

# Stress Detection System in Office Environment

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## Abstract

Stress is a significant factor affecting employee productivity, mental well-being, and overall workplace efficiency. A stress detection system in an office environment aims to monitor and analyze employees' stress levels using physiological, behavioral, and environmental data. This system utilizes a combination of wearable sensors, facial expression analysis, voice modulation detection, and keystroke dynamics to assess stress in real time. Machine learning algorithms process these data points to classify stress levels and provide actionable insights.

The proposed system can integrate with workplace wellness programs to offer personalized stress management recommendations, such as relaxation exercises, break reminders, and ergonomic adjustments. By leveraging AI-driven analytics, organizations can proactively address workplace stress, improve employee well-being, and enhance productivity. This research highlights the system's architecture, data collection methods, stress prediction models, and potential challenges related to privacy and ethical concerns.

**Index:** Stress, ML, AI, workspace

## Introduction

Workplace stress has become a growing concern in modern office environments, affecting employee well-being, productivity, and overall job satisfaction. High levels of stress can lead to burnout, decreased efficiency, and increased absenteeism, ultimately impacting an organization's performance. Identifying and managing stress in a timely manner is crucial for maintaining a healthy work atmosphere.

A stress detection system in an office environment aims to monitor and analyze employees' stress levels using a combination of physiological, behavioral, and environmental factors. Advances in artificial intelligence, machine learning, and sensor technologies enable real-time stress detection through various methods such as heart rate monitoring, facial expression analysis, voice modulation detection, and keystroke dynamics. By analyzing these data points, the system can identify patterns associated with stress and provide insights that help in stress management.

The implementation of such a system can offer significant benefits, including early stress detection, personalized stress management strategies, and improved workplace productivity. However, challenges such as data privacy, ethical concerns, and system accuracy must be addressed to ensure effective deployment. This study explores the architecture, methodology, and potential impact of a stress detection system in office environments, emphasizing the role of technology in fostering a healthier and more efficient workplace.

## Literature Survey

### 1. Physiological-Based Stress Detection

Several studies have explored the use of physiological signals such as heart rate variability (HRV), galvanic skin response (GSR), and electroencephalogram (EEG) data for stress detection. Research by Healey and Picard (2005) demonstrated that heart rate and skin conductance measurements could effectively identify stress levels in real-world office settings. Similarly, Kim et al. (2018) developed a wearable stress monitoring system using ECG and GSR sensors to classify stress conditions accurately.

## **2. Behavioral-Based Stress Detection**

Behavioral indicators such as facial expressions, voice modulation, and typing patterns have also been studied as reliable stress markers. A study by Zeng et al. (2009) highlighted the effectiveness of facial expression analysis in detecting stress-related emotions. Another research by Shaukat et al. (2021) demonstrated that voice-based stress detection using machine learning algorithms could achieve high accuracy in identifying stress levels based on speech patterns. Keystroke dynamics, including typing speed and pressure, were also analyzed by Epp et al. (2011) as an indicator of cognitive and emotional stress.

## **3. Machine Learning and AI in Stress Detection**

The advancement of machine learning has significantly improved stress detection accuracy. Deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used to process physiological and behavioral data for stress classification. Research by Sarker et al. (2020) demonstrated the effectiveness of AI-driven approaches in combining multiple stress indicators for real-time monitoring.

## **4. Workplace Stress Detection Systems**

Several workplace-oriented stress detection systems have been proposed to integrate stress analysis into corporate environments. Systems such as Smart Office (Goyal et al., 2019) and AI-based stress management platforms (Singh et al., 2022) have shown promising results in improving employee well-being by providing stress alerts and personalized recommendations. However, challenges related to privacy, ethical considerations, and user acceptance remain critical concerns.

## **Existing System**

Current stress detection systems primarily rely on physiological, behavioral, and environmental factors to assess stress levels. These systems are widely used in workplace environments, healthcare, and research studies to monitor stress and its effects. However, most existing solutions face limitations in terms of accuracy, real-time monitoring, and integration into office environments.

One common approach involves wearable devices such as smartwatches and fitness trackers that monitor physiological indicators like heart rate variability (HRV), electrodermal activity (EDA), and blood pressure. Devices like Fitbit, Apple Watch, and Garmin offer stress-tracking features based on heart rate analysis. However, these systems depend on user compliance, requiring individuals to wear them consistently. Additionally, external factors such as movement, ambient temperature, and physical exertion can affect the accuracy of stress measurements.

Another method involves facial expression and voice analysis to detect stress through micro-expressions and speech modulation. AI-powered applications process facial cues and changes in voice pitch, tone, and speed to determine stress levels. While promising, these systems face challenges in real-world office settings, including variations in lighting, background noise, and individual differences in expressions and speech patterns.

Keystroke dynamics and behavioral monitoring have also been explored as non-intrusive methods for stress detection. Research indicates that typing speed, key press pressure, and error rates can reflect cognitive stress levels. However, these methods may not be entirely reliable for every user, as individual typing habits and workplace distractions can influence results.

Many organizations also rely on self-reported surveys and wellness applications to assess employee stress levels. Platforms like Headspace, Calm, and Welltory offer guided meditation, relaxation exercises, and stress tracking based on user input. However, self-reported data can be subjective and may not provide real-time insights into an individual's stress levels.

Despite the advancements in stress detection technologies, existing systems still have significant limitations. Many lack real-time monitoring capabilities, suffer from accuracy issues due to external influences, and raise privacy concerns, especially when using facial and voice-based monitoring. Additionally, most stress detection solutions are designed for personal use rather than office environments, making it challenging to integrate them effectively into corporate settings.

**Drawbacks:**

- **Lack of Real-Time Monitoring:** Many systems do not provide continuous stress detection, leading to delayed interventions.
- **Accuracy Issues:** Physiological sensors and behavioral analysis can be affected by external factors such as movement, lighting, and noise.
- **Privacy Concerns:** Facial recognition, voice analysis, and keystroke monitoring may be perceived as intrusive, raising ethical and legal issues.
- **Limited Integration in Workplaces:** Most existing solutions are designed for personal use and are difficult to implement in office environments.
- **User Dependency:** Wearable devices require consistent usage, and self-reported surveys rely on active user input, reducing reliability.
- **Data Security Risks:** Storing and analyzing biometric and behavioral data poses potential security threats and regulatory challenges.
- **Inconsistent Results:** Individual differences in physiological responses and behavior can lead to inaccurate stress detection.

**Proposed System:**

The proposed stress detection system aims to overcome the limitations of existing methods by integrating multiple data sources, utilizing AI-driven analytics, and ensuring a non-intrusive, privacy-conscious approach to stress monitoring in office environments. This system is designed to provide real-time stress detection, improve accuracy, and seamlessly integrate into workplace wellness programs to enhance employee well-being and productivity.

To achieve high accuracy, the system employs a **multi-modal stress detection approach** by combining physiological, behavioral, and environmental data. Wearable sensors are used to track heart rate variability (HRV), galvanic skin response (GSR), and body temperature, which are key indicators of stress. In addition, facial expression analysis, powered by AI-based image processing, helps detect micro-expressions linked to stress. The system also incorporates voice modulation detection to analyze speech patterns, such as tone, pitch, and speed, for stress indicators. Keystroke dynamics and mouse movement tracking further provide insights into cognitive and emotional stress by assessing typing speed, pressure, and movement patterns.

To process this diverse set of data efficiently, the system leverages **artificial intelligence and machine learning models**. Deep learning algorithms and natural language processing (NLP) techniques are used to analyze collected data and classify stress levels based on detected patterns. The integration of AI enhances the accuracy and adaptability of the system, making it more reliable for real-time workplace monitoring.

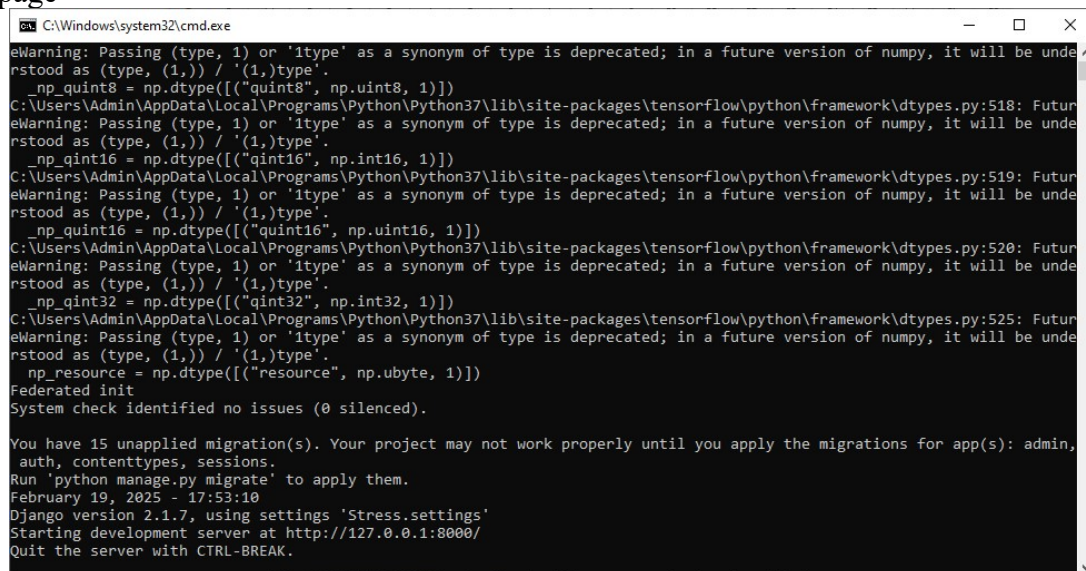
**Advantages:**

- **Real-Time Stress Monitoring:** The system continuously tracks stress levels, allowing for early detection and timely interventions to prevent burnout and decreased productivity.
- **High Accuracy with Multi-Modal Analysis:** By integrating physiological, behavioral, and environmental data, the system provides more precise stress detection compared to single-factor approaches.
- **AI-Powered Insights and Automation:** Advanced machine learning models enhance accuracy, adapt to individual stress patterns, and automate stress analysis without manual input.
- **Personalized Stress Management Recommendations:** Employees receive tailored suggestions, such as relaxation techniques, break reminders, and ergonomic adjustments, to help manage stress effectively.
- **Non-Intrusive and Privacy-Focused Approach:** The system ensures anonymous data collection, encryption, and compliance with workplace privacy regulations, maintaining employee trust.

- **Seamless Workplace Integration:** It can be integrated with existing corporate wellness programs, HR platforms, and productivity tools to support organizational stress management strategies.
- **Improved Employee Well-Being and Productivity:** By proactively addressing stress, the system helps reduce absenteeism, increase focus, and enhance overall workplace efficiency.
- **Minimal User Dependency:** Unlike self-reported surveys and wearable-dependent solutions, this system reduces reliance on user input, making stress detection more consistent and reliable.
- **Scalable and Adaptable:** The system can be customized for different workplace environments and adapted to suit various job roles and stress conditions.
- **Ethical and Transparent Implementation:** Employees have control over their data, and organizations can foster a healthier work culture without invasive surveillance.

## Results

To run project double click on 'runWebServer.bat' file to start python server and then will get below page

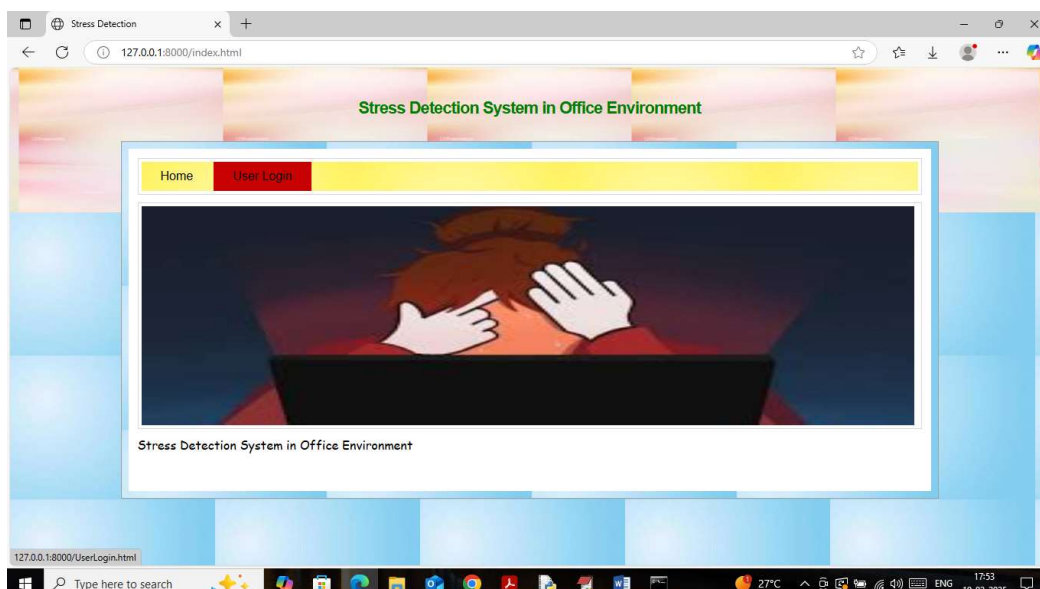


```

C:\Windows\system32\cmd.exe
Warning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np Quint8 = np.dtype([('Quint8', np.uint8, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtypes.py:518: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np Quint16 = np.dtype([('Quint16', np.int16, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtypes.py:519: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np Quint16 = np.dtype([('Quint16', np.uint16, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtypes.py:520: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np Quint32 = np.dtype([('Quint32', np.int32, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtypes.py:525: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([('resource', np.ubyte, 1)])
Federated init
System check identified no issues (0 silenced).

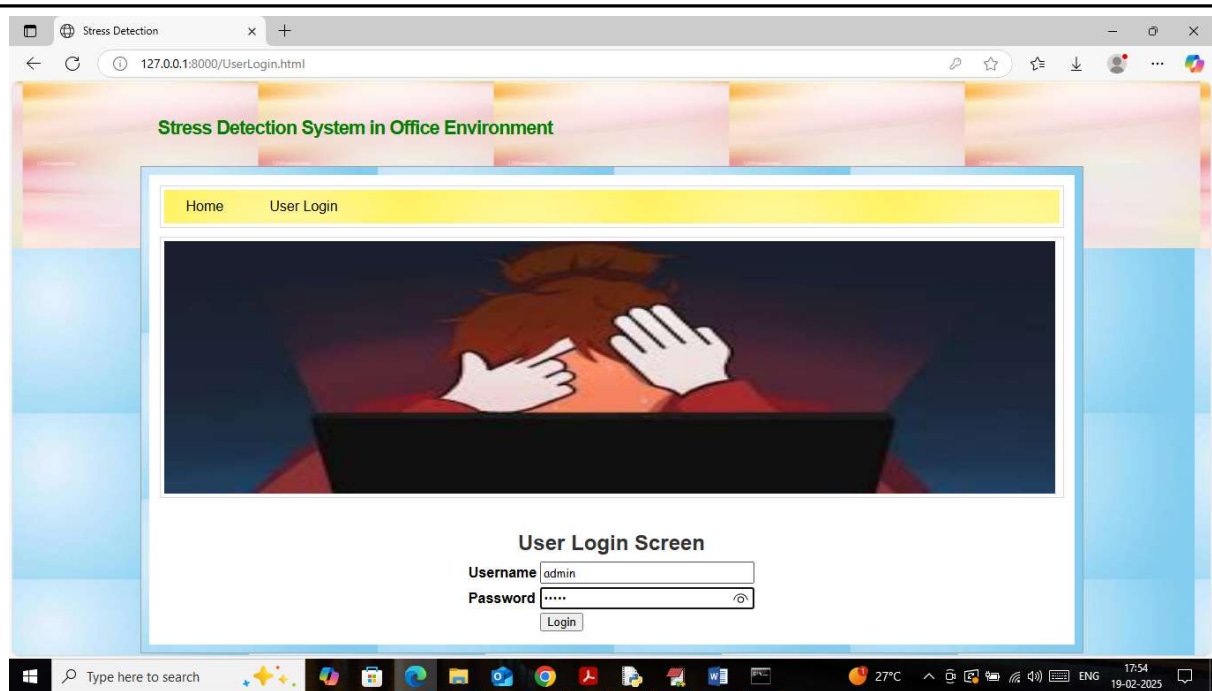
You have 15 unapplied migration(s). Your project may not work properly until you apply the migrations for app(s): admin, auth, contenttypes, sessions.
Run 'python manage.py migrate' to apply them.
February 19, 2025 - 17:53:10
Django version 2.1.7, using settings 'Stress.settings'
Starting development server at http://127.0.0.1:8000/
Quit the server with CTRL-BREAK.
  
```

In above screen python server started and now open browser and enter URL as <http://127.0.0.1:8000/index.html> and then press enter key to get below page

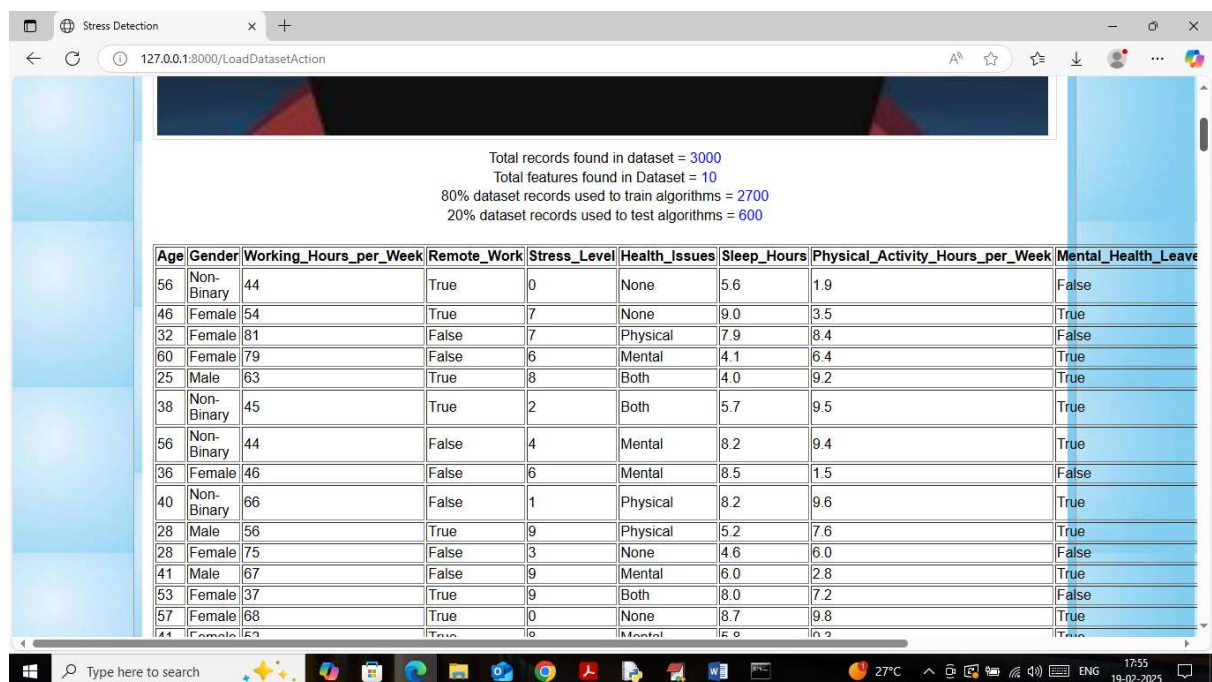


In above screen click on 'User Login' link to get below page





In above screen user is login by entering username and password as 'admin and admin' and then press enter key to get below page

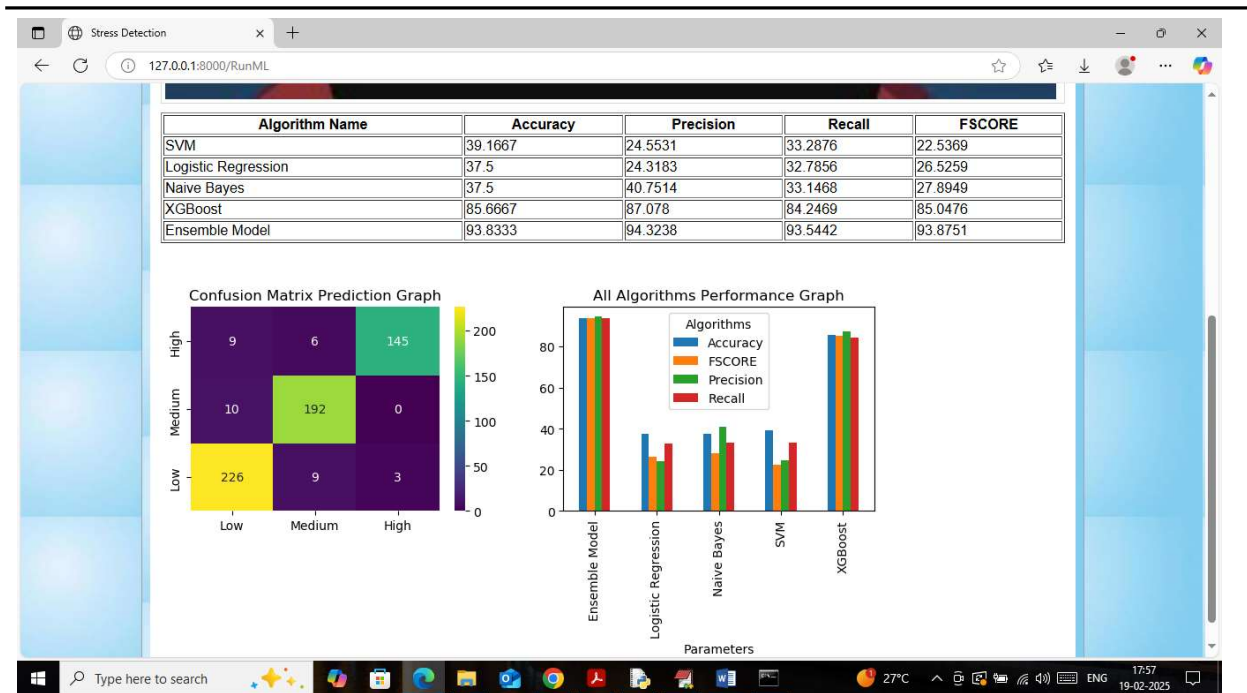


Total records found in dataset = 3000  
Total features found in Dataset = 10  
80% dataset records used to train algorithms = 2700  
20% dataset records used to test algorithms = 600

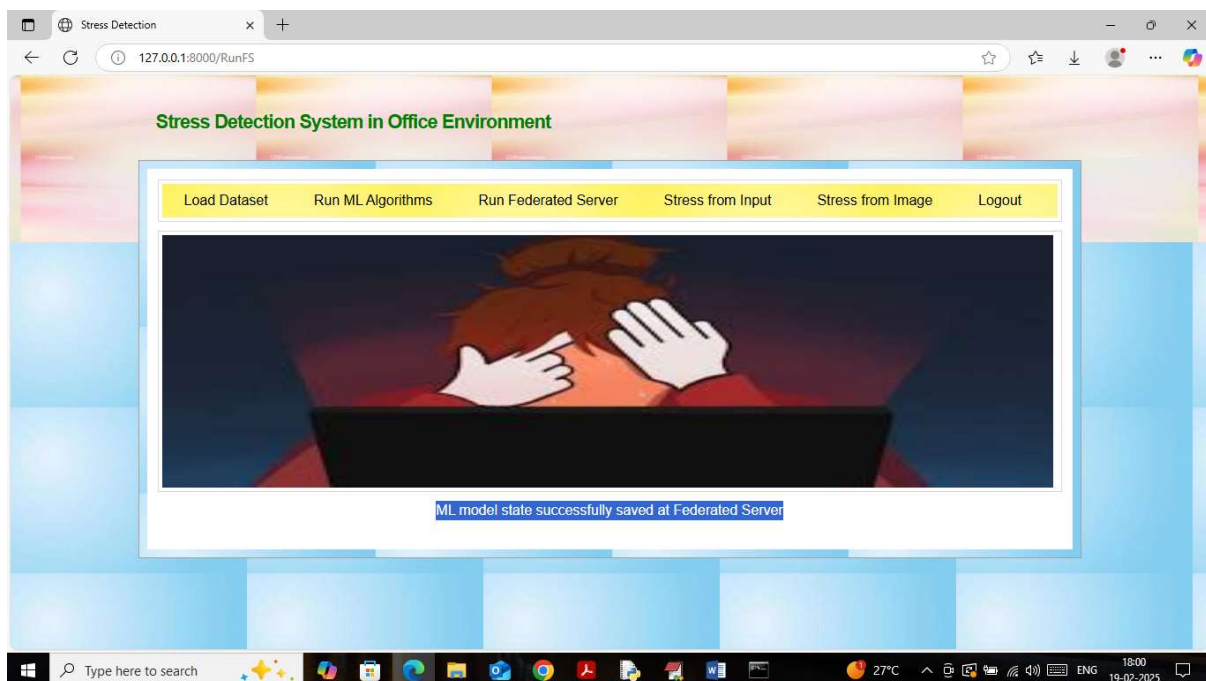
Age	Gender	Working_Hours_per_Week	Remote_Work	Stress_Level	Health_Issues	Sleep_Hours	Physical_Activity_Hours_per_Week	Mental_Health_Leave
56	Non-Binary	44	True	0	None	5.6	1.9	False
46	Female	54	True	7	None	9.0	3.5	True
32	Female	81	False	7	Physical	7.9	8.4	False
60	Female	79	False	6	Mental	4.1	6.4	True
25	Male	63	True	8	Both	4.0	9.2	True
38	Non-Binary	45	True	2	Both	5.7	9.5	True
56	Non-Binary	44	False	4	Mental	8.2	9.4	True
36	Female	46	False	6	Mental	8.5	1.5	False
40	Non-Binary	66	False	1	Physical	8.2	9.6	True
28	Male	56	True	9	Physical	5.2	7.6	True
28	Female	75	False	3	None	4.6	6.0	False
41	Male	67	False	9	Mental	6.0	2.8	True
53	Female	37	True	9	Both	8.0	7.2	False
57	Female	68	True	0	None	8.7	9.8	True
44	Female	52	True	6	Mental	6.6	6.2	True

In above screen dataset loaded and scroll down above page to view below graph

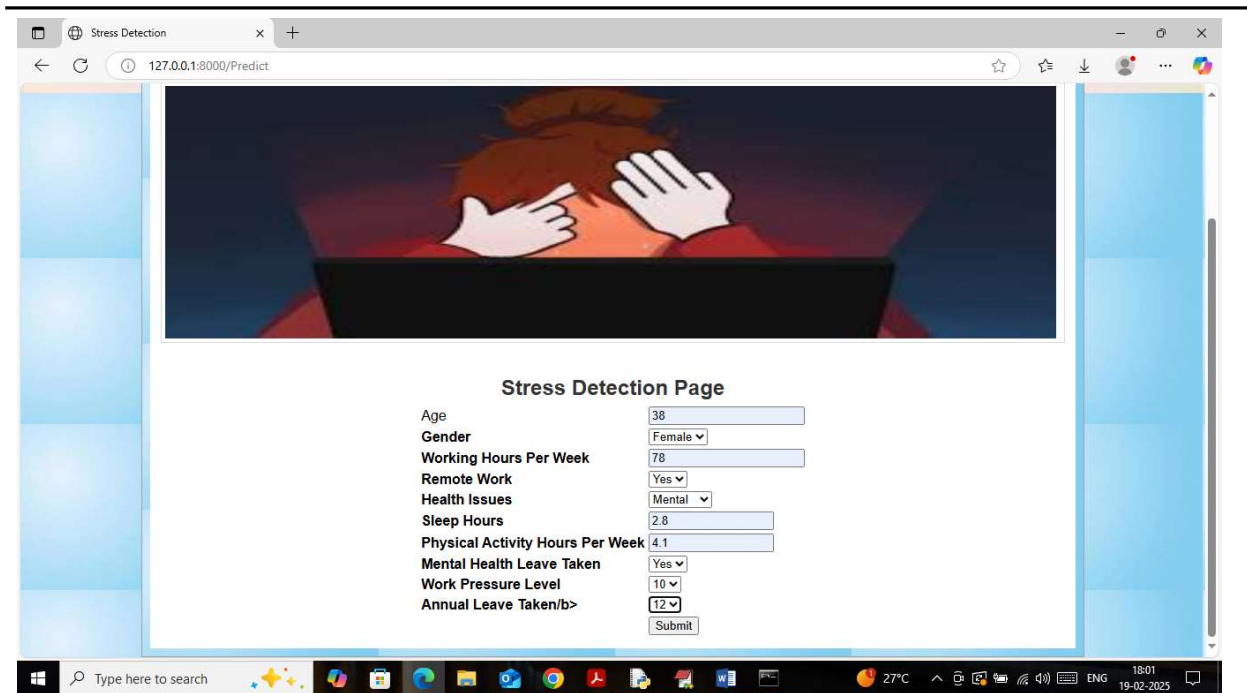
In above graph visualizing different class labels found in dataset where x-axis represents 'Class Label' and y-axis represents number of instances. Now click on 'Run ML Algorithms' link to train algorithms and then will get below page



In above screen in tabular format can see accuracy and other metrics for all algorithms and can see Ensemble model got high accuracy. In Confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and then all different colour boxes in diagonal represents correct prediction count and remaining boxes represents incorrect prediction count which are very few. In above bar graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and in all algorithms Ensemble got high accuracy. Now click on 'Run Federated Server' link to save best model to federated server and then will get below page



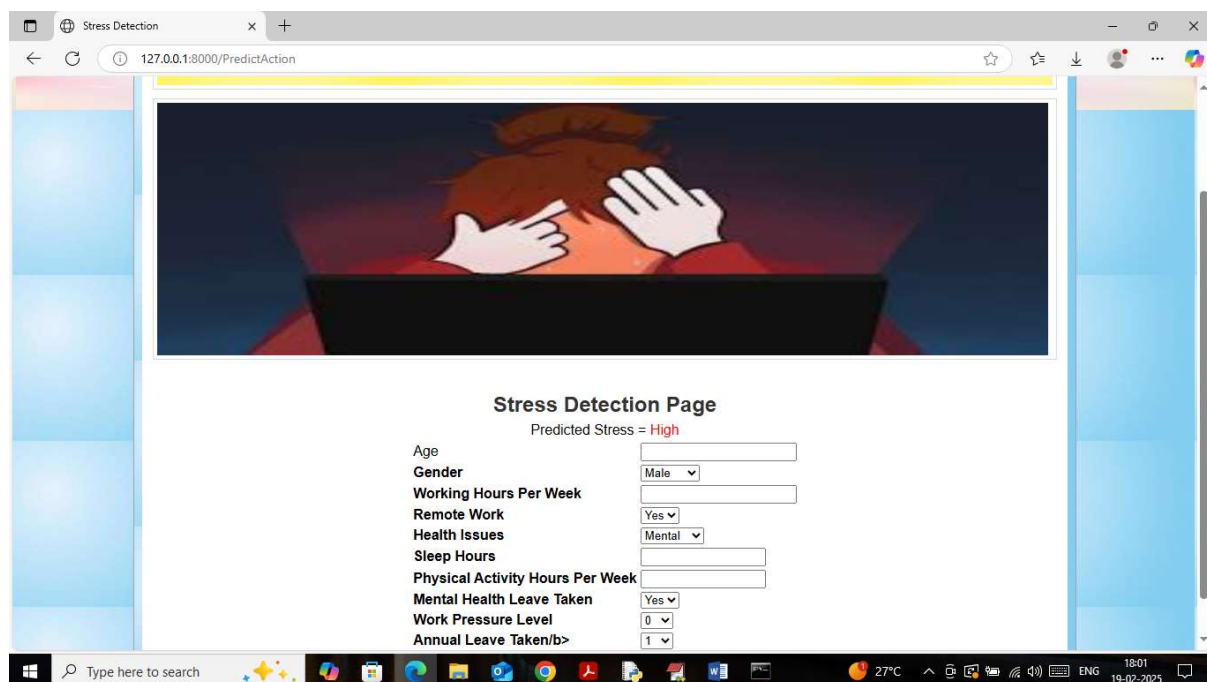
In above screen ML model saved to federated server and now click on 'Stress from Input' link to get below page



**Stress Detection Page**

Age	38
Gender	Female
Working Hours Per Week	78
Remote Work	Yes
Health Issues	Mental
Sleep Hours	2.8
Physical Activity Hours Per Week	4.1
Mental Health Leave Taken	Yes
Work Pressure Level	10
Annual Leave Taken/b>	12
<input type="button" value="Submit"/>	

In above screen I am giving some input values and then press button to get below page

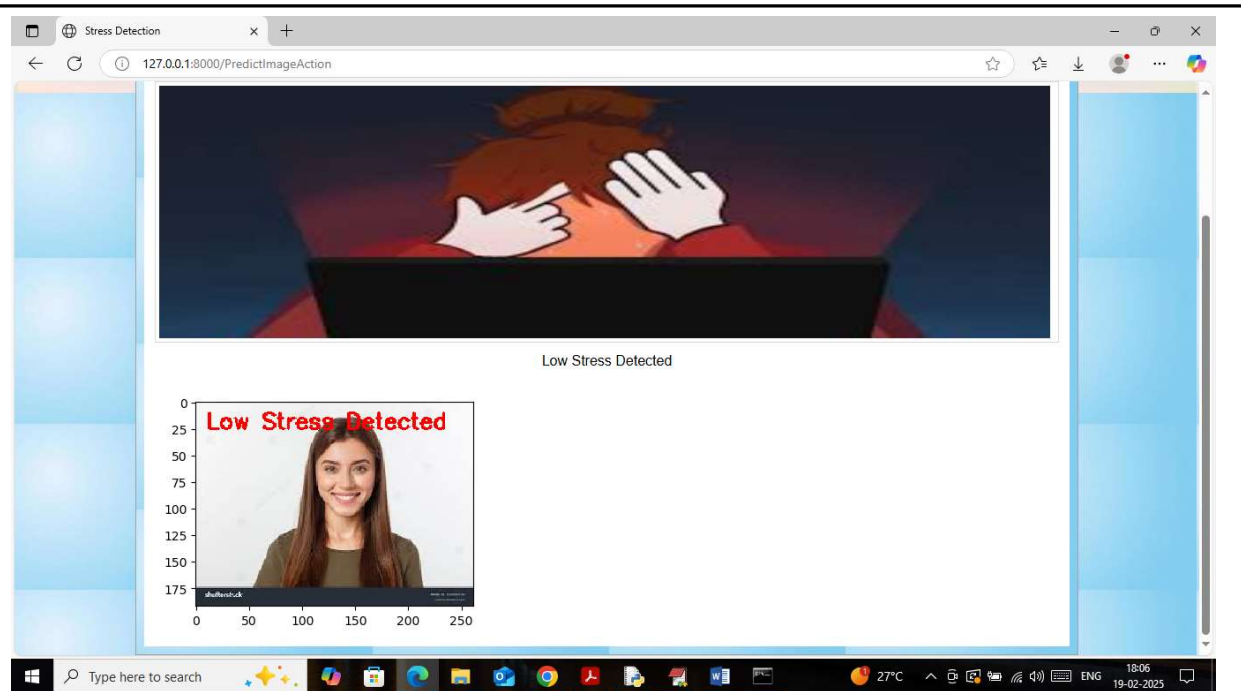


**Stress Detection Page**

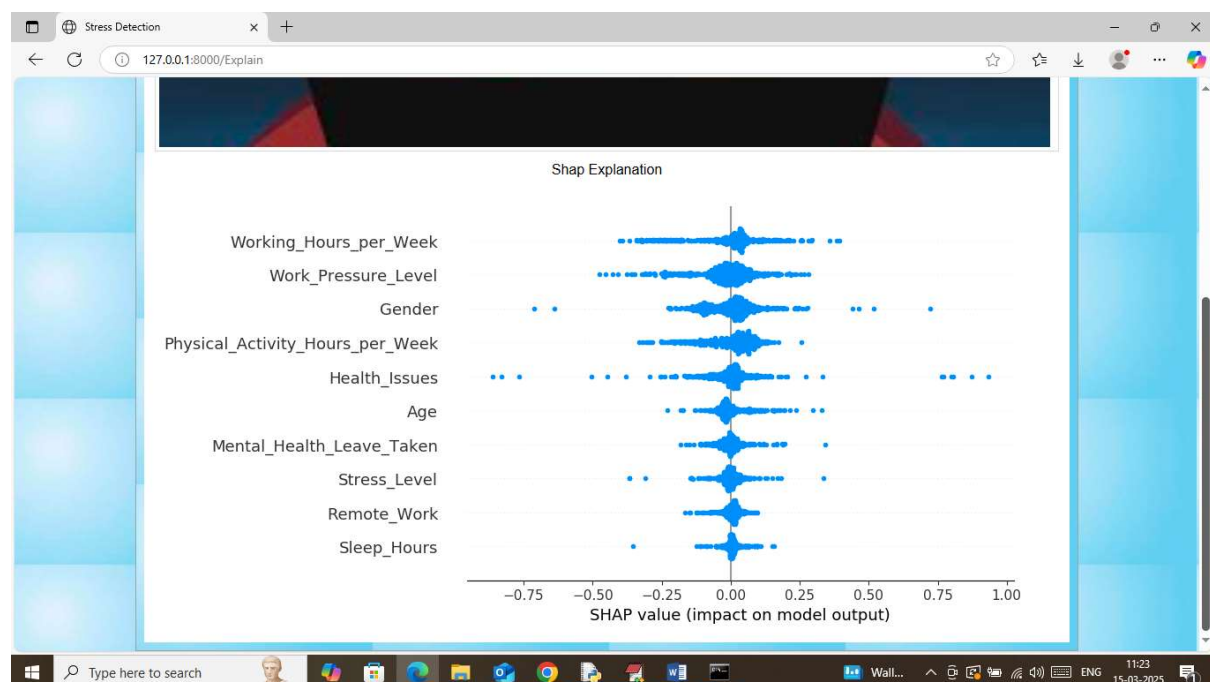
Predicted Stress = **High**

Age	
Gender	Male
Working Hours Per Week	
Remote Work	Yes
Health Issues	Mental
Sleep Hours	
Physical Activity Hours Per Week	
Mental Health Leave Taken	Yes
Work Pressure Level	0
Annual Leave Taken/b>	1

In above screen for given input we got predicted stress level is 'High' which can see in red colour text.



In above screen Low Stress detected from facial features



In above screen with column features names we are displaying SHAP summary plot which indicates which features contributes most for the prediction. In above graph more blue dots indicate high contribution from that features.

## Conclusion

The proposed stress detection system is designed to address the limitations of existing methods by integrating multi-modal data collection, AI-driven analysis, and real-time stress monitoring in office environments. By leveraging physiological, behavioral, and environmental indicators, the system enhances accuracy and provides early detection of stress, allowing employees and organizations to take proactive measures to improve workplace well-being.



One of the key advantages of this system is its **non-intrusive and privacy-focused approach**, ensuring that employee data is collected securely and used ethically. With features like real-time alerts and personalized stress management recommendations, the system empowers employees to manage stress effectively while maintaining productivity. Additionally, seamless integration with corporate wellness programs and HR platforms makes it a scalable and adaptable solution for various workplace settings.

By implementing this AI-driven stress detection system, organizations can foster a healthier work environment, reduce stress-related absenteeism, and improve overall employee performance. The combination of technology and proactive wellness strategies ensures that workplace stress is managed efficiently, ultimately leading to a more motivated and engaged workforce.

**Reference:**

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