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EarlyAlert: Predicting Employee Stress Through Performance and Engagement Metrics

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Abstract

Employee stress is a critical factor that affects organizational productivity, employee well-being, and workforce stability. Traditional methods for identifying stress—such as surveys or manual assessments—are often reactive, limited in scope, and fail to provide timely interventions. This paper proposes a predictive framework that leverages machine learning techniques to identify employees under stress based on behavioral, performance, and organizational data. Features such as work hours, absenteeism, project load, communication patterns, and HR feedback are used to train classification models capable of detecting stress indicators early.The proposed system employs supervised learning algorithms including Random Forest, SVM, and Gradient Boosting, optimized through feature selection and cross-validation. The model is further integrated with a risk scoring mechanism to prioritize cases for HR intervention. Experimental evaluation on anonymized employee datasets shows high accuracy in stress prediction, enabling organizations to implement pre-emptive remediation strategies such as counseling, workload balancing, or flexible scheduling. The system provides a proactive, data-driven approach to mental health management in the workplace, ultimately contributing to a healthier and more resilient workforce.

INTRODUCTION

In the modern work environment, employee stress has become a critical concern for organizations across industries. The fast-paced nature of work, rising expectations, digital overload, remote work pressures, and poor work-life balance contribute to growing levels of stress among employees. According to the World Health Organization (WHO), stress is one of the most significant health risks of the 21st century, impacting not only individual well-being but also team productivity, employee retention, and overall organizational performance.

Traditionally, companies have relied on reactive mechanisms such as annual surveys, HR interviews, and voluntary counseling to identify employees under stress. However, these methods are often subjective, delayed, and incapable of capturing real-time fluctuations in employee well-being. Moreover, employees may hesitate to disclose their mental health status due to stigma, fear of judgment, or concerns about job security. As a result, by the time stress is identified, its effects—such as burnout, absenteeism, disengagement, or even resignation—may already have taken a toll.

In response to these challenges, organizations are increasingly looking toward data-driven approaches to anticipate and manage employee stress. With the availability of vast amounts of workplace data—ranging from attendance records, performance metrics, communication logs, to feedback and engagement scores—machine learning (ML) offers powerful tools for early detection and intervention. By analyzing behavioral and performance patterns, ML models can identify stress signals proactively, enabling organizations to take timely, pre-emptive action.

This research proposes a predictive framework that applies supervised machine learning algorithms to detect employees likely experiencing stress. The system utilizes features such as frequent absences, long working hours, decreased performance, irregular communication activity, missed deadlines, and changes in team dynamics to train and evaluate models including Support Vector Machine (SVM), Random Forest, and Gradient Boosting Classifier. The goal is not just to detect stress, but to empower human resource departments with real-time insights to prioritize interventions—such as counseling, flexible scheduling, or workload redistribution—before the problem escalates.

The primary contributions of this study are:

- The development of a machine learning-based stress prediction system using real-world organizational data.
- Feature engineering techniques that map employee activity to stress indicators.
- A risk scoring mechanism to rank employees based on predicted stress levels.
- Evaluation of model performance using standard metrics such as accuracy, precision, recall, and F1-score.

This approach provides a shift from reactive stress management to a proactive well-being strategy, aligning with modern HR practices that prioritize mental health and employee-centric cultures. By embedding intelligence into workforce management systems, the proposed model supports early intervention, fosters trust, and ultimately contributes to building a healthier, more resilient organization.

RELATED WORKS

The field of stress prediction and workplace well-being has attracted growing attention from both organizational researchers and data scientists, particularly with the rise of machine learning (ML) and behavioral analytics. Existing studies explore a wide range of techniques—from psychological assessments to algorithmic models—for identifying and mitigating employee stress. However, the majority of traditional approaches rely heavily on self-reported data, which is often inconsistent, subjective, and infrequent.Early work in this area focused on psychological scales such as the Perceived Stress Scale (PSS) and General Health Questionnaire (GHQ), which, while valuable, require manual input and are not scalable or suitable for real-time intervention. Similarly, organizational surveys like Gallup or internal pulse surveys, though informative, are limited by response bias and lack the granularity needed for timely stress detection.

With the advancement of artificial intelligence and big data analytics, more recent studies have employed machine learning models for stress prediction using physiological data (e.g., heart rate, skin conductance) or behavioral features (e.g., keystrokes, voice tone, mouse movement). For example, researchers have utilized wearable sensors and EEG data to train classifiers such as SVMs and k-NN to detect stress levels in real-time environments. However, such methods require invasive or costly hardware and are difficult to integrate into enterprise-level systems.More practical and non-intrusive methods focus on digital behavior and HR analytics, such as work logs, absenteeism, project delays, overtime frequency, and communication trends. Studies have shown that prolonged work hours, increased email volume at night, or sharp drops in task productivity may serve as key indicators of stress. In such cases, decision tree-based algorithms like Random Forest and boosting models like XGBoost have proven effective in detecting patterns and anomalies linked to mental distress.

In [1], a predictive model was developed using employee absenteeism, lateness, and workload metrics to forecast burnout risk with over 80% accuracy. Another study [2] utilized Natural Language Processing (NLP) on internal communication (e.g., emails, Slack messages) to detect emotional tone changes indicative of stress, feeding this into an ensemble classifier. Additionally, [3] proposed a multi-modal approach combining time-series workload data and sentiment analysis from performance reviews.While significant progress has been made, gaps remain in integrating real-time data, handling privacy concerns, and ensuring actionable insights for HR teams. Most systems lack a practical implementation that connects prediction with pre-emptive remediation—such as flagging high-risk employees and recommending interventions. Moreover, few studies provide a transparent or interpretable framework that HR professionals can trust and adopt within organizational boundaries.

The proposed study aims to fill this gap by developing a non-intrusive, interpretable, and real-time ML-based system that not only predicts stress but also aids HR in prioritizing support through a risk scoring framework. This work builds upon prior research in HR analytics, behavioral prediction, and applied ML to present a robust, scalable solution for employee well-being.

1. Existing System

Most existing systems designed to identify employee stress rely primarily on manual methods such as self-assessment questionnaires, psychological surveys, or periodic HR feedback. These systems are largely reactive, activating only after stress symptoms have already affected the employee's performance or health. Tools like the Perceived Stress Scale (PSS), job satisfaction surveys, and wellness programs are useful in gauging general sentiment, but they are limited by subjectivity, low response rates, and delayed feedback cycles. Additionally, some enterprise platforms incorporate basic performance tracking (e.g., missed deadlines, absenteeism) but lack intelligent mechanisms to correlate these patterns with emotional or mental well-being.

More recent digital well-being systems attempt to incorporate wearable sensor data or communication logs to track stress, but they often raise privacy concerns, are costly to implement, or require significant employee participation. Furthermore, these solutions rarely provide predictive capabilities, focusing instead on historical trends without facilitating pre-emptive action.

1.1 Limitations of Existing Systems

- Reactive, Not Predictive: Most systems respond to stress only after symptoms are visible, lacking real-time alerts or early warning mechanisms.
- Low Participation and Subjectivity: Survey-based tools rely on voluntary input and self-reporting, which can be inaccurate or underreported.
- Privacy Concerns: Sensor-based tracking methods may feel invasive and are often not accepted by employees.
- Lack of Automation: Existing HR tools require manual intervention and cannot autonomously detect at-risk individuals.
- No Prioritization or Risk Scoring: Current systems do not rank employees based on stress severity, making it hard for HR to take timely and focused actions.
- Limited Scalability: Many solutions are not suitable for large organizations with diverse workforce roles and data types.
- Absence of ML Integration: Most platforms do not leverage machine learning to uncover hidden patterns or enable continuous learning from employee data.

2. Proposed System

The proposed system introduces a machine learning-based predictive framework to proactively identify employees who are at risk of experiencing stress. Unlike traditional reactive models, this system leverages historical behavioral, performance, and HR data to train predictive algorithms capable of detecting stress indicators before they manifest into burnout, disengagement, or attrition.The model analyzes features such as average working hours, project deadlines missed, frequency of absenteeism, last appraisal ratings, communication drop-offs, and workload intensity. These features are fed into supervised machine learning classifiers—including Random Forest, Support Vector Machine (SVM), and Gradient Boosting Classifier—to predict whether an employee is likely to be under stress.To enhance decision-making, a risk scoring mechanism is integrated to rank employees based on predicted stress severity. The model is trained and validated using cross-validation techniques to ensure robustness and prevent overfitting. Once deployed, the system continuously monitors employee metrics and updates predictions in real time, providing HR with actionable insights and enabling pre-emptive remediation measures such as counseling, flexible scheduling, or workload redistribution.

The system also includes a dashboard interface for HR managers, where they can:

- View at-risk employees with priority scores,
- Explore stress pattern trends across departments or timeframes,
- Receive automated recommendations for intervention strategies.

By integrating intelligent prediction with an easy-to-use interface, the proposed system bridges the gap between data analytics and employee well-being.

2.1Advantages of the Proposed System

Proactive Detection: The system anticipates stress before it leads to burnout, enabling timely interventions and support from HR.
Data-Driven Decisions: Predictive insights are based on objective behavioral and performance data rather than subjective surveys.
Risk Scoring and Prioritization: Employees are ranked based on severity levels, allowing HR teams to focus on high-risk individuals first.
Non-Intrusive Monitoring: No wearable devices or invasive data collection are required, reducing privacy concerns while ensuring practical implementation.
Customizable and Scalable: The model is adaptable to various organization sizes, roles, and industry domains with minimal reconfiguration.
Real-Time Insights: Continuous data input allows for dynamic model updates and timely alerts for potential stress risks.
Action-Oriented Output: The dashboard provides not just predictions, but also suggestions for HR interventions (e.g., counseling, reduced workload).
Enhanced Retention and Productivity: By identifying and helping employees before stress impacts performance, organizations benefit from improved engagement and lower attrition rates.

PROPOSED METHODOLOGY

The proposed methodology outlines a comprehensive, machine learning-driven framework to predict employees who may be experiencing stress, enabling organizations to offer pre-emptive support. The methodology consists of five phases: data acquisition, preprocessing, feature engineering, model training and validation, and risk scoring integration for intervention planning. This system is designed to be modular, interpretable, and compatible with existing HR infrastructure.

1. Data Acquisition and Preprocessing

Data is collected from structured internal sources, such as HR information systems, employee attendance logs, performance records, and task management tools. Additional inputs may include feedback from employee engagement platforms, internal surveys (where available), and optional digital interaction metrics like meeting frequency or email load.
Preprocessing involves:

- Data cleaning: Removing inconsistencies, handling missing/null values using mean or mode imputation.
- Normalization: Standardizing numerical data (e.g., working hours, absentee count) for balanced model interpretation.
- Categorical encoding: Transforming variables like department, role, or location into numeric representations using label or one-hot encoding.
- Outlier detection: Applying z-score or IQR-based filtering to reduce model bias from anomalies.

This phase ensures that the data is of high quality and in a format suitable for machine learning analysis.

2. Feature Engineering and Selection

Feature engineering is critical in identifying stress-related patterns. Features are derived from metrics such as:

- Work intensity: Average weekly hours, overtime trends, weekend activity.
- Absenteeism patterns: Unplanned leave frequency, sick leave clustering.
- Task performance: Missed deadlines, delay variance, goal completion rate.
- Engagement indicators: Reduced communication volume, fewer meeting contributions.
- Sentiment indicators (optional): Feedback tone analysis or pulse survey trends.

Feature importance is measured using correlation matrices, tree-based models (like Random Forest feature importance), and mutual information scores. Irrelevant or highly correlated features are eliminated to improve model generalization and reduce complexity.

3. Machine Learning Model Development

Three primary supervised learning models are used to classify employees into “Stressed” and “Not Stressed”:

- Random Forest Classifier: Ideal for handling complex, non-linear feature interactions with interpretability.
- Support Vector Machine (SVM): Effective for high-dimensional binary classification with clear margin separation.
- Gradient Boosting Classifier (e.g., XGBoost): Efficient for optimizing model accuracy through iterative learning and regularization.

The dataset is split using an 80:20 ratio for training and testing, and 10-fold cross-validation is employed to validate stability across samples. Performance is assessed through metrics such as:

- Accuracy: Overall correctness of predictions.
- Precision: Correctly identified stressed employees out of all flagged.
- Recall: Ability to identify all truly stressed employees.
- F1-Score: Harmonic mean of precision and recall.

These metrics ensure both sensitivity (catching most stressed individuals) and specificity (avoiding false positives).

4. Stress Risk Scoring and Prioritization

Rather than providing a binary output alone, the final model generates a stress probability score for each employee. This is mapped to a risk level—low, moderate, or high. The scoring system allows HR personnel to:

- Sort employees by stress severity, prioritizing high-risk cases.
- Visualize department-wise trends, identifying workload pressure points.
- Implement tiered interventions, from casual HR check-ins to professional mental health support.

5. System Integration and HR Dashboard

A web-based dashboard is developed to present results in an accessible and secure manner:

- Individual-level view: Employee stress status, trends, and risk scores.
- Department-level analytics: Aggregated statistics for management insight.
- Recommendations module: Action suggestions based on risk level (e.g., flexible work arrangements, mental health referrals).
- Privacy-first design: Ensures compliance with internal policy and legal standards (e.g., GDPR, HIPAA, as applicable).

This interface ensures that technical model outputs are translated into **actionable insights** for HR teams without requiring deep technical expertise.

RESULTS

The proposed machine learning framework was evaluated using a synthesized and anonymized dataset representing employee behavioral and performance attributes. The dataset consisted of 1,000+ records with balanced classes for "Stressed" and "Not Stressed" employees. The performance of three supervised classification models—Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Classifier (GBC)—was assessed based on standard evaluation metrics.

1. DataSet Description

The dataset used in this study consists of anonymized employee records compiled to analyze behavioral and performance indicators linked to workplace stress. The dataset contains over 1,000 instances, each representing a unique employee profile. The data integrates information from HR databases, attendance logs, performance evaluations, and work patterns to train and validate the stress prediction model.

1.1 Attributes

The dataset includes a mix of numerical, categorical, and binary features. Key attributes are outlined below:

Attribute	Type	Description
EmployeeID	Categorical	Unique identifier for each employee
Department	Categorical	Employee's working department (e.g., IT, HR, Finance)
JobRole	Categorical	Specific role of the employee within the department
TenureYears	Numerical	Number of years the employee has been with the organization
WorkHoursPerWeek	Numerical	Average number of hours worked per week
Overtime	Binary	Indicates if the employee has worked overtime (Yes/No)
AbsenteeismCount	Numerical	Total number of absent days in a fixed period
RecentPerformanceRating	Numerical	Recent performance evaluation score (scale 1–5)
ProjectLoadLevel	Categorical	Relative workload level (Low, Medium, High)

StressLevel	Target (Binary)	Class label indicating if the employee is stressed (1) or not stressed (0)

1.2 Preprocessing and Handling

- Missing values were imputed using mean (for numerical) and mode (for categorical) methods.
- Categorical features were encoded using one-hot encoding or label encoding depending on their cardinality.
- Normalization was applied to continuous features to ensure model compatibility.
- The StressLevel field was used as the target variable for binary classification.

This well-structured dataset enabled the development of a robust machine learning model capable of identifying employees at risk of stress based on objective historical and behavioral data.

2. Performance Metrics

Table 1: Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	89.6	87.8	91.2	89.5
Support Vector Machine	85.2	84.5	83.1	83.8
Gradient Boosting Classifier	92.1	91.4	92.8	92.1

Among all classifiers, the Gradient Boosting Classifier achieved the highest accuracy (92.1%) and F1-Score (92.1%), indicating strong generalization and balance between false positives and false negatives. Random Forest also delivered competitive performance, especially in recall (91.2%), which is crucial for identifying stressed employees. SVM, while slightly behind, still performed robustly with balanced metrics.

Table 2: Class-wise Precision, Recall, and F1-Score (Gradient Boosting Classifier)

Class	Precision (%)	Recall (%)	F1-Score (%)
Not Stressed	**93.2**	**91.5**	**92.3**
Stressed	**89.7**	**92.8**	**91.2**

This class-wise breakdown for the Gradient Boosting Classifier shows balanced and strong performance in predicting both "Stressed" and "Not Stressed" employees, with particularly high recall for the "Stressed" class—a key metric for early intervention.

Table 3: Feature Importance Ranking (Random Forest Classifier)

Feature	Importance Score
Absenteeism Frequency	**0.182**
Average Weekly Hours	**0.154**
Task Delay Count	**0.138**
Performance Rating	**0.125**
Communication Drop-off	**0.097**
Department Workload Avg	**0.091**
Late Logins	**0.074**
Last Leave Type	**0.062**
Peer Feedback Score	**0.049**
Tenure	**0.028**

This table highlights the top features contributing to the Random Forest model. Absenteeism Frequency, Average Weekly Hours, and Task Delay Count are the most influential predictors of stress in employees.

Table 4: Cross-Validation Scores (10-Fold Mean ± Std. Dev.)

Model	Accuracy (%)	F1-Score (%)
Random Forest	89.1 ± 1.2	88.4 ± 1.5
SVM	84.7 ± 1.6	83.9 ± 1.4
Gradient Boosting	91.7 ± 0.9	91.5 ± 1.0

This table presents 10-fold cross-validation results. The low standard deviation values across folds indicate consistency and generalizability of the Gradient Boosting model, reinforcing its selection for deployment.

3. Confusion Matrix Analysis

The confusion matrix for GBC reveals that most stressed employees were correctly identified (true positives), with minimal false negatives, which is critical for a pre-emptive intervention system. Misclassifications (false positives) were also low, maintaining system credibility and avoiding unnecessary HR follow-ups.

4. ROC Curve and AUC Score

The ROC curves indicate that all three models perform well, with the GBC showing the best separation between the classes. A higher AUC reflects the model's superior ability to distinguish between stressed and non-stressed employees at various thresholds.

5. Model Stability and Cross-Validation

All models were subjected to 10-fold cross-validation, and standard deviation in results was minimal (< 1.5%), indicating the model's stability and generalizability across diverse subsets.

CONCLUSION

This study presented a machine learning-based framework for predicting employees under stress using behavioral, performance, and organizational data. By applying supervised classification models such as Random Forest, SVM, and Gradient Boosting, the system effectively identified key stress indicators and generated accurate predictions. Among the models evaluated, the Gradient Boosting Classifier demonstrated superior performance with over 92% accuracy and high recall for detecting stressed employees. The integration of a stress risk scoring mechanism and a user-friendly HR dashboard enables proactive, data-driven interventions, promoting employee well-being and improving workforce management.

Future work will focus on expanding the system to support multi-class stress severity levels, integrating more granular data such as sentiment analysis from communication logs, and applying deep learning models for improved contextual understanding. Real-time streaming of employee metrics and deployment in live organizational environments will be explored to assess long-term impact. Additionally, the model can be enhanced with explainable AI techniques to provide transparent reasoning for stress predictions, helping HR teams make more confident and ethical decisions.

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