Grenze International Journal of Engineering and Technology, Jan Issue

An Empirical Study of Safety Models used in Driver Assistance Systems from a Statistical Perspective

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***Abstract*—Driving assistance systems (DAS) are responsible for enhancing the on-road driver experience in terms of lane safety, speed monitoring/control, drowsiness detection, vehicle to vehicle communication for incident alerts, etc. Each of these systems requires large amounts of input temporal data that is processed via machine learning algorithms. For instance, lane safety systems use a combination of image and depth data to analyze whether vehicles are following lane-rules or not. For this analysis, algorithms like convolutional neural networks (CNN), support vector machines (SVMs), and etc. is used. Each of these input-to-algorithm combinations has different advantages and nuances for each application. Thus, it is very difficult for system designers to identify best practices to evaluate and select these algorithms. In order to simplify selection of these algorithms for given systems, this text evaluates different recently proposed & highly efficient systems for each of these applications. This will assist researchers and system designers to select application-algorithm pairs for deploying highly efficient and customized driving assistance systems. The text also suggests various optimizations that can be done in these algorithms to further improve their performance when deployed in new or existing real-time systems.**

***Index Terms*— Driving assistance, on-road, machine learning, lane, speed, control.**

I. INTRODUCTION

Driving assistance includes a multitude of driver-related operations which include [1], but are not limited to, speed monitoring/control, drowsiness detection, lane detection/correction, driver-to-driver communications, parking assistance, etc. In order to perform these operations a series of steps are followed by system designers, these steps can be observed from figure 1, wherein the following blocks are used,

- Acquisition or sensing block, wherein data from different sources is collected. This block includes sensors like Camera, Radar, Infra-red camera, global positioning systems, vehicle to vehicle (V2V) and vehicle to infrastructure (V2I or V2X) communication systems.
- All these sensing elements are responsible for effective data reading and keeping it pre-processed for further processing.
- Data processing block, wherein data from acquisition block is taken and processed using systems like computer vision, radar processors, infra-red processors, V2V and V2X processors. This data processing requires a large number of algorithms, which include but are not limited to,
    - Data clustering algorithms for segregation of data
    - Classification algorithms for finding out different data patterns

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- Data analysis and inference blocks are different from data processing block. In this block, different data analysis operations like prediction, fusion, decision making, etc. are performed. Algorithms like CNN, Naïve Bayes, etc. are used in this block.
- Action & actuation block is the last block for any DAS architecture. In this block all the corrective and preventive measures for braking, throttling, steering, alerting, etc. take place. This block is also responsible for display of various intra and inter-vehicle parameters.

In order to design any DAS architecture, optimized design of these blocks as per driver requirements [2] is of utmost importance. Different algorithms have been suggested over the years for efficient design of individual blocks. The next section describes a survey of these blocks, which is followed by their statistical analysis. Finally, this text concludes with some acute observations about these algorithms and recommends ways to improve their performance.

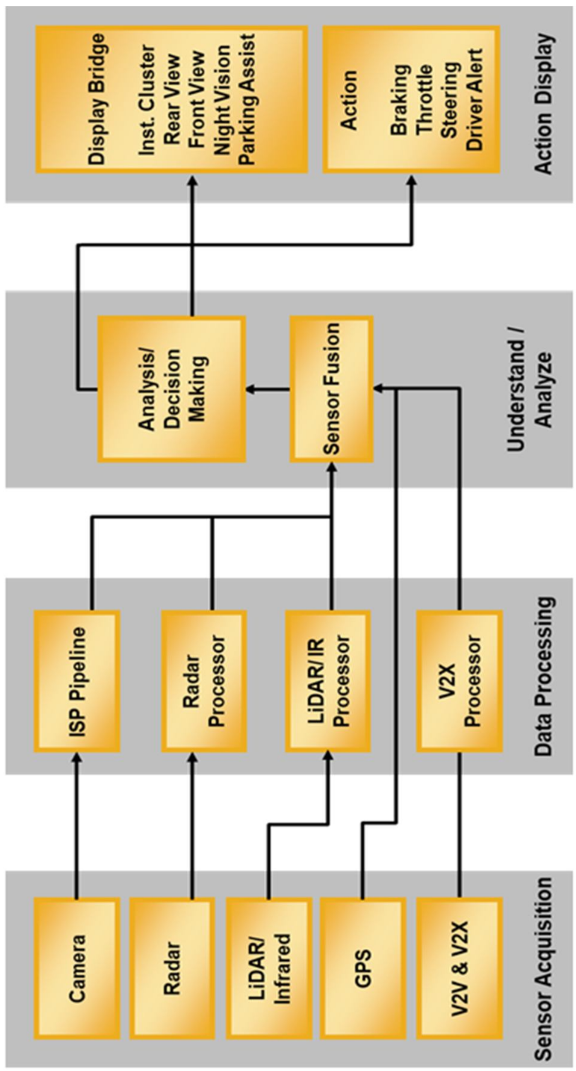

Figure 1. A sample DAS architecture

II. Literature Review

Effective driver assistance systems require implementation of efficient and accurate algorithms for different sub-DAS modules. The work in [3] proposes the use of recursive convolutional neural network (R-CNN) for effective object & lane detection, and using this data it also proposes architecture for effective collision prevention. It uses the following steps in order to integrate both the systems,

- Visual data for vehicles is extracted and processed using a canny edge detector & Hough transform for lane detection. The visual data is also used for object detection using a recursive CNN model.
- If lane deviation is detected, then the breaks are applied and vehicle is actuated to slow down to avoid collisions
- If object is detected, then distance analysis between the detected objects is done, and based on this the chances of collision are evaluated. In case there is any chance of collision, then the vehicle is alerted to slow down or stop depending upon the distance evaluated.
- If the vehicle is inactive, then detection is stopped, else the entire detection process is repeated

Due to the usage of R-CNN with Hough transform the overall collision avoidance accuracy is 98% on video datasets, which is very high. But the system is tested on a limited dataset of images and videos, thus extensive evaluation of the system must be done in order to predict is real-time performance. This accuracy can be further tuned for real-time usage with the help of random sample consensus (RANSAC) algorithm observed in [4], wherein RANSAC and CNN are combined for effective lane and collision detection. RANSAC allows for high accuracy edge-based lane detection. The output of this lane detection system is given to a CNN layer, from where the final lane probability is evaluated. Architecture for the proposed CNN can be observed from figure 2, wherein different convolutional (C) and Soft-max (S) layers are combined with a fully connected multi-layered perceptron to get the lane detection results. Due to this combination the accuracy of real-time lane & collision detection is improved to about 93%, which is lower than [3], but the mentioned accuracy is for real-time use-cases instead of dataset-based use-cases as given in [3]. This makes the system more reliable and readily deployable. Even though the accuracy of lane & collision detection is very high, these algorithms require large computational power, due to which they are not energy efficient. The work in [5] suggests offloading complex computations to the local edge node in order to improve its overall efficiency. The system uses double layer network which has the ability of transfer learning in order to adaptively learn from current and previous images. The system produces the following accuracy values,

- Lane detection under Insufficient light: 96.6%, which is 4% higher than VGG-FCN, SCNN, U-Net and Traditional CNN
- Under Shadow occlusion conditions: 97.85% which is 5% higher than other compared techniques
- Lane detection where there are missing lane lines: 95.88% which is 7% better than other methods
- For Curve lane line: 94.1% which is 6% better
- For normal road: 97.57% which is around 6% better than other methods

Due to the cloud-computing nature of this algorithm it can adapt to better, faster and more efficient algorithms for lane detection and collision prevention. This adoption can assist in extracting accurate lane information under soil hid, tree shadow and street light conditions. An architecture of CNN which works under these conditions can be observed from [6], wherein a pipeline of CNN with Hough transform & Kanade–Lucas–Tomasi (KLT) algorithm. Due to this pipeline the accuracy of lane detection is 98%, which is more than combinations of Guassian filter + Hough transform (89%), Maximally stable extremal regions + Hough transform (93%), Hue Saturation Value – Region of Interest + Hough transform (95%), simple CNN (96%), and Improved Lane Detection + Hough transform (97%). The architecture of this pipelined methodology can be observed from figure 3, wherein CNN, Lane detection and Lane tracing operations are showcased in details.

Detection of lane is often followed by lane-change detection. This assists in evaluating driving patterns and thereby assisting drivers to drive more carefully. The work in [7] proposes a light detection and ranging (LiDAR) based deep learning algorithm for lane change detection. It also uses inertial measurement unit (IMU) data like Force on brake pedal, Force on gas pedal, Velocity, angle of steering, Longitudinal & lateral acceleration for detection of lane change behaviour. The system then combines this data with image data using a 27 layered CNN which is a combination of convolutional, max pooling, and average pooling layers for obtaining a highly accurate lane change detection system. In order to combine the data from IMU and image frames, a concatenation-based architecture is devised. This architecture uses an average pooling layer for frame processing, and a linear classification layer for IMU processing. Data from both these layers is given to a fully convolutional layer, which is followed by a soft-max layer for final feature extraction. Due to a combination of these layers, it is possible to learn from both image data and vehicle statistical data.it is observed that only IMU data can provide an accuracy of 55% for lane detection, which is improved to 90% when IMU data is combined with LiDAR imaging data. This accuracy can be further improved using RNN and LSTM based networks. From these reviews it can be observed that CNN, RNN and its variants are capable of detecting lanes and avoiding

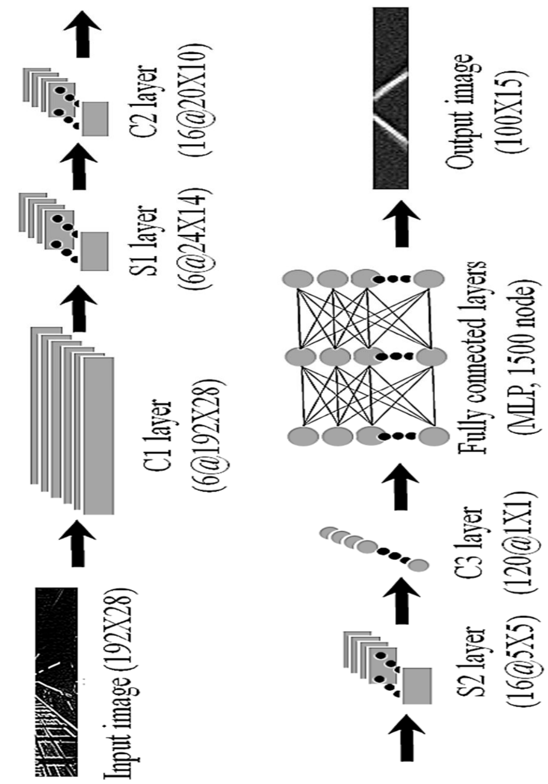

Figure 2. Combination of RANSAC with CNN for effective lane detection [4]

lane-based accidents with very high accuracy. Driving assistance systems can also be enhanced via detection of driver's physical conditions. The work in [8] proposes a novel driver drowsiness detection system using smartphones. This system utilizes 3D neural networks (3DNNs) for improving the accuracy of drowsiness detection. It uses the standard driver drowsiness detection dataset [8] for neural network training. Once the network is trained, then the system is tested on various scenarios including, No Glasses, Glasses, Sunglasses, Night time with No Glasses and Night time with Glasses. An accuracy of 75% is achieved under these complex scenarios, which indicates that the system will be able to detect correct driver drowsiness in 3 out of 4 frames, which is sufficient for real-time road scenarios. This 3D Neural Network (NN) system uses the following architecture for processing any input frame,

- Initially a 224*224*10*1 convolutional 3D layer is instantiated to process raw input frames
- This is followed by a bottleneck 3D layer of size 112*112*5*48
- These dimensions are reduced to 112*112*1*24 using a squeeze layer
- Then a series of 6 bottleneck layers is used to reduce this to 7*7*224 size
- Finally, a convolutional 2D layer, followed by an average pooling and another convolutional 2D layer is used for reducing feature dimensions to 1*1*1280

This architecture can be further optimized using LSTM, RNN and Transfer learning, which can help in real-time accuracy improvement. Other techniques for improving accuracy of drowsiness detection systems can be observed from [9], wherein different classifiers like CNN, support vector machines (SVM), Naïve Bayes, Random Forest (RF), etc. and different driver features like Steering wheel movement, Deviation & Lane position, Speed & Acceleration, Eye movement, Face expression and Head position are considered for improving drowsiness detection accuracy. The research also suggests usage of Physiological Signals like Brain activity (that includes electroencephalography (EEG) and Near Infrared Spectroscopy (NIS)), Ocular activity which is measured using electrooculography (EOG), Muscle Tone via electromyography (EMG), Cardiac activity using electrocardiography (ECG) and Blood Pressure levels, Respiration patterns using respiratory effort analysis, Nasal airflow, oral airflow, Blood gas levels, and snoring noise levels, Gastro intestinal parameters, Electro dermal activity which is measured using galvanic skin response, through skin resistance and

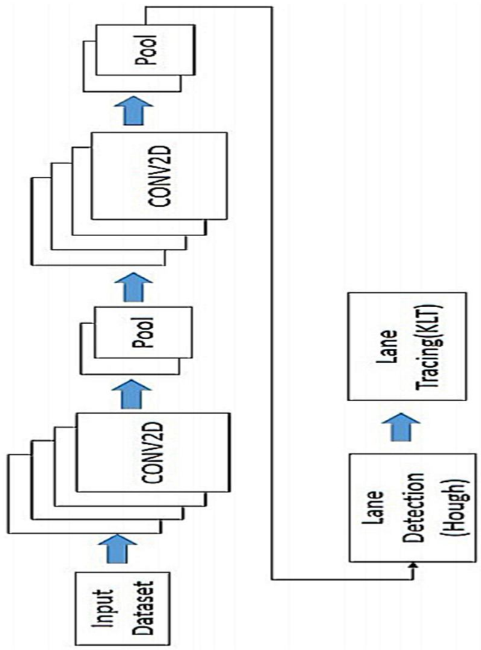

Figure 3. Pipelined architecture for lane detection [6]

conductance, core body temperature, etc. These are intrusive techniques, and thus cannot be used in real-time cases because normal people won't wear them during driving. This is due to the fact that these sensors require additional effort of wearing, calibration, interfacing, and/or synchronization during driving. Data from one or more of these sensors can be fused in order to obtain a highly effective drowsiness detection system. The work in [10] proposes a novel weight-based data fusion algorithm for accurate detection of drowsiness under real-time and lab-based conditions.

Effectiveness of the data collected from lane detection, drowsiness detection and other DAS modules can be further improved if this data is efficiently communicated to other vehicles. This communication can help other vehicles to take accident preventive actions and for better driving experience. The work in [11] proposes a multi-channel wave-based vehicle to everything (V2X) communication interface. This interface is based on the IEEE-WAVE standard and uses dedicated short-range communication (DSRC) for improved communication performance. Due to use of these layers an improvement of 15% is obtained in overall throughput of the system. This performance can be further enhanced with the help of machine learning models. The work in [12] suggests use of Generative adversarial networks (GAN) for improved communication, object detection and lane detection performance. This study is further enhanced using the research in [13], wherein different Vehicle Detection Systems are reviewed for better DAS performance. The work suggests other avenues like Traffic Sign Recognition and Aerial Vehicle Detection along with standard DAS modules to generate a highly effective system. While all these systems are based on enhancing application-level performance, the work in [14] proposes a E/E architecture which can improve overall performance of DAS via accurately modelling electronics hardware, network communications, software applications, and wiring in these systems. An efficiency improvement of 15% is achieved with the help of these E/E systems.

Due to the incorporation of E/E systems, faster and real-time signal processing is possible. The work in [15] suggests that audio-data inside the vehicle can be analysed using E/E with Random Forest and SVM classifiers for improving emotion recognition accuracy of the system. Via this emotion recognition module, driving assistance can be improved, in the following cases,

- Slowing down the vehicle in case the driver is angry or frustrated
- Speeding up vehicle if the driver is anxious
- Moderating the speed in case the driver is singing or excited

Based on this analysis, the work in [15] suggests that there is a 10% improvement in the overall driving behaviour of users. This information can be helpful while detecting vehicle context as suggested by [16], wherein context is only decided by relative positions of vehicles w.r.t. the host vehicle. The current context information as observed from figure 4, can be enhanced via addition of driver emotion to further understand and predict its future performance.

The context-based information can also be used for detection of lane-change [17] and drowsiness [18] detection behaviour. Both these concepts use the context as follows,

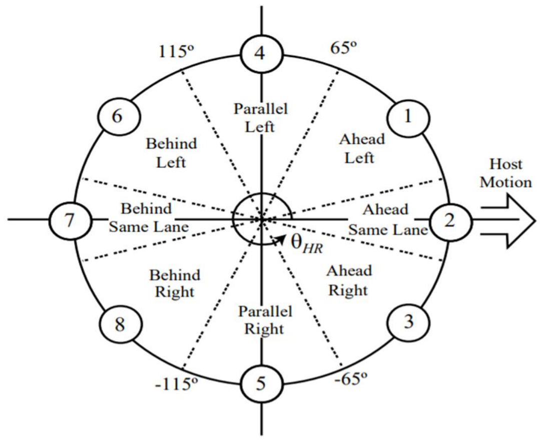

Figure 4. Position-based context for improving communication performance [16]

- Depending upon user emotion, vehicle position and speed, the next position of the vehicle can be predicted. This position can determine whether the driver is going to cross the lane or not
- Drivers who are sad, depressed and are not following proper contexts can be predicted to go into drowsy state with a higher probability than those who are happy, excited and are following proper context rules Using these directives, the work in [17] and [18] can be combined with emotion-based context for a better driver assistance system.

Structural analysis of lanes can be done in order to further improve the accuracy of lane detection. The work in [19] proposes a CNN based method for structural analysis of lanes and then identifying whether lanes are present or not. Architecture for such a system can be observed from figure 5, wherein a fully connected CNN is used along with lane structural information to identify lane presence. The results of lane detection are evaluated on different datasets like Caltech, Beijing, etc. and an accuracy of 99% is achieved using the proposed CNN architecture. This accuracy holds true even under day, night, expressway, urban roads, straight lanes, curved lanes, changing lanes, turn lanes and road writing conditions. Thus, this makes the system effective for real-time usage on different kinds of roads.

With the help of these algorithms, an autonomous driving system can be designed. This system allows integration of various DAS architectures in order to form an efficient and highly effective driving management system. The work in [20] proposes a CNN–LSTM-based architecture which includes,

- A Baseline CNN with Fully Connected Network (FCN) for initial classification of driver lanes
- Inception + FCN based network for improving lane detection accuracy along with object detection
- ResNet-50 + FCN as an extension to Inception-network for adding statistical and physiological parameters to the system
- Inception + LSTM + FCN for further improving real-time performance
- ResNet-50 + LSTM + FCN which is the final architecture involving all the previous layers, which allows for data fusion, decision analysis, drowsiness detection, lane detection, etc.

Such autonomous systems are capable of improving the efficiency of DAS to 98% with real-time conditions. This efficiency can be further enhanced by using improved vehicle detection algorithms for collision prevention. The work in [21] uses RBF (radial basis function) Neural Network for identification of tail-light pairs of vehicles with 97% accuracy. In order to perform this task, the following steps are followed,

- Image sequence is given to edge detection for finding presence of vehicle
- Composite features are extracted using vehicle’s bottom shadow and tail-lights
- From these features, region of interest (ROI) is determined for the candidate vehicle region
- The ROI features are given to the RBF Neural Network to get the final trained network
- Any new image is given to this network to obtain the final recognition result

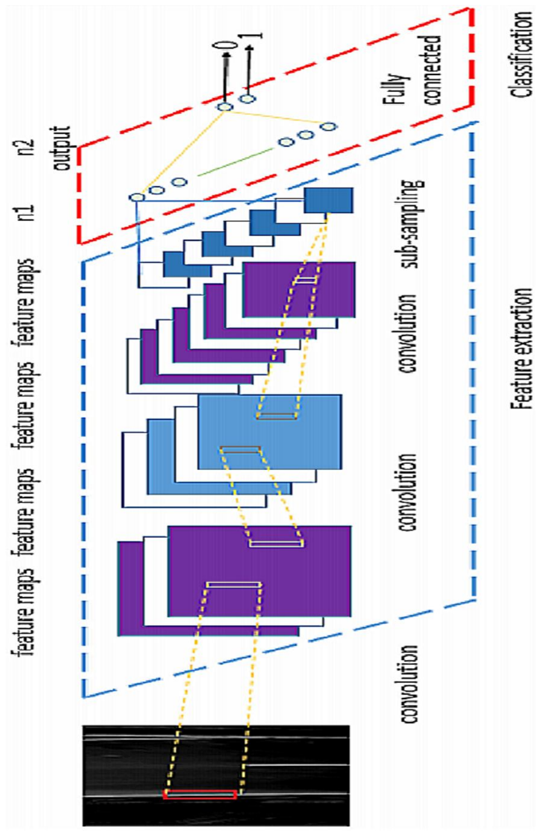

Figure 5. Lane detection based on lane structural analysis [19]

A flow of this process can be observed from figure 6, wherein RBF training and testing steps are seen in details.

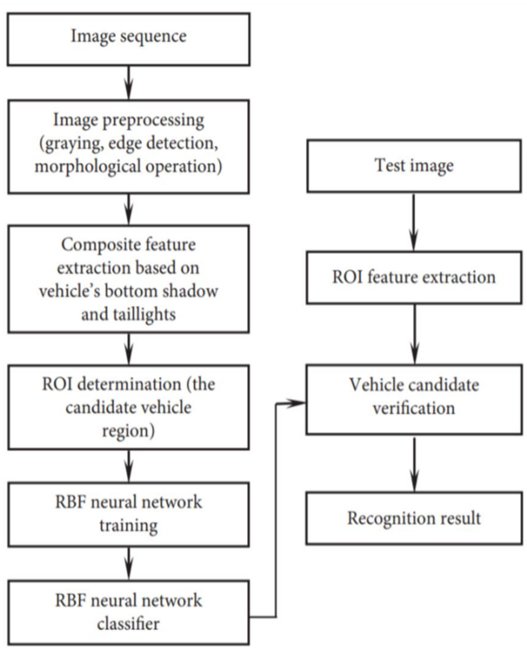

Figure 6. RBF based vehicle detection [21]

Along with vehicle detection, driving control methods are also important. The work in [22] suggests a EEG-based Recursive NN based Transfer & Deep Learning (TDL) method for improved driving control. As observed previously, usage of EEG for normal vehicles is infeasible, but using EEG with high cost and high maintenance vehicles can be done. Due to this, the work in [22] suggests the use of EEG for Tractor control. The method uses principal component analysis (PCA) for acceleration, brake, left turn and right turn operation automation. The system learns from car driving patterns, and uses this information to train the tractor-based neural network via transfer learning. A description of this approach can be observed from figure 7, wherein the transfer learning approach is seen to be working in detail. Due to the combination of PCA with Recursive NN and TDL an accuracy of 94% is achieved, which is low considering that these systems are applied for high-cost vehicles. Therefore, the accuracy must be improved with the help of better deep learning algorithms like Q-Learning, recurrent NNs, LSTM-based CNNs, etc. as described in [23] which tend to reduce error for accuracy improvement. Efficient DAS architectures can also be improved via identification of traffic zones. The work in [24] suggests use of Colour Recognition, Size and Distance Calculation, Noise Filtering and Target Marking for classification of red, green and blue traffic zones (referred as cones) with almost 94% accuracy. This work can be combined with [23] to further facilitate zone-based traffic detection, and its accuracy can be improved using Maximum Entropy Deep Inverse Reinforcement Learning as suggested in [24]. This algorithm is applied to car-following behaviour prediction, but can be used for any other classification-based use case. Average accuracy of 98% is achieved using this system, which is high enough to be used for any kind of DAS module. Other areas in which systems like these can be applied are observed from [25], wherein algorithms like SVM, CNN, extreme learning machine (ELM), Adaboost, etc. are applied for DAS applications like lane detection, vehicle classification, driving style prediction, pedestrian detection, etc. In this review, CNN-based methods have highest accuracy in the range of 96% to 99% for multiple application types.

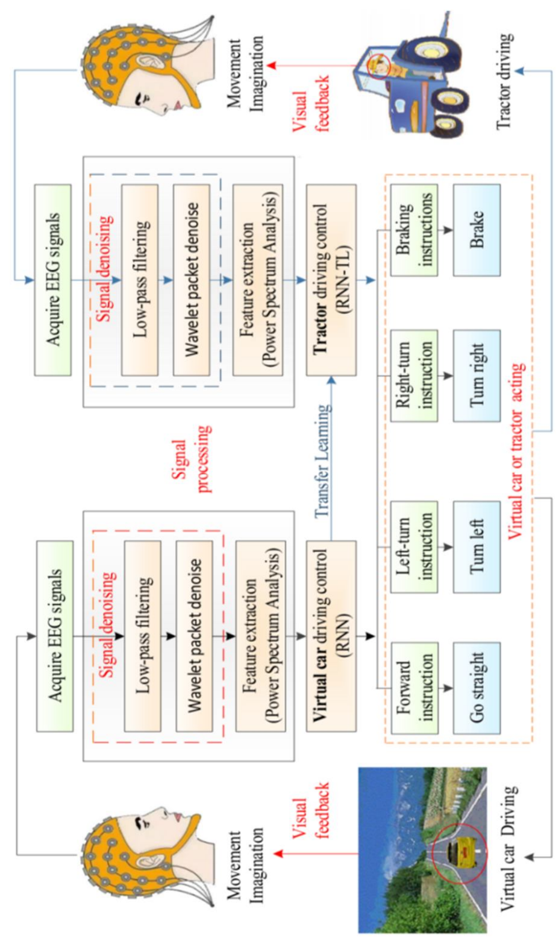

Figure 7. Transfer learning approach to improve accuracy of DAS [22]

Other methods like model predictive control (MPC) [27], kinetic theory [28], man-machine cooperative control based on electric power steering & electronic stability program [29] learning-based model predictive control [30] are also discussed by researchers. These methods provide accuracies in the range of 80% to 90%, and therefore are not effective for real-time use cases. Researchers have also proposed methods like infrastructure-based vehicle monitoring using linear classifiers [31], dynamic boundary extension decision-based vehicle control [32], Internet of Vehicles (IoV) powered image and command model with speech recognition and image processing [33] for enhancing vehicle control. These systems are also able to perform vehicle control operations with up to 90% accuracy, which can be improved by previously discussed LSTM and CNN-based systems. It is observed from [34] that with the use of CNN-based DAS modules for automatic driving systems, the efficiency of driving assistance is improved to 97% which makes these algorithms applicable for real-time usage. But before applying these systems for real-time usage, it is recommended that effective testing methodologies must be applied. The work in [35] suggests use of simulation environments like SUMO for initially testing these systems, and then deploying them for real-time use cases. Upon deployment, it is recommended that the personal health of driver should be monitored by drowsiness detection systems which are discussed previously.

III. Statistical Analysis

In order to evaluate the performance of DAS modules, this section separates each of the proposed systems as per their application areas and compares their performance in terms of their accuracy to perform that task. The following figure 1 reflects this analysis, wherein distinction is made as per method name, DAS module in which this particular method is applied, its application area which indicates the application for which this module is most suitable and finally its statistical performance accuracy, which indicates the effectiveness of using this module for the given application.

TABLE I. Performance comparison of DAS modules

Method	**DAS module**	**Application area**	**Accuracy (%)**
R-CNN [3]	Lane detection & collision avoidance	Urban traffic & static CCTV footage	98
RAN-SAC with CNN [4]	Lane detection	Real time traffic	93
Cloud CNN [5]	Lane detection	Insufficient light conditions	97
Cloud CNN [5]	Lane detection	Shadow occlusion conditions	98
Cloud CNN [5]	Lane detection	Missing lane lines conditions	96
Cloud CNN [5]	Lane detection	Curve lane line conditions	94
Cloud CNN [5]	Lane detection	Normal roads	98
CNN with KLT [6]	Lane detection and control	Urban traffic	97
Guassian filter + Hough transform [6]	Lane detection and control	Urban traffic	89
Maximally stable extrenal regions + Hough transform [6]	Lane detection and control	Urban traffic	93
Hue Saturation Value – Region of Interest + Hough transform [6]	Lane detection and control	Urban traffic	95
Simple CNN [6]	Lane detection and control	Urban traffic	96
LiDAR & IMU with CNN [7]	Lane change detection	Urban traffic	90
3DNN [8]	Drowsy driver detection	No Glasses, Glasses, Sunglasses, Night time with No Glasses and Night time with Glasses	75
CNN [9]	Drowsy driver detection	General driving condition	97
E/E systems with NN [14]	General DAS	Urban traffic	85
E/E Systems with SVM [15]	Driver emotion detection	General driving conditions	89
CNN with structure analysis [19]	Lane detection, warning and cruise control	Urban and rural traffic including day, night, expressway, urban roads, straight lanes, curved lanes, changing lanes, turn lanes and road writing conditions	99
CNN–LSTM [20]	DAS for Auto-nomous driving	Urban and rural traffic	98
PCA with Recursive NN and TDL [22]	General DAS modules	Tractor and high value vehicles under controlled conditions	94
kNN [24]	Traffic zone detection	Real time traffic	94
CNN [25]	General DAS modules	General traffic	98

From the statistical analysis it can be observed that CNN and LSTM-based architectures have highest performance efficiency for individual DAS modules, and thus must be used for improving the real time performance of these systems.

IV. Conclusion

Using the statistical analysis, it is observed that lane detection and control modules have an accuracy of 98% by using CNN-based architectures like RNN, LSTM and transfer learning. These architectures are tested on both real-time and CCTV based datasets, and tend to improve the accuracy for both systems. Cloud CNN architectures are also efficient, but require large communication delays for transfer of data between vehicle and cloud, which restricts its real-time performance. CNN modules are also effective for drowsiness detection and speed control, wherein each of the modules have an accuracy of 97%. Transfer learning approaches can be further explored to improve accuracy of each of the DAS modules via inter-module learning. Moreover, integration of these systems must be done for effective performance evaluation when using all DAS modules in tandem with each other.

References

[1] L. Yue, M. A. Abdel-Aty, Y. Wu and A. Farid, "The Practical Effectiveness of Advanced Driver Assistance Systems at Different Roadway Facilities: System Limitation, Adoption, and Usage," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 9, pp. 3859-3870, Sept. 2020, doi: 10.1109/TITS.2019.2935195.

[2] Abraham, H., Reimer, B. and Mehler, B. (2017) 'Advanced Driver Assistance Systems (ADAS): A Consideration of Driver Perceptions on Training, Usage & Implementation', Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 61(1), pp. 1954–1958. doi: 10.1177/1541931213601967.

[3] Agrawal R., Singh N. (2020) Lane Detection and Collision Prevention System for Automated Vehicles. In: Iyer B., Rajurkar A., Gudivada V. (eds) Applied Computer Vision and Image Processing. Advances in Intelligent Systems and Computing, vol 1155. Springer, Singapore. https://doi.org/10.1007/978-981-15-4029-5_5

[4] Kim J., Lee M. (2014) Robust Lane Detection Based On Convolutional Neural Network and Random Sample Consensus. In: Loo C.K., Yap K.S., Wong K.W., Teoh A., Huang K. (eds) Neural Information Processing. ICONIP 2014. Lecture Notes in Computer Science, vol 8834. Springer, Cham. https://doi.org/10.1007/978-3-319-12637-1_57

[5] Wang, W., Lin, H. & Wang, J. CNN based lane detection with instance segmentation in edge-cloud computing. *J Cloud Comp* **9,** 27 (2020). https://doi.org/10.1186/s13677-020-00172-z

[6] Satish Kumar Satti, K. Suganya Devi, Prasenjit Dhar, P. Srinivasan, A machine learning approach for detecting and tracking road boundary lanes, ICT Express, 2020, ISSN 2405-9595, https://doi.org/10.1016/j.icte.2020.07.007.

[7] Vision-Based Lane-Changing Behavior Detection Using Deep Residual Neural Network, arXiv:1911.03565

[8] Wijnands, J.S., Thompson, J., Nice, K.A. *et al.* Real-time monitoring of driver drowsiness on mobile platforms using 3D neural networks. *Neural Comput & Applic* **32,** 9731–9743 (2020). https://doi.org/10.1007/s00521-019-04506-0

[9] Doudou, M., Bouabdallah, A. & Berge-Cherfaoui, V. Driver Drowsiness Measurement Technologies: Current Research, Market Solutions, and Challenges. *Int. J. ITS Res.* **18,** 297–319 (2020). https://doi.org/10.1007/s13177-019-00199-w

[10] Bowman D.S., Schaudt W.A., Hanowski R.J. (2012) Advances in Drowsy Driver Assistance Systems Through Data Fusion. In: Eskandarian A. (eds) Handbook of Intelligent Vehicles. Springer, London. https://doi.org/10.1007/978-0-85729-085-4_34

[11] Kwon, Y.H. Improving multi-channel wave-based V2X communication to support advanced driver assistance system (ADAS). *Int.J Automot. Technol.* **17,** 1113–1120 (2016). https://doi.org/10.1007/s12239-016-0108-8

[12] Krishnarao S., Wang HC., Sharma A., Iqbal M. (2021) Enhancement of Advanced Driver Assistance System (Adas) Using Machine Learning. In: Yang XS., Sherratt R.S., Dey N., Joshi A. (eds) Proceedings of Fifth International Congress on Information and Communication Technology. ICICT 2020. Advances in Intelligent Systems and Computing, vol 1183. Springer, Singapore. https://doi.org/10.1007/978-981-15-5856-6_13

[13] Sakhare, K.V., Tewari, T. & Vyas, V. Review of Vehicle Detection Systems in Advanced Driver Assistant Systems. *Arch Computat Methods Eng* **27,** 591–610 (2020). https://doi.org/10.1007/s11831-019-09321-3

[14] Lapp A., Thiel T., Schaffert M. (2018) Impact of driver assistance systems on future E/E architectures for commercial vehicles. In: Isermann R. (eds) Fahrerassistenzsysteme 2016. Proceedings. Springer Vieweg, Wiesbaden. https://doi.org/10.1007/978-3-658-21444-9_17

[15] Requardt, A.F., Ihme, K., Wilbrink, M. and Wendemuth, A. (2020), Towards affect□aware vehicles for increasing safety and comfort: recognising driver emotions from audio recordings in a realistic driving study. IET Intell. Transp. Syst., 14: 1265-1277. https://doi.org/10.1049/iet-its.2019.0732

[16] Y. Liu, P. Watta, B. Jia and Y. L. Murphey, "Vehicle position and context detection using V2V communication with application to pre-crash detection and warning," 2016 IEEE Symposium Series on Computational Intelligence (SSCI), Athens, 2016, pp. 1-7, doi: 10.1109/SSCI.2016.7850093.

[17] Prediction of Lane-Changing Maneuvers with Automatic Labeling and Deep Learning, https://journals.sagepub.com/doi/full/10.1177/0361198120922210

[18] M. H. Alkinani, W. Z. Khan and Q. Arshad, "Detecting Human Driver Inattentive and Aggressive Driving Behavior Using Deep Learning: Recent Advances, Requirements and Open Challenges," in IEEE Access, vol. 8, pp. 105008-105030, 2020, doi: 10.1109/ACCESS.2020.2999829.
[19] Li, W., Qu, F., Liu, J. *et al.* A lane detection network based on IBN and attention. *Multimed Tools Appl* **79,** 16473–16486 (2020). https://doi.org/10.1007/s11042-019-7475-x
[20] Chen, S, Leng, Y, Labi, S. A deep learning algorithm for simulating autonomous driving considering prior knowledge and temporal information. *Comput Aided Civ Inf.* 2020; 35: 305– 321. https://doi.org/10.1111/mice.12495
[21] Vehicle Detection Based on Multifeature Extraction and Recognition Adopting RBF Neural Network on ADAS System, https://www.hindawi.com/journals/complexity/2020/8842297/
[22] Tractor Assistant Driving Control Method Based on EEG Combined With RNN-TL Deep Learning Algorithm, https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9186275
[23] C. Marina Martinez, M. Heucke, F. Wang, B. Gao and D. Cao, "Driving Style Recognition for Intelligent Vehicle Control and Advanced Driver Assistance: A Survey," in IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 3, pp. 666-676, March 2018, doi: 10.1109/TITS.2017.2706978.
[24] Advanced Driver-Assistance System (ADAS) for Intelligent Transportation Based on the Recognition of Traffic Cones, https://www.hindawi.com/journals/ace/2020/8883639/
[25] Yang Zhou, Rui Fu, Chang Wang, "Learning the Car-following Behavior of Drivers Using Maximum Entropy Deep Inverse Reinforcement Learning", *Journal of Advanced Transportation*, vol. 2020, Article ID 4752651, 13 pages, 2020. https://doi.org/10.1155/2020/475265
[26] Machine Learning for Next-Generation Intelligent Transportation Systems: A Survey, https://hal.inria.fr/hal-02284820v2/document
[27] Liu, J., Guo, H., Song, L. *et al.* Driver-automation shared steering control for highly automated vehicles. *Sci. China Inf. Sci.* **63,** 190201 (2020). https://doi.org/10.1007/s11432-019-2987-x
[28] Piccoli, B., Tosin, A. & Zanella, M. Model-based assessment of the impact of driver-assist vehicles using kinetic theory. *Z. Angew. Math. Phys.* **71,** 152 (2020). https://doi.org/10.1007/s00033-020-01383-9
[29] Wang, X., Cheng, Y. Lane departure avoidance by man-machine cooperative control based on EPS and ESP systems. *J Mech Sci Technol* **33,** 2929–2940 (2019). https://doi.org/10.1007/s12206-019-0540-6
[30] Y. Bian, J. Ding, M. Hu, Q. Xu, J. Wang and K. Li, "An Advanced Lane-Keeping Assistance System With Switchable Assistance Modes," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 1, pp. 385-396, Jan. 2020, doi: 10.1109/TITS.2019.2892533.
[31] Wang, H., Cui, W. & Ye, B. Lane Departure Assistance Coordinated Control System for In-Wheel Motor Drive Vehicles Based on Dynamic Extension Boundary Decision. *J Syst Sci Complex* **33,** 1040–1063 (2020). https://doi.org/10.1007/s11424-020-8340-8
[32] Malik, KR, Ahmad, M, Khalid, S, Ahmad, H, Al□Turjman, F, Jabbar, S. Image and command hybrid model for vehicle control using Internet of Vehicles. *Trans Emerging Tel Tech.* 2020; 31:e3774. https://doi.org/10.1002/ett.3774
[33] Stanton, NA, Eriksson, A, Banks, VA, Hancock, PA. Turing in the driver's seat: Can people distinguish between automated and manually driven vehicles? *Hum Factors Man.* 2020; 30: 418– 425. https://doi.org/10.1002/hfm.20864
[34] Integrating tools for an effective testing of connected and automated vehicles technologies, https://digital-library.theiet.org/content/journals/10.1049/iet-its.2019.0678
[35] Wolkow, A.P., Rajaratnam, S.M.W., Anderson, C., Howard, M.E. and Mansfield, D. (2019), Recommendations for current and future countermeasures against sleep disorders and sleep loss to improve road safety in Australia. Intern Med J, 49: 1181-1184. https://doi.org/10.1111/imj.14423
[36] Eskandarian A., Mortazavi A., Sayed R.A. (2012) Drowsy and Fatigued Driving Problem Significance and Detection Based on Driver Control Functions. In: Eskandarian A. (eds) Handbook of Intelligent Vehicles. Springer, London. https://doi.org/10.1007/978-0-85729-085-4_36