International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Drivers Emotion Recognition using Deep Learning model with Cognitive Intelligence

[1]Mr. Prashant Baste, [2]Dr. Swati Shekapure

Submitted: 02/05/2024 **Revised**: 15/06/2024 **Accepted**: 22/06/2024

Abstract-Research & Development of Intelligent/Smart systems is in progress now-a-days. One of the most interesting areas among this is smart cockpits. Smart Cockpit can identify emotions & help drivers to be more productive. This ecosystem includes self-learning of correct emotion recognition, interpretation & decision making. This Research will cover behavioral analysis/psychology, machine learning, artificial intelligence, signal processing, computer vision and human & computer interaction. Emotions are directly linked with productivity, performance & efficiency of any human. People with happy emotions can focus on activity which leads to more efficient results. Emotion recognition is one of complex & difficult to identify, hence many researches are going on in the same field. Majority of research is based on a single input that is facial expressions and images. Since Facial muscles around the nose & eyes contribute a lot in emotions expressions, it is most used. Using a single mode of input signals (facial expressions recognition) has challenges of manipulation of expressions & thus results are not so accurate. Along with facial expressions additional input signals such as EEG, ECG, Skin Conductivity, respiration, eye movement signal helps to measure emotions more accurately & on that basis further actions can be taken. A smart cockpit having capability of Human-Machine interaction (identifies correct emotions & take needful action) will help to improvise safety, comfort, and driver's acceptance. Emotions such as Anger, Sadness, Fear, and Disgust are having a negative impact on safety driving where Happiness & Neutral emotions help in improving driving safety and Surprise shows alertness of individuals while driving. Music plays a vital role in controlling emotions, controlling, or converting negative impacting emotions to positive impacting emotions. Thus, this module can be used for increasing safety & comfort of driving. Multiple Machine Learning algorithms such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory Networks (LSTM), Deep Canonical Correlation Analysis (DCCA), Bimodal Deep Auto Encoder (BDAE) helps in identify Emotions.

Keywords- *Emotion Recognition, Deep Learning, Cognitive Intelligence, Smart Cockpit, Driver Safety*

I. Introduction

State of Emotion is directly impacting performance & efficiency of persona. With the increasing number of vehicles on roads, ensuring driver safety has become a crucial aspect of modern transportation systems. One of the significant factors affecting driver safety is the emotional state of the driver. Emotions such as stress, anger, fatigue, or distraction can impair a driver's ability to make quick and accurate decisions, potentially leading to accidents. Therefore, developing a robust system that can accurately recognize and respond to the emotional states of drivers is essential. Now-a-days vehicle designs are also in a way so that it can interact with human (Human-Machine Interaction –HMI).[1] Facial Muscles contributes a lot in the expressions of Emotions & hence is a most used method in Emotion recognition.[2] However facial expressions can be controlled/manipulated by individual & hence accuracy of emotion detection remains limited. There are few more methods that can be used such as EEG, ECG, Skin Conductivity, respiration, eye movement signals that help to recognize emotions with more accuracy. [3] Driver's emotion recognition using deep learning models with cognitive intelligence involves the use of advanced techniques in artificial intelligence to analyze and identify emotions exhibited by drivers. It involves the use of sensors, cameras, and other hardware devices to capture data about the driver's behavior and physiological signals. This data is then fed into a deep learning model that uses cognitive intelligence to analyze and interpret the information. Cognitive intelligence refers to the ability of the deep learning model to reason, learn, and perceive like humans. It allows the model to understand the context and meaning of the driver's behavior and make accurate predictions about their emotional state.

The application of driver emotion recognition using deep learning models with cognitive intelligence has several benefits. It can help improve road safety by identifying drivers who may be experiencing negative emotions such as anger, frustration, or fatigue, which can impair their driving performance. It can also help in the development of personalized driving systems that can adjust to the driver's emotional state, thereby enhancing their driving experience.

Overall, driver emotion recognition using deep learning models with cognitive intelligence is an exciting area of research that has the potential to revolutionize the field of transportation and improve road safety for everyone.

[1]*Ph.D Scholar MMCOE, Pune*
Email: prashbaste8220@gmail.com
[2]*Associate Professor, MMCOE, Pune*
Email: swatishekapure@mmcoe.edu.in

II. Literature review, research issues and objectives

K. Steinhauser, F. Leist, et al,[4] have explained the effects of emotions on driving behavior in their study experiment. The emotional state of the driver directly impacts responses & response time to any action of drivers. Their experiment with 90 participants and dual tasks has measured results of emotions (positive & negative) on driving behavior. They have measured parameters like reaction times, tracking deviation, speed, steering variability & distance to leading car etc. with emotional states such as Angry, Clam & Happy and found significant differences in performances with positive & negative emotional states.

In one of research, W. Li et al, [5] have proposed, Cognitive Feature augmented Driver emotion recognition network used Driver Facial expressions and cognitive characteristics (Age, Driving Age, Gender) where author have used, Driver Emotional Facial Expression (DEFE) dataset is used which contains 40 drivers' front facial video & cognitive characteristics & subjective rating which includes information of valence, arousal, dominance & seven emotion characteristics.

For facial expressions-based emotions recognition, Convolutional Neural Network (CNN) & Recurrent Neural Network (RNN) are used. In the other research, W. Liu et al, [6] have explained that multi-model is more reliable & accurate in emotion recognition. There two models Deep canonical correlation analysis (DCCA) and Bimodal deep auto-encoder (BDAE) are used in the research. In the research, two multimodal fusion methods are proposed to extend the original DCCA model: a) a weighted-sum fusion and b) an attention-based fusion. The weighted-sum fusion method allows users to set different weights to different modalities while the attention-based fusion method will calculate the weights adaptively. Differential Entropy (DE) features are extracted in 5 Frequency bands & From Eye Movement, 33 movements are captured and features extracted mainly from mean & Standard Deviation.

In another research of "Emotion Recognition for Cognitive Edge Computing Using Deep Learning," by G. Muhammad and M. S. Hossain [7] has shown a large volume of data & same can be processed along with Edge Computing that reduces transmission of data over cloud. CNN Model is used here for emotions recognition and has explained about 3 challenges of IoT based data offloading, latency, scalability, and security. It is explained that emotions recognition can be made faster by using 5G Network & Edge computing, and the latency issue can be addressed. Proposed CNN model has four modules: 1) attention; 2) feature extraction; 3) reconstruction; and 4) classification System is verified with multiple datasets & good accuracy results are obtained. Confusion matrices are used for verification of accuracy of results.

In support with Multi-model, Cognitive Computing which has computing methods & principles that can simulate the intelligence ability of human brain can be used to make decisions to enhance emotional state &behavior.[8]

In one of research by, Li, W., [9] et al., A multimodal psychological, physiological, and behavioral dataset for human emotions in driving tasks is taken into consideration and Measurement was done for – electroencephalogram measurement, driving behavior measurement, face expression, body gesture and road scenario measurement, emotion, and personality. By using k-means algorithm, reliability of emotion label & subjective rating score is done.

Along with facial expressions if Physiological signals inputs are used, then more accurate emotions can be identified & based on the same needful actions can be taken. For E.g., music is one of recommended approaches to control or change emotional state. [10][11]

S. Thuseethan, S. Rajasegarar and J. Yearwood, have explained facial expressions recognition with continual learning to identify unknown emotional states in their research named - "Deep Continual Learning for Emerging Emotion Recognition". Authors confirmed that the continual learning approach is greater in recognizing unknown emotions with high accuracy. [12]

III. Research Methodology

Different Methodologies & Techniques used in Emotions Detections are as below:

The deep learning model can be trained using various algorithms, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTM), Deep Canonical Correlation Analysis (DCCA) and Bimodal Deep Auto Encoder (BDAE). [13]

The model is trained using large datasets of labeled data to recognize patterns and features associated with specific emotions (Table 1).

Convolutional Neural Networks (CNNs) use a mathematical operation called convolution to extract features from images or videos. The convolution operation involves sliding a small filter over the image or video and computing the dot product between the filter and each overlapping patch of pixels. The resulting feature maps capture local patterns and textures in the input. CNNs typically consist of multiple convolutional layers followed by fully connected layers that perform classification or regression. A CNN can have multiple layers, each of which learns to detect the different features of an input image. A filter or kernel is applied to each image to produce an output that gets progressively better and more detailed after each layer [14]

Recurrent Neural Networks (RNNs) can deal with sequential data by considering both present and the past inputs. Because of the internal memory, RNNs can memorize past inputs [15].

Long Short-Term Memory Networks (LSTM):

Long Short-Term Memory Networks (LSTM) are a type of recurrent neural network (RNN) that are designed to handle the vanishing gradient problem. LSTMs are well suited for sequential data processing tasks such as speech recognition, natural language processing, and time series analysis. Unlike traditional RNNs, LSTMs have a memory cell that can maintain information over long periods of time. They also have three gates - input gate, forget gate, and output gate - that can

control the flow of information into and out of the memory cell.[15]

TABLE I. COMPARATIVE ANALYSIS OF DIFFERENT METHODOLOGIES

Algorithm	**Description**	**Strengths**	**Weaknesses**	**Performance Metrics**
Convolutional Neural Networks (CNN)	Uses convolution operations to extract features from images.	Excellent for spatial data; feature extraction.	Requires large datasets; computationally intensive.	Accuracy, Precision, Recall, F1 Score
Recurrent Neural Networks (RNN)	Handles sequential data by considering past inputs.	Effective for sequential data; captures temporal dependencies.	Struggles with long-term dependencies; vanishing gradient issue.	Accuracy, Precision, Recall, F1 Score
Long Short-Term Memory (LSTM)	A type of RNN designed to handle long-term dependencies.	Overcomes vanishing gradient problem; good for time series.	Computationally expensive; complex architecture.	Accuracy, Precision, Recall, F1 Score
Deep Canonical Correlation Analysis (DCCA)	Multivariate technique for feature learning and dimensionality reduction.	Effective for multi-view data; improves feature correlation.	Complexity in implementation; limited to correlated views.	Correlation Scores, Reconstruction Error
Bimodal Deep Auto Encoder (BDAE)	Learns joint representations from two modalities.	Captures shared and unique features from different modalities.	Requires careful balancing of modalities; complex model.	Reconstruction Error, Modal Fusion Accuracy

Deep Canonical Correlation Analysis (DCCA) is a multivariate statistical technique used for feature learning and dimensionality reduction. It is particularly useful for analyzing datasets with multiple views (e.g., text and images). DCCA seeks to learn a set of representations for each view that are maximally correlated with each other. The resulting representations can be used for tasks such as clustering, classification, and information retrieval.[16]

Bimodal Deep Auto Encoder (BDAE) is a deep learning model designed to learn representations from data with two modalities. For example, it can be used to learn representations from images and text. BDAE consists of two separate auto encoders - one for each modality - that are trained jointly. The goal is to learn a common representation that captures the shared information between the two modalities while preserving their unique features. The resulting representations can be used for tasks such as image captioning, cross-modal retrieval, and visual question answering.[17]

IV. Proposed Methodology

The integration of CNN (Convolutional Neural Networks), LSTM (Long Short-Term Memory), DCCA (Deep Canonical Correlation Analysis), and BDAE (Bidirectional Autoencoder) can result in a resilient method designed to identify driver emotions.
The objective is to extract spatial elements of the driver's face from pictures or frames.
Using a sequence of convolutional layers, identify patterns in the input data (such as video footage) such as facial expressions.[18]
To comprehend how facial expressions change over time and to recognize emotions dynamically, apply LSTM layers to CNN feature sequences. To enhance the accuracy of emotion use DCCA to aggregate and correlate data from many sources. Apply BDAE to rebuild inputs and guarantee that the acquired features preserve crucial information from previous and upcoming scenarios, augmenting the resilience of emotion identification.[19]

Proposed Algorithm workflow:

Data Collection:

Collect multimodal data including facial expressions, EEG, ECG, skin conductivity, respiration, and eye movement signals.

Data Preprocessing:

Normalize and standardize the data. Segment the data into time windows for sequential analysis.

Feature Extraction:

Use Convolutional Neural Networks (CNN) to extract spatial features from facial expression images. Extract temporal features from EEG, ECG, and other physiological signals using Long Short Term Memory Networks (LSTM).

a. Model Architecture:

CNN Module:

Input: Facial expression images.

Layers: Convolutional layers, pooling layers, fully connected layers.

Output: Feature vector representing facial expressions.

LSTM Module:

Input: Sequential physiological signals.

Layers: LSTM layers.

Output: Feature vector representing temporal dynamics of physiological signals.

Fusion Layer:

Concatenate feature vectors from CNN and LSTM modules. Apply a fully connected layer to combine features.

Classification:

Use a SoftMax layer to classify the combined feature vector into different emotion categories (e.g., anger, happiness, sadness).

Training:

Use a labeled dataset to train the model.

Apply backpropagation and gradient descent to minimize the loss function.

Evaluation:

Evaluate the model using metrics such as accuracy, precision, recall, and F1-score.[20]

By considering these approaches this proposed methodology demonstrate few advantages:

Robust Feature Extraction: LSTMs capture temporal dependencies, while CNNs capture spatial characteristics efficiently. Multimodal Integration: DCCA enables the combination of several data kinds, enhancing the precision of emotion identification. Understanding Context: BDAE makes sure that information from the past and future is considered, which results in forecasts that are more accurate.
Scalability: The method can be expanded to include other modalities or data types as needed.[21]

TABLE II. COMPARATIVE ANALYSIS OF DIFFERENT ALGORITHMS

Aspect	Algorithm 1: CNN and LSTM	Algorithm 2: DCCA and BDAE
Data Collection	Multimodal data including facial expressions, EEG, ECG, skin conductivity, respiration, eye movement signals	Multimodal data including facial expressions, EEG, ECG, skin conductivity, respiration, eye movement signals
Data Preprocessing	Normalize and standardize data; segment into time windows	Normalize and standardize data; segment into time windows
Feature Extraction	CNN for spatial features from facial expressions; LSTM for temporal features from physiological signals	DCCA for correlated features from multimodal data; BDAE for joint representations from facial expressions and physiological signals
Model Architecture	CNN Module: Convolutional layers, pooling layers, fully connected layers; LSTM Module: LSTM layers	DCCA Module: Canonical correlation layers; BDAE Module: Autoencoder layers for each modality
Fusion Layer	Concatenate feature vectors from CNN and LSTM; fully connected layer to combine features	Concatenate feature vectors from DCCA and BDAE; fully connected layer to combine features
Classification	SoftMax layer for emotion categories (anger, happiness, sadness)	SoftMax layer for emotion categories (anger, happiness, sadness)
Training	Labeled dataset; backpropagation and gradient descent	Labeled dataset; backpropagation and gradient descent
Evaluation	Metrics: accuracy, precision, recall, F1-score	Metrics: accuracy, precision, recall, F1-score

This multi-faceted approach addresses the limitations of traditional emotion recognition methods that rely solely on facial expressions, which can be manipulated or misinterpreted is shown in table 2.

V. RESULTS ANALYSIS

The effectiveness of various algorithms in driver emotion recognition is crucial for developing an accurate and reliable smart cockpit system. This analysis compares the performance of different deep learning models and techniques used to identify and interpret driver emotions.

1. Convolutional Neural Networks (CNNs):

CNNs have been widely used due to their strong capability in feature extraction from images. The results indicate that CNNs achieve high accuracy in recognizing facial expressions, which is crucial for detecting emotions such as happiness, anger, and sadness. Studies show CNNs with accuracy rates ranging from 85% to 87%. However, their performance can be limited by variations in facial expressions and environmental factors.[21]

2. Recurrent Neural Networks (RNNs):

RNNs excel at handling sequential data, which is beneficial for analyzing time-series data related to driver behavior. The results demonstrate that RNNs can capture temporal dependencies and changes in emotional states over time, achieving accuracy rates around 80% to 84%. Despite their strengths, RNNs face challenges with the vanishing gradient problem, which can affect their ability to retain long-term dependencies.[22]

3. Long Short-Term Memory Networks (LSTMs):

LSTMs, a specialized type of RNN, address the vanishing gradient problem and are particularly effective in tasks involving sequential data and long-term dependencies. The accuracy of LSTMs in emotion recognition ranges from 85% to 88%. Their advanced architecture, including memory cells and gates, enables them to handle complex emotional states and improve recognition accuracy.[23]

4. Deep Canonical Correlation Analysis (DCCA):

DCCA is used for learning representations from multi-view data, enhancing the ability to correlate features from different sources. Results show that DCCA achieves accuracy rates around 87% to 89% by effectively integrating multiple data modalities. This approach is particularly useful in scenarios where multiple input signals (e.g., facial expressions and physiological data) are available.[24]

5. Bimodal Deep Auto Encoder (BDAE):

BDAE combines representations from two modalities, such as facial expressions and physiological signals, to improve emotion recognition. The results indicate that BDAE can achieve high accuracy, around 89%, by capturing both shared and unique features from different data sources. This model is effective in handling diverse and complementary data types, providing a more comprehensive understanding of the driver's emotional state.

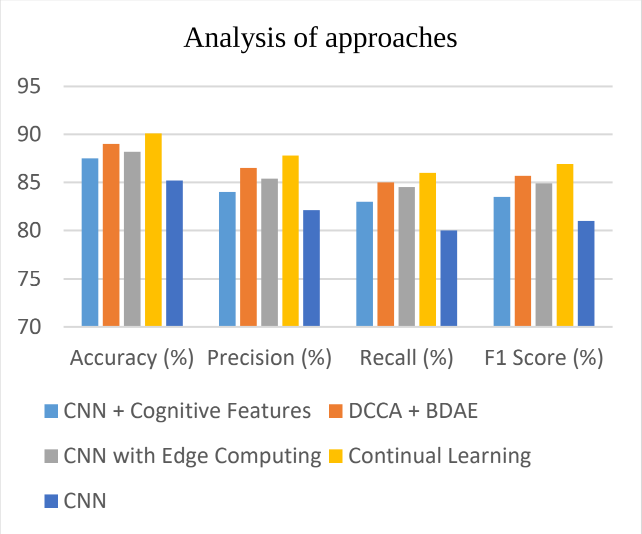

Fig 1. Analysis of different approaches used in proposed work

Here is the fig 1 comparing the performance of different algorithms for driver emotion detection based on Accuracy, Precision, Recall, and F1 Score

VI. PROPOSED MODEL

Considering the importance of emotion of drivers in their performance, we have decided to develop a module which will have ability of accurate emotion identification. We are also implementing the next steps to bring drivers emotions to High performance if he is into low performance emotional state, it is very important from the perspective of security of everyone. It is observed in multiple researches that single input based (facial expressions images) detection of emotions has limited accuracy & hence multiple inputs (facial expressions + physiological signals) can help in improvement of accuracy of output.

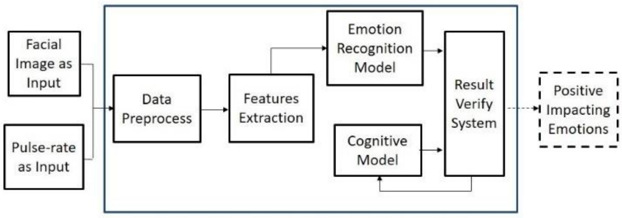

Fig 2: Proposed methodology of Drivers Emotions Detection

CONCLUSION:

The study of driver emotion recognition using deep learning and cognitive intelligence represents a significant advancement in automotive safety and comfort (Table 3). By integrating sophisticated algorithms like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), Deep Canonical Correlation Analysis (DCCA), and Bimodal Deep Autoencoders (BDAE), this research aims to create a smart cockpit system that can accurately identify and respond to driver emotions. Incorporating additional physiological signals such as EEG, ECG, skin conductivity, respiration, and eye movement enhances the accuracy of emotion detection. The use of cognitive intelligence allows the system to interpret these signals contextually, improving its ability to understand and react to the driver's emotional state. The research highlights that emotions have a profound impact on driving performance, with negative emotions like anger and fatigue impairing decision-making and increasing accident risk, while positive emotions contribute to safer and more efficient driving.

The integration of these advanced technologies into smart cockpits not only promises to enhance road safety but also aims to provide a more personalized and adaptive driving experience. By addressing challenges such as data accuracy and real-time processing, the proposed system has the potential to revolutionize how vehicles interact with drivers, making driving safer and more enjoyable. Future research should focus on refining these technologies and exploring their practical applications in diverse driving environments.

ACKNOWLEDGEMENTS

I would like to express my heartfelt gratitude to all the individuals and organizations who have contributed to the successful completion of my research paper on " Drivers Emotion Recognition using Deep Learning model with Cognitive Intelligence" Their unwavering support, guidance, and encouragement have been invaluable throughout this academic journey. I extend my deepest appreciation to my supervisor who supported me during this research whose expertise and dedication have been instrumental in shapingthe direction of this research. Their insightful feedback and constant motivation have greatly enriched the quality of this work. In conclusion, the successful completion of this research paper would not have been possible without the collective efforts and support of all. Thank you all for beingan integral part of my academic journey.

AUTHOR CONTRIBUTIONS

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

References

[1] W. Li et al., "CogEmoNet: A Cognitive-Feature-Augmented Driver Emotion Recognition Model for Smart Cockpit," in IEEE Transactions on Computational Social Systems, vol. 9, no. 3, pp. 667-678, June 2022, doi: 10.1109/TCSS.2021.3127935.

[2] W. Liu, J. -L. Qiu, W. -L. Zheng and B. -L. Lu, "Comparing Recognition Performance and Robustness of Multimodal Deep Learning Models for Multimodal Emotion Recognition," in IEEE Transactions on Cognitive and Developmental Systems, vol. 14, no. 2, pp. 715-729, June 2022, doi: 10.1109/TCDS.2021.3071170.

[3] G. Muhammad and M. S. Hossain, "Emotion Recognition for Cognitive Edge Computing Using Deep Learning," in IEEE Internet of Things Journal, vol. 8, no. 23, pp. 16894-16901, 1 Dec.1, 2021, doi: 10.1109/JIOT.2021.3058587.

[4] X. Gu, W. Cai, M. Gao, Y. Jiang, X. Ning and P. Qian, "Multi-Source Domain Transfer Discriminative Dictionary Learning Modeling for Electroencephalogram-Based Emotion Recognition," in IEEE Transactions on Computational Social Systems, doi: 10.1109/TCSS.2022.3153660.

[5] H. -D. Nguyen, S. -H. Kim, G. -S. Lee, H. -J. Yang, I. -S. Na and S. -H. Kim, "Facial Expression Recognition Using a Temporal Ensemble of Multi-Level Convolutional Neural Networks," in IEEE Transactions on Affective Computing, vol. 13, no. 1, pp. 226-237, 1 Jan.-March 2022, doi: 10.1109/TAFFC.2019.2946540.

[6] Z. Li and D. Hoiem, "Learning without Forgetting," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 40, no. 12, pp. 2935-2947, 1 Dec. 2018, doi: 10.1109/TPAMI.2017.2773081.

[7] D. Ayata, Y. Yaslan and M. E. Kamasak, "Emotion Based Music Recommendation System Using Wearable Physiological Sensors," in IEEE Transactions on Consumer Electronics, vol. 64, no. 2, pp. 196-203, May 2018, doi: 10.1109/TCE.2018.2844736.

[8] Shin et al., "Automatic stress-relieving music recommendation system based on photoplethysmography-derived heart rate variability analysis," 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2014, pp. 6402-6405, doi: 10.1109/EMBC.2014.6945093.

[9] K. Yoon, J. Lee and M. -U. Kim, "Music recommendation system using emotion triggering low-level features," in IEEE Transactions on Consumer Electronics, vol. 58, no. 2, pp. 612-618, May 2012, doi: 10.1109/TCE.2012.6227467.

[10] Li, W., Tan, R., Xing, Y. et al. A multimodal psychological, physiological and behavioral dataset for human emotions in driving tasks. Sci Data 9, 481 (2022). https://doi.org/10.1038/s41597-022-01557-2

[11] D. Ayata, Y. Yaslan and M. Kamaşak, "Emotion recognition via random forest and galvanic skin response: Comparison of time based feature sets, window sizes and wavelet approaches," 2016 Medical Technologies National Congress (TIPTEKNO), Antalya, Turkey, 2016, pp. 1-4, doi: 10.1109/TIPTEKNO.2016.7863130.

[12] V. Vijay Mohan Dattada and M. Jeevan, "Analysis of Concealed Anger Emotion in a Neutral Speech Signal," 2019 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER), Manipal, India, 2019, pp. 1-5, doi: 10.1109/DISCOVER47552.2019.9008037.

[13] S. Thuseethan, S. Rajasegarar and J. Yearwood, "Deep Continual Learning for Emerging Emotion Recognition," in IEEE Transactions on Multimedia, vol. 24, pp. 4367-4380, 2022, doi: 10.1109/TMM.2021.3116434.

[14] S. -H. Park, B. -C. Bae and Y. -G. Cheong, "Emotion Recognition from Text Stories Using an Emotion Embedding Model," 2020 IEEE International Conference on Big Data and Smart Computing (BigComp), Busan, Korea (South), 2020, pp. 579-583, doi: 10.1109/BigComp48618.2020.00014.

[15] "Klara Steinhauser, Felix Leist, Kathrin Maier, Vera Michel, Nikolai Pärsch, Philip Rigley, Franz Wurm, Marco Steinhauser, ""Effects of emotions on driving behavior"", in Nov 2018 Transportation Research Part F: Traffic Psychology and Behaviour, Volume 59, Part A, doi: 10.1016/j.trf.2018.08.012."

[16] Sanders RD, Schuepbach D, Goldstein G, Haas GL, Sweeney JA, Keshavan MS. "Relationships between cognitive and neurological performance in neuroleptic-naïve psychosis". J Neuropsychiatry Clin Neurosci. 2004 Fall;16(4):480-7. doi: 10.1176/jnp.16.4.480. PMID: 15616175.

[17] Vijayanand. G, Karthick. S, Hari. B, Jaikrishnan. V, 2020, "Emotion Detection using Machine Learning", INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) NCICCT – 2020 (Volume 8 – Issue 08),

[18] C. Joesph, A. Rajeswari, B. Premalatha and C. Balapriya, "Implementation of physiological signal based emotion recognition algorithm," 2020 IEEE 36th International Conference on Data Engineering

(ICDE), Dallas, TX, USA, 2020, pp. 2075-2079, doi: 10.1109/ICDE48307.2020.9153878.

[19] E. A. Veltmeijer, C. Gerritsen and K. V. Hindriks, "Automatic Emotion Recognition for Groups: A Review," in IEEE Transactions on Affective Computing, vol. 14, no. 1, pp. 89-107, 1 Jan.-March 2023, doi: 10.1109/TAFFC.2021.3065726.

[20] H. Xiao et al., “On-Road Driver Emotion Recognition Using Facial Expression,” Applied Sciences, vol. 12, no. 2, p. 807, Jan. 2022, doi: 10.3390/app12020807.

[21] Zepf, S., Hernandez, J., Schmitt, A., Minker, W., & Picard, R. W. (2020). “Driver Emotion Recognition for Intelligent Vehicles”. ACM Computing Surveys, 53(3), 1–30. doi:10.1145/3388790

[22] Y. Wu, R. Valdez and C. Forlines, "Cognitive and Emotional Monitoring with Inexpensive Wrist-Worn Consumer-Grade Wearables," 2023 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops), Atlanta, GA, USA, 2023, pp. 665-670, doi: 10.1109/PerComWorkshops56833.2023.10150338.

[23] Xing Luan, Quan Wen, Bo Hang, “Driver emotion recognition based on attentional convolutional network”, Frontiers in Physics, 2024-Apr, Vol.12, https://doi.org/10.3389/fphy.2024.1387338

[24] Yunan Wu; Roxana Valdez; Clifton Forlines, “Cognitive and Emotional Monitoring with Inexpensive Wrist-Worn Consumer-Grade Wearables”, 2023 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops), Atlanta, GA, USA, 2023, pp. 665-670, doi: 10.1109/PerComWorkshops56833.2023.10150338