International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No.12s,2025
https://theaspd.com/index.php

Facial Expression-Based Emotion Detection For Adaptive Teaching In Educational Environment

Prabakaran S[1], P Anbumani[2], K. Srinath Yadav[3], Shreetharan ST[4],Vasanth M[5], Vishnukumar A[6]
[1,2,3]Asst.Prof / Department of CSE,V.S.B.Engineering College,Karur, Tamil Nadu,
[4,5,6]Department of CSE,V.S.B.Engineering College,Karur, Tamil Nadu,
mokipraba@gmail.com,anbuanc@gmail.com,gkarthikkumaran@gmail.com,shreests07@gmail.com,
vasanth862004@gmail.com, arumugamvishnu200@gmail.com

ABSTRACT
Understanding how students interact in educational settings is essential for enhancing academic outcomes and student health. A new student activity categorization method uses facial expression detection technologies according to this research. The proposed system uses facial expression detection technology to monitor student emotions and state before classifying their activities. The research examines deep learning models for face emotion recognition across academic and non-academic activities from a single dataset. The system establishes the ability to detect four emotional states including happiness and sorrow as well as rage and surprise. The system utilizes extracted emotional traits to analyze student actions which demonstrate engagement alongside attentiveness along with puzzlement and indifference and other potential states. This student-tracking methodology can forecast real-time student interactions which enables teachers to make necessary adjustments that enhance academic results and learning quality. The framework presents opportunities to develop customized educational assistance alongside intelligent educational systems. We will develop a system for extracting face characteristics through this investigation. using the Grassmann method. The system detects student emotions during specific circumstances. The system uses emotion categorisation to predict active states before generating administration reports. Through this technique researchers can develop adaptive learning systems which dynamically alter instruction based on student emotional responses. Through student emotional responses a virtual tutor could alter exercise difficulty thereby creating a flexible and interactive learning scenario.

INTRODUCTION

The identification of students' engagement and emotions along with their activities remains crucial for educators to establish optimal teaching approaches in educational environments. Academic success and emotional well-being for students demonstrate direct correlations with their emotional states. Research introduces enhanced methods for quality improvement along with individualized educational assistance. A system uses facial expression recognition methods to classify student activities. The assessment of student participation and conduct depends primarily on the subjective methods of observation and self-reporting while maintaining limited visibility scope. Our technique implements deep learning and computer vision methods to process student emotional reactions for extensive and objective behavior categorization. This technique operates from face expression detection and has been transformed by Convolutional Neural Networks (CNNs). Deep learning models help scientists identify and categorize multiple emotions expressed through student facial movements in real time across different feelings such as happiness and sorrow and rage and surprise and additional expressions. The observations deliver essential knowledge about how students feel. Beyond emotion recognition capability this technology possesses. This system links observed emotions to particular assignments so we can tell whether students are participating in discussions or facing challenging concepts or showing no interest in independent work. Educational organizations along with instructors can utilize immediate research findings to create teaching improvements that lead to faster educational interventions for improving student achievement. This research enables developers to design intelligent learning processes which automatically adjust their content delivery based on student emotional states. When integrated with intelligent systems students can experience targeted modifications to their learning content while receiving adjusted levels of challenge and supplemental guidance for a more personalized educational outcome. The pursuit of breakthroughs requires us to prioritize ethical matters including data protection protocol together with informed consent procedures and solutions to prevent emotional bias identification systems. Face expression detection in education requires these considerations to maintain appropriate use. The application of facial emotion recognition technology advances significantly through this research for identifying multiple elements in student behavior. This technology will transform education by delivering immediate understanding of student actions and supporting a learning environment that responds dynamically while being effective. The current system appears like fig 1.

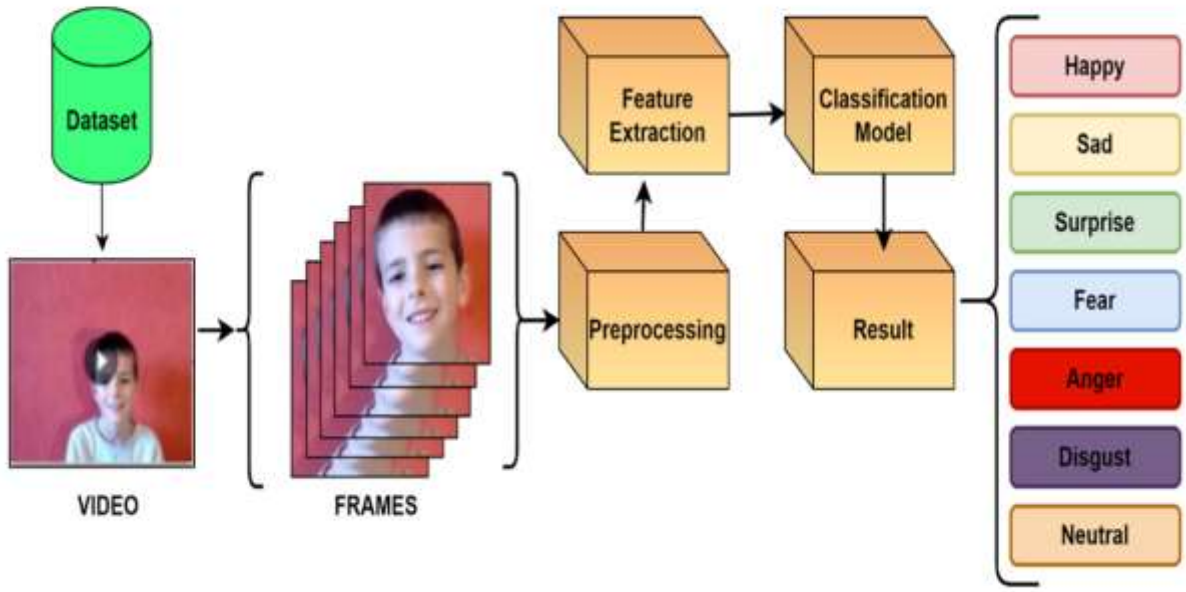

Fig 1: Video based facial emotion recognition

RELATED WORK

(Chahak Gautam et al., 2022). With the help of feature extraction and CNN, the novel and efficient framework for emotion identification is presented in [1]. Successful and rapid face emotion analysis may be possible with the use of explicit key-feature extraction from datasets, as shown in this work. When data collection is limited and you want to build the model without omitting any important or valuable information, handcrafted feature extraction is key. Data feature extraction is a powerful technique for enhancing accuracy, minimizing the danger of overfitting, speeding up training, improving data visualization, and processing, and these are the primary contributions and discoveries of the work. Emotion recognition technology is a subset of face detection and recognition that can derive an individual's emotional state from their facial expressions in addition to biophysical signs and symptoms like heart rate and brain activations. Image-based facial expression recognition becomes a very difficult task when attempting to infer an individual's emotional state in certain situations, such as when they are watching a TV show or movie, playing a video game, going shopping, or even fighting for their country. Emotions are now the most significant component due to the sudden increase in a variety of medical conditions, such as depression, cancer, paralysis, and trauma. This study suggests a method for emotion identification that makes use of convolutional neural networks and feature extraction. This includes Mahmut Dirik and colleagues. [2] proposed research on automatic face emotion recognition using face photos. Using the ANFISPSO classifier recognition model, trustworthy decision-support systems are constructed with rapid and accurate face recognition. We evaluated the suggested approach, GPA-based normalisation, against several classifiers that relied on AU characteristics. The ANFISPSO method enhances detection and exploitation by combining particle swarm optimization (PSO) with the ANFIS algorithm. A 99.6 percent accuracy rate was achieved using the suggested ANFISPSO-based classifier. To sum up, this study offered a novel framework and an extremely precise AU-based classification technique for identifying emotions. A number of criteria were used to assess the suggested model's efficacy. The proposed model outperformed its predecessors by a wide margin (99.6%). The research has limitations, such as its reliance on static images and its failure to account for the dynamic nature of face emotions across time. Research on emotion recognition from face photos is substantial and ongoing. Computer vision often makes use of facial features to decipher emotions, carry out cognitive science, and connect with people. A complex system using data and human-computer interaction is required for the proper analysis of facial emotions (such as pleased, angry, sad, surprised, disgusted, scared, and neutral). Developing a feature selection and emotion categorization method that is both effective and computationally simple is no easy task. Along with others, Sudheer Babu Punuri the third For accurate facial emotion recognition, a state-of-the-art transfer learning technique has been suggested. A mechanism called EfficientNet XGBoost is in charge of this. A unique combination of an XGBoost classifier, fully linked layers, a pre-trained EfficientNet architecture, and custom parameter tweaking proves the scheme's originality. After the input face photographs have been properly pre-processed, the custom model is used to extract features. We use many networks to get the feature points. The XGBoost Classifier, which can identify the labels for various emotions, is fed the final set of features after global average pooling has averaged the feature maps. For the purpose of validating the approach, four separate datasets are used. The results show that the CK+ dataset performed very well experimentally, with a total accuracy rate of 100%. On top of that, the proposed model can accurately identify facial expressions with almost little delay at all. The overall accuracy percentage is 98% according to datasets like JAFFE and KDEF. A benchmark accuracy of 72.54% was achieved by the use of geometric transformation methods for augmentation, even though the sample distribution in FER2013 was not uniform. We back up our assertion with a study that compares our findings to those of other researchers using the same datasets. Improving efficiency for imbalanced sample sets will be the next area of investigation. One reasonable strategy for identifying facial expressions from imbalanced datasets may be to investigate the use of custom GANs (generative adversarial networks). An novel approach to facial emotion identification was developed by Ninad Mehendale et.al. [4] using convolutional neural networks (CNNs) and supervised learning, which may be enabled by huge data. The 24-digit long EV feature matrix is the main advantage of the FERC method, which allows it to function with numerous orientations (less than 30°). A big help in accurately gauging emotions came from the background removal. Although it has always been easy for humans to accomplish, teaching a computer algorithm to recognize emotions in facial expressions is a challenging undertaking. Emotion recognition in images is now within reach, thanks to developments in computer vision and ML. Using convolutional neural networks (FERC), we provide a novel method for identifying face emotions in this research. The foundation of the FERC is a bilayer convolutional neural network (CNN) that separates the face feature vector extraction process from the background removal process. To classify the several common face expressions, the FERC model uses an expressional vector (EV). Information for the supervisor came from a database containing 10,000 images (154 people). Applying an EV of length 24 values allowed for a 96% accuracy rate in accurately emphasizing the emotion. The last Perceptron layer of the two-layer CNN changes the values of the weights and exponents with each iteration, and the CNN functions sequentially. Because FERC is not like other methods that rely on single-level CNN, it is able to achieve better accuracy. In addition, a novel method of removing backgrounds is carried out before electric vehicle manufacturing begins, which eliminates the need to deal with a multitude of potential issues, such as the distance from the camera. The authors Aayushi chaudhari et al. [5] devised a method for emotion recognition using publicly accessible unsupervised data and techniques for self-supervised learning (SSL). Compared to retraining the model or starting from scratch, this method allowed us to leverage pretrained self-supervised learning algorithms that are already available, saving us time. A robust and comprehensive fusion approach was necessary since the features produced by self-supervised learning were high-level features with enormous dimensions. The results suggest that combining intermodality interaction techniques with self-supervised learning (SSL) might help us address the challenge of multimodal emotion recognition. By employing pretrained self-supervised learning algorithms to extract characteristics, we focused on enhancing the emotion recognition job. To do this, we developed a multimodal fusion technique based on transformers. Additionally, we were able to accurately define our emotion categories by applying them in a two-dimensional (arousal and valence) way. First, we compared our model with robust baselines from RAVDESS datasets to show that our method outperformed previous state-of-the-art methods. Our ultimate goal is to put in place a system that can recognize emotions based on their surroundings and categorize them based on dominance, arousal, and valence. Additionally, we want to test our idea in the medical industry with the hope that it would aid doctors in making accurate diagnoses. Liam Schoneveld and colleagues, [6] An improved AVER method based on deep neural networks is detailed in the paper. For FER, the suggested model employs a deep convolutional neural network (CNN) trained on knowledge distillation; for SER, it employs a modified and improved VGGish version of the same network. Using a model-level fusion technique, the visual and aural feature representations are combined. Analyzing input that is both geographically and temporally represented allows recurrent neural networks to simulate the dynamics of time. An improved VGGish backbone, a model-level fusion architecture, and a visual feature extractor network are the components of the high-performance deep neural network-based method that this study suggests for AVER. By training AffectNet and FEC simultaneously, the improved face expression embedding network demonstrates how to get strong representations of facial expressions. Information distillation may further enhance face emotion recognition, as we also showed. Our improved VGGish backbone feature extractor shows promise as a novel approach to emotion inference in audio. Also, when it comes to emotion prediction on the RECOLA data, AVER outperforms state-of-the-art methods, proving that our shallow neural networks approach to multimodal fusion is helpful. (Dr. P. Sumathy and colleagues), [7] In the future of machine learning, emotion detection will definitely be a game-changer. The possibility of developing intelligent systems that properly understand emotions has become more plausible with the advent and broad use of Deep Learning and Machine Learning methods. The wide variety of human face expressions, physical characteristics, unusual body postures, and lighting situations makes feature and emotion recognition a difficult task. An improved picture pre-processing method using KNN and CA is presented, which enhances the photograph quality by reducing noise and lighting in the photographs of facial expressions. When compared to other methods, the suggested improved pre-processing strategy using ANN classification method outperforms the competition in terms of accuracy, detection rate, sensitivity, and specificity when it comes to identifying human emotions. One thing that may be seen while focusing just on the frequency domain is a filter, which can either increase or decrease the visibility of certain frequencies. Changing the size, color, and shading of photographs, among other things, is what image filters are mostly used for. Among the many possible uses for this filtering in image processing are sharpening, smoothing, and enhancing edges. Jung Hwan Kim and colleagues, [8] A device that can accurately detect a driver's facial expressions might be an effective tool in the fight against traffic fatalities. Aggressive driving, according to Ismail et al., puts other people's lives at jeopardy and increases the probability of accidents. A person might be shielded from angry drivers and prevented from tragic accidents with the use of facial expression recognition (FER) technology. Systems that detect facial emotions (FER) have a significant impact on drivers' dispositions. Reduced road rage is a result of autonomous cars' excellent facial expression detection. Training FER models without the required datasets results in poor performance in real-time testing, regardless of how complicated the model is. When it comes to FER system performance, dataset integrity is more important than algorithm correctness. Our proposed facial image thresh (FIT) machine enhances the efficacy of FER systems for autonomous automobiles by using new capabilities to face detection and learning from the Xception technique. The FIT machine required not only the data-augmentation method but also the removal of superfluous facial photographs, the acquisition of new facial photos, the restoration of lost face data, and the extensive merging of initial datasets. Authors M. A. H. Akhand and colleagues, [9] When taken in unrestricted settings (like public places) where frontal view photos aren't always possible, emotion identification from face photographs becomes more vital for smart homes, smart environments, and smart society. This can only be achieved with a robust FER that can recognize emotions from different angles and other facial viewpoints. When looking at a profile from a variety of angles, it is impossible to discern the landmark parts of the whole image, and traditional feature extraction algorithms also fail when trying to extract facial expression qualities from side views. So, the only practical way to tackle this difficult problem is to use the DCNN model to extract FER from high-resolution face pictures. The proposed FER system includes the TL-based method. By substituting dense layers for the upper layers of a pre-trained DCNN, we may make it compatible with FER and improve the model's performance when fed facial expression data. One unique aspect of the suggested method is the training procedure for fine-tuning pipelines: first, the thick layers are adjusted, and subsequently, the remaining DCNN blocks are modified one by one. Avigyan Sinha and colleagues, [10] In order to ascertain the subject's emotional condition, Facial Expression Recognition (FER) analyses emotions in both static and dynamic images. Facial expressions are a nonverbal way for humans to convey their feelings. Emotions like wrath, disgust, fear, joy, sorrow, neutral, and surprise are the basic emotions that the algorithm uses to categorize faces. In very unusual circumstances, a person's facial expressions may also convey their emotional or physiological status, such as when they are bored or exhausted. Speech, EEG, voice quality, and text may all be used to identify emotions. Face expressions are among the most popular examples of these personality traits since they may be observed, contain a range of important features for distinguishing emotions, and are easy to discern. To create a big face collection (rather than other methods for human identification). FER can also be used with biometric identification. Technology analysis of a variety of sources, such as voice, text, device-generated health information, or blood circulation patterns inferred from images, may increase its accuracy. The project's current technology identifies emotion using traditional means such as a person's voice, facial expression, EEG, text, and so on. Nonetheless, in the history of human-computer interaction, a computer's capacity to recognise an individual's emotions is very important. We constructed a CNN model utilising data given by Jonathan Oheix to get beyond the typical technique's failure to identify emotions in HCI (computer interaction).

BACKGROUND OF THE WORK

If computers could sense emotions, it would revolutionize several areas of human-computer interaction. One way to look about face detection is as a simple binary classification of image frames as either having faces in them or not. In order to train a classification model to identify whether or not a face is present in an image, we must first define what an image looks like. Two steps normally make up the current methodology: first, extracting ASM motion using a pyramid ASM model fitting approach; and second, classifying projected motion using Adaboost classifiers. Next, the system uses the three feature points that were retrieved—the nose and eyes—to align with the average shape of the ASM. It disregards the other part of the ASM and uses the average face shape to estimate the geometrical dislocation information between the current and average ASM point coordinates. The Adaboost classifier is then used to identify facial expressions from geometrical movement. Furthermore, Viola Jones is used to extract features. The wavelet-based properties were used by Viola and Jones. Square waves having only one high and one low wavelength are called wavelets. A square wave in two dimensions is just two adjacent rectangles, one light and one dark.Mukiri and Prasad [11] propose a novel ranking scheme aimed at decontaminating classified clustering datasets, enhancing data preprocessing for improved analytical outcomes. In a related study, Prasad and Mukiri [12] examine the emulation of human biases and bounded rationality within AI/ML systems, highlighting the importance of incorporating cognitive constraints for more realistic models. Bhoga et al. [13] focus on pedagogy, integrating active learning techniques to improve the delivery and comprehension of machine learning courses. Similarly, Srilatha et al. [14] propose the integration of assessment and learning platforms within traditional programming classrooms to foster continuous evaluation and engagement.

PROPOSED WORK

A new way to improve educational learning emerges through the suggested facial expression detection method created by using the Grassmann algorithm. The system utilizes the Grassmann algorithm as its basis for examining high-dimensional facial data using statistical analysis. The foundation for data collection includes acquiring vast quantities of student involvement data across different educational activities comprised of traditional classroom presence and online learning environments. The facial dataset comprises both images and video frames obtained from students during their various educational activities to ensure representation from every demographic. The data preprocessing steps apply normalization to pixel values whereas data augmentation improves both diversity and quality of the dataset. The face emotion recognition system utilizes the popular Grassmann algorithm to perform feature extraction and dimension reduction. Through this procedure the system obtains vital components from extensive dimensions of face information which reveal small facial movements and facial expressions used to communicate emotion. Grassmann demonstrates robust capabilities that position it perfectly for the interpretation of facial emotional data. The Grassmann method functions as Grassmannian subspace analysis for studying facial characteristics in computer vision-based facial recognition systems. One application of the Grassmann method involves reducing dimensionality which remains essential for managing high-dimensional face information. The Grassmann technique enables dimension reduction of facial feature vectors for critical information retention thus serving facial identification and emotion detection alongside expression analysis. The Grassmann method proves especially useful for extracting significant features. The method converts pixel data with high dimensions into a condensed format that shows vital facial signature features including texture patterns and shape alterations and landmark positions. Another aspect is subspace learning, in which the algorithm identifies subspaces within the feature space that characterise certain facial features or identities. Fig 2 shows the proposed architecture

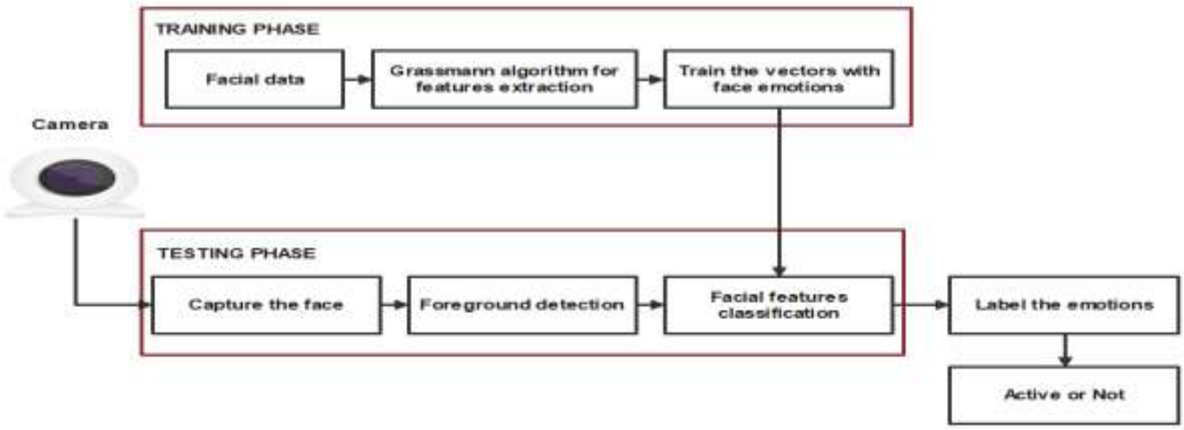

Fig 2: Proposed architecture

4.1 FRAMEWORK CONSTRUCTION

- This strategy offers instructors real-time feedback, which is a big advantage. Teachers can use emotion recognition technology to assess their students' emotional responses during classes, lectures, or conversations.
- This immediate feedback allows them to make adjustment on the spot to make certain students remain engaged and understand the material.
- In this module, we can design the scaffold for students
- Student can login to the system with their details
- Admin can view the particulars about students

4.2 FEATURES EXTRACTION

- Facial features extraction using Convolutional Neural Networks (CNN) is a admired approach for stress detection from facial images. CNNs are deep learning models that can robotically extract skin tone from images and learn complex patterns
- Acquiring a dataset of face pictures of people under various stress situations is the first stage in using CNN for fear detection.

4.3 MODEL BUILDING

- The next stage involves choosing a convolutional neural network (CNN) architecture that can extract face attributes.
- The sequential model is often used by CNN architectures for image recognition applications. For stress detection, this model may be fine-tuned after being pre-trained on big datasets.
- Following this, features may be extracted from the face photos using the CNN. A convolutional neural network (CNN) is used to quickly process the pictures and get activations from a final convolutional layer.

4.3 ACTIVITY CLASSIFICATION

• In terms of automatically learning skin tone across many network layers and their capacity to simulate complicated systems, deep neural networks have important benefits.
• Therefore, activities requiring a high degree of accuracy, such classification, are carried out by deep neural networks.
• Create a convolutional neural network (CNN) architecture that can detect stress levels from a face picture.

- Feature extraction from pictures is usually accomplished by means of max-pooling layers after several convolutional layers in the architecture. Fully linked layers, the network's last stage, determine whether an image is positive or negative.

4.4 REPORTS

- In this module, provide the intelligence for all students about activity state information
- And sentiment details stored in database for future verification

5. EXPERIMENTAL RESULTS

The false rejection rate quantifies the likelihood that a biometric security system would inadvertently reject an authorized user's attempt to get access. The ratio of the total number of identification attempts to the number of incorrect rejections is commonly used to calculate a system's false rejection rate (FRR).
FALSE REJECT RATE = FN / (TP+FN)
FN =Genuine Scores Exceeding Threshold

TP+FN = All Genuine Scores

Algorithms	**FRR**
Random Forest	0.42
Adaboost Classifier	0.35
CNN classifier	0.28

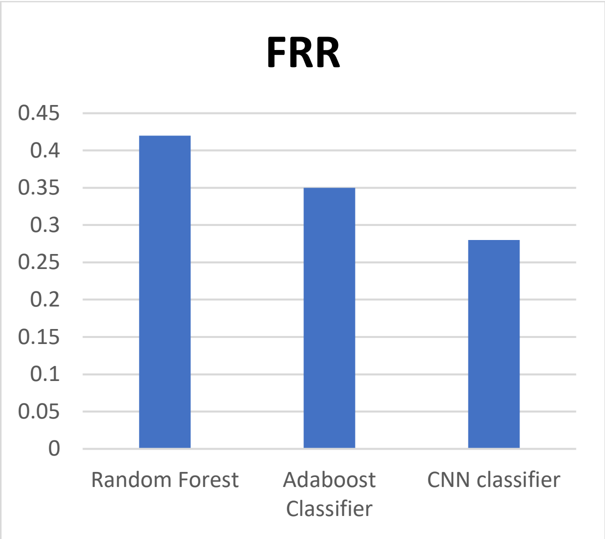

Fig 3: False rejection rate

The proposed system delivers better negative response outcomes than Random Forest and Adaboost classifier.

CONCLUSION

The use of Convolutional Neural Networks (CNNs) to identify student behaviors through facial expressions has the potential to transform educational settings. Deep learning powers this new approach which delivers detailed emotional profiling of students through different learning phases. Real-time emotional insights yielded from facial analysis enable the technology to offer educational improvements. Educators benefit from real-time emotional data through this technology to customize their strategies against students which creates better student interaction and learning comprehension. The identification of fundamental alongside sophisticated emotional states including perplexity and irritation and satisfaction enables educators to understand students better. This project successfully measures student engagement alongside well-being across both traditional classroom environments and remote and online learning spaces to create a flexible assessment system. Flexible operation aligns with the continuous shifts occurring within educational frameworks.

REFERENCES

[1] Gautam, Chahak, and K. R. Seeja. "Facial emotion recognition using Handcrafted features and CNN." Procedia Computer Science 218 (2023): 1295-1303.
[2] Dirik, Mahmut. "Optimized anfis model with hybrid metaheuristic algorithms for facial emotion recognition." International Journal of Fuzzy Systems 25.2 (2023): 485-496.
[3] Punuri, Sudheer Babu, et al. "Efficient net-XGBoost: an implementation for facial emotion recognition using transfer learning." Mathematics 11.3 (2023): 776.
[4] Mehendale, Ninad. "Facial emotion recognition using convolutional neural networks (FERC)." SN Applied Sciences 2.3 (2020): 446.
[5] Chaudhari, Aayushi, et al. "Facial emotion recognition with inter-modality-attention-transformer-based self-supervised learning." Electronics 12.2 (2023): 288.
[6] Schoneveld, Liam, Alice Othmani, and Hazem Abdelkawy. "Leveraging recent advances in deep learning for audio-visual emotion recognition." Pattern Recognition Letters 146 (2021): 1-7.
[7] Sumathy, P., and Ahilan Chandrasekaran. "An Optimized Image Pre-Processing Technique for Face Emotion Recognition System." Annals of the Romanian Society for Cell Biology 25.6 (2021): 6247-6261.
[8] Kim, Jung Hwan, Alwin Poulose, and Dong Seog Han. "The extensive usage of the facial image threshing machine for facial emotion recognition performance." Sensors 21.6 (2021): 2026.
[9] Akhand, M. A. H., et al. "Facial emotion recognition using transfer learning in the deep CNN." Electronics 10.9 (2021): 1036.
[10] Sinha, Avigyan, and R. P. Aneesh. "Real time facial emotion recognition using deep learning." International Journal of Innovations and Implementations in Engineering 1 (2019).
[11] Mukiri R.R.; Prasad B.V.V.S., "Novel approach: A new ranking scheme for decontaminate classified clustering datasets", Journal of Advanced Research in Dynamical and Control Systems, 10:4, 442
[12] Prasad B.V.V.S.; Mukiri R.R.," Emulating human biases and bounded rationality and advances in Ai/Ml", International Journal of Engineering and Advanced Technology, 8:6, 2016

[13] Bhoga, Ujwala, et al. "Integration of Active Learning Techniques for Effective Delivery of Machine Learning Course." Journal of Engineering Education Transformations 38.Special Issue 1 (2024).
[14] Srilatha, P., G. Vishnu Murthy, and P. Raja Sekhar Reddy. "Integration of Assessment and Learning Platform in a Traditional Class Room Based Programming Course." Journal of Engineering Education Transformations 33.Special Issue (2020).