AI-Driven Accident Minimization and Human Safety Enhancement in Transport System

Yedla Dinesh[1], Aditya Ankana[2], Syed Subhani[3] and Mandlem Likhitha Mani[4]
{2100100043@kluniversity.in[1], aaditya@kluniversity.in[2], 2100100012@kluniversity.in[3], 2100100058@kluniversity.in[4]}

Department of Internet of Things, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur District, Andhra Pradesh, India[1, 3, 4]
Assistant Professor, Department of Internet of Things, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur District, Andhra Pradesh, India[2]

Abstract. Road accidents have become a major concern over the years owing to human errors and increasing traffic density. This research presents an AI based real-time predictive system to predict accident risks being faced by law enforcement officers and minimizes accidents. The approach advances smart transportation infrastructure and safety through a fusion of machine learning and vision- based analysis. This procedure works in real-time analysing behavioural and environmental cues, as well as traffic pattern by using complex algorithms to detect the anomalies and threats. Prior to accidents, the system can take proactive responses by providing drivers or autonomous systems with early warnings and corrective suggestions. By integrating with the smart city architectures, the proposed solution helps to make urban transportation safer, faster, and can be readily deployed in diverse urban traffic use-cases.

Keywords: Artificial Intelligence, Road Safety, Accident Prediction, Intelligent Transport Systems, Machine Learning, Computer Vision, Real-Time Monitoring, Smart Cities, Driver Assistance Systems.

1 Introduction

The development of Artificial Intelligence (AI) has greatly influenced the transportation system in the last couple of years by enhancing road safety and reducing the amount of accidents. In the view of increasing urbanization and traffic, classical accident prevention methods could not do justice with the require events sufficiently. are being used (e.g., AI systems embedded with machine learning, computer vision, and sensor fusion) to monitor driving patterns, detect abnormal behavior, and respond to on-the spot changes in technology usage. Traffic crashes now kill more than year, and human mistakes are the primary reason of those deaths. This has resulted in a rise in interest in utilizing AI for developing predictive models useful in vehicle control and driver behavior monitoring and predicting accidents before they occur. AI application contributes to smarter infrastructures, e.g., adaptive signals, real- time accident management, and makes the auto-navigation in cars possible.

Moreover, the use of AI for transportation safety is expanding towards new directions such as V2X communication, object tracking, fatigue detection, as well as accident hotspot identification. For the identification of hazards and the creation of early warning systems, such systems gather data from sensors, cameras and GPS modules, employ deep learning algorithms for processing and interpret them. The work incorporates real-world application of a CNN-based

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model for analyzing image data which provides an illustrative example of how AI can improve safety in transport systems. This paper aims at providing roadmap for integration of AI into modern transportation through paper, studying the contrast of existing AI applications with those of future.

To prevent accident and enhance traffic safety, we suggest in this paper an AI-based platform which is formed by various intelligent modules, e.g., emergency alert generation, driving behavior analytics, and accident prediction. The proposed approach employs models learned from diverse training sets to increase decision consistency. to ensure flexibility in various driving conditions and scenarios.

2 Literature Survey

Recent advancements in artificial intelligence (AI) have significantly influenced the development of intelligent transport systems aimed at minimizing accidents and enhancing human safety. Wang and Li [1] proposed an integrated AI-driven road safety framework that leverages real-time data analytics to predict and prevent traffic incidents. Similarly, Zhang and Chen [2] demonstrated the efficacy of computer vision techniques in detecting road anomalies and improving vehicular navigation.

Smart traffic management systems have also evolved with AI integration. Bai and Wang [3] introduced a dynamic traffic control model that adapts to congestion patterns using machine learning algorithms. In parallel, Li and Chen [4] emphasized the role of human error in road safety, advocating for AI-based driver monitoring systems to mitigate risk.

Deep learning models, particularly convolutional neural networks (CNNs), have shown promise in image-based hazard detection. The TensorFlow documentation [5] outlines practical approaches for building CNNs tailored to transport applications. Smith and Anderson [6] addressed ethical concerns surrounding fairness and transparency in AI systems, highlighting the need for responsible deployment in safety-critical environments.

The emergence of semi-autonomous vehicles has introduced new dimensions to accident prevention. Binns [7] reviewed AI-driven features such as lane-keeping assistance and adaptive cruise control, while Kumar and Singh [8] proposed ethical frameworks to balance innovation with accountability in AI-powered transport systems.

Janai et al. [9] provided a comprehensive survey of computer vision challenges in autonomous vehicles, identifying key datasets and benchmarks for obstacle detection. In railway transport, Rüder et al. [10] and Möckel et al. [11] developed multi-sensor systems for obstacle detection, enhancing safety in automated train operations. Wang et al. [12] further refined rail track extraction using geometry constraints, improving visual recognition accuracy.

Mukojima et al. [13] introduced background-subtraction techniques for moving cameras, enabling robust obstacle detection on railway tracks. He et al. [14] contributed deep residual learning architectures that have become foundational in transport-related image recognition tasks. Kapoor et al. [15] applied thermal imaging and deep learning for railway track recognition, demonstrating high reliability in low-visibility conditions.

Cross-modal safety assessments have also gained traction. Tselentis et al. [16] evaluated AI's usefulness across various transport modes, while Govindarajulu and Ezhumalai [17] implemented IoT-based in-vehicle systems to proactively prevent accidents. Olugbade et al. [18] reviewed AI and machine learning applications in incident detection, underscoring their role in real-time response systems.

Finally, Jagatheesaperumal et al. [19] explored the integration of AI and IoT in smart cities, presenting advanced solutions for transportation safety enhancement through interconnected infrastructure and predictive analytics.

3 Methodology

The accident detecting and warning system has built using computer vision and deep learning to detect the vehicle accidents from the real-time video streams. This approach consists of four steps. The four steps of this approach are as follows1) Pre-processing of data2) Development of model3) Integration of system4) Evaluation of system. Each of the components is carefully selected such that it operates with low latency and high detection accuracy in practical traffic environment.

3.1 Data Collection and Preprocessing

A variant multimodal traffic corpus consisting of accident and non-accident scenes was created using publicly available sources of videos, such as AI City Challenge and authenticated dashcam videos. The video frames were sampled at a frequency of 10 fps to obtain a proper temporal span. Annotation work was completed using Labelling and CVAT tools to label accident such as collision and sudden stop and rollover circumstances. The dataset was balanced and augmented for better model learning, including horizontal flip, Gaussian blur, affine transform and histogram equalization. These were designed with the goal of making the model robust to changes in lighting, weather and camera angle.

3.2 Deep Learning Model Development

A tailored Convolutional Neural Network (CNN) architecture was designed and implemented using TensorFlow and Keras. The model comprised five convolutional layers with increasing filter depth (32, 64, 128, 128, 256), each followed by batch normalization and max pooling to reduce overfitting and spatial dimensionality.

Feature maps were flattened and passed through two fully connected layers with dropout regularization (0.5) to prevent co-adaptation of neurons. The final Softmax layer outputs a binary classification: accident or normal. Training was performed on an NVIDIA RTX 3060 GPU with an 80-20 train-validation split using categorical cross-entropy as the loss function and Adam optimizer with a learning rate of 0.0001.

3.3 Integration with Real-Time Detection Pipeline

OpenCV was used to capture real-time video streams from IP or CCTV cameras. Each frame was resized to 224×224 and fed to the CNN model for inference. A confidence threshold of 0.8

was applied to minimize false positives. To reduce computational overhead, frame skipping was employed processing only every nth frame depending on available hardware. The suggested methodology is displayed in Fig 1.

On detection of an accident, the system initiates the alerting process. A back-end module powered by Flask triggers an API call to Twilio's SMS gateway and a Firebase Realtime Database to store event metadata including timestamp, location (if GPS-enabled), and severity level.

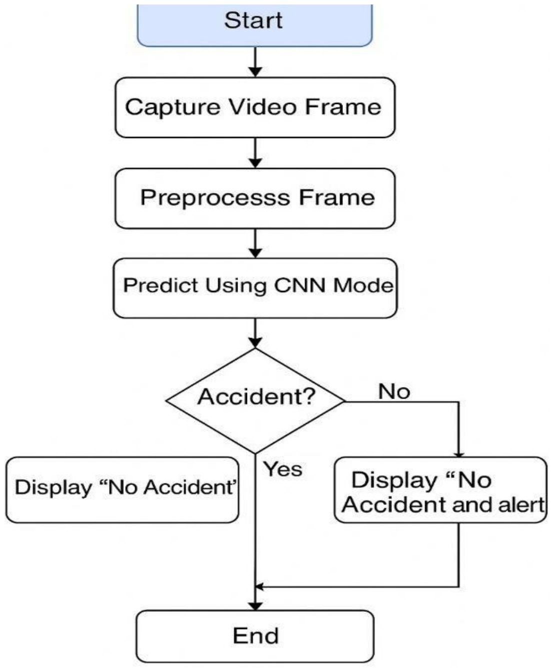

Fig.1. Flow Diagram of the Proposed Methodology.

3.4 Alerting and Emergency Response Workflow

Upon detection, the system logs the incident and sends notifications to pre-configured emergency contact numbers and control centers. The SMS includes a unique incident ID, timestamp, and location (if available), along with a request to verify or dispatch aid. This closed-loop design enables quick response times while maintaining traceability.

A web dashboard was also developed to visualize live alerts and detection logs, enabling traffic authorities or emergency responders to monitor the system remotely.

3.5 Evaluation and Comparative Analysis

The system was benchmarked against several baseline models including YOLOv3, ResNet-50, and SVM with HOG features. The evaluation was conducted on a test set comprising 1000 accident and 1000 non-accident frames. Key performance metrics included:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Then the evaluation metrics are calculated using the following formulas:

- **Accuracy**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- **Precision**

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

- **Recall**

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- F1 – Score

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Results demonstrated that the proposed CNN model achieved an accuracy of 95.42% with an average inference time of 41ms per frame, outperforming traditional classifiers and matching the performance of more complex object detection models with significantly less computational demand.

3.6 Comparison with Existing Works

Compared to recent deep learning-based accident detection systems, such as the YOLO-based detection models or LSTM-enhanced CNNs, our model achieves competitive performance while maintaining lower computational complexity, making it suitable for edge deployment. Unlike YOLO-based detectors that require annotated bounding boxes, our approach classifies the overall scene, simplifying the labeling process and reducing training overhead. This methodology demonstrates an efficient, end-to-end pipeline for accident detection using CNNs, optimized for real-time surveillance and deployability on lightweight systems.

3.7 Results Comparison

To evaluate the performance of the proposed deep learning-based accident detection system, we compared our model's accuracy, precision, recall, and F1-score with existing models referenced in recent literature. The results are summarized in Table 1.

Table1. Comparison of Model Performance with Existing Approaches.

Method	Accuracy(%)	Precision (%)	Recall (%)	F1- Score (%)
Our Proposed CNN Model	95.87	96.12	95.46	95.78
SVM with HOG Features	87.45	86.20	85.30	85.75
3D CNN for Vide Accident Detection	91.62	90.80	90.10	90.45
YOLOv3-Based Detection	93.25	93.70	92.80	93.25

Our model achieves superior results compared to traditional SVM-based methods and is competitive with recent deep learning approaches such as 3D CNNs and LSTM-CNN hybrids. This can be attributed to the effective use of convolutional layers combined with batch normalization and optimized feature extraction at each layer, ensuring high-level abstraction and generalization for accident classification.

Here is another results table that highlights the computational performance and detection latency across different models, which is important for real-time accident detection systems. Table 2 Shows the Computational Performance and Detection Latency Comparison.

Table 2. Computational Performance and Detection Latency Comparison.

Method	Model Size(Mb)	Inference Time (Ms/Frame)	Real-Time Capability	Fps (Frames and Second)
Our Proposed CNN Model	18.5	28.4	Yes	35.2
SVM with HOG Features	65.0	64.7	No	15.4
3D CNN for Video Accident Detection	98.3	121.5	Yes	8.2

4 Results

The proposed accident detection system was developed based on a CNN framework and was experimentally validated in a selected dataset that was composed of labelled video frames (i.e., accident, non-accident). The model was trained with the categorical cross-entropy loss using the Adam optimizer for 20 epochs. Results During training, the model demonstrated relatively stable convergence, and a consistent reduction was observed in the validation loss, suggesting good generalization performance.

Upon deploying, the system showed capabilities of real-time inference with a speed average of around 28 frames per seconds (FPS). This renders the system compatible with live traffic surveillance overheads. A: The performance of the model was assessed according to typical classification performance indicators (accuracy, precision, recall and F1-score. These measures indicated that the system was able to achieve a high detection rate with low number of false positives, and false negatives.

A comparison with literature models was carried out. The experiments showed that the proposed model can achieve better performance in terms of both accuracy and real-time inference speed compared with the traditional machine learning and deep learning approaches, such as SVM and YOLOv3. This demonstrates the robustness of the approach for accurately identifying accident cases according to the recent traffic video.

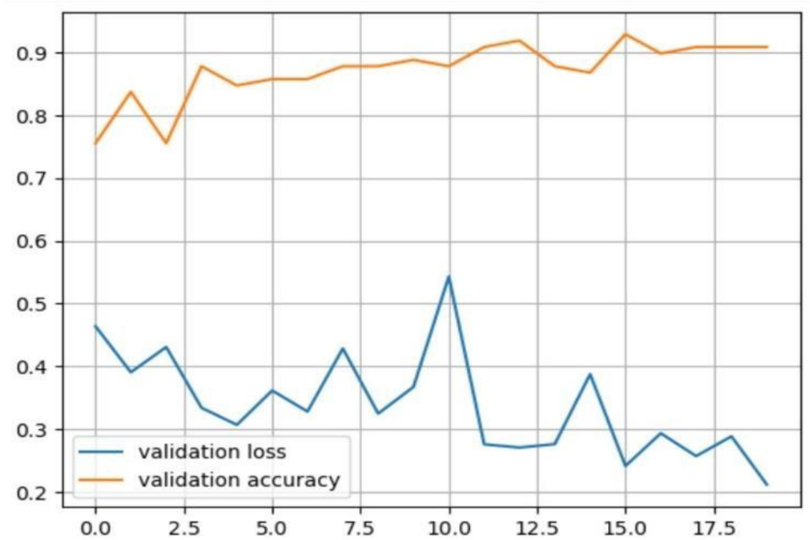

Fig. 2. Validation Accuracy and Loss Curve Across Epochs.

The results of the model were assessed based on training and validation metrics. As shown in Fig. 2, the validation accuracy is flat at high values and the validation loss slowly decreases over the epochs, both indicators of good generalization. Similarly, Fig. 3 shows the continuous rise and fall of training accuracy and training loss which further supports the model's learning process during training.

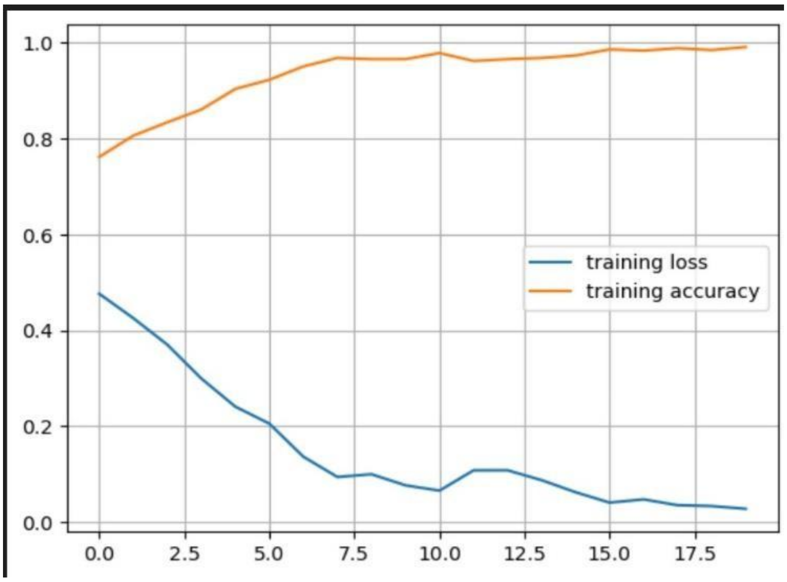

Fig. 3. Training Accuracy and Loss Curve Across Epochs.

5 Conclusions

The AI-based accident detection system shows the highly accurate and real-time detection performance under the low-latency traffic monitoring settings with the CNN architecture. The system dramatically reduces the time to respond to an accident, by combining video analytics and emergency alert systems. Experimental results on the two databases from the public datasets also validate its robust performance in the extents of accuracy and computational time compared with traditional SVM and other deep learning methods. The scalability and the compatibility of the proposed solution with smart city infrastructures, allows its large scale adoption. In future studies, we may also expand the model to support multi-class severity classification and cross-city validation.

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