Road Accident Detection and Timestamp Extraction using Deep Learning

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Abstract

In today's digital age, the proliferation of CCTV cameras has provided extensive surveillance coverage on roads, aiding in various aspects of safety and security. However, the manual inspection of hours of footage to identify road accidents remains a laborious and time-consuming task, particularly for insurance agents tasked with investigating claims. To address this challenge, we present an automated road accident detection system leveraging the YOLOv8 object detection algorithm. The system aims to streamline the process of identifying road accidents in CCTV footage by providing precise timestamps of accident occurrences, thus significantly reducing the time and effort required by insurance agents. Through the integration of YOLO, the system efficiently detects relevant objects indicative of accidents, offering a promising solution to enhance the efficiency of accident investigation processes.

Key words : YOLOv8, Deep Learning, Accident Detection, Timestamp Extraction

1.INTRODUCTION

In today's digital landscape, the proliferation of closed-circuit television (CCTV) cameras has brought about unparalleled surveillance capabilities, offering a critical tool for ensuring public safety and security. However, despite the vast amounts of data generated by these cameras, the process of manually combing through footage to identify road accidents remains a laborious and time-consuming endeavor, particularly for insurance agents tasked with verifying claims. This inefficiency underscores the urgent need for an automated solution capable of swiftly and accurately detecting road accidents in CCTV footage, thereby streamlining the investigative process and expediting claims processing.

The proposed project aims to address this pressing issue by introducing an innovative automated road accident detection system powered by the YOLO (You Only Look Once) object detection algorithm. At its core, the system seeks to revolutionize accident investigation procedures by providing precise timestamps of accident occurrences, thereby eliminating the need for manual video analysis and significantly reducing the time and resources expended by insurance agents.

In contrast to previous implementations utilizing convolutional neural networks (CNNs) such as VGG16 and ResNet50, which exhibited varying degrees of accuracy but often faltered when faced with certain types of videos, YOLO has emerged as the optimal solution due to its exceptional robustness and versatility across diverse video scenarios. YOLO's unique ability to perform real-time object detection and classification in a single pass has revolutionized the field of computer vision, enabling rapid and accurate detection of objects, including vehicles and pedestrians, amidst complex backgrounds and varying lighting conditions.

With its unmatched speed and accuracy, YOLO represents a paradigm shift in the realm of object detection, offering a scalable and efficient solution for automated accident detection in CCTV footage. By harnessing the power of YOLO, the proposed system not only enhances the efficiency of accident investigation processes but also empowers insurance agents to make more informed decisions based on timely and reliable accident data. In this introduction, we will delve into the problem statement surrounding manual accident proof retrieval, elucidate the project's innovative approach utilizing YOLO, and provide a comprehensive overview of the YOLO algorithm and its advantages over traditional methods. Through the integration of YOLO, the automated road accident detection system promises to revolutionize accident investigation procedures, offering a scalable and effective solution for mitigating the challenges posed by manual video analysis in the insurance industry.

2. Literature Survey

Y Zhang et al [1] Traffic Accident Detection Using Background Subtraction and CNN Encoder–Transformer Decoder in Video Frames. 2023. The authors utilized background subtraction and a CNN encoder–Transformer decoder framework to detect traffic accidents. Strengths include a diverse dataset covering various environmental conditions, enhancing robustness and generalizability. However, uncertainties regarding compatibility and feasibility complexity may pose challenges during implementation.

AK Agrawal et al [2] Automatic Traffic Accident Detection System Using ResNet and SVM, 2020. The authors developed an automatic traffic accident detection system utilizing ResNet and SVM. Vehicle distance analysis identified potential accidents, and ResNet50 extracted features. K-Means clustering generated Bag of Visual Words (BOVW), fed into an SVM for classification. The model achieved improved accuracy compared to traditional filters, achieving 94.4%. However, it presently detects only vehicular collisions and does not include accidents involving pedestrians or collisions with static objects like buildings or trees.

S Ghosh et al [3] Accident Detection using Convolutional Neural Networks. 2019. The authors employed a combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to detect accidents. CNNs extracted features from video frames, while LSTMs analyzed these features over time for accident prediction. The use of deep learning techniques, particularly the combination of CNNs and LSTMs, is innovative and suitable for processing sequential data like video frames. However, training and running CNN-LSTM models can be computationally intensive, especially for large-scale video datasets, potentially requiring high-performance computation resources.

N Pathik et al [4] AI Enabled Accident Detection and Alert System Using IoT and Deep Learning for Smart Cities. The paper proposes a cognitive agent-based collision detection system utilizing IoT and AI technologies to address the escalating issue of road accidents. An IoT kit detects accidents and transmits relevant data to the cloud, where a DL model validates the incident, triggering emergency response. Ensemble transfer learning minimizes false alarms, while a personalized dataset and comparative analysis demonstrate the efficacy of InceptionResNetV2. Real-world validation on a toy car confirms the system's potential for enhancing road safety in smart cities.

3. Motivation & Problem Definition

3.1 Motivation

The motivation behind this research stems from the pressing need to streamline accident investigation processes in the insurance industry. Manual scanning of extensive CCTV footage is time-consuming and resource-intensive for insurance agents. By automating the detection of road accidents, valuable time can be saved, leading to faster claims processing and improved customer satisfaction. This project aims to alleviate the burden on insurance agents by providing an efficient and accurate solution for identifying accident occurrences in CCTV footage.

3.2 Problem Definition

The problem lies in the inefficiency of manual accident proof retrieval from CCTV footage, burdening insurance agents with time-consuming tasks. Traditional convolutional neural network (CNN) methods lack the speed and accuracy needed for diverse video scenarios. This project aims to address this challenge by developing an automated road accident detection system using the YOLOv8 algorithm. The goal is to provide insurance agents with a reliable and efficient tool for expediting claims processing.

4. Design and Methodology

The accident detection process begins with the submission of CCTV camera footage to the system. Upon receiving the video, the system undergoes a preprocessing step where the video is segmented into individual frames. These frames are then sequentially passed through the system for accident detection utilizing the YOLOv8 object detection algorithm.

During detection, each frame is analyzed for the presence of objects indicative of an accident scenario. If an accident is detected in a particular frame, the system captures the timestamp corresponding to that frame and displays it alongside the detected frame. This enables users to quickly pinpoint the occurrence of accidents within the CCTV footage, facilitating efficient accident investigation and analysis.

4.1 Detection

The evolution of object detection has seen a transformative journey, starting with the traditional sliding window approach. While effective, this method was computationally intensive, requiring exhaustive scanning of images at multiple scales. The advent of R-CNN brought significant progress by incorporating region proposal methods, but it suffered from slow inference speeds due to independent processing of each proposed region. Fast R-CNN addressed this issue by unifying region proposal and classification within a single CNN framework, improving efficiency but still relying on separate region proposal methods.

Faster R-CNN further refined the process by introducing the Region Proposal Network (RPN), which directly generated region proposals from feature maps, eliminating the need for separate proposal mechanisms. Despite these advancements, YOLO (You Only Look Once) emerged as a game-changer, revolutionizing object detection with its single-stage detection approach. By simultaneously predicting bounding boxes and class probabilities in a single pass of the network, YOLO achieved real-time performance with high accuracy, marking a significant milestone in the evolution of object detection.

YOLOv8, developed by Ultralytics, represents a significant advancement in the realm of object detection models. Building upon the success of its predecessors, YOLOv8 introduces cutting-edge features and enhancements aimed at further elevating performance and versatility. Previous iterations of YOLO have established themselves as formidable contenders in the field of computer vision. However, they were not without their limitations. Earlier versions often struggled with accuracy, particularly in detecting small or heavily occluded objects. Additionally, speed constraints posed challenges for real-time applications, limiting their practicality in certain scenarios. In contrast, YOLOv8 addresses these shortcomings head-on, leveraging innovative techniques to deliver superior performance across the board. One of its key strengths lies in its speed-accuracy trade-off, achieving remarkable detection speeds without compromising on precision. This makes YOLOv8 well-suited for a diverse array of tasks, including object detection, tracking, instance segmentation, image classification, and pose estimation. Furthermore, YOLOv8's ease of use sets it apart as a user-friendly solution for practitioners of varying expertise levels. Its straightforward implementation and seamless integration make it accessible to researchers, developers, and industry professionals alike, democratizing the adoption of advanced computer vision techniques. Moreover, YOLOv8's adaptability extends beyond traditional object detection tasks, with the capability to handle complex scenarios such as multi-object tracking and instance segmentation. This versatility positions YOLOv8 as a versatile tool capable of addressing a wide range of challenges in computer vision applications.

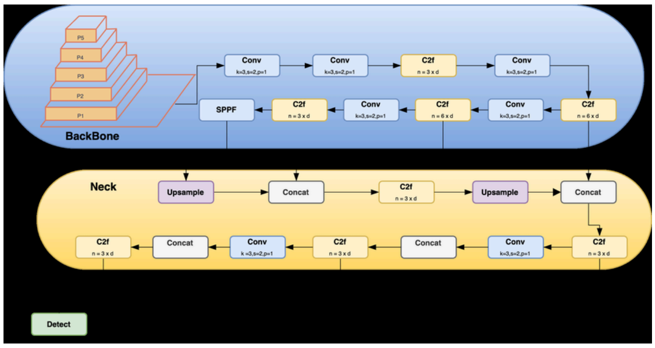

Fig 1. YOLOv8 Architecture

4.2 Software & Dataset

The project relied on Roboflow for dataset preprocessing, Jupyter Notebook for data analysis and model development, and Google Colab for efficient model training. Project management was handled through Jira, while Git and GitHub facilitated collaborative coding and version control. These software tools ensured seamless workflow integration and effective team collaboration throughout the project lifecycle.

The dataset used for training and validation comprises 7125 training images and 254 validation images. It offers a comprehensive representation of various accident scenarios encountered on roadways. These scenarios encompass a spectrum of accident types, including collisions between bikes and stationary objects, accidents involving pedestrians and bikes, as well as collisions between motor vehicles such as cars. Each image within the dataset is meticulously labeled to denote the specific accident type depicted, ranging from bike-bike accidents to car-person accidents. By encompassing such diverse scenarios, the dataset serves as a robust training and evaluation framework for developing accurate and reliable accident detection models.

4.3 Workflow

In the workflow, users open the application and upload the video. The video is then converted into frames and preprocessed to enhance quality. Feature extraction is applied, and frames are passed to the YOLO model for accident detection. Upon detection, the system extracts the timestamp associated with the accident frame, aiding in pinpointing the accident's occurrence within the video timeline. This streamlined process efficiently analyzes CCTV footage for insurance purposes or accident investigations.

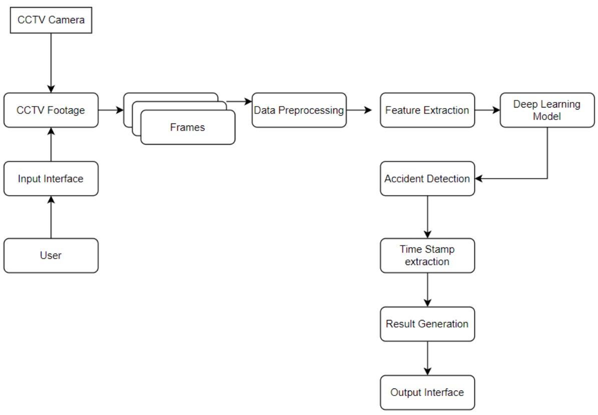

Fig. 2 Workflow diagram

5. Result and Observations

5.1 Model Evaluation

Class	Images	Instances	Box (P)	Box (R)	mAP50	mAP50-95
Bike-Bike Accident	254	14	0.456	0.571	0.423	0.248
Bike-Object Accident	254	2	1	0	0.662	0.222
Bike-Person Accident	254	9	0.498	0.667	0.633	0.292
Car	254	836	0.87	0.655	0.768	0.476
Car-Bike Accident	254	28	0.909	0.71	0.754	0.536
Car-Car Accident	254	94	0.75	0.862	0.79	0.604
Car-Object Accident	254	12	0.572	0.417	0.433	0.255
Car-Person Accident	254	4	1	0.787	0.995	0.613
Person	254	434	0.843	0.371	0.541	0.226

Table 1. Model Summary

5.2 Screenshots

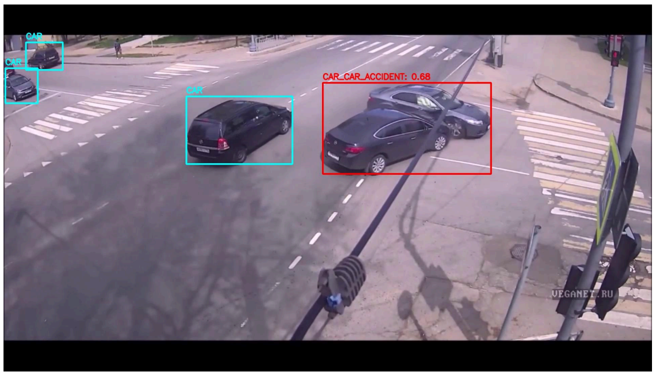

Fig 3. Accident Frame

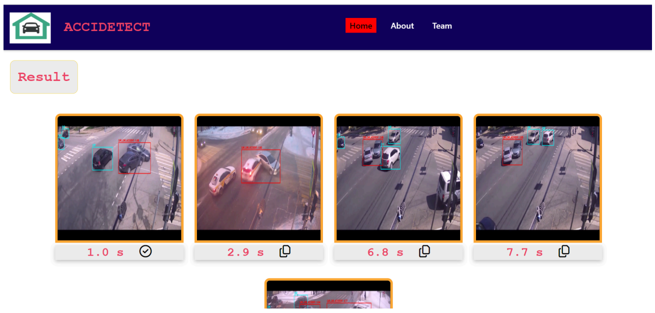

Fig 4. Accident with Timestamps

6. Conclusion:

The development of an automated road accident detection system utilizing ML and AI techniques, particularly leveraging the YOLOv8 object detection algorithm, represents a significant advancement in enhancing accident investigation processes. Through the integration of cutting-edge technologies, we have addressed the pressing need for efficient and accurate accident detection from video footage, thereby reducing the burden on insurance agents and expediting claims processing. The robustness and versatility of YOLOv8 have enabled precise timestamp extraction, revolutionizing the way accidents are identified and analyzed. Moving forward, the insights gained from this project lay the foundation for further research and development in the field of automated accident detection, with opportunities for real-time accident notification, enhanced data analytics. By embracing innovation and collaboration, we can continue to make strides towards creating safer road environments and mitigating the impact of accidents on communities and individuals.

7. Future Scope

The proposed automated road accident detection system presents significant opportunities for future research and development in several key areas:

Real-time Accident Notification: Integrating the system with real-time notification mechanisms can enhance its effectiveness in alerting relevant stakeholders, including emergency services and traffic management authorities, about accidents as they occur.

Enhanced Data Analytics: Advanced data analytics techniques can be applied to derive actionable insights from accident data, enabling stakeholders to identify high-risk areas and implement targeted interventions to prevent accidents.

Enhanced User Interface and Accessibility: Improvements in user interface design and accessibility features can enhance the usability of the system for stakeholders involved in accident investigation and claims processing.

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