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Object Detection Employing YOLOv8 in Conjunction with a Custom Dataset

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Abstract

In a variety of applications, including surveillance and safety systems, object detection is a very important characteristic. The objective of this study is to apply the sophisticated object identification model known as YOLOv8 to a particular dataset that has been developed for emergency collision avoidance systems specifically. For the purpose of conforming to the format specifications of YOLOv8, the dataset was painstakingly hand-labeled and polished. It included components such as autos, pedestrians, and barriers in a variety of situations. In order to improve the efficiency of the model, supplementary data and transfer learning strategies were applied. According to the results of the experiments, the model achieves a mean average precision (mAP) of [0.43], which demonstrates both its accuracy and efficiency. The ability of the device to detect potential threats in real-time may make it possible for it to be included in complete safety systems. For the purpose of optimizing real-time

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processing, additional modifications will be investigated in subsequent research, and the concept will be applied to edge devices.

Keywords: Bounding Box, Data Augmentation, Data Preprocessing, Dataset Splitting (train/test/validation), Object classes.

1. Introduction

The application of artificial intelligence (AI) in the automotive industry has resulted in significant improvements to the safety measures that are in place. The idea of real-accident identification is an essential component of passenger safety in automobiles since it has the potential to avoid future injuries while simultaneously alerting emergency personnel on time. In order to evaluate and identify accidents, the purpose of this project is to develop a system for accident detection that makes use of video input and artificial intelligence (AI) models. YOLO v8, Random Forest, Convolutional Neural Networks (CNN), and Logistic Regression are a few instances of these models.

The YOLO v8 model is used to analyze video footage, one of the methodology's most crucial inputs, to identify objects in real-time. Important traits that lead to accidents have been identified using this method. These features include collisions, quick movements, and other anomalies. Once the detection verification process is finished, data analysis is carried out by the CNN, Random Forest, and Logistic Regression models to improve the accuracy and responsiveness of the system. This makes it possible for the models to determine and assess the likelihood that an accident will occur.

One of the most difficult problems in computer vision is object detection. This subject entails locating and recognizing objects that are present in a picture or video. Strong object recognition models have been created as a result of deep learning advancements. One of the most well-known and effective of these models is the You Only Look Once (YOLO) architecture. The most recent version of the YOLO series, YOLOv8, builds on the achievements of its predecessors by offering increased precision, speed, and versatility. Because of this, it is a great option for applications that need to recognize objects in real-time.

Even though pre-trained YOLOv8 models thrive on common datasets such as COCO, fine-tuning the model on a custom dataset can greatly increase the model's efficacy for domain-specific applications. Custom datasets help improve detection accuracy in specialized applications like industrial automation, autonomous vehicles, and medical imaging by making it easier for the model to learn discrete item classes and adapt to environmental conditions.

This study assesses the application of YOLOv8 for object detection using a dataset designed especially for this use. Important steps include creating the dataset, annotating it, training the model, and assessing how well it performs. The conversation offers a thorough grasp of how to utilize YOLOv8 to create original object-detection applications. The main goal of this project is to create video-based accident detection technologies that can quickly identify accidents and send out timely alerts. In place of the current sensors, a sensor-based technology is being developed. By using computer vision and machine learning techniques to enable precise accident detection, this technology will increase vehicle safety.

2. Literature Review

The most significant framework that emerged from this study was the YOLO framework. The vehicle can analyze a single frame while it is moving forward and make timely decisions thanks to the use of YOLO for real-world environment recognition. Autonomous vehicles rely heavily on object detection because it allows them to respond rapidly to their environment.1. This study provides insight into the latest developments in object recognition within the field of computer vision. YOLOv5, YOLOv7, and YOLOv8 have effectively integrated these developments. The succinct overview offers a perceptive explanation of the fundamental significance of object detection, which is deeply interwoven with the main body of the study. The description of object detection, according to Afrin et al. (2023) and Goudah et al. (2023), emphasizes its importance in a range of scenarios, including the recognition of vehicles in a variety of scales and circumstances, illustrating the range of applications for this technique.

The team successfully carried out real-time detection and analysis of a broad range of road users using a specialized dataset for YOLOv8 training. In a similar vein, the method optimizes processing resources while making it simpler to identify multiple objects, enabling it to retain accuracy even in intricate traffic situations. It enhances the dependability and safety of automobiles that operate without human assistance.

The YOLOv8 detection framework highlights the value of object detection as a specialized topic and the importance of investigating new areas within the rapidly evolving fields of artificial intelligence and computer vision. It is predicted that the YOLOv8-based object detection system can be enhanced when functioning in challenging weather conditions by utilizing transfer learning and several weather datasets. Together, the ACDC and DAWN datasets—both of which are publicly available—are used to identify the key terms associated with road conditions during bad weather.

According to the dataset's characteristics, weights were created using the dataset and then used to integrate its variants and various subgroups (Ganesan et al., 2024; Safaldin et al., 2024; Kumar & Muhammad, 2023). The datasets used to identify personal protective equipment (PPE) worn by personnel include 5,000 images of safety helmets and vests (SHEL5K) and color helmets and vests (CHV). The databases contain items in eight different categories. These consist of helmets, vests, and goggles.

Following the division of the dataset into subsets for training, testing, and validation, several YOLOv8 models were assessed using metrics such as mAP50, precision, and recall. In the detection of personal protective equipment, YOLOv8x and YOLOv8l performed better, especially when it came to identifying the person and vest categories (Barlybayev et al., 2024).

The model incorporates the receptive field convolutional block attention module (RFCBAM) into the backbone network to improve feature extraction efficiency and lessen the spatial information sparsity brought on by downsampling. Additionally, for multi-scale feature integration, we developed a novel neck architecture called the balanced spatial and semantic information fusion pyramid network (BSSI-FPN) (Li et al., 2024).

In 2020, Tomaszewski and Osuchowski found that power line insulators are present in the Insulator Defect Image Dataset (IDID). This dataset includes two minor classes that represent various types of damaged insulators in addition to a large class of undamaged insulators. A major development in security surveillance technology, the integration of YOLOv8 for the detection of objects, people, and weapons in audio, along with distance estimation and email notifications, allows for quick threat identification and coordinated responses, among other features. To overcome the difficulties presented by the aquatic environment, (Jyothsna et al., 2024; Thakur et al., 2023) developed a YOLOv8-based system for underwater object detection. These difficulties include blur, color distortion, background noise, and lighting variations.

The dataset was initially limited, however the application of data augmentation techniques and an increase in training photos enhanced its robustness. The YOLOv8s model was employed, and each dataset was trained for 75 epochs, yielding a 23% enhancement in mAP@0.5 with the final dataset. The experiment assessed the enhancement in accuracy obtained by training the amended dataset with the bag of freebies method (principles of data augmentation) (Gupta et al., 2023).

The advancement of object detection techniques and the advantages of deep learning methodologies compared to conventional methods. Deep learning has gained significant interest in intelligent transportation systems applications that necessitate robust image processing techniques for vehicle recognition, localization, tracking, and counting in traffic scenarios (Bakirci, 2024).

The model initially distinguishes between motorbike riders who are wearing safety helmets and those who are not. Riders not wearing helmets are identified and recorded using OCR for license plate detection. The utilization of 3D vision techniques in automating logistical operations, utilizing deep learning for object identification and handling within organizations. The study builds a 3D vision system using Roboflow-trained models for object and key point detection and YOLOv8 (You Only Look Once version 8). The procedure entails data collection and annotation, outcome analysis, and the development of deep learning models (Krishna et al., 2024; Silveira et al., 2024).

3. Proposed System

3.1. *Objective of the work*

1. Train YOLOv8 on a custom dataset.
2. Detect specific objects from videos and images.
3. Evaluate the model's efficacy on novel data.

3.2. *Detailed Problem Statement*

This work aims to develop an accurate object detection methodology for a specific dataset using YOLOv8, a state-of-the-art platform for real-time object recognition. The goal is to develop a model that can track and identify objects in photos and videos with remarkable speed and accuracy.

3.3. *Software Requirements*

Google Colab is used while programming. Developers value this integrated development environment (IDE) due to its outstanding debugging capabilities, speedy performance, versatility for machine learning applications, and ease of use. Similar to Google Sheets or Docs, multiple people can work together simultaneously on the same notebook.

3.4. *System Implementation*

Using a pre-trained YOLO v8 model, the developed system analyses video input from wearable devices to continually track and identify occurrences. This identifying system enables real-time distinction between drivers, passengers, and hazardous accident conditions. The system routinely evaluates these detections to determine the probability of an accident. After cleaning and processing, the data is utilized to train various machine learning models.

The application identifies its most precise model and uses it to predict forthcoming occurrences. Training modifies the model's parameters to improve performance and produce accurate predictions. In order to bring notice to those designated items, labelled boxes and boxes featuring the terms "car," "person," or accident.

Fig. 1. Car Detection with bounding box value.

4. Experimentation and Results

Real-time recognition of objects using a YOLOv8 model was used, with an emphasis on automobiles, pedestrians, and potential crash events. A broad variety of photos and videos collected via public databases were employed to train the model. Techniques for data augmentation were used to improve the model's ability for generalization.

The trained YOLOv8 model was employed to create a system that continuously analyzes footage from connected devices. Real-time monitoring of the environment has been rendered possible by the use of frames and tags to indicate saw objects. The system's performance has been assessed using metrics like precision, recall, and mAP. According to the results, the simulator was able to precisely pinpoint objects of interest even under challenging conditions.

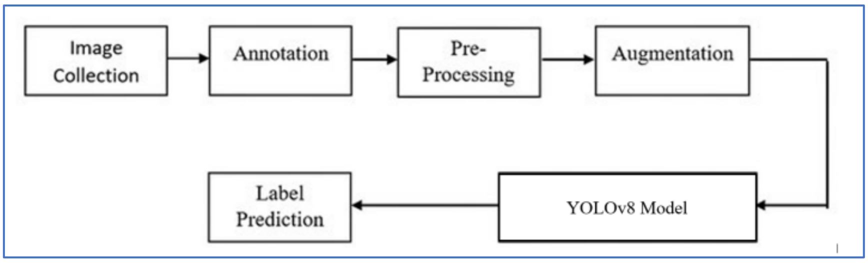

Fig. 2. YOLOv8-Based Accident Detection System Workflow.

4.1. *Data Collection & Preprocessing*

Starting from the data collection which is the first process in this project and undoubtedly the most important one. The obtained dataset is from Kaggle which is video and image files which are used to detect accidents. The video files are unlabeled. The image files are labelled with objects like persons, cars, and motorcycles. These labelled files are used to develop an accident detection model. Then these video files were converted to frames. Then each frame has its label which is used for the detection of objects.

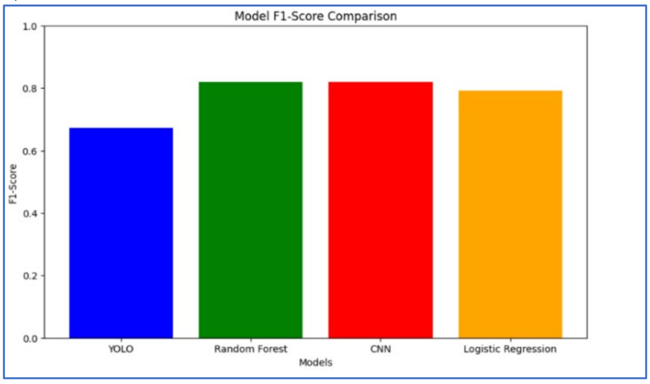

Fig. 3. Bar Chart: Object Detection Model Performance: F1-Score Analysis.

4.2. *Model Training and Evaluation*

The subsequent bar chart illustrates a comparison of the F1 scores of four distinct machine learning models: CNN, Random Forest, Logistic Regression, and Yolo. The

```
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.95      0.95     60253
           1       0.94      0.94      0.94     52565

    accuracy                           0.95    112818
   macro avg       0.95      0.95      0.95    112818
weighted avg       0.95      0.95      0.95    112818


Confusion Matrix:

Confusion Matrix :
[[57123  3130]
 [ 3011 49554]]
```

different models are displayed along the horizontal axis, while the F1-score, ranging from 0 to 1, is represented on the vertical axis. The Random Forest model outperforms the other three models in terms of F1-score, according to the graphic. A categorization report and a confusion matrix are presented in the provided graphic.

Fig. 4. Classification report of the Algorithm.

Figure 4 demonstrates that the classification report's elevated precision, recall, and F1-scores for both classes (0 and 1) indicate exceptional efficacy in identifying both positive and negative instances. The model's entire accuracy of 0.95 demonstrates the effectiveness of it. The misreading provides solid evidence for this conclusion.

5. Advantages of the Proposed System

- **High Accuracy & Speed** – YOLOv8 is one of the fastest and most accurate real-time object detection models, providing a strong balance between precision and inference speed, making it suitable for real-world applications.
- **Compatibility of Custom Datasets** – This approach permits training on a custom dataset, enhancing performance in domain-specific tasks, unlike pre-trained models constrained to general classes (e.g., medical imaging, industrial automation, or surveillance).
- **Improved Detection for Small Objects** – YOLOv8 incorporates enhanced feature extraction and multi-scale prediction, improving detection performance even for smaller objects in complex scenes.
- **The simplicity of Instruction and Implementation** – Featuring an intuitive architecture and support from frameworks such as Ultralytics, YOLOv8 streamlines the training process and facilitates effortless deployment on edge devices, cloud platforms, or embedded systems.
- **Scalability** – The system can be easily fine-tuned for different use cases by adjusting hyperparameters, expanding datasets, or integrating additional post-processing techniques.
- **Cost-Effective Solution** – By leveraging transfer learning and efficient model optimization, the system reduces computational costs while maintaining high detection performance.
- **Real-Time Processing** – YOLOv8's optimized architecture ensures real-time object detection, making it ideal for applications like autonomous vehicles, traffic monitoring, and security systems.

6. Social Welfare of the Proposed System

By increasing efficiency, safety, and accessibility, the suggested approach, known as "Object Detection using YOLOv8 with Custom Dataset," has the potential to greatly enhance societal welfare across a variety of industries. The following are significant areas where this system may benefit society:

- **Enhanced Public Safety & Security**
    - **Monitoring and preventing criminal activity**: To detect suspicious items (like weapons and unattended luggage) in real-time, the system can be implemented in public areas, airports, and traffic surveillance. This will support the efforts of law enforcement to deter criminal activity.
    - **Assistance with Emergencies**: Object detection can be useful in situations such as fires and natural disasters since it can make it easier

to identify survivors, hazardous goods, or blockages, which in turn improves the efficiency of rescue operations.

- **Improved Healthcare & Assistive Technologies**
  - The technology assists those who are visually impaired by identifying obstacles, traffic signals, and common items. As a result, the users' mobility and autonomy are strengthened.
  - **Systems for Automated Hospitals**: Assisting in the monitoring of medical equipment, recognizing anomalies in X-rays, and monitoring patient movements within healthcare facilities are all possible applications of this technology.
- **Agricultural & Environmental Benefits**
  - **Agriculturists** can use object detection to evaluate the health of crops, identify pests, and automate harvesting methods, which results in increased productivity and reduced manual labor. This is an example of precision agriculture.
  - **Conservation of Wildlife**: The technology can make forest surveillance easier, which can help discover endangered species or illegal poaching activities. This makes it possible for conservation efforts to be supported.
- **Smart Transportation & Traffic Management**
  - **Self-Driving cars**: Enhances autonomous cars by providing accurate recognition of pedestrians, automobiles, and traffic signs, hence reducing the number of accidents that occur.
  - Through the facilitation of the identification of traffic infractions, congestion, and crashes, traffic surveillance contributes to the improvement of urban planning and the reduction of travel times.
- **Industrial & Workplace Safety**
  - **Identification of Hazards**: The technology has the potential to identify potentially dangerous situations in industrial and construction sites, such as personnel who are not wearing protective gear and equipment that is not functioning properly, to prevent accidents.
  - The purpose of quality assurance is to facilitate the automated discovery of flaws in manufacturing processes, which ultimately results in improved product quality and reduced materials waste.
- **Accessibility & Inclusivity**
  - Real-time item identification for visually impaired individuals and voice-assisted navigation are two examples of the ways in which the system can be incorporated into smart devices to assist people with impairments.

A scalable and efficient solution that can be adapted to a wide range of real-world applications is provided by this system, which makes use of YOLOv8-based object identification in conjunction with a proprietary dataset. It is a significant technological innovation for social welfare because its application has the potential to result in improved community safety, superior resource management, and a raised quality of life.

7. Future Enhancements

The current system can be improved by including real-time detection in video streams or edge devices, refining the model through complex methods such as hyperparameter tuning and synthetic data augmentation, and expanding capabilities to include multi-object tracking in dynamic situations. All of these strategies are possible. Future studies may investigate the possibility of implementing the model on cloud platforms or devices with limited resources through the use of quantization and pruning, while simultaneously enhancing its interpretability through the utilization of visualization tools such as Grad-CAM. Adaptability might be improved through the implementation of domain-specific fine-tuning for applications in healthcare, agriculture, or autonomous systems. Additionally, the development of user-friendly interfaces for dataset annotation and automated training pipelines would make the system more accessible. For the purpose of improving performance and practical application, it may be beneficial to investigate advanced designs such as YOLOv9 and to integrate multi-modal data (for example, thermal or LiDAR).

8. Conclusion

Successfully configured and trained YOLOv8 using a dataset that was provided by the user. Real-time object detection is now complete. By successfully using YOLOv8 for object detection applications on a dataset created especially for the purpose, the study showed that it can accurately recognize and localize items in real-time. By adjusting pre-trained weights, transfer learning was used to enhance model performance and shorten training times. To improve the dataset and raise detection accuracy, techniques for data preparation, annotation, and augmentation were used. Results from experiments showed improved recall and precision, confirming the model's adaptability to different item detection scenarios. YOLOv8 is suitable for real-world uses like industrial automation, driverless cars, and surveillance because of its balance between speed and accuracy. Enhancing the dataset for better generalization, optimizing hyperparameters for better performance, and deploying the model on edge devices for real-time inference are possible future initiatives. The outcomes highlight YOLOv8 as a reliable and successful technique for custom object detection tasks.

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