REAL-TIME DRIVER DEPRESSION MONITORING FOR ACCIDENT PREVENTION IN SMART VEHICLES

Jagan M *1, Muruganandham P *2, Vijay Sanjay kumar K R *3, Anitha R *4

* 123 UG scholar, Department of Computer Science & Engineering, Chettinad College of Engineering & Technology, Karur, Tamilnadu, India.

*4Assistant Professor, Department of Computer Science & Engineering, Chettinad College of Engineering & Technology, Karur, Tamilnadu, India.

jaganm971@gmail.com, muruganandhamm7639@gmail.com@*, krvijaysanjaykumar257@gmail.com***, anitha@chettinadtech.ac.in †*

Abstract—Increase in road accidents due to impaired driver behavior requires real -time monitoring solutions. This study presents a system of detecting a transfer-based depression using VGG-16 for facial expression recognition in smart vehicles. The system captures real -time video through dashboard cameras, analyzes the emotional state of the driver, and automatically transforms control to the autonomous system of the vehicle when depression is detected. Experimental results show 96% accuracy, which cross traditional models such as Resanet50. The proposed system increases driver safety, reduces the risk of accident, and integrates deep learning with vehicle automation for intelligent transport solutions. This study examines the implications of automated intervention in reducing human error to ensure forward road safety. By taking advantage of a strong deep learning structure, the system effectively reduces risks associated with depression-induced impaired driving. Future reforms may involve integrating additional physical indicators for increased accuracy and reliability.

I. INTRODUCTION

I. INTRODUCTION

A. Depression and Driving Safety

Depression is a global mental health challenge affecting over 264 million people. Among its many impairments—reduced attention, slower reaction times, and emotional instability—driving performance is notably compromised. Studies link over 90% of accidents in light vehicles to human error, with mental health being a critical factor.

B. Existing Gaps

Traditional driver monitoring systems emphasize drowsiness and distraction. However, there remains a significant gap in depression-specific monitoring, particularly in real-time scenarios with actionable outcomes like control handover.

II. RELATED WORK

A. **Text and Voice-Based Approaches**
Yu et al. and Vázquez-Romero et al. explored depression detection in social media and voice data, achieving promising accuracies, yet lacking real-time adaptability.

B. **Facial Recognition and Emotion Models**
Nazira et al. used CNNs and Haar classifiers, achieving 81of the accuracy on facial depression datasets. Ge et al., Li et al., and others enhanced facial expression recognition using deep CNNs, supporting its applicability in affective computing.

C. **Real-Time System Limitations**
Prior systems often neglected continuous real-time analysis or integration into smart vehicular control systems, making them

III. PROPOSED SYSTEM

A. Dataset and Preprocessing
We compiled a dataset of 6500 images—equal parts depressed and normal—from open sources and web scraping. Preprocessing involved:

- Resizing to 224×224 pixels
- Gaussian blurring
- Normalization:
- Train-test split: 70% training, 30% testing

B. Deep Learning Model (VGG-16)
The VGG-16 architecture was fine-tuned with the following configuration:

- Input: 224×224×3
- 16 weighted layers using 3×3 convolutions
- Optimizer: Adam, learning rate: 0.001
- Output: Binary sigmoid (depressed/normal)

C. Real-Time Architecture
Using OpenCV, the system captures live video from a dashboard-mounted camera. Each frame is analyzed individually to classify driver behavior. If depression is detected, control is transferred from the human driver to the autonomous vehicle.

D. Control Transfer Logic

The control transfer includes:

- **Longitudinal Control:** Speed & distance management
- **Lateral Control:** Lane positioning & steering
- **Sequence Control:** Coordinated traffic interaction

IV. RESULTS

A. Model Performance

Metric	VGG-16	ResNet50
Accuracy	96%	84.6%
Precision	98%	85%
Recall	97%	83%

ROC and loss curves validated the superior performance of VGG-16 for our use case.

B. Real-Time Validation

The real-time system processed video at 30 FPS with OpenCV. The response time was sufficient to trigger safe intervention under depressive conditions.

V. DISCUSSION

This research bridges the gap between affective computing and automotive safety. Unlike previous models, our VGG-16-based architecture is fine-tuned for real-time facial emotion analysis and integrated into a control system capable of reacting to depressive states. Though our dataset was sufficient for a prototype, more diverse and ethically sourced datasets would improve model generalizability.

VI. CONCLUSION

We propose a novel depression detection system using transfer learning with VGG-16 and OpenCV for smart vehicles. The system demonstrates high accuracy and real-time responsiveness. Its integration with vehicle automation systems enhances road safety and contributes to the broader scope of intelligent driver assistance systems (ADAS).

Methodology

Capture real-time facial images using a camera module integrated with the On-Board Unit (OBU).

Send captured images to the OBU sensory module for initial preprocessing and filtering.

Perform data gathering to collect necessary facial features and behavioral patterns.

Process the images using the VGG-16 deep learning model for facial expression recognition.

Classify the driver's state as either "Normal" or "Depressed" based on the model's output.

If classified as "Normal," allow the driver to maintain control of the vehicle.

If classified as "Depressed," trigger the vehicle's sensory module for control intervention.

Initiate an automatic control shift mechanism by adjusting longitudinal, sequential, or lateral control of the vehicle.

Vehicular Ad-hoc Networks (VANETs) for enhanced safety and accident prevention.

Continuously monitor and update driver status in real-time to ensure adaptive system response.

Modules in project

Data Gathering Module

Captures real-time facial images using a camera module.

Prepares datasets for training the depression detection model.

Depression Detection Module

Utilizes the VGG-16 deep learning model for facial expression analysis.

Classifies the driver's state as "Normal" or "Depressed."

Communication Module

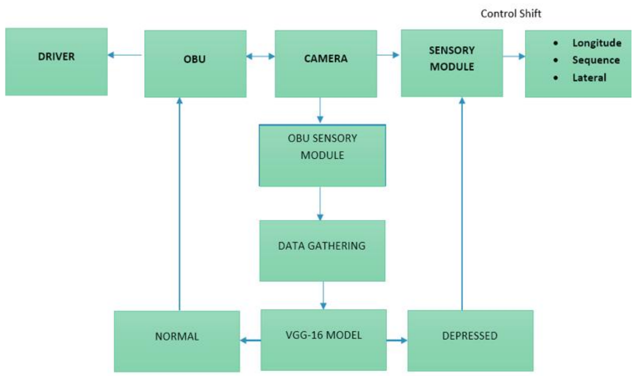
Integrates with Vehicular Ad-hoc Networks (VANETs) to share real-time driver status.

Ensures seamless interaction between vehicle systems and external monitoring units.

Monitoring & Alert System

Continuously tracks the driver's facial expressions.

Generates alerts and notifications when signs of depression are detected.



Future Work

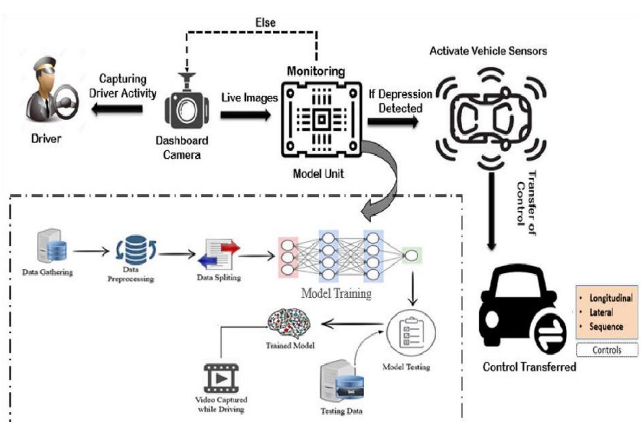
Optimization for Real-Time Processing – Improving computational efficiency to ensure real-time depression detection without overwhelming vehicle processing systems.

Exploration of Advanced Deep Learning Models – Evaluating alternative architectures such as transformers or hybrid models to enhance accuracy and performance.

Field Testing in Real-World Scenarios – Conducting extensive real-world trials to validate the model's effectiveness and reliability in various driving environments.

Adaptive Learning Mechanisms – Implementing personalized AI models that adapt to individual drivers over time for more precise depression detection.

Integration with Smart Vehicle Systems – Embedding the model into autonomous driving systems, GPS, and in-car monitoring tools for a holistic safety approach.



REFERENCES

[1] A. J. Gelenberg, ''A review of the current guidelines for depression treatment,'' *J. Clin. Psychiatry*, vol. 71, no. 7, p. 26478, 2010.

[2] M. Sajjadian, R. W. Lam, R. Milev, S. Rotzinger, B. N. Frey, C. N. Soares, S. V. Parikh, J. A. Foster, G. Turecki, and D. J. Müller, ''Machine learning in the prediction of depression treatment outcomes: A systematic review and meta-analysis,'' *Psychol. Med.*, vol. 51, no. 16, pp. 2742–2751, 2021.

[3] G. S. Alexopoulos, ''Mechanisms and treatment of late-life depression,'' *Transl. Psychiatry*, vol. 9, no. 1, p. 188, 2019.

[4] J. Ormel, S. D. Hollon, R. C. Kessler, P. Cuijpers, and S. M. Monroe, ''More treatment but no less depression: The treatment-prevalence paradox,'' *Clin. Psychol. Rev.*, vol. 91, Feb. 2022, Art. no. 102111.

[5] H. Eyre and B. T. Baune, ''Neuroimmunological effects of physical exercise in depression,'' *Brain, Behav., Immunity*, vol. 26, no. 2, pp. 251–266, Feb. 2012.

[6] L. L. Hill, V. L. Lauzon, E. L. Winbrock, G. Li, S. Chihuri, and K. C. Lee, ''Depression, antidepressants and driving safety,'' *Injury Epidemiol.*, vol. 4, no. 1, pp. 1–10, 2017.

[7] V. Kumar, S. Mishra, and N. Chand, ''Applications of VANETs: Present & future,'' *Commun. Netw.*, vol. 5, no. 1, pp. 12–15, 2013.

[8] F. Cunha, L. Villas, A. Boukerche, G. Maia, A. Viana, R. A. Mini, and A. A. Loureiro, ''Data communication in VANETs: Protocols, applications and challenges,'' *Ad Hoc Netw.*, vol. 44, pp. 90–103, Jul. 2016.

[9] G. Abbas, S. Ullah, M. Waqas, Z. H. Abbas, and M. Bilal, ''A position-based reliable emergency message routing scheme for road safety in VANETs,'' *Comput. Netw.*, vol. 213, Aug. 2022, Art. no. 109097.

[10] M. A. Elsadig and Y. A. Fadlalla, ''VANETs security issues and challenges: A survey,'' *Indian J. Sci. Technol.*, vol. 9, no. 28, pp. 1–8, Jul. 2016.

[11] Y. Xing, C. Lv, H. Wang, D. Cao, E. Velenis, and F.-Y. Wang,
''Driver activity recognition for intelligent vehicles: A deep learning approach,'' *IEEE Trans. Veh. Technol.*, vol. 68, no. 6, pp. 5379–5390, Jun. 2019.

[12] M. Saeed, R. Amin, M. Aftab, and N. Ahmed, ''Trust management technique using blockchain in smart building,'' *Eng. Proc.*, vol. 20, no. 1, p. 24, 2022.

[13] B. Soualmi, C. Sentouh, J.-C. Popieul, and S. Debernard, ''A shared control driving assistance system: Interest of using a driver model in both lane keeping and obstacle avoidance situations,'' *IFAC Proc. Volumes*, vol. 46, no. 15, pp. 173–178, 2013.

[14] L. M. Dang, K. Min, H. Wang, M. J. Piran, C. H. Lee, and H. Moon, ''Sensor-based and vision-based human

activity recognition: A comprehensive survey,'' *Pattern Recognit.*, vol. 108, Dec. 2020, Art. no. 107561.

[15] P. M. Niedenthal, A. Wood, M. Rychlowska, and S. Korb, ''Embodied simulation in decoding facial expression,'' in *Embodied Simulation in Decoding Facial Expression*. U.K.: Oxford Univ. Press, 2017, pp. 397–413.

[16] S. Surguladze, M. J. Brammer, P. Keedwell, V. Giampietro, A. W. Young, M. J. Travis, S. C. Williams, and M. L. Phillips, ''A differential pattern of neural response toward sad versus happy facial expressions in major depressive disorder,'' *Biol. Psychiatry*, vol. 57, no. 3, pp. 201–209, 2005.

[17] D. Delle-Vigne, W. Wang, C. Kornreich, P. Verbanck, and S. Campanella, ''Emotional facial expression processing in depression: Data from behavioral and event-related potential studies,'' *Neurophysiologie Clinique/Clin. Neurophysiol.*, vol. 44, no. 2, pp. 169–187, Apr. 2014.

[18] J. M. Girard, J. F. Cohn, M. H. Mahoor, S. Mavadati, and D. P. Rosenwald, ''Social risk and depression: Evidence from manual and automatic facial expressionanalysis,''in*Proc.10thIEEEInt.Conf.WorkshopsAutom.Face Gesture Recognit. (FG)*, Apr. 2013, pp. 1–8.

[19] N. Ahmed, R. Amin, H. Ayub, M. M. Iqbal, M. Saeed, and M. Hussain, ''Urdu sentiment analysis using deep attention-based,'' Found. Univ. J. Eng. Appl. Sci., Found. Univ. Islamabad, Tech. Rep. 1, 2022.

[20] A. Ghofrani, R. M. Toroghi, and S. Ghanbari, ''Realtime face-detection and emotion recognition using MTCNN and miniShuffleNet V2,'' in *Proc. 5th Conf. Knowl. Based Eng. Innov. (KBEI)*, Feb. 2019, pp. 817–821.

[21] A. Saxena, A. Khanna, and D. Gupta, ''Emotion recognition and detection methods: A comprehensive survey,'' *J. Artif. Intell. Syst.*, vol. 2, no. 1, pp. 53–79, 2020.

[22] H. Ge, Z. Zhu, Y. Dai, B. Wang, and X. Wu, ''Facial expression recognition based on deep learning,'' *Comput. Methods Programs Biomed.*, vol. 215, Mar. 2022, Art. no. 106621.

[23] J. Li, K. Jin, D. Zhou, N. Kubota, and Z. Ju, ''Attention mechanismbased CNN for facial expression recognition,'' *Neurocomputing*, vol. 411, pp. 340–350, Oct. 2020.

[24] S. Li and W. Deng, ''Deep facial expression recognition: A survey,'' *IEEE Trans. Affect. Comput.*, vol. 13, no. 3, pp. 1195–1215, Mar. 2020.

[25] S. M. S. Abdullah and A. M. Abdulazeez, ''Facial expression recognition based on deep learning convolution neural network: A review,'' *J. Soft Comput. Data Mining*, vol. 2, no. 1, pp. 53–65, 2021.

[26] L. Yu, W. Jiang, Z. Ren, S. Xu, L. Zhang, and X. Hu, ''Detecting changes in attitudes toward depression on Chinese social media: A text analysis,'' *J. Affect. Disorders*, vol. 280, pp. 354–363, Feb. 2021.

[27] A. Vazquez-Romero and A. Gallardo-Antolin, ''Automatic detection of depression in speech using ensemble convolutional neural networks,'' *Entropy*, vol. 22, no. 6, p. 688, 2020.

[28] R. Safa, P. Bayat, and L. Moghtader, ''Automatic detection of depression symptoms in Twitter using multimodal analysis,'' *J. Supercomput.*, vol. 78, no. 4, pp. 4709–4744, Mar. 2022.

[29] H. Zogan, I. Razzak, S. Jameel, and G. Xu, ''DepressionNet: A novel summarization boosted deep framework for depression detection on social media,'' 2021, *arXiv:2105.10878*.

[30] M. L. Joshi and N. Kanoongo, ''Depression detection using emotional artificial intelligence and machine learning: A closer review,'' *Mater. Today, Proc.*, vol. 58, pp. 217–226, Jan. 2022.

[31] B. Little, O. Alshabrawy, D. Stow, I. N. Ferrier, R. McNaney, D. G. Jackson, K. Ladha, C. Ladha, T. Ploetz, and J. Bacardit, ''Deep learning-based automated speech detection as a marker of social functioning in late-life depression,'' *Psychol. Med.*, vol. 51, no. 9, pp. 1441–1450, 2021.

[32] F. A. Nazira, S. R. Das, S. A. Shanto, and M. Mridha, ''Depression detection using convolutional neural networks,'' in *Proc. IEEE Int. Conf. Signal Process., Inf., Commun. Syst. (SPICSCON)*, Dec. 2021, pp. 9–13.

[33] B. Jin, L. Cruz, and N. Gonçalves, ''Deep facial diagnosis: Deep transfer learning from face recognition to facial diagnosis,'' *IEEE Access*, vol. 8, pp. 123649–123661, 2020.

[34] J. Gideon, S. Khorram, Z. Aldeneh, D. Dimitriadis, and E. M. Provost, ''Progressive neural networks for transfer learning in emotion recognition,'' 2017, *arXiv:1706.03256*.

[35] S. Sharma and A. Kaul, ''VANETs cloud: Architecture, applications, challenges, and issues,'' *Arch. Comput. Methods Eng.*, vol. 28, pp. 2081–2102, Mar. 2021.

[36] F. M. Shah, F. Ahmed, S. K. Saha Joy, S. Ahmed, S. Sadek, R. Shil, and Md. H. Kabir, ''Early depression detection from social network using deep learning techniques,'' in *Proc. IEEE Region 10 Symp. (TENSYMP)*, Jun. 2020, pp. 823–826.

[37] G. Gilanie, M. Asghar, A. M. Qamar, H. Ullah, R. U. Khan, N. Aslam, and I. U. Khan, ''An automated and real-time approach of depression detection from facial micro-expressions,'' *Comput., Mater. Continua*, vol. 73, no. 2, pp. 2514–2528, 2022.

[38] A. S. Rajawat, P. Bedi, S. Goyal, P. Bhaladhare, A. Aggarwal, and R. S. Singhal, ''Fusion fuzzy logic and deep learning for depression detection using facial expressions,'' *Proc. Comput. Sci.*, vol. 218, pp. 2795–2805, Jan. 2023.

[39] S. A. Nasser, I. A. Hashim, and W. H. Ali, ''Visual depression diagnosis from face based on various classification algorithms,'' *Eng. Technol. J.*, vol. 38, no. 11, pp. 1717–1729, 2020.

[40] C. Katrakazas, C. Antoniou, and G. Yannis, ''Identification of driving simulator sessions of depressed drivers: A comparison between aggregated and time-

series classification,'' *Transp. Res. F, Traffic Psychol. behaviour*, vol. 75, pp. 16–25, Nov. 2020.

[41] N. Marriwala and D. Chaudhary, ''A hybrid model for depression detection using deep learning,'' *Meas., Sensors*, vol. 25, Feb. 2023, Art. no. 100587.

[42] J. Chen, X. Lin, W. Ma, Y. Wang, and W. Tang, ''EEG-based emotion recognition for road accidents in a simulated driving environment,'' *Biomed. Sig. Process. Cont.*, vol. 87, 2024, Art. no. 105411.