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Identifying Employee Emotions Based on Facial Expression Analysis in IT Sector using Ensemble Learning Techniques: A Systematic Literature Review

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Abstract – Facial expression analysis is an important tool for determining employee emotions, especially in the IT sector, where knowing emotional states can have significant effects on productivity and well-being. Traditional techniques for emotion detection are frequently limited by their dependence on simple recognition models that may not fully represent the complexities of human emotions. However, recent research has investigated the possibilities of ensemble learning techniques to improve the accuracy and dependability of these systems. This systematic literature review examines the various approaches used in emotion recognition from 2011 to 2023, with a focus on how ensemble learning might increase the efficiency of facial expression analysis. An initial selection of 33 studies was taken from six internet databases, with 7 eventually being included in the final review. The findings show that integrating several analytical methodologies into models produces promising results, leading the path for more robust emotion identification systems in the workplace.

Keywords- Emotion detection, Ensemble learning, Facial expression analysis

Recommended APA Citation

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Introduction

In today's fast-paced workplaces, especially in the Information Technology (IT) industry, employees' emotional wellness is becoming increasingly recognized as critical to organizational success. High workloads, tight deadlines, and fast changing technological demands all contribute to stressful settings, which frequently result in emotional stressors that reduce job satisfaction and overall productivity. Employees in the IT industry, who are regularly needed to balance creativity, problem solving, and technical expertise, are especially sensitive to stress and burnout. As a result, treating employees' emotional well-being has transformed into an essential strategy for maintaining competitive advantage and promoting creativity in the workplace.

To cultivate a positive and productive work environment, organizations must prioritize understanding and managing the emotional states of their employees. (Subhashini & Niveditha, 2015). However, traditional methods of emotion assessment, such as surveys, interviews, and self-reports, often fall short (Kolodyazhniy et al., 2011) in providing an accurate reflection of employees' true emotional states due to inherent subjectivity and bias. These conventional approaches depend heavily on the individual's willingness to disclose their emotions, which can lead to misreporting or concealment of feelings in fear of workplace repercussions. Consequently, the need for more objective, reliable methods of emotional assessment is becoming increasingly apparent. Advancements in machine learning (ML) and facial expression analysis (Hassouneh et al., 2020), (Guo et al., 2018) have paved the way for innovative solutions in emotion detection. By harnessing the power of facial recognition technologies, organizations can detect non-verbal cues, such as facial expressions, to infer employees' emotional states with greater accuracy and in real time.

These technologies offer the potential to revolutionize the way emotions are monitored and addressed in the workplace, moving away from subjective self-reporting to more data-driven insights. Facial expression analysis has been shown to effectively capture subtle emotional nuances, providing a window into an individual's mood, engagement levels, and overall well-being. Incorporating these technologies into the workplace not only enhances the capacity for understanding emotional states but also offers actionable insights that can drive employee engagement and improve team dynamics. As studies have shown, employees who feel understood and supported emotionally tend to be more engaged, satisfied, and motivated, leading to better collaboration and higher overall productivity. Such advancements in emotion detection hold promise for enhancing organizational performance by facilitating more personalized, empathetic management practices.

Despite their enormous potential, there are substantial obstacles to efficiently adopting these technologies. One key difficulty is translating facial expression research results into practical applications that may be effortlessly integrated into existing workplace systems. The complexity of human emotions, combined with various cultural and individual variances in emotional presentation, poses a significant challenge to emotion identification systems. Furthermore, ethical considerations about privacy and data security must be carefully managed to avoid unknown effects, such as employee data manipulation or personal boundary violations.

To overcome these issues, ensemble learning approaches have emerged as a possible solution. By combining the strengths of multiple machine learning models, ensemble methods can enhance the accuracy, robustness, and generalization capabilities of emotion detection systems. In emotion detection tasks, ensemble learning allows for better handling of variability in facial expressions and improves the model's ability to make reliable predictions across diverse employee diversities. This approach mitigates some of the limitations faced by individual models, particularly in handling complex or undetermined emotional states.

Moreover, the flexibility of ensemble learning enables the creation of more adaptable systems that can cater to the unique emotional dynamics within an organization.

This literature review aims to systematically examine the existing research on facial expression analysis within the context of the IT sector, with a specific focus on the application of ensemble learning techniques. The review will explore the evolution of emotion recognition methodologies, assess the effectiveness of various approaches, and identify the challenges and opportunities associated with implementing these technologies in a workplace setting. Through this analysis, the goal is to provide a comprehensive understanding of the current state of the field and to highlight potential directions for future research and development.

Materials and Methods

This study uses a Systematic Literature Review (SLR) methodology to investigate the applications of machine learning (ML) and ensemble learning in predicting human emotions from facial expression analysis in workplace and IT contexts. (Anjaneyulu, 2023) The SLR process was divided into three phases: planning, conducting, and reporting.

The planning phase consists of identifying relevant databases (IEEE Xplore, Springer Link, ScienceDirect, ACM Digital Library, PubMed, and Google Scholar). Boolean search strings were created with keywords like "facial expression recognition," "emotion detection," "ensemble learning," "transfer learning," and "workplace/IT sector." In the conducting phase searches were performed in these databases, and duplicate results were eliminated. Additional research was discovered through snowballing. Titles, abstracts, and full texts were evaluated using inclusion/exclusion criteria to guarantee relevance and accuracy. In the reporting phase, the selected studies were synthesized and organized into a detailed analysis. The studies were documented with a focus on the understanding of ML applications in human emotion prediction. The summarized research was then compiled into structured documents that provide a comprehensive overview of the literature, highlighting key trends, methodologies, and future directions in the field.

This systematic review process, guided by established SLR protocols, ensures a thorough and objective evaluation of the existing literature, offering valuable insights into the potential of machine learning with ensemble learning in emotion detection.

Research Questions

Research questions are central to guiding a systematic literature review. Table 1 presents the research questions that this study aims to address. By examining these questions, we can identify gaps in the current literature and better understand the state of research in the application of machine learning for human emotion detection.

Table 1
Research questions

NO	Research Question
RQ1	Which machine learning techniques have been used for facial expression-based emotion recognition in the workplace or IT sector context?
RQ2	How have transfer learning approaches been used and reported in prior studies on facial expression recognition?
RQ3	Which ensemble learning techniques (bagging or boosting) demonstrate optimal performance, and under what conditions?

Search Strategy

The search was conducted in the following electronic databases: IEEE Xplore, Springer Link, ScienceDirect, ACM Digital Library, PubMed, and Google Scholar. Boolean search strings were formulated using keywords related to facial expression recognition, emotion detection, ensemble learning, and workplace applications. And an example query was:

("facial expression recognition" OR "emotion detection" OR "affective computing") AND ("ensemble learning" OR "bagging" OR "boosting" OR "stacking" OR "random forest") AND ("IT sector" OR "workplace" OR "employee")

Inclusion and Exclusion Criteria

Inclusion Criteria (IC):

The studies focus on emotion recognition through facial expression analysis. Research that specifically targets the IT sector or workplace environments. And papers that explore the use of ensemble learning techniques in emotion recognition. Studies those publications from peer-reviewed journals, conferences, and reputable academic sources. And the publications were published from 2011 to 2023.

Table 2

Inclusion Criteria (IC)

NO	Inclusion Criteria (IC)
IC1	Studies focus on facial expression-based emotion recognition.
IC2	Research applied to workplace or IT sector settings.
IC3	Use of machine learning, deep learning, transfer learning, or ensemble learning methods.

Exclusion Criteria (EC):

The studies do not specifically address the IT sector or workplace environments. The research focused solely on other forms of emotion recognition (e.g., text-based, physiological signals) without including facial expressions. And non-peer-reviewed articles, opinion pieces, or grey literature.

Table 3

Exclusion Criteria (EC)

NO	Exclusion Criteria (EC)
EC1	Studies based only on non-facial modalities (e.g., text sentiment, EEG-only).
EC2	Non-peer-reviewed or grey literature.
EC3	Studies not published in English.
EC4	Duplicate studies

Study Selection Process

The selection process followed the PRISMA 2020 guidelines. A total of 60 records were initially identified. After removing duplicates, 53 studies remained. Screening by title and abstract reduced this number to 40. A full-text review resulted in 33 papers, and finally 7 studies were included in the review.

The main reasons for exclusion at the full-text stage were:

I. Lack of workplace or IT relevance.

II. Use of non-facial modalities only.
III. Missing or incomplete evaluation metrics.

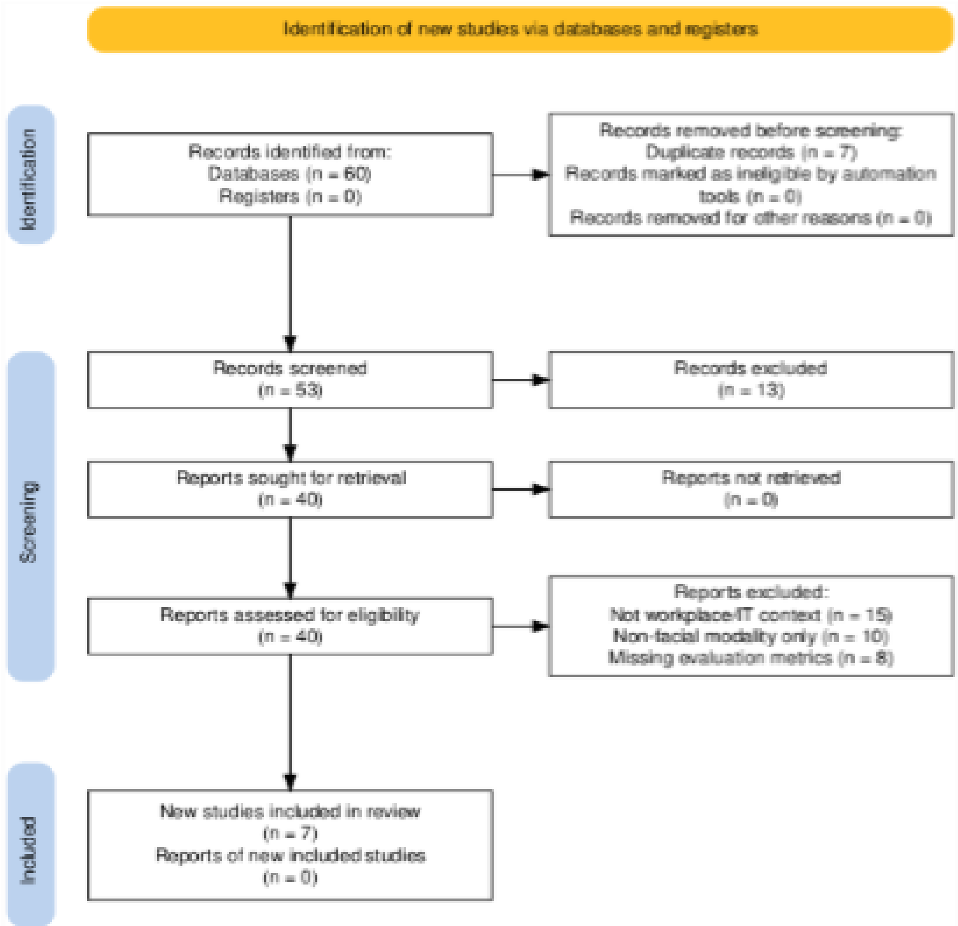

Figure 1. *PRISMA 2020 flow diagram of the study selection process*

Quality Appraisal

To evaluate the reliability of the included studies, applied a customized 8-item checklist tailored for machine learning-based facial expression recognition (FER). Items assessed were:

I. Clear objective and research question
II. Appropriate dataset (FER, CK+, RAF-DB, AffectNet, workplace-specific, etc.)
III. Adequate dataset size (>1,000 samples or justified)
IV. Description of preprocessing (e.g. face alignment, normalization, augmentation)
V. Transparent description of model architecture/algorithm
VI. Appropriate validation protocol (e.g. subject-independent, k-fold CV; not random split only)
VII. Performance metrics beyond accuracy (e.g. F1, confusion matrix)
VIII. Reproducibility cues (public code/data, or sufficient hyperparameter detail)

Each criterion was scored as either Yes = 1 or No = 0. All seven included studies were rated independently by two reviewers. Cohen's κ = 0.81 indicates that 49 out of 56 decisions were agreed upon. Disagreements (mostly over dataset adequacy and validation reporting) were handled through discussion. Scores varied from 3/8 to 7/8. More recent research (e.g., (Begaj et al., 2020) ;(Thiruthuvanathan et al., 2021)) performed better due to clear preprocessing, solid validation, and many metrics, but older studies (e.g., Subhashini & Niveditha 2015) lacked dataset size, validation accuracy, and reproducibility. Across all studies, reproducibility was consistently low, with no study giving complete open-source code or datasets.

Results

Emotion recognition through facial expressions has emerged as a crucial area of research, particularly in fields such as human-computer interaction, psychological analysis, and workplace productivity. As technology advances, various methods have been developed to improve the accuracy and efficiency of detecting emotions from facial cues. This section delves into the different approaches that have been explored in the literature, starting with a foundational understanding of emotion recognition, followed by an analysis of facial expressions as key indicators of emotional states, then transitions into the deep learning and machine learning techniques that have been applied to enhance emotion recognition, finally culminating in an exploration of ensemble learning methods that combine multiple models to achieve optimal performance. Each of these approaches contributes uniquely to the broader goal of accurately and effectively identifying emotions, particularly in complex environments like the IT sector.

Discussion

Introduction to Emotion Recognition

Observing and interpreting the emotional states of others is a common occurrence in our everyday lives and social interactions. Considerable effort has provided computers with the capacity to detect emotions. Emotional traits have a significant impact on social ability to learn, understand, and think logically. Examples of this impact include communication, comprehending how people act, and making various decisions. The significance of emotion in communication is crucial. A person's voice provides a form of oral communication. Nonverbal communication encompasses facial expressions, body language, and gestures. Facial expressions are a potent means of communicating human emotions. Due to the wide range of emotions individuals encounter daily, it is not unusual for their mood to vary throughout the day, from dawn to night. Contemporary psychological theory posits that there are six primary human emotions: joy, sadness, anger, fear, surprise, and disgust. The facial muscles of an individual manifest the emotional state they are experiencing. The eyes, nose, mouth, and eyebrows are the fundamental features of a face.

Facial expression recognition experiments have mainly focused on six categories like happy, surprised, fear, angry, sad, and disgust. However, training models using large images is complex and time-consuming. Affective computing researchers (Kolodyazhniy et al., 2011) have shown increased interest in fine-grained emotion analysis, specifically focusing on complex facial expressions, including dominant and complementary emotions like happily disgusted and sadly fearful. So, by examining past research works, this experiment was done under two compounded categories, such as normal and abnormal. Normal categories include happy, surprised, excited, and neutral emotions. And abnormal will include sadness, anger, disgust, and fear.

Facial Expression Analysis

Image preprocessing must be done as the first step before conducting facial expression analysis. (Guo et al., 2018) When starting image processing, it can be that images do not fulfil the same criteria, such as size and pixel sizes. So before doing analysis, it is compulsory to do the image pre-processing. Then inputs become more standard. Having the same background and same distance when capturing images is very effective. It helps to preprocess data comprehensively.

In the context of facial expression analysis Convolutional Neural Network (CNN) is the best among image analysing algorithms. (Kosti et al., 2020) CNN, short for Convolutional Neural Network, is a computational framework designed for deep learning algorithms. It is particularly effective in jobs that require image identification and the processing of pixel data. While there are other neural network architectures in deep learning, CNN is the preferred choice for the tasks of object identification and recognition.

Deep Learning Approach

In the deep learning approach, there are three different steps taken. Such as preprocessing, deep feature learning, and classification of deep features. Image preprocessing is crucial in this journey. It includes normalization and augmentation. Then after a deep feature learning stage, take the lead. There are many deep learning techniques like CNN (Convolutional Neural Network), Deep Belief Network (DBN), Deep Auto Encoder (DAE), Recurrent Neural Network (RNN), and Generative Adversarial Network (GAN).

Convolutional neural networks are a well-received technique that is used mostly in image processing and in image recognition. The accuracy of each and all algorithms are based on the dataset collected. And those techniques can be done simultaneously in more challenging conditions, like natural settings, outdoors. Several facial emotions can be detected by using different CNN architectures. CNN itself extracts the features and recognizes facial expressions. CNN identifies different emotions like happiness, sadness, anger, disgust, fear, and surprise.

Machine Learning Approaches in Emotion Recognition

Traditional machine learning (ML) methods played an essential role in early facial expression-based emotion recognition before deep learning became popular. Classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Naïve Bayes (NB), Decision Trees (DT), and Random Forests (RF) (Mishra and Bhatt, 2021) are frequently used in supervised learning to map facial features to emotional categories. These techniques showed reasonable accuracy on controlled datasets such as CK+ and JAFFE, but performance often degraded in unconstrained "in-the-wild" circumstances. For example, SVM and K-NN classifiers achieved accuracies ranging from 60% to 82%, depending on the dataset and emotion classification. Clustering methods have been used in unsupervised learning to classify face features based on emotion, but they frequently struggle with delicate emotions and considerable intra-class variability.

More recently, hybrid techniques include machine learning classifiers (Acheampong et al., 2020) with deep feature extraction. Convolutional Neural Networks (CNNs) are used to extract robust features from images, which are then identified using classic machine learning models like Support Vector Machines (SVMs) or Random Forests. (Begaj et al., 2020) This hybrid design has demonstrated better accuracy and generalization than either technique alone, particularly when datasets are limited. Ensemble machine learning approaches (bagging, boosting, and stacking) build on this by combining many classifiers to improve robustness, reduce variance, and improve performance. These methods regularly outperform single-model baselines, demonstrating the continued utility of machine learning approaches in modern FER pipelines, especially when combined with deep learning feature extractors.

Ensemble Learning in Emotion Recognition

Convolutional Neural Network (CNN) is famous for its use in computer vision tasks. (Thiruthuvanathan et al., 2021) CNN is an artificial neural network used with great effectiveness in the areas of computer vision, image recognition, and processing. These layers of CNN form a hierarchy and learn features directly from raw image pixels in an end-to-end manner. They work well when it comes to jobs like object recognition and classification.

Aggregate layers, pooling layer, activation functions, and fully connected layers are the principal parts of CNN.

Convolutional layers are responsible for recognizing complex patterns and characteristics in the data input. Convolution involves applying filters or kernels onto input images that enable the network to detect features. Pooling layers help in diminishing data dimensionality obtained from compression layers. This assists in preserving the critical features. Activation functions bring non-linearities into the network, which support it in understanding subtler patterns in the data.

Lastly, CNNs come with completely connected layers. These layers link every neuron with every neuron in the layers before and after them, therefore making higher-level reasoning possible. CNN's capability to learn the hierarchy of abstractions from raw data makes them good for tasks involving complex visual patterns. The structure of the convolutional neural network is in the figure.

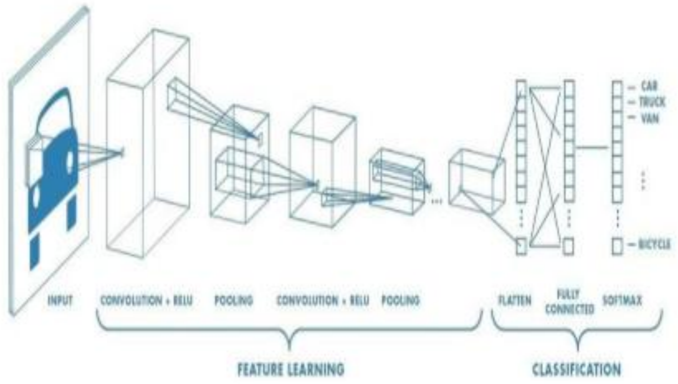

Figure 2. *Structure of Convolutional Neural Network*

Transfer learning involves taking a pre-trained model for a specific task, such as image recognition or natural language processing, and tuning it for the task you care about. This model, which was created using lots of data, is then modified to work with other information without requiring the large number of correctly labeled examples typically needed by systems performing machine learning from scratch. Many such transfer learning algorithms might exist to train sets while retaining high precision when predicting future outcomes. Included studies commonly fine-tuned pre-trained CNNs or compared transfer learning against CNNs. Backbones reported across the pool included Inception-v3/v4, MobileNetV2/V3, and EfficientNetV2. (Zhuang et al., 2021) CNN baselines used 3–5 convolution blocks with ReLU/Batch Norm and SoftMax heads. Transfer learning generally matched or exceeded from-scratch CNNs when class distributions were imbalanced, or data were limited. Reported accuracies for single-model baselines clustered around ~82–89%, with stronger results on CK+/FER2013 than on in-the-wild datasets. (Zhuang et al., 2021)

Ensemble learning is a machine learning approach that involves combining multiple model predictions to improve performance. The idea is that by using the collective intelligence of multiple models, the ensemble can often achieve better results than any single model. In classification, regression, and clustering, ensemble learning methods are widely used. Ensemble learning involves training multiple elementary models of the same or different types, forming a group. Ensemble model aggregation techniques to combine predictions, using averaging, voting, or weighted sums.

Batch modes include bagging, incrementing, and stacking. Bagging adds bootstraps, while boosting builds weak learners, each model correcting its predecessor's mistakes. Stacking trains a metamodel with predictions from multiple base models. Bagging works extract deep embeddings (penultimate layer) and training Random Forests to stabilize decision boundaries; gains are modest when classes are well separated but can improve minority class F1. Boosting on hand-crafted or hybrid features (e.g., SIFT/HOG + deep) shows consistent improvements in accuracy and macro-F1 (Tariq et al., 2011), (W. Li et al., 2021) over single CNNs, particularly under class imbalance. XGBoost over pooled deep features is frequently reported as strong. Stacking ensembles (Hussain et al., 2023) multiple CNNs (or CNN + classical ML) and learn a meta-learner (often logistic regression or shallow MLP) on out-of-fold predictions; this yielded some of the best accuracies in the pool.

Existing Related Applications

Emotions are detected using face recognition, feature generation, and classification using ensemble features like hierarchical gaussianization, scale invariant feature transform, and optical flow. The two main categories are geometric features and appearance features.

Another literature presents a novel method for analyzing job satisfaction based on individual emotions and desired job emotions. The model uses human emotion recognition, with faces identified, cropped, and converted to grayscale. The Indian Movie Face Database (IMFD) is used for emotion training, and Local Binary Pattern Histogram (LBPH) is used for training each pixel.

The Real-time Employee Sentiment Recognition System (RtEED) (Anjaneyulu, 2023) uses machine learning to detect employee sentiment, capturing, and highlighting emotional states. It uses advanced algorithms to process facial expressions, providing immediate insight into employee well-being. This system aims to transform workplace dynamics and increase job satisfaction, productivity, and overall satisfaction, offering significant advancements in emotion recognition and employee well-being. (Tumakuru et al., 2021)

Table 3

Summary of included studies

Topic	Method/Algorithm	Remarks	Accuracy
Detecting Employee Emotions	Bezier Curve	Existing dataset	-
Emotion Recognition from Ensemble of Features	Hierarchical Gaussianization (HG), SIFT, Optical Flow; SVM	Real world dataset, 10 actors	85%
Emotion Recognition	Discrete Emotion Models (DEMs), Dimensional Emotion Models (DiEMs)	Existing dataset	78.5%
Emotion Recognition from Facial Biometric System Using DCNN	Keras, TensorFlow, CNN Mode	Existing dataset	90%
Facial Expression Recognition	Dilb Face Recognizer, Local Binary Pattern Histogram	Indian Movie Face Database (IMFD)	85%

Engagement Detection	ResNet, Cohen's Kappa measure	Existing dataset	87.5%
Real-Time Employee Emotion Detection System (RtEED)	OpenCV, TensorFlow, ML Model	Existing dataset	82%
Emotion Recognition System	Machine Learning, Deep Neural Networks	Machine Learning, Deep Neural Networks	88%
Automatic Face Emotion Recognition	-	Existing dataset	79%
Machine Learning Based RealTime Employee Emotion Detection	-	Existing dataset	83%
Deep Belief Network (DBN)	DBN	Existing dataset	-
Fundamentals of RNN and LSTM Networks	RNN, LSTM	Existing dataset	-
Faster R-CNN for Object Detection	Faster R-CNN	Existing dataset	-
Emotion Recognition based on CNN	CNN	Existing dataset	89%

Examining and assessing existing methodologies reveals a considerable benefit in fixing the gaps in current models. Many studies have achieved high levels of accuracy. Typically, between 82 and 90% (Begaj et al., 2020) but they frequently used tiny, homogeneous datasets with low topic diversity. This limits generalizability in actual business settings.

Ensemble learning methods showed considerable advantages over single CNNs or transfer learning models. When dealing with class imbalance, ensembles improved accuracy by 1-4 percentage points and produced higher macro-F1 scores across all experiments assessed. For example, boosting methods (e.g., AdaBoost, XGBoost) enhanced recognition of minority classes such as fear and disgust, whereas stacking methods incorporating multiple CNNs obtained the highest overall accuracy (>90%). From the point of view of IT, these enhancements result in more robust and dependable monitoring of employee emotional states. Lightweight ensemble models, when deployed over efficient backbones like MobileNet or EfficientNet, could provide real-time workplace integration. (S. Li & Deng, 2022) However, there are still issues to assure justice, interpretability, and employee privacy.

Recent studies validate these conclusions. (Hussain et al., 2023) suggested a two-level CNN ensemble that obtained more than 90% accuracy on benchmark datasets, demonstrating ensemble power in FER. (S. Li & Deng, 2022) conducted a detailed survey of deep FER, emphasizing ensembles as a major direction. (Kollias & Zafeiriou, 2021) proposed a uniform framework for affect analysis in the wild, while (Ali Mollahosseini, 2017) expanded AffectNet to improve diversity. (Heidari, 2022) demonstrated that attention-based ensemble transfer learning enhanced performance on uncontrolled datasets (Heidari, 2022) such as FER+ and AffectNet. (Petluru, 2024) demonstrated that stacking ensembles of pre-trained CNNs regularly outperformed individual transfer learning models (Hussain et al., 2023) with accuracy levels close to 97%. These studies, while not part of the original seven included works, reinforce that ensemble-based FER continues to advance and strengthen workplace applicability.

Conclusion

This review has certain limitations. First, only seven papers met the demanding inclusion requirements, limiting the scope of integration. Second, repeatability was found to be a systematic issue: none of the investigations featured open-source implementations or fully described hyperparameters. Third, while ensemble approaches demonstrate increased accuracy, their computational complexity may impede adoption in resource-constrained workplace systems. Finally, cultural differences in emotional expression continue to provide a problem for FER models, potentially affecting fairness and inclusivity in workplace applications.

This review contributes to the field of emotion recognition by examining existing methodologies and datasets used for modelling emotional responses. The study highlighted that current approaches often rely on limited datasets with a small number of actors and use diverse programming languages, achieving significant but constrained accuracy. While various algorithms and techniques have been employed, including ensemble learning (S. Li & Deng, 2022), (Hussain et al., 2023) and different deep learning models, the limited actor diversity has led to less efficient emotion recognition. This review underscores the importance of expanding the dataset to include a greater number of actors to capture a more comprehensive range of emotions. By addressing these gaps, the model is expected to achieve higher accuracy and effectiveness compared to existing approaches. The findings aim to enhance the development of more robust emotion recognition systems and guide future research to overcome the current limitations and challenges in the field.

This review demonstrates how far emotion identification has progressed while also highlighting how much more space for improvement remains. Most recent studies achieve good accuracy using CNNs, transfer learning, and ensemble approaches, but they still rely on small, constrained datasets that cannot accurately represent the range of real human emotions. This renders present methods ineffective in real-world job contexts. Increasing datasets that include more individuals as well as a wider range of emotions will be essential to developing models that are not only more accurate but also more inclusive and reliable. By eliminating these gaps, future research can focus on developing really accurate emotion identification algorithms that better reflect the complex nature of human expression and promote healthier workplaces.

The conclusion summarizes the key findings and their implications. It reiterates the importance of the research and its contributions to the field. This section should be concise and focused, emphasizing the main points and leaving a lasting impression on the reader.

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