

# Advanced computational framework for effective stress prediction among corporate employees

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**Abstract** Academic exploration dedicated to employee stress prediction works to develop more productive work environments that promote better employee health. The development of machine learning (ML) algorithms yielded predictive models which precisely measure employee stress through diverse data about employees. The current models struggle with overfitting as well as poor interpretability and insufficient accuracy because they come from inadequate feature engineering and inefficient model tuning processes. To resolve existing limitations, the exploration introduces the Chimp Tuned Light Gradient Boosting Machine (CT-LGBM) as a new machine learning solution for stress prediction in corporate workplaces. The investigation leverages a publicly available dataset containing employee stress-related attributes. The data preprocessing procedure contains normalization steps that scale all features into comparable ranges to enhance performance and stability of the system. The researchers use PCA to deal with high-dimensional data and discover the most vital features because it effectively eliminates redundant elements without distorting meaningful data relationships. This investigation makes its primary contribution by uniting an optimization method based on chimpanzee intelligence with Light Gradient Boosting Machine (LGBM). When used as a predictor the CT-LGBM model successfully finds model hyperparameters that lead to better accuracy as well as generalization capabilities than standard systems. Evaluation of CT-LGBM model performance demonstrates better results when compared to regular methods through accuracy measurements and precision and recall and F1-score assessments. The proposed CT-LGBM model delivers outstanding performance by attaining an F1-score of 0.9798 and recall of 0.9793 as well as precision of 0.9820 and accuracy of 0.9840. The CT-LGBM model shows strong effectiveness for employee stress prediction when compared to standard methods according to evaluation results. Stress prediction benefits from advanced optimization techniques in ML models which produce a highly effective solution for organizations to evaluate and minimize workplace stress thus promoting employee wellness and performance.

**Keywords:** stress prediction, chimp tuned light gradient boosting machine (CT-LGBM), advanced computational framework

## 1. Introduction

Workplace stress has grown to be a serious issue in today's quickly changing business environment, impacting workers' general well-being, productivity, and health. Many industries are experiencing increased levels of stressors including overworked expectations, job insecurity, and inadequate work-life balance (Soto et al., 2021). To implement stress-reducing treatments tailored to promote employee mental health and productivity, firms need to understand and predict the stress levels of employees in their corporations. The present a complex computational model that predicts stress among corporate workers through data analytics and innovative techniques (Booth et al., 2022). Workplace stress is wider, ranging from psychological stress to physical, and emotional exhaustion. It adversely affects employee involvement, work enjoyment, and even the quality of making decisions it often leads to absenteeism and attrition. Other long-term health conditions that have been connected with stress include depression, anxiety disorder, and cardiovascular diseases have been associated with stress by investigation (Katarya & Maan, 2020). The managing stress to determine maintaining a workforce and ensuring maximum output at work. Although stress management in organizational settings is gaining more importance, stress anticipation remains a challenging task (Morshed et al., 2022). Many organizational and individual variables, such as workload, interpersonal connections, and coping strategies influence stress. The common methods of measuring stress, such as assessments and interviews are cumbersome and subjective (Tonacci et al., 2020). The unique computational framework combines several data sources, such as self-reported measurements of well-being, employee work patterns, and

physiological signals. Organizations can take prompt and focused actions by exploiting the framework, which endeavors to provide accurate predictions regarding the levels of stress (Fukuda et al., 2020). Early stress detection will make interventions, such as modifications of workload, individualized wellness programs, and mental health assistance easier. The outcome is increased productivity both in terms of the organization and employees (An et al., 2023). It establishes the applicability in several organizations by emphasizing on improvement in the computational models and enlargement in the framework to take broader varieties of stress-related factors. Productivity and employee well-being can be significantly enhanced by having a solid stress prediction system in place. Through the implementation of timely interventions that include changes in workload, mental health services, and team dynamics, data-driven-informed proactive stress management can help firms reduce turnover, absenteeism, and burnout (Shaikh et al., 2023).

Human resource management is the component of organizational operations that aims to balance workloads and achieve the best possible results. An essential component of the equilibrium is stress management. Although deep learning (DL) technology has been utilized in several fields, HRM has not much use (Patel et al., 2023). The research suggests a novel DL application that uses accuracy and F1-score to automatically categorize employees as either anxious or contented. DL-based solutions for improve workplace and task balance are made possible by the network's superior performance over comparable methods. Companies are very concerned with employee well-being it affects stress and mood. The investigation looks into the sources of stress in working people using a neural network technique. Recurrent conventional neural network (R-CNN) training, identification, Gabor filter extraction (GFE), and augmentation are all part of the strategy (Sugumar et al., 2023). Center loss, a multi-task loss function that regulates discriminative deep features for face/non-face classification, is the research's primary contribution. The proposed method performs more accurately than R-CNN in identifying stress in information technology (IT) professionals. The work recommended an ML-based approach in the fight against workplace stress through the identification of indicators of stress and providing customized therapies using image processing and real-time monitoring (Chauhan & Renjith, 2024). Through data collecting and user interfaces, the system intends to make the workplace more attractive and improve worker efficiency and well-being by combating the increasing levels of stress professionals face in modern work environments.

Numerous individuals worldwide face stress, which is an ordinary mood disorder. Researchers have explored ML algorithms to track emotions as well as stress. Two datasets are employed to operate the algorithms: Mental Health in Tech (MHT) and Human Stress Prediction (HSP) to predict stress, anxiety, depression, and sleeping disorders (Joshi et al., 2024). The average testing accuracies of the HSP and MHT datasets are shown in the results. Stress is the most common issue that people face in their lives, especially at work, where it leads to absenteeism and health issues. Even though it can be challenging to identify, stress detection has gained attention in recent times. The research collected data on workplace stress through a video-based plethysmography program (Rodrigues & Correia, 2024). Several stress detection models were developed based on data collected from volunteers over two months; the greatest resulted in an accuracy. For forecasting worker turnover in industries of high stress, the research uses ML approaches. It applies a dataset with variables including performance measurements, levels of stress, and job satisfaction (Adeusi et al., 2024). The accuracy and precision of the models are assessed, ranging from logistic regression (LR), decision trees (DT), and random forests (RF), to neural networks. From the results, it seems that ML can be utilized in HR procedures to ensure that turnover rates are minimized. The data and the DL methods should be explored in the research. The attempts to forecast the stress levels of working professionals are using the DL model called the Deep Recurrent Neural Network (DRNN). The model consists of DRNN classification, feature extraction, optimum feature selection, and dataset preparation (Sharma et al., 2024). It addresses issues like higher design complexity, high misclassification rates, mistakes, and lower efficiency associated with ML and DL algorithms. The model also completes missing data and removes redundant characteristics.

### 1.1. Objective of this research

The objective of the research is to develop an advanced computer model to predict the stress level of corporate workers. The research aims to enhance employee health by providing personalized stress management advice based on predicted insights, thereby enhancing work environments.

### 1.2. Key contribution

- ❖ To improve employee stress prediction, the research presents a new predictive model called the CT-LGBM, which combines the reliable LGBM approach with optimization techniques inspired by chimpanzees.
- ❖ To effectively reduce dimensionality, preserve the most important information, and improve model performance, the research uses Z-score normalization for preprocessing, and feature extraction using PCA.
- ❖ Using innovative feature engineering and model tuning techniques, the research addresses prevalent issues with current stress prediction models, including overfitting, poor interpretability, and inadequate reliability.

The research is organizing into the following sections: Section 2 explains the comprehensive approach. Results were depicted in Section 3, Section 4 covered in discussion, and a conclusion is given in Section 5.

## 2. Materials and methods

This method involves data collection for predicting the stress of employees, preprocessing, and normalization of the Z-score to maximize the stress-prediction accuracy and employing the PCA for feature extraction. For efficient stress forecasting, the model CT involves LGBM with a team dynamic describe using chimpanzee behavior to determine the optimal stress-forecasting model. To make the highest prediction and find relevant coping mechanisms, the CT optimization tasks involved in managing stress for an employee. Figure 1 illustrates the recommended method's flow.

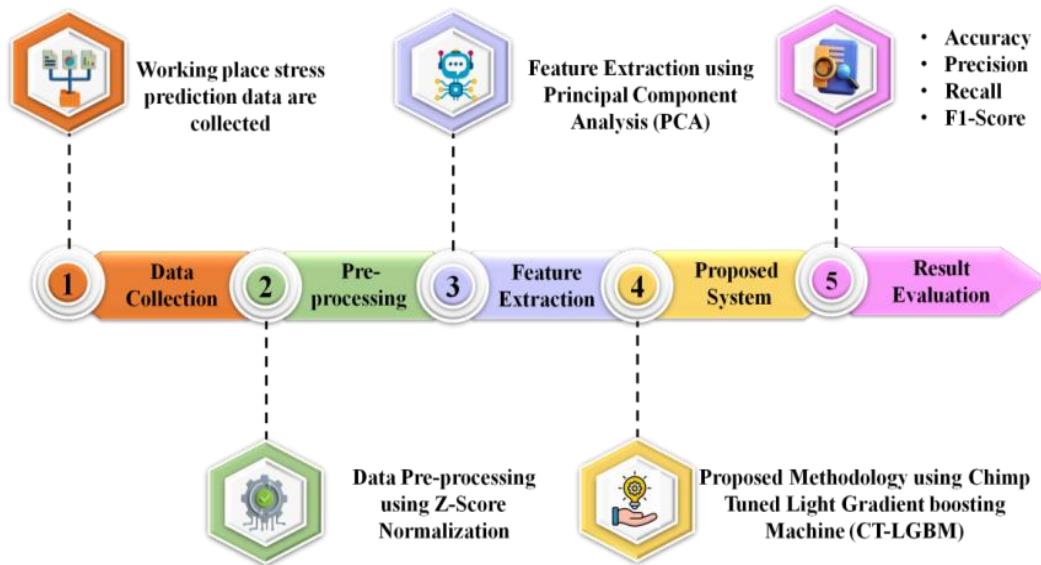


Figure 1 Recommended method's flow.

### 2.1. Dataset

The data were gathered from the open-source github website [GitHub - emiyacody/Stress-Prediction](https://github.com/emiyacody/Stress-Prediction). The main indicator of employees' stress levels is the mental exhaustion score, which is provided by the training and test files. The dataset also includes information on the employee's gender, company types, designation, resource allocation, and whether or not to work from home.

### 2.2. Z-score Normalization for Data Preprocessing

Data is normalized with the use of Z-Score Normalization, which provides continuous feature scaling in a manner that offers an improved predictive value of corporate workers' stress levels in dynamic work settings. The mean and standard deviation set for the scaled features, as is the case in uniformity of variables while applying Z-score normalization, during data preparation are both at 0 and 1, respectively. This method improves the predicted accuracy, which reduces the effect of outliers and different scales. Using this normalized data, predictive models are trained to assess variables like workload, job satisfaction, and work-life balance in dynamic settings to forecast employee stress. The approach helps companies to identify the workers who can be at high risk for stress and improve their management techniques. Equation (1) illustrates how the Z-score normalization increases a number from characteristic  $F$  to a previously undefined range.

$$u' = \frac{u_j - F_j}{std(F)} \tag{1}$$

The attribute needs to normalize the value of  $u'$ .  $F_j$  is the attribute mean, the normalized value is  $u'$ , while the attribute standard deviation is denoted by  $std(F)$ .

### 2.3. Feature extraction using PCA

The dimensionality reduction method entitled PCA reduces together large, complicated datasets into a smaller group of uncorrelated variables known as PCA. The PCA can be used to split many stress-related characteristics, such as workload, mental health, and work environment into their most essential components to assess them and effectively forecast stress in business employees. This enables a more effective model for stress level prediction, which facilitates the identification of the most important factors. Through the identification of underlying patterns in employee stress data, PCA improves predictive model accuracy. Emphasizing important stress signs also facilitates better decision-making. In general, PCA reduces the complexity of data, while keeping important details for stress-reduction techniques. The following describes the procedures for accurately estimating corporate employees' stress levels using several methods. The test vectors of the new stress



prediction data are represented as  $Z_r = (Z_1, Z_2, \dots, Z_l)$ , whereas the training vectors representing various employee data, such as work hours, workload, and personal well-being metrics, are represented as:  $Z_o = (Y_1, Y_2, \dots, Y_l)$ . For the training feature vectors, the covariance matrix is computed using equations (2) and (3).

$$\underline{Y} = \frac{1}{o} \sum_{l=1}^o Y_l \quad (2)$$

$$S = \frac{1}{o} \sum_{l=1}^o (Y_l - c) (Y_l - \underline{Y})^o = \Phi \Phi^o \quad (3)$$

The covariance matrix is represented by  $S$  in the equations above, while the training vector average is denoted by  $\underline{Y}$ . The following equation (4) can be used to get the eigenvalue  $\lambda_l$  and eigenvector  $H_l$  using this covariance matrix:

$$SH_l = \lambda_l H_l (1 \leq o) \quad (4)$$

Equations (5) and (6) are then utilized to reduce to  $n$ -dimensional space, and the training feature vectors  $U$  and  $Q$  are constructed using the to  $Q$  eigenvectors that correspond to the largest eigenvalues.

$$U = H_l (Y - \underline{Y}) (1 \leq l \leq o) \quad (5)$$

$$Q = H_l (Z - \underline{Y}) (1 \leq l \leq o) \quad (6)$$

The training vectors represent the various employee-related variables, which are stress level markers, such as workload, work-life balance, and job satisfaction. The test vectors correspond to the predicted stress levels obtained from real-time data, such as psychological, performance, and fatigue parameters. This approach enhances the prediction of stress levels and enables corporate environments to utilize more efficient stress management techniques by transforming these data inputs into numerical characteristics suitable for PCA.

#### 2.4. Chimp Tuned Light Gradient Boosting Machine (CT-LGBM)

CT-LGBM encompasses cooperative tactics of chimps to increase business settings stress forecasting by simulating team dynamics and coping practices. For example, employees can be designate as Attacker, Driver, Barrier, and Chaser to emulate managing habits of stress through the CT simulation. The LGBM dynamics of team and coping are simulated and adaptive modifications through, which the model iterates increase stress prediction.

##### 2.4.1. Light Gradient Boosting Machine (LGBM)

The implementation of the LGBM algorithm to employees to forecast corporate effective stress levels is this research. The effectiveness of LGBM, a potent GB approach, in managing huge datasets and producing precise predictions makes it useful. Finding the main causes of workplace stress, such as workload, work-life balance, and emotional intelligence, is the main goal of the research. The model's better capacity to identify intricate patterns in stress data is demonstrated, when its performance is compared to that of conventional ML approaches LGBM. The attempts to forecast stress levels offer insights for improved organizational efficiency and employee well-being. Developing focused strategies to lessen workplace stress can benefit from the findings. It also highlights, how crucial data-driven strategies for managing the mental health of employees. This adds to the expanding fields of HR analytics and business wellness. But by imposing a maximum depth restriction on the leaf top, LGBM prevents this overfitting, while providing great efficiency for stress predicting for employee. LGBM computations are displayed in the following: LGBM minimizes the expected values of certain loss functions  $K(z, e(w))$  by searching an approximation  $\hat{e}(w)$  to the function  $f^*(x)$  for a given training dataset  $W = \{(w_j, z_j)\}^n$ , using equation (7).

$$\hat{e}(w) = \arg \arg \min e_{F_{z,w}} K(z, e(w)) \quad (7)$$

$$H_s \cong \sum_{j=1}^M K(z_j, E_{s-1}(w_j) + e_s(w_j)) \quad (8)$$

The model is approximated using LGBM ensembles of several  $S$  regression trees  $\sum_{s=1}^S e_s(w)$ . When equation (8) to followed in regression trees can be defined as follows:  $x_{r(w)}, r \in \{1, 2, \dots, M\}$ , where  $x$  is a vector that reflects the sample weights of the leaf nodes,  $M$  is the several of tree leaves, and  $r$  is the tree's decision rule. At step  $s$ , the additive version of the model is trained.

##### 2.4.2. ChimpTuned (CT)

The CT was modified to maximize stress prediction among corporate workers, drawing inspiration from the cooperative behaviors seen in chimpanzee hunting strategies. Like the chimpanzee community, employees in a business setting take on many tasks. These positions fall under the following categories: Attacker Employees: these workers proactively detect possible stressors, including excessive workload or a tight deadline, and attempt to mitigate these elements through preventative measures. The primary responsibility of driver employees is to ensure that stress reduction programs are executed and upheld throughout teams, as well as to follow up on forecasts. Barrier Employees: that keeps the

stress levels from increasing over acceptable levels by setting boundaries on expected from a job. Chaser Workers: these workers track, thus stress is fluctuating in the system and try to impending anxiety or burnout. That social incentive through chimpanzee hunting can be applied to corporate workers whose drivers of motivation, job satisfaction or career progress. Accurately predicting stress brings more credit or promotions for the worker. The workers leaving work, which can cause confusion or lack of proper stress management. Enhancing dynamic roles and interactions might help employees manage stress effectively at work.

#### 2.4.3. Surround Prey

The process of evaluating and revising the stress levels to forecast the stress levels of corporate workers is described as follows:

$$c = |d \cdot w_{prey}(s) - n \cdot w_{chimp}(s)| \quad (9)$$

$$w_{chimp}(s + 1) = w_{prey}(s) - b \cdot c \quad (10)$$

The difference between an employee's actual stress level and their anticipated stress level is seen in equation (9). With  $s$  standing for the current iteration,  $w_{chimp}$  be a vector containing the employee's current stress levels, and  $w_{prey}$  individual a vector representing the employee's stress status over time, equation (10) updates the employee's stress position over time. Equations (11), (12), and (13) are used to determine the vectors  $b$ ,  $n$ , and  $d$ .

$$b = 2e \cdot q_1 - e \quad (11)$$

$$d = 2q_2 \quad (12)$$

$$n = \text{Chaotic\_Value}, \quad (13)$$

The convergence factor  $e$  decreases consistently from 2.5 to 0 during each iteration. The modulus of  $q_1$  and  $q_2$  are random values from the interval  $[0, 1]$ ;  $d$  is a random value from the interval  $[0, 2]$ ; and  $n$  is a chaos value derived from chaos graphs, signifying erratic stressors or variable stress affects in the workplace.

#### 2.4.4. Attack Prey

To replicate the way a corporate employee handles stress, the value of  $e$  steadily drops, which likewise lowers  $b$  the fluctuation range. As the method iterates, the value of  $e$  likewise changes inside the interval  $[-e, e]$ , when the value of  $e$  decreases linearly from 2.5 to 0. An employee's subsequent stress reaction can differ depending on whether their current stress level or the prospective stress trigger (prey) is present, when the value falls within this range. Employees' stress reactions in, which that respond to stresses and address or alleviate them, are seen as attacks when  $|b| < 1$ .

#### 2.4.5. Search for Prey

Depending on their stress reactions and coping strategies, such as awareness  $w_{Attacker}$ , coping skills  $w_{Barrier}$ , emotional support  $w_{Chaser}$ , and general resilience  $w_{Driver}$ , employees look for possible stressors (prey). Employees move independently while finding stressors but when that discover a major stressor, come together in a group effort to alleviate stress. According to the stress model's divergence, employees can distance themselves from stressors, when the random values of  $|b| > 1$  or  $|b| < -1$ , highlighting the need to experiment with different stress management approaches and encouraging a worldwide search for the greatest stress-reduction tactics. To find more efficient long-term stress management techniques, employees distance themselves from current stressors (local stressors) when  $|b| > 1$ . A parameter,  $d$ , is introduced by the algorithm to assist employees in learning new coping mechanisms. This promotes the discovery of more thorough, long-term stress reduction CT optimization techniques and helps the model prevent employees from slipping into habits of inefficient stress management. The CT-LGBM uses chimps to enhance stress forecasting in business settings by simulating team dynamics and coping practices. Employees are assigned roles like Attacker, Driver, Barrier, and Chaser, allowing for simulation of stress management habits. The model iterates through dynamic dynamics and adaptive modifications for improved stress prediction.

### 3. Results

This research made considerable use of Python 3.11. Give 28GB of storage and Windows 8 pre-installed on Intel Core i6 laptops. In evaluating the efficacy of the suggested system, assessment parameters like accuracy, precision, recall, and F1-score are used. Comparing 1D-convolutional neural network (1D-CNN) (Rescio et al. 2024), the proposed method CT-LGBM. Table 1 displays a numerical comparison of the suggested and current methods.

#### 3.1. Accuracy

Accuracy means the several instances, which have been correctly classified divided by the total instances in a dataset. As an application of stress prediction for the employees of organizations, this means, how often the classifier classifies well the employees being stressed. However, only accuracy does not serve, especially in the case of highly imbalanced datasets because this approach, also doesn't consider the frequency of instances of stress. In the evaluation, the performance of the existing techniques 1D-CNN scored (0.9688), while our proposed method CT-LGBM had (0.9840). The results show that, in comparison to the existing techniques, our proposed approach has the highest accuracy. The accuracy result is displayed in Figure 2.

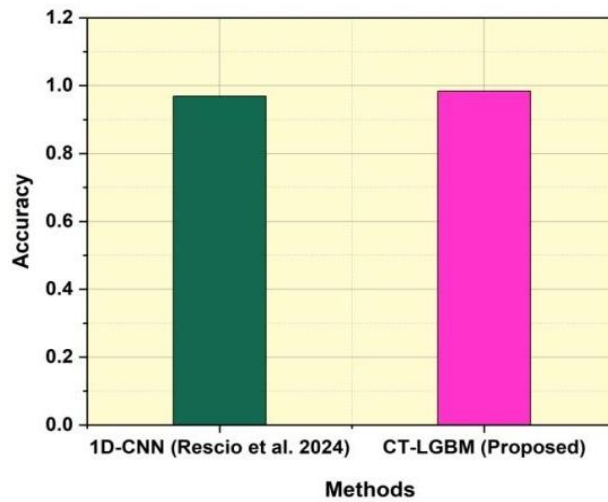


Figure 2 Outcome of accuracy.

Table 1 Numerical comparison for proposed and existing techniques.

Methods	Accuracy	Precision	Recall	F1-score
1D-CNN (Rescio et al. 2024)	0.9688	0.9708	0.9615	0.9687
CT-LGBM (Proposed)	0.9840	0.9820	0.9793	0.9798

### 3.2. Precision

The fraction of real positive predictions among all anticipated positives is determined by precision. In the case of stress prediction, it represents the model's accuracy in correctly identifying stressed employees to avoid false positives. With high precision, the higher probability of accuracy, when the model indicates stress, which is significant in a corporate setup because it avoids unnecessary action concerning stress-related activity. In the evaluation, the performance of the existing techniques 1D-CNN scored (0.9708), while our proposed method CT-LGBM had (0.9820). The results prove that our proposed approach produces the greatest precision as compared to the current methods. The outcome of precision is shown in Figure 3.

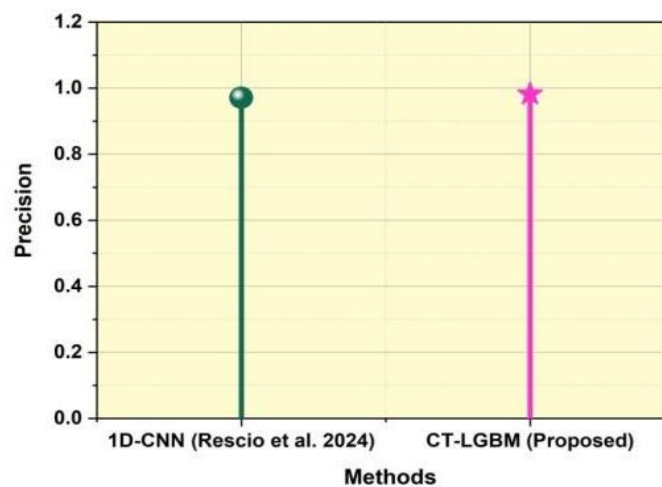


Figure 3 Outcome of precision.

### 3.3. Recall

The model's recall, also known as sensitivity, gauges its capacity to accurately detect every real positive case. The focus of recollection in stress prediction is on identifying all employees, who are truly under stress. In a corporate context, a strong recall is crucial for reducing the possibility of ignoring stressed persons and guaranteeing prompt detection and action to enhance employee well-being and avoid burnout. In the evaluation, the performance of the existing techniques 1D-CNN scored (0.9615), while our proposed method CT-LGBM had (0.9793). The results prove that our proposed approach produces the better recall as compared to the current methods. The outcome of recall is shown in Figure 4.

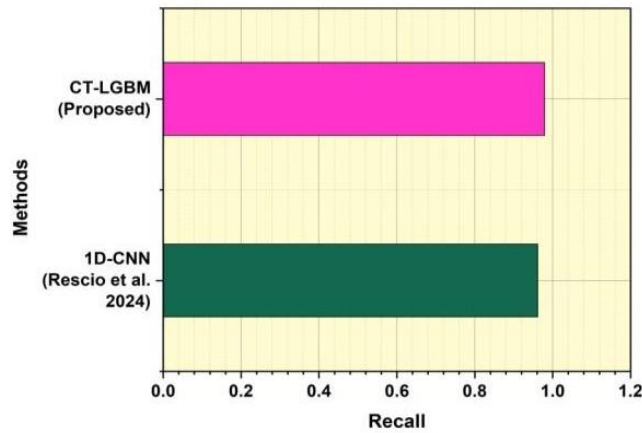


Figure 4 Outcome of recall.

### 3.4. F1-score

The harmonic mean of accuracy and recall is known as the F1-score. The False negatives and false positives can both be devastating; this metric becomes most useful. It enables an analysis of how well the model correctly identifies the stressed employees by accurate as possible without losing any recall that is not over-diagnosing and under-diagnosing stress. In the evaluation, the performance of the existing techniques 1D-CNN scored (0.9687), while our proposed method CT-LGBM had (0.9798). The results show that, in comparison to the existing techniques, our proposed approach has the best F1-score. The outcome of the F1-score is shown in Figure 5.

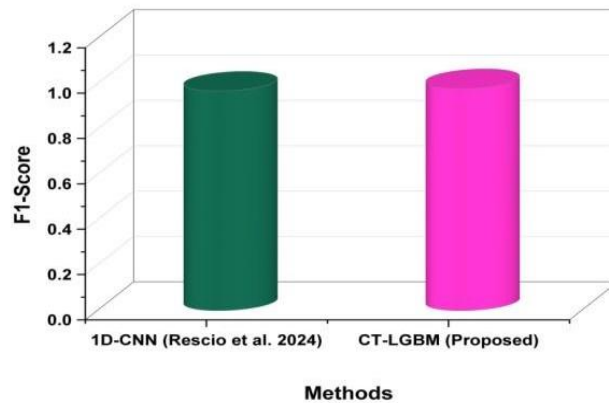


Figure 5 Outcome of F1-score.

## 4. Discussion

Joshi et al. (2024) had faced restrictions from using Highly Sensitive Person (HSP) and Mental Health Test (MHT) datasets because they might not apply to general population demographics. Data reported by individuals contains the risk of both biased and incorrect information. External confirmation of the CT-LGBM model requires testing on varied population-based datasets to validate its strong performance. The investigation examines static data while preventing the ability to make real-time stress predictions. The model's practical application potential could be diminished because environmental factors and contextual circumstances affecting stress were not taken into consideration.

Rodrigues and Correia (2024) had limited generalization potential because it worked with only 28 participants in its sample. It depended on participant self-assessment through questionnaires thus introducing possible bias to the results. Recording technology using plethysmography could be influenced under various conditions including changes in lighting and

actions of the face or picture resolution. Stress classification methods which use binaries often reduce the intricacy of real-world stress reactions. Expansion should include greater quantities of participants, multiple monitoring methods and continuous monitoring capabilities to improve accuracy and system reliability.

Adeusi et al. (2024) had faced limitations because missing or biased information in its database can affect the accuracy of the constructed models. The use of historical data reduces the investigator's ability to measure factors that drive employee choices because historical data remains fixed. The sectors with different stress factors tend to produce decreased generalization levels. Ethical problems connected to privacy along with investigations showing HR prediction misuse raise obstacles for decision-making in human resources departments. Future exploration needs to integrate real-time data input and conduct extended analysis over time for getting better results.

The primary disadvantage of employing a 1D-CNN to forecast employee stress prediction in dynamic work environments is its poor capacity to identify intricate, non-linear correlations in multi-dimensional data. The approach can have trouble accounting for a variety of contextual elements, such as interpersonal relationships or the workplace. Furthermore, temporal relationships in performance data can be difficult for 1D-CNNs to manage, which might eventually result in less accurate stress predictions. The assessments made by the model might not be clear enough, thus reducing the availability and reliability of its applications in practice. The proposed CT-LGBM method employs tree-based models for better modeling of complex interactions and non-linear correlations between multiple dimensions, which removes the disadvantages a 1D-CNN might have for predicting employee stress. CT-LGBM enhances the model's ability to incorporate various contextual variables by integrating contextual elements such as workplace and interpersonal interactions. Additionally, the technique improves the accuracy of stress prediction with the help of feature engineering and boosting for the management of temporal data. Increased transparency and usefulness in practical applications are guaranteed by the interpretability of the model.

## 5. Conclusions

The stress-predicting system for corporate workers uses behavioral analytics, physiological data, and ML algorithms to estimate the levels of stress. By assessing the variables that include workload, job satisfaction, and health measurements, it provides predictive information about stress management. The proposed method achieved the highest F1-score of 0.9798, recall of 0.9793, precision of 0.9820, and accuracy of 0.9840. The use of self-reported data that can add important organizational or environmental elements makes the prediction of stress among corporate personnel problematic.

## 6. Limitations and Future Scope

The few variables can produce less dependable findings in a variety of work contexts; it does not reflect the dynamic character of stress. Employee involvement or process trust can potentially be restricted by privacy issues. Future research might examine how corporate workers' stress levels and coping strategies are affected by distant work settings. Additionally, research might use Artificial intelligence (AI)-driven insights to examine the function of customized stress management programs. A deeper understanding of the long-term impacts of stress and, how it relates to professional advancement can be possible through longitudinal research. International workplace well-being efforts might also benefit from investigating cultural variations in stress perception and coping mechanisms.

### Ethical considerations

All datasets used in this study, including those sourced from github website (GitHub - emiyacody/Stress-Prediction), are publicly available and come with licenses that grant permission for research use.

### Conflict of Interest

The authors declare no conflicts of interest.

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