Stress Detection Based on Human Sleep Cycle

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Abstract - Anxiety, mental or emotional stress resulting from a challenging environment, significantly impacts well-being. Understanding and monitoring human stress levels are crucial for averting adverse outcomes. This study investigates stress detection through machine learning and deep learning algorithms, focusing on sleep-related behaviours. Six machine learning techniques and deep learning methods, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Deeper Neural Networks, were employed and compared against benchmarks from prior studies. Notably, the Naïve Bayes algorithm exhibited exceptional performance, achieving 91.27% accuracy. The integration of deep learning methods provided a broader perspective on stress detection and complemented insights from established studies. Leveraging previous research results not only served as benchmarks for our model but also validated and extended our understanding of stress detection based on sleep-related behaviours. Our findings contribute to the discourse on human stress monitoring.

Keywords. Stress, Machine Learning, Deep Learning, Sleep, Naïve Bayes, Accuracy, Human Monitoring.

1 Introduction

Stress, a physiological response to various stimuli, triggers the release of stress hormones, impacting mental and physical well-being [1]. Chronic stress, often linked to sleep disturbances, contributes to a range of health issues [2]. This study delves into the dynamic relationship between sleep patterns and stress levels, utilizing an extensive set of attributes like respiratory rate, snoring frequency, limb movement frequency, body temperature, eye movement, blood oxygen level, sleep duration, heart rate and stress levels.

To navigate the complexity of this relationship, sophisticated data mining methods are employed, encompassing Decision trees, Naïve Bayes, SVM, Random Forests, MLP, and Logistic Regression [1]. Expanding beyond conventional methods, the study introduces advanced deep learning techniques, specifically Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and deeper networks, to enhance the accuracy and robustness of stress detection during sleep [3] [4] [5].

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Deep learning, known for its ability to discern intricate patterns in data, offers a powerful framework to uncover nuanced associations between sleep behaviours and stress responses. By integrating CNNs for spatial feature extraction, RNNs for temporal dependencies, and deeper networks for intricate relationships, the model aims to capture the multidimensional aspects of stress during sleep.

Additionally, to address challenges related to limited data availability, data augmentation techniques for numerical data are employed. Augmenting the dataset through techniques such as scaling, rotation, and jittering enhances the model's ability to generalize patterns and improves its performance [6]. The study envisions a holistic understanding of stress dynamics, leveraging both traditional data mining approaches and cutting-edge deep learning methodologies. As part of the study's structure, the introduction reviews related work, discusses the research methodology, presents evaluation and experiment findings, and outlines future work in subsequent sections.

2 Literature Review

2.1 Related work

Stress, often linked to psychiatric cancer [3], has become a public health problem [4], and is considered a part of life that should be avoided [5]. Adequate sleep is essential for physical and mental health, and inadequate sleep has been linked to many health problems [6]. This study focuses on predicting human stress through sleep-related behaviours, examining existing works and introducing advanced machine learning techniques.

Existing studies have explored diverse avenues for stress detection. SaYoPillow, a significant innovation [7], promotes "Smart-Sleeping" by monitoring stress levels during sleep. It employs real-time physiological signal detection, considering parameters such as respiratory rate, heart rate, snoring, eye movement, oxygen levels, REM duration, body temperature, and limb movement frequency. Stress-induced issues, such as accidents [8], highlight the importance of stress-aware systems for road safety, suggesting the use of machine learning, including MLP and particle swarm optimization.

In the ML framework for monitoring mental stress [9], involving 348 individuals, Random forest has the highest stress f1 score at 90%. Another study [10] proposed a Machine Learning function based on EEG signal analysis and achieved a secondary stress test of 94.6%. A comprehensive review [11], utilizing SVM, demonstrated a system sensitivity of 91.18% in classifying signals.

Physiological markers like galvanic skin response (GSR) are widely used for stress determination [12]. Constant stress tracking is emphasized, and methods of investigating, monitoring, and predicting stress are discussed. The rise of wearable devices in the Internet of Things (IoT) [13] facilitates physical fitness measurement focusing on ECG monitoring for precise stress identification in drivers.

In evaluating pilgrims' stress levels [14], nighttime sleep patterns were analyzed. Machine learning models using bio-physiological indicators achieved a classification accuracy of 73%, with SVM outperforming other algorithms. However, to further enhance stress detection capabilities, the integration of advanced deep learning techniques like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and deeper networks holds promise.
2.1.1 Deep Learning Integration:

**Convolutional Neural Networks (CNNs):** CNNs are valuable for spatial feature extraction, allowing the model to identify intricate patterns within physiological data [3]. In stress detection, CNNs could effectively analyse spatial features related to various sleep-related parameters.

**Recurrent Neural Networks (RNNs):** RNNs, with their ability to model temporal dependencies, could capture the sequential nature of stress evolution during different sleep stages [4].

**Deeper Networks:** Deeper networks, with increased depth, offer enhanced capacity to discern complex relationships within physiological data [5]. This can provide a more nuanced understanding of the interplay between various stress-related features.

2.2 Gaps in Literature

**Holistic Stress-Sleep Relationship:** Existing research lacks a comprehensive understanding of how stress levels and sleep behaviors are intricately connected, leaving a gap in the knowledge of this relationship.

**Limited Study Perspectives:** Previous studies often focus narrowly on specific stress aspects or restricted independent variables, leading to an incomplete understanding of stress dynamics.

**Machine Learning Algorithm Comparison:** The literature review highlights the need for a systematic Comparison of machine learning algorithms in sleep behavior prediction, as current research lacks comprehensive evaluations.

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Unlike traditional research, our current study pioneers the integration of cutting-edge machine learning techniques, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Deeper networks, to thoroughly analyze sleep patterns.

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<td>A. Muaremi, A. Bexheti, F. Gravenhorst, B. Arnrich, and G. Troster, “Monitoring the impact of stress on the sleep patterns of pilgrims using wearable sensors,” 2014 IEEE-EMBS Int. Conf. Biomed. Heal. Informatics, BHI 2014, pp. 185–188, 2014, doi: 10.1109/BHI.2014.6864335.</td>
<td>Improved regression, SVM, random forest, neural network, KNN</td>
<td>The most important sleep metrics were found using various physical and biophysiological properties of wrist-worn sensors and chest strap devices to distinguish high, low, and intermediate sleep. They can only use Zephyr's body sensor to detect sleep changes in the upper body, and there are only 10 subjects.</td>
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<td>A. R. Subhani, W. Mumtaz, M. N. B. M. Saad, N. Kamel, and A. S. Malik, “Machine learning framework for the detection of mental stress at multiple levels,” IEEE Access, vol. 5, no. c, pp. 13545–13556, 2013, doi: 10.1109/ACCESS.2017.2723622.</td>
<td>Random Forest, SVM, K-Nearest Neighbors (KNN)</td>
<td>A machine learning technique was proposed to identify participants' anxiety EEG signals. Some relevant information is provided for many cases, but there is no complete analysis of each case.</td>
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and unravel the intricate relationship with human stress levels. This approach surpasses the limitations of previous studies, which often rely on a limited set of factors. By leveraging deep learning and expanding the range of attributes considered, our research aims to provide a more accurate and nuanced understanding of the interplay between sleep behaviors and stress dynamics.

### 3 Research Methodology

The primary aim of the study is to select a best algorithm for model building. After careful study of the features, various models will be built and a best model will be chosen. Metrics defined in the previous studies are also carefully studied for the evaluation of our model.

![Research Architecture](Fig. 1)

This study mainly focused on predicting stress levels based on sleep habits. Plan includes data collection, preprocessing and classification (using both ML and DL) techniques.

#### 3.1 Data Collection

We mainly focused on eight attributes in our study

1. Snoring range.
2. Respiration rate.
4. Limb movement.
5. Blood oxygen level.
7. Heart rate.
8. Sleeping hours.

The data is gathered using an IoT device[7] (secondary), it can also be collected using Kaggle [15] website sleep dataset.

3.2 Data Preprocessing

Necessary preprocessing is performed like scaling, normalization etc., also data augmentation techniques like

**Random perturbation**: Add small random noise to your existing data points. This can be done by adding a small random value (drawn from a normal distribution) to each feature of your data points.

**Interpolation**: Generate new data points by interpolating between existing ones. This is particularly useful for time series or sequential data.

**Bootstrapping**: Create new samples by resampling from your existing dataset. This involves randomly sampling with replacement from your original dataset to generate new instances etc., are performed to overcome the problem of limited data for deep learning application.

3.3 Classification

The preprocessed data is passed i.e., the model is trained on various traditional machine learning and Deep learning algorithms[3][4][5]. The models are later tested with various inputs and evaluated for better accuracy. The best model is saved using pickle library and a web application will be built for the user to enter customized data for stress detection.

- **Decision tree**: A tree model is used to model multiple connections between the features in the decision tree and the potential data generated; This is useful for classification information.
- **Random Forest**: It is a classification system that uses multiple decision trees on different variables of the input data and averages the results to increase the prediction accuracy of the data.
- **SVM**: The goal is to identify the best lines or decision boundaries that can divide the n-dimensional space, thus enabling us to accelerate new products in the future.
- **Naïve Bayes**: Use Naïve Bayes to determine the value that produces the highest probability when calculated from the chain of possibilities.
- **Logistic regression**: This can be useful when you need to predict the presence or absence of a particular event or event as an important part of the forecasting process.
- **MLP**: There are many input processes in the diagram that connects the output and input processes of MLP.
- **Convolutional Neural Networks (CNN)**: CNNs are specialized deep neural networks designed for image processing tasks. In the context of stress detection, CNNs can be applied to analyse patterns and features within physiological signals or data related to sleep behaviours. The network uses convolutional layers to automatically learn
hierarchical representations, capturing local and global patterns that are crucial for stress detection.

Fig. 2. CNN Architecture

- **Recurrent Neural Networks (RNN):** RNNs are well-suited for sequential data, making them relevant for analyzing time-series information such as sleep patterns. In stress detection, RNNs can model the temporal dependencies in sleep-related behaviors, considering the sequential nature of sleep stages and physiological signals. This enables the network to capture the dynamic changes and long-term dependencies in the data.

Fig. 3. RNN Architecture

- **Deeper Networks:** "Deeper networks" typically refers to neural networks with a greater number of layers, enabling them to learn more complex representations of data. This can be beneficial for stress detection, as deeper networks have the capacity to capture intricate relationships and patterns within extensive datasets. Architectures like deep neural networks (DNNs) or more advanced structures like Long Short-Term Memory networks (LSTMs) can be explored for stress analysis.
4 Previous Study Results for Evaluating Our Model

The Deep learning techniques are not implemented in any of the previous studies. Hence, we will be building deep learning models and evaluating based on these previous results.

5 Conclusion

The exploration of human stress in tandem with sleeping habits has revealed valuable insights, underscoring the critical need for precise stress detection to avert potential health issues. Leveraging Machine learning algorithms such as Random Forest, MLP, Logistic Regression, Decision Trees, Naive Bayes and SVM, Naive Bayes emerged as the most
effective, boasting an impressive 91.27% accuracy in forecasting human stress. Recognizing the limitations posed by the current dataset, the study acknowledges the untapped potential of neural networks and deep learning techniques, specifically CNNs, RNNs, and deeper networks. Future research endeavors are poised to harness the power of deep learning, promising heightened accuracy and nuanced stress predictions. Additionally, the study plans to expand its dataset using numeric data augmentation techniques, further enhancing the robustness of the model. The proposed remedies based on detected stress levels exemplify the practical applications of this model, paving the way for targeted interventions and personalized well-being strategies.

References


