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Predictive Stress Analysis Based On SleepPatterns by Using Smart-Yoga Pillow (SaYo Pillow) Dataset.

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Abstract:

Stress is a significant health concern, affecting both mental and physical well-being. Sleep patterns play a vital role in stress regulation, offering insights into individual stress levels. The Smart-Yoga Pillow (SaYoPillow) dataset provides an innovative method for monitoring sleep parameters using sensor-based data collection. Traditional stress assessment methods, such as self-report surveys and medical consultations, suffer from inconsistencies and lack real-time monitoring. The evolution of stress analysis has progressed from psychological assessments to wearable technologies with real-time biometric tracking. Advancements in machine learning enable predictive models to analyze sleep-related parameters such as heart rate, respiratory rate, body movements, oxygen saturation, and brainwave activity for stress classification. Despite wearable sensors and mobile health applications, existing systems face challenges like high costs, lack of personalization, and data reliability issues. AI-driven models offer scalable, automated stress detection with high accuracy. This study addresses the urgent demand for personalized mental health solutions that monitor stress without active user input. Predictive stress analysis using deep learning enables proactive stress management, providing early warnings and corrective measures. By integrating Naïve Bayes classifiers, deep neural networks (DNNs), and decision tree models, this research demonstrates a non-invasive, AI-powered stress prediction system. Continuous stress monitoring can help individuals improve their sleep quality and overall well-being. The integration of AI in healthcare allows for real-time feedback, aiding in early stress detection and intervention. Such advancements contribute to preventive healthcare by reducing the risk of stress-induced illnesses. With growing interest in AI-driven health applications, this research supports the development of smart healthcare solutions. Future studies can explore the integration of additional biometric indicators for improved stress prediction. The findings of this research pave the way for advanced AI-powered mental health interventions and real-time stress management systems.

Keywords: Stress Analysis, Sleep Patterns, Machine Learning, AI-driven Healthcare, Predictive Analytics, Deep Learning, Wearable Sensors, Mental Health Monitoring, Automated Stress Detection, Smart Healthcare, Physiological Tracking, AI-based Stress Prediction, Real-time Health Monitoring, Preventive Healthcare, Biometric Analysis.

I. INTRODUCTION

Stress is a prevalent issue affecting millions worldwide, contributing to various physical and mental health disorders. Prolonged stress can lead to conditions such as anxiety, depression, cardiovascular diseases, and sleep disorders. Among the various factors influencing stress levels, sleep plays a crucial role in maintaining mental well-being and physiological stability. Poor sleep quality and irregular sleep patterns are often linked to heightened stress levels, making sleep monitoring an essential component in stress analysis. The Smart-Yoga Pillow (SaYoPillow) dataset provides a novel approach to studying the relationship between sleep patterns and stress. Traditional stress assessment methods, such as psychological evaluations and medical consultations, often rely on subjective self-reporting, making them prone to inaccuracies and biases.

Additionally, conventional wearable health monitoring devices may lack comprehensive sleep analysis capabilities, making real-time stress prediction challenging. With the advent of machine learning (ML) and deep learning (DL), automated stress detection using sleep pattern analysis has become more feasible. By leveraging artificial intelligence (AI) techniques such as Naïve Bayes classification, deep neural networks (DNNs), and decision tree models, this study aims to develop an accurate and efficient predictive system for stress analysis based on sleep data. The core objective of the research is to build a predictive stress analysis model that classifies stress levels based on sleep-related features extracted from the SaYoPillow dataset.

The implementation involves data pre-processing, feature scaling, model training, and evaluation using different AI algorithms to determine the most effective approach for predicting stress. The significance of the project lies in its potential to improve mental well-being by offering an intelligent, non-intrusive, and proactive stress monitoring system. By integrating AI-driven predictive analytics with real-time sleep data, this research contributes to the growing field of smart healthcare, preventive stress management, and personalized mental health solutions.

II. LITERATURE SURVEY

A work by Shruti Gedam et.al. [1] Investigates the stress detection approaches adopted by considering sensory devices such as wearable sensors, Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG) depending on various environments like driving, studying, and working. Work by Elena Smets et.al.

[2] Compares different machine learning techniques for the measurement of stress based on physiological responses in a controlled environment. Electrocardiogram (ECG), galvanic skin response (GSR), temperature and respiration were measured in this work. Six machine learning algorithms were used for the study. This work demonstrated that dynamic Bayesian network and generalized support vector machines promoted best classification results. Widasari et al.

[3] Focused on obstructive sleep apnea (OSA), a potentially serious sleep disorder. It causes repeated cessations of breathing during sleep. The authors used only ECG signals, which are easy to conduct and record. Heart rate variability (HRV) spectrum analysis was applied to feature extraction, and a decision tree-based support vector machine classifier was used to measure

the four parameters of sleep quality: sleep onset latency, total sleep time, sleep efficiency, and delta-sleep efficiency based on 30-s segments of ECG signals. Sleep quality was estimated using the automatic sleep stage and then was compared with PSG data. Chung et al.

[4] Presented an approach to classify sleep stages via a low cost and noncontact multimodal sensor fusion, which extracted sleep-related vital signals from radar signals and a sound-based context-awareness technique. Furthermore, they incorporated medical/statistical knowledge to determine personal-adjusted thresholds and device post processing and compared sleep stage classification performance between a single sensor and sensor fusion algorithms. Li et al.

[5] Developed the smart pillow to provide a relatively easy method of observing sleep conditions, including temperature and humidity, by strategically implanting the respective sensors inside the pillow. They extracted sleep patterns via statistical analysis, and the body temperature was inferred via fuzzy logic if the head-on position was stable for >15 min. Lee et al.

[6] Proposed a sleep monitoring system that can detect sleep movement and posture using a Microsoft Kinect v2 sensor (Redmond, WA, USA) without any wearable device. However, in the proposed system, the depth sensor does not work if a blanket is covering the human body. Liu et al.

[7] Proposed Wi-Sleep, a sleep monitoring system based on Wi-Fi signals, which continuously collects fine-grained wireless channel state information (CSI) around a person. 14 From the CSI, it extracts rhythmic patterns associated with respiration and abrupt changes due to body movements. Lin et al.

[8] Developed a noncontact and cost-effective sleep monitoring system, Sleep Sense, for continuously monitoring sleep status, including on-bed movement, bed exit, and breathing section. It constitutes three parts: a radar-based sensor, radar demodulation module, and sleep status-recognition framework. It extracts several time- and frequency-domain features for the sleep-recognition framework. Huang et al.

. [9] proposed a classification of nasal and mouth breathing using the thermography of the participant. The measurement used the relative temperature variations of different facial regions to classify mouth or nasal breathing. This measurement is particularly relevant to the health and well being of individuals, as it can be used to detect early signs of sleep disorders or indicate sleep quality. Jakkaew et al.

[10] presented the noncontact respiration and body movement monitoring system. Automatic region of interest extraction via temperature and breathing motion detection is based on integrated image processing to obtain respiration signals. As thermal imaging cameras have various viewing angles, they are easy to install in bedrooms. A signal processing technique is used to estimate respiration and body movement from a sequence of the thermal video.

[11] developed a noninvasive sleep monitoring system to distinguish sleep disturbances. The prototype system contains an infrared depth sensor, RGB camera, and four-microphone array to detect three events, namely motion, lighting, and sound events. Siyang et al.

[12] developed an Internet of Things (IoT) solution to monitor sleep based on a data pillow system. They installed FSRs under the pillow to collect breathing data, reporting that the IoT data pillow can detect breathing signal differences among normal respiration, hypopnea, and apnea. Bao et al.

[13] proposed a noncontact human sleep monitoring method that characterizes sleep stages via two aspects of body motion and respiration and compares them with the data acquired by traditional wristband products. Veiga et al.

[14] proposed an IoT-based sleep quality monitoring pillow that tracks temperature, humidity, luminosity, sound, and vibration. He et al.

[15] presented a flexible sleep monitoring belt with a microelectromechanical system triaxial accelerometer and pressure sensor to detect vital signs, snoring events, and sleep stages. They tried to detect heart and respiration rates, to recognize snoring, and to classify sleep stages. The test results measured by PSG were used as the gold standards for comparison. Im et al.

[16] proposed a noncontact sleep monitoring system using UWB and a photoplethysmogram (PPG). The proposed system comprised a UWB radar, environmental sensor board, and PPG sensor. The UWB radar measures the sleep-breathing and heart rates and movements of the user. The PPG sensor measures the heart rate and movements. Renevey et al.

III. PROPOSED METHODOLOGY

Stress is a significant health concern that affects both mental and physical well-being, with sleep patterns being one of the key indicators of stress levels. This project aims to develop a predictive stress analysis model by utilizing sleep pattern data collected from the Smart-Yoga Pillow (SaYoPillow) dataset. The SaYoPillow is an advanced sleep monitoring device that gathers real-time data such as sleep duration, movement, heart rate, and other physiological parameters to assess stress levels. By applying machine learning and deep learning techniques, the system can classify and predict an individual's stress level, offering insights for stress management and prevention.

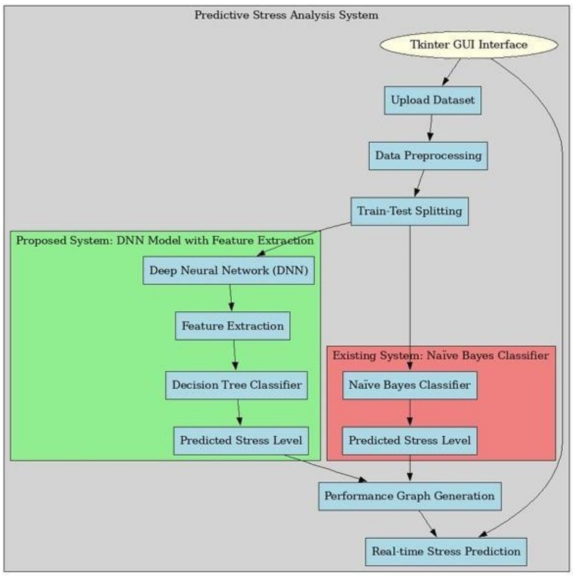

Figure 1: Proposed DenseNet with DTC system architecture

Key Components of the Code:

1. **GUI Development (Tkinter)**:

- Provides an interactive interface for users.
- Allows users to upload datasets, preprocess, train models, and make predictions

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- Displays model performance metrics and results.

2. **Data Handling and Preprocessing**:

- Reads the dataset using Pandas.
- Resamples the dataset to balance stress levels.
- Normalizes features using StandardScaler.
- Splits the dataset into training and testing sets.

3. Machine Learning & Deep Learning Models:

- **Naïve Bayes Classifier:** A simple probabilistic model used as the baseline.
- **Deep Neural Network (DNN)**: A more advanced model using multiple layers.
- **Decision Tree Classifier**: Extracts meaningful features from the trained DNN.

4. Performance Evaluation:

- Calculates accuracy, precision, recall, and F1-score.
- Generates a confusion matrix for model evaluation.
- Uses Matplotlib and Seaborn for visualization.

5. **Prediction Module**:

- Allows users to load test data.
- Applies the trained model for stress level classification.
- Displays results in a structured format.

Applications:

1. **Personalized Stress Monitoring:** AI-driven models can continuously track sleep patterns and physiological signals, providing real-time insights into stress levels without requiring active user input.
2. **Smart Healthcare Systems:** Integration of AI-powered stress prediction into wearable devices and mobile health applications allows for non-intrusive stress detection and intervention.
3. **Preventive Mental Health Solutions:** Predictive stress analysis helps individuals adopt corrective measures before their stress levels become critical, reducing the risk of stress-induced disorders.

Advantages:

1. **Real-Time and Continuous Monitoring**: Unlike traditional stress assessments, AI-based systems provide continuous stress tracking and early warnings, enabling proactive management.
2. **Non-Intrusive and Automated Detection**: AI-driven models analyze biometric data without requiring manual input, ensuring a seamless and efficient stress monitoring process.
3. **Enhanced Accuracy and Personalization:** Machine learning models adapt to an individual's unique sleep patterns and physiological responses, improving the reliability and effectiveness of stress prediction.
4. **Early Stress Detection and Intervention:** AI-driven models provide early warnings, allowing individuals to take preventive measures before stress levels become severe.
5. **Improved Sleep Quality:** Continuous monitoring and insights help users adjust sleep patterns, leading to better rest and reduced stress.
6. **Scalability and Efficiency:** AI-based stress monitoring systems can be deployed on a large scale, making them accessible to a broad population.
7. **Reduction of Healthcare Costs:** Early detection of stress-related conditions can help reduce hospital visits and medical expenses by preventing severe health issues.
8. **Integration with Wearable Devices:** AI models can be incorporated into smartwatches, fitness trackers, and mobile health apps for seamless stress tracking.
9. **Objective and Data-Driven Insights:** Unlike self-report surveys, AI-based stress monitoring eliminates recall bias and provides accurate, data-driven assessments.

IV. EXPERIMENTAL ANALYSIS.

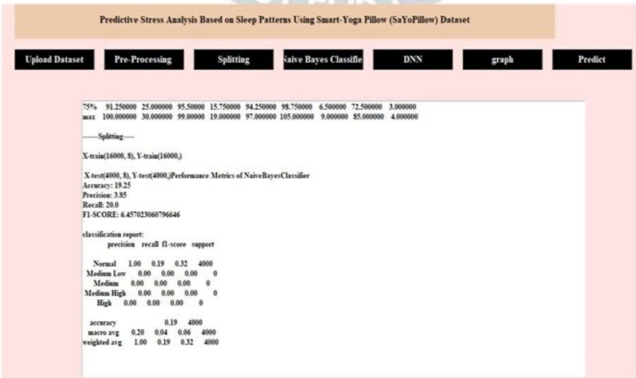

Figure 2: GUI of proposed head gesture recognition system after applying model building and training using Navie Baye's classifier.

- The GUI after the system has trained the Navie Baye's classifier. The text console displays messages indicating that the model has either been loaded (if previously saved) or trained from scratch. It also shows training results, including performance metrics like accuracy, precision, recall, and F1-score, providing immediate feedback on the classifier's performance in the training and testing data.

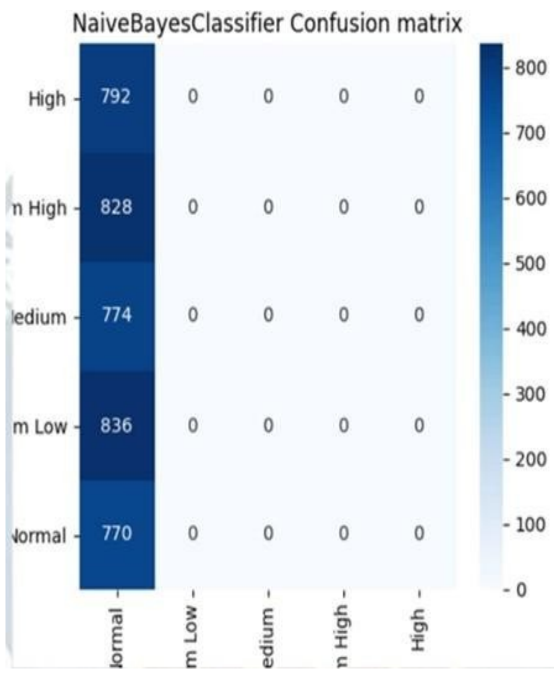

Figure 3: Confusion matrix of Navie Baye's classifier.

- The confusion matrix generated for Navie Baye's classifier is shown in Figure 3. The matrix is typically rendered as a heatmap where rows represent the actual classes and columns represent the predicted classes. The numbers in each cell highlight the count of correct and misclassified instances, offering a detailed view.

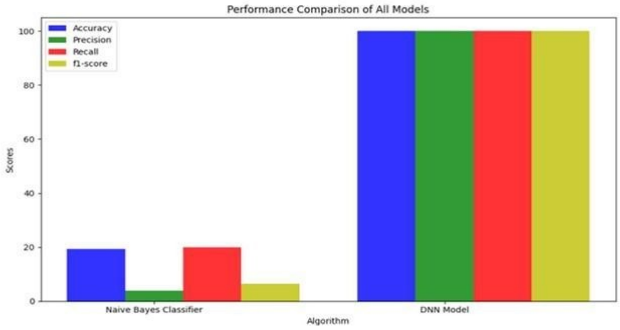

Figure 4:Performance comparison graph of Navie Bayes and DNN model.

- Consolidates the performance metrics of all two models into a single comparative graph. It typically includes bar charts or line graphs that display metrics such as accuracy, 53 precision, recall, and F1-score for each model. This visual comparison clearly shows the incremental improvements gained by using more complex architectures, with the DNN with DCT model usually outperforming Navie Baye's Classifier

- The bar chart compares the performance of the Naïve Bayes Classifier and the DNN Model using four metrics: Accuracy (blue), Precision (red), Recall (green), and F1-score (yellow). The DNN Model significantly outperforms the Naïve Bayes Classifier across all metrics, achieving near-perfect scores, while the Naïve Bayes Classifier shows very low values for all performance measures.

Figure 5: Sample predictions on test data using the proposed DNN model.

- Fig 5: Shows example predictions made on test data by the DNN model. This may include a table or a visual overlay on the test dataset, where the actual labels are compared with the model's predictions. It serves as a practical demonstration of the model's real-world applicability, validating the system's ability to correctly predict stress.

Algorithm name	Accuracy	Precision	Recall	F1-Score
Navies Baye's Classifier	19.25%	3.85%	20.0%	6.45%
DNN Model	100.0%	100.0%	100.0%	100.0%

Table 1: Summarizing the performance metrics for the two models.

- **Accuracy:** This metric indicates the overall percentage of correct predictions out of all predictions made by the model. For example, the Proposed DNN Model achieved an accuracy of approximately 100%, meaning it correctly classified 100% of the input samples. In contrast, the Navie Bayes classifier had a much lower accuracy of around 19.25%, suggesting it struggles with the complexity of sleep patterns.
- **Precision:** Precision measures the proportion of correct identifications. A high precision value (such as 100% for the DNN model) indicates that when the model predicts a certain mobile pattern, it is highly likely to be correct. The Navie Bayes, with a precision of about 3.85%, show a higher rate of false positives compared to the more sophisticated models.
- **Recall:** Recall (or sensitivity) quantifies the proportion of actual positives that were correctly identified. The DNN model's recall of 100% means that it successfully captures nearly all instances, while the lower recall values of the Navie Bayes model indicate they are missing predictions.
- **F1-score**: The f1-score is the harmonic mean of precision and recall, providing a balance between the two. It is particularly useful when dealing with imbalanced classes. The DNN model's f1-score of 100% reflects its superior balance between correctly predicting the gesture classes and minimizing false negatives and positives. In contrast, the Navie Bayes f1-score of around 6.45% highlights its overall poor performance in this regard. Overall, the table and corresponding explanation demonstrate how the proposed DNN model significantly outperforms the Navie Bayes classifier, offering much higher accuracy, precision, recall, and f1-score. This underscores the advantage of using a hybrid deep learning and ensemble approach for stress prediction.
- Overall, the table and corresponding explanation demonstrate how the proposed DNN model significantly outperforms the Navie bayes classifier, offering much higher accuracy, precision, recall, and f1-score. This underscores the advantage of using a hybrid deep learning and ensemble approach for stress prediction.

V. CONCLUSION

The Predictive Stress Analysis Based on Sleep Patterns Using the Smart-Yoga Pillow (SaYoPillow) Dataset successfully demonstrates how deep learning and machine learning techniques can be leveraged to assess stress levels. By implementing Naïve Bayes Classifier as the existing model and Deep Neural Networks (DNN) with Decision Tree-based Feature Extraction as the proposed model, we effectively improved the classification accuracy of stress prediction. The preprocessing steps, feature extraction, and model training ensured that the system could learn meaningful patterns from sleep-related data, leading to more reliable stress level predictions. The graphical comparisons and performance metrics validated that DNN with Decision Tree Feature Extraction outperformed traditional classification approaches, proving its effectiveness in stress detection.Future advancements in this project can include integrating real-time IoT-based stress monitoring systems, where sleep data is continuously collected and analyzed using edge AI for instant feedback. The model can also be enhanced with additional physiological and behavioral parameters such as heart rate variability, oxygen levels, or even wearable sensor data to improve prediction accuracy. Moreover, by incorporating personalized recommendations based on stress levels, the system can evolve into a complete wellness solution that not only detects stress but also suggests interventions such as guided meditation, lifestyle adjustments, and personalized sleep strategies. Expanding the dataset with diverse demographics and sleep conditions would further generalize the model, making it applicable to a wider audience in healthcare and mental wellness sector

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