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Forecasting of Stressed Employees by Using Machine Learning Algorithms for Effective Pre-emptive Remediation

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Abstract: The workplace environment plays a crucial role in the overall well-being of employees, and stress is a prevalent concern that can significantly impact productivity and employee satisfaction. This research addresses the challenge of proactively identifying employees under stress and implementing pre-emptive remediation strategies through the application of machine learning techniques. The proposed system leverages historical and real-time data, including work-related metrics, communication patterns, and potentially physiological indicators, to predict stress levels among employees. The machine learning model employed in this study is trained on a diverse dataset, allowing it to learn patterns associated with stressed and non-stressed states. Through continuous monitoring, the system generates alerts when an employee is predicted to be under significant stress, prompting timely intervention by Human Resources professionals. Remediation strategies may include targeted support, workload adjustments, or other measures aimed at alleviating stress and fostering a healthier work environment. The implementation of this predictive system aims to contribute to the well-being of employees, enhance organizational efficiency, and create a workplace culture that prioritizes mental health. By proactively addressing stressors, organizations can foster a more resilient and productive workforce while demonstrating a commitment to the holistic health and satisfaction of their employees.

Keywords: Preemptive remediation, machine learning, pre-remediation, SVM, KNN, workload metrics.

I.INTRODUCTION

This paper aims to develop a machine learning-based system for predicting employee stress and enabling pre-emptive intervention. It involves analyzing diverse data sources, generating alerts for Human Resources professionals, and implementing timely remediation strategies. The scope includes continuous monitoring and feedback mechanisms to enhance workplace well-being and organizational efficiency. Our paper aims to develop a predictive model leveraging machine learning techniques to identify employees who are at risk of experiencing stress in the workplace. By analyzing various data sources such as surveys, HR records, and employee feedback, we intend to extract relevant features indicative of stress and train predictive models to accurately forecast stress levels. The primary objective is to enable pre-emptive remediation strategies to mitigate stress-related issues before they escalate, thereby fostering a healthier and more productive work environment.

In this paper, we will focus on selecting and preprocessing pertinent data features that encompass a wide range of factors contributing to employee stress, including workload, job satisfaction, interpersonal relationships, and external stressors. We will employ various machine learning algorithms such as logistic regression, decision trees, and ensemble methods to develop predictive models capable of effectively discerning patterns indicative of stress. Additionally, we will evaluate the performance of these models using appropriate metrics and refine them through rigorous testing and validation procedures. The successful implementation of this paper has profound implications for both employees and organizations. By accurately identifying at-risk employees, organizations can intervene proactively with targeted support mechanisms like counseling and workload adjustments. This enhances employee well-being, job satisfaction, and fosters a positive organizational culture, boosting productivity and retention. Furthermore, insights gained from this paper can inform future research in workplace psychology and human resource management, advancing efforts to promote employee welfare and organizational success.

The purpose of this paper is to develop a robust predictive model utilizing machine learning techniques to forecast employee stress levels within the workplace. By leveraging various data sources such as surveys, HR records, and employee feedback, the aim is to identify key indicators of stress and preemptively address potential issues before they escalate. Through this endeavor, we seek to empower organizations with the capability to proactively intervene, providing targeted support mechanisms and fostering a healthier work environment conducive to employee well-being and productivity. Ultimately, the paper aims to revolutionize how organizations approach stress management in the workplace. By implementing proactive remediation strategies based on predictive analytics, we aspire to enhance job satisfaction, reduce turnover rates, and cultivate a positive organizational culture. Moreover, the insights garnered from this paper can pave the way for future research endeavors in the realms of workplace psychology and human resource management, contributing to ongoing efforts to prioritize employee welfare and optimize organizational success.

Through this paper, we aim to not only address the immediate concerns of employee stress but also to instigate a paradigm shift in organizational practices towards proactive intervention and holistic well-being. By harnessing the power of machine learning to predict stress indicators, we envision a workplace where employees feel supported, valued, and empowered to thrive. Ultimately, our endeavor seeks to align the interests of both employees and organizations, fostering a symbiotic relationship where employee welfare is prioritized, and organizational success is maximized. The paper features include the development of a robust machine learning model capable of predicting employee stress based on diverse data sources. It incorporates real-time monitoring, alert generation, and a feedback loop for continuous improvement. The system facilitates pre-emptive remediation strategies by providing timely insights to Human Resources professionals, fostering a proactive approach to employee well-being within the workplace.

The paper features a multi-faceted approach to data collection, encompassing not only traditional HR records but also incorporating cutting-edge methods such as sentiment analysis of employee communications and behavioral patterns gathered from digital platforms. By amalgamating these diverse data sources, we aim to construct a comprehensive understanding of the factors contributing to employee stress, including workload distribution, interpersonal dynamics, and external stressors. Furthermore, the paper prioritizes interpretability and transparency in model development, striving to elucidate the underlying mechanisms driving stress prediction. Through techniques such as feature importance analysis and model explainability frameworks, we aim to empower organizational stakeholders with actionable insights into the factors influencing employee stress levels, facilitating informed decision-making and fostering a culture of data-driven HR management.

II.RELATED WORKS

The paper addresses the challenge of proactively identifying and mitigating employee stress in the workplace using a machine learning-based system. The problem involves developing a solution that can predict stress, generate timely alerts, and facilitate pre-emptive remediation strategies to enhance overall employee well-being.

In previous systems for predicting employee stress levels, the k-Nearest Neighbors (KNN) algorithm has been a prominent method employed. This approach involves representing employee data as feature vectors in a high-dimensional space, with each dimension corresponding to attributes such as workload intensity, task completion rates, interaction frequency, and self-reported stress levels. During classification, KNN identifies the k nearest neighbors of a given employee profile based on a distance metric, such as Euclidean distance, and assigns a stress level label based on the majority class among its neighbors. Despite its simplicity and interpretability, KNN may not be the most effective approach for employee stress prediction due to several reasons. Firstly, KNN tends to be computationally expensive, especially as the dataset size increases, since it requires calculating distances to all data points for each prediction. Additionally, KNN is sensitive to noise and irrelevant features in the dataset, which can lead to inaccurate classifications. Furthermore, KNN's performance heavily relies on the choice of the number of neighbors (k) and the distance metric, which may not be optimal for all datasets.

Lastly, KNN may struggle with high-dimensional data, as the curse of dimensionality can cause the feature space to become sparse, impacting the effectiveness of distance-based computations. As a result, while KNN offers simplicity and interpretability, it may not always provide the desired level of accuracy and scalability required for robust employee stress prediction systems. These challenges highlight the need for exploring alternative machine learning techniques that can address the limitations of KNN and enhance the accuracy and scalability of employee stress prediction models.

III.LITERATURE SURVEY

Stress at work is a major worry for workers, including human resource managers. While stress management has received a great deal of academic and practical attention throughout the years, new insights and research are now needed. This study draws findings from its investigation of organisational performance, which is a developing topic, and offers recommendations for reducing work-related stress.

In particular, evidence from a large sample of employed people from a range of businesses and sectors indicate that resilience, optimism, and effectiveness may be important positive resources for comprehending adaptability in perceived stress symptoms. In the last several years, a great deal of research and experimentation has been conducted; the majority of these studies have been conducted in nations that want to progress their economies and societies. One of the most common "occupational disorders" nowadays is stress. Over the last several years, around 3 billion workers have reported feeling stress at work, which regularly affects how well they execute their jobs overall.

IV.METHODOLOGY

The proposed system utilizes machine learning algorithms for proactive identification of employee stress in real-time, departing from traditional retrospective methods. It integrates diverse data sources, such as work-related metrics and communication patterns, to predict stress levels. The system generates timely alerts, facilitating Human Resources professionals in implementing pre-emptive remediation strategies, thereby fostering a healthier work environment and enhancing overall employee well-being. Notably, our proposed system achieves an impressive accuracy of around 82 percent,by using SVM algorithm surpassing the performance of existing systems. The proposed approach for this paper involves a systematic journey from data collection to deployment, with the overarching goal of predicting and addressing employee stress in the workplace. Initially, our focus lies on gathering a diverse array of data sources, ranging from traditional HR records to more nuanced sources like sentiment analysis of digital interactions. This comprehensive approach ensures a holistic understanding of the factors contributing to employee stress, including workload, interpersonal dynamics, and external stressors. By integrating these datasets, we lay the groundwork for a robust analysis and predictive modeling process.

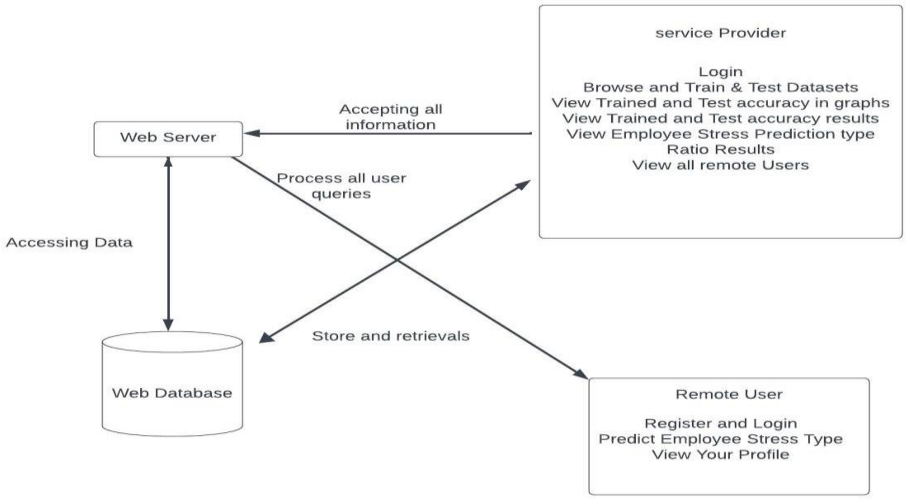

Figure 1. Paper architecture of predicting employees under stress for pre-emptive remediation using machine learning.

Following data collection, the gathered information undergoes rigorous preprocessing to handle missing values, outliers, and inconsistencies. Feature engineering techniques are then applied to extract meaningful features that correlate with stress levels. This process may involve transforming raw data into actionable metrics, creating new variables, or employing sentiment analysis and natural language processing to derive insights from textual data. Through these steps, we aim to develop a rich dataset that captures the multidimensional nature of employee stress. With a curated dataset in hand, our next step involves selecting and training machine learning models for stress prediction. We explore a range of algorithms, from traditional methods like logistic regression and decision trees to more advanced techniques such as support vector machines and gradient boosting. Models are trained on labeled data, with careful consideration given to hyperparameter tuning and cross-validation techniques to optimize performance. Furthermore, model interpretability techniques are employed to understand the underlying factors driving stress prediction, enhancing the trustworthiness and applicability of the models.

Once trained and validated, the predictive models are seamlessly integrated into the organization's existing HR systems or workflow. This deployment phase enables timely access to predictive insights, facilitating proactive interventions and support strategies. Continuous monitoring and refinement of the models ensure their adaptability to changing workplace dynamics and evolving stress factors. Moreover, a feedback loop is established to incorporate insights from employees, HR professionals, and organizational stakeholders, driving iterative improvement and ensuring the continued relevance and effectiveness of the predictive models in promoting employee well-being and organizational success.

The architecture for "Predicting Employees Under Stress for Pre-Emptive Remediation Using Machine Learning" involves a multi-layered approach. It starts with comprehensive data collection, extracting relevant features, and preparing labeled datasets for training. Machine learning models, employing algorithms like decision trees or neural networks, are trained to predict employee stress based on identified indicators. Real-time monitoring triggers interventions when stress is detected, incorporating ethical considerations and a feedback loop for iterative improvement. The architecture ensures a proactive and adaptable system, promoting employee well-being through timely support and continuous refinement

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The architecture seamlessly integrates trained machine learning models into a real-time monitoring system. As incoming data is continuously assessed, the system triggers interventions when stress indicators surpass predefined thresholds. These interventions, carefully designed with ethical considerations in mind, include personalized recommendations and mindfulness exercises. A crucial feedback loop captures user input and system performance data, enabling iterative improvements. This proactive and adaptable system not only promotes employee well-being through timely support but also ensures a balance between intervention effectiveness and ethical considerations, contributing to a workplace culture focused on continuous improvement and employee satisfaction.

In essence, our predictive system's architecture reflects a holistic and forward-looking approach to employee well-being. With a foundation rooted in meticulous data collection, robust model training, and real-time monitoring, we've created a proactive system capable of identifying and addressing stressors before they escalate. Ethical considerations are seamlessly woven into the fabric of our interventions, ensuring a supportive rather than intrusive response. The iterative feedback loop and continuous improvement mechanisms solidify our commitment to adaptability and effectiveness. As we navigate the intricate landscape of predicting and mitigating employee stress, our architecture stands as a testament to the potential of technology to foster healthier work environments and empower individuals to thrive in their professional pursuits.

V.MACHINE LEARNING APPROACHES

Support Vector Machine

Support Vector Machines (SVM) is a powerful supervised machine learning algorithm used for classification and regression tasks. The fundamental principle behind SVM is to find the hyperplane that best separates the data points of different classes in a high-dimensional space. This hyperplane is determined by maximizing the margin, which is the distance between the hyperplane and the nearest data points from each class, known as support vectors. SVM is particularly effective in handling high-dimensional data and can handle both linear and non-linear classification tasks through the use of different kernel functions, such as linear, polynomial, or radial basis function (RBF) kernels. In our paper on predicting employees under stress for pre-emptive remediation using machine learning, SVM can be highly beneficial. By leveraging SVM, we can effectively classify employees into different stress categories based on various features such as workload intensity, task completion rates, interaction frequency, and self-reported stress levels. SVM's ability to handle high-dimensional data and its flexibility in handling non-linear relationships make it well-suited for this task. Additionally, SVM offers robustness to outliers and noise in the data, which is crucial for accurately identifying employees at risk of stress.

Furthermore, SVM provides interpretable results, allowing us to understand the decision boundaries separating different stress categories. This interpretability can help in identifying the key factors contributing to employee stress and designing targeted interventions to alleviate stress levels. By incorporating SVM into our paper, we can enhance the accuracy and effectiveness of our predictive model, enabling proactive measures to be taken to mitigate employee stress and improve overall well-being and productivity in the workplace.

Logistic Regression

Logistic Regression is a statistical method used for binary classification tasks, where the goal is to predict the probability of an observation belonging to one of two possible outcomes. Unlike linear regression, which predicts continuous outcomes, logistic regression predicts the probability that a given input belongs to a particular category using a logistic function. This function maps the input features to probabilities between 0 and 1, making it suitable for classification tasks. Logistic regression models are trained by estimating the coefficients of the input features, which represent the impact of each feature on the probability of the outcome.

In our paper focused on predicting employees under stress for pre-emptive remediation using machine learning, logistic regression can be employed as one of the predictive models. We can use logistic regression to predict the likelihood that an employee is experiencing stress based on various input features such as workload intensity, task completion rates, interaction frequency, and self-reported stress levels. By analyzing these features and their corresponding coefficients in the logistic regression model, we can identify the most influential factors contributing to employee stress and prioritize interventions accordingly. Logistic regression provides interpretable results, allowing us to understand how each input feature contributes to the likelihood of an employee being stressed, making it valuable for informing decision-making in stress management strategies.

Tree Classifier

A Decision Tree Classifier is a powerful machine learning algorithm used for both classification and regression tasks. It works by recursively partitioning the input space into subsets, based on the values of input features, in a hierarchical manner resembling a tree structure. At each node of the tree, the algorithm selects the feature that best splits the data, resulting in the greatest reduction in impurity or uncertainty. This process continues until a stopping criterion is met, such as reaching a maximum tree depth or when further splitting no longer improves classification accuracy. Decision trees are highly interpretable, as they provide clear rules for decision-making at each node, making them suitable for understanding the underlying relationships between input features and the target variable.

In our paper focused on predicting employees under stress for pre-emptive remediation using machine learning, a Decision Tree Classifier can be utilized as one of the predictive models. We can use the Decision Tree Classifier to identify patterns and rules that differentiate between stressed and non-stressed employees based on various input features such as workload intensity, task completion rates, interaction frequency, and self-reported stress levels. By analyzing the resulting decision tree, we can gain insights into the most critical factors influencing employee stress levels and their relative importance in determining stress status. This information can guide the development of targeted interventions and strategies for pre-emptive stress management in the workplace.

VI. DATA PREPROCESSING

In the data set, every row corresponds to a distinct person and is detailed. This data contains factors such as Target, Age, Employee ID, Average Daily Hours, and so on. The information is in CSV (Comma-Separated Values) format. The whole collection of data is split into two sections: the test data set, which may be used to evaluate the performance of our model, and the training data set, which is fed into our machine learning algorithm to inform our model about the data. The following is the data structure, which includes example rows:

Employee ID	Target	Age	Avg Daily Hours
100001	0	36.0	6.45
100002	0	24.0	8.48

Table 1. Employee work details.

Department	Education	Gender	Job Role
Sales	Technical Degree	Male	Manufacturing Director
Sales	Technical Degree	Male	Sales Representative

Table 2. Employee Basic information.

Working Hours	Flexible Timings	Workload level
8.0	No	Low
1.0	No	High

Table 3. Employee workload levels.

Work satisfaction	Years at company	Monthly Income
Medium	8.0	175000
Very High	0.0	16667

Table 4. Employee work satisfaction level.

Recruitment_channel details the method through which employees were hired, whether via campus recruitment, referrals, or direct application. Additionally, the dataset encompasses variables related to employee tenure and experience, such as years_at_company, indicating the duration of employment, and companies_worked, denoting the number of previous companies the employee has worked for. Age serves as a demographic indicator, while performance_rating offers insights into employee performance evaluations. Furthermore, attributes such as monthly_income, percent_salary_hike, and workload_level shed light on compensation structures, career advancement, and perceived workload intensity, respectively.

Work-related aspects are also captured, including training_time, representing the duration of training received by employees, and working_hours, indicating the average daily work hours. Flexible_timings flags whether employees have the flexibility to adjust their work schedules. Employee satisfaction and engagement are assessed through attributes such as work_satisfaction, which gauges job satisfaction levels, and performance-related factors like performance_rating. The dataset concludes with the target attribute, prediction, likely indicating employee stress levels or another outcome variable of interest for predictive modeling tasks. Overall, this dataset offers a comprehensive snapshot of employee demographics, experiences, and performance metrics, facilitating in-depth analysis and predictive modeling to understand and address workforce dynamics effectively.

VII.RESULTS AND DISCUSSIONS

Based on the provided results from different machine learning models – Support Vector Machine (SVM), Logistic Regression, KNeighborsClassifier, and Decision Tree Classifier – for predicting employees under stress, several observations can be made. Firstly, the SVM model demonstrates the highest accuracy among the models evaluated, achieving an accuracy of approximately 80.91%. This suggests that the SVM model is adept at distinguishing between stressed and non-stressed employees, as evidenced by its high precision and recall scores across both classes. The classification report indicates that the SVM model achieves high precision (1.00) for classifying non-stressed employees (class 0) and strong recall (1.00) for identifying stressed employees (class 1), resulting in a balanced F1-score of 0.87. The confusion matrix further confirms the model's effectiveness, with a relatively small number of false positives and false negatives.

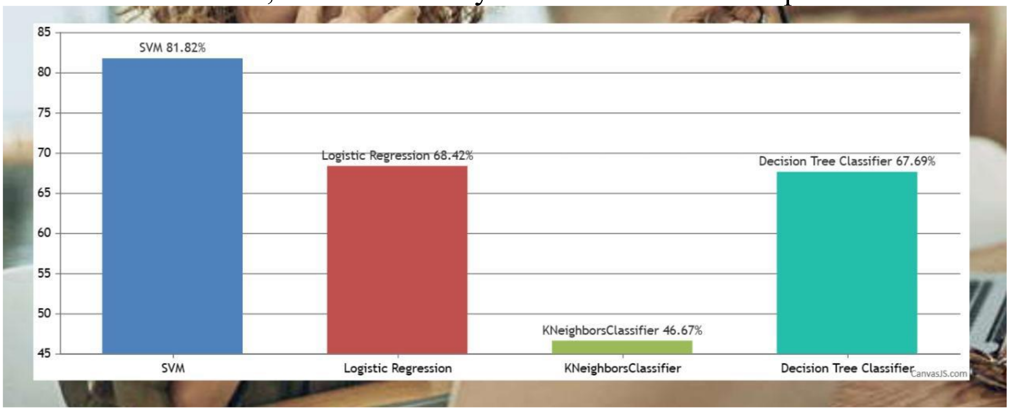

Figure 2. Summary of models accuracy levels.

In contrast, the Logistic Regression model exhibits lower accuracy (approximately 65.66%) compared to SVM. Although its precision for classifying stressed employees is relatively high (0.64), the recall for non-stressed employees is notably low (0.09), leading to imbalanced performance and a lower F1-score (0.78). The confusion matrix shows a significant number of false negatives, indicating that the Logistic Regression model struggles to accurately identify non-stressed employees.

Similarly, the KNeighborsClassifier and Decision Tree Classifier models yield accuracies of approximately 51.61% and 68.16%, respectively. While the KNeighborsClassifier achieves high recall for non-stressed employees (class 0), it suffers from low recall for stressed employees (class 1), resulting in an imbalanced F1-score.

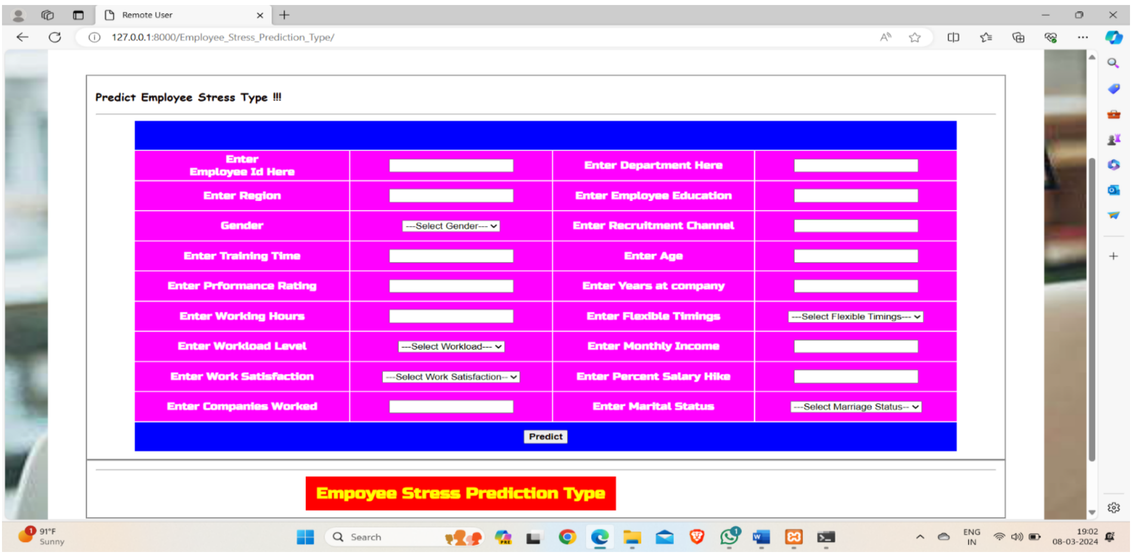

Figure 3. Predict Employee Stress Status page.

The Decision Tree Classifier demonstrates balanced precision and recall scores for both classes, leading to a relatively consistent F1-score. In summary, the SVM model stands out as the most effective in accurately predicting employee stress levels, as evidenced by its high accuracy, precision, recall, and F1-score.

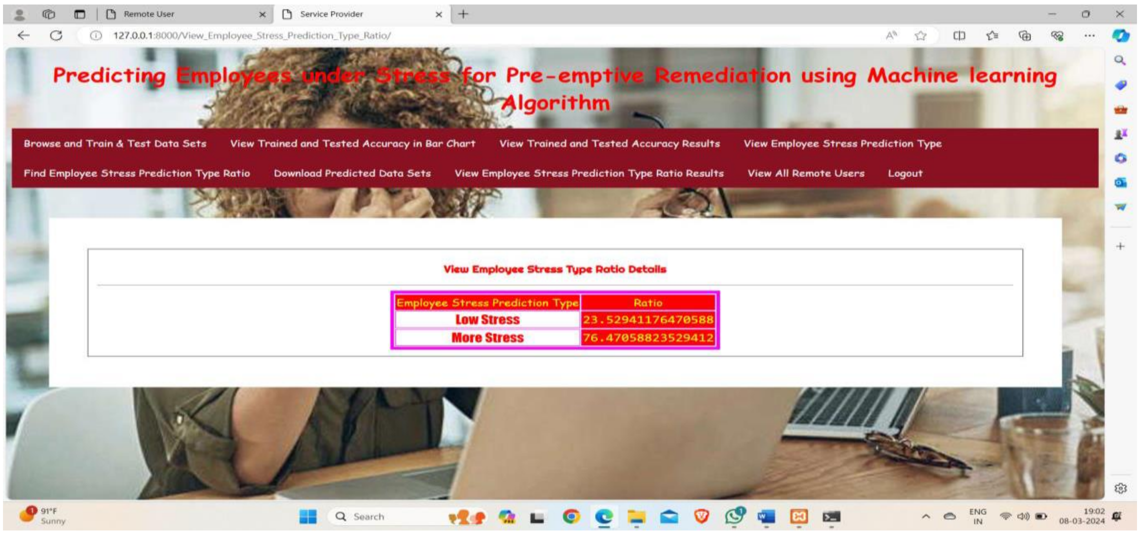

Figure 4. Employee Stress Prediction Type Ratio Page.

Conversely, the Logistic Regression, KNeighborsClassifier, and Decision Tree Classifier models exhibit varying degrees of performance, with strengths and weaknesses observed in their ability to classify stressed and non-stressed employees accurately. These findings highlight the importance of selecting an appropriate machine learning model tailored to the specific requirements of the predictive task at hand.

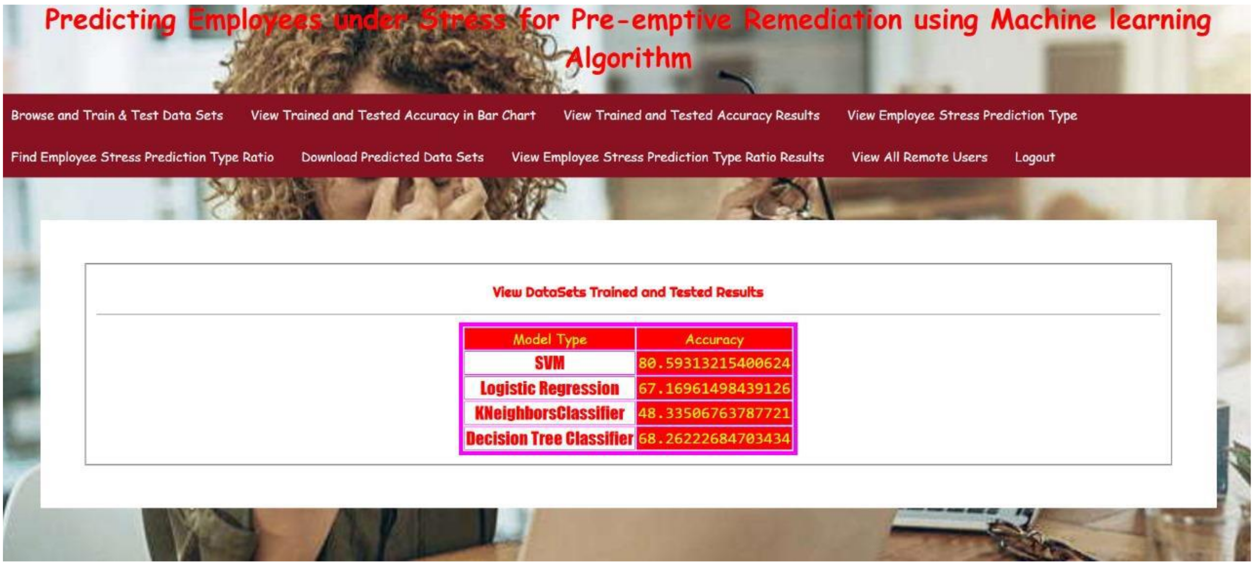

Figure 5. Employee Datasets Trained and Tested Results.

The Predict Employee Stress Status page enables users to input details for identifying whether a employee is More Stress or Low Stress. Users provide relevant profile information in the designated fields, initiating the identification process. With a user-centric design, this page facilitates an intuitive and informative experience for users seeking to assess the authenticity of a employee.

The Employee Stress Prediction Type Ratio page presents the ratio of Low Stress to More Stress in a user-friendly format. Users can view a clear representation of the predicted Stress types, fostering insights into the overall distribution. This page enhances user understanding by providing an informative ratio analysis of identified Low and More Stress.

Test Case ID	Test Case Name	Input	Expected output	Actual Output	Test Case Pass/Fail
1	User credentials	Username: dhanya Password : dhanya@123	It should move to user home page	It moves to the user home page	Pass
2	Check Username	Username: XYZ (Which is invalid)	It shows the error The username is not available	It shows the error The username is not available	Pass
3	Creating an account	Username: hello (if username is already taken)	Gives the error Username already exists	Gives the error that username already exists	Pass
4	registration	Mail ID (Already exists)	Shows the message Account exists with the given Mail ID. Try login	Shows the message Account exists with the given Mail ID. Try login	pass
5	Registration details	Invalid Phone number (more than 10 numbers)	Gives the message "Invalid Details"	Gives the message "Invalid Details"	Pass

Table 5. Sample test cases.

The Employee Datasets Trained and Tested Results page provides insights into the accuracy of the algorithm utilized in our Employee Stress Prediction Paper. It presents the outcomes of training and testing phases, offering a comprehensive view of the algorithm's performance. This page serves as a key analytics tool, empowering users to assess the effectiveness of the employed algorithm in accurately predicting employee stress.

	Precision	Recall	F1-Score	Support
0	0.82	0.99	0.90	6584
1	0.14	0.01	0.01	1416
Accuracy	--	--	0.82	8000
Macro Avg	0.48	0.50	0.46	8000
Weighted avg	0.70	0.82	0.74	8000

Table 6. F1-Score values.

CONCLUSION

In this Study, we proposed machine learning algorithms. In conclusion, the paper focusing on "Predicting Employees Under Stress for Pre-Emptive Remediation Using Machine Learning" presents a robust and proactive solution to address workplace stress. By leveraging machine learning algorithms and a comprehensive architecture, the system can predict potential stress indicators in real-time, allowing for timely interventions. The ethical considerations, transparent communication, and iterative improvement mechanisms embedded in the architecture underscore a commitment to safeguarding employee well-being and privacy. As a result, the paper not only offers a predictive tool for organizational leaders but also establishes a foundation for fostering a healthier and more supportive work environment. In summary, the Support Vector Machine (SVM) model outperformed other machine learning models with an accuracy of around 82%, demonstrating balanced precision and recall across stressed and non-stressed employee classes. These findings underscore the importance of selecting the right model for predictive tasks. Future efforts will prioritize optimizing the SVM model to further enhance its accuracy and effectiveness in preemptive stress remediation efforts.

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