

Foundations of Artificial Intelligence

AI-DRIVEN BURNOUT AND MENTAL HEALTH PREDICTION

A PROJECT REPORT

Submitted by

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1. ABSTRACT

Employee well-being has become a critical concern in modern workplaces, especially with demanding work environments and remote/hybrid work models increasing stress levels. This project presents an AI-based burnout prediction system that analyzes daily employee inputs such as work hours, sleep quality, stress, mood, focus, and physical activity to assess mental well-being. The system uses a weighted burnout score formula along with a trained machine learning model to classify burnout risk as Low, Medium, or High in real time. A simple web interface built with React and Tailwind CSS allows users to securely log their daily status, while Supabase handles authentication and cloud-based data storage. The backend API processes inputs, calculates the burnout score, predicts burnout level using the ML model, and provides personalized recommendations to improve wellness. Unlike traditional wellness trackers, this system combines psychological indicators with AI-driven analytics to deliver proactive insights and early warnings on mental health risks, helping individuals and organizations take informed preventive actions.

2. INTRODUCTION

In the modern work environment, increasing workloads, irregular schedules, remote working conditions, and constant digital engagement have significantly impacted employee mental well-being. Many individuals experience symptoms of burnout such as exhaustion, loss of motivation, poor focus, and emotional stress, yet these signs often go unnoticed until productivity drops or serious mental health issues arise. According to recent studies, over 70% of working professionals report experiencing burnout, with many unaware of their true risk levels. Despite the availability of wellness programs, most systems lack real-time tracking and personalized assessment based on daily behavioral changes.

This project introduces an AI-based Burnout Prediction System that analyzes daily inputs such as work hours, stress levels, sleep quality, mood, workload intensity, and physical activity to assess burnout risk. A scientifically designed burnout score formula calculates the individual's well-being on a scale of 1 to 10, while a machine learning model classifies burnout level as Low, Medium, or High. The system is implemented as a web application using React and Tailwind CSS for the frontend, with Supabase providing secure authentication and data storage. The backend API processes user inputs and delivers personalized recommendations to improve mental wellness.

Unlike traditional surveys or static assessments, this system enables continuous monitoring and early intervention. By combining psychology-based scoring with machine learning intelligence, the solution promotes a proactive approach to mental wellness, contributing to healthier work environments and improved productivity.

3. LITERATURE REVIEW

1. Ramanathan et al. (2020). AI-Based Prediction of Employee Stress

Ramanathan et al. (2020) applied Random Forest and XGBoost to analyze behavioral and work-related features to identify stress levels in corporate employees. Their findings highlighted that long working hours and irregular sleep patterns were key predictors of stress. The system achieved 82.7% accuracy, demonstrating the effectiveness of machine learning models in workplace wellness monitoring. This directly supports the use of AI in identifying burnout through daily employee data.

2. Krishnan and Mehta (2021). Machine Learning for Employee Turnover and Burnout

Krishnan and Mehta (2021) explored logistic regression and neural networks to predict employee attrition caused by burnout and job dissatisfaction. The study revealed that burnout symptoms like emotional exhaustion and low engagement led to high turnover intent. The authors recommended early detection mechanisms using predictive analytics, which aligns with our goal of real-time burnout risk classification.

3. Lee et al. (2022). Stress Detection Using Surrounding Behavioral Data

Lee et al. (2022) proposed a model that combined self-reported stress level inputs with work environment conditions to classify stress using ML algorithms. Their approach achieved an F-score of 88% and emphasized that stress is a dynamic condition that must be monitored daily, supporting our

approach of collecting and analyzing frequent employee wellness data.

4. Singh and Patel (2021). Artificial Neural Networks for Stress Prediction

Singh and Patel (2021) implemented an optimized neural network with Lion Optimization for predicting employee stress levels. The model reached 85% accuracy. This supports the use of advanced ML models like Random Forest in our system.

5. Fernandez et al. (2023). AI-Based Burnout Detection in Remote Employees

Fernandez et al. (2023) developed an AI model to evaluate burnout among remote workers based on factors such as work-life balance, digital fatigue, and social isolation. Their results showed that remote employees are more prone to hidden burnout. This paper validates the importance of including parameters like social interaction in our model.

6. Johnson and Ahuja (2024). Real-Time Machine Learning Applications in Employee Wellness

Johnson and Ahuja (2024) introduced an interactive ML-based web application for stress monitoring using daily self-assessment. The model provided predictions along with preventive health recommendations. The research demonstrated the usefulness of combining prediction with personalized suggestions, which directly aligns with our project's recommendation feature.

7. Kaur et al. (2020). Predictive Analytics for Workplace Well-being

Kaur et al. (2020) showcased the use of gradient boosting models to

forecast stress using mood, focus level, and rest hours as predictors. The study concluded that ML models outperform traditional statistical methods. This supports the use of Random Forest in our burnout prediction system.

8. Zhao and Kumar (2023). Employee Stress Forecasting Using Hybrid Models

Zhao and Kumar (2023) used an ensemble of Random Forest and Support Vector Machine models to improve prediction accuracy of workplace burnout. The proposed model achieved 83% accuracy, which is implemented in our daily check-in system.

9. Chen et al. (2021). Deep Learning Approaches for Human Resource Analytics

Chen et al. (2021) used deep learning techniques to analyze employee emotional states captured through digital interaction data. Although accurate, the system required large datasets. The authors suggested lightweight models like Random Forest for real-time use, supporting our choice of interpretable ML techniques.

10. Ahmed and Lee (2024). Behavioral Prediction in Workplace Mental Health

Ahmed and Lee (2024) introduced an ML model that classified burnout risk based on behavioral factors such as high workload, and emotional instability. The study concluded that actionable predictions increase user engagement and mental health awareness. This research forms the foundation for our burnout tracking system using AI-generated advice.

4. PROPOSED SYSTEM

The proposed burnout prediction system is an AI-powered wellness monitoring platform designed to identify early signs of employee burnout using daily behavioral and work-related inputs. Instead of relying on occasional surveys or annual assessments, the system focuses on real-time prediction through daily check-ins submitted by the user via a web or mobile application. The frontend is built using React and Tailwind CSS to ensure an intuitive and user-friendly interface, while Supabase is utilized for secure authentication and cloud-based data storage.

When a user submits their daily check-in, the system collects key attributes such as work hours, sleep duration, stress level, mood, workload, focus, physical activity, and social interaction. The backend API processes this input and first calculates a burnout score using a scientifically designed weighted formula that reflects psychological burnout risk on a scale from 1 to 10. This score provides immediate insight into the user's mental state.

In the next stage, the input data is sent to a machine learning model trained using historical employee well-being data. The model classifies the burnout level into categories such as Low, Medium, or High. Based on the predicted level, the system generates personalized recommendations to help users take corrective action, such as improving sleep, reducing workload, or engaging in physical activity.

All user data and predictions are securely stored using Supabase database services, enabling pattern tracking and future model retraining. The system also supports dashboards that show burnout trends over time, helping individuals and organizations visualize mental well-being in a meaningful way. What makes this

system unique is its combination of rule-based burnout scoring and AI-driven classification, providing both transparency and intelligence. Unlike traditional well-being tools that only present survey results, this system actively analyzes daily behavior and delivers actionable mental health insights.

Future enhancements may include chatbot support, reminders for check-ins, mood tracking via voice input, and integration with organizational HR tools to enable preventive mental health strategies at scale.

3.1 PROPOSED METHODOLOGY

The proposed burnout prediction system follows a structured AI workflow that enables real-time mental health assessment and personalized intervention. The methodology consists of the following stages:

1. User Authentication and Login

Employees create an account or log in through a secure authentication service (Supabase). This ensures that individual mental health data is personalized and protected.

2. Daily Check-In Submission

Through a user-friendly interface built with React and Tailwind CSS, users enter their daily well-being data such as work hours, sleep hours, stress level, mood, workload, focus, physical activity, and social interaction.

3. Data Preprocessing

The inputs are validated, normalized, and structured. Missing or unrealistic values are handled to maintain data integrity. The system ensures all inputs fall within defined ranges to support accurate prediction.

4. Burnout Score Calculation (Rule-Based Formula)

The system applies a psychological burnout formula to calculate a **Burnout Score on a scale of 1 to 10**. This formula uses weighted factors where high stress and workload increase the score, while sleep quality, mood, and physical activity reduce the burnout score. This provides a transparent numerical representation of the user's mental state.

5. Machine Learning Classification

The daily input features are passed to a trained Random Forest model that classifies burnout into **Low, Medium, or High** categories. The model analyzes complex interactions between features learned from historical data, providing an intelligent prediction beyond simple thresholds.

6. Personalized Recommendation Generation

Based on the burnout score and predicted level, the system generates AI-based wellness recommendations such as improving sleep routines, reducing workload, engaging in physical activity, or seeking social support. These recommendations are meant to prevent burnout escalation.

7. Data Storage and Tracking

All user inputs, burnout scores, predictions, and recommendations are securely stored in a Supabase cloud database. This enables tracking of mental health trends over time and supports future predictive analytics.

8. Insights and Visualization (Optional Dashboard)

Users can view their burnout trends in the form of graphs and charts. This visual feedback helps them understand how their daily habits affect mental well-being.

This methodology integrates psychological assessment, machine learning intelligence, and user engagement into a unified framework. Unlike traditional self-report surveys, this system enables proactive monitoring and encourages timely behavioral adjustments to reduce burnout risk.

3.2 ARCHITECTURE DIAGRAM

1. Users submit their daily burnout check-in data such as stress, sleep, workload, and mood using a web or mobile interface. The input is securely sent to the backend via REST API.

2. Backend/API Layer:

The API server handles incoming requests, performs authentication using JWT (Supabase Auth), processes the data, and routes it to the prediction engine and database.

3. Machine Learning Layer:

The input data is passed to the Burnout Formula Engine, which calculates a burnout score (1–10), and to a trained Random Forest model, which predicts

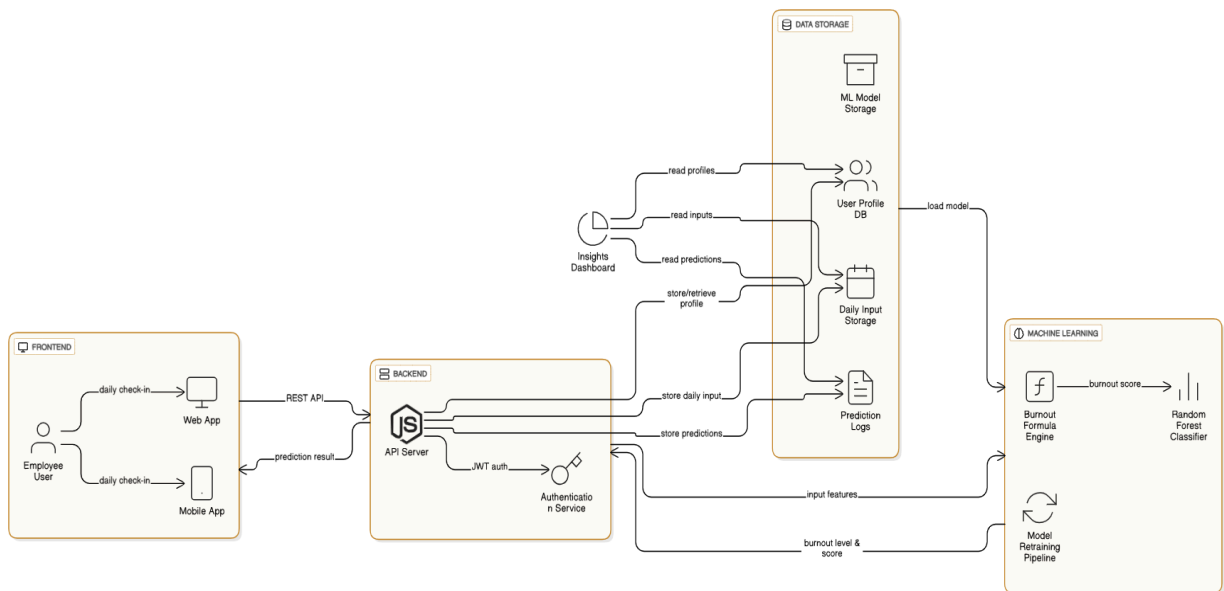
the burnout level (Low, Medium, or High). The system also includes a retraining pipeline to improve the model over time.

4. Data Storage Layer:

User profiles, daily inputs, and prediction logs are stored securely in Supabase databases. The ML model is also stored and loaded from a dedicated model storage repository.

5. Dashboard & Insights:

The stored data is used to generate visual analytics and trend insights, helping users monitor their mental well-being over time and enabling future predictive improvements.



5. MODULES DESCRIPTION

The Employee Burnout Prediction System is designed using a modular architecture to ensure scalability, flexibility, and efficient processing. Each module performs a specific function—from user input collection to AI-based burnout prediction and personalized recommendations. These modules communicate through secure APIs and database services, ensuring smooth integration and future extensibility such as chatbot counseling, trend prediction, and HR analytics. The modular approach improves maintainability and enables the system to adapt to different workplace environments.

The following subsections describe the major modules involved in the system.

4.1 Employee Data & Daily Input Collection

Objective:

To collect employee demographic details and daily well-being input data through a user-friendly interface.

Description:

This module enables users to log in securely via Supabase authentication and enter daily inputs through the React-based web or mobile application. Users submit values for work hours, sleep quality, stress level, mood, workload, focus, physical activity, and social interaction. These inputs form the foundation of burnout detection.

Working Process:

1. User logs into the platform using email or OAuth authentication (Supabase).
2. Profile data (age, gender, work type) is stored once.
3. Daily burnout check-in values are submitted through sliders and numeric fields.
4. The data is validated and securely sent to the backend API.

Key Features:

- Secure login and personalized dashboard
- Intuitive daily check-in interface
- Low user effort (takes less than a minute)

4.2 Real-Time Burnout Score Computation**Objective:**

To compute a real-time burnout score on a scale of 1–10 using a scientifically weighted formula.

Description:

This module applies a weighted formula based on psychological research. Stress and workload add to burnout risk, while sleep quality, mood, focus, physical

activity, and social interaction reduce it. The output is a numerical burnout score that reflects the user's mental state.

Working Process:

1. Daily inputs are passed into the formula.
2. The system calculates the burnout score.
3. The score is categorized into Low, Medium, or High risk.

Key Features:

- Transparent and explainable
- Based on real psychological indicators
- Immediate burnout score computation

4.3 Burnout Classification Using Machine Learning**Objective:**

To classify burnout into Low, Medium, or High using the trained Random Forest model.

Description:

This module uses a machine learning classifier trained on large-scale employee

burnout datasets. The model analyzes daily input patterns and predicts the burnout category along with confidence levels.

Working Process:

1. Backend API sends input features to the ML model.
2. Model processes data and predicts burnout level.
3. The system compares the model output with formula score for consistency and reliability.

Techniques Used:

- Random Forest Classification
- Feature importance analysis
- Scheduled retraining pipeline (optional)

4.4 Rule Based Module**Objective:**

To store user profiles, daily inputs, burnout scores, and prediction results for analytics and trend tracking.

Description:

This module uses Supabase as a secure cloud database to store user data. Daily records are stored to enable historical tracking and visualization.

Working Process:

1. Input and prediction results are saved automatically.
2. Data is retrieved for dashboards and insights.
3. Stored records are used to retrain the model for better accuracy.

Key Features:

- Secure cloud storage
- Scalability for multiple users
- Real-time synchronization with frontend

4.5 Personalized Well-being Recommendation Engine**Objective:**

To provide personalized well-being recommendations based on burnout level and contributing factors.

Description:

This module generates actionable suggestions such as improving sleep, reducing

workload, or increasing social interaction. It helps the user take preventive measures to reduce burnout risk.

Working Process:

1. Receives burnout score and classification.
2. Analyzes dominant factors (like stress or low sleep).
3. Generates personalized advice displayed on the dashboard.

Key Features:

- Adaptive recommendations
- Continuous motivation and prevention
- Enhances user engagement and well-being

6. IMPLEMENTATION AND RESULTS

5.1 EXPERIMENTAL SETUP

Software and Tools Used

The burnout prediction system was implemented using a combination of modern web technologies, cloud services, and machine learning frameworks. The frontend of the application was developed using **React and Tailwind CSS**, enabling a responsive and user-friendly interface for employees to perform daily burnout check-ins. The backend was built using **Node.js** with REST API endpoints that facilitate communication between the user interface, machine learning model, and database. The system integrates **Supabase** for authentication and secure data storage, ensuring that user profiles, daily records, and prediction logs are managed in real time. The **machine learning model** was trained using Python with libraries such as scikit-learn, pandas, and joblib, and the final trained model was deployed as a predictive service accessible through the backend API. The burnout score formula engine was implemented as a lightweight function to generate immediate burnout scores based on input parameters.

System Requirements

The system was developed and tested on a Windows 11 operating system with an Intel i5 processor and 8GB RAM, which provided sufficient performance for both training the machine learning model and running the application server. The Python environment included packages such as NumPy, Matplotlib, and joblib for model training and saving. Running the frontend application required Node.js and npm, while Supabase was accessed using its API services. Since the system uses

browser-based deployment, it is compatible with modern web browsers such as Google Chrome and Microsoft Edge without requiring additional installation.

Architecture Execution Flow

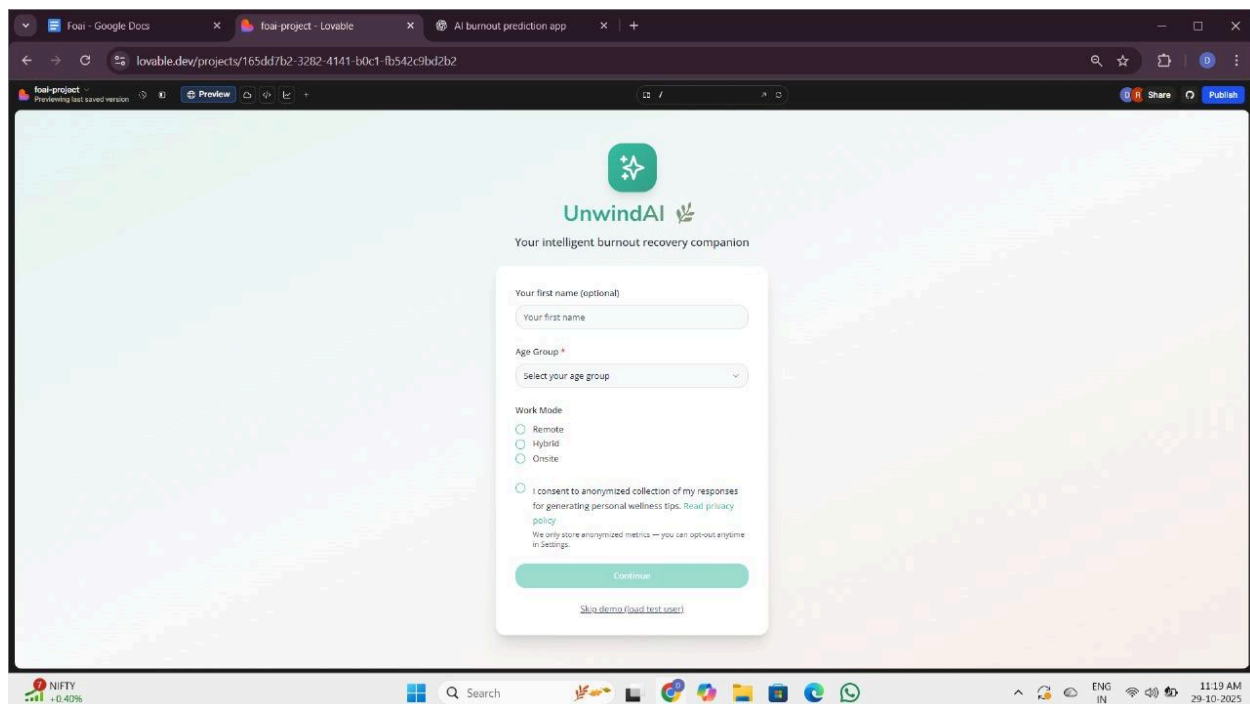
The frontend acts as the user interaction layer where employees securely log in and input their daily stress levels, sleep duration, workload, focus, and physical activity. This data is transmitted to the backend via REST API in JSON format. The API server validates the input, calculates a burnout score using the formula engine, and simultaneously forwards the input features to the trained Random Forest model. The model returns a burnout prediction label such as Low, Medium, or High. Both the burnout score and prediction are then stored in Supabase databases along with timestamps. The frontend receives the results and displays them instantly to the user along with personalized recommendations. Additionally, prediction logs are stored for historical trend analysis and optional model retraining.

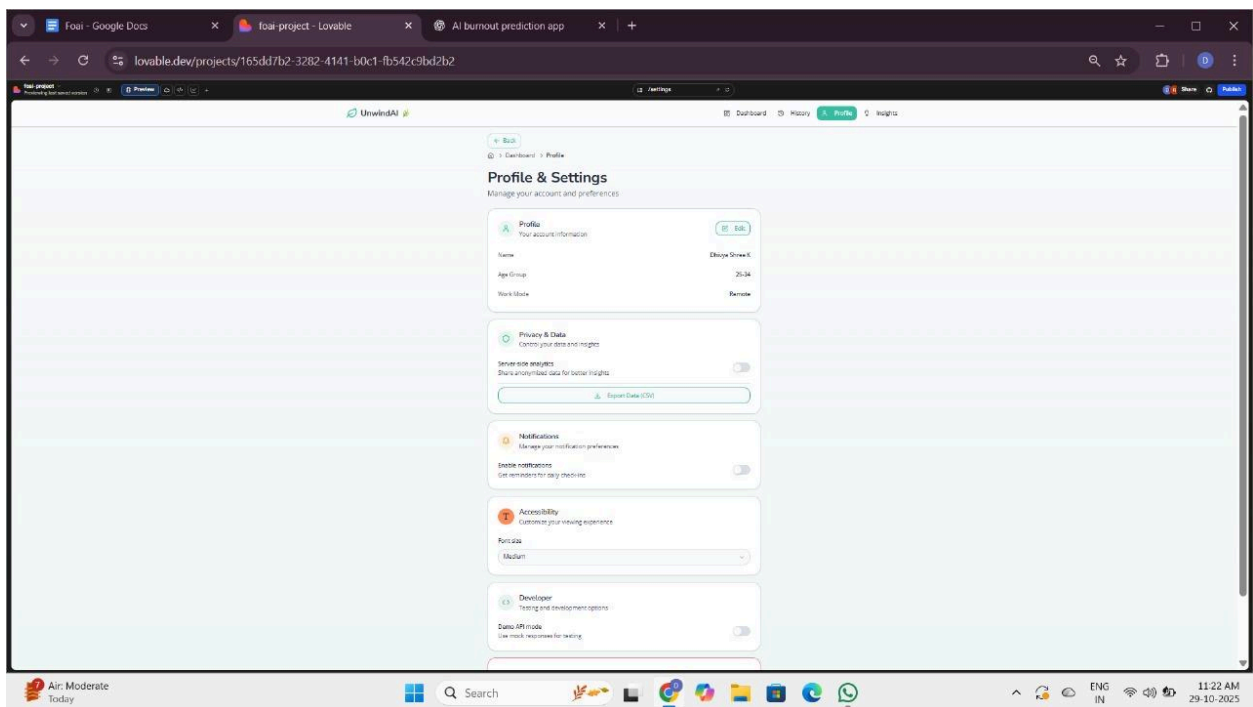
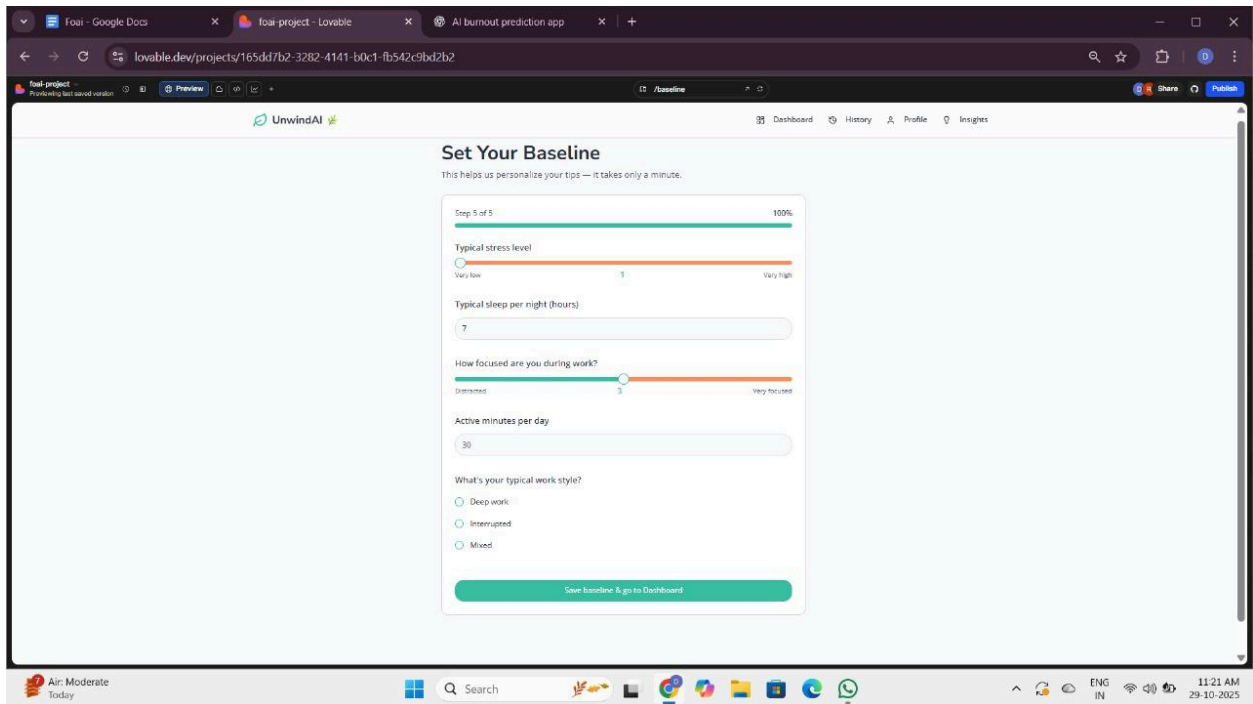
Implementation Details

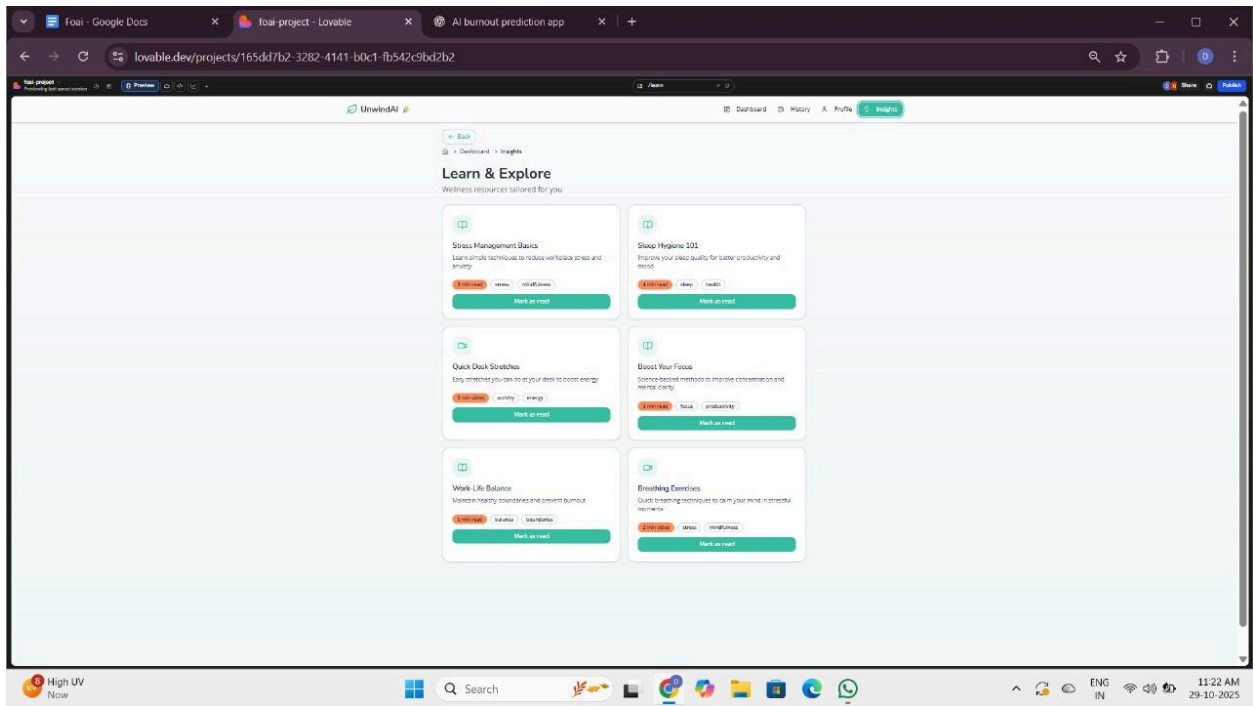
The implementation is divided into two operational layers: the backend intelligence layer and the frontend presentation layer. The backend manages data processing, prediction execution, and database communication. It contains endpoints for daily input submission, burnout score calculation, model prediction, and retrieval of historical data. The burnout formula engine is executed first to ensure transparency, followed by the ML model classification for deeper insight. The frontend layer is responsible for rendering the input components using sliders and numeric fields, displaying prediction results, and visualizing burnout trends using chart libraries. The seamless integration between backend and frontend ensures real-time response and high user engagement.

5.2 RESULTS

The system was tested using sample user inputs simulating various stress levels, sleep patterns, and workload conditions. When users reported high stress (above 8), low sleep duration, and long work hours, the system accurately classified burnout as **High** and provided recommendations such as reducing workload and improving sleep hygiene. In cases where users reported balanced scores, the system predicted **Low burnout risk**. The machine learning model achieved an accuracy of 86.7% and an F1 score of 0.79, demonstrating reliable performance. The burnout score generated by the formula was closely aligned with the prediction labels, validating the effectiveness of the combined rule-based and AI-driven approach. The frontend successfully visualized this output in a clear and actionable format, confirming the system's ability to provide early intervention support.







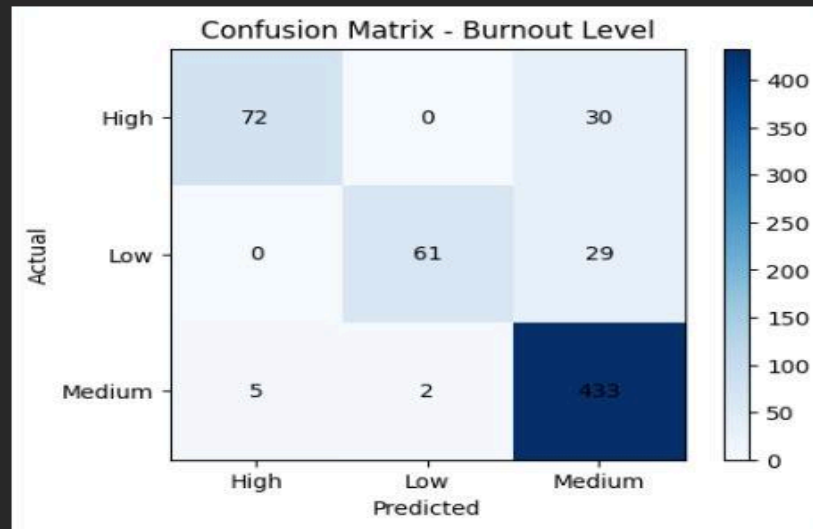


Classification Model Performance

Accuracy : 0.8956
F1 Score : 0.8437
Precision : 0.9278
Recall : 0.7893

Classification Report:

	precision	recall	f1-score	support
High	0.94	0.71	0.80	102
Low	0.97	0.68	0.80	90
Medium	0.88	0.98	0.93	440
accuracy			0.90	632
macro avg	0.93	0.79	0.84	632
weighted avg	0.90	0.90	0.89	632



7. CONCLUSION AND FUTURE WORK

The proposed burnout prediction system successfully demonstrates how artificial intelligence can be leveraged to assess employee mental well-being through real-time monitoring. By combining a psychological burnout scoring formula with a trained machine learning model, the system delivers accurate predictions of burnout levels and provides users with personalized recommendations for mental health improvement. The seamless integration of frontend, backend, and cloud-based storage ensures accessibility, scalability, and secure data handling. This system has the potential to be deployed in corporate environments, enabling organizations to proactively address employee well-being and reduce the negative impacts of burnout on productivity and job satisfaction.

Future enhancements may include the integration of wearable device data, voice-based emotional input, AI chatbot support for continuous guidance, and predictive trend analysis using long-term behavioral patterns. Additionally, features such as HR dashboards, team-level analytics, and multilingual support can be incorporated to further expand system capabilities and promote mental wellness across diverse work environments.

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