IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Harmony Sphere: Pioneering Stress Detection through Facial Recognition and Sleep Pattern Integration

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***Abstract*—** The first is evaluating and tracking the quality of sleep, recognizing the substantial influence of stress on physical well-being. The study also includes facial landmarks as an extra dimension for stress detection at the same time. The first part is evaluating and tracking the quality of sleep, recognizing the substantial influence of stress on physical well-being. The study also includes facial landmarks as a further dimension for stress detection at the same time. The new tactic is deriving visual information from face emotions using computer vision algorithms. In order to provide a user-friendly experience for stress detection, our technique strives to be non-invasive. The suggested hybrid method uses machine learning techniques to combine information from face landmarks and sleeping patterns to provide a thorough stress prediction. The final objective is to develop an AI model that offers a reliable and comprehensive method of stress detection by fusing the knowledge from facial expressions and sleep-related data. This groundbreaking study confirms the value of multi-modal techniques in comprehending and treating stress-related problems and advances the rapidly developing area of computational psychology.

***Keywords*—** Facial Expression, Stress, Sleep Disorders. Convolutional Neural Network (CNN), OpenCV, and Deep Learning.

I. Introduction

People's lives are affected by sleep, however the reasons behind this are still mostly unknown. When the body approaches close to total paralysis, the brain relaxes and integrates the day's events while respiration and pulse rate drop down. This is a way of getting better. Though its evolutionary origins remain largely unknown, sleep is essential for life as we know it. You may gauge the quality of your sleep by looking at physical or physiological traits like body movement, temperature, and heart rate.

The amount of stress we experience throughout the day has a direct impact on how well we sleep at night. It might be difficult to fall asleep and keep asleep during the day when rumination and hyperarousal are contributing factors to high levels of stress. Nevertheless, insufficient or non-existent sleep can exacerbate stress, decelerate your body's reaction to stress, hinder your ability to recover from stressful events, and hinder the use of coping strategies. A substantial amount of research shows a high correlation between stress-related sleep issues and other sleep issues, as well as the opposite.

The use of computational approaches is increasing because they can handle more complicated situations. Determining regular sleep patterns, investigating pertinent fields, and diagnosing sleep issues are a few of them. Additionally, IoT gadgets are getting better, opening up new possibilities, and gaining traction in research on sleep at home. With the use of home-based monitoring, sleep status may be frequently assessed and managed in the comfortable circumstances of one's own home. In this discipline, a wide range of technologies are employed, such as Doppler radar, radio waves, and smartphones. In order to identify significant sleep metrics and indications, the collected data is evaluated and analysed using data mining and machine learning approaches

Assessing and managing the quality of one's daily sleep while staying at home comfortably is achievable using home-based monitoring. This industry makes use of gadgets like Doppler radars, radio waves, and smartwatches. Once relevant sleep measurements and indications have been identified and categorized, the collected data is evaluated and examined utilizing data mining and machine learning approaches. Both people and scientists trying to learn more about the connections between, say, daily and nocturnal activities may find it helpful to utilize sensors to monitor sleep habits at home. A plethora of theoretical frameworks have been put out to elucidate the intricate relationships between stress and insomnia. A disruption in sleep may be predicted in terms of when it will happen, how long it will continue, and how effectively it will function by combining stress as a catalyst with sustaining (like stimuli control) and risk (like personality traits) factors. These findings are supported by the stress-diathesis and the "three-factor" behavioural model of insomnia. A person's obsession with sleep-related issues raises their level of arousal, which keeps them from falling and staying asleep, according to the cognitive model of insomnia, which is in line with associated theories. An already stressful scenario could get worse due to this dread of sleeplessness or real insomnia.

II. Literature Survey

The literature survey conducted for this study is summarized in a tabular format, providing a comprehensive overview of relevant research works. The table encompasses crucial details such as the name of the study, author(s), publication year, research objectives, and key advantages and disadvantages identified in each work.

Title	Authors	Year	Objectives	Advantages	Disadvantages
An efficient facial expression recognition system with appearance-based fused descriptors [1]	Yacine Yaddaden	2023	proposes a facial expression recognition system that leverages appearance-based fused descriptors to improve the accuracy and efficiency of facial expression classification.	It utilizes various appearance-based descriptors such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and deep learning-based features. These descriptors capture different aspects of facial appearance and texture. The proposed system can accommodate various types of appearance-based descriptors, allowing flexibility in feature representation and adaptation to different facial expression recognition tasks and datasets.	The fusion of multiple descriptors adds complexity to the feature extraction and classification process, requiring careful design and optimization of fusion strategies to avoid overfitting or computational overhead. The effectiveness of the system heavily relies on the quality and relevance of the chosen appearance-based descriptors. Selecting inappropriate descriptors or failing to properly integrate them may result in suboptimal performance.
A Comparative Study of Local Descriptors and Classifiers for Facial Expression Recognition	Antoine Badi Mame and Jules-Raymond Tapamo	2022	presents a comparative analysis of different local descriptors and classifiers for facial expression recognition.	1 By evaluating multiple combinations of descriptors and classifiers, the paper offers a comprehensive view of the available options, allowing researchers and practitioners to choose the most appropriate combination based on their specific requirements and constraints. The use of standard evaluation metrics such as accuracy, precision, recall, and F1-score enables a quantitative assessment of the performance of each approach, facilitating objective comparisons and informed decision-making..	The study may not cover all possible combinations of local descriptors and classifiers, potentially overlooking some promising approaches or variations that could yield better performance in specific scenarios. The performance of classifiers such as SVM or k-NN may be sensitive to hyperparameters or configuration settings, which could influence the comparative analysis results. Sensitivity analysis or parameter tuning may be required to ensure fair comparisons.
Mental Health Conditions According to Stress and Sleep Disorders	Ray M. Merrill,	2022	Stress and sleep disorders are closely linked to mental health conditions. Chronic stress can lead to anxiety disorders, depression, and other mood disorders. Similarly, sleep disorders such as insomnia or sleep apnea can exacerbate symptoms of anxiety and depression, while also increasing the risk of developing other mental health conditions.	By examining the interplay between stress, sleep disorders, and mental health conditions, the paper offers a more comprehensive understanding of the complex factors influencing mental well-being. Identifying the role of stress and sleep disorders in mental health allows for the development of targeted interventions and therapies aimed at improving sleep quality, reducing stress levels, and mitigating the risk of mental health problems.	Much of the research in this area is correlational, making it difficult to establish causality between stress, sleep disorders, and mental health conditions. The relationship between stress, sleep disorders, and mental health is bidirectional, with each factor influencing and exacerbating the others. Disentangling these complex relationships can be challenging.
Facial Expression Recognition System Based on SVM and HOG Techniques	Safa Rajaa, Rafika Harrabi & Slim Ben Chaabane.	2021	1. proposes a facial expression recognition system that utilizes Support Vector Machine (SVM) classifier and Histogram of Oriented Gradients (HOG) feature extraction technique.	HOG descriptors capture important local texture and shape information from facial images, providing a robust representation for facial expression recognition. The proposed system can generalize well to recognize facial expressions across different individuals and lighting conditions, thanks to the robustness of HOG features and SVM classification.	HOG descriptors may not capture contextual information or subtle variations in facial expressions, which could limit the discriminative power of the feature representation. SVM classification requires tuning of hyperparameters such as the kernel type and regularization parameter, which may require expertise and computational resources to optimize for optimal performance.

Title	Authors	Year	Objectives	Advantages	Disadvantages
A New Texture Descriptor: The Homogeneous Local Binary Pattern (HLBP)	Johan Debayle,	2020	A Self-Independent Method for Face Expression Recognition To overcome the limitations of LBP, our study suggests a reliable description of facial features that uses the CLBP to discern emotions from someone's face. The suggested CLBP operator uses the sign and magnitude information of the variances between the neighbour and centre gray values to provide a potent feature descriptor by appending additional P bits to the original LBP coding.	Strong Characteristic: By addressing the drawbacks of the conventional Local Binary Pattern (LBP), it provides a strong characteristic for interpreting facial expressions. In order to obtain the sign and magnitude information of the deviations between the neighbor and center Gray values, CLBP's ability to efficiently integrate additional bits with the original LBP code improves identification accuracy.	Complexity & Computational Cost: Compared to conventional LBP techniques, the addition of extra bits and the modification of sign and magnitude information may result in an increase in the computational complexity and processing time needed for feature extraction. This could restrict the CLBP approach's ability to be applied in real time in some circumstances.
Facial Expression Recognition with LBP and ORB Features	[1]Zhenxing Gao,[2]and Bingbing Guo[3], 12 Jan	2021	Real-time face emotion classification using local binary patterns Principal Component Analysis (PCA) is the suggested method for identifying a variety of facial expressions in this study, while the Haar classifier is used for face recognition. The Local Binary Patterns (LBP) histogram of a facial picture with various block sizes is used to create feature vectors. Real time applications of the expression classification technique are made possible by its low computational complexity.	Real-Time Implementation: Thanks to its real-time implementation, the suggested facial expression categorization system is appropriate for applications like emotion-aware systems and human-computer interaction where quick facial expression analysis is needed.	Restricted to Grayscale Frontal Face Images: The system's reliance on grayscale frontal face images may reduce its applicability in real-world scenarios where facial expressions need to be analyzed from various angles or in different lighting conditions. Furthermore, not all face characteristics may be properly captured in grayscale photos, which might result in inaccurate emotion assessment.
Facial Expression Recognition Model Depending on Optimized Support Vector Machine	Amel Ali Alhussan1 , Fatma M. Talaat2 , El-Sayed M. El-kenawy3 , Abdelaziz A. Abdelhamid4,5 , Abdelhameed Ibrahim6 , Doaa Sami Khafaga1, * and Mona Alnaggar7	2023	This paper provides a unique method using local binary patterns (LBP) and local Fisher discriminant analysis (LFDA) for face expression recognition. Using the original photos of the expressive faces, the LBP characteristics are first extracted. When high dimensional LBP features are retrieved, LFDA is utilized to build low dimensions discriminative embedded data representations.	High Recognition Accuracy: Using the JAFFE facial expression database, the suggested technique obtains a recognition accuracy of 90.7%, demonstrating its efficacy in precisely recognizing facial emotions. This high accuracy indicates the promise of Local Fisher Discriminant Analysis (LFDA) and Local Binary Patterns (LBP) together for face emotion identification tasks.	Complexity and Dimensionality Reduction: Although the approach produces remarkable results, the system may become more complicated when LFDA is used to reduce the dimensionality of high-dimensional LBP features into low-dimensional embedded data representations. It's possible that this complexity will result in more processing overhead and more resources needed to implement. Furthermore, the process could need meticulous parameter adjustment for best results, which could take some time.

Title	Authors	Year	Objectives	Advantages	Disadvantages
Facial Expression Recognition using Support Vector Machine (SVM) and Convolutional Neural Network (CNN)	Afeefa Muhammed1* , Ramsi Mol2 , L. Revathy Vijay3 , S. S. Ajith4 , A. R. Shamna5	2020	The facial emotion identification method presented in this article is based on Local Binary Pattern (LBP) and Principal Component Analysis (PCA) approaches. The testing focused on two databases: Japanese Female Facial Expression (JAFFE) and the recently released Mevlana University Facial Expression (MUFE) SVMs, or support vector machines, served as the classifiers. Based on all research done on both datasets, the average recognition rates for PCA+SVM and SVM with regard to the JAFFE and MUFE datasets are 87% and 77%, respectively.	PCA with LBP approaches can yield a comprehensive approach for the identification of facial emotions. PCA contributes to reduction of data dimensionality, whereas LBP records local texture information. The ability to describe facial emotions in more detail is made possible by this combo strategy, which improves identification accuracy.	Distinctive Recognition Rates: 77% of identifications are made using the MUFE database, whereas 87% are made with the JAFFE database. These results indicate different performance levels. When applied to the JAFFE database, the approach shows promise; but, when used to the MUFE database, it becomes less successful. This implies that there can be restrictions or difficulties when using the method widely on different datasets or populations.
Facial expression recognition using three-stage support vector machines	Issam Dagher, Elio Dahdah & Morshed Al Shakik	2019	Fostering Real-Time Face Expression Identification in Videos via Support Vector Machines With live video face expressions, our study presents a real-time method to recognize emotions. With our automated facial feature tracker, we do both face localization and feature extraction. The video stream's face feature displacements are used to train Backing Vector Machine classifiers. We evaluate the recognition effectiveness of our technique in several interaction and classification settings.	Real-Time Processing: The suggested method makes it possible to identify facial expressions in live video in real-time, enabling quick analysis and reaction in a variety of interactive situations. Applications needing prompt emotion detection, such emotion-aware systems or human-computer interaction, benefit from this real-time capacity.	Dependency on Facial Feature Tracker: The automated facial feature tracker's accuracy and dependability for face localization and feature extraction is a critical component of the approach's efficacy. Facial expression detection mistakes might be caused by inaccuracies or malfunctions in the tracker's operation, which would affect the system's overall dependability.
Stress Mining from Sleep-Related Parameters	Raisa Nusrat Chowdhury Mohammad Fahim Hassan, Md. Arshaduzzaman Fahim, and Sifat Momen	2023	Within the subject of computational sleep behavior analysis, the author of this book provides a comprehensive and in-depth assessment of recent developments. The most recent advancements in computational analytical tools, modeling, and home sleep monitoring that leverage cheaper, quicker, and more accessible sensor technologies are specifically	Comprehensive Assessment: This research offers a thorough and methodical evaluation of the latest advancements in computational sleep behavior analysis, including information on a range of topics including modeling, computational analytic techniques, and home sleep monitoring. A full grasp of the field's present status is made possible by this all-encompassing approach.	Limited to Recent Developments: While the study focuses on recent developments in computational sleep behavior analysis, it may lack historical context or insights into earlier methodologies or findings. This limitation could potentially impact the depth of understanding and interpretation of the field's evolution over time.
A clinical and technical methodological review on stress detection and sleep quality prediction in an academic environment	Sharisha Shanbhog M, Jeevan Medikonda	2023	This study compares and evaluates the outcomes of visual assessment and automated analysis of nocturnal sleep data. To validate the procedure, sixty individuals (thirty men and twenty women) were divided into three groups of twenty: twenty patients with depression, twenty patients with insomnia for which benzodiazepines had been prescribed, and twenty normal control subjects.	Objective and Consistent Analysis: By eliminating the possibility of subjectivity in interpretation and human mistake, the automated sleep staging system offers an objective and consistent analysis of sleep recordings from the night. When working with huge datasets, in particular, this might result in more consistent and repeatable outcomes.	Expert supervision is still necessary for unclear and unknown epochs, even if the automated approach has achieved a high agreement rate with expert rating. If a large amount of the night's data need human intervention, this supervision may add complexity and increase the time and effort required for analysis.

III. XGBoost based Method For Stress Detection

A well-liked method for learning ensemble modeling that turns poor classifiers into strong classifiers is called "boosting."

Using the available training data sets, it first builds a primary model and then verifies that it is sound.
The construction of an additional hypothesis and the integration of a new model are both done once the error has been located. Consequently, until the model is able to accurately predict values throughout the whole training set, additional approaches will continue to be incorporated.

Using a set of weak prediction models, such as decision trees, GBM enables us to build a predictive model.
Gradient boosting trees are the resultant strategy when the decision tree functions as a passive learner.

With its help, we may combine forecasts from several learner models to create a final forecasting model that is predicated on the correct information.

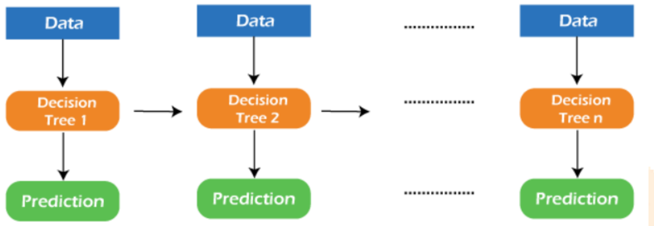

Fig 1.Schematic block diagram of XGBoost

A. Architecture

The following are some essential steps in making the algorithm better:

1. The method will produce a log of the likelihood of making accurate early predictions about the data. This is usually the proportion of positive to negative numbers.
2. Six cancer incidences in a dataset mean that log(odds) = log(4/3) 1.3 for the four cancer cases and the three non-cancer cases. However, the integer for the person who has not become ill is zero. On a scale of one to three, cancer patients will get ratings. To generate forecasts, use a logistic function to convert log(odds) to probability. It would be around 1 in this case.
3. that the log(odds) value relates to.
4. Since the value exceeds 0.5, the method will take 1.3 as the initial approximation for every instance.

   e * log(odds) divided by (1 + e * log(odds))

5. All of the practice set's incidences' residuals will be found using the previously outlined algorithm.
6. When finished, a decision tree is constructed to forecast the predicted residuals.
7. Users are able to employ the maximum amount of leaves when creating a hierarchy. Two things may happen from this:
   • There are several instances of the leaf, not just one. A formula must be used by users in order to alter these values.
   Σ Relative/Prior Probability (1-Prior Probability)
8. Now, some of us must complete two tasks:

- For every occurrence of the training set, obtain a log prediction.
- Calculate the likelihood of the anticipated result.

9. The following formula is used to provide predictions.

B. *Base log odds plus Xception(calculated residual value * learning rate)*

Transliterated as "extreme inception," Xception pushes the concepts of Inception to the limit. While distinct filters have been applied to each depth space, Inception reduced the original input using 1x1 convolutions. All Xception does is flip the phase. Rather, it uses distinct depth map filtering techniques and then uses 1X1 convolution across the depth to compress the input space. This technique is nearly the same as depthwise recoverable convolution, which has been around since 2014 and is utilized in neural network construction. There is one more thing that separates Xception and Inception. Following the first operation, a nonlinearity may develop or perform. No further nonlinearity is added by Xception, although both stages in the initial model exhibit ReLU nonlinearity.

A convolution neural network with only one depthwise separable layer is called the Xception architecture. Conceptually, it is possible to perceive cross-channel similarities and spatial correlations separately. The network is made up of 36 convolutional layers that facilitate feature removal and 14 units with linear connection residuals, excluding the main and final

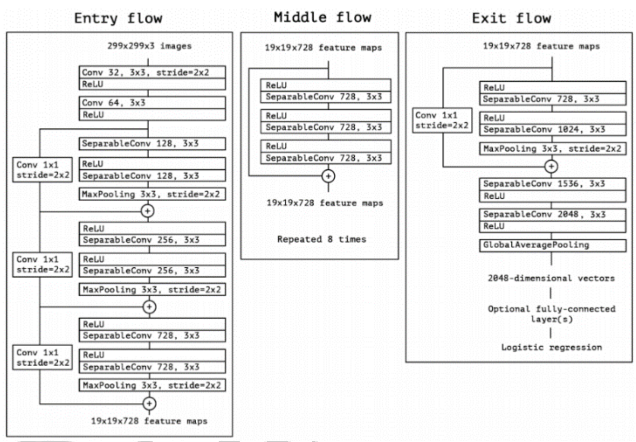

Fig 2.Schematic block diagram of Xception

IV. Methodology

The approach for identifying stress based on facial expressions and sleep patterns is complex and combines feature extraction, data collection, and machine learning. This is a summary of the process:

1. Gathering information about sleeping patterns:
Utilize smartphone applications and sleep tracking devices to gather data about sleep habits, including duration, quality, and interruptions.

To find out more about viewpoints and patterns of sleep, gather subjective data through surveys or sleep diaries.

Use camera-related imaging technology to record expressions in various sleep and wakeful states in order to get facial landmark data.

Face indicators such as eye, referential, and head movements may be extracted from facial images using computer vision algorithms.
2. Preparing data:
Preprocessing and cleaning of sleep data is necessary to eliminate inconsistent and missing results.

To guarantee uniformity among datasets, translate subjective sleep data into quantitative measures.

Preprocessing is normalizing and aligning face landmarks such that they are consistent across individuals.
Translate unprocessed facial landmark data into meaningful features such as expressions and movement routes.

3. The extraction of features:
Habits of Sleep Determine important details from sleep data, such average length, productivity, and frequency of disruptions.

Features of face Landmarks: Timing, movement strength, and frequency of expressions may all be extracted from face landmark data.

4. Combining Features:
Create a customized feature set by combining sleep patterns with facial landmarks.

5. Machine Learning Frameworks:
Consider the quantity of datasets, feature complexity, and interpretability when choosing a suitable learning method for stress detection.

Using a labelled dataset, determine the stress levels according to predefined standards to train the model.

Verify the generalizability of the result by conducting tests and validations on alternative datasets.
Utilizing the testing data, assess the model's performance by computing the F1 score, precision, accuracy, and recall

CONCLUSION

By combining facial signals and sleep patterns as complementary data sources, our work aims to close this gap in the field of integrated stress detection systems. The project's objective is to create a reliable, non-invasive method of early stress detection by using machine learning algorithms to analyze facial expressions and sleep data. Constructing comprehensive stress detection methods that can enhance general wellbeing and mental health is the ultimate objective.

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