

# Facial Recognition based Prediction of Employee Stress using Fuzzy Classification

N. Swapna<sup>1</sup>, Viqar Ahmed<sup>2</sup>, Mohammed Hameed Khan<sup>3</sup>, M.A Waris Rubaas<sup>4</sup>, Furqan Hussain Khan<sup>5</sup>

<sup>1,2,3,4,5</sup>Department of Computer Science and Engineering, Vijay Rural Engineering College, Rochis Valley, Manikbhandar, Telangana, India

swapananaralas@gmail.com, csebatch0808@gmail.com

## ABSTRACT

Stress has become increasingly common among employees due to the high demands and long working hours of their jobs. Stress can last for a short or long period of time, but it has a mental impact and can lead to a variety of health problems. Early prediction of stress levels can help organizations take proactive measures to prevent burnout and improve employee well-being. This paper presents Facial Recognition based prediction of Employee Stress using Fuzzy Classification. Cameras mounted on the office monitor which provide the image input for the described method. Fuzzy classifiers are based on fuzzy logic which accounts for the various ranges of possibilities between "yes" and "no" in order to simulate human decision-making. The Gabor filter initially identifies the eyes and lips, which are the most visible human facial features. Subsequently, the program will extract their movement information. Next the stress levels of the employees are calculated. Our system primary focuses on stress management, creating a healthy and spontaneous work environment for employees and maximizing their productivity during working hours. Classification accuracy, precision, False Positive Rate (FPR) and True Positive Rate (TPR) have all been used to evaluate the performance. With an accuracy of 98%, TPR of 97%, FPR of 3% and precision of 99%, the described mental health prediction model for employees is more effective than other models.

**Keywords:** *Stress, Fuzzy Classification, Employee, Images, FPR, TPR, Facial Recognition.*

## I. Introduction

Human stress is becoming the most trending topic in the field of research over last few decades in healthcare sector. Systems for managing stress are important for identifying the levels of stress that disrupts our socio economic lifestyle [1]. One in four citizens suffer from stress which is a mental health issue according to the World Health Organization (WHO) [2]. Human stress causes mental as well as socio-fiscal issues, lack of clarity in work, strained relationships at work, depression, and finally commitment of suicide in extreme situations.

Maintaining a stress-free work environment is crucial for greater employee wellbeing and productivity [3]. Career guidance, counseling assistance, stress management sessions and health awareness programs are some of the ways, working professionals can manage stress for their mental health [4]. The likelihood that such measures will be successful will rise with early identification of employees who will require such assistance. Human innovation and creativity are incorporated into the overall development of software systems. Knowledge sharing is a

component of the development process that is scattered. Different phases of a system's development require implementing several logical steps. An industry's software depends on human creativity [5]. To successfully implement all necessary stages of development, IT professionals need to pay close attention and exercise caution. As a result, stress levels have a significant impact on them [6].

New more advanced software and applications are being developed to study the stress levels in human body. Facial muscle contraction are the major factors in determining the stress from face [7]. A questionnaire is one of the traditional methods for identifying stress. Since people will be tremulous to state whether they are stressed or normal, this method is totally dependent on their responses [8]. Automatically detecting stress improves societal welfare and reduce the risk of health issues. This creates a scientific tool that uses physiological signals to automatically determines a person's stress level necessary [9].

Facial recognition has emerged as one of the most popular research topics in the era of continuous technological advancement. Facial recognition is widely used across many fields (e.g., as a psychological state measure and as a cell phone security measure) [10]. Since the millennial generation demonstrates that they are volatile and require attention, emotions are the most important topic in the fields. Facial expressions can plays an essential role in stress detection [11]. There are many factors that have significant role in evaluating stress like lips corner, eyes, forehead, eyebrows, etc. [12].

One method for identifying a model that characterizes and distinguishes the data model is classification. When a data object's class label is unknown, the model is used to determine its class. Noisy data is eliminated through data cleaning and a number of data mining preprocessing techniques. Unnecessary attributes for prediction analysis are removed using attribute relevance analysis [13]. Using facial recognition and fuzzy classification, employee stress is predicted. A facial recognition program that uses facial recognition to assess employees stress levels must be developed in order to handle high-stress workers. The suggested work depends on using mounted cameras to provide an image input on the office monitor. Classification accuracy, precision, False Positive Rate (FPR) and True Positive Rate (TPR) are all used in performance analysis

This paper is organizes as follows. An overview of related state-of-art is provided in Section II. Section III describes Facial Recognition based prediction of Employee Stress using Fuzzy Classification. The results obtained are discussed in Section IV. Finally, conclusions are described in section V.

## **II. Literature Survey**

In [14] focuses on developing an ElectroDermal Activity (EDA)-based automated pre-surgery stress detection system. The measurement setup uses a wrist-worn device to continuously monitor a subject's EDA in the most unobtrusive and non-invasive manner. For stress detection, a novel localized supervised learning scheme based on the dataset's adaptive partitioning was

used. The scheme outperformed the general supervised classification model with a classification accuracy of 85.06% on a new user dataset.

In [15] we describe a non-contact method for detecting psychological stress that makes use of a physiological reaction in humans. Specifically, we extract the tissue Oxygen Saturation (StO<sub>2</sub>) value as a physiological feature for stress detection using a HyperSpectral Imaging (HSI) technique. According to our experimental results, this new feature might not be affected by ambient temperature and perspiration. Using a binary classifier, the accuracy of stress recognition from baseline was 76.19 percent for automatic classifier threshold selection and 88.1 percent for manual classifier threshold selection.

In [16] it first suggests a variance-based feature selection method that uses the Q-Learning Embedded Starling Murmuration Optimiser (QLESMO) to select relevant features from a publicly accessible dataset that describes the stressors nurses faced during the COVID-19 pandemic through user surveys and bio-signals. After that, a 1D Convolutional Neural Network (CNN) model (QLESMO-CNN) is used to classify the reduced feature subset. Using a hybrid model that combines CNN, Reinforcement Learning and metaheuristic algorithms, the experiments offer a strong basis for identifying the characteristics that are most relevant for the early classification of mental stress.

In [17] a physiological signal-based stress detection system is suggested. In particular, it is suggested that noninvasive and nonintrusive measures like Heart Rate (HR) and Galvanic Skin Response (GSR) can reveal details about a person's mental health. When HR and GSR are acquired over a 10-second period, the stress-detection accuracy is 99.5%; additionally, rates exceeding 90% of success are attained when the acquisition period is decreased to 3–5 seconds.

In [18] The EEG correlates of stress and the potential use of resting EEG in measuring stress levels are examined in this study. Our 13-week longitudinal study which gathers data from each of the 18 participants over several days in classroom settings, focuses on the real-life experiences of college students. We use the adaptive synthetic (ADASYN) sampling algorithm for imbalanced data and the Sequential Backward Selection (SBS) method for feature selection. Results provide valuable insights into using EEG signals for assessing stress levels in real-life scenarios, shedding light on potential strategies for managing stress more effectively.

In [19] aimed to achieve higher accuracy over earlier studies, to obtain a new and important technique for identifying electrodermal activity signal and eye tracker parameters by differentiating between "stress" and "relaxation." Support vector machines, linear discriminant analysis and k-nearest neighbor classifiers were used to classify the features. The linear discriminant analysis classifier outperforms the others in terms of accuracy, with 88.43% in the Stroop and 91.10% in the mathematical.

In [20] we use a large-scale dataset from real-world social platforms to systematically study the relationship between users' stress levels and social interactions after discovering that a user's stress level is closely related to that of their social media friends. A novel hybrid model that uses

tweet content and social interaction information to identify stress by using a convolutional neural network with a factor graph model. According to experimental findings, the suggested model can enhance F1-score detection performance by 6–9%.

In [21] Multibranch LSTM (Long Short-Term Memory) and Hierarchical Temporal Attention (MuLHiTA) is a novel multiclass classification framework that is suggested for the early identification of mental stress levels. Two complementary branches were added to the Bidirectional Long Short-Term Memory (BLSTM) network, each of which integrated a specially designed attention module. This allowed for the simultaneous extraction of the most discriminative features from intraslice and interslice Electro Encephalogram (EEG) signals. Experimental results showed that MuLHiTA performed better than the state-of-the-art algorithms.

In [22] A Convolutional Neural Network (CNN) can quickly and accurately identify acute cognitive stress from Heart Rate Variability (HRV). The experimental results showed that CNN outperformed all six conventional HRV techniques with a detection error rate of 17.3% with a very short (10 s) time window. The results would be useful for real-time stress detection applications using HRV.

In [23] represents the architecture of a stress detection system based on machine learning that uses a few biosignals present in the human body. The "stressed" or "non-stressed" classes of labeled data are the reasons in which SVM was chosen for classification. By changing the Kernel type and feature number, multiple supervised machine learning (SVM) model types were verified. Our findings which demonstrated a 98.6% accuracy level using the Gaussian Kernel function and all available features, emphasizes the significance of respiratory information in machine learning-based stress detection.

In [24] emphasizes the exclusive use of machine learning methods and wearable ElectroDermal Activity (EDA) sensors for stress detection. First, EDA signals are analyzed to extract 87 distinct features. Due to variations in each person's physiological reaction, the data are then normalized per subject. Finally, five dominant characteristics for stress detection are chosen. In this study, we made use of a publicly accessible dataset called the wearable stress and affect detection dataset (WESAD). The findings show that the One-Leave-Out method detects stress with an accuracy rate of 97.03%.

In [25] designed to recognize and categorize physiological signals from a Smart Yoga Pillow (SaYoPillow) into five different classes: normal, medium, high, medium low and medium high. It is based on the four-layer Feed Forward Neural Network (4-FFNN) model. Compared to conventional stress identification methods, the smart pillow-made model is more robust and user-friendly, with an average accuracy of 99.9%.

### **III. Prediction of Employee Stress using Fuzzy Classification**

The block diagram of Facial Recognition based prediction of Employee Stress using Fuzzy Classification is represented in below Figure 1.

The first and most important method is to mount a camera on office computer monitors to continuously update information about the characteristics or movements that signify anxiety. This allows the camera to follow the employees' facial features. The face recognition module will attempt to determine whether or not a face is visible in the video while the camera is recording. Since the eyes and lips are the most noticeable facial features, the program will first try to identify them. The data will then be entered as real-time movement so that movement-related features, like the head moving quickly, can be identified.

The purpose of collecting the data from the remaining facial behavior is to verify that the object which was just detected is a face and not something that resembles one, such as a cardboard face that can be recognized by its eyes, lips, and head shape.

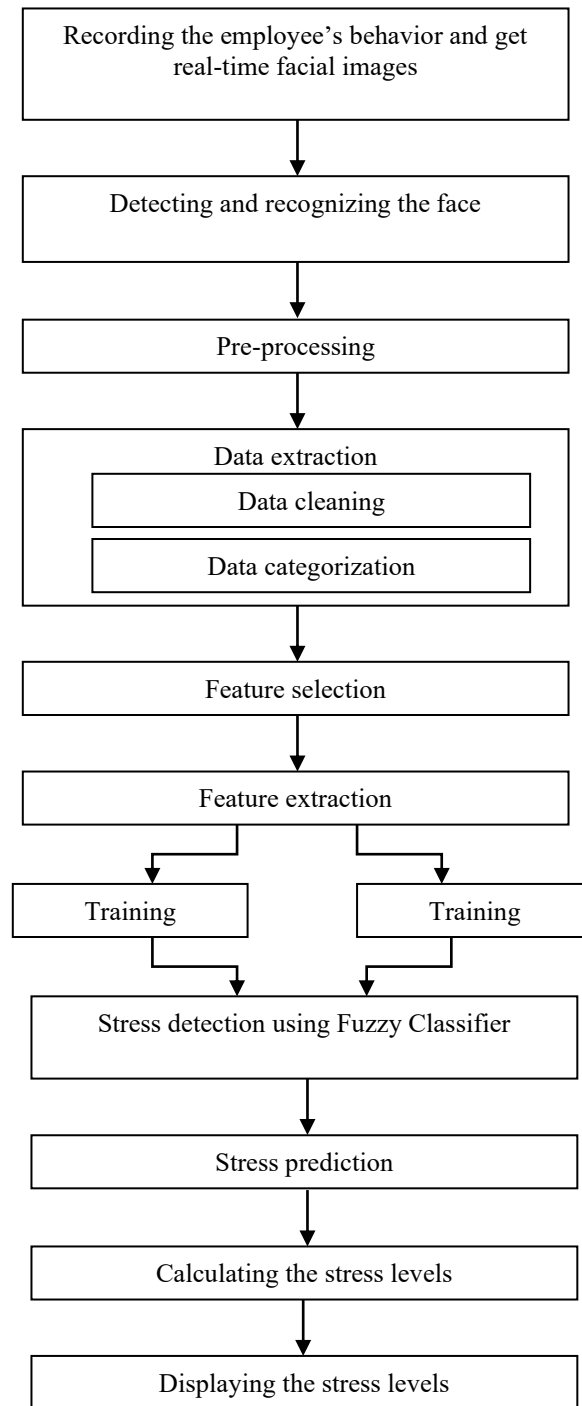
An essential component of data mining is data pre-processing, which involves cleaning and normalize the data before fitting it into a model to increase accuracy. It is required because the accuracy of the model may contain noise, missing values and duplicates in unprocessed raw data.

Data cleaning is the very next important step. All unnecessary information including duplicate records, white spaces and errors, will be eliminated in order to guarantee that the data collected is error-free. The cleaned and processed data will undergo a critical examination in the analysis step.

Our objective is to develop a computer program that can assess corporate employees' stress levels by examining their facial expressions or other characteristics. It will then compare these features with the data, we have collected about the factors that contribute to anxiety or stress in human faces. The process of reducing the number of information factors while promoting a predictive model is known as feature selection.

A gabor filter can be used to find or extract the relevant features from the faces. A Gabor filter bank can be used to extract the various features. Since not everyone handles stress or anxiety in the same way, detecting stress levels solely by facial movement is insufficient. As a result, identifying emotions that are connected to stress and anxiety will also be covered. Sadness, anger, or disgust are examples of negative emotions that are an indicator to increase the stress levels.

Training and testing data were then separated from the collected image data. The dataset was divided into a 25% testing set and a 75% training set.



**Figure 1:** Block diagram of Facial Recognition based prediction of Employee Stress

The computer will identify the stress behavior of the employee's face once we have the face and emotion data. The described model makes use of the fuzzy classification technique for that. The process of classifying elements into fuzzy sets whose membership functions are determined by a fuzzy propositional function's truth value is known as fuzzy classification. An expression with one or more variables that turns into a fuzzy proposition when values are assigned to them is comparable to a fuzzy propositional function. Consequently, the process of classifying people

with similar characteristics into a fuzzy set is known as fuzzy classification. Based on facial emotions, we will build the fuzzy sets. Comparing a list of features from the database with the features that were extracted. Next, based on how well the features match, calculate the stress level. Displaying the stress level prediction derived from the previously calculated data.

As a result, stress levels are identified based on the use of fuzzy classification to recognize facial features, and the effectiveness of this model can be determined by varying performance parameters.

#### IV. Result Analysis

This section examines the effectiveness of the Facial Recognition based prediction of Employee Stress using Fuzzy Classification. Real-time images are captured from the camera on office computer monitors so that the camera can track employee facial features and continuously update the features or movements that indicate stress or anxiety. Performance analysis uses classification accuracy, precision, False Positive Rate (FPR), and True Positive Rate (TPR).

Classification Accuracy: The classification model's efficacy is evaluated. Classification accuracy is the proportion of accurate predictions among all predictions. It can be used to rank the performance of different models.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

True Positive Rate (TPR): The percentage of positives that are appropriately categorized as such. It is called as Sensitivity. It is mathematically defined in below equation 2,

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2)$$

False Positive Rate (FPR): It is essentially a measurement of the number of times the model interpreted a negative event as positive. The better the model, the lower the false positive rate.

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \quad (3)$$

Precision: The percentage of accurate predictions that measurement of the precision is used in data mining. In other words, the model will classify an employee as such if they are experiencing stress and need treatment. Higher precision suggests that the model is successful in identifying people who need help.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (4)$$

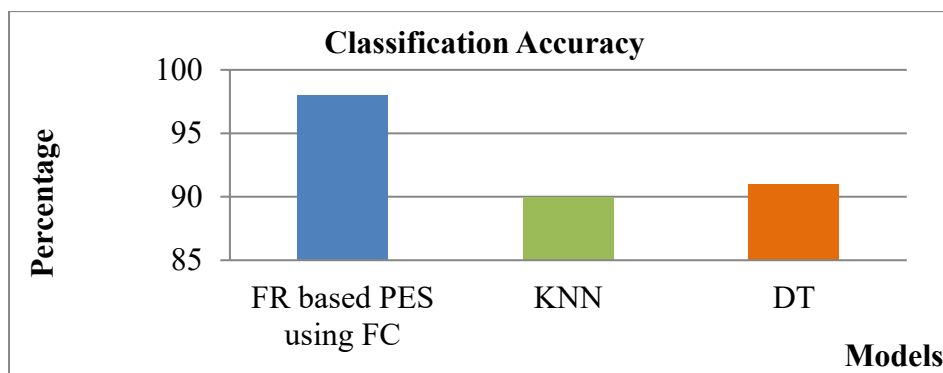
Below Table 1 shows the comparative analysis of described Facial Recognition based prediction of Employee Stress using Fuzzy Classification (FR based PES using FC) model and Employee Stress detection using K-Nearest Neighbor (ESD using KNN) classifier and Employee Stress

detection using Decision Tree (ESD using DT) in terms of Classification Accuracy, TPR, FPR and Precision parameters.

**Table 1:** Comparative graphical analysis

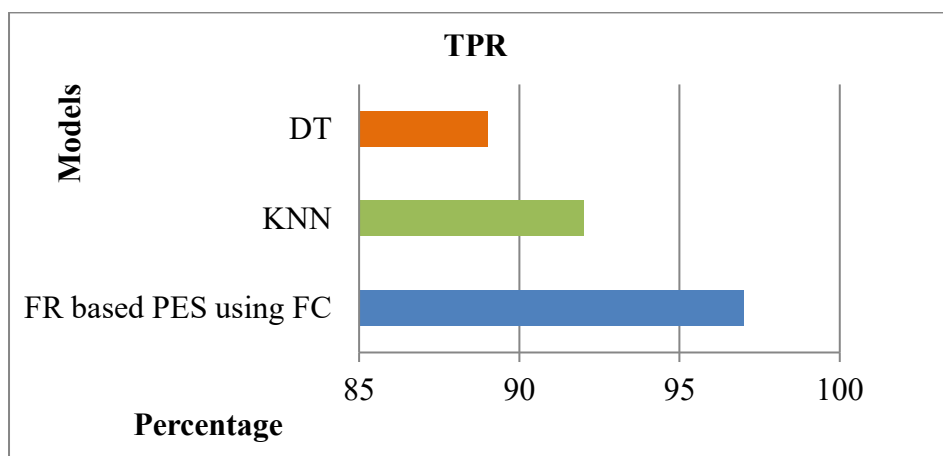
Parameters	Employee Stress prediction models		
	FR based PES using FC	KNN	DT
Classification Accuracy (%)	98	90	91
TPR (%)	97	92	89
FPR (%)	3	13	15
Precision (%)	99	91	90

Below figure 2 shows the comparative graphical representation of Classification Accuracy for described FR based PES using FC, ESD using KNN and ESD using DT models. From graph it is observed that, described model achieves high classification accuracy than other models.



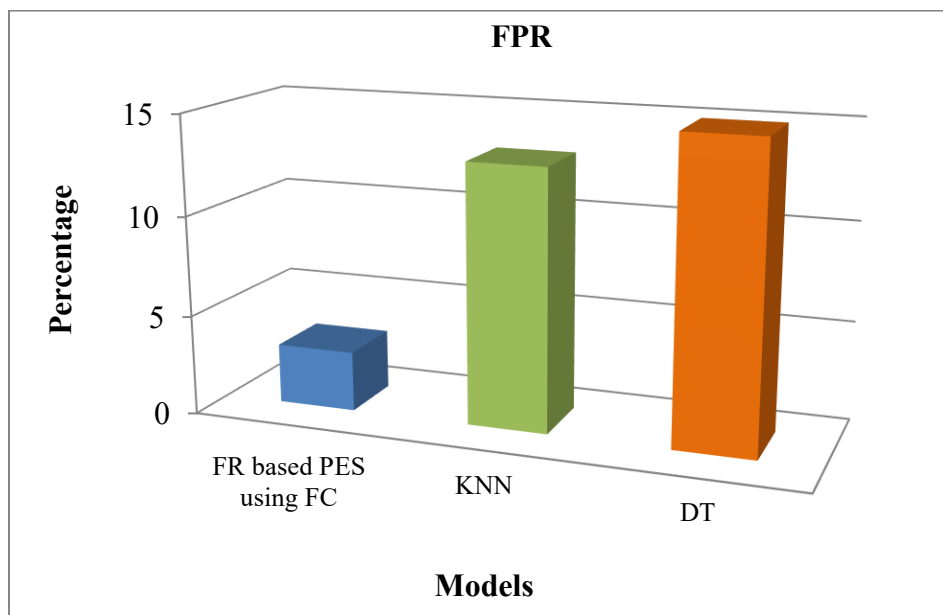
**Figure 2:** Classification Accuracy value comparative analysis

Figure 3 representation of TPR parameter comparative analysis for described FR based PES using FC, ESD using KNN and ESD using DT models, and it is observed that, TPR value high for described model.

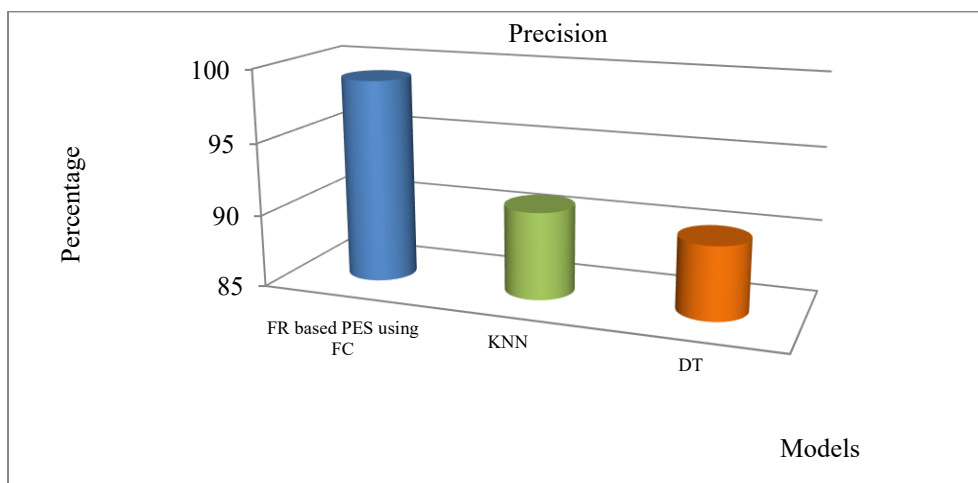


**Figure 3:** TPR value comparative analysis

Described FR based PES using FC, ESD using KNN and ESD using DT models FPR parameter comparative analysis is graphically represented in below Figure 4 and it is clear that, described model achieves less FPR than other model. Precision parameter of described FR based PES using FC, ESD using KNN and ESD using DT models is graphically analyzed in below Figure 5. Highest percentage of Precision value is gained for described model.



**Figure 4:** FPR value comparative analysis



**Figure 5:** Precision value comparative analysis

Table 2 shows the predicted stress levels based on facial features. In the results stage, 0 indicates that the input image shows no stress because the person's facial features indicate happy emotions; similarly, stage 1 indicates mild stress, and stage 3 indicates severe stress if the input image shows Contempt Features.

**Table 2:** Predicted stress level according to facial features

Emotions based on facial features	Predicted stress levels
Happy Features	No stress (stage 0)
Disgust Facial features	Mild stress (stage 1)
Contempt Features	Severe or deep stress (stage 3)

From the overall analysis, it is found that the described Facial Recognition-based prediction of Employee Stress using Fuzzy Classification is highly efficient across all parameters. The obtained parameter values are 99% precision, 98% classification accuracy, 97% TPR, and 3% FPR.

## V. Conclusion

In this paper, Facial recognition-based prediction of Employee Stress using Fuzzy Classification is described. Since many corporate workers have taken extreme measures, like suicide, it is crucial to assess their stress levels. In this work, real-time images are captured from the camera on office computer monitors so that the camera can track employee facial features and continuously update the features or movements that indicate stress or anxiety. The eyes and lips are two important facial features that can be found or extracted using a Gabor filter. Subsequently, the program will extract their movement information. The described model uses the Fuzzy Classification technique for predicting stress levels. Classification Accuracy, True Positive Rate (TPR), False Positive Rate (FPR), and Precision are used as performance metrics. From the overall analysis, it is found that the described Facial Recognition-based prediction of Employee Stress using Fuzzy Classification is highly efficient across all parameters. The obtained parameter values are 99% precision, 98% classification accuracy, 97% TPR, and 3% FPR.

## VI. References

- [1] M. T. Tomczak et al., "Stress Monitoring System for Individuals with Autism Spectrum Disorders," in *IEEE Access*, vol. 8, pp. 228236-228244, 2020, doi: 10.1109/ACCESS.2020.3045633.
- [2] K. Lai, S. N. Yanushkevich and V. P. Shmerko, "Intelligent Stress Monitoring Assistant for First Responders," in *IEEE Access*, vol. 9, pp. 25314-25329, 2021, doi: 10.1109/ACCESS.2021.3057578
- [3] W. Seo, N. Kim, C. Park and S. -M. Park, "Deep Learning Approach for Detecting Work-Related Stress Using Multimodal Signals," in *IEEE Sensors Journal*, vol. 22, no. 12, pp. 11892-11902, 15 June 15, 2022, doi: 10.1109/JSEN.2022.3170915
- [4] E. Alyan, N. M. Saad, N. Kamel and M. A. Rahman, "Investigating Frontal Neurovascular Coupling in Response to Workplace Design-Related Stress," in *IEEE Access*, vol. 8, pp. 218911-218923, 2020, doi: 10.1109/ACCESS.2020.3040540

- [5] Amirmohammad Mohammadi, Mohammad Fakharzadeh, Bardia Baraeinejad, "An Integrated Human Stress Detection Sensor Using Supervised Algorithms", IEEE Sensors Journal, Volume: 22, Issue: 8, Year: 2022
- [6] Muhammad MohsinRaza, "Impact of stress on software engineers knowledge sharing and creativity", International Journal of Data Mining and Applications Vol. 4, 02 December 2015.
- [7] L. Rachakonda, S. P. Mohanty, E. Kougianos and P. Sundaravadivel, "Stress-Lysis: A DNN-Integrated Edge Device for Stress Level Detection in the IoMT," in IEEE Transactions on Consumer Electronics, vol. 65, no. 4, pp. 474-483, Nov. 2019, doi: 10.1109/TCE.2019.2940472.
- [8] Y. S. Can et al., "Real-Life Stress Level Monitoring Using Smart Bands in the Light of Contextual Information," in IEEE Sensors Journal, vol. 20, no. 15, pp. 8721-8730, 1 Aug.1, 2020, doi: 10.1109/JSEN.2020.2984644
- [9] T. Y. Wen and S. A. Mohd Aris, "Hybrid Approach of EEG Stress Level Classification Using K-Means Clustering and Support Vector Machine," in IEEE Access, vol. 10, pp. 18370-18379, 2022, doi: 10.1109/ACCESS.2022.3148380.
- [10] F. J. Ming, S. Shabana Anhum, S. Islam and K. H. Keoy, "Facial Emotion Recognition System for Mental Stress Detection among University Students," 2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), Tenerife, Canary Islands, Spain, 2023, pp. 1-6, doi: 10.1109/ICECCME57830.2023.10252617.
- [11] S. Voleti, M. S. NagaRaju, P. V. Kumar and V. Prasanna, "Stress Detection from Facial Expressions using Mini-Xception Model," 2023 Global Conference on Information Technologies and Communications (GCITC), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/GCITC60406.2023.10425899.
- [12] Y. Liu and C. Jiang, "Recognition of Shooter's Emotions Under Stress Based on Affective Computing," in IEEE Access, vol. 7, pp. 62338-62343, 2019, doi: 10.1109/ACCESS.2019.2916147.
- [13] G. Ribeiro, O. Postolache and F. F. Martín, "A New Intelligent Approach for Automatic Stress Level Assessment Based on Multiple Physiological Parameters Monitoring," in IEEE Transactions on Instrumentation and Measurement, vol. 73, pp. 1-14, 2024, Art no. 4001714, doi: 10.1109/TIM.2023.3342218.
- [14] A. A. S. et al., "Electrodermal Activity Based Pre-surgery Stress Detection Using a Wrist Wearable," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 1, pp. 92-100, Jan. 2020, doi: 10.1109/JBHI.2019.2893222.
- [15] T. Chen, P. Yuen, M. Richardson, G. Liu and Z. She, "Detection of Psychological Stress Using a Hyperspectral Imaging Technique," in IEEE Transactions on Affective Computing, vol. 5, no. 4, pp. 391-405, 1 Oct.-Dec. 2014, doi: 10.1109/TAFFC.2014.2362513.

- [16] S. K. R. Moosavi, M. H. Zafar, F. Sanfilippo, M. N. Akhter and S. F. Hadi, "Early Mental Stress Detection Using Q-Learning Embedded Starling Murmuration Optimiser-Based Deep Learning Model," in *IEEE Access*, vol. 11, pp. 116860-116878, 2023, doi: 10.1109/ACCESS.2023.3326129.
- [17] A. de Santos Sierra, C. Sanchez Avila, J. Guerra Casanova and G. Bailador del Pozo, "A Stress-Detection System Based on Physiological Signals and Fuzzy Logic," in *IEEE Transactions on Industrial Electronics*, vol. 58, no. 10, pp. 4857-4865, Oct. 2011, doi: 10.1109/TIE.2010.2103538
- [18] H. -C. Tseng, K. -Y. Tai, Y. -Z. Ma, L. -D. Van, L. -W. Ko and T. -P. Jung, "Accurate Mental Stress Detection Using Sequential Backward Selection and Adaptive Synthetic Methods," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 32, pp. 3095-3103, 2024, doi: 10.1109/TNSRE.2024.3447274.
- [19] M. S. Yousefi, F. Reisi, M. R. Daliri and V. Shalchyan, "Stress Detection Using Eye Tracking Data: An Evaluation of Full Parameters," in *IEEE Access*, vol. 10, pp. 118941-118952, 2022, doi: 10.1109/ACCESS.2022.3221179.
- [20] H. Lin et al., "Detecting Stress Based on Social Interactions in Social Networks," in *IEEE Transactions on Knowledge and Data Engineering*, vol. 29, no. 9, pp. 1820-1833, 1 Sept. 2017, doi: 10.1109/TKDE.2017.2686382.
- [21] L. Xia et al., "MuLHiTA: A Novel Multiclass Classification Framework With Multibranch LSTM and Hierarchical Temporal Attention for Early Detection of Mental Stress," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 12, pp. 9657-9670, Dec. 2023, doi: 10.1109/TNNLS.2022.3159573
- [22] J. He, K. Li, X. Liao, P. Zhang and N. Jiang, "Real-Time Detection of Acute Cognitive Stress Using a Convolutional Neural Network From Electrocardiographic Signal," in *IEEE Access*, vol. 7, pp. 42710-42717, 2019, doi: 10.1109/ACCESS.2019.2907076
- [23] M. F. Rizwan, R. Farhad, F. Mashuk, F. Islam and M. H. Imam, "Design of a Biosignal Based Stress Detection System Using Machine Learning Techniques," 2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), Dhaka, Bangladesh, 2019, pp. 364-368, doi: 10.1109/ICREST.2019.8644259.
- [24] E. Hosseini et al., "A Low Cost EDA-based Stress Detection Using Machine Learning," 2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Las Vegas, NV, USA, 2022, pp. 2619-2623, doi: 10.1109/BIBM55620.2022.9995093.
- [25] H. Altaf and P. K. Yadav, "Human Stress Detection in and through Sleep – A Deep Learning Approach," 2023 International Conference on Next Generation Electronics (NEleX), Vellore, India, 2023, pp. 1-6, doi: 10.1109/NEleX59773.2023.10421056.