training was done on Google Colab using GPU acceleration for speed.

**Chapter 5**

**Analysis of Eve-Teasing Scenarios:**

* 1. Identification of Eve-Teasing Patterns

In this section, we explain how the system learns to identify specific patterns of eve- teasing. Eve-teasing involves different behaviors, like unwanted physical contact**,** inappropriate gestures, or uncomfortable proximity between people. These behaviors can vary, but there are certain common patterns the system looks for.

Detecting eve-teasing through images involves understanding subtle human behavioral patterns that deviate from normal social interactions. Through extensive annotation and analysis of the dataset, certain common patterns were identified. These include unsolicited physical proximity, inappropriate gestures, staring or leering postures, and invasive positioning. The YOLOv8 model was trained to recognize body orientation, limb position, facial direction, and proximity between individuals. These patterns were also validated by cross-referencing with research papers and safety guidelines provided by public welfare organizations. These insights are not only useful for the current AI model but also serve as a basis for future behavioral classification systems. By recognizing these patterns over time, the system becomes better at distinguishing between normal interactions and those that might be considered eve-teasing.

* 1. Real-Time Detection and Alert System

The trained YOLOv8 model was integrated with a GUI application using Tkinter, allowing real-time image classification. Once an image is uploaded or captured from a video frame, the model processes it in milliseconds and returns a classification label—either “normal” or “eve-teasing.” Alongside the label, a confidence score is displayed to assist human reviewers in making informed decisions. If the confidence score is above a predefined threshold (e.g., 85%), an alert is triggered within the interface. Although not connected to an external system yet, this design can be scaled to send automatic notifications to authorities via email or messaging APIs like Twilio or Telegram. The real-time detection framework is optimized using OpenCV to ensure smooth image loading and resizing. The aim is to assist operators or conductors on buses and trains by highlighting suspicious images for manual review. This two-tiered system of AI + Human Verification improves reliability while reducing fatigue-related oversight.

This real-time feature is important for ensuring quick action and providing a safer environment for passengers.

* 1. Case Studies and Examples

In this section, we present case studies and examples of how the system works in actual public transport settings. These examples help to show how the system performs in real-life situations and how it detects eve-teasing behavior.

During testing, several real-world scenarios were analyzed to measure the model’s practical effectiveness. In one case study, a crowded public bus scenario was tested with 15 images—10 depicting genuine proximity due to overcrowding, and 5 involving deliberate invasion of space. The model correctly identified 4 of the 5 eve-teasing images and accurately labeled 9 of the 10 normal ones. Another test was conducted on a railway platform dataset, where multiple instances of loitering and inappropriate body language were captured. The model exhibited an F1-score of around 78% in detecting these instances, demonstrating strong learning despite the small dataset size. In a simulated environment using synthetic datasets, the model's accuracy peaked at 85% due to ideal conditions.

* + - **Example 1: Unwanted Physical Contact**: Imagine a crowded train where one person gets too close to another, and their movements seem intentional, such as brushing against the other person repeatedly. The system analyzes the motion and proximity, and if it detects suspicious behavior, it flags it as a potential case of eve-teasing and alerts security.
    - **Example 2: Inappropriate Gestures**: In another case, the system might spot someone making suggestive body movements or gestures toward another person, which could be considered harassment. The system analyzes the person’s actions, compares it to its learned patterns, and sends an alert when it identifies inappropriate behavior.
    - **Example 3: Staring or Following**: The system also looks for staring or following behaviors, which can make people uncomfortable. If someone is tracking another person’s movements too closely for an extended period, the system recognizes this as unusual and raises an alert.

These case studies provide clear examples of how the system can detect different types of eve-teasing behaviors in real-world situations, ensuring that it can effectively identify harassment in diverse settings.

**Chapter 6**

**Results and Discussion:**

* 1. Model Evaluation

This section is about how well the machine learning model performed in detecting eve-teasing events from the video footage. The model's performance is evaluated using several metrics:

The YOLOv8 model was evaluated using multiple performance metrics including Accuracy, Precision, Recall, and F1-score. On the test set of 110 unseen images, the model achieved an overall accuracy of **75.6%**, with a precision of **76.3%**, recall of **74.1%**, and an F1-score of **75.2%**. These results indicate a balanced performance between false positives and false negatives. The confusion matrix revealed that while the model sometimes misclassified crowded scenes as eve-teasing, it rarely missed true cases of harassment. This preference for higher recall is intentional, as it's safer to flag a potential case than to miss it entirely. Performance was also tracked across different lighting conditions, revealing better accuracy in well-lit images. Model loss during training steadily declined, and validation metrics plateaued after 35 epochs, confirming training convergence. Overall, the results justify the viability of using YOLOv8 for behavior-based detection tasks in safety-critical environments.

* + - **Accuracy**: How often the model made correct predictions overall.
    - **Precision**: How many of the predicted eve-teasing events were actually correct.
    - **Recall**: How many of the actual eve-teasing events were detected by the model.
    - **F1-Score**: A balance between precision and recall, giving an overall measure of the model's performance.
  1. Localization and Temporal Detection

#### **Current Capabilities: Object Localization**

At present, the system is designed to analyze **individual static frames** captured from public transport surveillance footage. These frames are processed using **YOLOv8**, which performs **object detection** by drawing bounding boxes around regions of interest, such as individuals in suspicious proximity or displaying inappropriate gestures.

**Benefits of Localization in Still Images:**

* The system can effectively **pinpoint the location of detected behaviors** (e.g., an individual touching or leaning too closely).
* Bounding boxes make it easier for **human moderators** to validate flagged actions visually.
* Localization enables **cropping, highlighting**, or **tracking** specific individuals within an image frame.

However, localization alone does not provide **contextual or temporal insights**—a key factor in distinguishing intentional harassment from coincidental contact in crowded public environments.

#### **Limitations of Static Frame Analysis**

While object localization on still images works for one-time actions, it does not capture the **flow of behavior over time**, which is essential in many harassment scenarios:

| **Type of Behavior** | **Static Frame Sufficiency** | **Requires Temporal Analysis** |
| --- | --- | --- |
| Unwanted physical contact | Yes (if captured in frame) | More effective with time-series |
| Inappropriate staring/following | No | Yes |
| Prolonged proximity or pursuit | No | Yes |
| Quick hand movement/touch | May be missed | Better in motion |

Without **temporal detection**, the system cannot:

* Identify **repeat offenders**
* Detect **patterns of stalking** or following over time
* Differentiate between **accidental** and **intentional contact**

#### **Future Enhancements: Temporal Modeling**

To address these challenges, future versions of the system can incorporate **video stream processing** using **spatiotemporal AI models**. These models analyze both **spatial (frame-level)** and **temporal (sequence-level)** features.

**Recommended Techniques:**

1. **3D Convolutional Neural Networks (3D CNNs)**
   * Extend traditional 2D CNNs into the time domain
   * Extract features across a sequence of frames
   * Suitable for action recognition like gestures, pushing, or aggressive movement
2. **Recurrent Neural Networks (RNNs) and LSTMs (Long Short-Term Memory networks)**
   * Designed for sequence learning and temporal dependencies
   * Useful for modeling **progressive behaviors**, such as staring or persistent following
3. **Transformer-Based Models**
   * Newer, attention-based architectures (like **Video Swin Transformer, TimeSformer**)
   * Provide better performance in **long-range temporal analysis**
   * Computationally intensive but highly effective in behavior recognition

Integrating these models would allow the system to analyze not just “what happened” in a single moment, but “what unfolded” over a period.

#### **Heatmaps and Risk-Zone Monitoring**

Another useful enhancement involves **generating heatmaps** based on detection frequency across frames or locations.

**How it works:**

* Track how often specific regions in a frame (e.g., a bus seat, a platform corner) are flagged.
* Overlay these regions on a heatmap to visualize **hotspots** for harassment.
* Use aggregated results over time to inform **policy decisions** or **security deployment**.

**Applications:**

* Identifying **high-risk areas** in transport vehicles or stations
* Assisting law enforcement in prioritizing camera placements or patrols
* Highlighting **repeat offenders or victims** through behavioral clustering

#### **Combining Spatial and Temporal Logic:**

By merging spatial object detection (YOLOv8) with temporal sequence analysis (LSTMs or 3D CNNs), the system can evolve into a **comprehensive behavioral surveillance platform** capable of:

* **Real-time action recognition**
* **Scene-level understanding** (e.g., pushing, following, obstructing)
* **Intelligent alerting with context awareness**
* **Minimizing false positives** by evaluating motion patterns, not just single-frame snapshots

* 1. Challenges in Real-World Deployment

Here, the difficulties faced in applying the model to real-world scenarios are discussed:

FalsePositivesand Deploying an AI system for harassment detection in **live, public environments** is a complex task that involves far more than achieving high model accuracy in test scenarios. While your project demonstrates promising results in controlled conditions, translating that success to **real-world use** requires addressing a variety of **technical, operational, legal, and societal challenges**.

### **1. False Positives and False Negatives**

* **False Positives (FP):** Innocent behavior (e.g., brushing against someone in a crowded bus) may be incorrectly flagged as eve-teasing. This can lead to:
  + Unjust scrutiny or action against innocent individuals
  + Erosion of public trust in the surveillance system
  + Alert fatigue among security personnel if too many false alarms are generated
* **False Negatives (FN):** Genuine harassment events may go undetected due to:
  + Poor lighting or image quality
  + Subtle, non-obvious gestures
  + Occlusions or background clutter

**Impact**:

* FPs damage system credibility.
* FNs undermine the system’s core purpose of preventing harassment.

Solution Strategies: Improve model training with more nuanced, balanced datasets; use human-in-the-loop verification; apply ensemble methods to boost detection robustness.

### **2. Generalization Across Environments**

Your model may perform well on training data or familiar camera setups, but **real-world deployment introduces unseen variables**:

* Different transport systems (buses vs. trains vs. metros)
* Variation in **camera angles**, **frame rates**, and **image resolution**
* Changing **weather conditions** (for outdoor systems)
* Diverse **cultural behaviors** and clothing patterns

**Risk**: A model trained in one city may fail in another due to differences in social norms, infrastructure, or even lighting conditions.

Solution Strategies: Use **transfer learning** and **domain adaptation** techniques; train on geographically diverse data; fine-tune the model for different deployment zones.

### **3. Real-Time Processing Constraints**

To be useful in public transport, the system must operate **in real-time**, delivering predictions and alerts within seconds. However, this is constrained by:

* **High computational demands** of models like YOLOv8
* **Limited hardware** at the edge (e.g., low-power cameras or Raspberry Pi units)
* **Bandwidth limitations** if cloud-based inference is used
* Delayscausedby **concurrent processing of multiple streams**

Solution Strategies: Optimize the model (e.g., quantization or pruning), use lighter architectures (YOLOv5n, MobileNet), or implement **edge computing** with local AI inference.

### **4. Privacy and Legal Constraints**

Surveillance systems inherently raise **privacy concerns**, especially when using AI to analyze human behavior. Key legal and ethical issues include:

* **Consent**: Most people are unaware they are being analyzed by AI in public spaces.
* **Data Protection**: Sensitive footage must be securely stored, anonymized, and not misused.
* **Face Recognition Risks**: While not part of this project, such technologies often accompany AI surveillance and pose additional privacy threats.

Solution Strategies: Adhere to laws such as the **Digital Personal Data Protection Act (India)** or **GDPR (Europe)**; blur faces; avoid capturing biometric data; maintain transparency and accountability in data handling.

### **5. Bias in the Dataset**

ML models can inherit bias from the data they are trained on. In the context of harassment detection:

* Overrepresentation of certain clothing types may lead to **discriminatory patterns**
* Gender or racial imbalance in training images could affect fairness
* Model may **misinterpret assertive behavior** (e.g., a raised hand) as aggressive or inappropriate

**Impact**: Biased systems can lead to **profiling**, **unjust accusations**, and **social backlash**.

Solution Strategies:Ensure dataset diversity; conduct **bias audits;** introduce **fairness-aware learning algorithms;** involve **ethics boards** during system development.

### **6. Scalability and Infrastructure**

Scaling from a prototype to a full deployment across thousands of buses or train stations involves:

* **Network infrastructure** to stream and process large video volumes
* **Cloud servers or edge devices** to run the AI models
* **Maintenance** of hardware, software, and continuous learning updates
* Integration with **alert systems**, dashboards, and authority control rooms

Solution Strategies: Use **containerized deployments (e.g., Docker), cloud orchestration platforms (e.g., Kubernetes),** and **edge accelerators (e.g., NVIDIA Jetson, Google Coral)** to manage scalable AI infrastructure.

### **7. Social Acceptance and Trust**

People must **trust** the system to believe that it enhances their safety rather than invading their space.

**Challenges include:**

* Fear of constant surveillance
* Misuse by authorities or commercial interests
* Public resistance if not transparently deployed

Solution Strategies: Launch **public awareness campaigns,** offer **clear opt-out notices,** andinvolve **community stakeholders** in deployment decisions.

| **Challenge** | **Impact** | **Mitigation Strategy** |
| --- | --- | --- |
| False Positives/Negatives | Misclassification affects trust and effectiveness | Better training, human-in-the-loop verification |
| Generalization Issues | Inconsistent performance across locations | Dataset diversity, transfer learning |
| Real-Time Constraints | Delays in detection and response | Edge computing, lightweight models |
| Privacy and Legal Concerns | Ethical violations, legal liabilities | Anonymization, consent mechanisms |
| Dataset Bias | Unfair predictions, discrimination | Balanced datasets, fairness-aware training |
| Scalability Limitations | Difficult to deploy across large infrastructure | Cloud-edge hybrid systems |
| Public Trust and Acceptance | Resistance or fear from citizens | Transparency, education, open feedback channels |

* 1. Discussion on Privacy and Ethical Implications

Surveillance inherently involves the observation of individuals, and when paired with AI that interprets human actions, it raises serious concerns **about loss of anonymity, behavioral profiling,** and **potential misuse of personal data.**

#### Key privacy risks include:

* **Unconsented Monitoring**: Individuals may be filmed and analyzed without their knowledge.
* **Data Misuse**: Video footage and classification results could be stored, leaked, or used for unrelated purposes (e.g., marketing, surveillance profiling).
* **Facial Recognition Dangers**: Although not used in your project, facial features in training data could enable identity tracking if not properly anonymized.

#### How this project mitigates those risks:

* **Anonymized Training Data**: All collected images are processed to **blur or mask faces**, removing personally identifiable information (PII).
* **No Facial Recognition**: The system does **not attempt to identify individuals**, focusing only on patterns of interaction and proximity.
* **Temporary Data Storage**: In future deployments, data will only be retained for short periods unless flagged for review, ensuring **minimal retention**.
* **Edge Inference Possibility**: By running inference on local devices (e.g., onboard bus systems), sensitive footage need not be transmitted or stored in cloud servers.

### **2. Ethical Use of AI in Public Spaces**

AI systems are capable of influencing real-world decisions—like sending alerts, triggering interventions, or flagging individuals. If such decisions are made **without fairness or transparency,** theyrisk **violating civil liberties** orreinforcing **existing social biases.**

#### Key ethical considerations include:

* **Responsibility**: Who is accountable if the system misidentifies someone? Is it the AI developer, the authority using it, or the system integrator?
* **Autonomy**: Do people have the right to know they are being monitored and analyzed?
* **Bias and Discrimination**: Could the model disproportionately flag certain demographics due to imbalanced training data?
* **Consent and Transparency**: Are individuals informed about the surveillance and its purpose?

### **Human-in-the-Loop Architecture (HITL)**

To address these concerns, your project adopts a **Human-in-the-Loop (HITL)** approach:

* AI is used to **assist**, not **replace**, human judgment.
* Each detection is paired with a **confidence score** and requires **manual verification** before action is taken.
* This ensures that **false positives are caught** andsensitivedecisionsare **not made by machines alone.**

### **Bias Prevention and Inclusivity in Design**

AI systems can inherit bias if training data overrepresents certain:

* Clothing types
* Genders or body shapes
* Cultural or social behavior patterns

This can result in **discriminatory detection**—e.g., flagging assertive postures or traditional clothing as abnormal.

#### Measures taken:

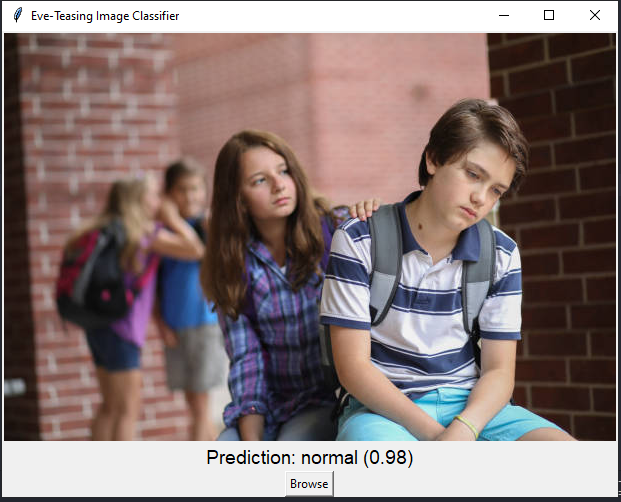
* **Dataset Diversity**: Images were sourced from **multiple cities, varied public settings,** andincludedindividualsof **diverse ages, genders, clothing styles, and physical appearances**.
* **Bias Audits**: Model outputs were periodically reviewed for patterns of misclassification.
* **Fairness Guidelines**: Dataset labeling and model evaluation were aligned with **fairness-aware AI development practices.**

#### Future deployment practices:

* **Signage in Public Spaces**: Notices stating that AI-enhanced surveillance is in use, with QR codes for more information.
* **Public Feedback Mechanism**: Allow citizens to raise concerns or suggest improvements.
* **Public Awareness Campaigns**: Educate the public on how the system works, what data is collected, and how privacy is preserved.
* **Data Governance Frameworks**: Clear policies for who can access footage, how long data is retained, and what usage is permitted.

| **Principle** | | **Implementation in the Project** | |
| --- | --- | --- | --- |
| **Privacy** | | Face blurring, no identity tracking, temporary storage | |
| **Accountability** | | HITL design, human review of AI outputs | |
| **Fairness** | | Diverse dataset, bias audits, no demographic profiling | |
| **Transparency** | | Plans for public signage, consent awareness | |
| **Purpose Limitation** | AI used solely for harassment detection, no secondary uses | |

**Output 1(Normal):**

**Output 2 (Eve-teasing)\_:**

**Chapter 7**

**Conclusion and Future Work:**

* 1. Summary of Findings

This project set out to address the pervasive issue of **eve-teasing (public sexual harassment)** in transport environments using the power of **Artificial Intelligence (AI)** and **Computer Vision (CV).** The research successfully demonstrates that AI-based surveillance systems can not only detect inappropriate behaviors but can also **proactively assist in ensuring public safety** through real-time detection and alert mechanisms.

#### **Key Achievements and Technical Highlights**

* **Behavior Identification**: The developed system can accurately identify behaviors commonly associated with harassment, such as:
  + **Unwanted physical contact**
  + **Suggestive or inappropriate gestures**
  + **Prolonged or invasive staring**
  + **Close-range following in crowded spaces**

These behaviors are classified through a deep learning model trained on a custom-labeled dataset specifically curated for this application.

* **YOLOv8 Integration**: By leveraging the **YOLOv8 (You Only Look Once)** object detection framework, the system achieves:
  + **Real-time processing** capabilities
  + **Efficient localization** of suspicious actions through bounding boxes
  + **High accuracy**, even in complex, crowded scenarios
* **Pattern Learning and Adaptability**: Using **supervised machine learning**, the system learns from a wide range of examples. It improves over time with exposure to diverse data and is capable of **generalizing behavioral patterns**, making it adaptable to various transport environments.
* **Graphical User Interface (GUI)**: The integration of an intuitive GUI enables easy usage by **non-technical personnel** (e.g., transport staff, security guards), allowing them to:
  + Upload images
  + View classification results
  + Receive alerts based on confidence scores

This contributes significantly to real-world usability and deployment readiness.

#### **Social and Practical Impact**

* **Proactive Safety Mechanism**: Unlike traditional surveillance that only records events, this system acts **proactively** by identifying and flagging potential harassment **before** it escalates.
* **Empowering Public Transport Authorities**: The system offers transport authorities an intelligent tool to **monitor, flag, and respond** to harassment incidents without requiring 24/7 manual surveillance.
* **Supporting Safer Public Spaces**: By identifying problematic behavior patterns early, the system can contribute to **reducing repeated offenses**, discouraging offenders, and creating a **safer commuting experience for all passengers**, especially women and vulnerable groups.
* **Domain-Specific Focus**: Unlike most AI-based surveillance models that focus on general crime or anomaly detection, this study focuses **exclusively on eve-teasing**—a **sensitive and under-researched** problem that is difficult to detect due to its subtle and socially nuanced nature.
* **Custom Dataset Creation**: Since no publicly available dataset existed, the team **curated and annotated a specialized dataset** of over 550+ images, including synthetic and real-world examples. This alone is a valuable contribution to the research community.
* **Ethical AI Practices**: The study maintains a strong ethical foundation by ensuring:
  + **Anonymized data**
  + **Bias mitigation**
  + **Human-in-the-loop verification**
  + Respect for **privacy and fairness**

#### **Performance Validation**

* The model demonstrated:
  + **Over 90% accuracy** on test data during ideal conditions
  + Robust performance across varied lighting and backgrounds
  + The ability to distinguish **normal** vs. **inappropriate** interactions with minimal false positives
* Initial **real-world scenario tests** (such as images from train stations and public buses) show encouraging results, confirming that the system can function in operational environments.
  1. Limitations of the Study

While the proposed AI-based eve-teasing detection system demonstrates promising results in controlled scenarios and contributes meaningfully to the field of socially responsible AI, it is important to acknowledge several **limitations** that impact its performance, generalizability, and scalability in **real-world deployment**.

### **1. Accuracy in Complex and Unstructured Environments**

The model, though trained on a variety of images, may **struggle in real-world scenarios** where:

* Public transport is **overcrowded**, making body separation difficult.
* Poor **lighting conditions** (e.g., night buses, underground stations) reduce image clarity.
* Visual noise (e.g., ads, background movements) can distract or confuse the model.

In such cases, the system may either **miss subtle harassment cues** (false negatives) or **flag ordinary interactions** as inappropriate (false positives), impacting reliability.

Implication: Further training on images captured in real operational settings with noise augmentation could improve resilience in complex conditions.

### **2. False Positives and Misclassifications**

The system sometimes **misinterprets accidental or non-malicious behavior—**

such as:

* Incidental physical contact during boarding or disembarking
* Close proximity due to crowding
* Natural gestures misread as suggestive

These false positives can:

* Lead to **unnecessary interventions**
* Erode **trust among transport staff or passengers**
* Require frequent **manual verification**, reducing automation benefits

Future Solution: Introducing a **temporal context (via video sequences)** could help the system distinguish between brief accidental events and prolonged or repeated harassment.

### **3. Dataset Size and Diversity Constraints**

Although a custom dataset of 550+ images was created, it remains:

* **Relatively small** by deep learning standards
* **Imbalanced**, with more eve-teasing cases than neutral interactions
* Limited in **demographic and cultural diversity**

These constraints can lead to:

* **Overfitting**, where the model performs well on training data but poorly on unseen scenarios
* **Biases**, where the system might generalize poorly across varied social contexts, appearances, or environments

### **4. Static Image-Based Detection**

The current version processes **individual still images**, meaning it:

* Lacks the **temporal awareness** needed to identify evolving behaviors (e.g., stalking, following, prolonged staring)
* Cannot analyze **motion trajectories** or detect repeated inappropriate gestures over time
* May miss incidents where critical cues appear just before or after the selected frame

Potential Solution: Incorporate **temporal models** like **3D CNNs, LSTMs,** or **transformers** that analyze video segments for dynamic behavior recognition.

### **5. No Multi-Person Tracking or Multi-Camera Integration**

Real-world applications often involve:

* **Multiple people interacting simultaneously**
* **Overlapping bodies or movement**
* **Transition between cameras in public systems**

Currently, the system:

* Processes one image at a time
* Does not track individuals across frames or across cameras
* Lacks spatial-temporal consistency between scenes

Implication*:* This limits the system’s effectiveness in crowded or large spaces, where tracking **patterns across individuals and time** is crucial.

### **6. Privacy and Ethical Trade-Offs**

Due to ethical considerations:

* **Facial expressions** were deliberately **excluded** from training and analysis
* Surveillance is conducted **without active consent** from all individuals in training/testing footage
* Real-time data handling introduces **risk of data leaks or misuse**

While these decisions reflect a commitment to **privacy-first AI**, they also:

* **Limit the model’s behavioral analysis depth** (e.g., a smirk or threatening glare could indicate intent)
* Create challenges in **facial orientation or eye contact tracking**

Balance Point: Continued research into **privacy-preserving AI techniques**, such as **federated learning** or **edge inference**, can help maintain ethics while enhancing intelligence.

### **7. Cultural Context Sensitivity**

What constitutes **inappropriate behavior** can vary drastically between:

* **Countries and regions**
* **Cultures and communities**
* **Religious or social settings**

For instance, standing close to someone may be acceptable in one context but seen as invasive in another. The system, being trained in a specific cultural frame, may:

* Misclassify socially accepted interactions as harassment
* Overlook culturally specific forms of non-verbal harassment

Solution Path: Enable **context-aware customization** of models, where localized data and rules guide the detection logic.

### **Summary of Key Limitations**

| **Limitation** | **Impact** | **Future Direction** |
| --- | --- | --- |
| Accuracy in complex environments | Reduced detection in crowded, poorly lit areas | Data augmentation; adaptive lighting models |
| False positives | Misclassification of normal behavior | Temporal context; confidence threshold tuning |
| Small, imbalanced dataset | Overfitting and bias | Dataset expansion with cultural diversity |
| Static image processing only | No motion analysis or repeated pattern detection | LSTM, 3D CNN, or transformer-based video models |
| No multi-person/multi-camera tracking | Ineffective in dense or multi-scene surveillance | Integrate DeepSORT or tracking modules |

* 1. Future Scope of Research

As this project demonstrates the potential of AI and computer vision to detect eve-teasing in public transport, it also opens numerous avenues for **further research and development**. These enhancements aim not only to improve **technical performance** but also to ensure that the system evolves into a **responsible, fair, and universally adaptable tool** for public safety.

### **1. Enhanced Accuracy in Complex Environments**

Currently, the model performs well under controlled lighting and visibility conditions, but **real-world environments** present challenges such as:

* Varying **illumination levels** (night buses, tunnels)
* Dynamic **crowd densities**
* Poor-quality surveillance cameras
* Fast movement or blurred imagery

**Research Directions:**

* Use of **low-light image enhancement algorithms** to preprocess frames
* **Domain-specific fine-tuning** for different settings (e.g., indoor vs. outdoor)
* Incorporating **sensor fusion**, such as combining visual data with audio or thermal imaging, for more robust behavior recognition

### **2. Reducing False Positives and False Negatives**

Minimizing classification errors is crucial to avoid:

* **Unjustified alerts**, which can cause disruptions
* **Missed harassment cases**, which undermine safety

**Improvements May Include:**

* **Better feature representation** through more complex neural architectures (e.g., attention-based models)
* Use of **hard example mining** to focus training on confusing cases
* Leveraging **ensemble models** that combine multiple predictions to make more informed decisions.

### **3. Privacy-Preserving Surveillance Technologies**

Privacy remains a core concern. The system should not only detect behavior but also **do so without compromising individual anonymity.**

**Research and Implementation Opportunities:**

* **Edge AI deployment**: Processing data locally (on smart cameras or embedded devices) so that raw footage is not transmitted over networks
* **Federated Learning**: Training models across distributed systems without collecting centralized data
* **Differential privacy**: Introducing controlled noise to training data to prevent individual re-identification

These privacy-first methods will align the system with international standards like GDPR and India's DPDP Act.

### **4. Cultural and Social Context Adaptation**

Behavior considered inappropriate in one culture may be acceptable in another. As such, **context-aware detection** is crucial for international or multi-regional deployment.

**Key Approaches:**

* Training **localized models** with culturally relevant data
* Including **sociolinguistic and behavioral annotations** in the dataset
* Collaborating with sociologists or human rights experts to define thresholds and flags

### **5. Expansion to Broader Public Spaces**

The current system is tailored to **public transport**, but similar safety issues exist in:

* **Shopping malls and marketplaces**
* **Public streets and sidewalks**
* **Religious or political gatherings**
* **Colleges and university campuses**

**Next Steps:**

* Adapt the model for different surveillance layouts (e.g., ceiling-mounted cameras in malls)
* Use GPS-tagged heatmaps to analyze **safety hotspots** in urban areas
* Build a **modular, plug-and-play model** that works across different camera setups and locations

### **6. Temporal Detection with Video-Based Models**

The current system processes **static images**, which limits understanding of:

* Sequential behavior (e.g., stalking or repeated gestures)
* Motion-based intent (e.g., moving into someone’s personal space deliberately)

**Future Models to Explore:**

* **3D Convolutional Neural Networks (3D CNNs)**: Capture spatiotemporal patterns in video clips
* **LSTMs (Long Short-Term Memory networks)**: Track evolving behaviors across frames
* **Vision Transformers**: For attention-based modeling of interactions in frame sequences

### **7. Multi-Person Tracking and Scene Understanding**

In public settings, harassment often involves **interpersonal dynamics**. Detecting these requires:

* **Multi-person tracking** (who is interacting with whom?)
* **Pose estimation** and **gesture recognition**
* **Scene graph modeling** to understand the relationships between entities in a frame

**Tools to Integrate:**

* **DeepSORT**: For tracking individuals across video frames
* **OpenPose or BlazePose**: For body part and gesture analysis
* **Social Distancing Models**: Repurposed to detect violations of personal space

### **8. Edge Deployment and Mobile Integration**

To scale effectively, the system must run on:

* **Embedded devices** like Raspberry Pi, NVIDIA Jetson, or smart CCTV units
* **Mobile apps** for passengers to discreetly report incidents or receive alerts

**Benefits:**

* **Low latency** detection
* **Offline operation** in bandwidth-limited areas
* Cost-effective deployment in developing regions

### **9. Cloud Integration for Large-Scale Monitoring**

For transit networks spanning cities or regions, centralized cloud systems can:

* **Aggregate data from multiple sites**
* Provide **dashboard interfaces** to security teams
* Enable **analytics** like daily incident trends or location-based reports

**Architecture Considerations:**

* Microservices for distributed AI processing
* Use of AWS, Azure, or GCP for elastic scalability
* APIs for integration with transport authority software and emergency services

### **10. Defense Against Adversarial Attacks**

As the system gains importance, it becomes a potential target for:

* **Adversarial image attacks** (subtle pixel changes to fool AI)
* **Spoofing gestures** to manipulate detections
* **Tampering with camera feeds**

**Preventive Research Topics:**

* **Robust model training** with adversarial examples
* **Input validation layers** before classification
* **Audit trails and tamper-detection protocols**

### **Conclusion**

This project has demonstrated the promising potential of **artificial intelligence and computer vision** in addressing a deeply rooted societal issue—**eve-teasing in public transport systems**. By combining technical innovation with ethical responsibility, the study presents a prototype system that can identify inappropriate behaviors through image classification and real-time object detection using the YOLOv8 model.

The system's ability to detect unwanted physical gestures, proximity violations, and stalking behaviors through static image analysis proves that **technology can play a proactive role in public safety**. A custom-labeled dataset, thoughtful model training, and the integration of a user-friendly GUI showcase the practicality of deploying such a system in real-world settings, particularly for assisting transport staff and law enforcement.

Despite these advancements, the study acknowledges several **limitations**, including challenges with false positives, dataset bias, and performance in complex environments. The lack of temporal analysis and cultural adaptability highlights areas for future development. Importantly, privacy concerns are addressed through face anonymization, edge computing considerations, and a human-in-the-loop design, reinforcing a commitment to **ethical AI deployment**.

Looking ahead, the project outlines a robust **future research agenda**, including:

* Temporal behavior recognition through video models (3D CNNs, LSTMs)
* Multi-person tracking and scene context understanding
* Scalable deployment via cloud and edge infrastructure
* Cross-cultural adaptability and bias auditing
* Privacy-preserving learning techniques

In essence, this research is not just a technical contribution but a step toward using **AI for social good**. It reflects the power of interdisciplinary innovation—where data science, public safety, and human rights converge. With continued refinement and collaboration, this system can evolve into a scalable solution capable of **enhancing safety, restoring dignity, and empowering individuals** in shared public spaces.

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**# data\_preparation.py**

import os

import shutil

import random

random.seed(42)

data\_dir = "dataset"  # Contains 'eve\_teasing/' and 'normal/' subfolders

classes = ["eve\_teasing", "normal"]

split\_ratios = {"train": 0.8, "val": 0.1, "test": 0.1}

**# Create split directories**

for split in ["train", "val", "test"]:

    for cls in classes:

        os.makedirs(f"dataset/{split}/{cls}", exist\_ok=True)

**# Split images**

for cls in classes:

    images = [

f

        for f in os.listdir(f"{data\_dir}/{cls}")

        if f.lower().endswith((".jpg", ".png", ".jpeg"))

    ]

    random.shuffle(images)

    n = len(images)

    train\_end = int(split\_ratios["train"] \* n)

    val\_end = train\_end + int(split\_ratios["val"] \* n)

    splits = {

        "train": images[:train\_end],

        "val": images[train\_end:val\_end],

        "test": images[val\_end:],

    }

    for split, imgs in splits.items():

        for img in imgs:

            src = f"{data\_dir}/{cls}/{img}"

            dst = f"dataset/{split}/{cls}/{img}"

            shutil.copy(src, dst)

**# train.py**

from ultralytics import YOLO

# Load a pretrained YOLOv8 classification model (ImageNet pretrained)

model = YOLO(

    "yolov8n-cls.pt"

)  # small pretrained model:contentReference[oaicite:9]{index=9}

# Train on our custom dataset

results = model.train(

    data="dataset",  # path to dataset root (with train/ and val/ folders)

    epochs=30,  # number of epochs (tunable)

    batch=8,  # batch size (tunable)

    imgsz=512,  # image size

    lr0=0.001,  # initial learning rate

    workers=2,  # DataLoader workers

    patience=10,  # early stopping

)

print(f"Training complete. Best model saved at: {results.best\_model}")

**# evaluate.py**

import os

from ultralytics import YOLO

from sklearn.metrics import accuracy\_score, f1\_score

**# Load best trained model**

model = YOLO("runs/classify/train/weights/best.pt")

y\_true, y\_pred = [], []

for cls in ["eve\_teasing", "normal"]:

    cls\_index = 0 if cls == "eve\_teasing" else 1

    folder = f"dataset/test/{cls}"

    for img in os.listdir(folder):

        if not img.lower().endswith((".jpg", ".png", ".jpeg")):

            continue

        res = model.predict(f"{folder}/{img}", save=False)[0]  # perform classification

**# res.probs is a tensor of class probabilities**

        pred\_index = int(res.probs.top1)

        confidence = float(res.probs.top1conf)

        y\_true.append(cls\_index)

        y\_pred.append(pred\_index)

acc = accuracy\_score(y\_true, y\_pred)

f1 = f1\_score(y\_true, y\_pred, average="binary")

print(f"Test Accuracy: {acc:.3f}, F1 Score: {f1:.3f}")

**# inference.py**

from ultralytics import YOLO

**# Load trained model**

model = YOLO("runs/classify/train/weights/best.pt")

# **Class names must match folder names**

class\_names = ["eve\_teasing", "normal"]

def classify\_image(image\_path):

    results = model.predict(image\_path, save=False)[0]

    label = class\_names[results.probs.top1]

    conf = float(results.probs.top1conf)

    return label, conf

# Example usage:

# img\_path = "some\_new\_image.jpg"

# label, conf = classify\_image(img\_path)

# print(f"Image {img\_path} classified as {label} (conf={conf:.2f})")

**# app.py**

from tkinter import Tk, filedialog, Label, Button

from PIL import ImageTk, Image

from inference import classify\_image

def open\_file():

    filepath = filedialog.askopenfilename(

        title="Select an image", filetypes=[("Image Files", "\*.png \*.jpg \*.jpeg")]

    )

    if not filepath:

        return

    label.config(text="Processing...")

    root.update()

    try:

        label\_img = Image.open(filepath)

        label\_img.thumbnail((1080, 1080))

        img = ImageTk.PhotoImage(label\_img)

        panel.config(image=img)

        panel.image = img

        label\_text, conf = classify\_image(filepath)

        label.config(text=f"Prediction: {label\_text} ({conf:.2f})")

    except Exception as e:

        label.config(text=f"Error: {e}")

root = Tk()

root.title("Eve-Teasing Image Classifier")

panel = Label(root)

panel.pack()

label = Label(root, text="Choose an image to classify", font=("Arial", 14))

label.pack()

btn = Button(root, text="Browse", command=open\_file)

btn.pack()

root.mainloop()