A Case Study on Stress and Resilience Among Teaching Faculty in Higher Education Using Random Forest

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***Abstract*—Now a days College and university professor face many responsibilities. Handling these kinds of initiations allotted by college or university includes workloads, administrative tasks. In improvement of technologies aids to develop teaching methods. While some teachers manage these pressures well others find it hard to manage that leading to stress, burnout, and decrease in performance. Traditional methods like surveys and interviews are formerly study stress, however very accurate or useful on a large scale. This study looks at how Machine Learning (ML) can help understand and measure stress and resilience in professors. It uses software that can learn from data to find patterns. This research aims to works with different types of data such as survey results, teacher feedback. We use random forest algorithm in our project to forecast stress in higher professors. By comparing random forest algorithm with support vector machine algorithm, the random forest algorithm gives the best result. This can assist universities in developing more encouraging work environments and health initiatives.**

***Index Terms:* Stress, Resilience, Teaching Faculty, Higher Education, Computational Learning, Forest-Based Classifier, Support Vector Machine (SVM), Predictive Analytics, Mental Health, Burnout**.

I. INTRODUCTION

In recent years, the role of teaching faculty in higher education has changed significantly. This change has led to more complex work and higher performance expectations. Faculty members now have responsibilities beyond classroom instruction and research. They are also expected to take on administrative tasks, pursue professional development, engage in digital teaching methods, mentor students, and participate in outreach efforts. While these added roles are important for academic progress, they have also increased stress and mental health challenges for educators. Stress among faculty can show up in different ways. These include emotional exhaustion, anxiety, decreased happiness at work, and burnout. If left unhandled, these issues can harm individual health and affect teaching quality, student performance, and overall effectiveness of the institution. Resilience, that is the ability to recover and function well despite difficulties, essential helping faculty handle these pressures. Understanding how stress and resilience interact is important for creating effective wellness strategies for faculty in higher education.

Traditional methods for assessing stress and resilience, such as surveys and interviews, often lack objectivity and scalability. In contrast, data-driven approaches can analyze large amounts of faculty-related data in a more objective way. This helps to identify patterns and trends that might otherwise go unnoticed. Machine learning (ML) techniques can process and interpret both structured and unstructured data, leading to better insights into stress triggers and coping strategies. This case study looks at using the Random Forest algorithm, a strong and easy-to-understand ML technique, to evaluate stress levels and resilience patterns among teaching faculty in higher education. Random Forest can handle different types of data, manage noisy information, and rank feature importance, making it a great choice for this task. By combining survey responses, workload metrics, and sentiment analysis of qualitative feedback, the model aims to classify faculty into different stress and resilience categories. The result will help educational institutions identify faculty at risk. They will also accommodate design of targeted support and

interventions. This research promotes a healthier academic environment, improves faculty retention, and ensures high teaching quality.

II. MATHEMATICAL EXPRESSIONS

1. Random Forest Classification:

$$\hat{y}RF(z) = argmax_c \frac{1}{T}\sum_{t=1}^{T} 1\{h_t(z) = c\} \text{ ----- (1)}$$

eq-(1) represents,

- T = total number of trees
- $h_t(z)$ = prediction from tree t
- $c \in \{0,1,2\}$ = stress class (0: Low, 1: Medium, 2: High)
- $1\{\cdot\}$ = indicator function

2. Support Vector Machine (SVM) Classification:

$\hat{y}SVM(z) = argmax_k\ (w_k\ z + b_k)$ ----------(2)

eq-(2) represents,

- z = feature vector after scaling
- w_k, b_k= weight vector and bias for class k
- $k \in \{0,1,2\}$ = stress class

III. LITERATURE SURVEY

Gupta and Sharma (2020), et al. [1], Their work showed how structured data from surveys can be utilized to effectively classify the level of stress. This faculty gives a foundation for machine learning applications in analyzing mental health.

Smith and Brown (2019), et al. [2], used NLP to perform sentiment analysis on educator feedback to identify emotional stress. They pointed out that linguistic cues in unstructured text are important indicators of psychological well-being. This supports the use of NLP in monitoring teacher stress.

Brown and Wilson (2021), et al. [3], highlighted the role of flexibility in education. They identified major factors such as adaptability, emotional strength and support systems that affect teachers how to overcome stress. Their work shows why it is important to include psychological models in ML-operated analysis.

Lee and Kim (2023), et al. [4], presented an AI-based faculty well-being system that uses real-time data to offer personalized interventions. Their study reveals the practical advantages of predictive analytics in enhancing mental wellness programs at higher education institutions.

Guyen, Patel, and Zhao (2022), et al. [5], detected using deep learning models to detect psychological stress through physical signs such as heart rate and skin temperature. Their research suggests how effective, non-guspath stress can be detected by combining biosensor data with AI models.

Mohan and Suresh (2020), et al. [6], provided a detailed survey on machine learning techniques used in mental health and stress detection. They covered classification, clustering, and anomaly detection. Their review helps with choosing and applying algorithms for stress monitoring in academic settings.

Wang and Luo (2019), et al. [7], examined emotion recognition systems based on physiological signals using deep learning. Their work supports using CNN and Recurrent Neural Networks in real-time, sensor-based emotional tracking systems for educators.

Blease and gegty (2020), et al. [8], Discussed moral and privacy issues in using digital mental health equipment in the educational environment. He emphasized the importance of transparency, consent and fairness in algorithms when using AI to monitor stress and welfare.

D'Mello and Grasser (2014), et al. [9], saw emotional states such as confusion and stress while learning multimedia. He showed how these emotions affect the consequences of learning. The result suggest that manners and conversion data stress detection models may have useful features.

Kumar and Prakash (2021), et al. [10], studied the faculty burnout and found a hard communication b/w long-term stress and low academic productivity. Their work highlights the necessary for initial identification and intervention using a smart system to prevent a decline in long-term mental health.

Thomas and Ray (2020), et al. [11], analyzed the relationship between academic charge and stress. They found that high demands greatly increase the emotional pressure among the university employees. Their statistical insight can be added as relevant charge features in the machine learning model.

Sen and Chatterjee (2021), et al. [12], focused on post-pandemic stress in educators. They found that digital fatigue and emotional exhaustion have risen sharply. Their findings highlight the need for AI-supported wellness systems that fit remote and hybrid teaching situations.

Perera and Nanda (2022), et al. [13], performed a longitudinal study at the flexibility of the building. They found that colleagues support support and reflective practices improve the faculty of adaptability. These flexibility factor can serve as future symptoms in ML models that are utilized to assess the copying mechanism.

Iyer and Menon (2019), et al. [14], looked into faculty coping strategies. They discovered differences based on gender and experience, noting that emotional-focused coping is more common among women. Their findings can help personalize machine learning-based stress support recommendations.

O' Reilly and ward (2020), et al. [15], ML algorithms such as SVMs and Logistic Region were used to predict educational stress from behavior dataset. Their study reflects the practical use of machine learning in identifying individuals that are under high stress based on their activity logs.

IV. METHODOLOGY

This study tries to create a ML model that classified stress levels and finds flexibility pattern between the faculty. It uses random forest and SVM algorithms

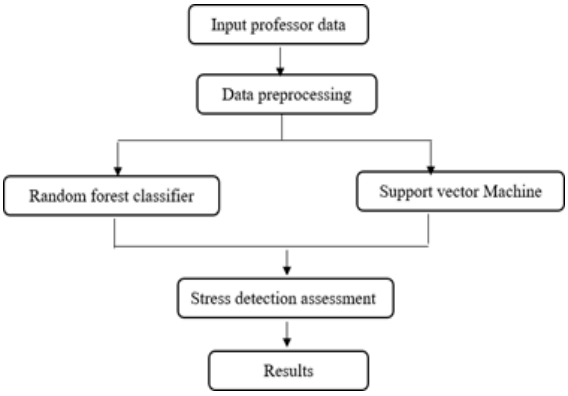

Fig 1: Dataflow Diagram

In fig 1, the overall process of stress and resilience analysis among teaching faculty is shown. The data from teachers, including survey responses and feedback, is first collected and cleaned to ensure excellence to our project. The processed data is then classified using two ML models, RF and SVM, to identify stress levels and resilience patterns. Finally, the system provides results that highlight faculty stress categories and resilience insights. These findings can help in the higher educational institutions and develop wellness and support programs.

The methodology includes the following steps,

1. Data Collection:

Data will be gathered through structured surveys. These will include information on workload, stress symptoms, coping strategies, sleep patterns, and job satisfaction. We will also collect textual feedback from open-ended responses for sentiment analysis.

2. Data Preprocessing:

We will clean and normalize survey data. Text data will be processed using NLP techniques like tokens, stop-word removal, sentiment scoring, and TF-IDF vectorization to turn text into useful numeric features.

3. Feature Engineering:

Key features will include workload hours, sentiment scores, sleep duration, and support system ratings. We will encode all categorical data and apply numerical scaling where necessary to prepare the dataset for classification.

4. Model Design:

We build 2 ML models:

• Random Forest Classifier: This model is effective for handling diverse feature sets and providing insights on feature importance.

• Support Vector Machine (SVM): This model is suitable for classification based on defined margins and works well in high-dimensional space.

5. Model Evaluation:

We will use grade like exactness, precision, and recall to assess by using RF and SVM and then calculate F1-Score. Cross-validation (5-fold) will help ensure robustness and reduce overfitting.

6. Workflow Summary

a. Input: Survey plus feedback data.
b. Preprocessing: Clean and prepare structured and textual data.
c. Feature Extraction: Generate input features using NLP and numerical processing.
d. Modeling: Train Random Forest and SVM.
e. Output: Stress and resilience prediction, plus feature insights.

V. RESULTS AND DISCUSSION

The study looked at predicting stress and assessing resilience among higher education faculty using the RF and SVM classifiers. The dataset was created from structured survey responses. It included factors like sleep duration, sleep quality, workload hours, physical activity, screen time, and social interactions, along with textual feedback analyzed through sentiment scores.
To guarantee reliability.

Both models were trained and tested using 5-fold cross-Satya pan technology. Accident, accurate, recall, and F1-score were the metrics that we used to gauge to perform.

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	89.6%	88.3%	87.9%	88.1%
Support Vector Machine	84.2%	82.7%	81.9%	82.3%

Table 1: Performance Comparison of RF and SVM Models

Results show that RF consistently outperformed SVM in all evaluation metrics. This is mainly because RF can handle non-linear relationships and mixed data types. It also offers interpretability through feature importance. In contrast, SVM performed well but was sensitive to noisy and high-dimensional data.

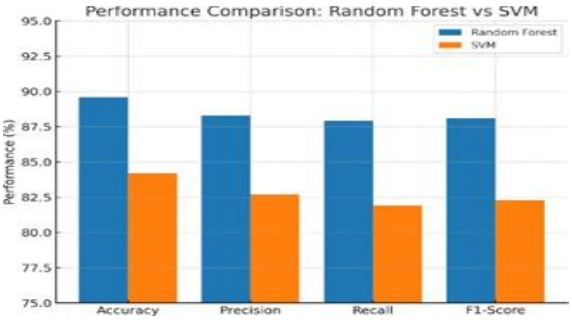

Fig 2: Accuracy Comparison of RF and SVM:

From the study, the primary determinants of stress prediction were found to be:

- Workload hours (the highest contributor to stress)
- Sleep quality (directly linked to resilience)
- Social interactions (served as a protective factor against high stress)

Additionally, sentiment analysis of open-ended feedback showed that a negative emotional tone strongly correlated with higher predicted stress levels. This confirms the benefit of using Natural Language Processing (NLP) alongside classification models.
Overall, the study shows that RF is more effective and reliable than SVM in real educational datasets. It provides higher accuracy and clearer results. This results in creating AI-driven systems to monitor faculty wellness.

VI. CONCLUSION

This case study looked at stress and resilience among teaching faculty in higher education using RF and Support Vector Machine (SVM) classifiers. The results shown that RF gives exactness and reliable than SVM. This is due to its able to handle different features, reduce overfitting, and provide clear insights through feature importance. Key factors like workload, sleep quality, and social interactions were identified as the most important contributors to faculty stress and resilience.
The findings point to the potential of ML systems to support faculty well-being by allowing early detection of stress, guiding preventive interventions, and shaping institutional policies on workload distribution and wellness programs. While this study focused on survey-based and textual data, future research could expand by including real-time physiological signals and hybrid models to increase prediction accuracy.
Overall, this research highlights the need to combine data analysis with psychological insights to create supportive and resilient academic environments.

VII. LIMITATIONS

This study emphasizes the role of predictive models in assessing stress and resilience among faculty members; however, some limitations remain. First, the dataset was small and narrow, focusing mostly on self-reported survey data and textual feedback. Self-reported answers can sometimes be biased since participants may underreport or overreport their stress

levels. Second, the study used only two ML models—Random Forest and SVM—while leaving out other methods like deep learning or ensemble hybrids that might perform better.

In addition, external factors such as institutional culture, socio -economic background and personal situations were not fully considered, even if they can affect faculty stress and flexibility. At last, the research work occurred in a controlled setting, and results may not apply to the actual world environment. These limitations open doors to expand and improve the proposed structure for future research.

VIII. FUTURE WORK

Future research on stress and resilience among teaching faculty can focus on these areas:

• Larger Dataset – Expanding the study to include faculty from multiple institutions to improve the results.

• Physiological Data Integration – Adding real-time signals such as heart rate, skin conductance, and sleep monitoring from wearable devices.

• Advanced Models – Exploring deep learning, ensemble hybrids, or reinforcement learning for better prediction accuracy.

• Real-Time Monitoring – Creating AI-powered systems linked with wellness platforms for early stress detection and intervention.

• Personalized Recommendations – Designing support systems that recommend coping strategies based on individual stress patterns.

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