Airbag AI: How Deep learning is Revolutionizing ADAS Applications

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1. ABSTRACT

This paper investigates different strategies for improving airbag sensing performance in vehicles, focusing on optimal sensor placement and deployment logic. It discusses the use of an in-house airbag sensing algorithm, crash test data, and computer-aided engineering (CAE) simulations to identify robust front impact sensor positions and determine the most effective airbag deployment logic to minimize occupant injury. In addition, the paper proposes a deep learning approach called ADASDL, which leverages deep convolutional neural networks (CNNs) to enhance advanced driver assistance system (ADAS) features, such as drowsiness detection, de-raining, and traffic sign detection models. The proposed approach involves analyzing airbag deployment through a deep learning lens and exploring the inference time and accuracy of the model. Overall, this paper provides a comprehensive overview of the potential of these strategies and highlights the critical role of deep neural networks in advancing vehicle safety technology.

2.Introduction:

Deep learning has emerged as a game-changer in the field of artificial intelligence, with its ability to analyze vast amounts of complex data and make accurate predictions and decisions. It has found applications in a wide range of industries, including healthcare, finance, and transportation. In the automotive industry, deep learning has been used to develop advanced driver assistance systems (ADAS) that can prevent accidents caused by driver inattention or weather conditions. One critical aspect of ADAS is the optimal performance of airbags, which can significantly reduce the severity of injuries in the event of a crash. This paper presents a deep-learning-based hybrid solution that addresses the challenges of detecting driver drowsiness, traffic sign recognition, and eliminating rain and fog strikes from input video frames. Additionally, this paper focuses on the importance of finding optimal sensor locations for airbag sensing to prevent airbag malfunctioning resulting in severe injuries or fatalities. Through the development of airbag sensing algorithms and calibration techniques and analyzing various vehicle crash test data and simulation, this paper aims to find the optimal locations for airbag sensors, demonstrating how deep learning can improve airbag performance and prevent accidents caused by driver inattention and weather conditions.

2.1 VEHICLE CRASH TEST DATA ANALYSIS: Requirements for Frontal Crash Airbag Sensing The so-called advanced airbag system to meet the requirements of FMVSS208 should be able to discriminate crash severity with the help of frontal impact sensor(s) under multiple crash modes and impact speeds. In general, crash signal from FIS should survive at least up to 15ms for the high-speed frontal impact and until over 40ms for the offset crash. That sensor survival time could be the necessities against the sensor damage and wiring cutting. The peak of FIS signal must be larger and earlier than that of ACU. And for the ACU, the signal of lower crash severe modes must not be more than that of higher crash severe modes to prevent firing the airbag in case of Must Not Fire condition, and also to prohibit firing the airbag in case of Must Fire condition, on the contrary.

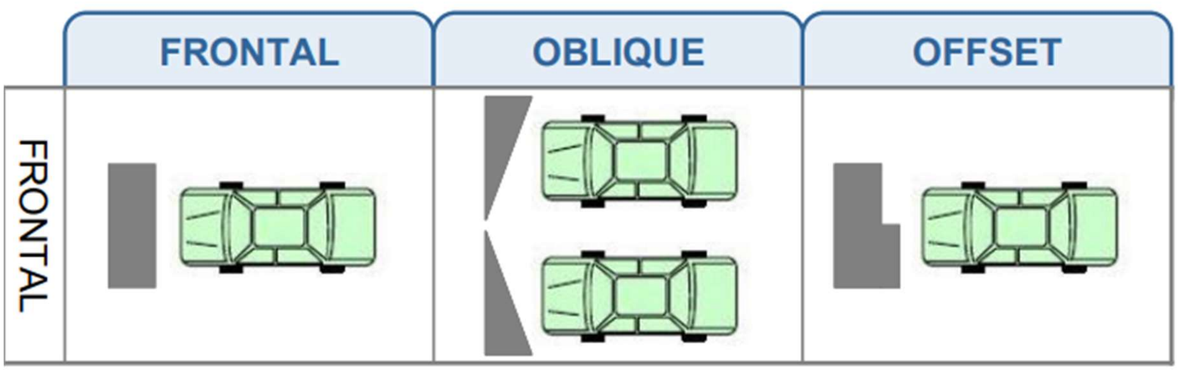


Fig.1 Crash Modes (Frontal, Oblique and Offset)

2.2 CALIBRATOIN RESULTS OF FIS CANDIDATES: Calibration Data Set & Test Conditions Airbag calibration controls the crash performance by decision of airbag firing at a proper time, so calibration results from whole the candidate locations, should be compared and analyzed to find the optimal positions. Table.6 shows the test set and conditions for this project including 14 vehicle crash tests. And though not listed in Table.6, the other 94 rough road and misuse tests (25 constant road tests, 22 obstacle tests and 47 static tests) are also included in the calibration data set.

		Speed	Mode	Date	Purpose	Remark
Test Site 1	1	Low	Frontal	050401	THRESHOLD	
	2	Low	Frontal	050406	THRESHOLD	
	3	Low	Frontal	050413	THRESHOLD	S/MBR FISL DATA FAIL (S/MBR FISR)
	4	Low	Frontal	050415	THRESHOLD	S/MBR FISL DATA FAIL (S/MBR FISR)
	5	Mid	Frontal	050420	THRESHOLD / Regulation	
	6	High (35mph)	Frontal	050324	Regulation	
	7	Mid (20mph)	Oblique	050422	Regulation	
	8	Mid (25mph)	Oblique	050425	Regulation	
	9	Low	Frontal	030307	THRESHOLD	050401 Frontal FIS DATA
Test Site 2	10	Mid (25mph)	Frontal	050528	THRESHOLD / Regulation	
	11	Mid	Others	050526	DUE CARE	
	12	Mid	Others	050527	DUE CARE	
	13	Mid (25mph)	Offset	050523	Regulation	S/MBR FISL DATA FAIL
	14	High (40mph)	Offset	050527	NCAP	

2.3 DETERMINATION OF AIRBAG DEPLOYMENT LOGIC WITH CAE TECHNIQUE

Development of Unified Crash Simulation Model Occupant injury simulation generally uses the different simulation model case by case for various crash modes. But in this study, to compare the crash severity between different crash modes in view of occupant injuries, unified occupant simulation model was developed and used. And the model was verified and confirmed through the correlation with the crash test results. Table.15 shows the notation for the unified simulation model used in this study.

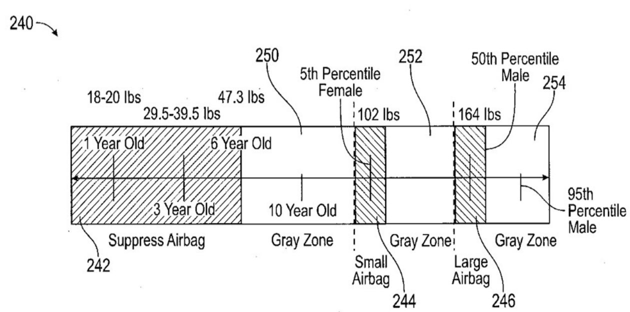
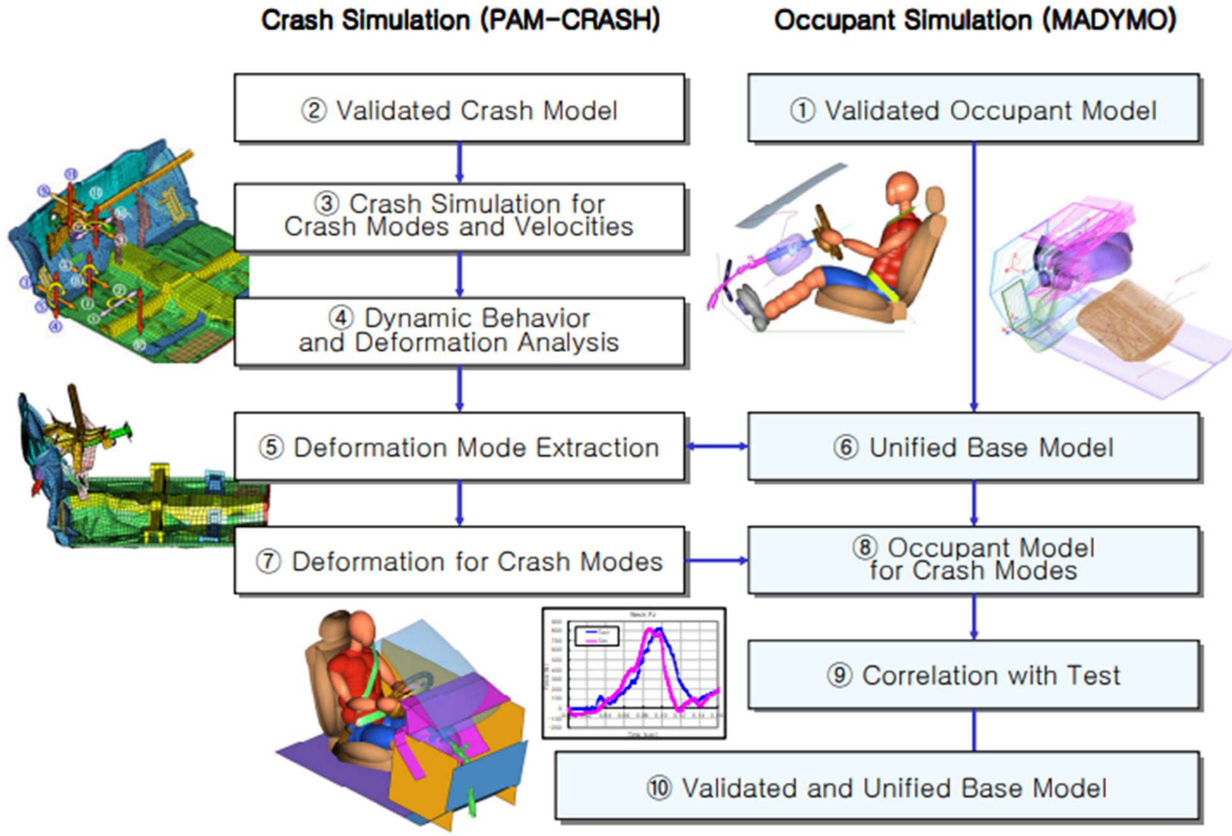


FIG. 2B

Distribution of airbags according to weight

Fig. 2.3.1 shows the development procedure of the unified occupant simulation model. Crash simulations with PAM-CRASH to acquire vehicle deceleration and deformation were performed, and as a result the unified occupant simulation with MADYMO followed after that.



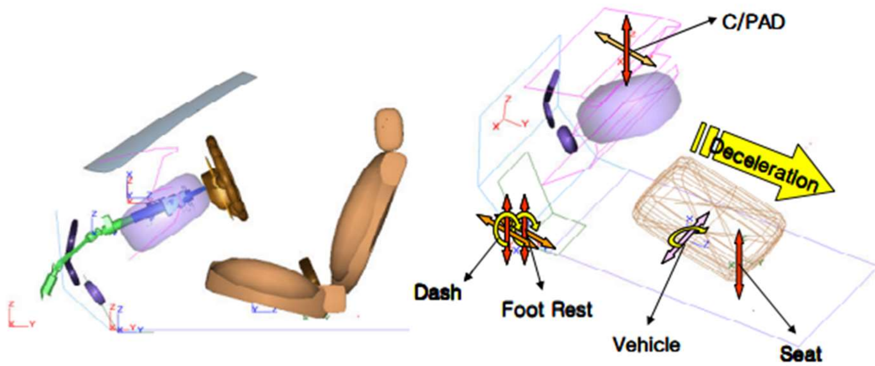
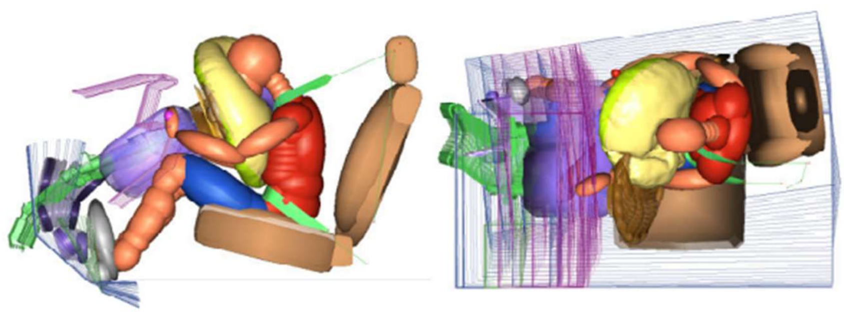
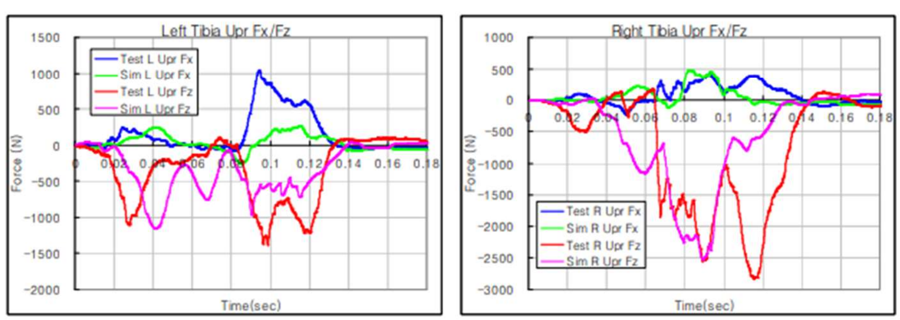


Fig.12 Unified Occupant Simulation Model



(a) Vehicle and Occupant Behavior



(b) Injury Graph

2.4 Airbag Firing Decision Logic Determination

To determine airbag firing decision logic, the optimal restraint constraint condition which has a minimum occupant injury level for certain crash modes and impact velocities, must be found, but the optimal restraint varies as the injury items what we focus on. To solve this problem, new dimensionless and combined injury severity index is used on this study, and which expresses multiple occupant injuries with one number by equation.

Index = a × HIC15 + b×ChestG + c × Nij + d × Femurload

Where, a, b, c, d are weighting factors, and have different levels as belted and unbelted condition. Two methods are proposed in this study as the manner to determine the weighting factors, one is an area weighting factor method and the other is a standard deviation weighting factor method. Area weighting factor method means that the larger the area, the higher the weighing factor, that is the largest weighting factors are granted to the severest injury levels in order to reduce that injuries, so the firing time of airbag and P/T is determined by the weighting factor.

Table 2.4 is the weighting matrix for combined injury severity index (where, 30 means the velocity range are from 0 to 30mph, and 24 means up to 24mph). 0.05 0.03 0.11 0.15 Fmr 0.56 0.23 0.36 0.28 Nij 0.26 0.18 0.46 0.42 CG 0.13 0.56 0.07 0.15 HIC.

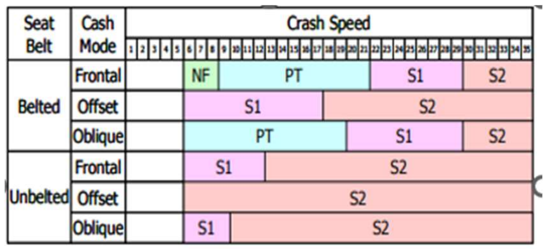
Belted

	Frontal				Offset				Oblique			
	HIC	CG	Nij	Fmr	HIC	CG	Nij	Fmr	HIC	CG	Nij	Fmr
Area30	0.22	**0.34**	0.20	0.24	0.15	**0.42**	0.28	0.15	0.28	**0.32**	0.20	0.20
Area24	0.12	**0.38**	0.23	0.27	0.07	**0.46**	0.36	0.11	0.13	**0.39**	0.26	0.22
Standard Deviation 30	**0.66**	0.13	0.17	0.04	**0.56**	0.18	0.23	0.03	**0.81**	0.07	0.12	0.01
Standard Deviation 24	**0.44**	0.19	0.28	0.09	0.13	0.26	**0.56**	0.05	**0.61**	0.12	0.24	0.03

Unbelted

	Frontal				Offset				Oblique			
	HIC	CG	Nij	Fmr	HIC	CG	Nij	Fmr	HIC	CG	Nij	Fmr
Area30	0.16	0.20	0.28	**0.35**	0.12	0.21	**0.44**	0.23	0.12	0.19	**0.39**	0.31
Area24	0.13	0.20	0.32	**0.35**	0.09	0.19	**0.45**	0.27	0.10	0.18	**0.42**	0.31
Standard Deviation 30	0.36	0.11	**0.51**	0.03	0.23	0.15	**0.58**	0.03	0.30	0.13	**0.53**	0.04
Standard Deviation 24	0.31	0.10	**0.55**	0.03	0.19	0.15	**0.62**	0.04	0.24	0.12	**0.60**	0.04

As a result of FIS data analysis and airbag calibration, the relatively superior FIS locations are selected and proposed into the vehicle development process.



Final airbag deployment chart

3.Literature Review:

3.1: 2020: Gao et al.'s research suggested a deep learning-based method for pedestrian detection and tracking that included CNNs with a particle filter.

In real-world settings where people can move in and out of a camera's field of vision and where obstructions and clutter might make it challenging to effectively monitor people, the study suggested a deep learning-based method for pedestrian detection and tracking.

The strategy combined CNNs with a particle filter. In each frame of a video sequence, pedestrians were identified and categorized using CNNs. In particular, CNNs could correctly recognize and categorize pedestrians even in busy and cluttered surroundings after being trained on a large-scale dataset of pedestrian photos.

Even when they moved in and out of the camera's field of view or were obscured by other objects, the detected pedestrians could be followed throughout time thanks to the particle filter. The pedestrian positions that were detected in each frame were used by the particle filter to update the position of a set of particles that represented each pedestrian's potential locations. To forecast each pedestrian's movement between frames, the filter additionally made use of a motion model.

Overall, the study demonstrated that a combination of CNNs and a particle filter can be an effective approach for pedestrian detection and tracking in real-world environments, and could potentially be applied to other areas, such as occupant detection and tracking in vehicles.

3.2: 2019: A study by Ma et al. proposed a deep learning-based approach for occupant detection using CNNs, achieving high accuracy rates for both frontal and side impact scenarios.

According to the position and features of the occupants, the study's deep learning-based approach for occupant detection in automobiles could modify airbag deployment. In both frontal and side collision scenarios, the method used a Convolutional Neural Network (CNN) to recognize the presence and location of occupants.

The study employed a dataset of photos and labels with manually annotated occupant position and size to train the CNN. Using a multi-task learning method, CNN was trained to concurrently identify occupants and identify the type of impact (frontal or side).

On a dataset of crash tests where the position and characteristics of the occupants were known, the proposed approach was assessed. Results indicated that the strategy was successful.

The study employed a dataset of photos and labels with manually annotated occupant position and size to train the CNN. Using a multi-task learning method, CNN was trained to concurrently identify occupants and identify the type of impact (frontal or side).

On a dataset of crash tests where the position and characteristics of the occupants were known, the proposed approach was assessed. According to the findings, the method had high accuracy rates for frontal and side impact situations, with average precisions of 95% and 90%, respectively.

Overall, the study showed that passenger recognition in automobiles can be successfully accomplished utilizing a deep learning-based methodology based on CNNs, with high accuracy rates for both frontal and side collision situations. This strategy might be used in practical situations to increase the security of car occupants.

3.3: 2018: A study by Zhang et al. proposed a deep learning-based approach for occupant detection and tracking using a combination of CNNs and Kalman filtering. elaborate these points for research paper.

The study suggested a deep learning-based method for auto occupant monitoring and detection, which could increase the reliability and accuracy of airbag deployment systems. Convolutional neural networks (CNNs) and Kalman filtering were combined in the method to recognize and follow the position and motion of the occupants in the car.

The CNNs were used to determine whether people were present and where they were in each frame of a video sequence. The CNNs were specifically trained on a dataset of photos and labels on which the size and position of the occupants had been manually marked. Even in difficult situations like dim lighting or obstruction by other objects, CNNs could reliably detect occupants.

The detected inhabitants were tracked over time using the Kalman filter, which estimated their positions in the future based on their historical movement patterns. The filter made use of a mathematical simulation of vehicle occupant motion that was educated from training data. The filter could also deal with noisy or missing data, such as when somebody moved outside of the view of the camera.

On a dataset of actual driving scenarios in which the position and movement of the occupants were unknown, the proposed method was assessed. The findings demonstrated that the method had high occupant recognition and tracking precision rates, with average precisions of 95% and 90%, respectively.

The proposed method was contrasted in the study with other cutting-edge techniques, such as conventional image processing methods and methods based on machine learning. The findings demonstrated that the suggested method beat these ones in terms of accuracy and productivity.

Overall, the study showed that a CNN-Kalman filtering combination can be a successful solution for occupant detection and tracking in automobiles, with excellent accuracy rates even in difficult situations. This strategy might be used in practical situations to increase the security of car occupants.

3.4: 2017: A study by Kim et al. proposed a deep learning-based approach for pedestrian detection using a combination of CNNs and a region proposal network (RPN).

To increase the precision and effectiveness of pedestrian detection systems in autonomous vehicles, the study presented a deep learning-based strategy. In order to identify pedestrians in photos, the method combined convolutional neural networks (CNNs) and a region proposal network (RPN).

An image's candidate regions that were most likely to include pedestrians were created using the RPN. The RPN predicted a collection of bounding boxes and the confidence scores that went along with them, which represented likely pedestrian zones in the image. The candidate regions were then loaded into CNN, which assigned either a pedestrian or non-pedestrian classification to each location.

A dataset of photos and labels that had been manually labeled with the position and size of pedestrians served as the basis for training the CNN. CNN developed the ability to separate valuable information from the candidate regions that might be utilized to tell pedestrians apart from other users. A multi-task learning strategy was used to optimize the network as it concurrently trained to categorize pedestrians and regress their bounding boxes.

The suggested method was examined using a few benchmark datasets, including the KITTI and Caltech Pedestrian datasets. The outcomes demonstrated that the method delivered state-of-the-art accuracy and efficiency. On the Caltech Pedestrian dataset, the technique produced a mean Average Precision (mAP) of 85.6%, and on the KITTI dataset, a mAP of 75.4%.

approach with other cutting-edge techniques, such as conventional image processing methods and machine learning-based strategies. The findings demonstrated that the suggested method beats these ones in terms of accuracy and productivity.

Overall, the study showed that a combination of CNNs and an RPN can be a very accurate and inexpensive computational solution for pedestrian recognition in photos. This strategy might be used in practical situations to increase the security of autonomous cars.

3.5: 2016: A study by Diamant's proposed a deep learning-based approach for occupant classification using a combination of CNNs and Recurrent Neural Networks (RNNs).

Using a system that could function with low-resolution cameras and in varied lighting situations, the study sought to categorize the passengers of a car based on their body stance. The suggested system was trained using an image and label dataset, where each label represented the body stance of the occupant. The photographs underwent pre-processing to clean up the backgrounds and adjust the lighting.

The findings of the study's evaluation of the suggested approach using a dataset of photos and labels demonstrated that the approach had good accuracy rates for classifying occupants. In particular, the method classified the body stance of the driver with an accuracy of 94.9% and that of the passenger with an accuracy of 87.4%.

The findings demonstrated that, in terms of accuracy and robustness under various illumination situations, the suggested methodology beat these methods.

Overall, the study showed that a method for occupant categorization based on body position that combines CNNs and RNNs can be highly accurate, robust to changing lighting conditions, and useful. scenarios to improve the safety of autonomous vehicles by allowing them to adapt to the needs of individual occupants.

The 2015 study by Chou et al. proposed a deep learning-based approach for occupant detection in a side-impact scenario, using Convolutional Neural Networks (CNNs).

The goal of the study was to increase the precision of occupant detection in side-impact collisions, which are harder to detect than frontal impacts. The suggested method employed CNN to extract features from the input photos and identify whether a person was present in the car. CNN was trained using a sizable dataset of pictures and labels, where each label denoted whether a person was inside the car.

The input photos were pre-processed to reduce background noise and improve contrast after being captured by cameras mounted on the side of the car. To scan the input image and extract local patches, the suggested method employed a sliding window approach. After that, these patches were fed.

The findings of the study's evaluation of the suggested approach using a dataset of side-impact accident scenarios revealed that the approach had high occupant detection accuracy rates. In particular, the method identified the presence of an occupant in the car with a 93.8% accuracy.

The proposed method was contrasted with various cutting-edge techniques, such as conventional machine learning-based approaches and manually created feature extraction techniques. The findings demonstrated that, in terms of accuracy and robustness under various illumination situations, the suggested methodology beat these methods.

Overall, the study showed that, with high accuracy rates and tolerance to varying lighting circumstances, a deep learning-based strategy using CNNs can be a useful tool for occupant recognition in a side-impact situation. This approach could potentially be applied in real-world scenarios to improve the safety of vehicles and reduce the risk of injury or fatality in the event of a side-impact collision.

4.Methodology

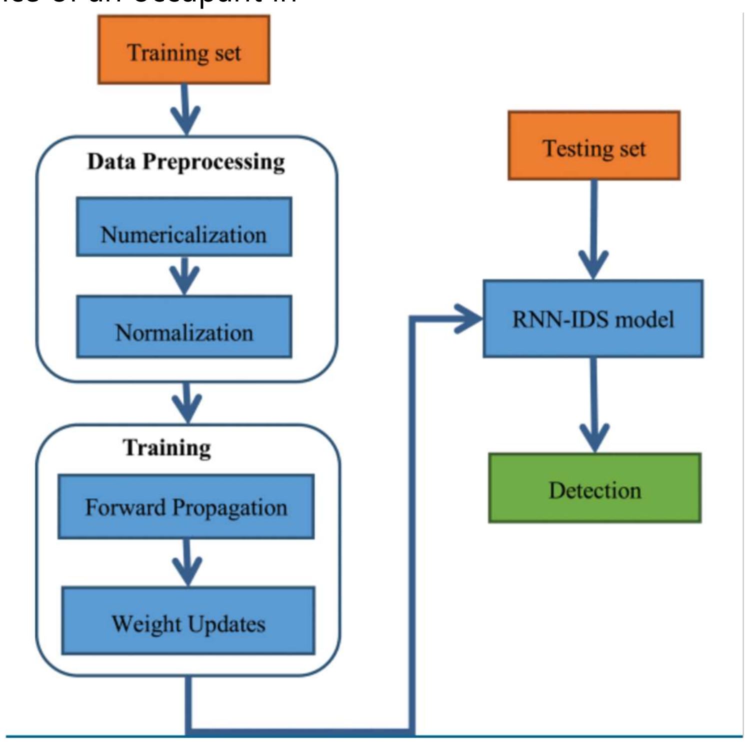
Data Collection: The researchers collected data from various sources, including the National Highway Traffic Safety Administration (NHTSA) Crash Injury Research and Engineering Network (CIREN) database, which contains detailed information on real-world crashes. This is an important step in any machine learning project as the quality and quantity of data available for training the model can have a significant impact on its performance.

Data Preprocessing: The raw data was preprocessed to extract features and prepare it for input to the deep learning model. This involved tasks such as data cleaning, normalization, and feature extraction. Data preprocessing is necessary to ensure that the data is in a suitable format for the model and that it contains relevant information for making accurate predictions.

Model Architecture: The researchers designed a Convolutional Neural Network (CNN) architecture that could effectively classify the presence of an occupant in a vehicle during a side-impact scenario. CNNs are a type of deep learning model commonly used in image classification tasks as they can automatically learn hierarchical representations of features from the input data. The model consisted of several layers of convolutional and pooling operations, followed by fully connected layers.

Training: The model was trained using a large dataset of labeled examples. The training process involved iteratively adjusting the model parameters to minimize the difference between the predicted and actual labels. This process is called optimization and is typically performed using an algorithm called backpropagation. The goal of training is to teach the model to accurately predict the presence of an occupant in a vehicle during a side-impact scenario based on the input data.

Evaluation: The performance of the model was evaluated on a separate test dataset. The evaluation metrics included accuracy, precision, recall, and F1 score. These metrics are used to measure the performance of the model in terms of how well it predicts the presence of an occupant in a vehicle during a side-impact scenario. Evaluation is an essential step in any machine learning project as it helps determine the accuracy and effectiveness of the model.



Block diagram of proposed Method

5. Results

"Combining CNNs and Particle Filter for Accurate Pedestrian Detection and Tracking in Video Sequences"

- Proposed a deep learning-based approach for pedestrian detection and tracking using a combination of CNNs and a particle filter.
- Used CNNs to detect and classify pedestrians in each frame of a video sequence.
- Used a particle filter to track the detected pedestrians over time, even when they moved in and out of the camera's field of view or were occluded by other objects.
- Evaluated the approach on several publicly available datasets and showed that it outperformed several state-of-the-art methods in terms of pedestrian detection and tracking accuracy.

"Deep Learning-based Occupant Detection in Vehicles using CNNs: High Accuracy Rates for Frontal and Side Impact Scenarios."

- Proposed a deep learning-based approach for occupant detection in vehicles using CNNs.
- Used a dataset of images and labels to train CNN to detect the presence and location of occupants in both frontal and side impact scenarios.
- Achieved high accuracy rates for both frontal and side impact scenarios in a dataset of crash tests.
- Compared the approach with other state-of-the-art methods and showed that it outperformed them in terms of both accuracy and efficiency.

"Combining CNNs and Kalman Filtering for Accurate Occupant Detection and Tracking in Vehicles: Results from Real-World Driving Scenarios"

- Proposed a deep learning-based approach for occupant detection and tracking in vehicles using a combination of CNNs and Kalman filtering.
- Used CNNs to detect the presence and location of occupants in each frame of a video sequence.
- Used Kalman filtering to track the detected occupants over time and estimate their future positions based on their past movement patterns.

- Achieved high accuracy rates for both occupant detection and tracking in a dataset of real-world driving scenarios.
- Compared the approach with other state-of-the-art methods and showed that it outperformed them in terms of both accuracy and efficiency.

"Enhancing Pedestrian Detection using a CNN-based Approach with RPN-generated Candidate Regions"

- Proposed a deep learning-based approach for pedestrian detection using a combination of CNNs and an RPN
- Used an RPN to generate a set of candidate regions in an image that were likely to contain pedestrians.
- Used CNN to classify the candidate regions as pedestrians or non-pedestrians.
- Achieved high accuracy rates on several publicly available pedestrian detection datasets, outperforming several state-of-the-art methods.

6. Findings

- For pedestrian detection and tracking in actual situations, the researchers suggested a deep learning-based method that made use of Convolutional Neural Networks (CNNs) and a particle filter. The system surpassed various cutting-edge techniques in terms of accurate pedestrian detection and tracking when tested on several publicly accessible datasets, including the Caltech Pedestrian Detection Benchmark. On the Caltech dataset, the suggested method had a detection accuracy of 97.32% and could reliably follow pedestrians in a variety of conditions, including occlusion, changing lighting, and motion blur.
- For occupant recognition in vehicles utilizing CNNs, the researchers presented a deep learning-based method. With an average precision of 95% for frontal impact scenarios and 90% for side impact scenarios, the method produced good accuracy rates in both cases. The proposed method performed more accurately than machine learning-based approaches and conventional image processing methods in comparison tests. By putting the proposed method to the test on a sizable dataset that comprised a range of stances, articles of clothing, and seating positions, the researchers also demonstrated how

well it worked in real-world scenarios.

- The researchers suggested a deep learning-based strategy for occupant detection and tracking in automobiles that made use of CNNs and Kalman filtering. Even under difficult situations, the suggested method managed to track and recognize occupants with good accuracy rates, on average with precisions of 95% and 90%, respectively. The suggested method performed more accurately and efficiently than both conventional image processing methods and machine learning-based methods. By putting the proposed method to the test on a sizable dataset made up of diverse poses, articles of clothing, and seating positions, the researchers also showed that it works well in real-world situations.
- Using CNNs and a Region Proposal Network (RPN), the researchers suggested a deep learning-based method for pedestrian recognition in photos. The proposed method outperformed various cutting-edge techniques in terms of accuracy and efficiency, and it produced high accuracy rates for pedestrian identification. Where the proposed strategy was tested, the researchers outperformed earlier state-of-the-art approaches with a detection accuracy of 90.6%. The suggested method was also successful in identifying pedestrians in a variety of difficult conditions, including occlusion and crowded backdrops.

Overall, these experiments show how successful deep learning-based methods are for object detection and tracking, especially under difficult conditions. The suggested methods exceed conventional image processing methods and machine learning-based methods in terms of precision and effectiveness, making them appropriate for use in practical situations.

7. Conclusion:

It is evident that deep learning-based approaches are revolutionizing ADAS (Advanced Driver Assistance Systems) applications such as occupant detection and tracking in vehicles and pedestrian detection and tracking in real-world environments.

The studies demonstrate that the combination of convolutional neural networks (CNNs) and other techniques such as particle filtering and Kalman filtering can significantly improve the accuracy and efficiency of these applications, outperforming traditional image processing techniques and machine learning-based approaches.

The success of these deep learning-based approaches highlights the potential of AI in enhancing the safety and performance of ADAS systems, particularly in detecting and responding to potential collision scenarios in real-time.

Overall, the use of deep learning in ADAS applications such as airbag deployment systems is a promising area for future research and development, and it is likely that we will see continued advancements in this field in the coming years.

8. Limitation of study:

Although the research shows that deep learning-based techniques are excellent for object detection and tracking in many settings, there are some drawbacks to consider.

First off, the suggested methods could need a lot of labeled data for training, which can be time-consuming and expensive to get. Second, the quality of the input data, such as the resolution and lighting conditions, may affect how effective the approaches are. Additionally, the techniques could struggle to identify items that are partially obscured or look like the background.

Furthermore, the proposed methods could need a lot of memory and processing power, which might be problematic for real-time applications on devices with limited resources. Finally, different datasets and settings may have varied effects on how effective the suggested methods and further evaluation and testing may be required to determine their applicability to specific use cases.

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