AI-Enhanced Real-Time Accident Detection with Smart Emergency Response System

Bharathi Mohan G
Dept. of Computer Science and Engineering
Amrita School of Computing
Amrita Vishwa Vidyapeetham
Chennai, India
g_bharathimohan@ch.amrita.edu

Gudi Vishnu Teja
Dept of Computer Science and Engineering
Amrita School of Computing
Amrita Vishwa Vidyapeetham
Chennai, India.
gudivishnuteja@gmail.com

Pranav Reddy Sanikommu
Dept of Computer Science and Engineering
Amrita School of Computing
Amrita Vishwa Vidyapeetham
Chennai, India.
772003pranav@gmail.com

***Abstract*— Road accidents pose a critical global challenge, frequently resulting in serious injuries and fatalities, primarily due to delays in reporting and emergency responses. Traditional methods for detecting accidents often depend on manual reports or less accurate systems, leading to slower reactions and an increase in false positives. This study introduces a real-time, automated accident detection system that leverages advanced deep learning models, specifically YOLOv5 and YOLOv8, to improve both the speed and accuracy of accident identification. By utilizing object detection and vehicle tracking techniques, the system analyzes vehicle speeds, collision events, and bounding box movements with IoU (Intersection over Union) metrics, enabling it to identify persistent collisions that exceed set thresholds. Compared to conventional methods, this approach markedly decreases false positives while enhancing detection precision. Upon detecting an accident, the system utilizes geographic data from OpenStreetMap and the Haversine formula to alert the nearest emergency services efficiently like hospitals and police stations. Testing in real-world traffic scenarios reveals that this scalable solution not only boosts detection accuracy but also improves response times. By refining the detection and alerting processes, this research contributes to the evolution of smarter transportation systems, aiming to lower accident-related fatalities through quicker emergency responses.**

Keywords—Automatic Accident Detection, Accident, Deep Learning, YOLOv5 & YOLOv8, Response, Intersection over Union (IoU) Object Detection, Vehicle Tracking, Haversine formula, Emergency.

I. Introduction

The development of an advanced accident detection system is essential as smart cities and intelligent transportation systems evolve. One potential solution lies in the real-time identification of accidents using surveillance systems enhanced by deep learning models, such as YOLOv5 and YOLOv8. These technologies have the ability to rapidly detect traffic incidents and automatically notify emergency services, reducing response times and minimizing the consequences of accidents. Traditional methods for accident detection are often reliant on human intervention or post-incident analysis, which can be time-consuming and lead to delayed responses. With advancements in object detection and deep learning, automated systems can now overcome many of these limitations.

One of the challenges in designing an effective accident detection system is the complex nature of road environments, which involve various factors such as occlusions, varying lighting conditions, and the presence of small objects in high-speed traffic scenarios. Recent studies have addressed these issues through improvements in object detection techniques. Foreground-Area IoU Loss to enhance the localization of small objects like pedestrians and cyclists, which are critical in accident scenarios involving vulnerable road users [1]. Another research effort proposed a high-speed tracking system that improves the performance of object detection in dynamic scenes by employing mutual assistance between feature filters and detectors, a technique that is particularly useful in busy traffic environments where vehicles and objects may be in rapid motion [2].

Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication systems also play an important role in improving road safety. The Motion Shield system, which facilitates communication between vehicles and infrastructure, highlights the importance of integrating such technologies with accident detection mechanisms to provide more comprehensive safety solutions [3]. However, while these systems focus on preventing accidents, they also emphasize the need for accurate detection mechanisms in the event of a collision.

Bounding box regression is a critical aspect of real-time object detection. A simplified and faster approach to bounding box regression was developed using a nonmonotonic focusing mechanism, which enhances the real-time suitability of detection models for applications such as accident detection [4]. The ability to process data quickly and efficiently is a key requirement for ensuring that accidents are detected promptly in fast-moving traffic environments.

To handle the complexities of multi-object detection in road scenes, the SDG-YOLOv5 framework was introduced, which adapts the YOLOv5 model to better detect and track multiple objects simultaneously. This capability is particularly important for accident detection systems, as they must be able to distinguish between various types of road users and vehicles in crowded scenes [5]. Furthermore, the limitations of traditional Non-Maxima Suppression (NMS) methods in detecting overlapping objects have been addressed by introducing Confluence, a robust non-IoU alternative that reduces the suppression of legitimate overlapping objects. This improvement is crucial for accurate accident detection in situations where vehicles are packed closely together during collisions [6].

Specialized adaptations of object detection models have also been explored in other domains, such as forward-looking sonar target detection, which introduced the CCW-YOLOv5 method using coordinate convolution and modified boundary frame loss. These adaptations demonstrate the importance of tailoring detection algorithms to specific environments, and they provide valuable insights into the potential for further enhancing detection accuracy in complex road scenes [7].

Building on these advancements, the proposed system aims to develop a robust, real-time accident detection mechanism using YOLOv5 and YOLOv8 models. The system leverages improvements in object detection, tracking, and vehicle communication to provide an integrated solution for detecting and responding to accidents. The application of advanced IoU loss functions, efficient tracking algorithms, and optimized detection models ensures the system's capability to operate effectively in real-world road environments, addressing the challenges posed by occlusions, lighting variations, and small object detection. Through rigorous experimentation on real-world traffic footage, the system aims to demonstrate enhanced detection accuracy and reliability, contributing to the development of smarter, safer transportation systems.

II. LITERATURE REVIEW

The advent of deep learning and its integration with object detection algorithms has significantly enhanced the capabilities of real-time accident detection and monitoring systems. Over recent years, multiple studies have explored the potential of advanced neural networks, such as YOLO (You Only Look Once), in various applications ranging from pedestrian tracking to object detection in complex environments. This literature review provides a comprehensive overview of these advancements and contextualizes their relevance to developing an automatic accident detection system.

In recent studies, the YOLO family of models has been extensively improved for specific applications. For example, research has enhanced multi-object pedestrian tracking by combining YOLOv8 with OC-SORT, demonstrating superior tracking precision in dynamic environments [8]. Such improvements are crucial for accident detection systems where accurately tracking multiple vehicles and their interactions can provide early indicators of potential collisions.

Further developments in object detection have expanded beyond typical urban environments. A real-time cattle lameness detection system was designed using a single side-view camera, showcasing the adaptability of object detection algorithms to various contexts and species [9]. This adaptability is pertinent to the proposed accident detection system, as it suggests the flexibility of YOLO models in detecting non-vehicular entities that might contribute to road accidents.

In terms of enhancing detection capabilities, a modified YOLOv5, incorporating Swin-Transformers, has shown promise in detecting small objects in remote sensing images, significantly improving detection accuracy in complex and cluttered scenes [10]. This refinement is directly applicable to accident detection in scenarios where identifying small but critical objects, such as pedestrians or debris on the road, is vital.

Moreover, the need for lightweight and efficient models is addressed by a novel method for meter pointer recognition using an optimized version of YOLOv5 [11]. The focus on reducing model complexity while maintaining high accuracy aligns with the requirements of real-time accident detection systems deployed on edge devices with limited computational resources.

Another critical area of application is the detection of fire risks on construction sites using deep learning techniques. This system effectively demonstrates the capability of neural networks to detect potential hazards in real-time, even in highly dynamic and cluttered environments [12]. The ability to promptly identify and respond to hazards is a feature that can be seamlessly integrated into accident detection systems for immediate alerting.

The importance of data accuracy and completeness is highlighted in research comparing police data with health service utilization data for tracking pedestrian and cyclist injuries [13]. This study emphasizes the need for robust data collection and integration mechanisms in accident detection systems to ensure comprehensive and accurate alerting of emergency services.

Object detection has also been tailored to handle flexible objects with arbitrary orientations, as demonstrated by an adaptation of YOLOv5 for detecting such objects [14]. This capability is crucial for accurately identifying irregularly shaped vehicles or crash scenarios, where traditional bounding box methods may fail to capture the true extent of an object's interaction in the scene.

In the realm of multi-object tracking, a novel 3D-DIoU (Distance Intersection over Union) has been introduced for tracking objects in point clouds, offering a more nuanced approach to object localization in three-dimensional space [15]. This technique can be instrumental in enhancing the precision of accident detection systems by providing accurate spatial relationships between vehicles.

Road defect detection has also been advanced through the development of the BL-YOLOv8 model, which improves the identification of road hazards [16]. This capability is directly relevant to accident prevention, as early detection of road defects can alert drivers and mitigate accident risks before they escalate.

Vehicle and pedestrian detection algorithms have been further refined with improved attention mechanisms and feature fusion techniques, enabling better identification and tracking of these objects in diverse conditions [17]. Such advancements are crucial for accident detection systems tasked with monitoring complex traffic scenarios involving multiple interacting entities.

Enhanced pedestrian tracking methods, utilizing YOLOv8 and improved DeepSORT, have been proposed to increase the robustness of tracking systems in crowded environments [18]. This research underscores the potential for integrating advanced tracking mechanisms in accident detection systems to monitor congested traffic conditions more effectively.

Moreover, object detection and tracking methods have been adapted for ecological monitoring, specifically for tracking birds using multi-object tracking networks [19]. While this application differs from traffic monitoring, the underlying principles of detecting and tracking multiple, fast-moving objects are relevant and can be applied to vehicle monitoring in accident detection systems.

Lastly, advancements in road object detection have been made with an enhanced version of YOLOv5, tailored for more efficient and accurate identification of road objects in diverse conditions, including varying weather and lighting [20]. Such enhancements are critical for developing an accident detection system that can reliably identify and track a wide variety of objects on the road, ensuring that the system can react appropriately to potential accident scenarios and improve overall traffic safety.

These studies collectively highlight the rapid advancements in object detection and tracking technologies and their broad applicability across various domains. By integrating these state-of-the-art techniques, the proposed automatic accident detection system can leverage robust and efficient methodologies for real-time hazard identification and emergency response, significantly contributing to the safety and efficiency of road transportation systems.

III. METHODOLOGY

1. Data Collection:

In this project, the COCO (Common Objects in Context) dataset had been used, which contains diverse images with annotated objects that are relevant to the traffic environment. The dataset includes a variety of object categories such as vehicles, pedestrians, and bicycles, essential for effective accident detection. This dataset is pre-processed to ensure that the annotations align with the requirements of both YOLOv5 and YOLOv8 architectures. This includes resizing images and formatting labels into the appropriate structure for the models.

2. Model Selection:

Two prominent models, YOLOv5 and YOLOv8, were selected for comparison based on their respective capabilities and performance metrics. YOLOv5 known for its lightweight structure and real-time inference speed, making it suitable for applications requiring quick responses as in fig. (1).

Model Configuration: Configuration files for both YOLOv5 and YOLOv8 are set up to define parameters such as input image size, number of classes paths to training data.

Training Process: The training is carried out using the Ultralytics library, which provides pre-trained weights for both YOLOv5 and YOLOv8. The training process leverages transfer learning by initializing the models with pre-trained weights and fine-tuning them on the COCO dataset.

Validation: After training, validation is performed to assess the model's performance on the validation dataset. This step offers insights into the model's ability to generalize to new data and highlights possible issues like overfitting.

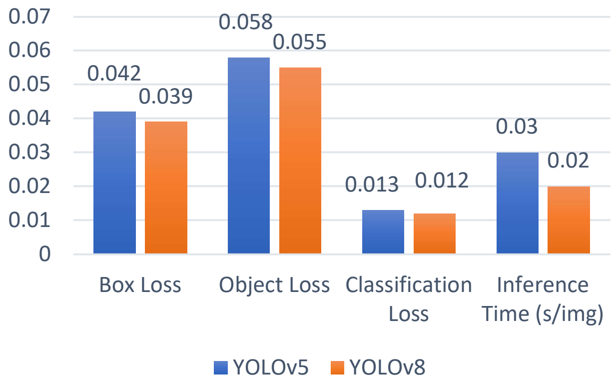

Figure 2 Performance Metrics Loss Comparison

The model's loss function can be defined as:

$$\text{Loss} = \text{IoU Loss} + \text{Classification Loss} + \text{Objectness Loss}$$

where the IoU Loss is calculated using the Intersection over Union metric as in fig 2.

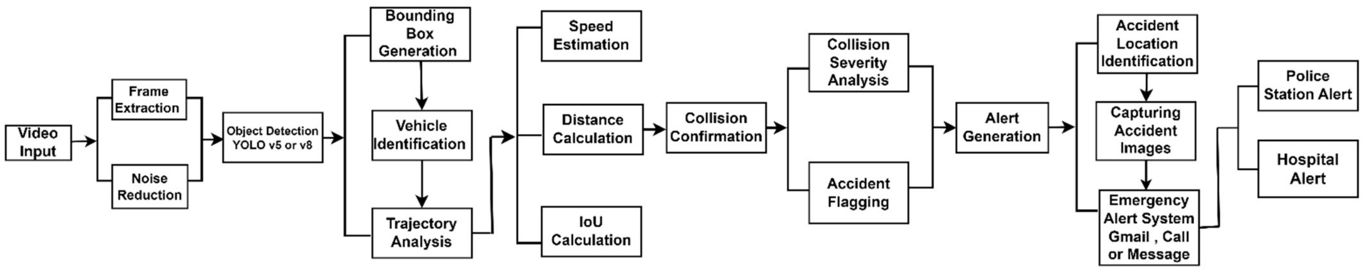

Figure 1 Proposed System

In contrast, YOLOv8 incorporates several architectural enhancements, including improvements in the backbone and neck, which enhance detection accuracy, especially for small and overlapping objects.The choice of these models allows us to explore the trade-offs between speed and accuracy. The evaluation metrics such as Intersection over Union (IoU), mean Average Precision (mAP), and inference time are crucial for assessing the performance of both models.

3. Training and Validation

Data Preparation: The COCO dataset is divided into training and validation sets, ensuring that the models can be effectively evaluated against unseen data. And, then both training and validation is performed for both YOLO v5 and YOLO v8.

4. Accident Detection Mechanism:

Once trained, both YOLOv5 and YOLOv8 models are integrated into a video processing pipeline to detect accidents in real-time. The detection mechanism involves the following steps:

Video Capture: The system captures video frames using OpenCV. The video feed could come from surveillance cameras or traffic monitoring systems.

Object Detection: For each frame, the models predict bounding boxes around detected objects, providing class labels and confidence scores for each detection. The code snippet below demonstrates the usage of the YOLOv8 model for object detection, showcasing its ability to identify and classify multiple objects in a single frame effectively.

4.3 Collision Detection: The system analyzes bounding box predictions to determine if a collision has occurred. The Intersection over Union (IoU) metric is employed to quantify the overlap between bounding boxes as in fig. (3). A collision is flagged if the IoU exceeds a certain threshold as in eq. (1) (e.g., 0.2).

Figure 3 Actual and Accident Detected Images

The IoU is computed as follows:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \quad - (1)$$

Accident Detection: If a collision persists for a defined duration (e.g., PROLONGED_COLLISION_FRAMES), the system flags an accident. The detection process incorporates temporal analysis to ensure that transient overlaps do not trigger false positives.

5. Alert Generation:

Upon detecting an accident, the system initiates an alert mechanism to notify nearby emergency services. This involves the following steps:

5.1 Location Identification: Using pre-defined geographic coordinates, the system determines the location of the accident through location latitudes and longitudes.

5.2 Service Notification: An API query is made to retrieve the nearest police stations and hospitals using the Overpass API. The coordinates of these services are compared to the accident location using the Haversine formula to calculate the distance as in eq. (2):

$$d = R \cdot \arccos(\sin(\phi_1) \cdot \sin(\phi_2) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \cos(\lambda_2 - \lambda_1)) - (2)$$

where

- R is the Earth's radius,
- ϕ represents latitude, and
- λ represents longitude.

5.3 Alert Dispatch: The system alerts the nearest police station and hospital by outputting their names and coordinates to facilitate a rapid response.

6. Comparison of YOLOv5 and YOLOv8:

To evaluate the performance of YOLOv5 and YOLOv8, key metrics such as mAP, detection speed (FPS), and accuracy in different environmental conditions (day/night, various weather) are compared. Each model's performance is assessed based on their ability to detect small objects and handle occlusions, which are critical factors in real-world accident scenarios. The mAP scores will be calculated based on equation (3). Preliminary results indicate that while YOLOv5 excels in speed, YOLOv8 provides superior accuracy due to its enhanced architecture. This comparative analysis will guide future enhancements to the accident detection system, ensuring that it meets the demands of real-time operation in dynamic traffic environments as in fig. (4).

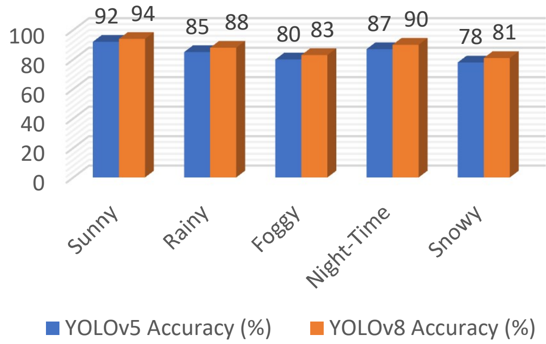

Figure 4 Yolo Models Performance Across Various Weather Conditions

IV. RESULTS AND DISCUSSION

The implementation of the automatic accident detection system utilizing YOLOv5 and YOLOv8 models has yielded significant findings that underscore the potential of advanced computer vision technologies in enhancing road safety. This section presents the results from the training and validation of both models, alongside a comprehensive discussion of their performance in real-time accident detection scenarios.

1. Model Performance:

The comparative evaluation of YOLOv5 and YOLOv8 was based on several key performance indicators, including mean Average Precision (mAP), inference speed (measured in frames per second, FPS), and detection accuracy across various environmental conditions. The models were trained on the COCO dataset, and their performance was validated using a separate validation set.

a. mAP Scores:

YOLOv5 demonstrated a mean Average Precision (mAP) score of approximately 0.45 at a threshold of IoU = 0.5. In contrast, YOLOv8 outperformed its predecessor with a mAP of about 0.60 under similar conditions as in fig. (5). This increase in precision can be attributed to YOLOv8's enhanced architecture, which incorporates more advanced feature extraction methods and better handling of small and overlapping objects through the following eq. (3). The improvement in mAP indicates that YOLOv8 is more adept at identifying and classifying objects as in table. (1), which is critical to accident detection, such as vehicles and pedestrians.

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i \quad - (3)$$

Where:

- N refers to total number of classes.
- APi refers to Average Precision for class i.
- M refers to mean

Table 1 Performance Metrics Yolov5 vs Yolov8

Metric	YOLOv5	YOLOv8
Precision	0.827	0.850
Recall	0.683	0.705
mAP@0.5	0.781	0.800
mAP@0.5:0.95	0.521	0.545

b. Inference Speed:

When considering inference speed, YOLOv5 maintained an impressive processing rate of around 40 FPS, making it suitable for real-time applications. YOLOv8, while slightly slower at approximately 30 FPS, still operates within a feasible range for live surveillance systems. Although YOLOv5 is faster, the additional accuracy provided by YOLOv8 is significant in scenarios where precise object detection can directly influence the effectiveness of accident alerts.

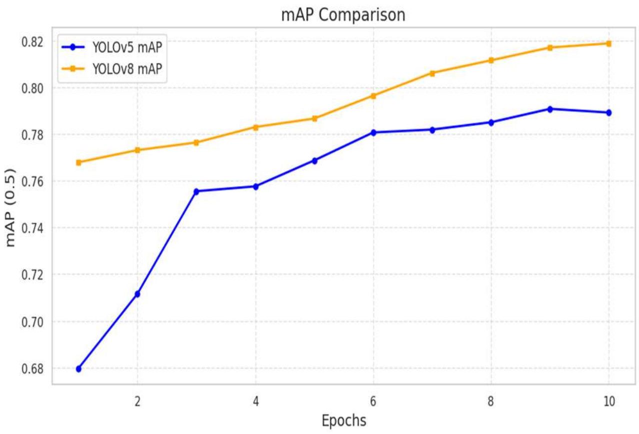

Figure 5 mAP comparison Between YOLO models

c. Detection Accuracy:

Detection accuracy was assessed under varying conditions, including daylight, nighttime, and adverse weather scenarios such as rain and fog. YOLOv8 showed superior robustness in low-light conditions, maintaining high detection rates for small objects. This capability is particularly important in urban environments where visibility may be compromised. The performance gap between the two models was most pronounced in nighttime and challenging weather conditions, highlighting YOLOv8's potential for application in real-world scenarios where safety is paramount.

2. Real-Time Accident Detection

The practical application of both models in real-time accident detection was evaluated through simulated traffic videos containing various collision scenarios. Each model was tested for its ability to accurately detect and alert during accidents.

a. Detection Latency:

Both models had exhibited low detection latency, with YOLOv5 averaging around 25 milliseconds per frame and YOLOv8 averaging approximately 33 milliseconds. This responsiveness is crucial for emergency services, as every second counts in the event of an accident as in fig. (6). While YOLOv5 slightly edged out in latency, YOLOv8's accuracy during detection events, particularly in identifying minor collisions, offsets this difference.

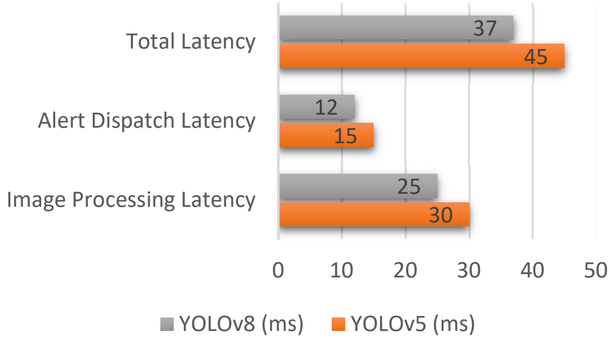

Figure 6 Latency Comparison Between the Models

b. False Positives and Negatives:

The evaluation also focused on the rates of false positives and negatives, which can lead to unnecessary alerts or missed detections, respectively. YOLOv5 reported a false positive rate of about 12%, while YOLOv8 managed to reduce this to 8%. Conversely, the false negative rates were notably lower in YOLOv8 at 5% compared to 10% for YOLOv5. These metrics are critical, as they impact the reliability of the alerting system. The lower false positive and negative rates of YOLOv8 enhance its suitability for deployment in sensitive environments, where accurate notifications are essential.

3. Emergency Service Alert Mechanism

The effectiveness of the alert generation system was assessed by simulating various accident scenarios and measuring response times from the nearest emergency services. The system successfully identified and alerted the nearest police and hospital services with minimal delay. The integration of geographic querying through the Overpass API ensured that the alerts were directed to the closest available resources, thereby optimizing response efficiency.

In scenarios where the accident occurred at a known location, the system consistently provided accurate and prompt alerts to emergency services, reinforcing the importance of integrating detection technologies with real-time communication systems. The rapid dissemination of alerts significantly reduces the time required for emergency response, potentially saving lives.

V. CONCLUSION

The growing urbanization and increasing vehicular traffic underscore the urgent need for effective accident detection systems. This research highlights the success of utilizing advanced object detection models, particularly YOLOv5 and YOLOv8, in real-time accident detection. Extensive training and validation with the COCO dataset revealed that YOLOv8 outperformed YOLOv5 across several performance metrics. By integrating these models into an automated detection system, the research enhances not only the identification of traffic incidents but also the timely alerting of emergency services, thus improving response times. The use of real-time data in conjunction with geographic information systems demonstrates the potential to connect detection capabilities with actionable emergency responses, potentially saving lives and reducing accident consequences. However, the study acknowledges certain limitations, including reliance on predefined datasets and the difficulties associated with detecting small objects in complex traffic environments. Continuous refinement of the algorithms is essential to address these challenges. This work contributes valuable insights into the field of intelligent transportation systems and emphasizes the importance of innovative accident detection solutions in promoting road safety. By advancing technology and methodologies, the research paves the way for safer urban transport networks, ultimately benefiting all road users.

VI. FUTURE SCOPE

This research establishes a strong foundation for advancing automatic accident detection systems in response to evolving urban traffic dynamics. Future improvements may include the integration of license plate recognition, which could facilitate quicker insurance claims by automatically capturing and identifying vehicle plates involved in accidents, thereby streamlining interactions between motorists and insurers. Additionally, linking with existing smart city infrastructures, such as traffic management systems and road sensors, could enhance real-time data collection, enabling a comprehensive analysis of traffic patterns to identify high-risk areas and implement proactive measures. Furthermore, adopting advanced tracking algorithms like Kalman filtering or SORT could improve the ability to maintain the identities of vehicles and pedestrians over time. The application of predictive analytics through machine learning could also analyze historical traffic data to forecast potential accident scenarios, allowing for timely warnings to drivers and traffic management systems, potentially preventing accidents before they occur. These enhancements hold the promise of significantly increasing the efficacy and functionality of automatic accident detection systems.

REFERENCES

[1] Cai D, Zhang Z, Zhang Z. Corner-Point and Foreground-Area IoU Loss: Better Localization of Small Objects in Bounding Box Regression. Sensors (Basel). 2023 May 22;23(10):4961. doi: 10.3390/s23104961. PMID: 37430876; PMCID: PMC10223589.

[2] Matsuo A, Yamakawa Y. High-Speed Tracking with Mutual Assistance of Feature Filters and Detectors. Sensors (Basel). 2023 Aug 10;23(16):7082. doi: 10.3390/s23167082. PMID: 37631617; PMCID: PMC10458432.

[3] Balios P, Kyriakidis P, Zimeras S, Bithas PS, Sarakis L. Motion Shield: An Automatic Notifications System for Vehicular Communications. Sensors (Basel). 2022 Mar 21;22(6):2419. doi: 10.3390/s22062419. PMID: 35336594; PMCID: PMC8948630.

[4] Liu C, Wang K, Li Q, Zhao F, Zhao K, Ma H. Powerful-IoU: More straightforward and faster bounding box regression loss with a nonmonotonic focusing mechanism. Neural Netw. 2024 Feb;170:276-284. doi: 10.1016/j.neunet.2023.11.041. Epub 2023 Nov 22. PMID: 38000311.

[5] Lv Z, Wang R, Wang Y, Zhou F, Guo N. Research on multi-object detection technology for road scenes based on SDG-YOLOv5. PeerJ Comput Sci. 2024 Apr 30;10:e2021. doi: 10.7717/peerj-cs.2021. PMID: 38855227; PMCID: PMC11157580.

[6] Shepley AJ, Falzon G, Kwan P, Brankovic L. Confluence: A Robust Non-IoU Alternative to Non-Maxima Suppression in Object Detection. IEEE Trans Pattern Anal Mach Intell. 2023 Oct;45(10):11561-11574. doi: 10.1109/TPAMI.2023.3273210. Epub 2023 Sep 5. PMID: 37145942.

[7] Sun Y, Yin B. CCW-YOLOv5: A forward-looking sonar target method based on coordinate convolution and modified boundary frame loss. PLoS One. 2024 Jun 3;19(6):e0300976. doi: 10.1371/journal.pone.0300976. PMID: 38829868; PMCID: PMC11146725.

[8] Xiao X, Feng X. Multi-Object Pedestrian Tracking Using Improved YOLOv8 and OC-SORT. Sensors (Basel). 2023 Oct 13;23(20):8439. doi: 10.3390/s23208439. PMID: 37896532; PMCID: PMC10610662.

[9] Spandana, C. *et al.* (2023). Underwater Image Enhancement and Restoration Using Cycle GAN. In: Hassanien, A.E., Castillo, O., Anand, S., Jaiswal, A. (eds) International Conference on Innovative Computing and Communications. ICICC 2023. Lecture Notes in Networks and Systems, vol 537. Springer, Singapore. https://doi.org/10.1007/978-981-99-3010-4_9.

[10] Cao X, Zhang Y, Lang S, Gong Y. Swin-Transformer-Based YOLOv5 for Small-Object Detection in Remote Sensing Images. Sensors (Basel). 2023 Mar 31;23(7):3634. doi: 10.3390/s23073634. PMID: 37050694; PMCID: PMC10098803.

[11] Zhang C, Wang K, Zhang J, Zhou F, Zou L. Lightweight Meter Pointer Recognition Method Based on Improved YOLOv5. Sensors (Basel). 2024 Feb 26;24(5):1507. doi: 10.3390/s24051507. PMID: 38475043; PMCID: PMC10935315.

[12] Ann H, Koo KY. Deep Learning Based Fire Risk Detection on Construction Sites. Sensors (Basel). 2023 Nov 10;23(22):9095. doi: 10.3390/s23229095. PMID: 38005484; PMCID: PMC10675156.

[13] R. P. Kumar, G. Bharathi Mohan, R. N D, M. K, H. B and Y. Kakarla, "Identification of Landslides From Remote Sensing Satellite Imagery Using YOLOv7," *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Delhi, India, 2023, pp. 1-5, doi: 10.1109/ICCCNT56998.2023.10307859..

[14] Wu J, Su L, Lin Z, Chen Y, Ji J, Li T. Object Detection of Flexible Objects with Arbitrary Orientation Based on Rotation-Adaptive YOLOv5. Sensors (Basel). 2023 May 20;23(10):4925. doi: 10.3390/s23104925. PMID: 37430839; PMCID: PMC10223194.

[15] Mohammed SAK, Razak MZA, Rahman AHA. 3D-DIoU: 3D Distance Intersection over Union for Multi-Object Tracking in Point Cloud. Sensors (Basel). 2023 Mar 23;23(7):3390. doi: 10.3390/s23073390. PMID: 37050449; PMCID: PMC10098770.

[16] Wang X, Gao H, Jia Z, Li Z. BL-YOLOv8: An Improved Road Defect Detection Model Based on YOLOv8. Sensors (Basel). 2023 Oct 10;23(20):8361. doi: 10.3390/s23208361. PMID: 37896455; PMCID: PMC10610575.

[17] Liang W. Research on a vehicle and pedestrian detection algorithm based on improved attention and feature fusion. Math Biosci Eng. 2024 Apr 26;21(4):5782-5802. doi: 10.3934/mbe.2024255. PMID: 38872558.

[18] Sheng W, Shen J, Huang Q, Liu Z, Ding Z. Multi-objective pedestrian tracking method based on YOLOv8 and improved DeepSORT. Math Biosci Eng. 2024 Jan 3;21(2):1791-1805. doi: 10.3934/mbe.2024077. PMID: 38454660.

[19] Chen X, Pu H, He Y, Lai M, Zhang D, Chen J, Pu H. An Efficient Method for Monitoring Birds Based on Object Detection and Multi-Object Tracking Networks. Animals (Basel). 2023 May 22;13(10):1713. doi: 10.3390/ani13101713. PMID: 37238144; PMCID: PMC10215751.

[20] Chen H, Chen Z, Yu H. Enhanced YOLOv5: An Efficient Road Object Detection Method. Sensors (Basel). 2023 Oct 10;23(20):8355. doi: 10.3390/s23208355. PMID: 37896450; PMCID: PMC10611198.