International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Human Stress Level Based Motor Speed Controlling System Using AI

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ABSTRACT
Human psychological stress and emotions are deeply interconnected and play a critical role in shaping behaviour , particularly in high-pressure environments like driving. This project introduces a multi-modal stress detection system utilizing Convolutional Neural Networks (CNNs), which integrates facial recognition, emotion analysis, and physiological data to assess real-time driver stress levels. By monitoring stress indicators, the system enables an adaptive vehicle speed control mechanism that responds to the driver's stress, enhancing road safety. The proposed model validates stress levels through theoretical and experimental analysis using a labelled dataset. Biomarkers and physiological responses linked to stress are analyzed to predict stress in previously unobserved individuals, ultimately fostering an intelligent and safety-oriented driving ecosystem.

Keywords: Stress detection, CNN, PWM, artificial intelligence, machine learning, user experience.

1. INTRODUCTION

The demands of modern life often create an imbalance between work and leisure, resulting in elevated stress levels. According to the Indian Psychological Association, 33% of Indians experience severe stress, with 48% reporting increased stress over the past five years. Globally, rising stress levels contribute to health issues, strained relationships, and decreased productivity. Stress, particularly among drivers, poses a significant safety risk, often leading to impaired driving and Traditional stress detection methods, such as subjective questionnaires, are limited by biases, reluctance to disclose emotions, and the difficulty of objectively measuring stress. Recent advancements in machine learning and computer vision offer innovative solutions. CNNs, with their ability to identify intricate patterns in data, provide a robust framework for detecting stress through facial expressions and physiological signals. This study proposes a CNN-based approach to classify stress levels using facial and physiological data and integrates this detection system with adaptive vehicle speed control. The system aims to enhance driver safety by mitigating risks associated with stress-induced impairments.

2. LITERATURE REVIEW

Most existing research on human stress levels has focused on identifying unethical design techniques and their effects on user experiences and rights. While heuristic evaluations and manual inspections have been widely used to detect such patterns, these methods lack scalability and may miss subtle changes. Recent advancements in artificial intelligence and machine learning have enabled more efficient and accurate detection of deceptive patterns.

1. Malik Hasnain Ahmed et al. (2024): The rising incidence of road accidents highlights the urgent need for advanced vehicle safety technologies. This study focuses on detecting driver depression using facial expression recognition, employing transfer learning with the VGG-16 model. A dataset of driver images is used to train and test the model, which achieves a 96% accuracy rate in detecting depression. The system enables automatic intervention by transferring vehicle control to automated systems upon identifying depressive behaviors, significantly reducing accident risks.
2. Sumaiya Malik et al. (2023): This study proposes a cost-effective solution for improving road safety through real-time monitoring and data analytics. Sensors for accident detection, driver drowsiness monitoring, and vehicle tracking are integrated with wireless communication. The system provides high accuracy in detecting accidents (95% in urban areas, 70% in rural areas) and driver drowsiness (96%). Alerts are sent via SMS and mobile apps, facilitating immediate intervention and sustainable transportation.
3. Tong Zhao et al. (2022): With advancements in Level 3 and Level 4 autonomous vehicles (AVs), ensuring safety in complex manoeuvres has become critical. This study reviews state-of-the-art formal methods for safety verification and validation in AVs, proposing a unified framework for scenario-based safety verification. The work aligns with ISO 21448 guidelines and Vision Zero's goal of eliminating highway fatalities.
4. R Phani Vidyadhar et al. (2023): This paper introduces a vehicle security system combining fingerprint authentication, GSM-based owner authorization, and alcohol detection to prevent drunk driving. The system also includes sensors for monitoring emergencies and alerting designated contacts, ensuring driver and passenger safety.
5. Abhimanyu Mandal et al. (2019): This study addresses the integration of electric vehicles with renewable energy sources, emphasizing challenges such as charging infrastructure and vehicle-to-grid technology. The findings highlight the importance of considering unique electric vehicle characteristics for sustainable development in emerging markets like India.
6. Jianlin Song et al. (2019): This work proposes an intelligent control system for brushless DC motors (BLDCMs) to address slow responses and overshoots during startup. The system uses genetic algorithms for parameter optimization and demonstrates improved robustness and performance compared to traditional PID control systems.
7. G. Giannakakis et al. (2018): This study examines stress and anxiety detection through video-recorded facial cues, focusing on features like eye and mouth activity, head motion, and camera-based heart rate analysis. The selected features achieve high

accuracy in discriminating stress states, offering a reliable framework for stress detection.
8. P. S. Pandey et al. (2017): Using heart rate data and machine learning, this study develops an IoT-based system to predict stress levels and alert individuals about acute stress conditions, promoting healthier lifestyles.

3. SYSTEM MODEL

3.1 EXISTING SYSTEM

Vehicle safety systems primarily address external and physical aspects, such as speed, braking, and collision prevention, while often overlooking the driver's psychological state. While some systems monitor physiological signals like heart rate or eye movement, these are typically treated as secondary inputs rather than core components of vehicle control. Existing driver assistance technologies may include rudimentary stress indicators, but they lack advanced machine learning models capable of predicting or mitigating stress-related driving risks. A more proactive approach is needed—one that continuously assesses the driver's stress levels and dynamically adjusts the vehicle's operational settings to improve safety.

3.2 DRAWBACKS OF EXISTING METHOD

Absence of Real-Time Adaptation: Present systems fail to modify vehicle parameters dynamically based on real-time stress evaluations. Minimal Utilization of Advanced Models: Most solutions rely on basic indicators instead of employing deep learning models for precise stress prediction.
Reactive Design: Current technologies respond to problems after they occur rather than taking preventive measures proactively.

3.3 THE SYSTEM PROPOSED

The system combines real-time stress level assessment with vehicle speed control to enhance driving safety. A deep convolutional neural network (CNN) analyses physiological and behavioural data to accurately evaluate the driver's stress levels. These metrics are transmitted to a microcontroller, which adjusts the vehicle's speed dynamically using pulse-width modulation (PWM) based on the identified stress levels. By operating proactively, the system aims to prevent accidents caused by stress, responding to the driver’s psychological state. This approach not only enhances road safety but also promotes the driver’s well-being by minimizing stress-induced driving errors. The system's reliability and effectiveness will be validated through comprehensive simulations and real-world testing.

3.4 BLOCK DIAGRAM DESCRIPTION

3.4.1 Data Collection (Physiological and Behavioural):

Sensor Data Collection - This module gathers data from sensors that monitor the driver's physiological (e.g., heart rate, skin conductivity) and behavioural (e.g., facial expressions, steering patterns) responses. These inputs are critical for the stress detection process.

3.4.2 Deep CNN Model:

A Deep Convolutional Neural Network (CNN) processes the collected data, analysing patterns and features linked to stress. This model provides accurate, real-time identification of the driver’s stress levels.

3.4.3 Stress Level Analysis:

Utilizing the output from the Deep CNN model, this module estimates the driver's stress level and classifies it into predefined categories, such as low, moderate, or high stress.

3.4.4 Microcontroller Integration:

The stress level data is sent to a microcontroller, which serves as the central control unit. The microcontroller processes this information and determines the appropriate adjustments for vehicle speed.

3.4.5 PWM Based Speed Control:

The microcontroller employs Pulse Width Modulation (PWM) to generate signals that dynamically regulate the vehicle’s throttle or speed, ensuring smooth and proportional adjustments aligned with the driver’s stress level.

3.4.6 Real-Time Vehicle Speed Adjustment:

The system modifies the vehicle’s speed in real-time based on the detected stress level, enhancing safety and fostering more controlled driving conditions.

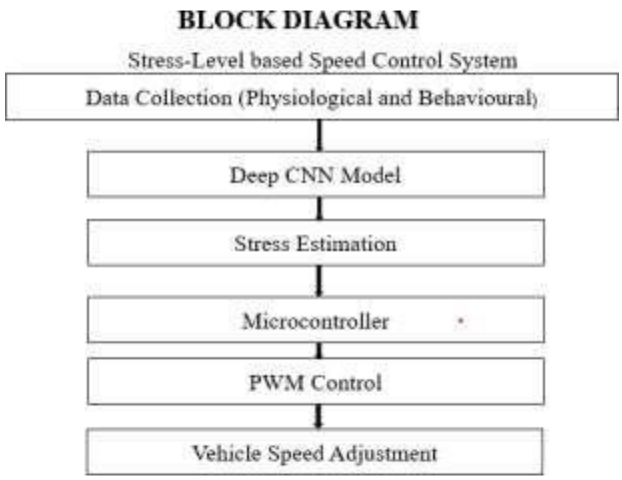

Fig.1. Block diagram for Stress Level Detection

3.5 ADVANTAGES OF PROPOSED SYSTEM:

3.5.1 Improved Road Safety:

The system minimizes the risk of accidents caused by stress-induced driving errors by dynamically regulating the vehicle's speed based on real-time stress assessments.

3.5.2 Proactive Stress Intervention:

By continuously monitoring physiological and behavioral stress signals, the system acts preemptively to prevent stress levels from reaching critical thresholds while driving.

3.5.3 Precision in the Stress Detection:

Leveraging a deep convolutional neural network (CNN) enables precise analysis of physiological and behavioral data, ensuring accurate evaluation of the driver’s stress levels.

4. SYSTEM IMPLEMENTATION

4.1 MODULE 1: DATA COLLECTION

The system uses an onboard camera installed inside the vehicle to capture real-time facial images of the driver. OpenCV is utilized to detect the face and isolate facial regions for stress analysis. Key facial landmarks, such as eye shape, brow furrows, and mouth tension, are identified, as these features are known to correlate with stress. This data plays a vital role in creating the dataset required for stress level detection using a CNN model.

Fig.2. Dataset Collection

4.2 MODULE 2: DATA PREPROCESSING

After capturing facial images, preprocessing is performed to ensure the input data is consistent and of high quality. This process involves resizing images to a fixed dimension compatible with the CNN model, converting them to grayscale to reduce complexity, and using histogram equalization to enhance contrast. Facial landmarks are extracted, and data augmentation techniques such as rotation and flipping are applied to artificially expand the dataset, enhancing the model's robustness under varying lighting and angle conditions.

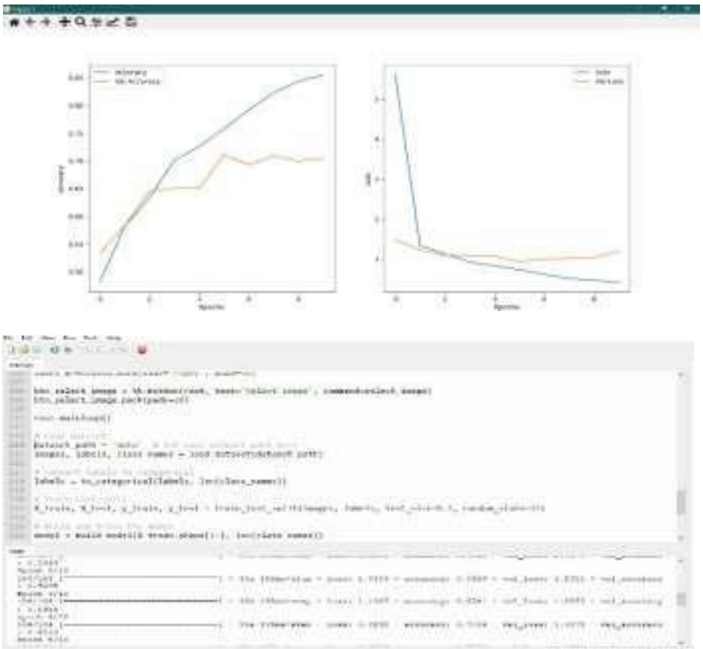

Fig.3. Data Preprocessing of Stress Level Detection

4.3 MODULE 3: FEATURE EXTRACTION

Facial expressions associated with stress are the key features extracted for training the model. Methods such as Haar cascades are employed to identify specific facial features, including eye openness, brow furrowing, and lip tension, which are indicative of stress. These features serve as input for the CNN model. Furthermore, spatial information from the entire facial region is retained in the images, enabling the model to capture both localized and overall stress-related variations in facial expressions.

4.4 MODULE 4: CNN MODEL DESIGN AND TRAINING

A deep convolutional neural network (CNN) is developed to analyze pre-processed facial images and determine the driver's stress level. The model includes multiple convolutional layers for extracting features, pooling layers to reduce the size of feature maps, and fully connected layers for classifying stress levels. The network employs the ReLU activation function and is trained using the Adam optimizer. A SoftMax layer at the output generates a probability distribution across stress categories (e.g., low, medium, high). Training is conducted on a dataset of labelled facial images representing different stress levels.

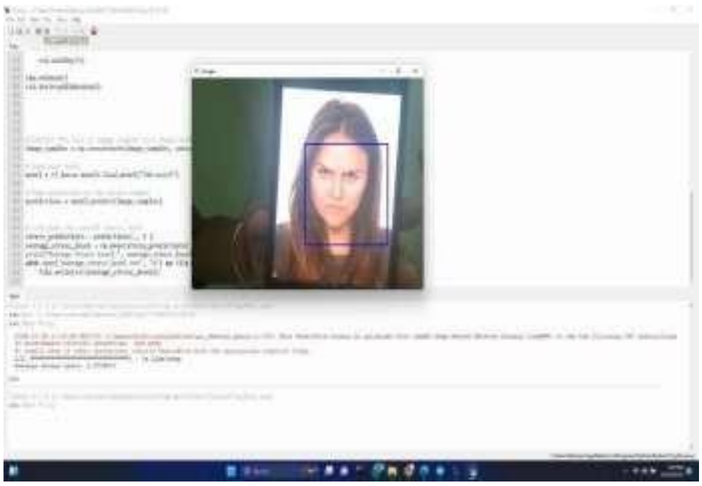

Fig.4. Stress Level categorization of Stress Level Detection

4.5 MODULE 5: INTEGRATION WITH NODEMCU

Once trained, the CNN model is integrated into the vehicle's onboard system. In real-time operation, the onboard camera captures the driver's facial expressions, which are processed by the CNN to assess stress levels. The model generates stress scores that are transmitted to the NodeMCU ESP8266 via Wi-Fi. Based on these predictions, the NodeMCU regulates the vehicle's speed. When high stress levels are detected, the NodeMCU utilizes pulse-width modulation (PWM) to adjust and reduce the speed, promoting safer driving conditions. This seamless communication between the CNN model and the NodeMCU enables continuous real-time monitoring and adaptive speed control.

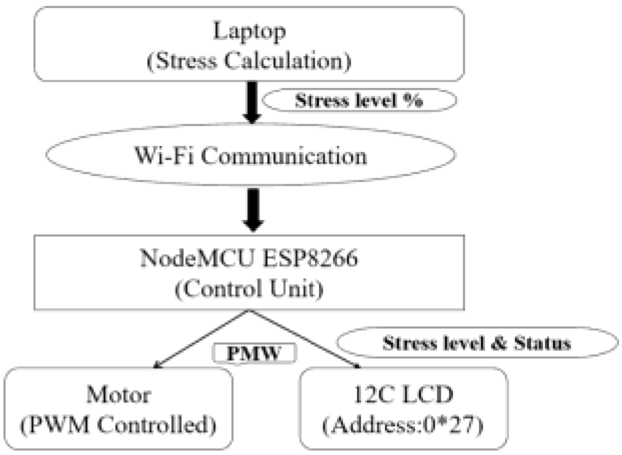

Fig.5. Workflow of Motor Speed Controlling System

5. FUTURE WORK AND CONCLUSION

In conclusion, the design and implementation of a CNN-based stress detection system for vehicle speed regulation signify a notable breakthrough in automotive safety and driver assistance technologies. This innovative approach harnesses the power of machine learning, specifically convolutional neural networks, to continuously monitor and respond to driver stress levels in real-time. The result is a non-invasive, adaptive solution aimed at enhancing road safety and mitigating risks associated with high-stress driving conditions.

Stress is widely recognized for its adverse effects on human performance, particularly in complex tasks such as driving, where cognitive demands and emotional states are critical. While traditional methods for detecting stress—such as questionnaires and physiological assessments—are effective in controlled environments, they fall short in real-world applications due to their intrusive nature, reliance on manual input, and lack of real-time functionality. In contrast, the proposed CNN-based system provides a holistic, real-time evaluation of facial expressions and physiological signals, enabling the detection of stress patterns with high precision without requiring any direct interaction from the driver. This makes it a highly practical and effective solution for dynamic and unpredictable driving conditions.

The project methodology, encompassing data collection, model training, and real-time deployment, underscores the feasibility of using CNNs to identify stress levels through facial and physiological indicators. Key facial features, such as eye movement and muscle tension, are analyzed in conjunction with biomarkers like heart rate to create a comprehensive assessment of the driver's emotional and psychological state. This multimodal approach is a major strength of the system, allowing it to account for a broad spectrum of stress indicators. Additionally, the model's ability to adapt to diverse drivers and function under varying environmental and lighting conditions highlights its robustness and practicality.

The system's response mechanism, which dynamically adjusts the vehicle's speed based on detected stress levels, represents a significant advancement toward intelligent, adaptive driving systems that prioritize driver well-being. By reducing vehicle speed during periods of high stress, the system actively mitigates risks, fostering a safer and more controlled driving experience. This proactive intervention not only helps prevent accidents caused by stress-induced impairments but also promotes a calmer driving environment, contributing to improved road safety and long-term driver health.

In summary, this CNN-based system for stress detection and vehicle speed adjustment offers a pioneering solution to address driver stress in a practical and real-time manner. Its capacity to enhance safety by moderating speed during stressful situations serves as a forward-thinking measure with significant implications for accident prevention and driver wellness. As this technology evolves, it has the potential to inspire further advancements in human-centred intelligent transportation systems, paving the way for safer and more responsive driving experiences in the future.

6. REFERENCE

[1] P. S. Pandey, "Machine Learning and IoT for Predicting and Detecting Stress," presented at the 17th International Conference on Computer Science and Its Applications (ICCSA) 2017. DOI:10.1109/ICCSA.2017.8000018.

[2] S. Sriramprakash, V. D. Prasanna, and O. V. R. Murthy, "Stress Detection in the Workforce," published in *Procedia Computer Science*, vol. 115, pp. 359–366, 2017. DOI: 10.1016/j.procs.2017.09.090.

[3] M. Gjoreski, H. Gjoreski, M. Luštrek, and M. Gams, "Continuous Stress Detection Using a Wrist Device: Laboratory and Real-Life Applications," in *Adjunct Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp)*, pp. 1185–1193,2016.DOI: 10.1145/2968219.2968306.

[4] E. Vildjiounaite et al., "Unobtrusive Stress Detection Based on Smartphone Usage Data," published in *Personal and Ubiquitous Computing*, vol. 22, no. 4, pp. 671–688, 2018. DOI: 10.1007/s00779-017-1108-z.

[5] Giannakakis et al., "Detection of Stress and Anxiety Using Facial Cues from Video Data," published in *Biomedical Signal Processing and Control*, vol. 31, pp. 89–101, 2017. DOI: 10.1016/j.bspc.2016.06.020.

[6] A. R. Surve, V. R. Ghorpade, and A. S. Patthe, *Continuous Facial Emotion Recognition System Using PCA for Ambient Living*, vol. 839. Springer Singapore, 2019.

[7] S. Gedam and S. Paul, "A Review on Mental Stress Detection Using Wearable Sensors and Machine Learning Techniques," published in *IEEE Access*, vol. 9, pp. 84045–84066, 2021. DOI:10.1109/AC CESS.2021.3085502.

[8] Stanley Leonard Tito, "A Simplified Outpatient Health Monitoring System in Resource-Constrained IoT Infrastructure," published in *International Journal of Engineering Research and Advanced Technology (IJERAT)*, vol. 5, no. 12, December 2019.

[9] J. Wijsman, B. Grundlehner, H. Liu, H. Hermens, and J. Penders, "Towards Mental Stress Detection Using Wearable Physiological Sensors," presented at the 2011

Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 1798–1801. DOI: 10.1109/IEMBS.2011.6090512.

[10] M. A. Elsadig and Y. A. Fadlalla, "VANETs Security Issues and Challenges: A Survey," published in *Indian Journal of Science and Technology*, vol. 9, no. 28, pp. 1–8, July 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," published in *IEEE Transactions on Vehicular Technology*, vol. 68, no. 6, pp. 5379–5390, June 2019.

[12] M. Saeed, R. Amin, M. Aftab, and N. Ahmed, "Trust Management Technique Using Blockchain in Smart Building," published in *Engineering Proceedings*, vol. 20, no. 1, p. 24, 2022.

[13] B. Soualmi, C. Sentouh, J.-C. Popieul, and S. Debernard, "A Shared Control Driving Assistance System: The Use of a Driver Model for Lane Keeping and Obstacle Avoidance," published in *IFAC Proceedings 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," published in *Pattern Recognition*, vol. 108, December2020.DOI: 10.1016/j.patcog.2020.107561.