Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 13 Issue 08, August-2024

Stress Detection using AI and Machine Learning

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Abstract- **Stress is a pervasive issue that affects millions worldwide, significantly impacting both mental and physical health. The Human-Stress-Detection-System is an innovative, interactive platform designed to predict stress levels and provide personalized stress management recommendations. Leveraging a RandomForestClassifier algorithm, the system analyzes various physiological data points, such as snoring rate, respiration rate, and heart rate, to generate accurate stress predictions. Additionally, the platform features an AI assistant that offers real-time, interactive support and guidance through a chat interface. This combination of machine learning and AI-driven interaction enhances user experience by delivering immediate, tailored advice to help manage and alleviate stress. This paper details the system's architecture, data processing techniques, and the effectiveness of personalized AI recommendations in stress management, aiming to demonstrate the potential of integrating machine learning algorithms with AI-driven interactions for improving mental and physical health outcomes. Our findings suggest that such a system can provide significant benefits in everyday stress management and offer valuable insights for future research in this field. The study underscores the importance of personalized, real-time support in effectively addressing stress.**

Index Terms- Stress Detection, Random Forest Classifier, Physiological Data, AI Assistant, Personalized Recommendations, Interactive Platform, Machine Learning, Stress Management, Real-Time Support, Mental Health.

I. INTRODUCTION

Stress is a global issue with profound effects on both mental and physical health. With increasing awareness about its impact, there is a growing need for effective tools to detect and manage stress. The Human-Stress-Detection-System addresses this need by integrating advanced machine learning techniques with real-time AI-driven support. This system employs a RandomForestClassifier algorithm to analyze physiological data, such as snoring rate, respiration rate, and heart rate, to accurately predict stress levels. Incorporating an AI assistant**,** the system offers personalized and interactive guidance through chat, enhancing user engagement and providing tailored stress management recommendations. This paper explores the development and functionality of the Human-Stress-Detection-System, detailing its architecture, data processing methodologies, and the effectiveness of its AI-driven features. By combining machine learning with real-time interaction, the system aims to provide a comprehensive solution for stress management, contributing valuable insights to both the field of mental health and the broader research community.

1.1 Evolution of Mental Health and Stress Management

Mental health and stress management have evolved significantly over the years, reflecting changes in societal understanding, scientific research, and treatment approaches.

Early Understanding**:** Historically, mental health issues were often misunderstood and stigmatized. Early civilizations attributed mental disorders to supernatural forces or moral failings. Treatments were rudimentary and often involved harsh methods such as exorcisms or confinement.
19th Century Advances**:** The 19th century marked the beginning of a more scientific approach to mental health. The establishment of asylums and the advent of psychiatry provided more humane and structured care. The development of psychoanalysis by Sigmund Freud and the introduction of psychological theories laid the groundwork for modern mental health practices.

20th Century Developments**:** The 20th century saw significant advancements in understanding mental health and stress. The development of psychotropic medications revolutionized treatment, while behavioral therapies and cognitive-behavioral therapies (CBT) offered new methods for managing mental health conditions. Research into stress as a psychological and physiological phenomenon began to gain traction, leading to a deeper understanding of the impact of stress on overall health.

Contemporary Approaches**:** In recent decades, there has been a growing emphasis on holistic and integrative approaches to mental health and stress management. Advances in technology have introduced new tools for stress detection and management, including wearable devices and AI-driven platforms. The focus has shifted towards personalized care, recognizing the need for individualized treatment plans that address the specific needs of each person.

Current Trends**:** Today, mental health and stress management continue to be areas of active research and innovation. The integration of machine learning and artificial intelligence into mental health care represents a significant leap forward, offering new possibilities for real-time monitoring and personalized support. Ongoing research aims to further enhance our understanding of mental health and develop effective strategies for managing stress in a rapidly changing world.

1.2 AI and ML Contributions to Stress Management

Artificial Intelligence (AI) and Machine Learning (ML) are making significant strides in the field of stress management by offering sophisticated tools for detection, prediction, and intervention. These technologies leverage complex algorithms to analyze vast amounts of physiological and behavioral data, thereby enhancing the accuracy and effectiveness of stress management strategies. AI systems, through advanced techniques like RandomForestClassifier and neural networks, can process data such as heart rate variability, snoring rate, and sleep patterns to deliver personalized stress predictions. This capability allows for the creation of individualized stress profiles, offering insights tailored to each user's unique physiological and psychological characteristics. Real-time monitoring is one of the most impactful contributions of AI and ML in stress management. Wearable devices and smart sensors equipped with AI technology continuously track physiological signals such as heart rate and skin conductivity. This constant monitoring provides users with immediate feedback on their stress levels, enabling them to recognize and address stressors as they occur. The ability to provide real-time insights ensures that users can implement coping strategies promptly, which is crucial for effective stress management. This immediacy in feedback helps in maintaining a proactive approach to managing stress, reducing its impact before it escalates.

AI and ML also play a crucial role in offering personalized recommendations for stress management. Machine learning models analyze individual stress patterns and historical data to generate customized intervention strategies. These recommendations may include specific relaxation techniques, cognitive-behavioral exercises, or lifestyle adjustments based on the user's unique stress profile. This personalized approach enhances the relevance and effectiveness of the recommendations, making it easier for users to adopt and adhere to stress management practices. By tailoring advice to the individual's specific needs, AI-driven systems provide more meaningful support in managing stress. The accessibility and engagement provided by AI-driven platforms, such as virtual assistants and chatbots, represent another major advancement in stress management. These interactive tools offer real-time support and guidance, making it easier for users to engage with stress management resources. AI assistants can provide instant responses to user queries, offer coping strategies, and guide users through stress reduction exercises. This level of accessibility increases user engagement and adherence to stress management routines, as users can receive support whenever they need it, without the constraints of traditional therapy or support sessions.

Moreover, the role of AI and ML in analyzing stress trends across populations offers valuable insights for researchers and healthcare providers. By processing large-scale datasets, AI can identify broad patterns and trends in stress levels, contributing to a better understanding of stress-related issues on a societal level. This information aids in the development of targeted interventions and public health strategies, addressing stress-related challenges more effectively. The ability to analyze and predict stress trends helps in crafting preventive measures and creating tailored support programs that can be implemented on a larger scale. Ultimately, AI and ML are transforming stress management by providing advanced, personalized, and real-time solutions. Their integration into stress management practices enhances the precision of stress detection, improves user engagement, and supports the development of innovative mental health resources. As technology continues to evolve, AI and ML will likely offer even more advanced tools and strategies for managing stress, ultimately contributing to better mental health outcomes and improved quality of life for individuals.

Summary:

1. **Historical Perspective**: Evolution of stress management from traditional to modern practices, highlighting key milestones and the growing awareness of stress's impact on health.
2. **Technological Advancements**: Impact of wearable devices, smart sensors, and digital platforms in improving stress monitoring and management.
3. **AI and ML Applications**: Use of AI and ML to analyze physiological data, predict stress levels, and offer personalized recommendations for better stress management.
4. **Business and Health Benefits**: Advantages of AI and ML in stress management, including enhanced user engagement, real-time support, and improved mental health and productivity.
5. **Future Prospects**: Exploration of future technological advancements and innovations in AI/ML for developing more sophisticated stress management tools and strategies.

II. PROBLEM STATEMENT

The increasing prevalence of stress-related health issues demands more effective and personalized solutions for stress management. Traditional approaches often lack precision and adaptability, leading to suboptimal outcomes. This research aims to address these limitations by developing a sophisticated system that leverages Artificial Intelligence (AI) and Machine Learning (ML) to improve stress prediction and management. By utilizing advanced algorithms, the proposed system seeks to provide accurate, personalized stress assessments and tailored recommendations, thereby enhancing overall mental well-being and intervention efficacy.

III. LITERATURE REVIEW

[L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: Blockchain-Integrated PrivacyAssured IoMT Framework for Stress Management Considering Sleeping Habits", IEEE Transactions on Consumer Electronics (TCE), Vol. 67, No. 1, Feb 2021, pp. 20-29]

In today's fast-paced lifestyle, people often overlook the crucial benefits of quality sleep. The Smart-Yoga Pillow (SaYoPillow) aims to bridge this gap by exploring the connection between stress and sleep through innovative technology. SaYoPillow features an edge device equipped with a processor and model that analyzes physiological changes and sleeping habits. It predicts stress levels for the following day based on these insights. The device includes a user-friendly interface that allows individuals to manage their data accessibility and visibility. SaYoPillow stands out with its novel approach, integrating security features and tailored sleep habit considerations for effective stress reduction, achieving an accuracy of up to 96%.

[L. Rachakonda, S. P. Mohanty, E. Kougianos, K. Karunakaran, and M. Ganapathiraju, "Smart-Pillow: An IoT based Device for Stress DetectionConsidering Sleeping Habits", in Proceedings of the 4th IEEE International Symposium on Smart Electronic Systems (iSES), 2018, pp. 161—166.]

The quality of sleep profoundly impacts daytime productivity. To maximize daily performance, it is essential to understand how factors such as stress can disrupt sleep. Advances in technology enable self-analysis of these conditions. We propose a system that assesses stress levels based on sleep patterns. This system evaluates physiological parameters like temperature, blood pressure, respiration rate, and heart rate, which vary across sleep stages such as NREM (Non-Rapid Eye Movement) and REM (Rapid Eye Movement). It also considers non-physiological factors, including the number of sleeping hours, snoring intensity, sleeping position, and environmental conditions. By integrating these factors, the system predicts stress levels and categorizes them into four states: Low, Medium, High, and Very High.

IV. METHODOLOGY

The methodology for developing and evaluating the Human-Stress-Detection-System is outlined in this section. It details the structured approach adopted for data acquisition, preprocessing, feature extraction, and model evaluation. The methodology focuses on employing machine learning techniques to enhance the accuracy and effectiveness of stress prediction. Each step is described to provide insight into how the system was developed and validated, ensuring robust and reliable outcomes.

1. Data Collection

Data collection is a crucial foundational step in the development of the Human-Stress-Detection-System. This phase involves the acquisition of detailed physiological data necessary for precise stress prediction. The dataset, available in CSV format, comprises a range of critical metrics including snoring rate, respiration rate, body temperature, limb movement, blood oxygen level, rapid eye movement, sleep hours, and heart rate. These parameters were carefully selected based on their established link to stress levels, as supported by extensive research literature. The dataset was obtained from a reputable online platform specializing in health and physiological data. This platform provides a comprehensive collection of physiological indicators, ensuring that the data is both diverse and representative of real-world conditions. The CSV format facilitates easy integration and manipulation of the data, enabling efficient preprocessing and analysis. To maintain the integrity and reliability of the stress detection model, it was imperative to ensure the quality of the collected data. This included verifying the accuracy of the recorded values, addressing any inconsistencies, and handling missing or erroneous entries appropriately. High-quality data is essential for developing a robust model, as it directly affects the system's ability to accurately predict and manage stress levels.

2. Data Pre-processing

Data preprocessing is crucial for preparing raw data for effective analysis and modeling. It involves several key activities to enhance data quality and model performance. Cleaning the data addresses errors, inconsistencies, and outliers, ensuring accuracy and reliability. Handling missing values through imputation techniques, such as replacing them with the mean or median, maintains dataset completeness and prevents skewed analysis. Normalization scales features to a uniform range, typically between 0 and 1, to prevent any single feature from disproportionately influencing the model. Additionally, feature selection focuses on retaining the most relevant attributes while removing redundant or irrelevant ones, which reduces model complexity and improves its predictive power. Collectively, these preprocessing steps transform raw data into a clean, reliable, and well-structured format, leading to more accurate and effective machine learning models. These processes are fundamental for ensuring that the data is not only accurate but also optimally formatted to extract meaningful insights and build robust predictive models. Effective data preprocessing sets the foundation for the success of machine learning projects by making sure that the input data is ready for the algorithms to learn and make predictions with high reliability.

3. Feature Engineering

Feature engineering is a critical component in the development of the Human-Stress-Detection-System, designed to enhance the accuracy and performance of stress prediction models. This process begins with feature extraction, where meaningful metrics are derived from raw physiological data, such as average heart rate variability and breathing rate variability. Following extraction, feature creation involves generating new, composite features like a "sleep quality index" by combining related physiological metrics, providing a more comprehensive view of stress-related factors. Feature transformation is then applied to standardize features, such as normalizing blood oxygen levels and rapid eye movement data, to ensure they contribute equally to model training. This step enhances the comparability of features and reduces bias, improving the model's ability to learn from diverse data sources.

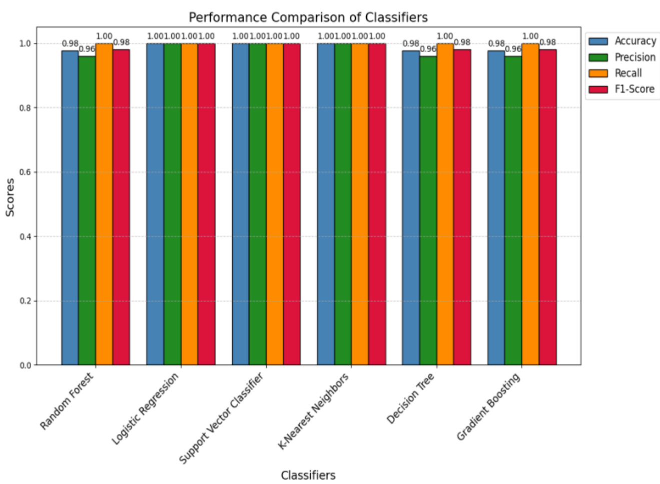
Finally, feature selection is employed to retain only the most relevant features, using techniques like correlation analysis and feature importance scores to identify those with the strongest

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 13 Issue 08, August-2024

predictive power. This approach ensures that the model is trained on high-quality, informative data, ultimately leading to more accurate and effective stress prediction and management. By focusing on the most impactful features, the system can better detect subtle patterns in stress indicators and provide more reliable recommendations for users.

4. Model Selection

In the evaluation of machine learning classifiers for stress prediction, several models were tested to identify the most effective one. The classifiers examined included Random Forest, Logistic Regression, Support Vector Classifier (SVC), K-Nearest Neighbors (KNN), Decision Tree, and Gradient Boosting. To ensure a thorough assessment, each classifier was evaluated using stratified 10-fold cross-validation, with performance metrics such as accuracy, precision, recall, and F1-score being calculated for each model. To visualize and compare the performance of these classifiers, a comprehensive comparison visualization was created. This visualization illustrates the performance metrics—accuracy, precision, recall, and F1-score—of each classifier, providing a clear and concise overview of their relative effectiveness.



By presenting these metrics in a comparative format, the visualization facilitates an informed decision on the most suitable classifier for stress prediction, highlighting the strengths and weaknesses of each model. This approach ensures that the selected classifier is the most appropriate for accurately predicting stress levels based on the evaluated metrics. The RandomForestClassifier was chosen for the Human-Stress-Detection-System due to its advantages in managing complex data and improving prediction accuracy. Its ensemble learning approach reduces overfitting and enhances generalization, while its robustness ensures reliable performance across various scenarios. Additionally, the model's ability to assess feature importance provides valuable insights into which physiological parameters are most significant for predicting stress. These features make Random Forest the optimal choice for effective and interpretable stress prediction.

5. Model Training

Training is a crucial step in developing the RandomForestClassifier for predicting stress levels as it allows the model to learn and generalize from the data. By exposing the classifier to a diverse set of examples with known stress levels, the model gains the ability to recognize patterns and relationships between physiological features and stress classifications. This learning process involves adjusting the internal parameters of the model to minimize errors and improve accuracy. During training, the RandomForestClassifier builds multiple decision trees based on different subsets of the data, each learning to identify features that distinguish between stress levels such as Low/Normal, Medium Low, Medium, Medium High, and High. This ensemble approach helps to reduce overfitting and ensures that the model can generalize well to new, unseen data. Proper training ensures that the classifier can make reliable predictions when faced with real-world data, making it an essential component of the stress detection system. In summary, training the RandomForestClassifier is essential because it enables the model to learn from historical data, identify critical patterns, and make accurate stress level predictions, ultimately leading to effective stress management solutions.

6. Prediction and Recommendations

After training, the next step is to use the RandomForestClassifier for prediction and personalized recommendations. Here's an overview of the process:

Prediction: Once the RandomForestClassifier is trained, it is utilized to predict stress levels based on new physiological data. For each input, the classifier evaluates the data against the patterns learned during training and assigns a stress level category: Low/Normal, Medium Low, Medium, Medium High, or High. This classification provides a clear indication of the user's stress level, enabling targeted interventions.

Personalized Recommendations: To enhance the user experience, the system integrates Gemini 1.0 Pro, a generative AI model. Based on the predicted stress level and input data, Gemini 1.0 Pro generates personalized recommendations tailored to the user's specific needs. These recommendations may include stress management techniques, lifestyle changes, or relaxation exercises designed to address the user's individual stress level and improve overall well-being.

In summary, the prediction phase involves classifying the user's stress level using the trained RandomForestClassifier, while the recommendation phase leverages Gemini 1.0 Pro to provide customized advice and strategies for managing stress effectively. This combined approach ensures both accurate stress detection and actionable, personalized support.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 13 Issue 08, August-2024

7. Integration of AI Assistant

The integration of Gemini 1.0 Pro, a generative AI model, into the Human-Stress-Detection-System brings a significant enhancement to the platform's capabilities by incorporating personalized and interactive support. Once the RandomForestClassifier has assessed and predicted the user's stress level based on physiological data, Gemini 1.0 Pro steps in to provide customized guidance and recommendations tailored to the individual's stress profile. Gemini 1.0 Pro uses the stress prediction, along with additional input data, to generate detailed and relevant advice. For example, if the model identifies a high stress level, it may suggest specific stress-relief techniques such as mindfulness exercises, breathing techniques, or lifestyle changes to manage stress effectively. The AI assistant is designed to offer practical, actionable steps that users can implement in their daily lives, addressing their unique stressors and improving their overall well-being.

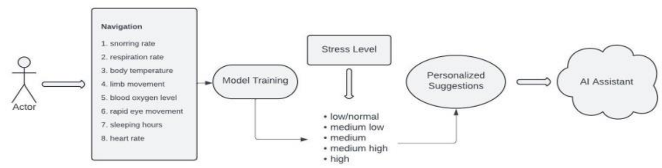
The user interacts with Gemini 1.0 Pro through an intuitive chat interface, which facilitates real-time communication. This interaction allows users to ask questions, seek clarification, and receive immediate feedback. The AI assistant's responses are crafted to be both supportive and informative, enhancing the user experience by providing timely and relevant recommendations. Additionally, Gemini 1.0 Pro's capacity to continuously learn from user interactions ensures that the advice it offers evolves over time, incorporating new insights and techniques to stay current with advancements in stress management. Furthermore, the integration of Gemini 1.0 Pro not only provides immediate support but also helps users build long-term strategies for managing stress. By offering personalized guidance that adapts to the user's evolving needs, the AI assistant contributes to more effective and sustained stress management. This approach not only improves the overall effectiveness of the stress detection system but also fosters a more engaging and supportive user experience.

In summary, the incorporation of Gemini 1.0 Pro as the AI assistant within the Human-Stress-Detection-System enhances the platform by delivering personalized, actionable recommendations and interactive support. This integration improves user engagement and ensures that the stress management strategies provided are both relevant and adaptable to individual needs.

8. User Interface

The user interface for the Human-Stress-Detection-System is built using Streamlit, chosen for its ease of use and functionality. This interface facilitates a seamless interaction between users and the system. Users start by inputting their physiological data into the Streamlit app. The system then processes this input through the RandomForestClassifier, which predicts the user's stress level. Based on this prediction, personalized recommendations are generated to help manage and alleviate stress. To further enhance user engagement, the interface integrates an AI assistant, powered by Gemini 1.0 Pro. This assistant provides real-time, interactive support, offering additional guidance and answering user queries. The combination of straightforward data input, predictive modeling, and AI-driven interaction ensures a user-friendly and effective stress management experience.

The diagram below illustrates the user interface of the system, highlighting the input fields, stress prediction display, personalized recommendations, and the interactive AI assistant. This visual representation helps to understand the layout and flow of the user interaction with the system.



9. Feedback

Effective stress management relies on accurate and personalized insights, making user feedback crucial for refining predictive systems. The stress detection system incorporates an innovative feedback loop to continuously improve its performance. Users provide valuable input on predictions and recommendations through intuitive forms, with their feedback stored securely in an SQLite database. Admins access this feedback via a dedicated admin panel, where they analyze it to identify patterns and areas for enhancement. This analysis drives updates to the system's algorithms and recommendation engine, ensuring that the predictions remain precise and the recommendations are relevant. By integrating real user experiences into the system's evolution, this feedback mechanism not only boosts accuracy but also tailors stress management solutions to individual needs. This dynamic process fosters continuous improvement, making the system a more effective tool for managing stress and optimizing well-being.

A. Algorithms

```
import os
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, accuracy_score
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import pickle
from sklearn.ensemble import RandomForestClassifier
import streamlit as st
import pickle
from PIL import Image
import google.generativeai as genai
```

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ISSN: 2278-0181
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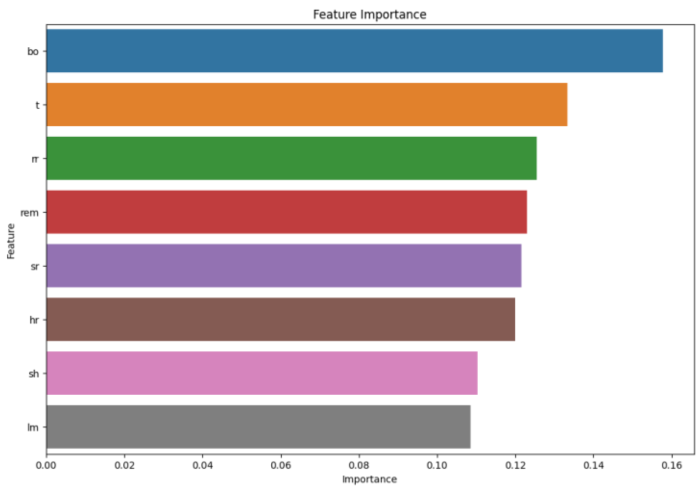
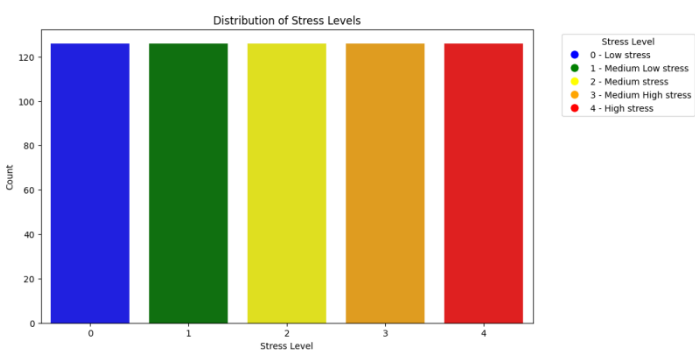
B. EDA and Data Visualization

To gain a comprehensive understanding of the dataset and assess the performance of the stress detection model, Exploratory Data Analysis (EDA) and visualizations were conducted. This phase involves analyzing the dataset to uncover patterns, relationships, and anomalies, which are critical for refining the model and ensuring its robustness. The visualizations presented offer insights into the significance of different features in stress prediction and the distribution of stress levels across the dataset.



The feature importance plot, demonstrates the significance of each physiological parameter in predicting stress levels using the RandomForestClassifier. This visualization reveals the key features influencing the model's predictions, with parameters such as snoring rate and heart rate highlighted as particularly impactful.



The above fig. showing the distribution of stress levels, provides a histogram of how frequently each stress category appears in the dataset. Color-coded categories, ranging from low to high stress, illustrate the prevalence of various stress levels among subjects. This distribution helps in understanding the model's performance and aligns predictions with the dataset's actual stress profile.

V. TESTING

1. Introduction:

Testing is a fundamental phase in the development of any predictive system, including the Human-Stress-Detection-System. It ensures that the system is reliable, accurate, and effective in real-world scenarios. Proper testing verifies that the model performs well on unseen data, maintains robustness across various conditions, and meets user expectations. By systematically evaluating the system's predictions and handling of different inputs, testing helps in identifying potential issues such as overfitting, underfitting, and data biases. This process is crucial for ensuring that the system provides trustworthy stress predictions and useful recommendations for stress management.

2. Testing Objectives:

The primary objective is to verify the accuracy of the stress prediction models, ensuring they correctly classify stress levels into categories such as Low, Medium, High, and Very High based on both physiological and non-physiological data. Additionally, the testing aims to assess the model's generalizability by evaluating its performance on unseen data, ensuring it can effectively handle various user scenarios. Performance metrics such as precision, recall, F1 score, and ROC-AUC are used to gauge the model's effectiveness.

```
Classifier: Random Forest
Accuracy: 0.9761904761904762
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        23
           1       1.00      0.92      0.96        24
           2       0.97      1.00      0.98        28
           3       1.00      0.96      0.98        26
           4       0.96      1.00      0.98        25

    accuracy                           0.98       126
   macro avg       0.98      0.98      0.98       126
weighted avg       0.98      0.98      0.98       126
```

Robustness testing is conducted to ensure the model can handle diverse and extreme inputs without compromising performance. User feedback is integrated to align predictions with real-world stress levels and ensure the recommendations are practical and relevant. Iterative refinement based on testing results and feedback helps improve the model continuously. Finally, real-world validation confirms the system's effectiveness and usability, ensuring it meets user needs and performs well in practical applications.

VI. OUTPUT

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ISSN: 2278-0181
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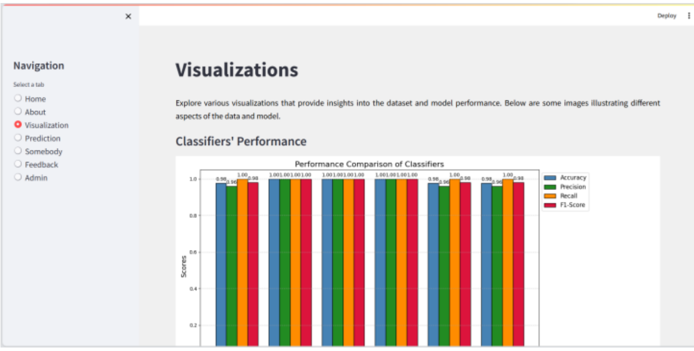
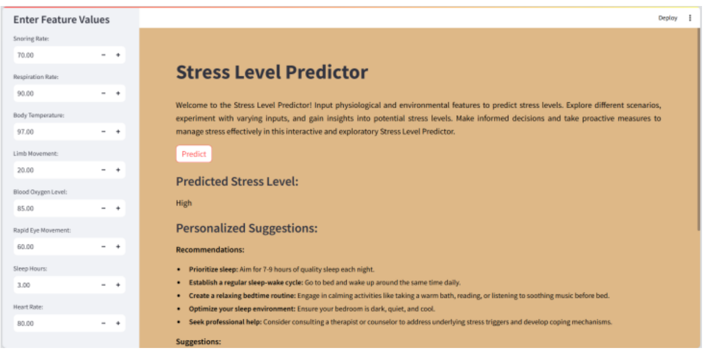
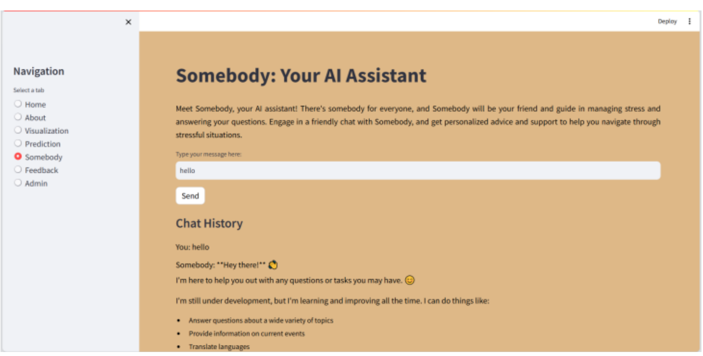
This image displays the main interface of the Happify (Stress Detection System) app, highlighting its navigation and core features.



Featuring graphical representations of stress-related data, this image provides insights into various metrics and trends.



This image presents the output from the stress level prediction models, illustrating how predictions are communicated.



Showcasing the AI assistant in action, this image reveals how users interact with and receive support from the virtual assistant.

VII. CONCLUSION

The Human Stress Detection System represents a significant advancement in personalized stress management by utilizing physiological and environmental data for accurate stress level predictions. The integration of advanced machine learning models, particularly Random Forest, enhances the system's performance and robustness. Random Forest's efficiency in handling high-dimensional data, managing overfitting, and providing feature importance makes it an ideal choice for this application. The system's user-friendly interface and tailored recommendations offer practical insights and actionable strategies for stress management. The iterative process of testing, refinement, and user feedback underscores the system's commitment to continuous improvement and relevance. This project not only sets a foundation for future developments in stress prediction but also demonstrates the practical advantages of using efficient algorithms like Random Forest to enhance individual well-being through sophisticated, adaptive tools.

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