International Journal of Scientific Research in Science and Technology
Available online at : www.ijsrst.com
Print ISSN: 2395-6011 | Online ISSN: 2395-602X
doi : https://doi.org/10.32628/IJSRST

Crash Sense: Motor Vehicle Collision Detection and Severity Prediction

Mrs. Beena A.I[1], Amina Ashraf[2], Anu Anna Baby[2], Elsa Anju Siby[2]

[1]Assistant Professor, Department of Computer Science and Engineering, Viswajyothi College of Engineering and Technology, Vazhakulam, Kerala, India

[2]Department of Computer Science and Engineering, Viswajyothi College of Engineering and Technology, Vazhakulam, Kerala, India

ARTICLEINFO

Article History:
Published : 05 April 2025

Publication Issue :
Volume 12, Issue 12
March-April-2025

Page Number :
167-178

ABSTRACT

Road accidents are a major public safety concern, often leading to severe injuries or fatalities. In many cases, immediate medical attention within the golden hour is critical for saving lives. However, accidents in remote areas or situations where the driver is unconscious may result in delayed emergency response. To address this issue, this paper presents CrashSense, a deep learning-powered accident detection and severity prediction system. CrashSense integrates real-time video-based accident detection, automatic number plate recognition (ANPR), and severity classification using machine learning. The system consists of a Flutter-based web application, a YOLOv8-based accident detection model, an OCR-based ANPR module, and YOLOv8 for severity prediction. When an accident is detected, the system extracts vehicle registration details and classifies accident severity based on multiple factors, such as vehicle speed, road type, and environmental conditions. The experimental results demonstrate that the accident detection model achieves an accuracy of 92%, while the severity classification model reaches 91% accuracy. These findings suggest that CrashSense can serve as an efficient tool for enhancing road safety and emergency response efficiency.

Index Terms—Accident Detection, Severity Prediction, Com- puter Vision, Machine Learning, YOLOv8, CNN, Road Safety, Real-time Alert System.

INTRODUCTION

Road traffic accidents are a universal problem, resulting in injuries, deaths, and financial losses. With growing urbaniza- tion and car usage, advanced accident detection and emergency response systems are essential. Conventional surveillance em- phasizes traffic observation but does not provide real-time accident detection and severity evaluation. This paper presents a CCTV Collision Alert System based on real-time video surveillance, machine learning, and deep learning that identi- fies accidents, rates severity, and sends immediate alerts. With YOLO-based object detection and deep learning algorithms, the system automatically detects collisions, determines impact force, and provides license plate recognition and pedestrian detection support to aid law enforcement and insurance or- ganizations in intelligent traffic management. While it has advantages, challenges are variations in CCTV quality, compu- tational intensity, and environmental interference on accuracy. Real-time processing requires efficient hardware and exten- sive annotated datasets for deep learning training. Interoper- ability with existing traffic systems means coordination with stakeholders. Improving accuracy and scalability will come from future breakthroughs in AI, video analytics, and self- supervised learning. GPS and vehicle telemetry will further enhance detection. Mass adoption of AI can revolutionize road safety, minimize response times, and maximize traffic management. The paper is organized as follows: Section 2 discusses related works, Section 3 explains the system archi- tecture, Section 4 compares CNN, and YOLOv8 models, and Section 5 concludes with results and future work.

RELATED WORKS

Numerous studies have been conducted to find innovative techniques for detecting car accidents and determining ac- cident severity. Such methods use machine learning, deep learning, and computer vision in order to make road safety systems better.

The Deep Hybrid Attention Network (DHAN) [1] improves emergency response to road crashes by combining spatial and temporal attention mechanisms. It was trained on a French crash dataset (2011–2017) and attained an AUC of 0.820 and 76.1% accuracy, which is effective for real-time detection. Its single-dataset limitation restricts generalizability, and the lack of weather and road condition information lowers predictive accuracy. Future enhancements should include diverse datasets and multi-modal sources to improve adaptability.

A multi-level distillation approach [2] enhances fine-grained accident detection in videos by using a teacher-student net- work for efficient knowledge transfer. It tackles sparse and irregular video data through accident classification, spatial- temporal detection, and severity estimation. Experiments on the FAD dataset (1,603 videos) showed improved accuracy and efficiency. However, the method is resource-intensive and depends on the teacher model's quality, highlighting the need for optimization for wider deployment.

A deep learning ensemble method [3] improves real-time traffic accident detection in smart cities by combining RGB and optical flow information. Employing a dual-branch struc- ture with I3D and ConvLSTM, it preserves spatial and motion dynamics for accuracy improvement. Built for edge IoT de- ployment, it is cost-effective and scalable. Evaluated on Traffic Camera and Dash Camera datasets, the model demonstrated excellent performance but is dependent on high-quality video data, restricting its use in low-resolution or resource-limited environments.

A machine learning framework [4] automates accident detection, segmentation, and duration prediction to improve traffic management. It uses PeMS and CTADS data to analyze traffic patterns with Chebyshev and Wasserstein metrics, and Random Forest and CatBoost predict accident duration. Seg- mentation enhances accuracy but is hampered by scalability due to high computational requirements and data format incon- sistencies, which makes more flexible frameworks necessary. A collision risk assessment model [5] improves vehicle safety by approximating risks at low, moderate, and high intensities using Extended Kalman Filtering (EKF) and proba- bilistic motion estimation. It enhances autonomous and driver- assisted decision risk prediction but is hindered in real-time application by high computational requirements and depen- dence on quality sensor information. An AI-based optimiza- tion approach can mitigate computational costs and enhance efficiency. Also, fusing information from multiple sensors and external sources can improve accuracy in various driving conditions.

A survey of accident detection [6] techniques based on dash- cam videos classifies methods into supervised, self-supervised, and unsupervised methods. Techniques such as GANs and Mask-RCNN identify anomalies based on reconstruction er- rors, improving real-time accident detection for autonomous vehicles. Although increasing dashcam data enhances model training, high computational requirements, dataset imbalance, and video quality sensitivity restrict scalability in dynamic settings.

An appearance-motion network [7] improves crash detection in dense traffic by integrating spatial and motion-based fea- tures. It utilizes a two-stream architecture where an auxiliary network with triplet loss differentiates crashes from visually similar non-crash events, while an optical flow learner captures fine-grained motion details. A temporal attention module enhances detection accuracy by focusing on critical frames, re- ducing false alarms by 28.07% and missed crashes by 27.08%. Despite its effectiveness, the model depends on fixed camera angles and performs best in urban environments, limiting its adaptability to rural areas and high-speed roadways.

A multimodal self-supervised crash detection system [8] for accurate crash and severity detection employs deep learning using IMU and GPS sensor modalities. It combines convolu- tional layers for feature extraction with bidirectional GRUs for temporal analysis and delivers good precision (0.9 for crash detection, 0.76 for severity classification). Its performance is compromised under harsh conditions such as rough ground or extreme high-speed maneuvers.

A data-driven method [9] predicts crash risk during lane- changing maneuvers based on real-world traffic data. It uses Gaussian mixture modeling to detect traffic regimes and a crash severity indicator (CRIM) to measure collision impact. Based on the highD dataset and drone video, the research shows that lane-changing behavior, particularly in heavy traffic conditions, has a substantial effect on crash risk. Although the approach improves risk prediction precision, its computa- tionally intensive nature and limited application to urban road networks emphasize the necessity for further development to suit varied traffic conditions.

An automated system [10] predicts the severity of road traffic accidents based on transformer-based models such as EfficientNet and MobileNet, incorporating Shapley values for explainability. MobileNet was the most accurate (98.17%), but explaining deep learning processes remains a challenge for stakeholders. The research calls for striking a balance between accuracy and explainability for successful road safety deployment.

These researches evolve crash detection and severity es- timation to form CRASHSENSE, combining AI and real- time video processing to enhance accuracy and responsiveness. While detection is enhanced with deep learning models, these encounter limitations of datasets, increased computation, and scalability. Segmentation is facilitated by machine learning but suffers when faced with huge datasets, while collision risk models ensure higher accuracy at the expense of real-time implementation. Detection by vision does not offer flexibility, and transformer models require interpretability improvement. Optimizing resources, maximizing flexibility, and fusing mul- timodal data are essential to scalable road safety solutions.

As discussed in the literature survey (see Table 1), various approaches have been proposed for accident detection and severity prediction.

TABLE I TECHNIQUES, MERITS, AND DEMERITS OF VARIOUS ACCIDENT DETECTION SYSTEMS

Title	Techniques	Merits	Demerits
”Deep Hybrid Attention Frame- work for Road Crash Emergency Response Management (2024)”, Mohammad Tamim Kashif [1]	Deep Hybrid Attention Network (DHAN), LSTM (Long Short-Term Memory), Attention Mechanism	Timely EMS Dispatch, Hybrid Deep Learning Model, Practical Data Requirements	Focus on Location and Time, Com- putational Complexity
”Smart City Transportation: Deep Learning Ensemble Approach for Traffic Accident Detection (2024)”, V. A. Adewopo, N. Elsayed [2]	I3D (Inflated 3D Convolutional Neural Network), CONVLSTM2D (Convolu- tional LSTM), Trainable RGB + Opti- cal Flow Model	Comprehensive Approach, Real- Time Detection, High Sensitivity to Motion, Environmental Variability	Latency, Computational Load
”Multiple-Level Distillation for Video Fine-Grained Accident Detection (2024)”, Hongyang Yu, Xinfeng Zhang, Yaowei Wang, Qingming Huang, Baocai Yin [3]	Knowledge Distillation, Multi-Level Distillation	Enhanced Detection Accuracy, Multi-Task Learning	Dependence on Teacher Model, Generalization to Different Scenar- ios
”An Appearance-Motion Network for Vision-Based Crash Detection: Improving the Accuracy in Con- gested Traffic (2023)”, Wei Zhou, Chen Wang [4]	Appearance Network, Motion Network	Superior Accuracy, Improved Fea- ture Extraction, Reduced False Alarms	Complexity, Dependency on Fixed Camera Angles, Real-Time Imple- mentation
”Deep Crash Detection from Ve- hicular Sensor Data with Mul- timodal Self-Supervision (2022)”, Luca Kubin, Matteo Simoncini [5]	Novel Deep Learning Model from IMU and GPS Speed	Robust Feature Extraction, Effec- tive Data Augmentation	Complexity, High Computational Resources, Dependency on Data Quality
”Crash Risk Estimation Due to Lane Changing: A Data-Driven Approach Using	Traffic Regime Identification, Crash Risk Estimation	Granular Analysis of Risk, Flexi- bility in Clustering Approaches	Complexity in Risk Evaluation, Dependency on Accurate Cluster- ing

Title	Techniques	Merits	Demerits
Naturalistic Data (2022)", Vishal Mahajan, Christos Katrakazas [6]			
"Review of Accident Detection Methods Using Dashcam Videos for Autonomous Driving Vehicles (2024)", Arash Rocky, Qingming Jonathan Wu, Wandong Zhang [7]	Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Object Tracking Algorithms	Incident Classification, Focus on Real-Time Accident Detection, Emphasis on Driver Behavior Analysis	Dependence on Human Annotation for Labeling, Limited Context in Short Video Clips, Sensitivity to Environmental Factors
"Automatic Accident Detection, Segmentation, and Duration Pre- diction Using Machine Learning (2024)", Artur Grigorev, Adriana-Simona Mih, Khaled Saleh, Fang Chen [8]	Vehicle Detection System, Automatic Number Plate Recognition (ANPR), Traffic Flow Analysis, Incident Detec- tion	Quick Alerts, High Accuracy, Less Manual Work, Easily Expandable	Needs Lots of Data, High Resource Use, Mistakes Possible, Complex Setup, Costly
"Collision Risk Assessment for Intelligent Vehicles Considering Multi-Dimensional Uncertainties (2024)", Zhenhai Gao, Mingxi Bao, Taisong Cui [9]	Multi-Dimensional Uncertainties CRA, Extended Kalman Filter, Trajectory Prediction Models	Better Predictions, Considers Driver Behavior, Error Correction, Useful for Real- World Applications	Complex to Implement, Relies on Assumptions, Need for More Test- ing, High Computational Demand

PROPOSED SYSTEM

The fig.1. shows the architecture diagram of the proposed system:

To enhance the survival rate of accident victims, particularly in head-on and single-vehicle high-speed collisions, this paper proposes an advanced deep learning-based intelligent system, CrashSense, aimed at immediate and accurate detection of such accidents. The CrashSense system is designed to function in real-time, leveraging cutting-edge AI and machine learning models to automatically recognize high-speed collisions as they occur. By utilizing deep learning algorithms and state-of- the-art object detection methods like YOLOv8, the system can accurately identify the type of collision and assess its severity almost instantaneously. This rapid detection is crucial, as it triggers an automated emergency notification system that alerts nearby hospitals, law enforcement, and rescue services within the critical golden window following an accident. The system's capabilities go beyond mere detection; it processes accident data, including visual, textual, and sensor-based inputs, to generate a comprehensive assessment of the collision. Once an accident is detected and classified, the system automatically uploads relevant accident information to a cloud-based service platform, which stores and organizes the data for further analysis. Additionally, it triggers emergency alerts to first responders, ensuring that rescue services are deployed swiftly and efficiently. This intelligent and automated framework not only aims to minimize the response time in critical situations but also integrates seamlessly with other emergency systems to provide a robust, scalable solution to road safety. The Crash- Sense system is a proactive step toward improving emergency response times, reducing fatalities, and enhancing the overall safety of road networks.

METHODOLOGY

1) **DATASET:** To build a robust system capable of real- time accident detection and severity prediction, CrashSense utilizes several carefully selected datasets:

1.1 **Accident Collision Dataset:** The CrashSense system uses a publicly available dataset containing real-world footage of road accidents, primarily sourced from dashcams and surveillance cameras. This dataset serves as the foundation for training the YOLOv8 model for accurate detection of accident scenarios. The footage includes various types of accidents, such as collisions, vehicle rollovers, and more, enabling the model to learn diverse accident patterns in real-world settings. Dataset Link: Accident Detection from CCTV Footage

1.2 **Number Plate Dataset :** A dedicated dataset con- taining images of vehicle license plates was used to train an Optical Character Recognition (OCR)-based Automatic Number Plate Recognition (ANPR) system. This dataset is crucial for identifying vehicle information post-collision, such as the vehicle's registration number, which helps in processing data and potentially identifying involved parties. Dataset Link: Vehicle Registration Plates (Truck)

1.3 **Severity Prediction Dataset :** To predict the sever- ity of accidents, CrashSense employs a dataset containing accident records with a wide range of features, including vehicle speed, impact force, road conditions, and weather. This dataset is used to train YOLOv8, which classifies accidents based on their severity—low, medium, or high. Accurate severity predictions are vital for informing emergency response services about the urgency and scale of the collision. Dataset Link: Road Traffic Accidents

2) **DATA PREPROCESSING:** Data preprocessing plays a crucial role in transforming raw data into a usable form for model analysis and training. This step ensures that the data is clean, well-organized, and ready for processing, directly influencing the accuracy of model predictions. The prepro- cessing process in this study incorporates various techniques, including data cleaning, augmentation, feature selection, and addressing data imbalance, all of which contribute to enhanc- ing model performance and ensuring the data's suitability for deep learning tasks.

2.1. **Image Preprocessing:** Preprocessing is an important step in getting accident and vehicle number plate images ready for training deep learning models. For consistency and compatibility, all images are resized to a standard dimension so that the model can process them effectively. It is impor- tant to standardize image sizes to ensure input uniformity throughout the dataset to avoid inconsistencies that may affect model performance.To further improve the training process, several image augmentation methods are used to enhance data diversity and avoid overfitting. Rescaling is used to ensure images conform to the model's input needs proportionally, and shear transformations adjust image angles to enable the model to cope with minor differences in perspective. Second, hori- zontal flipping produces mirror images, allowing the model to learn from various perspectives and enhance its capacity to generalize over a wide range of real-world situations. Such augmentation methods overall lead to a stronger and better deep learning model for accident detection and vehicle identification.

2.2. Preprocessing for Severity Prediction Dataset: For severity prediction, preprocessing begins with missing value removal and duplicate record removal to ensure data integrity and eliminate biases. Exploratory Data Analysis (EDA) assists in pattern and relationship identification, influencing feature selection to achieve the best model performance.

Chi-square ($\chi 2$) tests to choose the most significant features, discarding duplicate variables. For dataset balancing, SMOTE creates synthetic samples for minority classes in order to carry out learning with balanced datasets. These pre- processing steps—data cleansing, feature selection, and bal- ancing—improve efficiency of the model, enhancing accident detection and severity prediction accuracy.

$\chi 2 = \Sigma$ (Oi – Ei)

Ei

where: $\chi 2$ = Chi-squared statistic Oi = Observed value Ei = Expected value

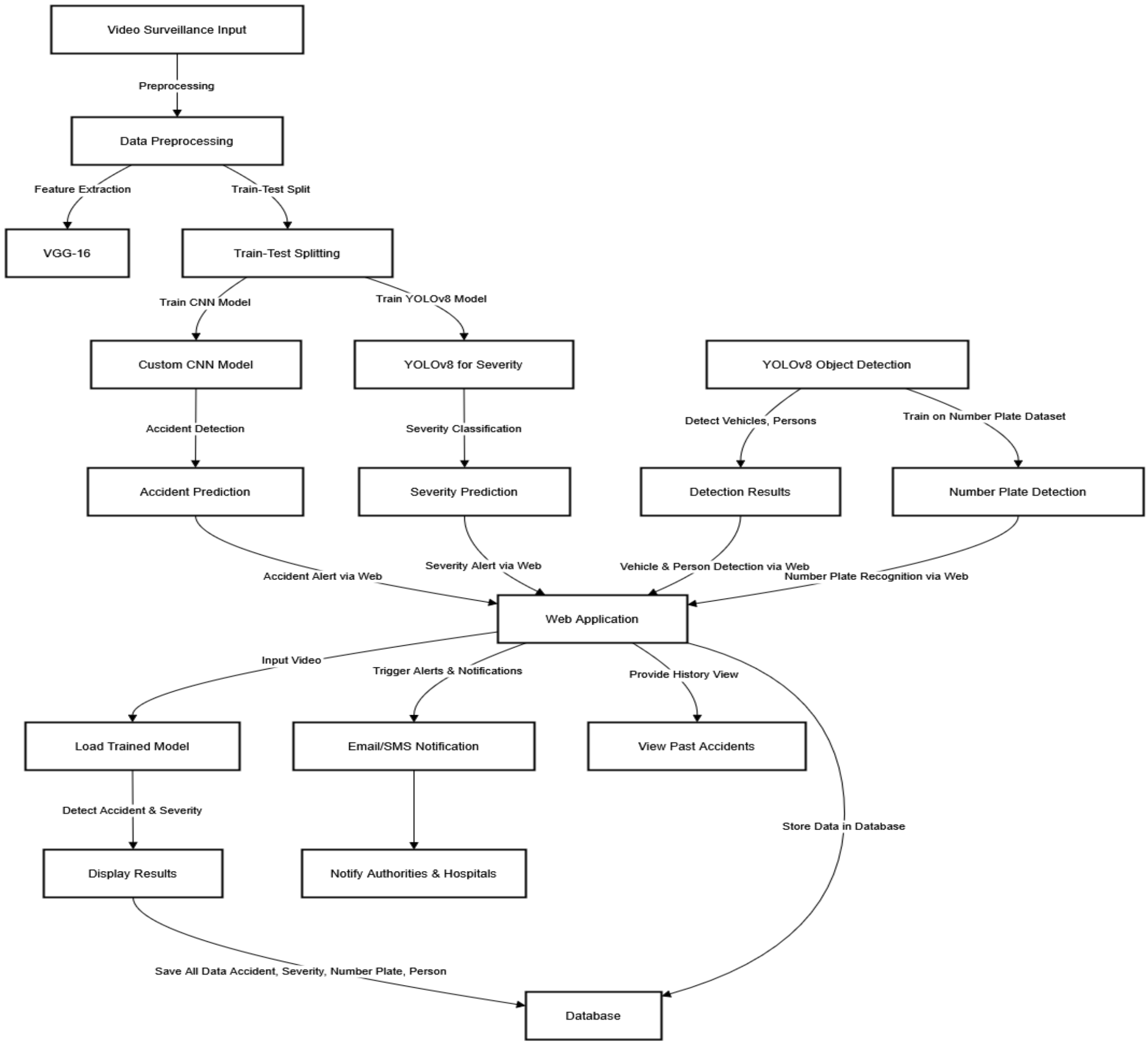

Fig. 1. Architecture diagram of CRASHSENSE

3) **MODEL TRAINING LAYER:** The Model Training Layer is a crucial component of the CrashSense system, where various deep learning models are trained to perform specific tasks. These models are essential for accident detection, severity prediction, and object recognition. Below, each sub-section elaborates on the specific models and the training process used in this layer.

Algorithm 1 Collision Detection Using VGG-16 and CNN

1) **Import Libraries**
   - Import TensorFlow, Keras, OpenCV, NumPy.
   - Load the VGG-16 model.
2) **Preprocess Frames**
   - Extract frames from the video.
   - Resize frames to 224×224.
   - Normalize pixel values.
3) **Feature Extraction with VGG-16**
   - Pass frames through VGG-16.
   - Extract features from the convolutional layers.
4) **Define CNN Model**
   - Use extracted features as input.
   - Add convolutional, pooling, and fully connected layers.
   - Use an activation function to classify results.
5) **Compile and Train the Model**
   - Use an optimizer like Adam.
   - Train with labeled accident and non-accident im- ages.
6) **Collision Detection**
   - Process incoming video frames.
   - Extract features and classify them.
   - If the probability is low, an accident is detected.
7) **Display Results**
   - Show predictions on the video.
   - Trigger alerts if an accident is detected.

Algorithm 2 Object and Collision Detection Using YOLOv8

1) **Prepare Dataset**
   - Collect and label road images.
   - Convert labels to YOLO format.
   - Split dataset into train, validation, and test sets.
2) **Train YOLOv8 Model**
   - Set training parameters (epochs, image size, batch size).
   - Train the model using labeled data.
3) **Object Detection**
   - Load a test image.
   - Run YOLOv8 to detect objects.

- Draw bounding boxes around detected objects.

4) **Real-Time Detection**
   - Capture video from a camera.
   - Process each frame and detect objects.
   - Display detected objects on the screen.
5) **Collision Detection**
   - Analyze detected objects for potential collisions.
   - Trigger alerts if a collision is detected.

Algorithm 3 Severity Prediction Using YOLOv8

1) **Setup Environment**
   - Install dependencies and import required libraries.
   - Load the YOLOv8 model.
2) **Prepare Dataset**
   - Convert images to YOLO format.
   - Split data into training, validation, and test sets.
3) **Train Model**
   - Set training parameters (epochs, image size, batch size).
   - Train the model using labeled data.
4) **Validate Model**
   - Evaluate performance on validation data.
5) **Detect Accidents**
   - Load an image or video frame.
   - Run YOLOv8 to detect accidents.
   - Draw bounding boxes on detected objects.
6) **Real-Time Detection**
   - Capture live video and process frames.
   - Perform inference and display results.
7) **Classify Severity**
   - Analyze confidence scores to determine severity.
   - Display severity label (Minor, Moderate, Severe).
8) **Trigger Alerts**
   - Store accident details and send alerts if severity is high.
9) **Exit Program**
   - Release video and close frames.

Algorithm 4 Web Application Module

1) **User Authentication**
   - Login and validate credentials. Redirect to dash- board or show error.
2) **Video Upload**
   - Upload video, validate file format, store in database.
3) **Accident & Severity Detection**
   - Load model, extract video frames, preprocess and detect accidents.

- If accident, classify severity using YOLOv8 and store results.

4) **Alert System**
   - If severity ¿ threshold, send email alert and show notification.
5) **History Page**
   - Display previous records with search functionality.
6) **Web Interface**
   - Render results dynamically using HTML, CSS, JS, AJAX.
7) **Exit and Cleanup**
   - Close database connections, release resources.

PERFORMANCE ANALYSIS AND EVALUATION

TABLE II MODEL PERFORMANCE METRICS OVER EPOCHS

Epochs	Training Accuracy (%)	Validation Accuracy (%)
5	72.4	75.8
10	80.6	83.2
15	85.7	88.4
20	89.3	90.1
25	91.5	92.8
30	92.6	93.75

Table II presents the training and validation accuracy at different epochs, highlighting the model's learning progress. Initially, at epoch 5, the model achieved a training accuracy of 72.4% and a validation accuracy of 75.8%, indicating that it was effectively learning features from the dataset. As training progressed, the accuracy steadily improved. By epoch 15, the model surpassed 85% accuracy in both training and validation, demonstrating effective generalization.

By epoch 25, the validation accuracy reached 92.8%, show- ing significant improvement. However, in the final epochs, the rate of accuracy increase slowed, and the validation accuracy plateaued at 93.75% at epoch 30. The logs (Table 1) confirm that validation accuracy did not improve beyond this point, suggesting that the model had reached its peak performance. The performance of the proposed model was evaluated based on training and validation accuracy trends over multiple epochs. Figure 2 illustrates the accuracy progression, providing insights into how well the model learned from the dataset.

Initially, at epoch 5, the model achieved a training accuracy of 72.4% and a validation accuracy of 75.8%, showing rapid improvement in early learning stages. The validation accuracy surpassed 85% by epoch 15, indicating strong generalization capabilities. The learning curve continued to rise, reaching a peak validation accuracy of 93.75% at epoch 30, as seen in Figure 2. The plot in Figure 2 demonstrates a consistent upward trend, with validation accuracy closely following the training accuracy. Minor fluctuations indicate natural varia- tions in the dataset but do not suggest overfitting, as both accuracies improve together. This confirms that the model effectively captures patterns in collision data without excessive bias toward training samples.

Fig. 2. Training and Validation Accuracy Graph

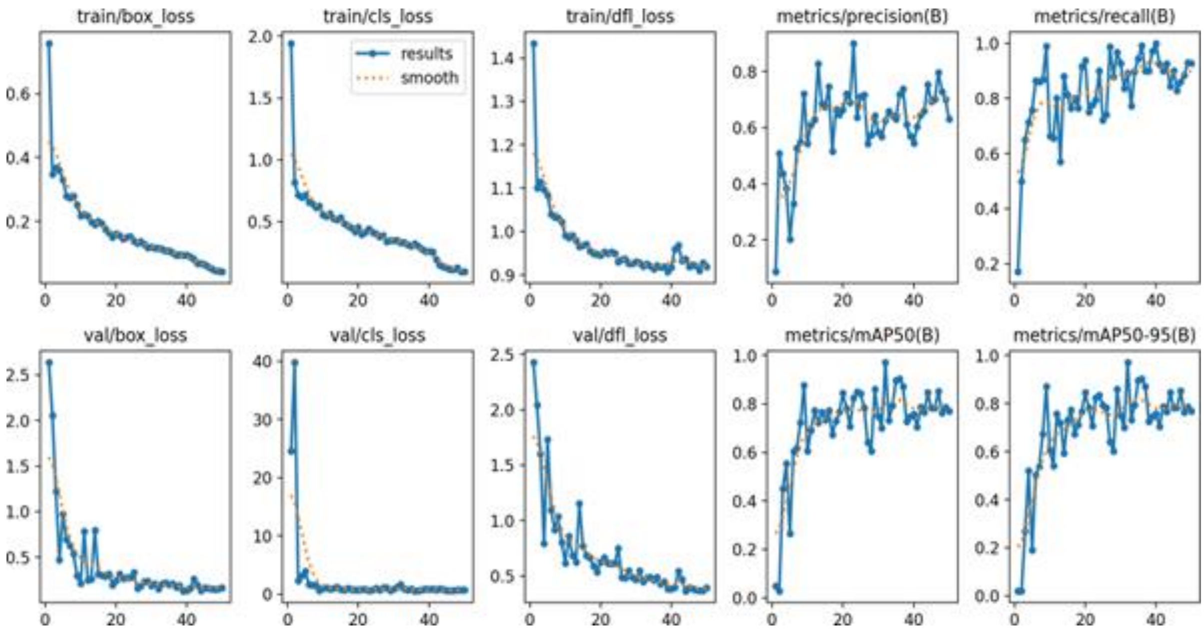

Fig. 3. Model Performance Metrics and Loss Curve

Furthermore, Figure 3 provides a detailed breakdown of loss reduction and precision-recall trends, reinforcing the claim that the model is well-optimized. The stagnation in accuracy improvements, as observed in Figure 2, suggests that further performance enhancements could be achieved through tech- niques like learning rate scheduling or advanced regularization. With a final validation accuracy of 93.75%, the model exhibits strong predictive capabilities, making it suitable for real-world deployment in motor vehicle collision severity assessment.

CONCLUSION AND FUTURE WORK

CrashSense is an accident detection and severity prediction system in real-time using deep learning and web technologies. It combines YOLOv8 for object detection, CNN with VGG16 for accident detection, and YOLOv8 for predicting severity, making it highly accurate. The web application based on Flut- ter offers real-time monitoring, video upload, and automatic emergency alerts, which improve road safety and efficiency in emergency response.Future developments include the inte- gration of next-generation object detection models, optimizing performance under changing conditions, and increasing dataset sizes for greater generalization. Increased real-time processing, predictive analysis, and post-crash analysis will enhance the system. In the long term, CrashSense can develop into a key element of intelligent city infrastructure to enhance road safety and response time to emergencies.

REFERENCES

[1]. Zhou, W., Wen, L., Zhan, Y. and Wang, C., 2023. An appearance-motion network for visionbase crash detection: Improving the accuracy in congested traffic. IEEE transactions on intelligent transportation systems.

[2]. Adewopo, V.A. and Elsayed, N., 2024. Smart city transportation: Deep learning ensemble approach for traffic accident detection. IEEE Access.

[3]. Yu, H., Zhang, X., Wang, Y., Huang, Q. and Yin, B., 2023. Multiple- Level Distillation for Video Fine-grained Accident Detection. IEEE Transactions on Circuits and Systems for Video Technology.

[4]. Zhou,W., Yu, Y., Zhan, Y. andWang, C., 2022. A vision-based abnor- mal trajectory detection framework for online traffic incident alert on freeways. Neural Computing and Applications,34(17), pp.14945-14958.

[5]. Ismail Fawaz, H., Forestier, G.,Weber, J., Idoumghar, L. and Muller, P.A., 2019. Deep learning for time series classification: a review. Data mining and knowledge discovery, 33(4),pp.917-963.

[6]. Li, Y., Lu, J. and Xu, K., 2017. Crash Risk Prediction Model of Lane- Change Behavior on Approaching Intersections. Discrete Dynamics in Nature and Society, 2017(1), p.7328562.

[7]. Rocky, A., Wu, Q.J. and Zhang, W., 2024. Review of Accident Detection Methods Using Dashcam Videos for Autonomous Driving Vehicles. IEEE Transactions on Intelligent Transportation Systems

[8]. Grigorev, A., Mihˇait¸ˇa, A.S., Saleh, K. and Chen, F., 2023. Auto- matic Accident Detection, Segmentation and Duration Prediction Using Machine Learning. IEEE Transactions on Intelligent Transportation Systems.

[9]. Gao, Z., Bao, M., Cui, T., Shi, F., Chen, X., Wen, W., Gao, F. and Zhao, R., 2024. Collision Risk Assessment for Intelligent Vehicles Considering Multi-Dimensional Uncertainties.IEEE Access.

[10]. Yang, Y., He, K., Wang, Y.P., Yuan, Z.Z., Yin, Y.H. and Guo, M.Z., 2022. Identification of dynamic traffic crash risk for cross-area freeways based on statistical and machine learning methods. Physica A: Statistical Mechanics and Its Applications, 595, p.127083.