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Intelligent Stress Detection and Healthcare Monitoring using Facial Emotion Recognition and Physiological Signals

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Abstract: Persistent stress can have detrimental effects on the physical and psychological well-being of individuals, resulting in the development of cardiac conditions, anxiety, depression, tiredness, and insomnia. For this reason, the design of intelligent healthcare solutions that continuously detect and monitor stress levels has become increasingly significant. This paper describes a proposed intelligent stress-detection and monitoring system that uses facial emotion and physiological analysis techniques. Facial images are used in the system to determine whether one's emotion can be identified, which includes happy and stressed. Furthermore, the system uses physiological data to evaluate a person's overall health status of a person. Physiological data includes heart rate, hours of sleep, SpO2, and ECG. For instance, the analysis of waveforms of ECG can be done in order to detect abnormal heartbeat rhythm and arrhythmia, as well as cardiac stress conditions. With the emotional and physiological study, the model has been able to determine the level of stress and provide intelligent health care recommendations that support the preventive health care management. According to experimental results, it is observed that the combination of the two methods makes the stress evaluation and health monitoring more efficient. The system designed offers a low-cost, intelligent healthcare solution for stress monitoring, remote healthcare surveillance, and biomedical research.

KEYWORDS: Sleep Patterns, ECG Readings, SpO2 Values

I. INTRODUCTION

It has now become a very common phenomenon that stress has emerged as one of the most common problems faced by people in contemporary times, where individuals at all stages in their lives may be prone to developing stress owing to various factors such as increased academic pressure, work pressure, and lifestyle issues. However, prolonged stress is not only damaging to a person's mental state but can also affect a person physically and lead to various medical conditions.

Recent advances in artificial intelligence, machine learning, computer vision, and physiological sensing technologies have enabled the development of automated systems for stress analysis and healthcare monitoring. Emotional states are closely related to stress levels, making emotion recognition an effective approach for assessing mental well-being. Mishra et al. [1] proposed an emotional intelligence framework that utilizes speech and facial recognition techniques to analyze stress conditions, demonstrating the importance of multimodal emotional information in stress assessment. Similarly, Kumar et al. [3] highlighted the role of face-expression observation systems in recognizing human emotions and behavioral patterns, emphasizing their potential in healthcare and psychological monitoring applications.

Recognition of emotions by analyzing faces has proven to be one of the potential ways of detecting stress. The researchers Giannakakis et al. [4] presented a methodology of automatic analysis of stress by deep facial action unit recognition of faces using videos, proving that deep learning is applicable in the detection of patterns related to stress. On the other hand, Xu et al. [6] came up with a facial emotion recognition approach to stress analysis, indicating that facial features can play a significant role in assessing emotions and mental states.

Apart from analyzing facial expressions, physiologically based technologies are used for monitoring purposes within healthcare. Using wearable devices and wireless body area networks (WBAN), physiological parameters such as heartbeat, electrocardiogram (ECG) signals, oxygen saturation, and information related to sleep monitoring can be

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continuously acquired. In Himanshu et al. [2], an introduction of health monitoring system using WBAN was discussed, and the significance of the system in the healthcare monitoring process was pointed out. Physiological information can help to analyze stress and manage healthcare in a smart way. Machine learning and sensors have been used together to make stress detection systems even more precise and reliable. Kyamakya et al. [5] reviewed the sensors and machine learning approaches associated with emotions and stress detection; their focus was on the importance of intelligent algorithms for the analysis of physiological and emotional signs. They proved that the combination of sensor and machine learning information is extremely helpful for classifying stress effectively.

Despite considerable advancements in emotion detection and physiological monitoring techniques, most of the current systems focus solely on analyzing either facial emotions or physiological signals. Thus, an integrated system that uses both facial emotion detection and physiological signal detection can be more effective and accurate in detecting stress. This paper addresses intelligent stress detection and health monitoring based on facial emotion detection and physiological signals. Through the integration of information from emotional and physiological perspectives, this technique intends to achieve increased precision in stress analysis and health monitoring.

II. RESEARCH BACKGROUND

Analysis of physiological signals is considered to be one of the most efficient methods of stress detection and healthcare monitoring since physiological reactions manifest themselves as a result of any emotional or psychological changes that occur in a person's body. A great deal of studies have been dedicated to the identification of stress states on the basis of heart rate, ECG, respiratory activity, GSR, and sleep patterns. Proposed by Palanisamy et al. [7], there was a human stress detection system that used multiple physiological signals with non-linear classifiers. This work showed that using multiple physiological signals leads to better stress classification accuracy than using a single physiological signal. The use of non-linear classifiers allowed for the identification of complex patterns in physiology associated with stress more precisely. However, their study involved only physiological signals.

In Singh et al.'s paper [8], the comparative analysis of different types of neural-network classifiers for identifying the level of stress among automotive drivers based on physiological signals was done. This research analyzed how different neural-network architectures can be used to classify stress among drivers and concluded that it is possible to classify different levels of stress using artificial neural networks. In Bong et al., a detailed study has been conducted on the different methodologies used to determine emotional stress using physiological parameters. In their study, Bong et al. highlighted different physiological parameters such as ECG, heart rate variability, skin conductance, and respiration for determining emotional stress. Their study emphasized that physiological parameters can be used for assessing stress and developing intelligent healthcare monitoring systems.

The authors Chen et al. [10] have developed a multimodal feature analysis system for recognizing driving-related stress through physiological signal processing. The system implemented kernel-based classifiers along with various physiological signals for better classification performance. The experimental findings revealed that by considering several physiological signals simultaneously, the detection reliability was improved for identifying driving stress. But the research only considered applications in automobiles. The methodology for quantitative stress assessment through analysis of physiological signals was designed by Arza et al. [11]. This technique mainly concentrated on measuring the reaction to acute stress by considering various physiological variables, and it was found that quantification of stress may offer useful information about mental disorders of human beings.

Personalized stress evaluation using physiological signals was developed by Xu et al. [12] using a cluster-based method. In contrast to generalized stress classification schemes, this scheme utilized personalized physiological parameters for better stress evaluation performance. The findings indicate that personalized stress evaluation schemes have greater potential compared to generic schemes. Xia et al. [13] proposed a relatively early solution of stress condition detection using physiological signals. Stress recognition and determination became critical for early diagnosis when physiological manifestations have not yet appeared. This solution used biomedical signal processing techniques to help achieve early detection and provide preventive care measures.

According to Orozco-Mora et al. [14], an algorithm was proposed for the calculation of stress level based on physiological signals within virtual reality environments. This work combines physiological measurements and virtual environment usage to test stress levels in users within virtual reality environments. It has been shown that stress levels can be calculated using physiological signals in interactive virtual reality environments. Geetha et al. [15] conducted research on stress detection in humans using sleep pattern analysis through machine learning algorithms. This study emphasized the significant correlation between sleep quality and stress states. Machine learning methods have been

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used for analyzing sleep patterns and predicting stress levels. It was concluded that sleep pattern analysis is an efficient way to monitor mental health issues and stress states. In their investigation on the influence of stress on the behavior of individuals in sleep, Muaremi et al. [16] utilized wearable devices to examine how stress affects sleep pattern. The study investigated pilgrims using wearable health technology devices, and their findings indicated that stress highly affects sleep duration and behavior.

III. PROPOSED METHODOLOGY

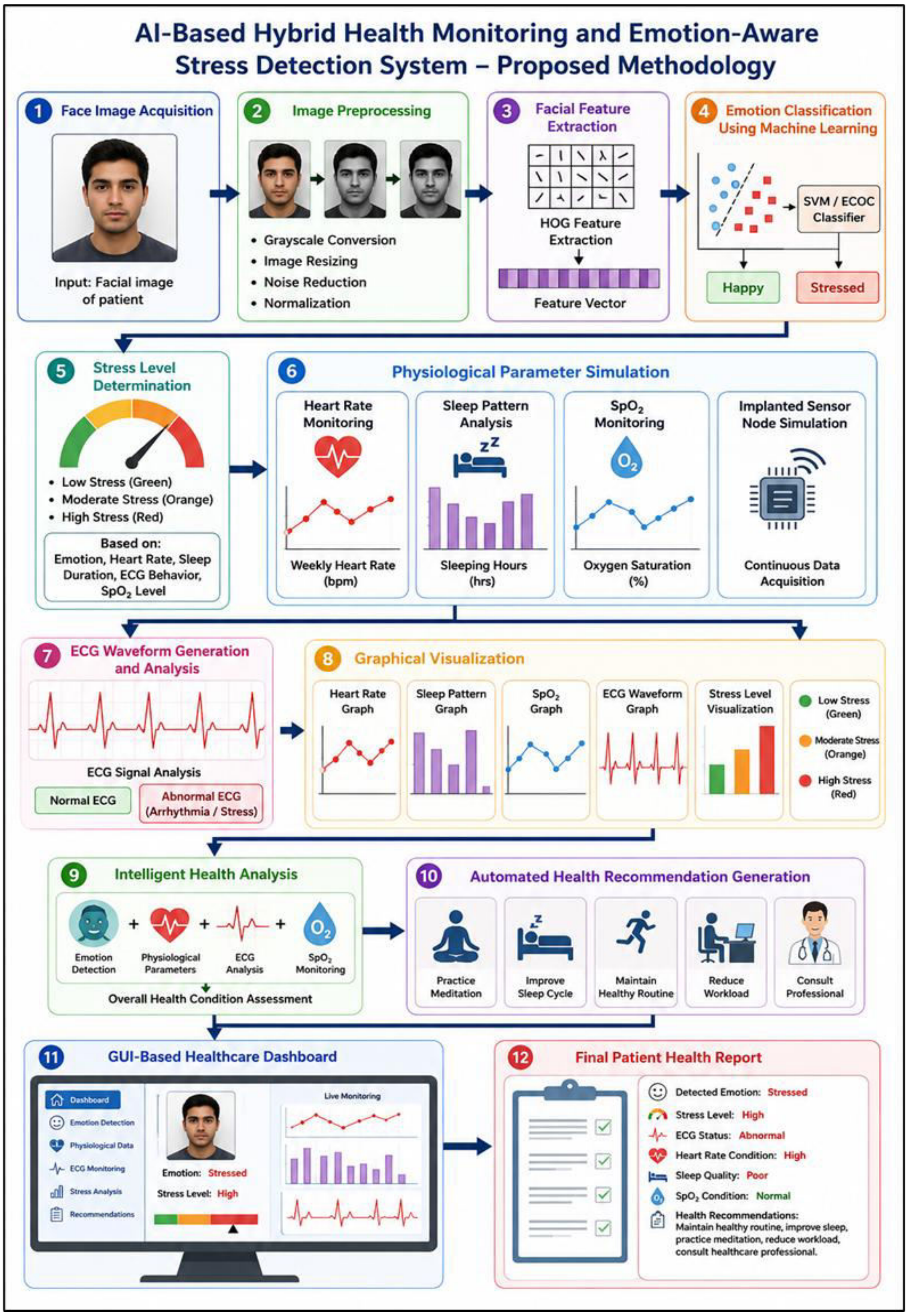

Figure 1: Proposed Methodology

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Step 1. Face Image Acquisition: Acquisition of Face Images is the first step in the system where the image of the face of the individual is acquired by selecting an appropriate face image using the MATLAB graphical user interface. The image that has been selected acts as the input required to perform emotion recognition and stress detection. The images used can be captured by a camera or chosen from a pre-set database having faces of both happy and stressed expressions. In case the collected image is a gray-scale image, then it can be mathematically represented as:

$$I(x,y) = f(x,y) \tag{1}$$

where: I (x, y) represents the intensity value of the image pixel,

Step 2. Image Preprocessing: The purpose of image preprocessing is to enhance the image before feature extraction. Preprocessing involves steps like grayscale transformation, resizing, filtering, and normalization for cleaning noise and bringing uniformity to the image. This makes the facial features more prominent. The RGB facial image obtained is then transformed into a grayscale image. This is to make the computation less complex by reducing the image to just one channel, the intensity channel. This is achieved mathematically by:

$$Ig(x,y)=0.2989R(x,y)+0.5870G(x,y)+0.1140B(x,y) \tag{2}$$

where: Ig represents the grayscale image,

Step 3. Facial Feature Extraction: The process of facial feature extraction extracts relevant facial features that capture emotions expressed. The proposed system employs the Histogram of Oriented Gradients (HOG) approach for facial texture, edge, and contour features extraction. This method converts facial features into numeric vectors for further analysis through machine learning techniques. The process of feature extraction starts with calculating the gradient of the facial image in the horizontal and vertical directions. Mathematically, these can be represented as follows:

$$Gx = I(x+1,y) - I(x-1,y) \tag{3}$$

$$Gy = I(x,y+1) - I(x,y-1) \tag{4}$$

where: Gx and Gy represent the horizontal and vertical image gradient, respectively.
Based on these gradients, the magnitude and direction of the gradient at each pixel are computed. The formula for the gradient magnitude is given as:

$$M(x,y) = \sqrt{{G_x}^2 + {G_y}^2} \tag{5}$$

where: M(x,y) represents the gradient magnitude.
Local histograms of gradient directions are constructed for each cell depending on the edge directions in the cell. The local histograms are then normalized to enhance the illumination invariance and feature robustness. The normalized HOG feature vector is represented as:

$$H = \frac{h}{\sqrt{|h|^2+\epsilon^2}} \tag{6}$$

where: H represents the normalized HOG feature vector, h represents the original histogram vector. The extracted HOG features help capture essential facial features like eyes, eyebrows, mouth, and facial contour that change under different emotional states. The feature vectors are used by the machine learning classifier for classification and prediction purposes.

Step 4. Emotion Classification Using Machine Learning: The extracted facial features are provided to a machine-learning classifier to determine whether the person is happy or stressed. Support Vector Machine (SVM) classifiers are commonly used because of their high classification accuracy and robustness. For the emotion classification phase, feature vectors extracted through HOG are used as input to a machine-learning classifier. In the proposed system, an SVM-based ECOC classifier is employed for emotion recognition. Machine learning classifiers learn the critical facial patterns from the training images and classify the test facial images into specified emotional classes. The training set comprises a series of labeled facial images belonging to two emotional classes: Happy and Stressed. The SVM classifier tries to find the best hyperplane boundary for separating various emotional classes. The hyperplane boundary used for classification can be expressed as:

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$$w^T x + b = 0 \quad (7)$$

where: f(x) represents the predicted emotional class, sign() determines whether the image belongs to the happy or stressed category.

Step 5. Stress Level Determination: The fundamental goal of this phase is to determine of individual's stress state, based of their emotional and physiological factors. Stress impacts the physical and mental health of individuals and can cause various conditions, such as cardiovascular diseases, fatigue, anxiety, insomnia, and respiratory issues. Thus, it becomes imperative that stress level estimation be accurate. The following are some of the factors involved in determining the stress level in the proposed system: Facial emotion detection, Heart rate, Sleep time, ECG, and SpO2. The calculation of the stress score depends on the weight of various physiological factors. The proposed method uses the stress-score formula described as follows:

$$S = \alpha(HR) + \beta(SH1) \times 100 \quad (8)$$

where: S represents the stress score, HR represents heart rate, SH represents sleep hours, and the alpha α (0.6) and the beta β (04) are weighting coefficients.

Step 6. Physiological Parameter Simulation: The system simulates physiological signals such as heart rate, sleep hours, oxygen saturation (SpO2), and ECG values. These parameters represent the physical health condition of the patient and are used for intelligent health analysis. Implanted sensor nodes keep on collecting and transmitting physiological information to the healthcare monitoring system for analysis and presentation. Sensor node output will be as follows:

$$S(t) = \{HR(t), SH(t), SpO2(t), ECG(t)\} \quad (9)$$

where: S(t) represents the physiological sensor signal set, and HR(t), SH(t), SpO2(t), and ECG(t) represent time-varying physiological parameters.

Step 7. ECG Waveform Generation and Analysis: ECG waveforms can be generated with the help of periodic sine wave forms used to model the heart's rhythmic electrical activities. The generated ECG waveform can be expressed mathematically as follows:

$$ECG(t) = A1sin(2\pi f1t) + A2sin(2\pi f2t) \quad (10)$$

where: ECG(t) represents the ECG signal, A1 and A2 represent signal amplitudes, f1 and f2 represent signal frequencies, and t represents time.

The evaluation of physiological condition depends on a comparison between the measured value and preset limit values. Higher heart rate, bad quality of sleep, ECG irregularities, and lower oxygen saturation imply high levels of stress and risk of health problems. Decision-making is done using logic-based and ML-based approaches for assessing health. The risk of the health problem assessment process is expressed as:

$$R = \sum_{i=1}^{N} w_i p_i \quad (11)$$

where: R represents the overall health-risk score, Pi represents individual physiological parameters, and Wi represents weighting coefficients assigned to each parameter. Based on the health-risk score, the patient’s condition is assigned to various health categories: Healthy Condition, Moderate Health Risk Condition, and Critical Stress Condition.

Step 8. Automated Health Recommendation Generation: Facial emotion, heart rate, sleep pattern, ECG wave pattern, stress level, and oxygen saturation level. The recommendation system utilizes intelligent decision-making mechanism in order to make decisions about the current health situation of the patient with respect to stress-induced risks. The formula for generating the final recommendation will be:

$$RH = f(E, HR, SH, ECG, SpO2, S) \quad (12)$$

where: RH represents health recommendation, E represents emotional state, HR represents heart rate, SH represents sleep time, ECG represents the ECG state, SpO2 represents the oxygen saturation level, and S represents stress level. At first, the system calculates the stress level of the user. If all the physiological measurements are normal and the emotional state of the patient is positive, the system determines that his/her state is good and provides him/her with

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healthcare recommendations. On the contrary, if any of the abnormalities, such as an increased heart rate, bad sleep, irregular ECG readings, or decreased oxygen saturation, are detected, the system generates stress warnings and recommendations.

IV. SIMULATIONS OUTPUTS

Figure 2: Detected Emotion: Happy

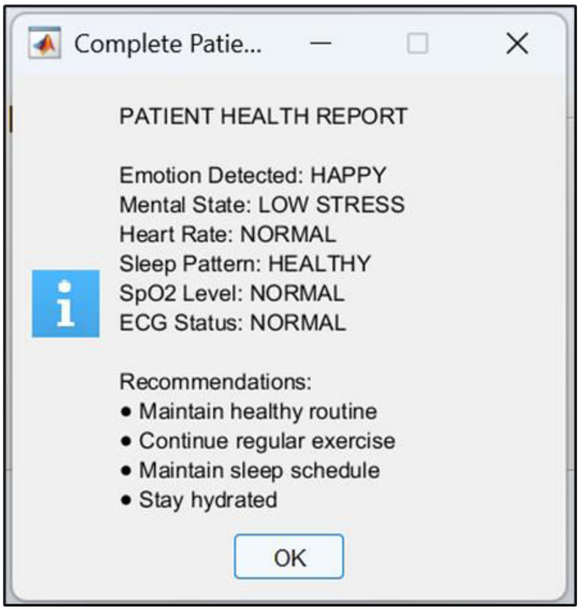

Figure 3: Patient report and Recommendations

The GUI dashboard for analyzing and classifying the face into the category of HAPPY, along with monitoring various physiological parameters such as heart rate, amount of sleep, ECG wave pattern, and SpO2 level, is presented in Figure 2. It can be observed from the results that the individual has normal heart functioning, good sleep pattern, appropriate oxygen saturation level, and LOW STRESS condition. The figure presenting the automatically generated patient health

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report is shown in Figure 3, wherein an overall analysis is performed based on emotion, stress condition, ECG wave pattern, heart rate condition, sleep pattern, and SpO2 level.

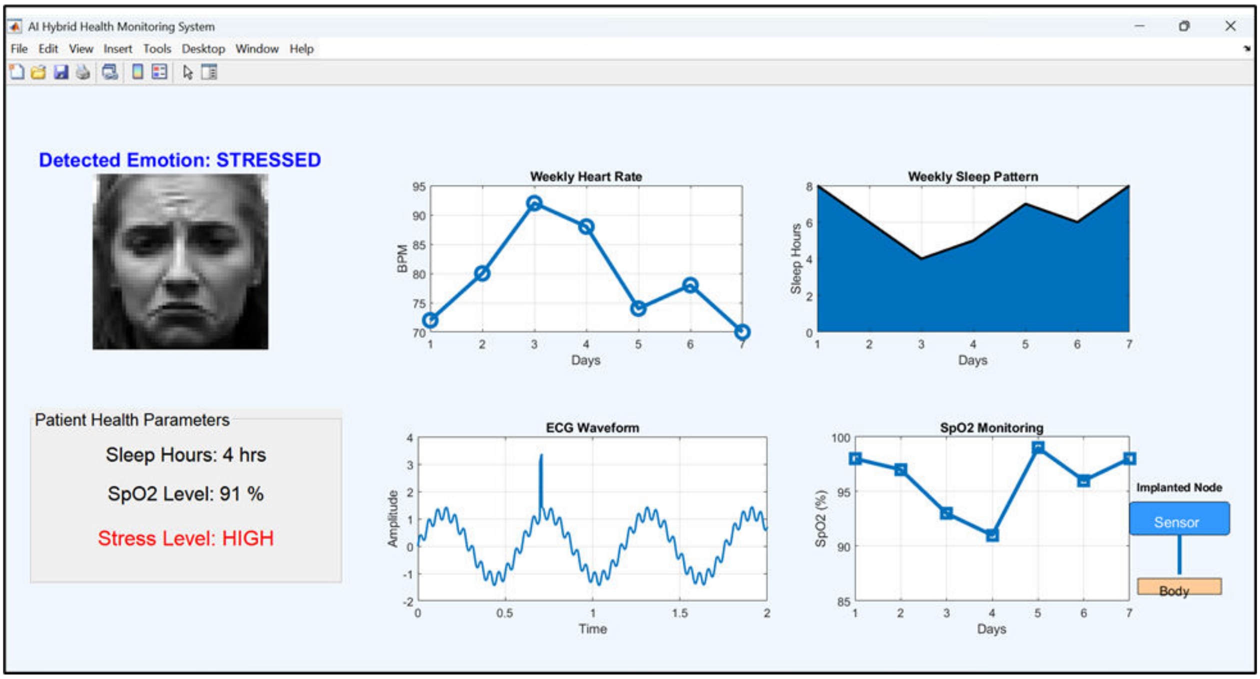

Figure 4: Detected Emotion: Stressed

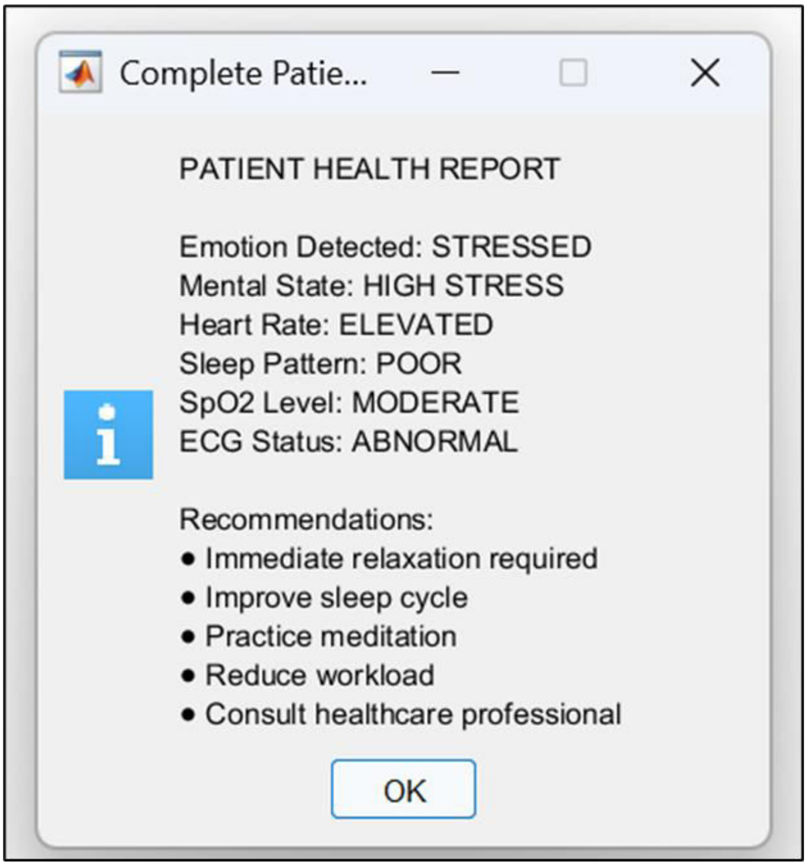

Figure 5: Patient report and Recommendations

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The working of the AI-based Hybrid Health Monitoring System for the detection of STRESSED emotion is shown in Figures 4 and 5. The system identifies the status of the patient as being in a state of high stress and then analyzes various parameters like heart rate, sleeping time, ECG wave shape, and SpO2 percentage. From the above findings, it can be observed that there is a higher heart rate, less sleeping time (4 hours), less oxygen saturation percentage (91%), and an abnormal ECG wave shape. There could be serious consequences of health due to stress from this result. Therefore, based on these findings, the patient's health report indicates that the patient is under high stress, with poor sleep quality, a moderate SpO2 level, and abnormal heart conditions.

V. CONCLUSION

In this study, an Intelligent Stress Detection and Healthcare Monitoring System was suggested, which integrates the techniques of facial emotion detection with physiological signal processing to evaluate one's overall health status. In this innovative system, the use of images of faces is made to detect emotions like happy and stressed, alongside with the measurement of physiological features such as heart rate, amount of sleep, ECG data, and SpO2 levels. The MATLAB interface was used to display the details about patients, physiological data, ECG waveform, level of stress, and health advice in an easy-to-understand way. From experimental studies, it was evident that the proposed framework could be utilized in identifying the difference between stress and non-stress. The system detected normal readings in relation to ECG, sleeping patterns, oxygen saturation, and stress among happy faces. In regard to the stressed faces, there were high readings concerning stress, shorter sleeping patterns, irregular readings for the ECG, and low readings for SpO2. From the analyzed results, it became easy for the system to provide appropriate health care recommendations based on the patient's health condition. Through the proposed framework, there is an affordable means of health assessment and patient monitoring for future use in smart healthcare.

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