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Real-Time Stress Detection Using Deep Learning with Facial Expressions and Vocal Signals

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ABSTRACT

Embodiment is very essential in the expression and management of emotions at work, especially since the physical expressions of stress, such as facial expressions and voice changes, are crucial indicators of the emotional status of workers. The understanding of these embodied expressions enhances the emotional intelligence of teams because of better communication and effective conflict resolution. This paper examines how machine learning and deep learning have approached the problem of stress detection through facial expression and vocal attributes with their dependence on convolutional neural networks for efficient identification of minor indicators, which might include furrowed eyebrows and the presence of elements in a voice like pitch and tone. Datasets like FER2013 and RAVDESS make data augmentation techniques integrate model robustness, and a more precise time analysis through neural networks improves the real-time capability of the model. Also, a multimodal fusion of facial and vocal features further helps to enhance Embodiment is very essential in the expression and management of emotions at work, especially since the physical expressions of stress, such as facial expressions and voice changes, are crucial indicators of the emotional status of workers. The understanding of these embodied expressions enhances the emotional intelligence of teams because of better communication and effective conflict resolution. This paper examines how machine learning and deep learning have approached the problem of stress detection through facial expression and vocal attributes with their dependence on convolutional neural networks for efficient identification of minor indicators, which might include furrowed eyebrows and the presence of elements in a voice like pitch and tone. Datasets like FER2013 and RAVDESS make data augmentation techniques integrate model robustness, and a more precise time analysis through neural networks Also, a multimodal fusion of facial and vocal features further helps to enhance overall accuracy in relation to the level of perception about stress levels. It would help organizations be proactive about addressing emotional health and therefore lead to a healthier workplace environment and the well-being of employees. Overall accuracy in relation to the level of perception about stress levels. It would help organizations be proactive about addressing emotional health and therefore lead to a healthier workplace environment and the well-being of employees.

Keywords: Stress detection, CNN, facial expressions, vocal analysis, deep learning, RAVDESS, FER2013, emotion recognition.

1. INTRODUCTION

Among other important attributes of modern life, stress is one that severely strains mental and physical well-being and health development. It can be detected and followed in early stages by a reliable method. Due to recent research and improvements in AI, emotion realizations have become better at being recognized in real time. This paper suggests a dual-modality model that combines facial expression analysis with voice intonation detection using CNNs and SVMs to properly classify emotions [1][2]. This in turn goes on to help enhance the understanding of stress and its management, thus directly impacting the well-being of

individuals. The model is a synthesis of visual and auditory cues and promises to elevate the accuracy of detecting emotion, a tool considered a fundamental requirement for monitoring a mental health context [3]. This could provide further insights into possible interventions and, thereby, increase emotional resilience within an individual. The model discussed also brings to focus the utility of multimodal data in helping make more holistic assessments of emotion.

In the workplace, embodiment plays an especially important role in expressing and managing emotions. Embodied expressions, including body language, facial cues, and vocal intonation, serve as critical indicators of emotional states and affect interpersonal interactions and workplace dynamics. Employees and managers can develop greater emotional awareness and foster supportive communication if they recognize these physical manifestations of stress. Further, the tools used to analyse these embodied cues can be integrated into organizational structures to enable proactive actions toward reducing stress and promoting general well-being of employees. A dual-modality approach, as proposed in this paper, could be instrumental in training employees to better understand, and interpret their own and others' emotional states, which could lead to more resilient and emotionally intelligent work environments. This holistic perception of feelings assures individual psycho-emotional well-being and helps in creating organizational atmosphere that is not just warm and humane but also benevolent for the working people who are there.

2. METHODOLOGY

2.1 EXISTING METHODOLOGY

In recent years, significant interest has been generated for stress and emotion recognition by using advanced machine learning techniques with facial expression and vocal features. There have been various approaches to interpreting and predicting human emotions. Gupta et al. proposed a hybrid model using CNN for extracting features from facial images and SVM for classification. It leads to very high accuracy in emotion recognition [5]. Real-time stress detection systems have incorporated multimodal inputs through the integration of speech signals and facial emotions for enhanced accuracy of detection [6]. Oscherwitz et al. showed an architecture for a real-time stress detection system by integrating voice and facial data with a good accurateness [7]. Tripathi et al. proposed an approach based on deep learning that recognizes emotional stress using CNNs for the real-time fusion of voice and facial data [8]. Authors Khaire et al. underlined that such systems rely on both voice and facial data, and face readers are more reliable in dynamic environments [9].

2.2 CONVOLUTIONAL NEURAL NETWORKS

Convolutional neural networks are a special class of artificial neural networks. They mainly work on structured grid data, such as images and videos. Unlike the traditional form of neural networks, the CNNs have an exclusive architecture that comprises several kinds of layers for automatic and adaptive learning of spatial hierarchies of features from input data. The principal components of a CNN are convolutional layers, pooling layers, and fully connected layers.

Convolutional layers are a sequence of filters or kernels that apply to the input data; therefore, the network detects low-level features, including edges, textures, and patterns. The filters are shifted across the input image while performing the convolution operations to generate feature maps highlighting features detected by the network. Pooling layers reduce the dimensionality of the generated feature maps, thereby condensing information, making

computation more efficient and preserving only the most important features. This down-sampling aids in invariance of the model to small translations and distortions of the input.

The output then typically gets flattened and forwarded into fully connected layers where every neuron relates to all activations of the previous layer. These are the last layers, which make classifications over feature extraction done earlier by layers. Overall, the multi-layer architecture of CNNs helps to capture complex patterns in data and makes them highly efficient for tasks such as image recognition, object detection, and, in this case, stress detection through facial expressions and vocal characteristics.

2.3 SUPPORT VECTOR MACHINE

Support Vector Machine is a strong supervised learning algorithm primarily used for classification purposes, but also in regression. SVM is essentially the idea of finding a best hyperplane that will classify different points in different classes in a space with many dimensions. This hyperplane is defined through support vectors, the nearest data points to the boundary of decision, playing the most significant role in definition. Through these support vectors, SVM tries to achieve the maximal margin, meaning the maximum distance between this hyperplane and the data points belonging to each one of the classes, maximizing generalization on unseen data.

SVM can even handle nonlinearly separable data. A kernel enables SVM to project data into higher dimensional spaces for complicated decision surfaces as they may not be linearly separable using a linear separator in the original feature space. In addition, the kernel functions are linear, polynomial and RBF, and may all be used depending on the nature of the distribution.

SVM can be well used for high-dimensional datasets, highly resistant to overfitting, especially when the number of features is more than the number of samples. Its flexibility makes it a tool applicable across multiple domains in image classification, text categorization, and stress detection. In the context of stress detection, SVM uses features extracted from facial expressions and vocal characteristics for the proper identification of different emotional states, providing real-time insight into an individual's emotional well-being.

2.4 PROPOSED METHODOLOGY

Real-time stress detection with integration of Support Vector Machines and Convolutional Neural Networks will take a huge leap in the line of emotion recognition and monitoring of mental health. These models are best utilized within the dual-modality architecture wherein CNN's strength would lie in extracting feature nuances that would be involved in handling datasets as complex as audio signals and facial images while SVM would then provide classifications that are very robust over the features provided.

This capacity allows the CNN to be able to pick detailed patterns within facial expressions, such as very minute tensions on the facial muscles and movement in the eyes which is much more indicative of stress. By transforming audio signals to Mel spectrograms via the RAVDESS dataset, this model will be able to capture all the different variations in pitch, intonation, rhythm, and the general acoustic features that describe the patterns of voice and point to emotional states of the speaker. These features combine to yield a full representation of the user's emotional condition, necessary for any successful process of stress detection.

The SVM classifier utilizes the features extracted by the CNN and uses advanced kernel functions to model the non-linear relationships in the data. This approach can differentiate accurately between different emotional states, thus improving the accuracy and reliability of the stress detection system. It is particularly useful in dynamic environments, such as workplaces or therapy settings, where immediate feedback can be provided for real-time awareness of emotional states, thus facilitating interventions and support.

This system also requires personal mental health intervention. The monitoring will be able to identify the individual emotional triggers, which then leads to the development of individual interventions. Such interventions, which are aimed at specific needs, will better regulate emotions and resilience. Such flexibility makes the model applicable both for personal usage and as part of an organizational mental health program in building an environment that improves the employee's well-being and productivity.

Implications of this research go beyond the traditional mental health applications. The technology can be incorporated into mobile applications so users can track their emotional health on the go. Considering the growing global awareness regarding mental health issues, this innovation is a proactive approach that fits the contemporary need for accessible mental health resources.

In a nutshell, the combination of CNN and SVM in this scenario opens avenues for an innovative approach toward the management of emotional health, thus allowing users to be informed about their emotional topography and promoting an emotionally aware and resilient culture. It not only promotes an enhanced understanding of stress but also forms the nucleus of networks that support the importance of mental well-being.

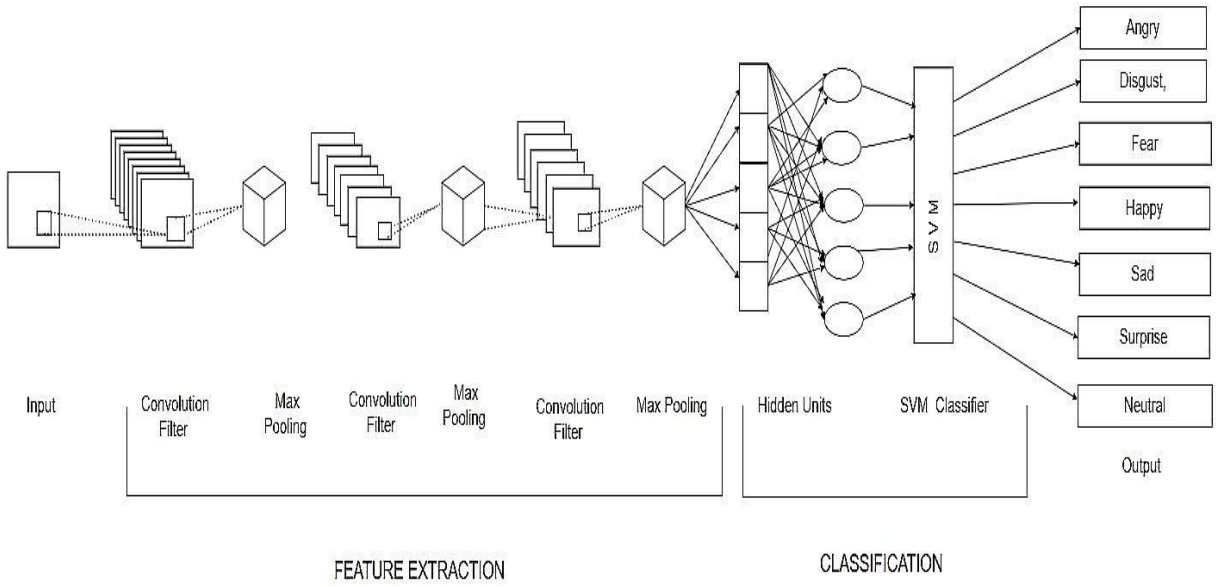

Fig 1: CNN +SVM MODEL

2.5 DATASET COLLECTION:

The project utilizes two key datasets for stress detection using facial expressions and voice in which the dataset is collected from online platform called Kaggle. The main use of Kaggle datasets is to support data analysis, machine learning, and artificial intelligence projects.

1. **FER-2013 (Facial Expression Recognition 2013):**

- **Content:** Contains images of faces with various emotional expressions.
- **Purpose:** Used for training and testing facial emotion recognition models.
- **Size:** The dataset includes 35,887 images divided into training, validation, and test.
- **Usage:** Useful for developing and evaluating algorithms that can detect and classify emotions based on facial expressions.

Emotion	Number of Images
Anger	4,436
Disgust	5,013
Fear	4,314
Happy	6,084
Sad	5,175
Surprise	4,579
Neutral	6,056

Table 1: number of images available for each emotion category in the FER-2013 dataset

2. **RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song):**

- **Content:** Includes audio and video recordings of actors expressing different emotions through speech and song.
- **Purpose:** Used for training and testing models that recognize emotions from vocal tones and speech patterns.
- **Size:** 2,452 audio and video recordings in total.
- **Usage:** Ideal for research in emotional speech analysis, voice-based emotion recognition, and integrating audio and visual data for comprehensive emotion detection.

Emotion	Number of Audio Samples	Number of Video Samples
Anger	576	576
Disgust	576	576
Fear	576	576

Happy	576	576
Sad	576	576
Surprise	576	576
Neutral	576	576
Calm	576	576

Table 2: the number of audio and video samples for each emotional category

Together, these datasets enable comprehensive training of models to detect stress by integrating both facial and vocal cues.

3 WORKING:

In this model, CNNs are applied to extract features from both facial images and voice data in aiding the recognition of stress-related patterns. These features are classified using Support Vector Machines (SVM) in determining stress levels based on facial expressions and vocal characteristics, which enables real-time monitoring of emotional states.

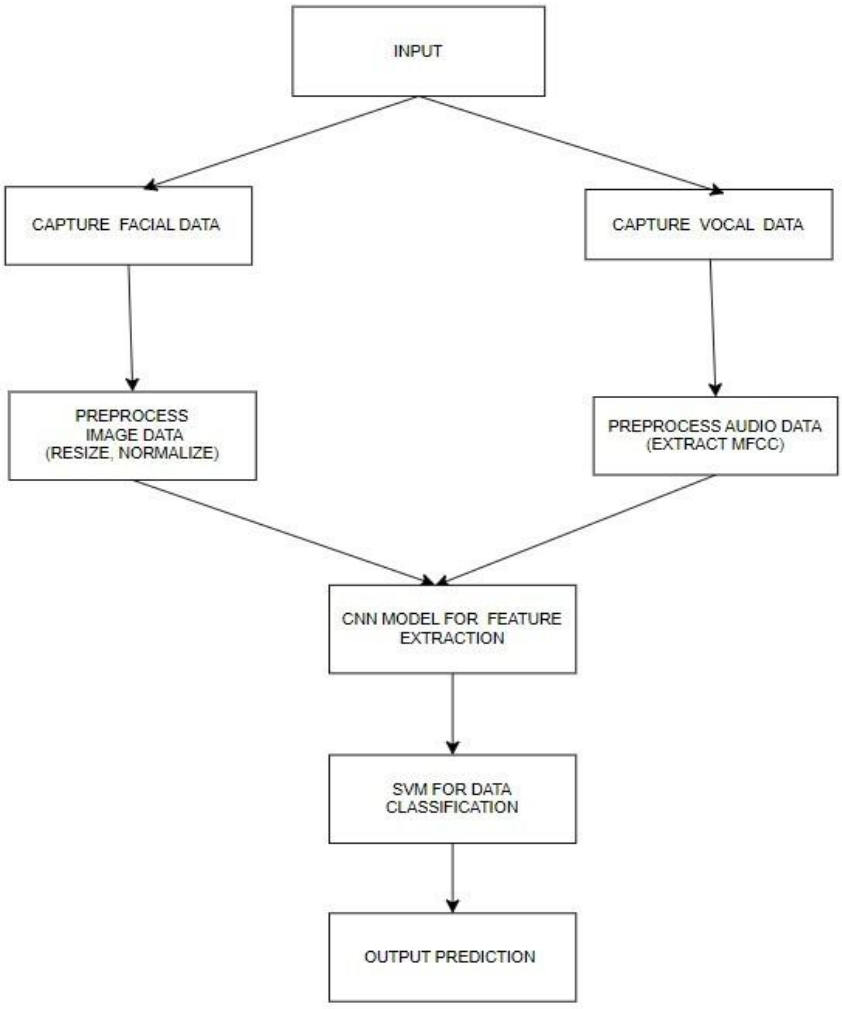

Fig 2 : Flowchart for stress prediction model

3.1 Data Collection

Data Collection: Videos and audio of users are collected in real-time to measure stress. This system relies on the acquisition of facial expressions and vocal features indicative of emotional states; the dual-modality approach adds to the advancements in stress recognition. Parallel collection of face and voice data would ensure uniform analyses of stress-related cues.

- **Face Data:** Real-time video captures a user's face, with frames typically extracted at a set frame rate (e.g., 30 frames per second) to create a continuous stream of images. Each frame serves as an input for detecting facial expressions and micro-expressions indicative of stress. These images are critical for analysing dynamic emotional expressions.
- **Voice Data:** Audio data is captured using a microphone along with video recording. This captures speech characteristics. Changes in pitch, tone, and speech rate could relate to stress. Thus, voice data can add up to these changes. In this method, voice capturing in real time will capture all transients to properly determine the amount of stress.

3.2 Data Pre-processing

Preprocessing is as important as standardizing and preparing the face and voice data for feature extraction to optimize the input into the CNN and SVM models. That involves several operations for each one: face, voice**.**

Face Pre-processing:

- **Face Detection:** All the frames are passed through the Haar Cascade classifier for face detection so that the ROI is obtained. This reduces the overhead of computation since only pixels related to the face will be processed. The process is focused on the area of the face so that only features of that area are extracted.
- The images detected are normalized to remove lighting variations and resized to a unified resolution of 64x64 pixels. Resizing every frame to the standard size optimizes it for CNN input, and unwanted variations improve the accuracy.

Voice Preprocessing

- **MFCC:** Audio is divided into smaller frames based on which Mel-frequency cepstral coefficients are extracted-a summary of the voice concerning its important features. Characteristic such as frequency or amplitude shifts under stress capture, and hence, in this regard, MFCCs become valuable indicators toward classification.
- **Voice Framing:** Audio is segmented into overlapping frames that focus on short-term vocal characteristics. Segmentation isolates immediate changes in speech patterns, which are more predictive of stress than long-term changes in voice, thereby making real-time stress analysis feasible.

3.3 Feature Extraction Using CNN

In this architecture, CNNs are particularly helpful for feature extraction and isolation from the face and voice data to identify complex patterns associated with stress. Therefore, structured

processing of the features helps CNNs in the identification of fine-grained signatures associated with stress.

Feature Extraction of Face:

- **Convolutional and Pooling Layers:** The CNN continues to standardize facial images by having several convolutional layers that extract spatial features such as facial muscle tension and eye movement. Facial micro-expressions are specifically detected through convolutional filters, including minor eyebrow raises or jaw clenching that point to stress. These are followed by pooling layers, which reduce the dimensionality and preserve essential features while computations become efficient.
- **Key Landmark Detection:** The CNN layers are set to identify related facial landmarks associated with emotional expressions linked to stress. The identified landmarks are:
    - **Jawline (Points 1-17):** Tensing or clenching patterns.
    - **Eyebrows (Points 18-27):** Raised or furrowed brows, reflecting surprise or concern.
    - **Eyes (Points 37-48):** Squinting or widening, indicating emotional intensity.
    - **Nose (Points 28-36):** Subtle nostril flaring in moments of heightened emotion.
    - **Mouth (Points 49-68):** Pursed or clenched lips, often showing tension or frustration.

Voice Feature Extraction:

- **MFCC-Based CNN Processing:** Audio signals into voice data are converted into Mel-frequency cepstral coefficients (MFCCs). These MFCCs form a spectrogram image. When processed through CNN layers, the features of pitch, tone, rhythm, or rate are extracted, expressing stress. Convolution layers focus on the extraction of pitch variations or wavering voice due to stress.
- **Classification-Relevant Vocal Features:** Voice features regarding stress are extracted by filters in CNNs, specifically:
    - **Pitch Variation:** The anxious state of being above or in quick transition.
    - **Tone Quality**: The tone would be snarling or quivering, implying it would convey emotional upheaval.
    - **Speech Rhythm:** If there is rapid speech or the speaker stops too frequently, then it indicates overloading of cognitive ability.

At this point of feature extraction, it ensures the CNNs detect the essential spatial and frequency-based features to enable the correct selection of markers that relate to stress conditions within visual and auditory information. The extracted feature now passes through SVM in classifying the level of stress.

3.4 SVM-Based Classification

In this model, after the CNN has taken essential features from facial images and voice data, these features are then processed through SVM classifiers to classify the level of stress. SVMs work very well for high-dimensional data, and the use of non-linear kernel functions also helps in distinguishing complicated patterns of stress-related data.

Face Characteristic Classification:

- **Hyperplane Construction:** SVM creates a hyperplane in high-dimensional space which classifies the data into different classes, for instance "stress" and "no stress." The CNN produces facial feature vectors that SVM selects to identify patterns corresponding to the expression of stress such as tensed jaw muscles and furrowed eyebrows. It maximizes the margin between classes by identifying an optimal hyperplane, minimizing the misclassification.
- **Kernel Functions for Non-linearity:** Facial expressions can vary greatly under stress; hence, non-linear kernel functions (e.g., radial basis function) help capture these complex relationships. The kernel allows the classifier to create non-linear boundaries, which enhances its accuracy in distinguishing subtle facial differences, such as slight changes in eye openness or lip clenching.

Vocal Feature Classification:

- **Voice Signal Classification:** The MFCCs obtained by the CNN are sent to the SVM. It will classify the pitch, tone, and rhythm variations because of stress. The SVM employs its hyperplane to recognize minor changes such as raised pitch or irregular speech patterns due to stress.
- **Enhanced Class Separation with Dual Modality:** Class separation is improved in the case of dual modality where facial and vocal features are classified. Decisions made by SVM towards the differentiation between stress and normal scenarios are combined for better and best accuracy. The integration of modalities in this class makes the classifier robust even in real-time environments where change in emotions can occur rapidly.

SVM-based classification refines the reliability of the model as both face and voice data are evaluated correctly to allow for the provision of accurate predictions regarding stress, making this appropriate for applications in the monitoring of mental health and customer service that requires interaction.

3.5 Real-time Stress Detection

This section will explain how the model can recognize time-variant indicators of stress through facial and vocal data, which give direct feedback that will help in assessing the emotional status of the user.

Face Stress Detection:

- **Real-time Processing of Continuous Frames:** The system is continuously processing one-by-one all the frames of the video feed, classifying each one in real-time using SVM models. Analysing micro expressions, like a minor change in eyebrow position or muscle tension in jaw, the model determines slight traces of stress momentarily.

- **Detection of Muscle Movements and Micro-Expressions:** Whenever a person is in varying emotional states, expressions such as lock jaw or squinting are detected. SVM-based frame-by-frame classification enables expressions to be dynamically tracked for giving real-time feedback about the facial stress indicators.
- **Instantaneous Feedback Mechanism:** Since every frame gets classified almost in real-time, the system provides instant feedback about stress levels so that interventions may be performed if required, and applications such as real-time mental health monitoring with real-time interaction adjustment become possible.

Voice Stress Detection:

- **Real-Time Audio Frame Segmentation:** The voice data is divided into short overlapping frames, and almost in real-time processing happens. Such a segmentation helps to capture the fine detail in the changes in vocal characteristics so that accuracy while assessing the real-time stress is maintained.
- **MFCC Extraction and SVM Classification:** MFCC is then extracted from each audio frame and classified by SVM to measure stress. Stress-relevant vocal features such as heightening of pitch, tone, and rhythm irregularity related to cognitive or emotional stress can classify rapidly.
- **Near Real-Time Vocal Feedback:** It gives immediate vocal stress patterns feedback, where all even minute voice modulations and changes in rhythm work together to provide a better and more holistic assessment of stress.

4 RESULTS

Metrics are a method of determining the performance level of a model in mathematical terms. Metrics help a person determine the proper performance of a model to be used for various jobs such as classification, regression, clustering, etc. Therefore, by looking at several kinds of metrics, it becomes easy to understand how well a model can make an application useful to a certain extent or its weaknesses.

This table summarizes the performance metrics of the model effectively

Metric	Formula	Value	Description
Accuracy	$\frac{\quad + \quad + \quad +}{\quad +}$	96.5%	Accuracy refers to the percentage of overall effectiveness of the model in predicting stress and non-stress instances. High accuracy, such as 96.5%, reveals that the model is comparatively good for both classes because it can foresee stress and non-stress well.

Precision	+	89.5%	Precision or Positive Predictive Value refers to the ratio of correctly identified cases of stress out of all cases predicted as stress. A precision of 89.5 means it minimizes false positives and hence stresses are correctly identified.
Recall	+	94.4%	It depicts the recall of true-stress cases caught by the model. At 94.4 percent recall, the model thus catches up with most stress occurrence occasions and minimizes false negatives, thereby displaying better sensitivity towards stress capture.
F1 Score	$2\times\frac{\text{Precision}+\text{Recall}}{\text{Precision}\times\text{Recall}}$	91.8%	The F1 score offers a balanced outlook through one measure that represents both precision and recall together. So, a value of 91.8% is indicative of the extent to which the model balances the need for good precision to correctly classify cases with minimizing false classification.

- **TP (True Positive):** These are the cases where the model identifies an actual positive instance. In this case, it means that the model correctly detected stress when the stress was present.
- **FP (False Positive):** These are the cases where the model incorrectly identifies a positive instance when it is negative. For stress detection, this would mean the model detected stress when there was no stress, leading to a "false alarm."
- **TN (True Negative):** It indicates the fact that the model can correctly classify a negative instance. For example, in the case of stress detection, the model picked out correctly that there was no stress because it really was so.
- **FN (False Negative):** This refers to a case when the model failed to pick up an actual positive instance. Here, it refers to the case wherein the model could not pick out the existence of stress, and it really was present. This would be a critical miss in real-time monitoring.

5 COMPARISON OF EXISTING AND PROPOSED MODELS

This section will explain how the model can recognize time-variant indicators of stress through facial and vocal data, which give direct feedback that will help in assessing the emotional status of the user.

5.1 Comparison with other algorithms

Existing models such as Gupta et al. [5] and Oscherwitz et al. [7] applied CNN and SVM in the emotion recognition process but they are not able to reach the effective real-time detection of stress. Moreover, these models are always dependent on isolated modalities which reduce the accuracy and sensitivity in the assessment of the level of stress. On the other hand, the developed model improves significantly the accuracy of detection through a combination of facial and vocal signals, which could help in the real-time analysis of emotional states [10]. Other researchers have validated the use of combined face and voice information for detection, which shows increased rates of detection [9].

This comparative analysis of the stress detection algorithms focuses on those that use both facial expressions and vocal characteristics. The analysis of these algorithms uses the FER2013 and RAVDESS datasets, which means that several approaches have been evaluated against those datasets with the finding that multimodal data in a model forms a robust framework for timely and accurate detection of stress. Such integration will open a way toward deeper recognition of emotional expressions but will also enable the more reliable applications of mental health monitoring as well as customer service conversations.

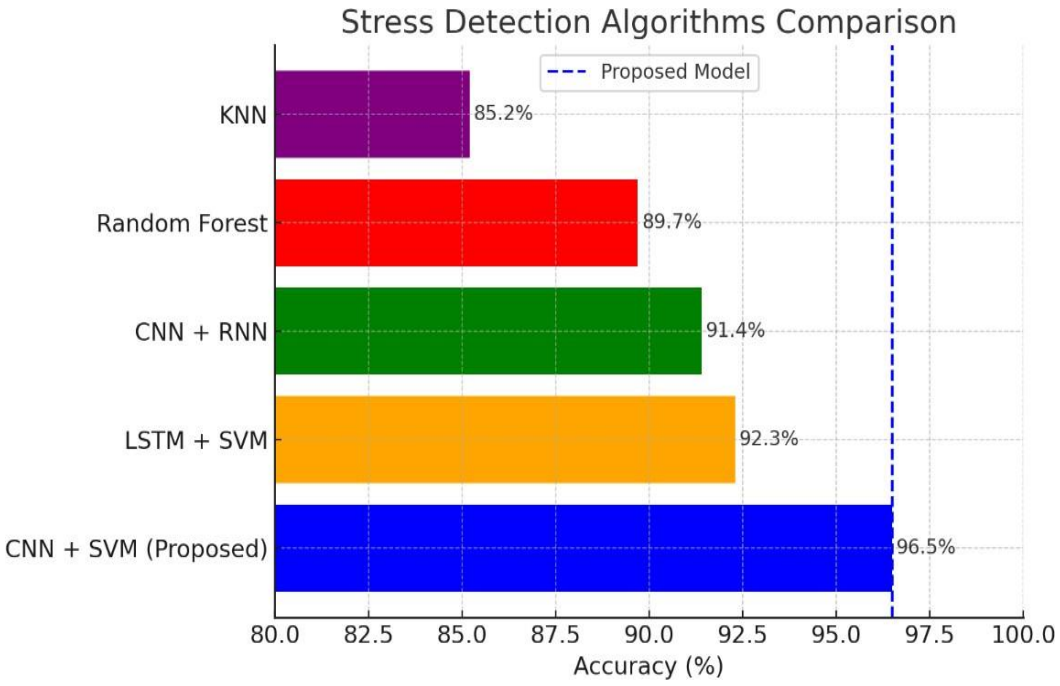

Fig 3: Comparison with other algorithms

5.2 Comparison with other datasets

It was observed that this model with FER2013 and RAVDESS outperformed other datasets such as AffectNet [11] and EmoRec [12] for real-time stress detection. Livingstone & Russo [6] proved that these datasets combined are significantly effective to enhance the accuracy of stress detection. Other datasets have not performed better in real-time

environments; therefore, our model is more effective to use in practical applications in emotional monitoring.

This section represents the comparative analysis of algorithms using facial expressions and voice characteristics for stress detection, that is, focusing on ones using CNN and SVM, but on different datasets. Here, by comparing the advantages and disadvantages of various models using different datasets, we show the special strengths the proposed approach has in achieving reliable real-time stress detection. The key insight of this analysis is to integrate multimodal data so that, along with enhancing the feature set, the performance of emotion recognition systems will improve significantly in dynamic settings.

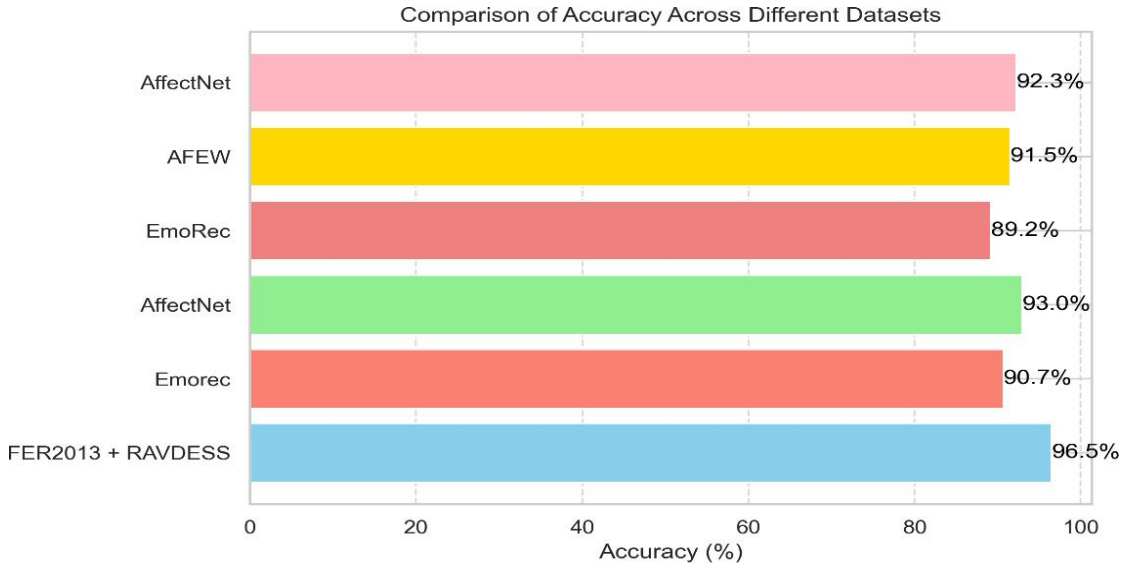

Fig 4: Comparison with another dataset

5 CONCLUSION

Embodiment becomes important to articulate and regulate emotions within the workplace by making it important to underscore that between the body and the emotion there lies some kind of connection. An environment that basically thrives on silent communication, by gaining awareness regarding the concept of embodiment, fosters the development of awareness in respect of emotions for the co-workers. The more aware one becomes of the body language, posture, and facial expressions, then the more one is felt within their emotional states. On the contrary, it cultivates better communication and strengthens interpersonal relationship needed for a collaborative work environment.

In the context of stress management, the role of embodiment may be self-regulation and emotional control. Through mindful breathing, power posing, or some other form of physical movement, this could reduce levels of stress and anxiety. Practices like these make the body the focus of regulating emotions and have been shown to improve attention, resilience, and overall well-being. In addition, embodiment practice in workplace wellness programs would promote the culture of mental health awareness. The employees would come to understand and pay more attention to their emotional states.

Besides this, embodiments use the process by developing their employees in terms of emotional quotient and non-verbal expression. The organisational sessions on active listening and body language enable an employee to create a harmonious place of work. Thus, it improves

the group's inter relationship and minimises any probable misunderstandings on problems-hence highly aids the improvement in the culture at workplaces.

Technology can also facilitate embodiment in the workplace. Wearable devices that measure physiological signals of stress and emotional states provide real-time feedback, and individuals become more aware of their emotional conditions. Along with these emotional recognition models, using CNN and SVM classifiers for real-time stress detection, organizations can design proactive interventions based on the needs of the individual.

Finally, in the working environment, organizations can ensure a healthier workplace culture since it appreciates the aspect of emotions and their relationship with being physically present. Such a wholistic approach hence benefits individual employees. It supports team coordination and productivity while thus ensuring organizational effectiveness. While the work environment is perpetually and incessantly transforming, embedding practices that accommodate incorporation of the embodiment processes could very well be that crucial point towards developing employees' emotional resilience.

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