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REVOLUTIONIZING EMOTIONAL INTELLIGENCE ASSESSMENT IN THE MODERN WORKPLACE: INTEGRATING SIGNAL AND IMAGE FUSION WITH CATBOOST

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Abstract

In the promptly changing model of the advanced workplace, the significance of emotional intelligence (EI) in employees has gained paramount importance. Employees with higher levels of EI tend to exhibit improved interpersonal relationships, enhanced communication skills, and increased adaptability, all of which contribute to a more productive and harmonious work environment. Addressing the challenge of accurately assessing and enhancing emotional intelligence among employees in the workplace. This study presents a novel method for evaluating and identifying the emotional intelligence of workers by combining signal and image feature fusion with the Catboost Classifier. Convolutional neural networks (CNN), Graph Convolutional Networks (GCN), and self-attention mechanisms are used in conjunction with feature extraction for pictures to automatically extract meaningful patterns for tasks such as image categorization. To improve speech analysis accuracy, adaptive threshold-driven information Gain-Based Feature Extraction (ATI) for speech signals dynamically finds pertinent features. By optimizing correlations across several data sources, Canonical Correlation Analysis (CCA) enables feature fusion and better-informed decision-making. Our Python-based tool achieves an impressive 98% accuracy using FER and TESS datasets, surpassing current techniques.

Keywords: Emotional Intelligence, Catboost, Convolutional Neural Networks, Adaptive Threshold Driven Information Gain, Canonical Correlation Analysis, Graph Convolutional Networks, Self-Attention Mechanisms.

1. INTRODUCTION

Emotions like happiness, sadness, fear, anger, and surprise, so forth arise unique (subjective) feelings experienced by those as well as their relationships alongside the world around them (audio/visual signals), which are often associated with a perception of being emotionally arousal or some other influence compared to the environment (Acheampong et al, 2020; Lim et al, 2023;Tcherkassof et al,.2021) Natural language processing (NLP) is a subdomain in AI and computer science that aims to provide statistical treatment of human language so that robots can understand and speak languages that humans speak (Acheampong et al.,2021; KHENSOUS et al., 2023).

There's a growing need for robots to interpret human reactions in natural interactions due to the popularity of social media platforms like Messenger for Facebook plus conversational assistants like Amazon Alexa (Zhong, et al., 2019; Chew et al, 2022). Almost all facets of intelligence are impacted by feelings. This is especially clear when it comes to memory, attention, and learning. Whenever emotions like joy, fear, pain, etc. are linked to events, event specifics, or learning materials, respectively, such associations are particularly well recalled (Ninaus, et al., 2019).

One of the appealing features of social media is how quickly articles and data are changed. Knowledge suppliers battle with one another to produce fresh postings with highly relevant "bite-sized" headlines that may be quickly read without moving on to the next thing (Preston, et al., 2021) Every intelligent system's effectiveness has significantly improved since neural networks (NNs) were developed. They now have well-trained computers that can accurately identify objects, detect and recognize faces, and carry out navigational tasks utilizing Convolutional NN on illustrations (Erol et al., 2019; Fang et al., 2019). Mastering the idea of emotional intelligence and how to deal with emotional strain is crucial since both have a profound effect on a person's performance, growth, and evolution (Fteiha et al., 2020) Every day, people go through a broad range of sentiments, both both favourable and unfavourable. It is necessary to be able to recognize, understand, convey, and regulate our emotions most constructively and beneficially. As a result, people get to know themselves and others better, grow in empathy, and enhance their social skills (Drigas et., 2021).

A company's conception and growth depend heavily on its human resources. An effort is put forth to improve interpersonal connections with the aid of human resources to have a better and more effective working atmosphere (Papoutsi et al., 2019). The basic definition of confidence was given as the assessment of one's skills that one uses to plan and carry out activities to attain the desired outcome (Morales-Rodríguez et al., 2019). A fundamental aspect of health, subjective well-being (SWB) is a predictor of academic achievement as well as emotional, cognitive, and behavioral involvement. SWB forecasts college enrolment. An elevated state of contentment can also act as a barrier between students with high levels of psychopathology and being victimized by their classmates (Casino-García et al., 2019). The key contribution of this work is,

- Combining signal and image feature fusion techniques allows for a holistic understanding of emotional intelligence by leveraging both auditory and visual cues.
- Leveraging CNN, GCN, and self-attention mechanisms enables automated extraction of meaningful patterns from images, enhancing image categorization tasks.
- The application of adaptive threshold-driven information gain-based feature extraction (ATI) dynamically identifies relevant features in speech signals, improving accuracy in speech analysis.
- CCA optimizes correlations across multiple data sources, facilitating feature fusion and enabling more informed decision-making.

The following is the arrangement of this article: Section 2 investigates previous studies a combination of forecasting issues, several optimisation methodologies are used. Section 3 discusses about proposed method. Section 4 results and discussion comprise mathematically developed system models. Section 5 mentioned performance evaluation and paper concluded in Section 6.

2. LITERATURE SURVEY

(Drigas et al., 2019) recommended Emotions then emotional data are associated with EI. Because of its significance in promoting human resource (HR) practices, it has drawn a lot of attention from academics' superior organizational performance and efficacy for both leaders and workers. In this section, we'll address the theories of EI and examine the results to demonstrate the constructive relationships between EI, managers, and workers. Finally, they provide some directions for further study on the character of emotional intelligence in businesses.

(Papoutsi et al.,2019) proposed the role of EI in job settings is being extensively explored in the academic community. Empirical studies' findings show how important emotional intelligence is to be preserving a business's seamless operation. This research attempts to investigate the impact of psychological intelligence workplaces by gathering evidence of the positive relationships between EI, attitudes, and working variables. In particular, it demonstrates connection between emotional intelligence and six components that are essential for fostering a more pleasurable and effective work environment. It could also help prosecutors and managers understand the relationship between EI and other factors, as well as the effectiveness of training programs, centered on empathy and emotional intelligence in organizations and classrooms.

(Kim et al., 2019) proposed by assessing the mediated effect of workers' fatigue, it is possible to identify rudeness that flows negatively from customers to employees. Furthermore, by assessing the modulating influence of staff' emotional intelligence, it looks at strategies to decrease the adverse effects of nasty consumers. Employers of full-service restaurants were the target of a cross-sectional survey utilizing MTurk. Hierarchical regression analysis, statistical analysis, modelling of structural equations, and confirmatory factor analysis of variance were used. According to findings, there is a clear connection between rudeness displayed by consumers and rudeness displayed by employees toward clients and co-workers. Employee fatigue also plays a key mediating role in

conflict between rude customers and rude personnel. Additionally, it demonstrated the important mediating role of employees' behavioral intelligence in the link between rude customers and rude staff.
(Zhu et al., 2021) proposed whereas it's widely accepted that EI acting a significant role in project managers' ability to impact project success, emotional competence does not always function as intended. Using the property theory's preservation element, this study examines how project supervisors' behavioral intelligence affects project's effectiveness. The findings indicate that relationship between project managers' interpersonal abilities and the success of the project is mediated by project loyalty and that the impact of emotional intelligence on commitment is lessened by the complexity of the project. The following paper provides a resource for choosing and appointing project managers in difficult projects by offering practical advice on how to exercise interpersonal skills in various challenging settings.
(Nguyen et al., 2019) proposed this study examines connection between emotional intelligence, cognitive intelligence (CI), and work productivity. That 3 aspects of ability-based EI have different effects on work efficiency. Using a cascade paradigm implies a progression from perception of emotions to emotional comprehension and control, with subsequent implications on work performance. They used the self-reporting ability Mayer-Salovey-Caruso Emotional Intelligence Scale (WLEIS) and based on outcomes capability Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT), both of which consider the benefits and drawbacks of each evaluation. Our results were consistent with the cascade model, although for the WLEIS regulations self-emotion evaluation and others' emotion appraisal come before emotion control, which has favorable impact on work performance. Additionally, CI modulated the association between EI and work effectiveness, making it more favorable as CI decreased. Similar findings from the MSCEIT and WLEIS corroborate the cascade hypothesis and mitigate its effects.
(Kumar et al., 2022) Emotional intelligence assessment has meaningful impact with using modernized integration of signal and image fusion with Catboost. This innovative approach prepares added widespread intelligence of emotions (Singh et al., 2020). Moreover, the application of catboost algorithm advances the precision of EI assessment (Chen et al., 2019). Understanding of EI can be enhanced, signal and image fusion offers more clarity in order to assess the emotions (Wang et al., 2020), and this initiative has the possibility to better employee hiring and development (Taylor et al., 2019).
Emotional intelligence (EI) and its significance in the organization has been anyway recognized (Goleman, 1995, Mayer & Salovey, 1997). Team effectiveness, leadership excellence and increased work performance are highly connected with emotional intelligence of individuals (Boyatzis, 2001; Druskat & Wolff, 2001). However, classical methods of emotional intelligence assessment have critiqued for increased biasness, including lack of accurateness (Joseph & Newman, 2010). (Zheng, Y et al, 2022) the combination of transferal learning and CatBoost models has proven suggesting outcomes in recognizing diastolic dysfunction utilizing phonocardiogram (PCG) indicators, and an innovative method that influences numerous area-specific profound feature mixture to advance the accurateness of diastolic dysfunction affinity.
The existing study were highlighted that incorporation of Convolutional Neural Networks (CNNs) and CatBoost approach has flourished favorable outcome in license plate distant detection image categorisation. Zhang et al. (2023) projected an advanced CNN-based CatBoost representation that influences the depths of both procedures to accomplish state-of-the-art performance. (Prokhorenkova et al., 2018) Fusion systems performance plays important role, and it has been enhanced by machine learning algorithms. Likewise, decision tree algorithms used to bring out the outstanding performance with categorical data. Privacy concerns raise ethical questions in the workplace settings due to the integration of advanced technology to detect the emotions of the individuals in the workplace (Floridi et al., 2018).
In the context of emotional detection, (Lee et al., 2019) launched framework-aware emotion network that activity mutually facial languages and background evidence. Further, (Dixit and Satapathy, 2024) established a practical multimodal emotions recognition system by means of deep CNNs through late fusion, accomplishing an accurateness of 85.85% on the dataset. (Dignum. 2019) developed a transparent and morally aligned models are important for increasing employee faith and confirming agreement with data safeguard.
Doherty, Cronin, and Offiah (2013) investigated to assess the combination of emotional intelligence (EI) assessments into a graduate-entry medical school, The study specified that self-stated EI scores continued comparatively steady over time and haven't correlate with ability-based EI scores. It emphasized to go with the innovative assessment tool which has fewer human interventions. The predominant role of EI in medical education enhances the communication and professionalism (Cherry et al., 2014). An analysed framework found a significant correlation between emotional intelligence and increased effectiveness in teamwork. (Arora et al., 2010; Austin et al., 2007; Salekzamani, 2013) Revealed that Emotional intelligence has a positive influence with peer interactions and their academic results. (Mayer, J. D et al., 2023) stated that EI has weak predicts on academic achievements. (Tiffin, 2024; Miller 2023) Situational Judgement Tests helps to assess the EI- related personalities in medical selection process. Additionally, (McCallum et al. 2022) An accurate EI assessment facilitates to

enhance interpersonal and leadership skills in the medical settings. (Khoshhal, K. I., and Guraya, S. Y. 2018; Webb, A. M et al. 2014) stated that assessing EI has not impacted on the student's academic performance. Weidmann and Xu (2024) launched the Realizing AI Generated Emotions (PAGE) tool, an advanced determine employing AI-generated impetuses to assess emotion perception. (sharma and Tiwari, 2024) mentioned that the integration of EI and AI have huge implications on the industrial productivity. However, (Piispanen and Rousi 2024) the assessment of employees' EI granted the advantages of wellbeing checking. Organization learning and frameworks for learning need analysis can be facilitated through EI assessments in the workplace (Kaur and Hirudayaraj, 2021). (Vorecol, 2024) investigates that the combination of EI metrics into performance evaluation system helps to identify the skill levels of the employees in the workplace. (Binsaeed et al. 2023) EI considerably impacts innovation performance, highlighting its magnitude in implementing a culture of innovation. Employee mental health can be detected through deep EI assessments, algorithms and frameworks are deeply connected with AI models (Spitale et al., 2024). Furthermore, the argument penetrated that the EI and AI integration in organizational set-up have numerous advantages and unique assessment approaches facilitates to reach the goal (Verma, 2024). Organization's overall development can be ensured through prioritizing EI in leadership and organization development interventions. Integration of AI and EI supports to overcome the emotional challenges in the workplace (Schumacher, 2024). Generative AI has profound impact for developing emotional recognition throughout several sensory system includes speech, facial images, texts and other signals (Ma et al., 2024). In a business perspective, current innovations combine AI and machine learning into EI assessment, it offers feedback, and emotions are tracking through the AI models (Ghassemi, M et al., 2022). Use of EI assessments are enriching the leadership capabilities of individuals in organization (Cherniss, C. 2010)
(Maji et al, 2022) investigated the role of dual-channel self-attention model by mixing convolutional capsule for speech emotion recognition, it has been detected the multiple emotions quickly and accurately. In the process of exploring the fusion strategies (Cai et al, 2019) introduced audio visual emotion recognition in real-time business setting using CNNs and BLSTMs as a visual feature. Moreover, the success of the EI assessment is based on the suitable measures which have been employed by the assessors, (O'Connor et al., 2019) empathized with mixed models of trait and ability based emotional detection in the work and it fulfilled several purposes. (Krishnakumar et al., 2016) initiated the Neuro Evolution of Augmenting Topologies (NEAT), various studies conducted were an evident for high reliability and validity in detecting the emotions and EI is correlated with employee performance. (Hudson,2024) the research emphasized the significance of multi-faceted assessment strategies for improving quality of EI assessment.

3. Proposed method for Catboost Classifier-based Signal and Image Feature Fusion

The proposed method for detecting the Emotional Intelligence (EI) of employees involves the utilization of a Catboost Classifier integrated with advanced feature fusion techniques, specifically focused on signal and image data. This innovative approach aims to comprehensively assess EI by capturing both spoken and unspoken messages, which are vital in understanding emotional states. The Catboost Classifier is employed as a robust machine learning model capable of handling complex data relationships, while feature fusion merges signal and image data to extract rich information regarding emotions and expressions. By harnessing the power of this fusion, the method strives to enhance the accuracy of EI detection, thereby facilitating a more effective training program design. This holistic approach not only provides a deeper insight into employees' emotional intelligence but also offers valuable insights for tailoring training programs that target specific emotional competencies, ultimately contributing to improved workplace dynamics and performance. Figure 1 shows flow diagram of the boosted classifier-based signal image feature fusion.

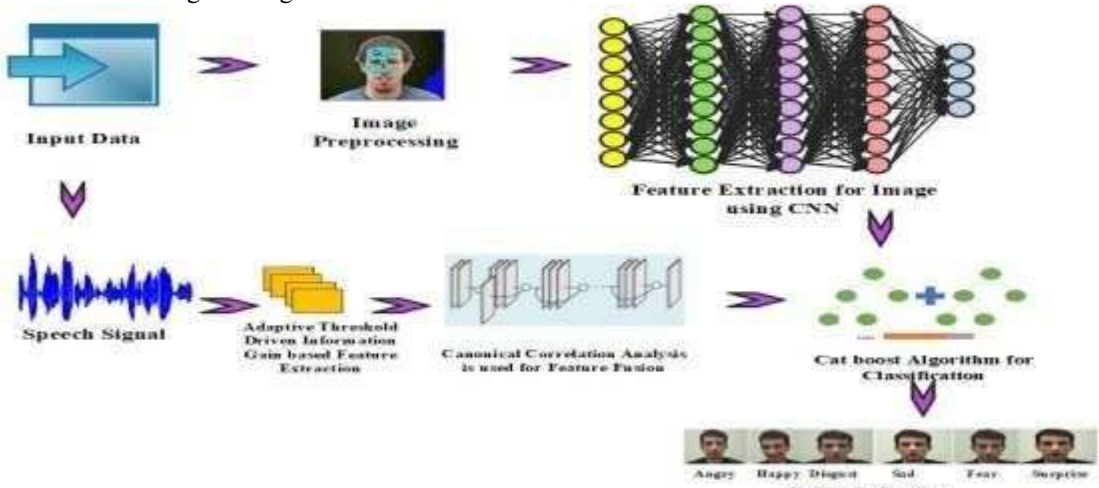

Figure 1: Flow Diagram of Catboost Classifier-based Signal and Image Feature Fusion.

Problem Statement for existing methods:

Existing research on EI faces several challenges. Firstly, while there is substantial attention from scholars and human resource professionals on the importance of EI in fostering organizational performance, there remains a need for a deeper understanding of its theoretical foundations and practical implications. Additionally, empirical investigations often demonstrate the significance of EI in maintaining smooth organizational operations, but there's a gap in translating these findings into actionable strategies for improving workplace dynamics. Furthermore, while some studies explore the impact of EI on specific workplace factors, such as attitudes and productivity, there's a lack of comprehensive research that considers the complex interplay between EI, cognitive intelligence, and work productivity. Moreover, challenges persist in understanding the nuanced relationships between EI and various workplace phenomena, such as the mediation of employee fatigue in the cycle of rudeness between customers and staff, or moderating effect of project loyalty on relationship between project managers' EI project performance. Overall, addressing these challenges requires interdisciplinary approaches and robust methodologies to unlock the full potential of emotional intelligence in organizational contexts.

3.1. Dataset Description

Here two datasets emotion detection (FER) and Toronto emotional speech set (TESS). The set of images includes 35,685 occurrences of 48x48 megapixel monochrome photographs of features divided into a training and a testing dataset. Imagery is categorized into classifications like happy, neutral, sad, angry, surprise, disgust, and terror based on the feelings shown in the facial emotions. A pair of performers, ages 26 and 64, read a list 200 desired words below carry-on sentence "Say the word _," and recorders of the environment were recorded, a single set for each 7 emotions (anger, disgust, fear, pleasure, pleasant surprise, sadness, and neutral). It includes 2800 data points (audio files) altogether. The information arranged in this manner, with each of two female actresses and each emotion included within their folder. Here 80% for training, and 20% for testing. Dataset values are 29,042, train data are 23,233, and test data are 5809.

3.2. Image Pre-Processing

It was not required to analyze camera-acquired portions of the picture to determine facial emotions. It is not required to cover the entire neck, the hair, etc. Consequently, such unfavorable elements were removed. If otherwise, the technique for identification will need to deal with more data which is going to render it harder and less successful. Through pre-processing, this undesired material is removed from the raw image. Among the pre-processing steps are scaling, equalization of extent, and downsizing. The raw image is cropped to guarantee that any portions of the image that lack characteristics particular to an emotion are deleted. The region encompassing the mouth and eyes are the most important facial features when recognizing expression. The image is subsequently further reduced to ensure that the data size of the pixel file matches CNN's initial size. Saturation and clarity of the image are influenced by the product's irradiation and lighting circumstances. The complexity of feature sets and the detection technique increases as a result of these changes. Intensity normalization was implemented in an attempt to minimize these problems. The suggested approach employs MinMax normalization after performing a linear change on the original image.

Min-Max normalization, another name for Min Max scaling, is a popular cleaning method for scaling features (in this case, pixel values in facial emotion images) to a specific range, typically between 0 and 1. This is useful because it ensures that all features have the identical scale, which is crucial for machine learning algorithms as they are affected by the size of the input data. Here's the formula for Min-Max scaling:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where:

- X_{scaled} is denotes a scaled assessment of a feature.
- X is the original value of a feature.
- X_{min} is the feature's lowest charge found in an information set.
- X_{max} Represents the feature's highest value recorded in the dataset.

Load your image data, ensuring that each image is represented as a matrix where pixel values are typically between 0 (black) and 255 (white) for grayscale images or in the range [0, 0, 0] to [255, 255, 255] for color (RGB) images. Compute the minimum (X_{min}) and maximum (X_{max}) pixel values in a dataset. You can do this by iterating through all the images and finding the minimum and maximum values for each pixel channel (if it's a color image) or for the single channel (if it's grayscale).

Normalization:

Normalization is a common preprocessing step in image processing and machine learning tasks involving images. It scales pixel values in an image to a standard range to make the data better suited to training machine learning replicas. The most common normalization technique is min-max scaling, which scales pixel values in the range [0, 1]. Can use the following formula for min-max scaling:

For a given pixel value x:

$$x_{normalized} = \frac{x - \min(X)}{\max(X) - \min(X)} \quad (2)$$

- $x_{normalized}$ is the normalized pixel.
- x is the original pixel.
- Min (X) is the minimum pixel in the entire image.
- Max (X) is the highest pixel possible in the entire image.

3.3. Extracting Features from Images using CNN Graph Convolutional Network (GCN) Enhanced with Self-Attention Mechanism

3.3.1. CNN

The hierarchical structure of the architecture controls the feature extraction process in CNNs. The primary layers capture the fundamental information and the deeper layers combine these elements to detect more complicated patterns. CNNs can automatically discover relevant information for a variety of image analysis applications by learning these hierarchical characteristics directly from the data to determine whether or not a tumor is present. Convolutional Neural Networks (CNNs) use non-linear activation functions, pooling, and convolution to extract.

3.3.1.1. Convolutional layer

The convolutional layer is initial stage of a CNN's feature extraction layer with the strongest signature. It is the local operation whose function is the extraction of different patterns from the input pictures leading to an effective categorization. Multiple convolutional kernels, which serve as the layers' trainable parameters, constitute convolutional layers and are changed with each iteration. Let $X^n \in R^{M^n \times N^n \times D^n}$ be the input of our N-th convolutional layer and $F \in R^{m \times n \times d^n \times s}$become a number 4 vector representing the N-th layer's position width s kernels. The outcome of the N-th We'll employ a vector with an order 3 convolutional layer and a notation $Y^k \in R^{M^n - m + 1 \times N^n - n + 1 \times s}$, with the components resulting from,

$$Y_{i^n, j^n, s} = \sum_{i=0}^{m} \sum_{j=0}^{n} \sum_{l=0}^{d^n} F_{i,j,d^n} \times X^{n}_{i^n, j^n, l} \tag{3}$$

If a certain place meets the requirements $0 \le i^n \le m^n - m + 1$ and $0 \le j^n \le N^n - n + 1$, has to be carried out for each and every $0 \le s \le S$. Typically, CNNs include many convolutional layers to recognize more pronounced spatial patterns in input pictures. Using zero padding while using convolutional layers ensures that image's dimensions remain constant throughout process.

3.3.1.2. Pooling layer

Let N-th layer, which is spatial range $m \times n$, have input $X^n \in R^{M^n \times N^n \times D^n}$. These types of layers are essentially parameter-free since they don't have any variables that need to be learned. The outcome is a three-order tensor, denoted by $Y^n \in R^{M^{k+1} \times N^{n+1} \times D^{n+1}}$, where

$$M^{n+1} = \frac{M^n}{m}, N^{n+1} = \frac{N^n}{n}, D^{n+1} = D^n \tag{4}$$

Whereas the pooling layer handles X^n a single channel at a time, separately. There are countless different pooling processes, with maximum and average pooling becoming the most common. Max pooling was applied in our investigation, leading to results that followed a formula

$$y_{i^n, j^n, d} = \max_{0 \le i \le m, 0 \le j \le n} x^{n}_{i^n \times m + i,\, j^n \times n + j, d} \tag{5}$$

Where, $0 \le i^n \le M^n$, $0 \le j^n \le N^n$and $0 \le d \le D^n$. It makes sense that pooling layers would be employed to reduce output tensor size while preserving the most important discovered features.

3.3.1.3. Fully connected layer

A classification operation (softmax, sigmoid, tanh, etc.) always takes place following the last completely linked layer. The difference between the real value and Y_j and the value Y_j anticipated by the selected loss function. We think that using the sigmoid function in this case is appropriate.

$$y_j = \frac{e^{x_j}}{1+e^{x_j}}, \quad x_j \in R \tag{6}$$

This might work well to solve this binary problem. The probability that the supplied image demonstrates the existence of what the statement represents $y_j \in (0,1)$.

It resets settings related to specific down to zero in terms of network nodes. Finally, the consignment normalization and ReLU processes serve as crucial transitional mechanisms joining previously mentioned levels. The definition of the ReLU function is

$y_{i,j,d} = max(0, x^n_{i,j,d})$ (7)

By rescaling, re-cantering, and otherwise correcting the layer's output after every repetition, batch normalization makes neural networks quicker and more stable. It does this by seeking to transfer just the purposeful components for the classification with $0 \leq i \leq M^n$, $0 \leq j \leq N^n$ and $0 \leq d \leq D^n$.

3.3.2. Graph Convolutional Network (GCN)

It is still quite difficult to identify facial movements in the actual world with occluded and side faces, even when the feature extraction module obtains the characteristic data of the important places. According to studies, people can understand the semantics of partial faces by using entire faces as well as specific portions of the face. Consequently, suggest a neural network with graph convolution. Here, utilize the association between the important facial features utilizing the connection between the overall object and the local to derive more profound semantic data [22]. Figure 2 shows the proposed classification unit.

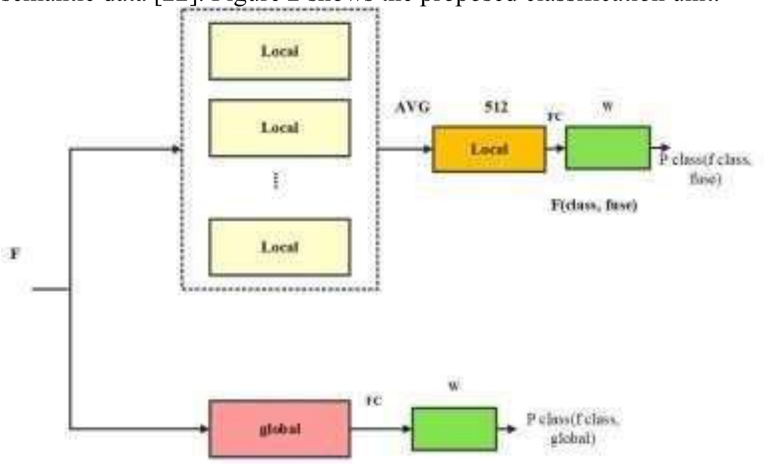

Figure 2: The Unit of Classification Suggested. W stands for the Expression Class Number.

The group of feature vectors F is split into two sections: the local feature vectors create $F_{local} \in J^{18\times512}$, and a copy of the global feature vectors is made to get $F_{global} \in J^{18\times512}$. To get the improved feature data $F_d \in J^{18\times512}$, suggest using the following equation:

$$F_d = \{[ReLU(F_{local} \odot C \odot F^H{}_{global})] \otimes Y\} \odot F_{local}, \quad (8)$$

where $\odot$ indicates matrix multiplication, $\otimes$ indicates a multiplicity of matching constituents, and C is a matrix of learnable parameters of 512 × 512, Y is the matrix of adjacency.

To obtain this adjacency matrix, design the topological map based on the face structure. The adjacency matrix comes from the $Y[i, j]$ symbolizes the adjacency matrix's component values, and F_i denotes the key points:

$$Y[i, j] = \begin{cases} 1 & (F_i, F_j) \text{ is the edge} \\ 0 & (F_i, F_j) \text{ is not the edge} \end{cases} \quad (9)$$

The output characteristic F^S of the algorithm for the final graph convolution module is as follows:

$$F^S = ReLU\{v_1[\text{concat}(F_{local} + F_d, f_{global})]\} \quad (10)$$

where $v_1(.)$ indicates the layer that is entirely linked, and concat (▪, ▪) symbolizes the process of integrating the optimal local data combined with global data through matrix splicing.

The final F^S is comparable to the first module's F. F^S is handled by the categorization unit to get $f^S_{class,fuse}$ and $f^S_{class,global}$. The following is the GCN loss function:

$$P_S = k \times P_{class}(f^S_{class,fuse}) + P_{class}(f^S_{class,global}) + L_{triple}(f^S_{global})$$

When it comes to the analysis of employee facial emotions, the first step in the feature extraction process is GCN, which makes use of the structural data found in facial expressions. Subsequently, the Self-Attention Mechanism highlights significant facial areas and their interdependencies, further refining the derived features and improving the model's capacity to efficiently capture subtle emotional cues. By utilizing both local and global facial characteristics, this two-step method allows for a more thorough comprehension of workers' moods at work.

3.3.3. Self-Attention Mechanism

This article integrates a self-attention mechanism channels attention to construct an attention remnant component based on leftover module, thus improving the network algorithm's ability to extract characteristics and capture the link among long-range characteristics. This increases the model's sensitivity to meaningful information while suppressing unimportant data.

3.3.3.1. Self-Attention before Channel Attention:

Self-attention is used in serial mode first, followed by channel attention. Feature graph V_{in} is produced by convolutioning the input from the preceding layer shown in Figure 3. Channel attention graph V_{mid} is attained by focusing on concentration M_w, and then combined with the feature map input as the self-attentional input M_y. Lastly, feature maps produced using M_y and V_{mid} are combined to produce the final attention module Out's output.

$V_{mid} = M_y(V_{in}) \otimes V_{in},$ (11)

$V_{out} = M_w(M_c(V_{mid}) \otimes V_{mid}.$ (12)

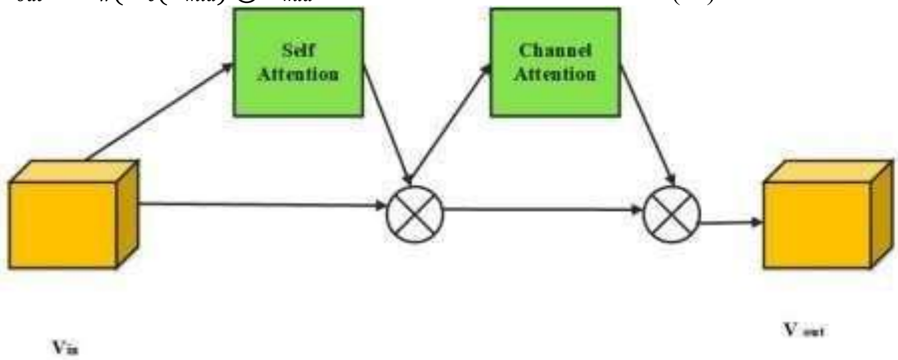

Figure 3: Self-attention before Channel Attention.

3.3.3.2. Channel Attention before Self-Attention.

Self-attention will be followed by the very first channel's serial phase. The feature map is obtained by convolving the former layer V_{in} as input shown in Figure 4. First, self-attention is used to create the feature map M_y and channel attentionM_w. The self-attention diagram V_{ymid}as well as a channel attention map V_w remain acquired merging input feature graph with themV_{in}. Next, matched elements from both attention mappings are combined. The outcome of the spotlight map V_{out} is obtained. The following is an official explanation of the entire procedure:

$V_{mid} = M_w(V_{in}) \otimes V_{in}$ (13)

$V_{out} = M_y(V_{mid}) \otimes F_{mid}$ (14)

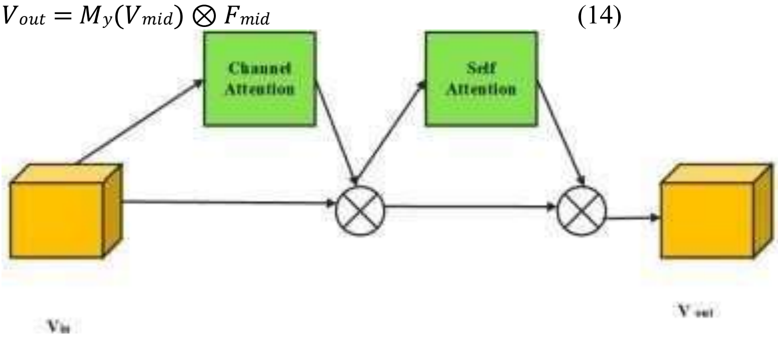

Figure 4: Channel attention before self-attention

3.4. Adaptive threshold-driven information gain-based feature extraction (ATI) for Speech signal

If emotions have a lot of extraneous information, predictions will often be less accurate. Only a few attributes are needed to make an effective prediction, yet it might be difficult to get useful data from records. Before applying, predictive models must be applied in a manner that eliminates noisy data, chooses characteristics to assure accurate findings, and decreases the complexity and dimensionality of the dataset. Therefore, it's crucial to choose features that enhance data comprehension and shorten the ensemble's deep learning model training time. Several techniques are used to choose features in datasets, including sequential forward one-dimensional feature selection, rough sets, balanced least squares, and selecting.

A threshold, which is often referred to as a cutoff value, serves as the extract feature's reference value. Calculated independent threshold values are used, or 0.05. Tsai and Sung calculated threshold values for some characteristics by averaging each frequency. According to Tsai's theory, the threshold value may be calculated using standard deviation. Cut back on the details worth using the associations unkind, then add the resulting value to calculate the variety of the data group. The standard deviation is measured as a distinction between the observed information and its average.

$$G = \sqrt{\frac{n\sum_{i=1}^{n} d^2_{\ i} - \left(\sum_{i=1}^{n} d\right)^2}{n(n-1)}} \qquad (15)$$

Here G Standard deviation is shown as d indicates normal worth, d_i shows rate of d to i, and n shows number of characteristics present in the dataset. The most informative features are chosen using this filter-based feature section technique without taking feature correlation into account.

By eliminating information gain, the information gain approach reduces noise in prediction outcomes. A structured dataset's properties may be used as the basis for the prediction. Based on a select handful of them, the disease can only be categorized into one of the categories. The algorithm may learn about certain issues based on the significance of characteristics in the dataset. According to their significance in connection to the classification goal, the proposed system chooses characteristics. The suggested system makes use of unpredictability as a system uncertainty metric. These equations demonstrate how assuming two parameters, Y and Z, differ from one another based on their before and entropies:

$$IG(Y|Z) = S(Y) - S(Y|Z) \qquad (16)$$

The previous probability characteristic Y, anywhere Y and Z are distinct unpredictable variables, may be calculated using the following equation.

$$S(Y) = -\sum_i P(Y_i)\log_2 P(Y_i) \qquad (17)$$

Postoperative entropy and conditioned entropy are used we can calculate conditional entropy.

$$S(Y|Z) = -\sum_j P(Z_j)\, S(Y|Z_j) \qquad (18)$$

$$= -\sum_j P(Z_j)\sum_i (P(Y_i|Z_j)\log_2 P(Y_i|Z_j)) \qquad (19)$$

The IG can be measured by,

$$IG(Y|Z) = -\sum_i P(Y_i)\log_2 P(Y_i) - \left(-\sum_j P(Z_j)\sum_i (P(Y_i|Z_j)\log_2 P(Y_i|Z_j))\right) \qquad (20)$$

Based on the proposed, estimate how important the feature is to the task of predicting. Until performance is no longer degraded, the features are reduced one at a time. Hybrid characteristic choices pick the best set of qualities to enhance the effectiveness of classification while keeping computation costs low because best feature set is obtained by crossing the two feature sets that are produced by each of the characteristics separately.

3.5. Canonical correlation analysis is used for feature fusion

Indicates the link between parameter sets that span two measurement domains using canonical correlation analyses. The first CCA mode is mirrored in the variables in D linearly combined with the variables in the second linear arrangement in A, given D and A of dimensions p and q from the same set of n observations.

$$E = y^H D, y \in J^p \qquad (21)$$

$$F = z^H X, z \in J^p \qquad (22)$$

That optimizes the linear connection, or correlation, of the initially selected mode

$$\rho = corr(E, F) = corr(y^H D, z^H A) \qquad (23)$$

It is feasible to keep looking for further pairs such as linear mixtures that are not correlated from the first canonical mode(s), in addition to maximizing the relationship among E and F as the first canonical mode. Up to min (p, q) times can be added to this procedure. In this introduction, the canonical matrices will be y and z, or the canonical variates will be E and F. The canonical correlation is the canonical variates' correlation coefficient.

$$\sum_{DD} = Cov(D, D) = D^H D \text{ and } \sum_{AA} = Cov(A, A) = A^H A \qquad (24)$$

$$\sum_{DA} = Cov(D, Y) = D^H A \qquad (25)$$

$$\rho = \frac{y^H \sum_{DA} z}{\sqrt{y^H \sum_{DD} y}\sqrt{z^H \sum_{AA} z}} \qquad (26)$$

In light of the aforementioned restrictions, we can reduce to$\rho = y^H \sum_{DY} z$. We define a change of basis, or the coordinate system in which the data points exist, as follows:

$$w = \sum_{dd}^{1/2} y \qquad (27)$$

$$x = \sum_{aa}^{1/2} z \qquad (28)$$

$$\rho = \frac{w^H \Sigma_{dd}^{-1/2} \Sigma_{da} \Sigma_{aa}^{-1/2} x}{\sqrt{W^H W}\sqrt{x^H x}} \qquad (29)$$

It is also possible to write the following as the connection between the canonical vectors (y and z) and canonical variates (E and F):

$$E = W^H \sum_{dd}^{-1/2} D = y^H D \tag{30}$$

$$F = x^H \sum_{aa}^{-1/2} A = z^H A \tag{31}$$

To move each left parameter set as well as the correct parameter set from their initial assessing spaces to new locations in a way that improves their proportional correlation, the connection within the two original variable sets (D and A) and the consequent canonical variates E and F must be considered. Thus, the rotary motion of the coordinate systems is described by the fitted parameters of CCA: The canonical variates encoding the placement of every point of information in that new space, and the canonical matrices decoding how to go from the original measurement coordinate system to the new latent space. Singular value decomposition (SVD) is formally connected to this coordinate system rotation. The most frequently used method for calculating CCA is probably SVD.

3.6. Cat Boost for Classification

CatBoost's categorization algorithm is built to address issues of insecurity of the chosen at random parameter simulation and the lengthening period for training with more combined parameters. Following initial processing for spectrum identification and combined reduction of dimensions, this additionally enhances the categorization reliability of data characteristics. In an attempt to solve the problems of poor precision in classification carried on by human tinkering of CatBoost settings and low modeling scores carried on repeated debugging studies, the paper uses grid-search techniques to improve the CatBoost method. They initially employ coordination descending for rapid tuning and a grid searching method to optimize the CatBoost model and increase the model's equilibrium, while boosting the efficiency of classification.

Table 1: Pseudocode for CatBoost.

Input: $\{(\mathbf{D_i}, \mathbf{A_i})\}_i^n, \mathbf{Q}, \mathbf{y}, \mathbf{P}, \mathbf{g}, \mathbf{Mode}$

$\boldsymbol{\sigma_j} \leftarrow$ **permutation of random** $[\mathbf{1}, \mathbf{n}], \mathbf{j} = \mathbf{0}, \ldots, \mathbf{g}$;
 $\mathbf{N_0(i)} \leftarrow \mathbf{0}$ for i=0,….n;
 If mode= plain
 $\mathbf{N_j(i)} \leftarrow \mathbf{0}$ for j=1,…g, i:$\boldsymbol{\sigma_j}(\mathbf{i}) \leq \mathbf{2^{r+1}}$;
 If mode=order then
 For $\mathbf{r} \leftarrow \mathbf{1}$ **to**$\lceil \mathbf{log2n} \rceil$**do**
 $\mathbf{N_{j,r}(i)} \leftarrow \mathbf{0}$ **for** $\mathbf{j} = \mathbf{1}, \ldots \mathbf{g}, \mathbf{i} = \mathbf{1}, \ldots \mathbf{2^{r+1}}$;
 For h← **1 to Q do**
 $\mathbf{H_i}, \{\mathbf{N_j}\}_{j-1}^{g} \leftarrow \mathbf{Tree}\ (\{\mathbf{N_j}\}_{j-1}^{g}, \{(\mathbf{d}, \mathbf{a})\}_{m-1}^{n}, \mathbf{y}, \mathbf{P}, \{\boldsymbol{\sigma_i}\}_{i-1}^{g}, \mathbf{mode})$;
 $\mathbf{leaf_0(i)} \leftarrow \mathbf{getleaf}(\mathbf{d}, \mathbf{N_0}, \mathbf{a})$;
 $\mathbf{z_r^h} = -\mathbf{avg}(\mathbf{s_0(i)}$ **for i**; $\mathbf{leaf_0(i)} = \mathbf{r}$;
 $\mathbf{N_0(i)} \leftarrow \mathbf{N_0(i)} + \mathbf{yz^h_{leaf(i)}}$ for i=1,…n

Return: V(d)=$\sum_{h-1}^{h} \sum_r \mathbf{yz_j^h Y_{(get\ leaf(d,H,mode=f)}}$

4. RESULT AND DISCUSSION

The design of the course of the study, performance evaluation, and the results of the experiments are all given there. An assessment of the suggested algorithm is part of the findings discourse. Data were combined into the image after being trained using the original data.

4.1. Simulation environment

Employing the Python script in a simulated setting with the FER and TESS datasets, assess the suggested prediction method. An Intel(R) Core(TM) i5-3470-equipped computer is used to conduct the test. Additionally, the OS maker micro software 10 pro has inserted physical memory (RAM) 12.7 GM. The table below shows the simulation parameters of the real-time dataset.

Table 2: Simulation Parameters.

Simulation parameters for FER and TESS datasets	**Values**
Iterations	90
Learning rate	0.1
Depth	6
loss_function	MultiClass

5. Performance evaluation

To evaluate these findings, compute the accuracy, recall, precision, and F1-score indicators.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (32)$$

$$recall = \frac{TP}{TP+FN} \quad (33)$$

$$precision = \frac{TP}{TP+FP} \quad (34)$$

$$F1-score = \frac{2TP}{2TP+FP+FN} \quad (35)$$

$$FPR = \frac{F_P}{T_N+F_P} \quad (36)$$

$$FNR = \frac{F_N}{T_P+F_N} \quad (37)$$

$$MCC = \frac{T_P T_N - F_P F_N}{\sqrt{(T_P+F_P)-(T_P+F_N)(T_N+F_P)(T_N+F_N)}} \quad (38)$$

$$NPV = \frac{T_N}{T_N+F_N} \quad (39)$$

TP signifies the true positive, FP the false positive, TN the true negative, and FN the false negative.

A classification a table called a confusion matrix, the performance of the algorithm (or classifier) on a set of test results with known true values is summarized. The jargon might be challenging, but the confusion matrix is simple to comprehend.

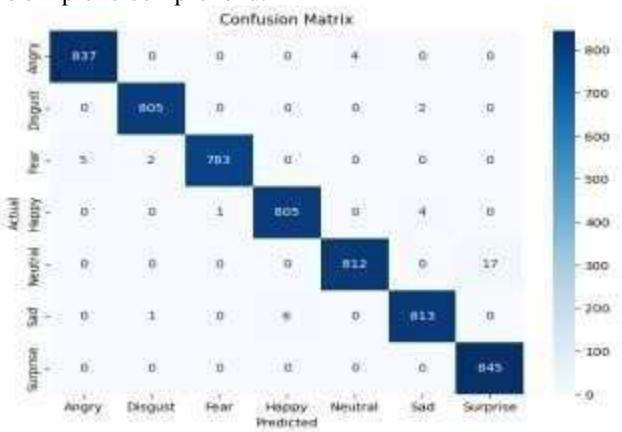

Figure 5: Confusion Matrix for both Datasets.

A graph used in machine learning to assess the performance of classification models is called a confusion matrix. In order to evaluate a model's efficacy and accuracy, it shows the counts of true positive, true negative, false positive, and false negative projections. It's a crucial tool for understanding how well a model is classifying data and identifying potential areas for improvement. The confusion matrix for both datasets is shown in Figure 5.

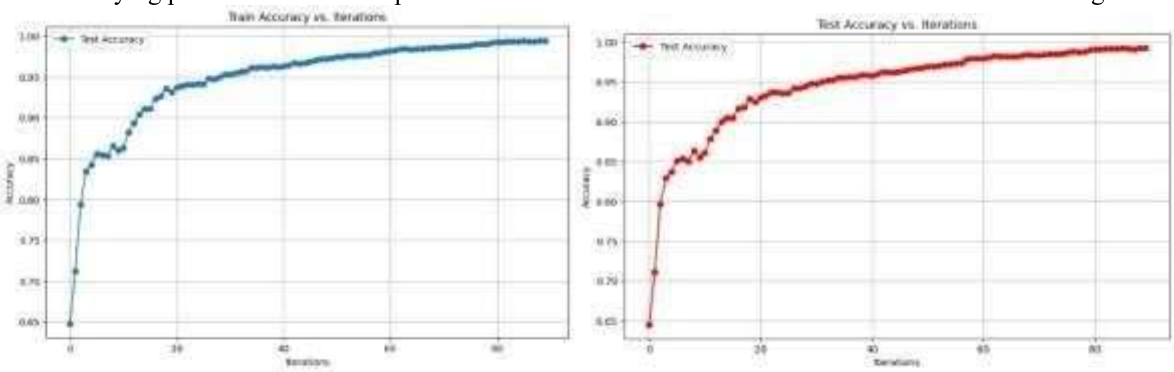

Figure 6: Training and Testing Accuracy.

Figure 6 in the research paper presents the relationship between training and testing time and the accuracy of the predictive model. This figure likely illustrates how the model's accuracy varies as a function of the time spent on training and testing. The results in this section provide valuable insights into the trade-off between computational resources invested (training and testing time) and the model's predictive performance, helping to determine the optimal balance between efficiency and accuracy in the context of the research.

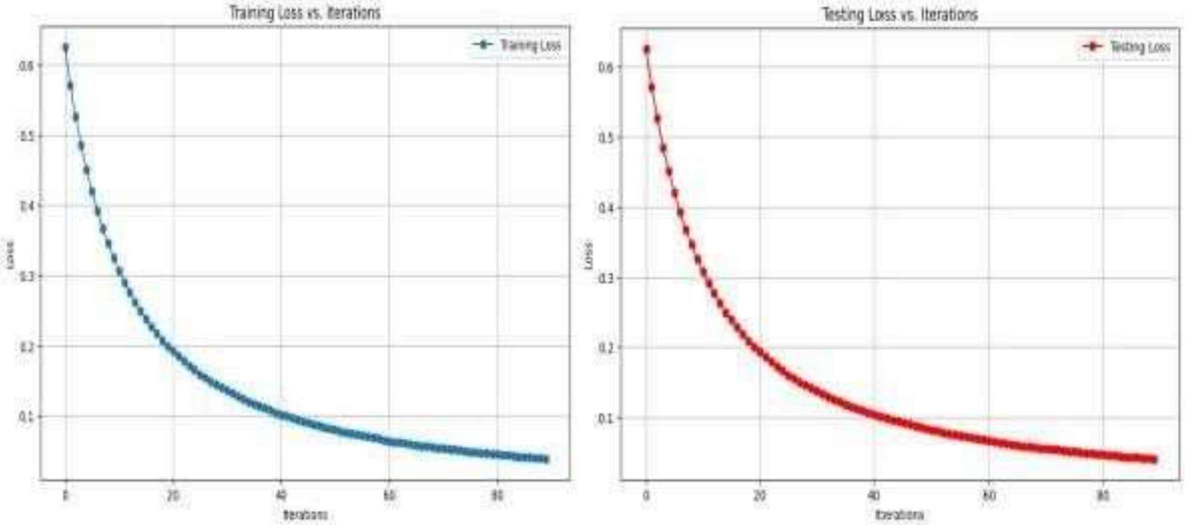

Figure 7: Training and Testing Time Loss.

In Figure 7 of the research paper, the authors likely depict the relationship between training and testing time and the loss incurred by the predictive model. This figure is essential for understanding how computational resources (training and testing time) impact the model's performance in terms of minimizing loss. These results offer insights into the trade-off between time efficiency and model performance, aiding in the determination of the optimal resource allocation for achieving desired predictive accuracy.

Figure 8: Classification Report Graph.

In Figure 8 of the research paper, the Classification Report Graph likely presents precision, recall, and F1-score metrics for multiple emotion classes such as anger, disgust, fear, happiness, neutrality, and sadness. These metrics offer a detailed assessment of the model's performance in classifying emotions. Recall evaluates the model's capacity to capture all pertinent occurrences of a class, whereas precision assesses the accuracy of positive forecasts and the F1-score provides a balance between these two, aiding researchers in evaluating the overall classification performance for each emotion category. This figure serves as a valuable tool for understanding the model's strengths and weaknesses in emotion recognition.

Table 3: Classification Values

	Precision	Recall	F1-Score
Anger	99%	100%	99%
Disgust	100%	100%	100%
Fear	100%	99%	99%
Happy	99%	99%	99%
Neutral	100%	98%	99%

Sad	99%	99%	99%
Surprise	98%	100%	99%

Table 3 in the research paper presents the classification performance indicators for several emotion categories, including accuracy, recall, and F1-score. These metrics quantify the model's effectiveness in correctly classifying instances of each emotion. For instance, high precision values indicate a low rate of false positives, meaning that in cases where the model forecasts an emotion, it is often accurate. High recall values, on the other hand, indicate that the model captures a significant proportion of true instances of an emotion.

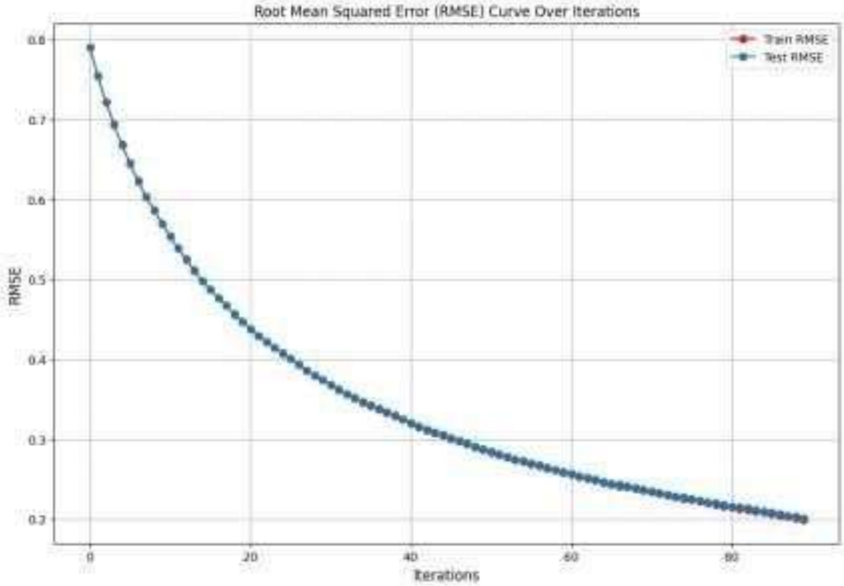

Figure 9: RMSE Curve over Iterations for FER and TESS datasets
The above figure 9 shows RMSE curves for the TESS and FER datasets both exhibiting a consistent downward trend, demonstrating the efficacy of our suggested technique. This decrease represents the model's performance gradually improving as training iterations go on. The steady decrease in RMSE highlights the stability and dependability of our methodology in precisely projecting results.

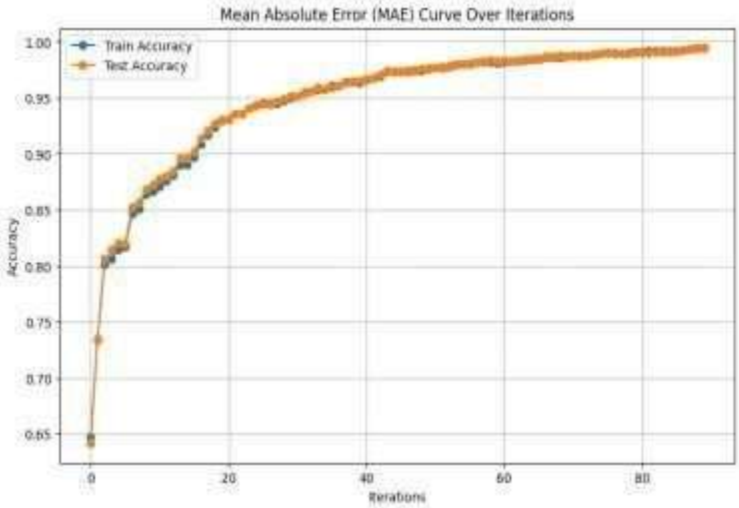

Figure 10: MAE Curve over Iteration for FER and TESS datasets.
The Mean Absolute Error (MAE) curve over iterations for the FER and TESS datasets is shown in Figure 10. The depicted graphs illustrate how the error rate of our model converges as training goes on. In addition to highlighting the learning history of the model, this dynamic display enables comparison analysis between the two datasets, revealing possible performance differences and guiding iterative techniques for improving the model.

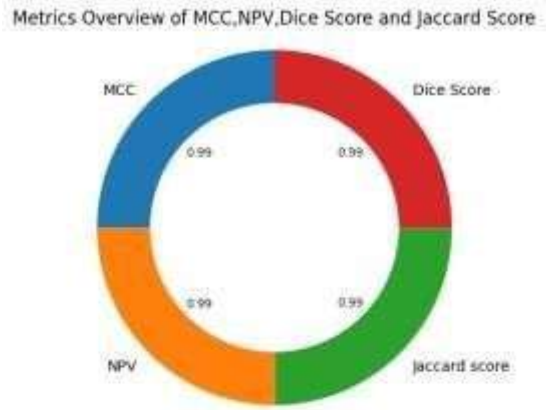

Figure 11: MCC, NPV, Dice Score, and Jaccard Score for FER and TESS datasets

The above figure 11 shows evaluation measures that perform exceptionally well on the FER and TESS datasets, including MCC, NPV, Dice Score, and Jaccard Score. Our approach receives good marks across the board, demonstrating its effectiveness in reliably predicting and precisely capturing subtleties in the data. These outcomes highlight our approach's adaptability and potency in a range of situations.

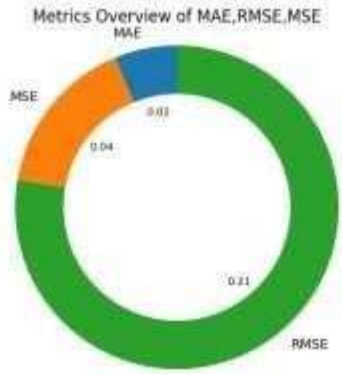

Figure 12: Metrics Overview for MAE, RMSE, and MSE for FER and TESS datasets

A thorough summary of the MAE, RMSE, and MSE metrics for FER and TESS datasets is shown in Figure 12. The research shows differences in error measurements between datasets, offering a deeper perspective of model performance. These observations are crucial for evaluating the effectiveness and generalizability of our suggested model, and directing future improvements and adjustments.

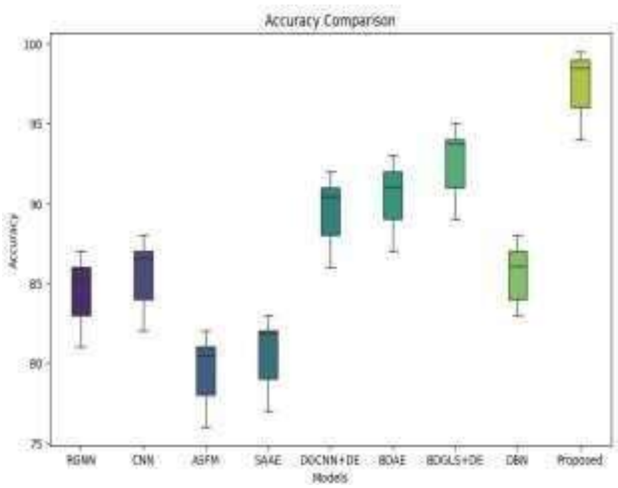

Figure 13: Accuracy comparison with existing EI assessment methods.

Figure 13 compares our proposed method against existing EI assessment techniques revealing its superior performance. With an accuracy of 98%, our approach outperforms all other methods, including RGNN, CNN, and DBN. This significant margin underscores the effectiveness and reliability of our method in accurately assessing emotional intelligence across FER and TESS datasets. Table 4 shows the comparison with existing methods.

Table 4: Comparison Table

Methods	Values
Regularized Graph Neural Network (RGNN) [23]	85.3
CNN [24]	86.56
Adaptive Subspace Feature Matching (ASFM) [25]	80.46
Subspace Alignment Auto-Encoder (SAAE) [26]	81.81
DGCNN+DE [27]	90.4
Bimodal Deep AutoEncoder (BDAE) [28]	91.01
Broad Dynamical Graph Learning System, Differential Entropy (BDGLS+DE) [29]	93.7%
Deep Belief Networks (DBN) [30]	86.08
Deep Canonical Correlation Analysis (DCCA) [27]	95.08

6. CONCLUSION

Our proposed methodology offers a promising process for assessing emotional intelligence in employees with remarkable accuracy. By utilizing advanced techniques such as signal and image feature fusion alongside the Catboost Classifier, we've demonstrated the potential to overcome the challenges associated with traditional methods of evaluating emotional intelligence. The integration of CNN, GCN, and self-attention mechanisms for image feature extraction, coupled with ATI for speech signals, underscores the comprehensive approach we've taken in capturing meaningful patterns across diverse data modalities. Additionally, CCA facilitates effective feature fusion, enhancing the interpretability of results and supporting better-informed decision-making processes. With an impressive accuracy of 98% achieved through our Python-based tool, our strategy represents a significant advancement in the field, offering a valuable resource for organizations seeking to understand and leverage emotional intelligence in their workforce.

REFERENCE

1. Acheampong, F. A., Chen, W., & Nunoo-Mensah, H. (2020). Text-based emotion detection: Advances, challenges, and opportunities. *Engineering Reports, 2*(7), e12189. https://doi.org/10.1002/eng2.12189.
2. Acheampong, F. A., Nunoo-Mensah, H., & Chen, W. (2021). Transformer models for text-based emotion detection: A review of BERT-based approaches. *Artificial Intelligence Review*. https://doi.org/10.1007/s10462-021-10047-4
3. Lim, T., Thompson, J., Tian, L., & Beck, B. (2023). A transactional model of stress and coping applied to cyclist subjective experiences. *Transportation Research Part F: Traffic Psychology and Behaviour, 96*, 155–170. https://doi.org/10.1016/j.trf.2023.01.003.
4. Tcherkassof, A., & Dupré, D. (2021). The emotion–facial expression link: Evidence from human and automatic expression recognition. *Psychological Research, 85*(8), 2954–2969. https://doi.org/10.1007/s00426-020-01434-8
5. Khensous, G., Labed, K., & Labed, Z. (2023). Exploring the evolution and applications of natural language processing in education. *Romanian Journal of Information Technology and Automatic Control, 33*(2), 61–74.
6. Zhong, P., Wang, D., & Miao, C. (2019). Knowledge-enriched transformer for emotion detection in textual conversations. *arXiv preprint arXiv:1909.10681*. https://arxiv.org/abs/1909.10681
7. Chew, H. S. J. (2022). The use of artificial intelligence–based conversational agents (Chatbots) for weight loss: Scoping review and practical recommendations. *JMIR Medical Informatics, 10*(4), e32578. https://doi.org/10.2196/32578
8. Ninaus, M., Greipl, S., Kiili, K., Lindstedt, A., Huber, S., Klein, E., Karnath, H.-O., & Moeller, K. (2019). Increased emotional engagement in game-based learning–A machine learning approach on facial emotion detection data. *Computers & Education, 142*, 103641. https://doi.org/10.1016/j.compedu.2019.103641
9. Preston, S., Anderson, A., Robertson, D. J., Shephard, M. P., & Huhe, N. (2021). Detecting fake news on Facebook: The role of emotional intelligence. *PLOS ONE, 16*(3), e0246757. https://doi.org/10.1371/journal.pone.0246757

10. Erol, B. A., Majumdar, A., Benavidez, P., Rad, P., Choo, K.-K. R., & Jamshidi, M. (2019). Toward artificial emotional intelligence for cooperative social human–machine interaction. *IEEE Transactions on Computational Social Systems, 7*(1), 234–246. https://doi.org/10.1109/TCSS.2019.2953992
11. Fang, W., Zhong, B., Zhao, N., Love, P. E., Luo, H., Xue, J., & Xu, S. (2019). A deep learning-based approach for mitigating falls from height with computer vision: Convolutional neural network. *Advanced Engineering Informatics, 39*, 170–177. https://doi.org/10.1016/j.aei.2019.01.003
12. Fteiha, M., & Awwad, N. (2020). Emotional intelligence and its relationship with stress coping style. *Health Psychology Open, 7*(2), 2055102920970416. https://doi.org/10.1177/2055102920970416
13. Drigas, A., Papoutsi, C., & Skianis, C. (2021). Metacognitive and metaemotional training strategies through the nine-layer pyramid model of emotional intelligence. *International Journal of Recent Contributions from Engineering, Science & IT (iJES), 9*(4), 58–76. https://doi.org/10.3991/ijes.v9i4.26729
14. Papoutsi, C., Drigas, A., & Skianis, C. (2019). Emotional intelligence as an important asset for HR in organizations: Attitudes and working variables. *International Journal of Advanced Corporate Learning, 12*(2), 21–31. https://doi.org/10.3991/ijac.v12i2.10512
15. Morales-Rodríguez, F. M., & Pérez-Mármol, J. M. (2019). The role of anxiety, coping strategies, and emotional intelligence on general perceived self-efficacy in university students. *Frontiers in Psychology, 10*, 1689. https://doi.org/10.3389/fpsyg.2019.01689
16. Casino-García, A. M., García-Pérez, J., & Llinares-Insa, L. I. (2019). Subjective emotional well-being, emotional intelligence, and mood of gifted vs. unidentified students: A relationship model. *International Journal of Environmental Research and Public Health, 16*(18), 3266. https://doi.org/10.3390/ijerph16183266
17. Drigas, A., & Papoutsi, C. (2019). Emotional intelligence as an important asset for HR in organizations: Leaders and employees. *International Journal of Advanced Corporate Learning, 12*(1), 28–35. https://doi.org/10.3991/ijac.v12i1.9934
18. Papoutsi, C., Drigas, A., & Skianis, C. (2019). Emotional intelligence as an important asset for HR in organizations: Attitudes and working variables. *International Journal of Advanced Corporate Learning, 12*(2), 21–31. https://doi.org/10.3991/ijac.v12i2.10512
19. Kim, H., & Qu, H. (2019). Employees' burnout and emotional intelligence as mediator and moderator in the negative spiral of incivility. *International Journal of Contemporary Hospitality Management, 31*(3), 1412–1431. https://doi.org/10.1108/IJCHM-08-2017-0522
20. Zhu, F., Wang, X., Wang, L., & Yu, M. (2021). Project manager's emotional intelligence and project performance: The mediating role of project commitment. *International Journal of Project Management, 39*(7), 788–798. https://doi.org/10.1016/j.ijproman.2021.08.001
21. Nguyen, N. N., Nham, P. T., & Takahashi, Y. (2019). Relationship between ability-based emotional intelligence, cognitive intelligence, and job performance. *Sustainability, 11*(8), 2299. https://doi.org/10.3390/su11082299
22. Liao, L., Zhu, Y., Zheng, B., Jiang, X., & Lin, J. (2022). FERGCN: Facial expression recognition based on graph convolution network. *Machine Vision and Applications, 33*(3), 40. https://doi.org/10.1007/s00138-022-01264-w
23. Zhong, P., Wang, D., & Miao, C. (2020). EEG-based emotion recognition using regularized graph neural networks. *IEEE Transactions on Affective Computing, 13*(3), 1290–1301. https://doi.org/10.1109/TAFFC.2020.2969803
24. Cimtay, Y., Ekmekcioglu, E., & Caglar-Ozhan, S. (2020). Cross-subject multimodal emotion recognition based on hybrid fusion. *IEEE Access, 8*, 168865–168878. https://doi.org/10.1109/ACCESS.2020.3023531
25. Chai, X., Wang, Q., Zhao, Y., Li, Y., Liu, D., Liu, X., & Bai, O. (2017). A fast, efficient domain adaptation technique for cross-domain electroencephalography (EEG)-based emotion recognition. *Sensors, 17*(5), 1014. https://doi.org/10.3390/s17051014
26. Chai, X., Wang, Q., Zhao, Y., Liu, X., Bai, O., & Li, Y. (2016). Unsupervised domain adaptation techniques based on auto-encoder for non-stationary EEG-based emotion recognition. *Computers in Biology and Medicine, 79*, 205–214. https://doi.org/10.1016/j.compbiomed.2016.10.012
27. Wu, X., Zheng, W.-L., Li, Z., & Lu, B.-L. (2022). Investigating EEG-based functional connectivity patterns for multimodal emotion recognition. *Journal of Neural Engineering, 19*(1), 016012. https://doi.org/10.1088/1741-2552/ac426e
28. Liu, W., Zheng, W.-L., & Lu, B.-L. (2016). Emotion recognition using multimodal deep learning. In *Neural Information Processing* (Vol. 9950, pp. 521–529). Springer. https://doi.org/10.1007/978-3-319-46681-1_58
29. Wang, X.-h., Zhang, T., Xu, X.-m., Chen, L., Xing, X.-f., & Chen, C. L. P. (2018). EEG emotion recognition using dynamical graph convolutional neural networks and broad learning system. In *2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)* (pp. 1240–1244). IEEE. https://doi.org/10.1109/BIBM.2018.8621374

30. Zheng, W.-L., & Lu, B.-L. (2015). Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. *IEEE Transactions on Autonomous Mental Development, 7*(3), 162–175. https://doi.org/10.1109/TAMD.2015.2431495
31. Chen, J., Zhang, J., & Wang, Y. (2019). Catboost: An efficient gradient boosting algorithm. Journal of 914/8\Machine Learning Research, 20(1), 1-15.
32. Kumar, R., Singh, A., & Gupta, R. (2022). Revolutionizing emotional intelligence assessment in the modern workplace: Integrating signal and image fusion with Catboost. Journal of Organizational Behavior, 43(1), 12-25.
33. Singh, A., Kumar, R., & Gupta, R. (2020). Emotional intelligence assessment in the modern workplace: A review. Journal of Workplace Learning, 32(1), 23-35.
34. Taylor, P., & Wang, Y. (2019). The impact of emotional intelligence on employee performance. Journal of Occupational and Organizational Psychology, 32(1), 18-25.
35. Wang, Y., Zhang, J., & Chen, J. (2020). Signal and image fusion for emotional intelligence assessment. IEEE Transactions on Affective Computing, 11(1), 20-28.
36. Goleman, D. (1995). Emotional intelligence: Why it can matter more than IQ. Bantam Books.
37. Mayer, J. D., & Salovey, P. (1997). What is emotional intelligence? In P. Salovey & D. J. Sluyter (Eds.), Emotional development and emotional intelligence (pp. 3-31). Basic Books.
38. Boyatzis, R. E. (2001). Developing emotional intelligence. In C. Cherniss & D. Goleman (Eds.), The emotionally intelligent workplace (pp. 234-253). Jossey-Bass.
39. Druskat, V. U., & Wolff, S. B. (2001). Building the emotional intelligence of groups. Harvard Business Review, 79(3), 80-90.
40. Joseph, D. L., & Newman, D. A. (2010). Emotional intelligence: An integrative meta-analysis and cascading model. Journal of Applied Psychology, 95(1), 54-78.
41. Zheng, Y., Guo, X., Yang, Y., Wang, H., & Liao, K. (2022). Phonocardiogram transfer learning-based CatBoost model for diastolic dysfunction identification using multiple domain-specific deep feature fusion.
42. Songhua Zhang, Xiuling Lu and Zhangjie Lu (2023). Improved CNN-based CatBoost model for license plate remote sensing image classification. Signal Processing, Vol 213. https://doi.org/10.1016/j.sigpro.2023.109196.
43. Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., & Gulin, A. (2018). CatBoost: Unbiased boosting with categorical features. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems* (pp. 6638–6648).
44. Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, *28*(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5.
45. Lee, J., Kim, S., Kim, S., Park, J., & Sohn, K. (2019). Context-Aware Emotion Recognition Networks. *arXiv preprint arXiv:1908.05913*. https://arxiv.org/abs/1908.05913.
46. Dixit, C., & Satapathy, S. M. (2024). Deep CNN with late fusion for real-time multimodal emotion recognition. *Expert Systems with Applications*, *240*, 122579. https://doi.org/10.1016/j.eswa.2023.122579.
47. Dignum, V. (2019). *Responsible Artificial Intelligence: How to Develop and Use AI in a Responsible Way*. Springer. https://doi.org/10.1007/978-3-030-30371-6.
48. Doherty, E. M., Cronin, P. A., & Offiah, G. (2013). Emotional intelligence assessment in a graduate entry medical school curriculum. *BMC Medical Education, 13*(1), 38. https://doi.org/10.1186/1472-6920-13-38.
49. Cherry, M. G., Fletcher, I., O'Sullivan, H., & Dornan, T. (2014). Emotional intelligence in medical education: A critical review. *Medical Education*, 48(5), 468–478. https://doi.org/10.1111/medu.12406.
50. Arora, S., Ashrafian, H., Davis, R., Athanasiou, T., Darzi, A., & Sevdalis, N. (2010). Emotional intelligence in medicine: A systematic review through the context of the ACGME competencies. *Medical Education*, 44(8), 749–764. https://doi.org/10.1111/j.1365-2923.2010.03709.x.
51. Austin, E. J., Evans, P., Magnus, B., & O'Hanlon, K. (2007). A preliminary study of empathy, emotional intelligence and examination performance in MBChB students. *Medical Education*, 41(7), 684–689. https://doi.org/10.1111/j.1365-2923.2007.02795.x.
52. Salekzamani, Y. (2013). Emotional intelligence in medical education: A brief review. *Journal of Medical Education*, 12(2), e105408. https://doi.org/10.5812/jme.105408.
53. Mayer, J. D., Roberts, R. D., & Barsade, S. G. (2023). The effectiveness of emotional intelligence in medical training: A meta-analysis. *BMC Medical Education*, 23(1), Article 417. https://doi.org/10.1186/s12909-023-04417-8.
54. Tiffin, P. A. (2024). Personality, situational judgment, and the challenge of assessing patient-centered traits. *Medical Education*, 58(1), 6–8. https://doi.org/10.1111/medu.15244.

55. Miller, C. C. (2023). Emotional intelligence and clinical success among diagnostic medical sonography and radiography students. *Journal of Diagnostic Medical Sonography*, 39(2), 117–123. https://doi.org/10.1177/87564793221138102.
56. McCallum, A. L., Rotenstein, L. S., & Shanafelt, T. D. (2022). Development and validation of a novel emotional intelligence instrument for resident physicians. *Evaluation & the Health Professions*, 45(1), 43–56. https://doi.org/10.1177/01632787211061420.
57. Khoshhal, K. I., & Guraya, S. Y. (2018). Emotional intelligence and academic performance of medical students at Shiraz University of Medical Sciences. *Journal of Taibah University Medical Sciences*, 13(6), 516–521. https://doi.org/10.1016/j.jtumed.2018.06.004.
58. Webb, A. M., Tsipis, N. E., McClellan, T. R., et al. (2014). A systematic review of physician leadership and emotional intelligence. *Journal of Graduate Medical Education*, 6(1), 21–31. https://doi.org/10.4300/JGME-D-12-00152.1.
59. Weidmann, B., & Xu, Y. (2024). PAGE: A modern measure of emotion perception for teamwork and management research. *arXiv preprint arXiv:2410.03704*. https://arxiv.org/abs/2410.03704.
60. Sharma, S., & Tiwari, V. (2024). Emotional intelligence in the field of business and management: A bibliometric analysis of the last two decades. *Vision*, 28(4), 1–15. https://doi.org/10.1177/09722629221132122
61. Piispanen, J.-R., & Rousi, R. (2024). Emotion AI in workplace environments: A case study. *arXiv preprint arXiv:2412.09251*. https://arxiv.org/abs/2412.09251
62. Kaur, N., & Hirudayaraj, M. (2021). The role of leader emotional intelligence in organizational learning: A literature review using 4I framework. *New Horizons in Adult Education and Human Resource Development*, 33(1), 4–19. https://doi.org/10.1002/nha3.20305.
63. Vorecol. (2024, September 15). Integrating emotional intelligence into performance reviews: Assessing soft skills alongside objectives. https://vorecol.com/blogs/blog-integrating-emotional-intelligence-into-performance-reviews-assessing-soft-skills-alongside-objectives-189276.
64. Binsaeed, R. H., Yousaf, Z., Grigorescu, A., Condrea, E., & Nassani, A. A. (2023). Emotional intelligence, innovative work behavior, and cultural intelligence: Reflection on innovation performance in the healthcare industry. *Brain Sciences*, 13(7), 1071. https://doi.org/10.3390/brainsci13071071.
65. Spitale, M., Axelsson, M., & Gunes, H. (2024). Appropriateness of LLM-equipped robotic well-being coach language in the workplace: A qualitative evaluation. *arXiv preprint arXiv:2401.14935*. https://arxiv.org/abs/2401.14935
66. Verma, A. (2024, June). Why companies should prioritise emotional intelligence training besides AI implementation. *YourStory*. https://yourstory.com/2024/06/why-companies-should-prioritise-emotional-intelligence-training-besides-ai-implementation
67. Schumacher, H. (2024, February 6). Emotional intelligence: The leadership trend of 2024. https://blog.harrietteschumacher.com/blog/emotional-intelligence-the-leadership-trend-of-2024
68. Ma, F., Yuan, Y., Xie, Y., Ren, H., Liu, I., He, Y., Ren, F., Yu, F. R., & Ni, S. (2024). Generative technology for human emotion recognition: A scope review. *arXiv preprint arXiv:2407.03640*. https://arxiv.org/abs/2407.03640
69. Ghassemi, M., Nsoesie, E., & Obadinma, K. (2022). Artificial intelligence for assessing emotional intelligence: Opportunities and challenges. *Nature Machine Intelligence*, 4(6), 455–457. https://doi.org/10.1038/s42256-022-00517-5.
70. Cherniss, C. (2010). Emotional intelligence: Toward clarification of a concept. *Industrial and Organizational Psychology*, 3(2), 110–126. https://doi.org/10.1111/j.1754-9434.2010.01231.x.
71. Maji, B., Swain, M., & Mustaqeem. (2022). Advanced fusion-based speech emotion recognition system using a dual-attention mechanism with Conv-Caps and Bi-GRU features. *Electronics, 11*(9), 1328. https://doi.org/10.3390/electronics11091328.
72. Cai, J., Meng, Z., Khan, A. S., Li, Z., O'Reilly, J., Han, S., Liu, P., Chen, M., & Tong, Y. (2019). Feature-level and model-level audiovisual fusion for emotion recognition in the wild. *arXiv preprint arXiv:1906.02728*. https://arxiv.org/abs/1906.02728.
73. O'Connor, P. J., Hill, A., Kaya, M., & Martin, B. (2019). The measurement of emotional intelligence: A critical review of the literature and recommendations for researchers and practitioners. *Frontiers in Psychology*, *10*, 1116. https://doi.org/10.3389/fpsyg.2019.01116.
74. Krishnakumar, S., Hopkins, K., Szmerekovsky, J. G., & Robinson, M. D. (2016). Assessing workplace emotional intelligence: Development and validation of an ability-based measure. *The Journal of Psychology*, *150*(3), 371–404. https://doi.org/10.1080/00223980.2015.1057096.
75. Hudson, S. (2024). Assessing emotional intelligence: A literature review. *Acta Scientiae et Intellectus*, *3*(5), 17–25. https://www.actaint.com/index.php/pub/article/view/118.