Grenze journal name, Volume. 1, Issue.1,April 2025

Comparative Analysis of Road Accident Detection Using SVM and YOLOv8 in a Flask-Based Web Application

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Abstract— Road accidents pose a serious global threat, causing significant loss of life and economic impact. This study presents a comparative analysis of two road accident detection methods—Support Vector Machine (SVM) optimized with Sequential Minimal Optimization (SMO), and the YOLOv8 deep learning algorithm—implemented within a Flask-based web application. While SVM focuses on image-based classification, YOLOv8 enables real-time object detection of various accident scenarios. The integrated system enhances detection accuracy, response speed, and overall road safety, offering promising advancements in intelligent traffic surveillance.

Index Terms—Road accident detection, SVM, YOLOv8, Flask web application, Sequential Minimal Optimization, machine learning.

I. Introduction

Since traffic accidents continue to be the primary cause of fatalities and injuries worldwide, road safety is still of utmost importance. The World Health Organisation (WHO) reports that traffic accidents cause millions of injuries and over 1.3 million fatalities annually, placing a heavy socioeconomic strain on communities and healthcare systems. Beyond just the acute physical suffering, these incidents have an impact on public health systems, families, and economies. There has never been a more pressing need for efficient and prompt acci dent detection systems in light of these concerning data. By facilitating quick emergency response, early detection can greatly lessen the effects of traffic accidents, potentially saving lives and lessening the severity of injuries. Recent technological developments have made it possible to create intelligent systems that can effectively and precisely identify traffic incidents. In order to analyse video data and instantly detect accident scenarios, these systems make use of machine learning and deep learning algorithms. In this research, two cutting-edge approaches for detecting traffic accidents—Support Vector Machines (SVM) and YOLOv8 (You Only Look Once, version 8)—are compared. Both methods are used in a web application built using Flask that aims to offer an intuitive platform for video-based accident detection. An SVM classifier is used in the first method, and it is trained using a labelled dataset that includes pictures of both accident and non-accident situations. By effectively identifying the best hyperplane for classification, the Sequential Minimal Optimisation (SMO) technique improves the performance of the SVM model. The SVM model is capable of successfully differentiating between typical traffic situations and possible collisions by extracting pertinent visual information from video frames. On the other hand, the second approach makes use of the YOLOv8 object detection algorithm, a cutting-edge deep learning model known for its accuracy and speed. YOLOv8 has been specially trained to identify several types of accidents, such as collisions between cars, collisions between cars and motorcycles, and occurrences involving pedestrians. By processing video frames in real-time, our model improves situational awareness for emergency responders and drivers by enabling the prompt detection of important occurrences on the road. By including safe login and registration features that guarantee user authentication and data protection, the Flask application improves user experience. After logging in, users can analyse recorded movies using either YOLOv8-based detection or SVM-based detection. A direct comparison of the two approaches is made possible by the system's real-time processing capabilities, which also highlight occurrences that have been spotted and offer predicted 2 insights. The purpose of this study is to assess and contrast the accuracy, processing speed, and robustness of SVM and YOLOv8. This study advances the continuous development of intelligent accident detection systems by illuminating the advantages and disadvantages of each strategy. In addition to improving accident detection skills, the combination of machine learning and deep learning approaches into a single platform encourages the use of technology-driven solutions to tackle the urgent problems in road safety. The ultimate goal of this endeavour is to promote safer driving conditions and enhance emergency response tactics by advancing the field of intelligent traffic surveillance

II. METHODOLOGY

The proposed system, Road Accident Detection using SVM and YOLOv8, is designed as a Flask-based web application that offers users two distinct methodologies for accident detection. The system architecture consists of the following components:

3.1 SVM-Based Approach

SMO Optimisation using Support Vector Machine (SVM)
Histogram of Orientated Gradients (HOG) is used in the SVM technique to extract features. A feature descriptor called HOG efficiently encodes key visual patterns that are necessary for differentiating between accident and non-accident situations by capturing the distribution of gradient orientations in certain areas of an image.
Model Training: The Sequential Minimal Optimisation (SMO) approach is used to optimise an SVM classifier that receives the extracted features. SMO ensures convergence and computational efficiency, especially when working with large datasets, by effectively resolving the quadratic programming issue that comes up during SVM training.
Model Evaluation: The test dataset is used to evaluate the trained SVM model's performance. To measure how well the model classifies accident and non-accident events, evaluation metrics like accuracy, precision, recall, and F1-score are used

3.2 YOLOv8-Based Approach

Model Training: The annotated dataset is used to train YOLOv8, a cutting-edge deep learning-based object recognition model. By detecting objects and their spatial relationships among video frames, our model learns to recognise specific accident scenarios by using a single neural network to forecast several bounding boxes and class probabilities for those boxes simultaneously.
Real-Time Detection: The YOLOv8 model recognises and locates accident scenarios by processing incoming video frames in real-time after training. The output gives a visual representation of the detection results by highlighting detected accidents with labels and bounding boxes.

4 Flask Web Application

The online application has a user-friendly interface that includes a number of important features:
User authentication: To guarantee safe access and safeguard user information, the program has standard login and registration features.
Detection Options: Following a successful login, users have a choice of two detection techniques:

SVM Detection: Using this option, the video is processed frame-by-frame and each frame is classified as either an accident or a non-accident.
YOLOv8 Detection: This feature finds and highlights particular kinds of mishaps in the video clips.
Video Processing: Videos uploaded by users undergo frame-by-frame processing. Results are shown visually by the system, along with labels and bounding boxes for any accidents that are recognised (in the case of YOLOv8).

5 Performance Comparison

The approach makes it easier to compare the SVM and YOLOv8 models using a number of performance indicators:

The percentage of true positive detections in relation to all actual accidents is known as detection accuracy.
Processing Speed: This statistic, which is expressed in frames per second (FPS), shows how well each model processes video data.
Robustness: To gauge the models' dependability in practical applications, they are tested in a variety of settings, such as various lighting conditions, meteorological variables, and occlusions.

6 Result and Output

Bounding boxes and labels are used to indicate any mishaps that are spotted in the processed videos that the system outputs. Users are also shown a summary of detection findings that highlights the detection details and accuracy for both approaches. This dual-method approach guarantees a thorough assessment of accident detection strategies and offers insightful information for improving intelligent road safety systems.

8 Experimental result

The experimental evaluation focuses on assessing the performance of the SVM and YOLOv8 models for road accident detection. Both models were trained and tested using the prepared datasets, and their results were compared using metrics such as accuracy, precision, recall, F1-score, and processing speed (frames per second). Below are the results of the experiments:

8.1 Dataset Details

Total Images	10,000
Training Set	70% (7,000 images)
Validation Set	15% (1,500 images)
Test Set	15% (1,500 images)
Classes	Accident, Non-Accident

Table 1: Dataset Details

8.2 SVM Model Results

Metric	**Value**
Training Time	2 hours
Feature Extraction	Histogram of Oriented Gradients (HOG)
Optimizer	Sequential Minimal Optimization (SMO)
Accuracy	89.5%
Precision	87.2%
Recall	85.6%

F1-Score	86.4%
Processing Speed	20 frames/sec

Table 2: SVM Model Results

The SVM model performed well in distinguishing accident and non-accident frames but showed some limitations in detecting complex accident scenarios with partial occlusions or low lighting.

8.3 YOLOv8 Model Results

Metric	**Value**
Training Time	8 hours on an NVIDIA RTX 3090 GPU
Detection Scenarios	Car-Car Collision, Car-Bike Collision, Car-Person Collision
Accuracy	94.8%
Precision	93.2%
Recall	92.5%
F1-Score	92.8%
Processing Speed	45 frames/sec

Table 3: YOLOv8 Model Results

The YOLOv8 model demonstrated superior accuracy and robustness, particularly in complex accident scenarios and varying environmental conditions. The real-time processing speed and ability to detect multiple objects simultaneously make YOLOv8 suitable for dynamic applications.

8.4 Comparison of SVM and YOLOv8

Metric	**SVM**	**YOLOv8**
Accuracy	89.5%	94.8%
Precision	87.2%	93.2%
Recall	85.6%	92.5%
F1-Score	86.4%	92.8%
Processing Speed	20 frames/sec	45 frames/sec

Table 4: Comparison of SVM and YOLOv8 Performance

8.5 Visual Results

- **SVM Output:** Classified frames with ”Accident” or ”Non-Accident” labels.
- **YOLOv8 Output:** Annotated video frames with bounding boxes and labels such as ”Car-Car Accident” or ”Car-Bike Accident.”

This study presented a comparative analysis of two methods for road accident detection: Support Vector Machine (SVM) with Sequential Minimal Optimization (SMO) and YOLOv8, a state-of-the-art object detection model. Both methodologies were integrated into a Flask-based web application, allowing users to upload recorded videos and choose between the two detection methods.

III. Conclusions

This study presented a comparative analysis of two methods for road accident detec tion: Support Vector Machine (SVM) with Sequential Minimal Optimization (SMO) and YOLOv8, a state-of-the-art object detection model. Both methodologies were integrated into a Flask-based web application, allowing users to upload recorded videos and choose between the two detection methods.

Acknowledgment

The authors declare no competimg interests and have no funding to disclose

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