



International journal of basic and applied
research

www.pragatipublication.com

ISSN 2249-3352 (P) 2278-0505 (E)

Cosmos Impact Factor-5.86

Real time Facial Emotion Recognition with emoji's Using Convolutional Neural Network

M.S.R. Pavani¹, S.P. NandaKishore Reddy², S. Sai Kiran³, B. Harish⁴,

A.Vijay Bhaskar⁵, P. Venkata Lingaiah⁶

#1 Assistant Professor in Department of CSE, Raghu Institute of Technology, Visakhapatnam.
#2#3#4#5#6 B.Tech in Computer Science and Engineering (Data Science) in Raghu
Engineering College, Visakhapatnam.

Abstract _ Deep learning algorithms have made significant progress in a variety of domains, including computer vision. Without a doubt, a convolutional neural systems (CNN) model can be trained to deconstruct images and distinguish facial expressions. We created a convolutional neural network that can classify human emotions based on dynamic facial expressions in real time. We create a framework that recognises understudies' emotions based on their appearances. Our methodology consists of three stages: face recognition using Haar Falls, standardisation, and emotion recognition using CNN on the FER 2013 database with seven types of demeanors. Acquired results demonstrate that face emotion recognition is feasible in training, and thus it can help educators adapt their introduction based on the feelings of the understudies.

1.INTRODUCTION

Emojis have become a vital aspect of today's digital communication. They are utilised to express a person's emotions through text in ways that words alone cannot. Emotion is one of the most basic forms of human

expression. The recognition of facial expressions is a popular topic in computer vision. Facial expressions are a type of nonverbal communication since they are a direct manifestation of human emotions. Human facial expressions convey a lot of



information visually rather than verbally and play an important role in human-machine interaction. Many applications exist for automatic facial expression recognition systems, including, but not limited to, human behaviour understanding, detection of mental diseases, and synthetic human expressions. Facial expression identification by computer with a high recognition rate remains a difficult task. Geometry and appearance are two typical strategies used in the literature for automatic FER systems. Pre-processing, face detection, feature extraction, and expression classification are the four stages of facial expression recognition. We used deep learning methods (convolutional neural networks) to identify the key seven human emotions in this project: anger, disgust, fear, happiness, sorrow, surprise, and neutrality. The finest strategy that assists people in saving time by manually checking/searching for the proper emoji that represents nonverbal communication. With all of this in mind, we propose the use of Deep Learning techniques such as face detection, emotion

identification, and feature extraction in the application to convert live facial expressions to emoji, where the user can obtain the mapped emoji depending on the input image. The goal of creating this application is to provide the option of sending the emoji/avatar based on the user's live expression. Many social networking apps now allow users to send emoji, but they cannot recognise users' real-time facial expressions. As a result, with this project, we are assisting users in doing the same. As a result, it gives a solution for individuals to save time by not having to manually check/search for the suitable emoji.

2.LITERATURE SURVEY

[1] **R. G. Harper, A. N. Wiens, and J. D. Matarazzo, Nonverbal communication: the state of the art. New York: Wiley, 1978.**

The notion in the value of nonverbal communication is not new. Martin Luther, the sixteenth-century Protestant reformer, was famous for saying, "Do not watch a person's tongue, but his fists." However, the word "nonverbal communication" appears to



be a twentieth-century innovation, but it is not always apparent what it signifies. Because the term "nonverbal" solely refers to communication that is not verbal, the qualities that it can encompass are nearly unlimited. It can refer to communication via touch or smell, artefacts like as masks and clothing, or codified mechanisms such as semaphore. It has also been used to encompass vocal characteristics such as intonation, stress, speech rate, accent, and loudness, though this is debatable. Furthermore, it can refer to several types of body movement, such as facial expression, gaze, pupil size, posture, gesture, and interpersonal distance. The topic of this article is communication through bodily movement.

Nonverbal behaviour does not have to be intended as communication in order to occur. A person's intentions are not always evident; therefore, nonverbal communication may occur even when the encoder's spoken intentions are not. A lecturer's audience member may strive hard to appear attentive, but he or she is unable of

resisting the occasional yawn. Despite their greatest efforts, the listener may still express boredom to the speaker! Communication can also occur without conscious knowledge, in the sense that neither encoder nor decoder can identify the nonverbal clues used to transfer a message. People may be left with the idea that someone was furious or angry without being able to pinpoint the particular cues that caused that perception. Nonverbal communication can be distinctive as well. Hand gestures, for example, may derive their meaning from their visual likeness to the objects or acts they intend to convey, or from the manner in which they are performed.

[2] **P. Ekman and W. V. Friesen, "Constants across cultures in the face and emotion," *Journal of Personality and Social Psychology*, vol. 17, no 2, p. 124-129, 1971.**

The subject of whether any facial expressions of emotion are universal was investigated. Recent studies demonstrating that members of literate cultures associated the same emotion concepts with the same



facial behaviours were unable to demonstrate that at least some emotional facial expressions are universal; the cultures compared had all been exposed to some of the same mass media presentations of facial expression, and these may have taught the people in each culture to recognise the unique facial expressions of other cultures. To demonstrate that members of a preliterate culture who had little exposure to literate cultures would associate the same emotion concepts with the same facial behaviours as members of Western and Eastern literate cultures, data were collected in New Guinea by telling 342 Ss a story, showing them a set of three faces, and asking them to choose the face that displayed the emotion appropriate to the story. Ss were members of the Fore linguistic-cultural group, which was an isolated Neolithic material culture until 12 years ago. The findings provide evidence to support the idea. (30 references) ((c) 2016 APA, all rights reserved) PsycINFO Database Record [3] **C. Tang, P. Xu, Z. Luo, G. Zhao, and T. Zou, “Automatic Facial Expression Analysis of**

Students in Teaching Environments,” in Biometric Recognition, vol. 9428, J. Yang, J. Yang, Z. Sun, S. Shan, W. Zheng, et J. Feng, Éd. Cham: Springer International Publishing, 2015, p. 439-447.

The teacher in class can know the students' comprehension of the lecture based on their facial expressions, which has been a standard of teaching effect evaluation. To address the issue of high costs and low efficiency associated with using human analysts to observe classroom teaching effects, we offer in this paper an innovative and high-efficiency prototype system that automatically analyses students' expressions. The approach makes use of a fusion feature known as Uniform Local Gabor Binary Pattern Histogram Sequence (ULGBPHS). Using a K-nearest neighbour (KNN) classifier, we get an average recognition rate of 79 percent on a database of students' expressions with five types of expressions. The experiment demonstrates that the proposed approach is feasible and capable of increasing the efficiency of teaching assessment.



3.PROPOSED SYSTEM

In comparison to previous image classification techniques, a Convolutional Neural Network (CNN) is a deep artificial neural network that can identify visual patterns from input images with minimal pre-processing. This means that the network learns the filters that were previously hand-engineered in traditional techniques. A neuron is the most significant unit within a CNN layer. They are linked together in such a way that the output of neurons at one layer becomes the input of neurons at the next.

Convolution Layer: is the initial layer involved in the process of extracting features from an input image. The fundamental purpose of Convolution in the case of a ConvNet is to extract features from the input image. Convolution preserves the spatial relationship between pixels by learning picture properties from small squares of input data [21]. It computes the dot product of two matrices, one of which is the image and one of which is a kernel.

Pooling Layer: The dimensionality of each feature map is reduced while the most important information is kept. Maximum pooling, average pooling, and sum pooling are the three types of pooling. The aim of pooling is to gradually reduce the spatial scale of the input representation, making the network unresponsive to minor transformations, distortions, and translations in the input image.

Fully connected layer: is a traditional multilayer perceptron with an activation function in the output layer. Every neuron in the preceding layer is coupled to every neuron in the succeeding layer, according to the term "Fully Connected." The Fully Connected layer's goal is to categorise the input image into multiple classes based on the training dataset using the output of the convolutional and pooling layers. As a result, the Convolution and Pooling layers extract features from the input image, while the Fully Connected layer performs classifier duties.



3.1 IMPLEMENTATION

1. Data Collection: Collect sufficient data samples and legitimate software samples. □

2. Data Preprocessing: Data Augmented techniques will be used for better performance

3. Train and Test Modelling: Split the data into train and test data Train will be used for training the model and Test data to check the performance

4. Modelling: CNN model build and model is saved

5. Predict Select an single image and do basic image processing and predict using CNN model

3.2 ALGORITHM

Convolutional Neural Networks (CNN) are used in a variety of applications. It is undoubtedly the most well-known deep architectural study. The recent rise in interest in deep learning is due to the widespread acceptance and success of convnets. CNN's pastime began with AlexNet in 2012, and it

has developed enormously since then. In just three years, researchers progressed from an eight-layer AlexNet to a 152-layer ResNet..

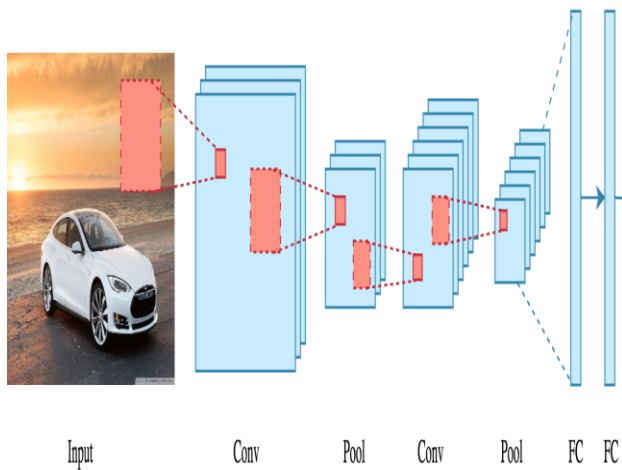
CNN is now the go-to model for any photograph-related issue. They blow the opposition out of the water with precise language. It is also useful in recommender systems, herbal language processing, and other applications. The primary advantage of CNN over its predecessors is that it recognises crucial aspects automatically without the need for human intervention. For example, given a large number of photographs of cats and pups, it learns unique characteristics for each group by itself.

CNN is also computationally efficient. It employs one-of-a-kind convolution and pooling techniques, as well as parameter sharing. CNN styles may now run on any device, making them globally appealing.

Overall, this sounds like pure magic. We're working with a highly efficient and environmentally friendly mannequin that



uses automated characteristic extraction to achieve superhuman precision (yes CNN models now do photograph classification higher than humans). Hopefully, this post will help us discover the secrets and procedures of this amazing approach.



5.RESULTS AND DISCUSSION

Fig 1: CNN

4.DATASET INFORMATION

We have downloaded dataset from kaggle website

Dataset:<https://www.kaggle.com/deadskull7/fer2013>

Classify facial expressions from 35,685 instances of grayscale 48x48 pixel photos of faces. The emotion expressed in the facial expressions is used to categorise the images (happiness, neutral, sadness, anger, surprise, disgust, fear).

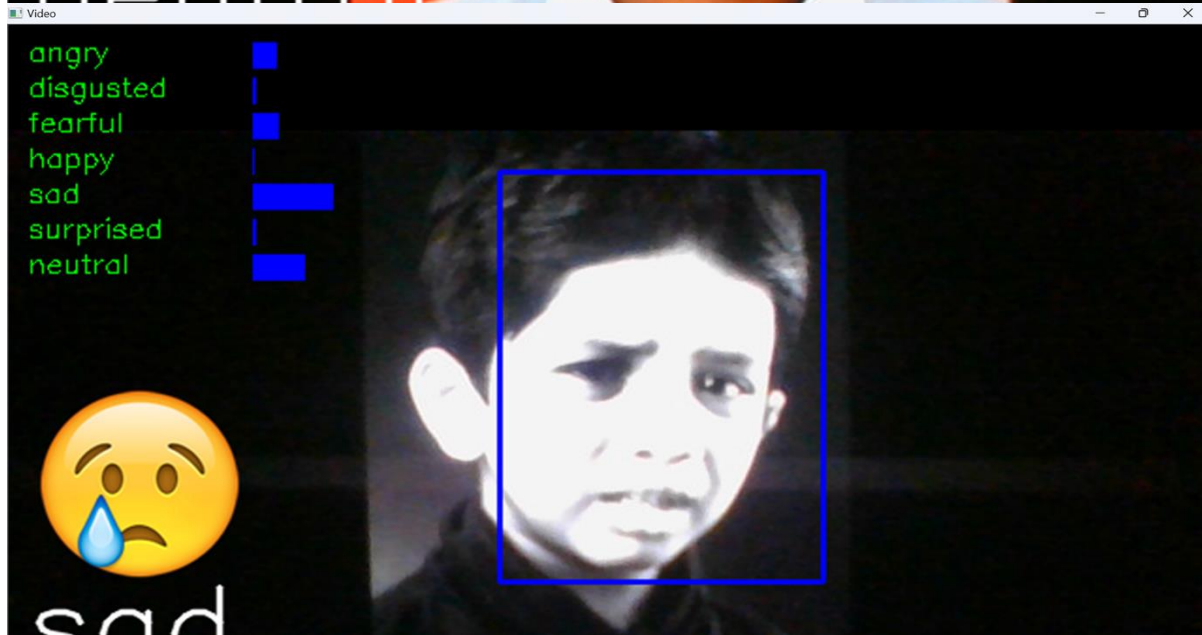
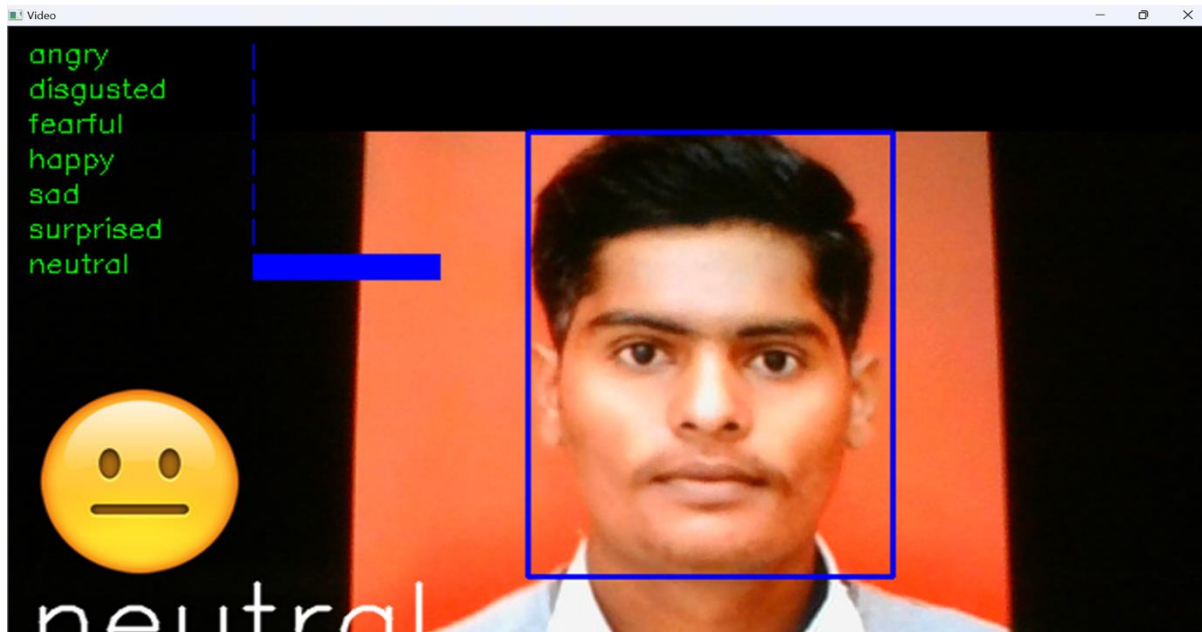


International journal of basic and applied
research

www.pragatipublication.com

ISSN 2249-3352 (P) 2278-0505 (E)

Cosmos Impact Factor-5.86



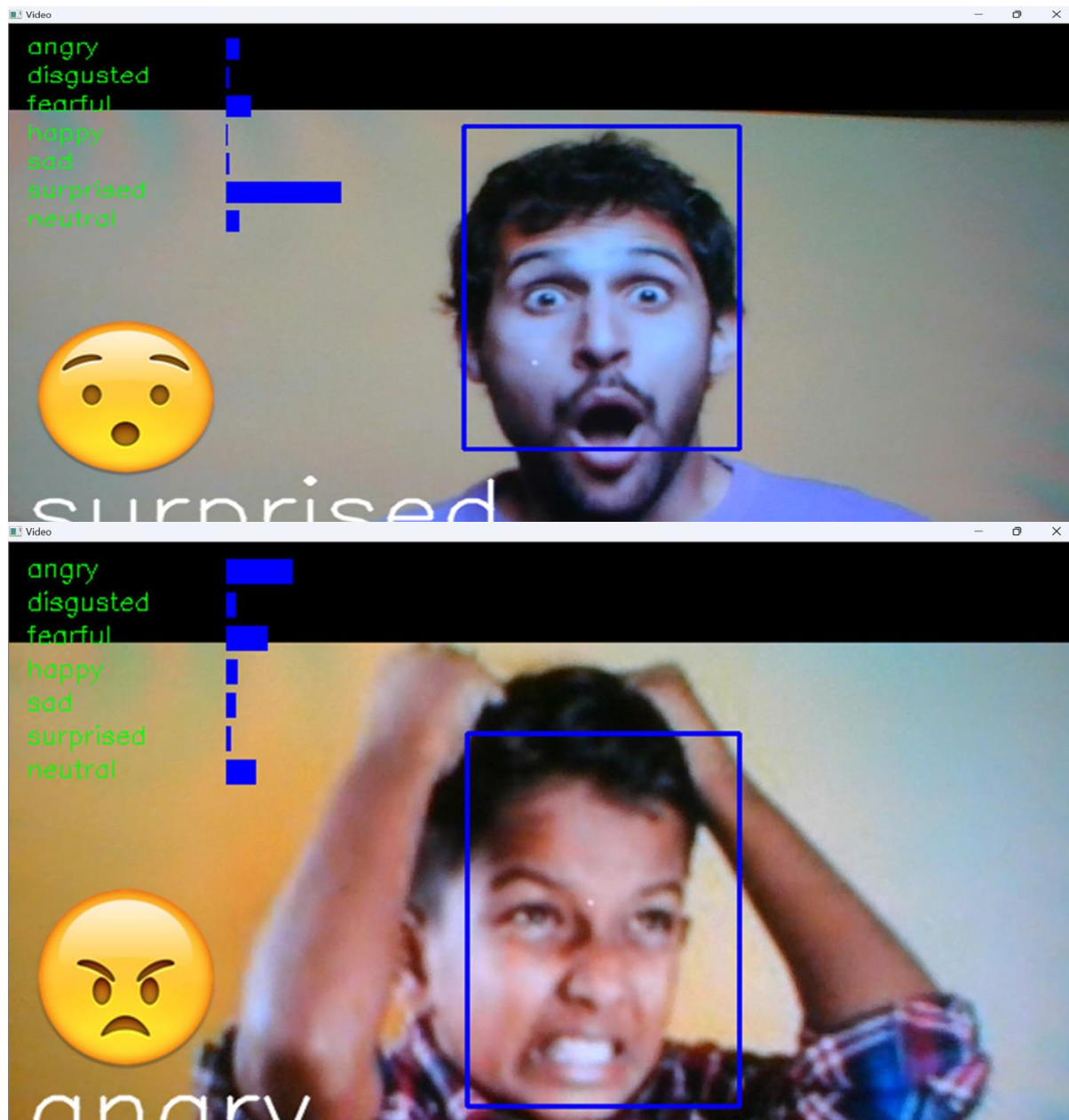


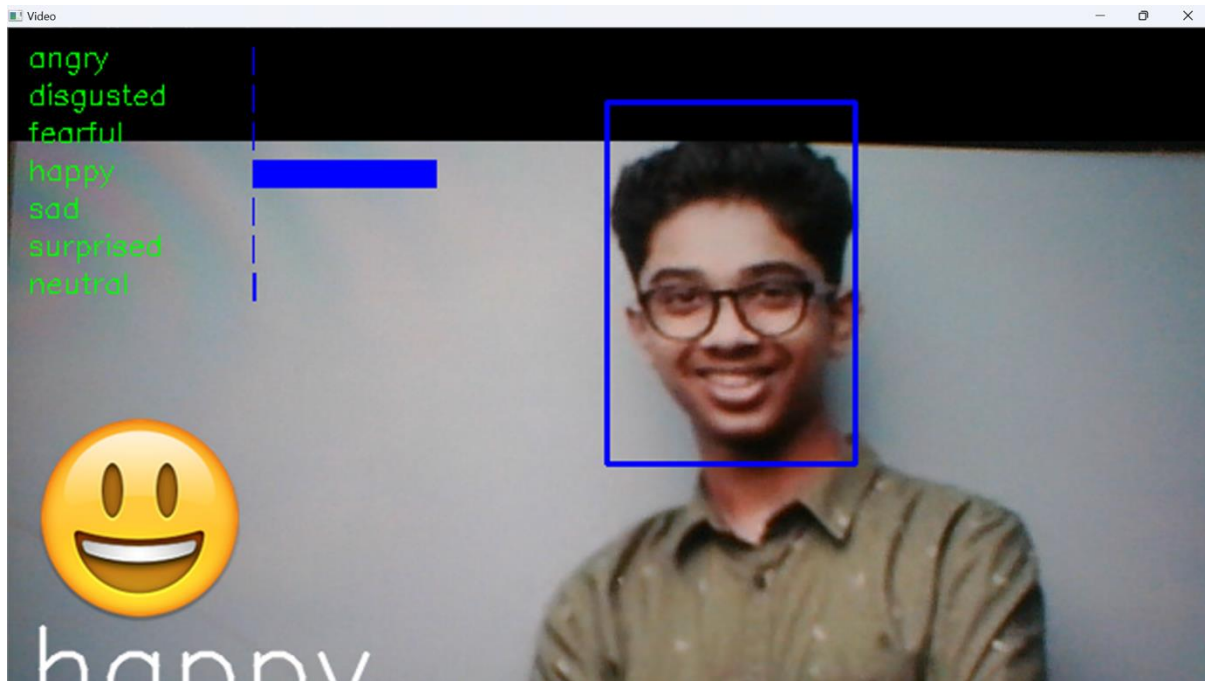
International journal of basic and applied
research

www.pragatipublication.com

ISSN 2249-3352 (P) 2278-0505 (E)

Cosmos Impact Factor-5.86





6.CONCLUSION

In this paper, we propose a facial expression recognition method based on a CNN model that extracts face features successfully. When compared to existing methods, the suggested method can automatically learn pattern features and reduce the incompleteness induced by artificial design elements. The proposed approach directly inputs the picture pixel value using training sample image data. Autonomous learning can implicitly learn more abstract picture

feature expressions. The training technique of the proposed method includes appropriate weight initialization, which has a substantial impact on weight updating. When compared to prior literature, our extensive experimental investigation shows that the proposed strategy can boost the detection rate of facial expressions in difficult backgrounds to some extent. In comparison to existing approaches, the proposed model's CNN convergence performance in complex backdrop circumstances is significantly



faster. In addition, the proposed approach has a higher recognition rate..

REFERENCES

- [1] R. G. Harper, A. N. Wiens, and J. D. Matarazzo, *Nonverbal communication: the state of the art*. New York: Wiley, 1978.
- [2] P. Ekman and W. V. Friesen, "Constants across cultures in the face and emotion," *Journal of Personality and Social Psychology*, vol. 17, no 2, p. 124-129, 1971.
- [3] C. Tang, P. Xu, Z. Luo, G. Zhao, and T. Zou, "Automatic Facial Expression Analysis of Students in Teaching Environments," in *Biometric Recognition*, vol. 9428, J. Yang, J. Yang, Z. Sun, S. Shan, W. Zheng, et J. Feng, Éd. Cham: Springer International Publishing, 2015, p. 439-447.
- [4] A. Savva, V. Stylianou, K. Kyriacou, and F. Domenach, "Recognizing student facial expressions: A web application," in *2018 IEEE Global Engineering Education Conference (EDUCON)*, Tenerife, 2018, p. 1459-1462.
- [5] J. Whitehill, Z. Serpell, Y.-C. Lin, A. Foster, and J. R. Movellan, "The Faces of Engagement: Automatic Recognition of Student Engagement from Facial Expressions," *IEEE Transactions on Affective Computing*, vol. 5, no 1, p. 86-98, janv. 2014.
- [6] N. Bosch, S. D'Mello, R. Baker, J. Ocumpaugh, V. Shute, M. Ventura, L. Wang and W. Zhao, "Automatic Detection of Learning-Centered Affective States in the Wild," in *Proceedings of the 20th International Conference on Intelligent User Interfaces - IUI '15*, Atlanta, Georgia, USA, 2015, p. 379-388.
- [7] Krithika L.B and Lakshmi Priya GG, "Student Emotion Recognition System (SERS) for e-learning Improvement Based on Learner Concentration Metric," *Procedia Computer Science*, vol. 85, p. 767-776, 2016.
- [8] U. Ayvaz, H. Gürüler, and M. O. Devrim, "USE OF FACIAL EMOTION RECOGNITION IN E-LEARNING SYSTEMS," *Information Technologies and Learning Tools*, vol. 60, no 4, p. 95, sept. 2017.



[9] Y. Kim, T. Soyata, and R. F. Behnagh, "Towards Emotionally Aware AI Smart Classroom: Current Issues and Directions for Engineering and Education," IEEE Access, vol. 6, p. 5308-5331, 2018.

[10] D. Yang, A. Alsadoon, P. W. C. Prasad, A. K. Singh, and A. Elchouemi, "An Emotion Recognition Model Based on Facial Recognition in Virtual Learning Environment," Procedia Computer Science, vol. 125, p. 2-10, 2018.

[11] C.-K. Chiou and J. C. R. Tseng, "An intelligent classroom management system based on wireless sensor networks," in 2015 8th International Conference on Ubi-Media Computing (UMEDIA), Colombo, Sri Lanka, 2015, p. 44-48.

[12] I. J. Goodfellow et al., "Challenges in Representation Learning: A report on three machine learning contests," arXiv:1307.0414 [cs, stat], juill. 2013.

[13] A. Fathallah, L. Abdi, and A. Douik, "Facial Expression Recognition via Deep Learning," in 2017 IEEE/ACS 14th International Conference on Computer

Systems and Applications (AICCSA), Hammamet, 2017, p. 745-750.

[14] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001, Kauai, HI, USA, 2001, vol. 1, p. I-511-I-518.

[15] Y. Freund and R. E. Schapire, "A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting," Journal of Computer and System Sciences, vol. 55, no 1, p. 119-139, août 1997.

Author's Profiles



M.S.R. Pavani working as Assistant Professor in Department of CSE, Raghu Institute of Technology. She completed her M. Tech in Computer Science from Krishnaveni Engineering College for



International journal of basic and applied
research

www.pragatipublication.com

ISSN 2249-3352 (P) 2278-0505 (E)

Cosmos Impact Factor-5.86

Women. She has 10 years of teaching
experience in various Engineering colleges.



S.P. NandaKishore Reddy B. Tech in
Computer Science and Engineering in
Raghu Institute of Technology,
Visakhapatnam.



S. Sai Kiran B. Tech in Computer Science
and Engineering in Raghu Institute of
Technology, Visakhapatnam.



B. Harish B. Tech in Computer Science and
Engineering in Raghu Institute of
Technology, Visakhapatnam.



A. Vijay Bhaskar B. Tech in Computer
Science and Engineering in Raghu Institute
of Technology, Visakhapatnam.



P. Venkata Lingaiah B. Tech in Computer
Science and Engineering in Raghu Institute
of Technology, Visakhapatnam.