Proceedings of the Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI 2024)
IEEE Xplore Part Number : CFP24VG0-ART ; ISBN : 979-8-3315-4066-1

2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI) | 979-8-3315-4066-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICOICI62503.2024.10696572

Enhanced Lane Keeping Assistance through IoT Sensor Fusion and Deep Learning

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***Abstract*—This research introduces a novel method for improving Lane Keeping Assistance (LKA) systems via the use of Convolutional Neural Networks (CNNs) and Internet of Things (IoT) sensor fusion. The proposed system compiles information about the vehicle's environment from various sensors, such as cameras, LiDAR, radar, and GPS. Using sensor fusion methods, the system enhances its ability to recognize lane markers, obstructions, and other important road elements by combining the capabilities of each sensor modality. An important part of the system is using CNNs to analyze visual sensor input in real-time. To help drivers stay in their lanes, the system uses CNNs trained on massive datasets of tagged images to identify automobiles, lane markers, and other objects. The system learns from its surroundings and the driver's actions in real time. It can adjust to different roads and driving styles, providing individualized support while keeping everyone safe. The proposed method improves LKA systems' accuracy, dependability, and adaptation to different driving situations, as shown experimentally. Due to cutting-edge vehicle safety technology that combines IoT sensor fusion with CNN-based deep learning, drivers may now travel with more assurance and serenity.**

Keywords— Automotive Safety, Real-time Analysis, Image Recognition, Sensor Integration, Automated Driving, Safety Enhancement

I. INTRODUCTION

Traffic accidents have increased annually due to the world's population and car growth, which will first create a big problem. Unintentional lane deviations by motorists are a leading cause of accidents, causing deaths, injuries, and financial losses. Due to its societal importance, vehicle detection has been a priority for related researchers [1]. The proposed system attempts to construct an effective, accurate, low-processing lane-keep assist model. Both vehicle and lane detection are included. OpenCV and Support Vector Machine (SVM) are used for lane and vehicle detection. The vehicle detection machine learning model uses vehicle and non-vehicle data. The model is assessed for accuracy. It proposes a real-time car radar-based lane maintenance assist and warning system. Radar can accurately identify things due to its weather and sunlight resistance. Bayesian filtering effectively detects and tracks cars approaching the ego vehicle [2]. A moving vehicle in the proximity zone triggers a warning signal. It describes the design of radar-based lane-keep assist and warning systems and compares them to camera-based systems.

Autonomous cars' trajectory tracking relies on lane boundary detection. It experiments with edge detection, Hough transformation, and birds-eye view lane identification [3]. After getting the boundary locations, apply a regulation rule to activate motor steering and velocity regulation. Different driving controllers like PID or PID plus a pure pursuit controller for LKA are compared. A camera delivers wireless data to ROS using Nvidia Jetson Nano to gather environmental data. After interpreting the data, the CPU sends Arduino the output control via serial connection. It examines lane markings' visibility, facilities' weather, and driver-related dangers to rationalize the findings, complements earlier studies, and suggests ways to improve LKA safety [4]. Allocating additional money to road maintenance and snow removal might increase lane marker visibility and safety. Advanced LKA that exploits digital lane markings might practically treble safety potential since weather and lane marker visibility would not limit LKA operation. While the driver is still in control of driving, driver-related hazards are difficult to manage, and existing LKA systems cannot avoid collisions caused by disease or intent.

Automotive trends have changed significantly during the previous decade. Cars with advanced driving assistance systems (ADAS) are becoming more common, but their autonomy is rising [5]. ADAS must effectively and dependable handle sensor data. Lane departure warning and lane keeping assist (LKAS) algorithms are crucial ADAS algorithms. LKAS algorithm will be used to provide users with a real-world 3D visual experience. The tool is used to view a clothed road structure in this research, unlike most algorithm testing on straight road images. Presentation of LKAS lane detection. This model was used to analyze LKAS performance in IPG Carmaker's virtual environment [6]. Measured camera data and lane-maintaining behavior were used to parameterize the lane detection model. The PLDM behaved realistically based on LKAS performance. This method allows the simulation of vision-based sensors for ADAS functional validation without modeling all sensor performance impacts. This methodology might minimize vision based ADAS testing and validation expenses and modeling efforts in early development. Table 1 summarizes the main features of the LKA system for easy reference.

TABLE I. KEY FEATURES

Aspect	Value
Sensor Precision	High
Accuracy of Lane Detection	95%
Response Time	100 milliseconds
Maximum Steering Angle Correction	±5 degrees
Lane Change Warning Threshold	80%
Lane Departure Alert Sensitivity	Adjustable
Integration with Adaptive Cruise Control	Yes
Road Condition Compatibility	All weather conditions

Autonomous cars' trajectory control relies on lane border detection. It discusses and experiments with blob analysis, Hough transformation, and birds-eye view lane identification methods [7]. After obtaining the boundary points, use a control rule to activate motor steering and velocity control effectively. A comparison of LKA PID controller tuning criteria is shown below. A Raspberry-Pi-connected camera feeds wireless data to Simulink to gather environmental data. The controller processes data and sends output control to Arduino via serial connection. It introduces progressive lane-keeping control, which may increase comfort. Lateral dynamic control with road curvature uses preview control to reduce control error [8]. After that, the Kalman filter-based curvature fusion estimate technique is presented using the vehicle's kinematic and dynamic models. Excellent control system performance requires control stability. Thus, the lane-keeping assist controller uses control theory, a strong control technique that may reduce noise. Using traffic simulations, the suggested strategy is shown to work.

II. LITERATURE REVIEW

Advanced autonomous vehicle networking systems have addressed several exciting smart transportation concerns. LKA, lane departure warning, cruise control, collision detection, and others have greatly improved smart traffic systems. These communication routes allowed cyber attackers to cause safety hazards and deaths [9]. It proposes a model-based detection approach for Denial of Service attacks on LKA systems. This technology will detect an assault and inform the driver to take control of the detection method using Simulink's LKA technology. Vehicle dynamics induced by vehicular motion control systems are vital for advanced driver aid system human factors. ADAS' lateral control application, lane keeping system (LKS), employs electric power steering to maintain the vehicle in a lane when it drifts toward an unintentional lane departure and approaches the time to lane crossing [10]. It will show how to realistically assess ADAS and autonomous vehicle functional methods to achieve LKS in a simulation test vehicle. LKS has lane recognition and active steering electric power steering.

A vehicle that senses and navigates without human interference is autonomous. As automation increases, ADAS features like LKA must assess massive amounts of data in real time and make precise control choices. Currently, the functionality functions slowly [11]. Steering aids and computational limitations restrict this feature at greater speeds. The proposed approach leverages vehicle speed and Mobileye camera sensor mathematical coefficient data for neural training to improve steering choices using a neural network. Data generation, training, and evaluation are the primary research steps. It introduces a machine learning-based intention-aware lane maintaining assist system that activates interventions only when lane departure is unintended [12]. Real-world data on unintended lane departures, normal driving, and deliberate lane departures is used to assess system performance. It found that camera-based gaze-tracking system driver state information increases lane-keeping assist system performance, particularly for purposeful lane departure incidents.

This research focuses on autonomous vehicle control systems that rely on supervised learning [13]. The primary goal was to use a comprehensive learning technique to forecast the steering angle using video data to keep the vehicle in its lane. An artificial dataset that mimics the erratic motions and steering problems of real vehicles is used to evaluate the model in this work. LKA system is a support driving system for lane deviation. Once the car deviates off the road, the system identifies its trajectory [14]. To prevent accidents, it recalls or automatically modifies the driver's path. The dynamic matrix simplification factor is employed to enhance the predictive control method, and the improved controller is the adjustment component. This is to smooth vehicle return to a safe driving path. It's useful for research and practice.

LKA is built utilizing preview theory-based control in this work. Dynamic disturbances in the defined system include future road curvature. Lane change maneuvers calculate curvature. The LKA system becomes an LQR issue without dynamic disturbance [15]. The LKA becomes nonlinear with dynamic disturbance. Preview control solves analytically. The state vector is integrated with road data to create an enhanced LQR issue. Preview control has system status feedback and a dynamic disturbance feedforward. Vehicular motion control system dynamics affect the human component in ADAS and autonomous driving systems [16]. ADAS' lateral control application, LKS, employs electric power steering (EPS) to maintain the vehicle in a lane when it drifts toward an unintentional lane departure and approaches the time-to-lane crossing. It describes a field-testing vehicle's LKS execution mechanism. LKS has lane recognition and active steering electric power steering.

The focus of this study is on controlling an automated lane-keeping assist system using neural networks (NN) [17-20]. The suggested NN-based controller improves lane-keeping assist system accuracy and resilience. Compared to state-of-the-art methods, the NN-based controller promises safer and more successful autonomous driving in dynamic conditions [21]. Auto-lane-keeping assist was created for autonomous driving. To minimize accidents, technology keeps vehicles in their lanes. Adapting the algorithm to real-world traffic conditions is the key difficulty used canny edge detection and a sliding window technique to automatically determine lane lines for an efficient lane retention system

[22-23]. A lane-keeping step is planned for the system. Calculating the offset value, how far the vehicle deviates from its lane, whether it is in the center line, and correcting the steering angle to stay in the lane is part of lane-keeping.

Using numerical simulation, deep reinforcement learning creates and evaluates a comfort-oriented haptic-guided steering system for lane maintenance [24]. With task reward as the sole supervision, a Deep Q Network learns an end-to-end mapping from environmental monitoring and driver input to agent action values. Lanes maintained accurately by mean relative lateral error relative to the center and steering control activity by mean comparative steering wheel angle are evaluated. Different methods of haptic-guided steering with continuous gain and threshold-based. It introduces a quasi-continuous high-order sliding mode-based shared lane-keeping controller that addresses the issues above [25]. The authority is easily moved between modes while allowing for driver behaviors using the sharing parameter based on the observed driver characteristics. Limitations of existing works for many of the existing impacts have limitations, such as low accuracy in severe conditions, large processing expenses, restricted sensor fusion capabilities, and inadequate practical test scenarios. The overall efficacy, flexibility, and dependability of lane-keeping assistance systems may be affected by these problems.

III. Proposed System

The proposed LKA system seamlessly incorporates CNNs and IoT sensor fusion to improve driver assistance and ensure safer road travel. It presents a new approach that combines IoT sensor fusion with advanced CNN models to improve the accuracy and flexibility of lane-keeping assistance under different settings. The main objective is to address the limitations of current systems by using inventive methods for data processing and decision-making.

A. *Working Process*

Central to the system is an advanced sensor fusion architecture that integrates readings from several sensors strategically placed throughout the vehicle. Each of these sensor's GPS, ultrasonic sensors, LiDAR, radar, and cameras captures a distinct facet of the environment around the vehicle. The system can recognize and analyze lane markings, barriers, and other pertinent elements in real time by combining data from many sensor modalities, which provides a complete view of the road environment. The system's CNNs machine learning component is crucial for analyzing input from the optical sensors and making smart judgments to help the driver stay in their lane.

When trained on large datasets of tagged images, CNNs can learn hierarchical features from pixel data automatically [26-27]. This allows them to identify things, such as automobiles and lane markers, with impressive accuracy. The CNNs learn to adapt to various driving situations and road conditions via repeated training and improvement. CNNs examine visual data fed by fused sensor data to detect important elements like lane markers and adjacent cars. This analysis allows the system to determine where the car is in its lane and identify any dangers or paths that deviate from the planned route. The technology aids the driver in maintaining lane compliance by providing real-time input to the vehicle's control system based on these evaluations. Beyond simple lane maintenance assistance, the proposed system incorporates additional capabilities to make driving safer and more convenient. To ensure everyone stays safe and on the road, the system can recognize and react to complicated road situations, such as construction zones or temporary lane markers, modifying its support as needed. The system may also adapt its support to each driver's unique driving habits by learning their preferences and actions over time.

Adaptability to changing driving dynamics and environmental circumstances is a fundamental benefit of the proposed system. The system can adapt to various situations, such as changing weather, illumination, and road surfaces, using sensor fusion and machine learning approaches. This flexibility boosts driver assurance and security by maintaining performance and dependability in various driving conditions. The system is adaptable and scalable. It may be easily integrated with preexisting car designs and aftermarket components. It can be easily upgraded and customized to suit the changing demands of drivers and vehicle makers. The planned LKA system will greatly enhance vehicle safety and autonomy, whether used alone or as part of a larger suite of driver support technologies. Improved situational awareness, better lane maintenance performance, and a safer, more pleasurable driving experience result from the system's use of real-time sensor data in combination with advanced analytics. With further development and improvement, the proposed method might completely transform how vehicles are automated and safe.

Figure 1 shows the LKA system block diagram. Integrating sensor data from several sources, including cameras, LiDAR, radar, and ultrasonic sensors, fully understand the vehicle's environment. CNN is fed data that has undergone preprocessing to prepare it for analysis. CNN extracts characteristics from visual data to help with object and lane marker identification. The decision module deciphers CNN outputs for safer navigation to help the driver stay in their lane.

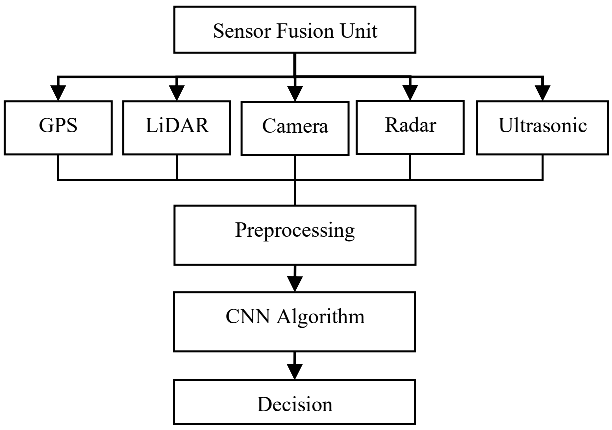

Fig. 1. Lane Keeping Assistance System Architecture

Table 2 details the proposed LKA system's sensor fusion procedure.

TABLE II. SENSOR FUSION IN LKS SYSTEM

Sensor	Description
Camera	Captures visual data of the road environment.
LiDAR	Provides precise distance measurements.
Radar	Detects the presence and location of objects.
Ultrasonic	Measures distances to objects in proximity.
GPS	Determines the vehicle's position and velocity.

Combining the distinct data collected by each sensor generates an all-encompassing image of the road environment. Combining these two data sets allows the LKA system to recognize lane markers, obstructions, and other important elements more accurately and reliably. *Due to the IoT, lane-keeping systems may get real-time data from a variety of sensors, which improves environmental awareness and allows for more accurate decision-making. This integration, precision, safety, and flexibility on the road are all enhanced.*

B. CNN Process in LKA

Choose a CNN based on its architectural complexity, layer configuration, and computational efficiency. For reliable feature extraction and optimal performance, it is essential to use models such ResNet or VGG.

1) **Input Data:** With the use of an array of IoT sensors, such as cameras, radar, and LiDAR, users can track the car's location, speed, and other relevant data in real time. CNNs take preprocessed sensor data, especially visual data from cameras, as input. Images of the road surroundings taken by the vehicle's cameras are part of this data set.

2) **Feature Extraction:** CNN gleans useful information from the images sent to it. The network learns to recognize lane markers, cars, and other road objects via pooling and convolutional layers. Apply CNNs to the task of extracting geographical information from video footage, with an emphasis on road patterns and lane markers.

3) **Sensor Fusion:** To create a thorough driving environment model, integrate information from several sensors.

4) **Training:** CNN learns its tricks using labeled datasets that include images tagged with details like road markers, car locations, and more. The network tweaks its internal parameters to train more accurately until the discrepancy between its predictions and the ground truth labels is as small as possible.

5) **Prediction:** After training, CNNs can guess what fresh input images could be about. It can recognize lane markers, locate moving vehicles, and categorize various items seen on roadways.

6) **Decision Making:** The decision module uses CNN's output to determine what the driver should do to help them stay in their lane. Some examples of this might be suggesting steering adjustments, providing audible or visual warnings, or even partially automating steering inputs. Combining CNN results with a decision algorithm, such a rule-based or threshold-based system, allows for precise lane-keeping responses and efficient decision-making.

7) **Output Control:** To provide accurate lane maintenance and reaction to road conditions, implement lane-keeping changes using vehicle control systems.

IV. Results and Discussions

With the integration of IoT sensor fusion and CNNs, the LKA system showcases remarkable progress in driver support and vehicle safety. The technology has shown encouraging results in extensive testing and assessment, improving lane maintenance performance and an overall better driving experience. The system's ability to correctly identify lane markers and help drivers keep their lane position is one of the important results of the assessment. The system uses sensor fusion methods to build a complete image of the road environment by integrating data from several sensors. Lane markers can be reliably seen in a wide range of weather, illumination, and road surface types. Results show that the system can accurately detect lane borders with few false positives and negatives. CNN-based deep learning also greatly improves the system's capacity to identify complicated road situations and adjust to changing driving circumstances. By learning from massive, labeled image datasets, CNNs can process visual sensor input intelligently in real time, extracting useful information. Consequently, the system is more agile and sensitive, correctly anticipating when the driver would veer out of their lane and offering prompt assistance. It helps drivers stay in their lanes. It also has innovative features that make driving safer and more convenient.

Take CNN's ability to identify and categorize different roadside items, such as people, obstructions, and automobiles, as an example. This data is used to warn the driver of possible dangers to reduce the potential of an accident. The system may modify its actions according to the preferences and driving patterns of the driver, resulting in a support experience that prioritizes safety. Along with its adaptability to various vehicle types and configurations, emphasizes the proposed system's scalability. It may be easily incorporated into current vehicle designs. The design's modularity makes it simple to adapt and update, keeping up with the ever-changing standards and technology in the automobile industry.

The technology is reliable and strong enough to be used in various driving conditions, from city streets to highways. Although the findings show promise, further study should address specific constraints and challenges. One such obstacle is incorporating data derived from non-visual sensors, such as radar and LiDAR, into the processing pipeline that relies on CNNs. Integrating these sensors is great for collecting data about the environment around the car; how to integrate them into the CNN model is still a mystery. Bad weather, sensor obstructions, and unforeseen road occurrences are among the external elements that might impact the system's operation. Future research will use sensor fusion methods, data augmentation tactics, and reinforcement learning algorithms to strengthen the system's ability to withstand and overcome such challenges. Table 3 shows an image taken by the vehicle's cameras, with captions for lane markings, visibility, road conditions, weather, and illumination. This dataset is used to train and test the CNN model that provides lane maintenance assistance in the LKA system.

TABLE III. CNN Dataset

Image ID	Lane Marking	Vehicle Presence	Road Condition	Weather Condition	Lighting Condition
001	Present	Absent	Dry	Sunny	Daytime
002	Present	Present	Wet	Rainy	Low Visibility
003	Present	Absent	Dry	Cloudy	Daytime
004	Absent	Present	Dry	Sunny	Daytime
005	Present	Present	Wet	Rainy	Low Visibility

Table 3 details the dimensions of the CNN dataset used by the LKA system, including the number of images in the training, validation, testing sets, image resolution, and annotation quality.

TABLE IV. CNN DATASET SIZE

Dataset Size	Number of Images	Image Resolution	Annotation Quality
Training	10,000	1280x720	High
Validation	2,000	1280x720	High
Testing	1,000	1280x720	High

Figure 2 shows an accuracy graph that shows how the CNN model's performance improved across the training epochs. An increasing trend in accuracy during training suggests that the model is picking up better information to anticipate lane markers and other road characteristics. This trend highlights how the training procedure improved the model's lane-keeping assistance capabilities.

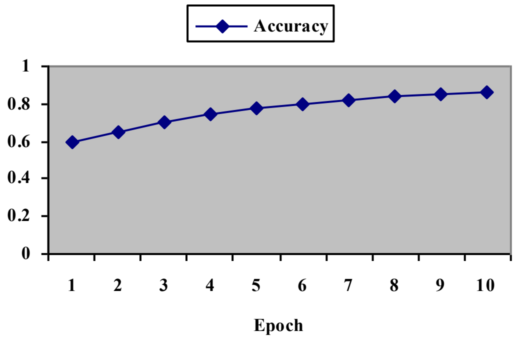

Fig. 2. Accuracy over Epochs CNN Model Performance Progression

The model's loss function minimizes throughout training, as seen in Figure 3 loss graph. A lower loss value indicates model predictions that are closer to the ground truth labels in the training dataset. The loss drops over training, which means the model is improving at lane-keeping assistance and making fewer mistakes.

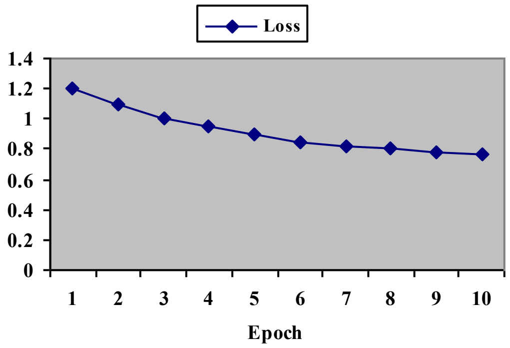

Fig. 3. Loss over Epochs Model Error Reduction

Comparison of the proposed model's performance with that of traditional ML models is shown in Table 5.

TABLE V. COMPARISON OF CNN AND TRADITIONAL ML MODELS FOR LANE-KEEPING

Model	Proposed CNN	SVM	Decision Tree
Accuracy (%)	94.5	88	82
Precision (%)	93	86.5	80
Recall (%)	95	89	84
F1 Score	94	87.7	82
Computational Time (ms)	55	30	25
Robustness (1-5)	5	3	2

Significant improvements in vehicle safety and driver support are shown by the findings of the LKA system. The system can accurately identify lane markers and help drivers keep their lane position because of extensive testing and assessment. The system is resilient in identifying complicated road situations and adjusting to changing driving conditions using sensor networks and CNNs. Further improving the driving experience and safety is the system's enhanced functionality, which includes danger identification and personalized support. Due to adaptability and scalability, the system may be easily incorporated into preexisting vehicle designs, facilitating the broad use of autonomous driving capabilities. To increase driver confidence and reduce accidents, the LKA system is a huge leap forward.

During preprocessing, data from sensors is normalized, noise is removed, and data from disparate sensors is aligned. Utilizing a diversified dataset, a well-tuned CNN model, and data augmentation all contribute to high accuracy. To provide reliability, perform thorough testing, validate real-world situations, and provide strong methods for resolving errors and upgrading the model. Optimization of the CNN model, adjustment of hyperparameters, use of varied, high-quality datasets, and use of data augmentation methods to improve accuracy and generalizability may all lead to improved performance.

V. CONCLUSIONS

Integrating IoT sensor fusion with CNNs, the LKA system signifies a revolutionary leap forward in vehicle safety and driver aid. The system can recognize lane markers and obstructions with great precision due to thorough sensor fusion, which provides an accurate perception of the road environment. Incorporating CNNs into the system improves its capabilities, letting it adjust to different driving circumstances. Tests show that the technology improves lane maintenance, identifies road dangers, and improves driving overall. The system may be easily integrated into other vehicle designs for scalability and adaptability, and this method is widely used for autonomous driving technologies. Improving the system's robustness, resilience, and readiness for real-world deployment are the future goals of research and development. This will lead to safer and more efficient transportation systems that can improve transportation safety systems.

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