RESEARCH PAPER

# A Respiration Quality Analysis and Prediction Using AI and ML Algorithms

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**Abstract:** The study looks at the relationship between physiological indicators like respiration and electroencephalogram (EEG) activity and emotional states, particularly anxiety. Physiological data were gathered from a total of 550 students, comprising respiration signals and multi-channel EEG recordings. Upon conducting the initial analysis, it was discovered that people with high anxiety levels have the tendency to show abnormal respiratory patterns; for instance, they can breathe irregularly and shallowly along with certain EEG changes that are the most common such as the increase of beta band power and the decrease of alpha band power. These were the physiological signals that the participants experienced to be with high anxiety level. A structured intervention involving Kriya yogic practices, such as regulated pranayama and specific yogic postures known for their calming and regulating effects on the autonomic nervous system, was conducted under the supervision of an expert for a subset of students who had elevated anxiety levels. Data collected after the intervention revealed a considerable drop in anxiety levels, accompanied by a rise in alpha band activity and a fall in high-beta activity. Confirming its relaxing impact, the yoga intervention also enhanced respiratory signals. After training a Random Forest classifier to identify emotional states, it was able to differentiate between high-anxiety and post-intervention states with an accuracy of 84%. According to the study, the effectiveness of mind-body therapies can be increased by combining yoga practices with physiological monitoring and machine learning classification to offer a non-pharmacological approach to mental health and emotional management.

**Keywords –** Anxiety, Breathing, Electroencephalogram (EEG), Emotions, Kriya Yoga, Pranayama.
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## 1. Introduction

Breathing is not just a metabolic mechanism of gas exchange rather it is a highly sophisticated physiological process which relies on the Central Pattern Generator (CPG) located in brainstem. The central pattern generator is a neural network found in spinal cord (for locomotion) and brainstem (for respiration and swallowing) that acts independently to generate rhythmic motor patterns such as walking, breathing and chewing without requiring continuous brain commands. The breathing Central Pattern Generator (bCPG) is mainly located in medulla oblongata and Pons of brainstem. The breathing Central Pattern Generator (bCPG) in the brainstem, generates rhythmic respiratory patterns. The modulation of bCPG with limbic and cortical structures links breathing directly to emotional states and cognitive behaviour. Our emotion and cognitive states affect breathing such as when we are stressed, relaxed or attentive to solve a problem [1]. Reversing this causality breathing can affect emotion and cognition both in ordinary day to day life and in more extreme / pathology conditions such as fear, anxiety and panic that is shown in Figure 1.

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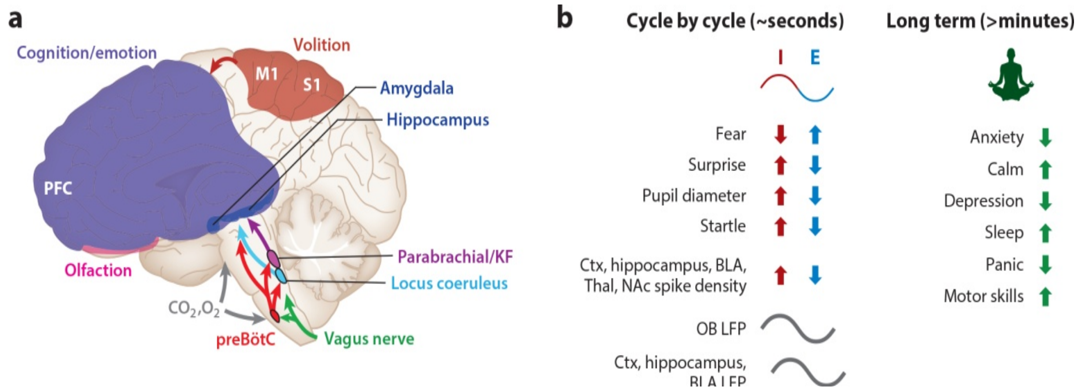


**Figure 1. (a) Forebrain regions involved in cognition/emotion & (b) The global breathing rhythm modulates behavior through entrainment of local neuronal dynamics and breathing-locked LFPs across several brain regions on a cycle-by-cycle basis (left) and through plasticity affected by breathing practices (right).**

Emotions play a key role in human life. It has an effect on the mental process, functions and state. Our perceptions, assessments, judgments, and activities like memory concentration, problem solving and planning are all influenced by emotions. Our physical health is greatly affected by various types of emotions. The anxiety and anxious states are one such state that is becoming increasingly common. The academic pressure, freak change in the lifestyle and social status are some of the most common triggers and reasons for the anxious states in students and young adults. This frequently results in low mental health and less productivity in life. Consequently, there is growing scientific interest in understanding how emotional states like anxiety manifest in measurable physiological processes [2].

Psychophysiology studies the relationship between psychological experience and physiological responses. The state of feelings does not only express conscious experience but also induce a patterned change in the pattern of the nervous system. Nervous system changes occur which produce physiological responses that can be observed in heart rate, respiration, muscular activity, and electroencephalography (EEG). Respiration and EEG signals are most significant with respect to associatively with a regulation of feelings and autonomic nervous activity [3].

We primarily consider respiration as an automatic biological process maintaining gas exchanges in the body. Nevertheless, breathing is more than just a mere metabolic coordination reflex. Alternatively, a neural mechanism can produce those rhythmic breathing patterns despite the absence of chemical or metabolic feedback. Actually, it turns out that the CPG stands for central pattern generator. It consists of many interlinked neurons [4]. It should be noted that these circuits are functionally connected to higher brain areas in the limbic system and cerebral cortex. The two brain regions are crucial for emotions and thinking. There is a high sensitivity of emotional rhythmic pattern of breathing.

Different emotional experiences like anxiety, stress, fear or relaxation cause different airways. Breathing at an anxious state is rapid, shallow or irregular however breathing in a calm state is slow, deep and regular. Behavioural respiratory system shows changes in breathing pattern depending upon emotions, like when to cry, laugh or having a mental state. As a result of this close link, respiration has emerged as a useful biological marker for emotional and anxiety status.

In parallel, electroencephalography (EEG) is a painless and non-invasive test for observing brain activities. It measures electrical activity in the brain using electrodes attached to scalp. EEG successfully measures the electrical activity of large number of neurons in the cerebral cortex. EEG has excellent temporal resolution which helps detecting fast changes in brain activity. Hence, EEG is appropriate to study rapid changes in neural activity related to emotional processing and to identify representations of brain states at different spatial locations [5]. Similarly, EEG signals are often classified in frequency bands: delta, theta, alpha, beta, and gamma, each reflecting different brain states.

Among the bands, alpha and beta rhythms are especially pertinent to research on their role in emotion and anxiety. Alpha activity often reflects relaxation, calm awareness or a reduction in mental effort. Beta activity on the other hand reflects alertness, cognitive engagement and arousal. Several studies reported an enhanced beta power along with a reduced alpha power in anxious and stressed people [6]. Basically, both these rhythms are considered objective markers of emotional deregulation.

Most recently, have presented classes whether the valance or Arousal can be classified with the help of EEG based on spectral, temporal, and connectivity-based EEG based features [7]. Some of the classes which have been usually used for this task are Support Vector Machines (SVM), Decision trees, Logistic Regression, Naïve Bayes, and Random Forest classifiers [8]. Another method is deep learning-based classification that has recently been introduced. This approach gives better results than the other approaches because it tries to capture complicated spatial–temporal patterns from EEG [9]. Even with these developments, it is still a challenge to recognize emotion through EEG alone because of noise, variability between subjects, and emotion interaction. To overcome these limitations, researchers increasingly utilized multi-modal approach of EEG with other signals to obtain robustness and accuracy [10]. Respiration is a particularly effective complementary signal to EEG. Since EEG reflects neural dynamics from the cortex, thereby capturing the autonomic and behavioural response that gets directly impacted by the emotion. The simultaneous recording of EEG and respiratory signals allows a better understanding of mind–body interactions. According to earlier research, combining respiratory features with EEG data gives better classification accuracy of emotional states than EEG data alone [11]. Moreover, cortical oscillations can be influenced by respiratory rhythms through respiratory-neural coupling mechanisms. This suggests that respiration is not just a result of emotions but plays a role in modulating brain activity [12]. As a result, assessing the quality of respiration in addition to EEG allows for the study of emotional regulation processes.

Aside from just watching these events, there is growing interest in non-drug ways of regulating emotions. Practicing yoga, pranayama and meditation can help with breathing pattern alteration. Breathing control improves parasympathetic activity, reduces stress and aids relaxation [13]. Physiological observations have shown improved respiratory rhythmicity. Following the yoga intervention, EEG reports demonstrate increased alpha activity and decreased beta activity after changes to the breathing pattern [14]. This paper investigated the respiration quality and EEG activity of more than 550 university students. Individuals with high anxiety showed irregular breathing, greater beta power and less alpha power, according to the researcher. Moreover, a subgroup of participants underwent Kriya yogic therapy that included breathing exercises and postures for calming the nervous system. The quality of respiration and anxiety were improved after the yogic intervention. Post yogic practice, the activity of an EEG was noted to have restored. An evaluation of the emotional condition in an objective way and to check the effect of the intervention. They used Learning algorithms. They used physiological characteristics before and after the procedure for training. There were different classifiers, which included Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), and Naïve Bayes (NB). The RF is a better classifier among others. The Random Forest classifier produced the best results with an accuracy of approximately 84%, successfully distinguishing between anxious and relaxed states. In general, it mixes physiological signals with neuroscience, AI and the traditional practice of yoga. Thus, it offers a reliable, non-invasive and non-drug treatment for anxiety detection and emotional well-being with the usage of respiration quality analysis and EEG based emotion recognition and machine learning classification used as a tool.

## 2. Related Work

Physiological signals like EEG, heart rate and breathing come from diverse systems in the body and give us information on distinct physiological processes [2]. These signals are useful for analysing human emotions since they react to emotional situations. It is challenging to correctly identify emotions since they are complicated and commonly affected by psychological, environmental and physiological factors and do not always have distinct restrictions [3-4]. A growing amount of research indicates that physiological signals convey significant information about emotional states despite this complexity [5-10]. A significant improvement in affective computing was made in 2001 when Professor Rosalind Picard resulted the way in research on emotion recognition using AI by analysing physiological signals to determine emotional states [11]. More recently, deep learning techniques have been applied to these signals specifically EEG and skin conductance with positive outcomes. These techniques are capable of recognizing complex features and patterns frequently matching the accuracy of traditional machine learning techniques [12]. This development indicates the growing scope of AI-driven emotion recognition systems for use in healthcare and mental health. A common alternative therapy is mind-body medicine (MM) which includes yoga and meditation [13]. These methods are becoming a growing trend as they are often used to manage daily stress and enhance overall health. Meditation is a core component of MM which bridge the gap between mental processes and physical health which helps to manage stress, calms the mind and helps in gaining insights. Mindfulness meditation is stated as "paying attention, in a particular way: on purpose, in the present moment, and non-judgmentally". Mindfulness Meditation practices constitute an important group of meditative practices that have received growing attention. Mindfulness-Based Cognitive Therapy (MBCT) and Mindfulness-Based Stress Reduction (MBSR) which are well known treatments have been tested and applied with various clinical groups depend on this kind of practice. MBCT is mainly effective in reducing replaces of depression in patients whereas MBSR has shown efficiency for many psychiatric and physical conditions patients. A method called electroencephalography that captures electrical activity in the brain is frequently used to investigate the physiological effects of meditation. Spectral analysis, coherence and synchrony measures are used in EEG based research to detect modifications correlated with relaxing states. These analyses shows changes in EEG voltage and power across particular frequency bands, imply that meditation may have an impact on brain function. The differences could result in deviations in responses from participants, meditation techniques and research methodology [14-19].

## 3. Materials and Methodology:

### *3.1* Study Design

A prospective interventional study was conducted at Ravenshaw University, Cuttack, and Odisha to analyze the relationship between respiration quality, EEG activity and emotional states. This study is aimed to evaluate the detection of anxiety using physiological signals as well as the effectiveness of yogic intervention by artificial intelligence and machine learning techniques.

### *3.2* Study Population

This study covered boys and girls from +3 first year through PG final year. University students are suitable for this study as they are under academic pressure and emotional stress.

### *3.3* Sample Size

This research involved 550 students.

### *3.4* Study Period

This study was conducted from January, 2025 to April, 2025.

### *3.5* Exclusion Criteria

Students who really practice Yoga and those who regularly engage in any type of physical exercise were excluded from the study.

### *3.6* Questionnaires & Materials Used

#### 3.6.1 Questionnaires

| Emotion-Linked Breathing Questionnaire (EBQ) | Date: | | | | | | |
|---|---|---|---|---|---|---|---|
| Directions: Please indicate how much you agree or disagree with the following statements.<br>Remember, we are interested in how you are feeling or responding *RIGHT NOW* as you fill out this questionnaire.<br>**Questions** | Disagree Completely (1) | Disagree Somewhat (2) | Disagree A Little (3) | Neither Agree/Disagree (4) | Agree A Little (5) | Agree Somewhat (6) | Agree Completely (7) |
| 1. I notice changes in my breathing when I experience strong emotions. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 2. I frequently experience sudden emotional shifts. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 3. I feel physical sensations during emotional changes. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 4. During stressful situations, I tend to breathe faster or more shallowly. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 5. I can consciously alter my breathing to calm myself down. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 6. I use breathing or relaxation techniques to manage my emotions. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

**Figure 2. Questionnaires Points**

#### 3.6.2 Material Used

- EEG recordings: To capture brainwave activity across frequency bands i.e. alpha, beta, theta and gamma.
- Respiration monitoring: Using chest band sensors for breathing patterns.
- Emotional state assessments: Pre and post-intervention anxiety scales.
- Power Supply
- Yoga Mats
- Notebook

### *3.7* Intervention& Data Collection Procedure

#### 3.7.1 Intervention

Figure 3 depicts that a 21-day guided yogic program focused on:

- **Pranayama** – It is a breathing technique, slow, deep, and rhythmic. The parasympathetic nervous system is activated, physiological arousal is decreased, and relaxation occurs.
- **Ashwini Mudra** - By using Ashwini Mudra, the pelvic floor muscle group can contract and relax rhythmically, enhancing neuromuscular coordination and helping regulate emotional stability through better mind/body Mastery.
- **Mula Bandha –** It is also known as the root lock. It involves the gentle contraction of muscles at the base of the spine. It is associated with improved autonomic balance and mental focus.
- **Neuro-Linguistic Programming (NLP) Techniques –** Basic NLP techniques include conscious mind control, positive thought patterns, and emotional awareness. These techniques complement physical practices by addressing cognitive aspects of anxiety.

#### 3.7.2 Data Collection Procedure

EEG and respiration data were recorded:

- Before the intervention (baseline)
- After completion of the 21-day program

All recordings were conducted under controlled conditions to reduce noise and external disturbances.

### *3.8* Data Analysis and Machine Learning

These features were based on the power spectral intensity of different frequency bands, with the EEG data as backing material. Respiratory features had breathing rate, variability and regularity in the breath that is shown in Figure 4.

Machine learning classifiers were applied to classify emotional states based on EEG and respiration data including:

- Random forest
- Logistic regression
- Decision tree
- Support vector machine (SVM)
- Naive Bayes

Performance metrics used are accuracy, precision, recall, and F1 score.

EEG is a test that records electrical activity in the brain. Your brain cells, i.e., neurons, communicate using tiny electrical signals, and an EEG helps measure and record these signals. In EEG, brain waves are patterns of electrical activity in the brain. They are categorized by frequency (i.e., speed) and are associated with different mental states.

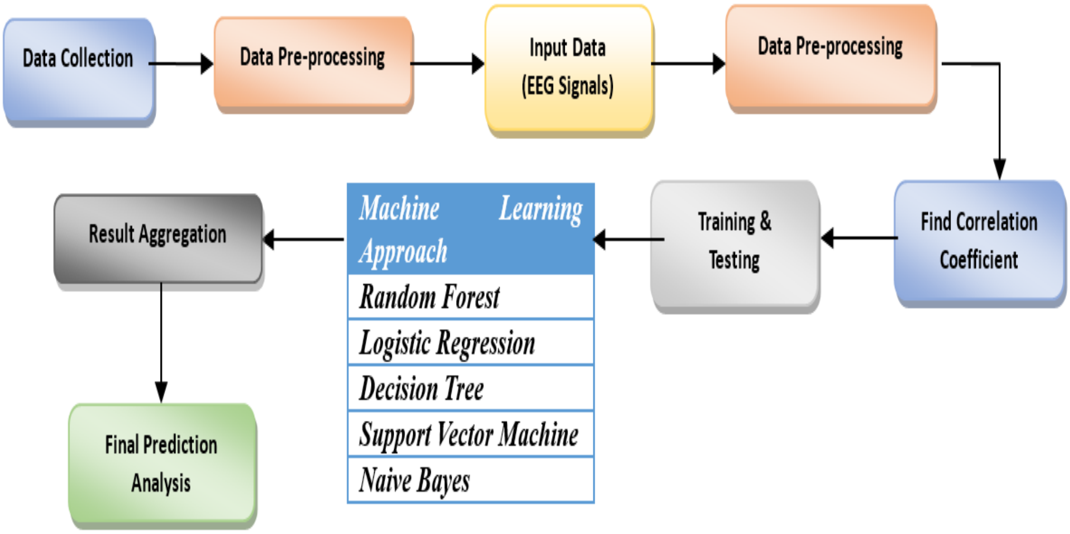


**Figure 3. Process Flow Diagram**

| Brain Wave | Frequency (Hz) | State of Mind | Function |
|---|---|---|---|
| **Delta (δ)** | 0.5 – 4 Hz | Deep sleep, unconscious state | Healing, growth, deep rest |
| **Theta (θ)** | 4 – 8 Hz | Light sleep, deep relaxation, creativity | Dreaming, memory, meditation |
| **Alpha (α)** | 8 – 13 Hz | Calm, relaxed but awake | Relaxation, focus, learning |
| **Beta (β)** | 13 – 30 Hz | Active thinking, problem-solving | Attention, alertness, mental work |
| **Gamma (γ)** | 30 – 100 Hz | High-level cognitive processing | Learning, perception, consciousness |

**Figure 4. Types of Brain Waves**

How breathing affects EEG:

- Slow, deep breathing → Increases alpha and theta waves (relaxation)
- Rapid or shallow breathing → can increase beta activity and sometimes even trigger spike-wave discharges in people with epilepsy.

## 4. Results

### *4.1* Correlation Matrix for All Variables

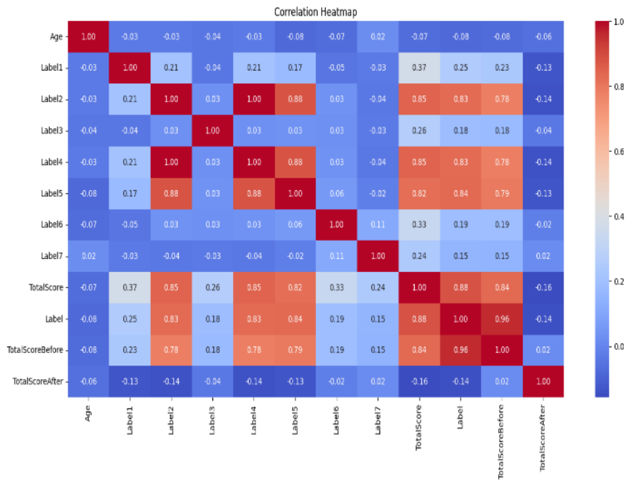


**Figure 5: Correlation matrix of all variables**

Figure 5 represents the complete correlation matrix among all numeric variables, including emotional assessment scores and respiration parameters. It shows unique association patterns between neural and respiratory features.

In fact, a positive correlation exists between beta band activity and anxiety score, with higher scores representing greater levels of perceived anxiety corresponding to increased arousal within the cortex during more anxious states, as shown in Figure 6. In contrast, alpha band power has a negative correlation with anxiety levels, which indicates its connection to relaxation and lower stress.

The respiration-related variables show meaningful correlations with EEG frequency bands. Reactivity in respiration regularity positively correlates with increased alpha and theta activity, lending credence to the idea that controlled breathing augments neural oscillations associated with relaxation. In contrast, irregular or rapid breathing patterns positively correlate with beta activity.

This figure highlights the specific physiological markers related to predicting emotional state. This clean correlation matrix brings forth the strongest relationships among:

- Alpha power
- Beta power
- Respiration rate
- Total anxiety score

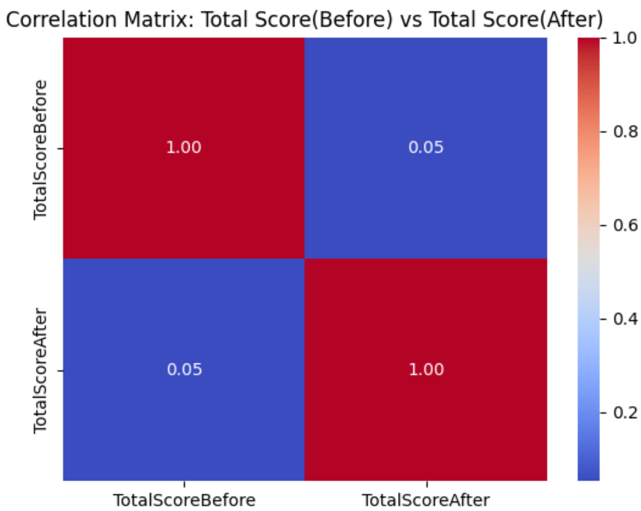


**Figure 6: Correlation matrix of key variables**

The results clearly demonstrate:

- Low correlation with alpha power and anxiety
- Beta Power Positively Correlates with Anxiety
- Respiration regularity is negatively correlated with anxiety

Our targeted examination supports a synergistic approach of utilizing both respiration and EEG features to improve detection accuracy for emotional states.

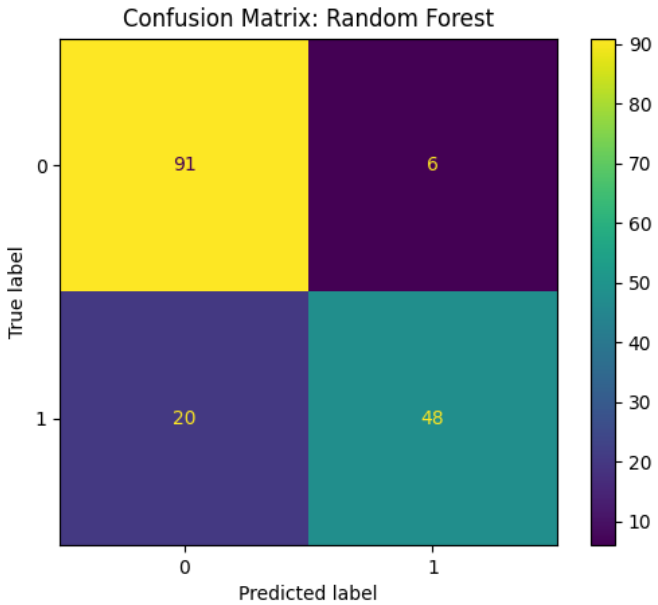


**Figure 7: Confusion matrix for random forest**

The Figure 7 confusion matrix for random forest classification shows the lowest misclassification rate among all classification models. The numbers of true positives and true negatives are notably higher than false positives and false negatives, which implies a strong generalization capability.

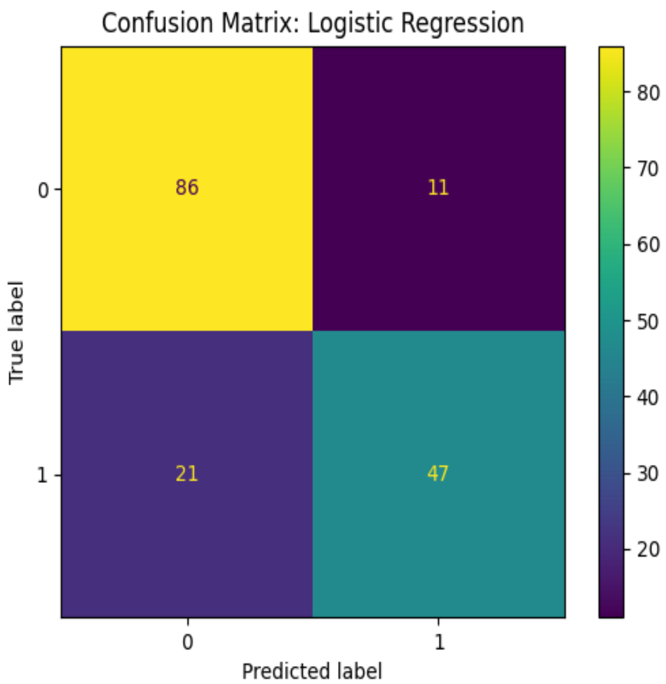


**Figure 8: Confusion matrix for logistic regression**

The Figure 8 confusion matrix for logistic regression shows good classification performance. As compared to random forest, it has slightly higher false negative, which indicate lower sensitivity in detecting anxiety states.

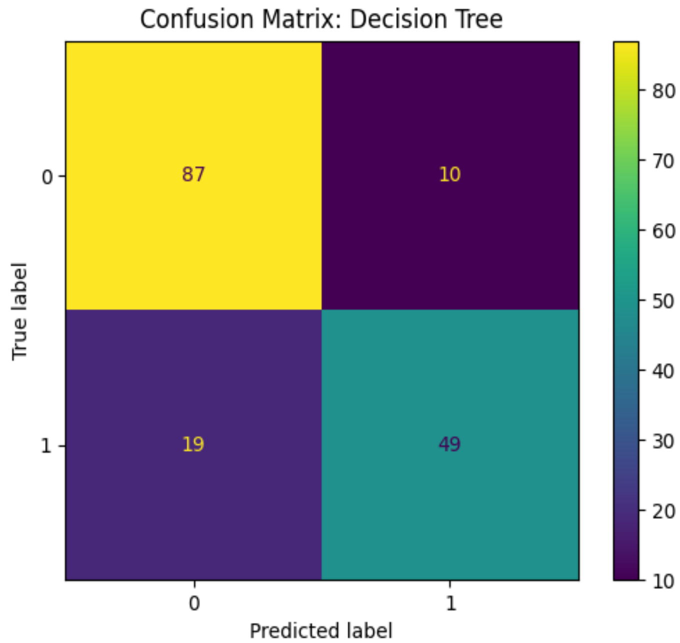


**Figure 9: Confusion matrix for decision tree**

The Figure 9 confusion matrix for decision tree shows moderate classification accuracy but displays greater variability in predictions. This shows higher susceptibility to overfitting compared to ensemble methods.

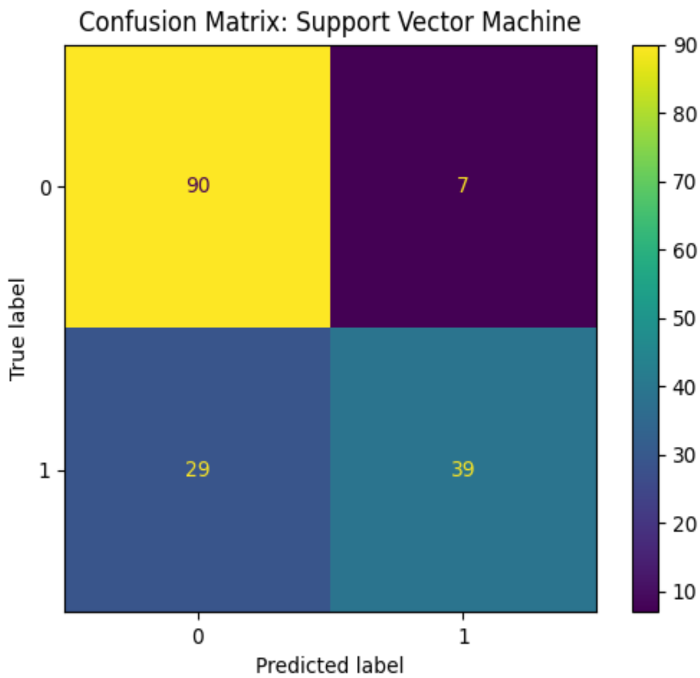


**Figure 10: Confusion Matrix for SVM**

The Figure 10 confusion matrix for SVM demonstrates the stable classification performance but shows slightly increased false positives compared to Random Forest.

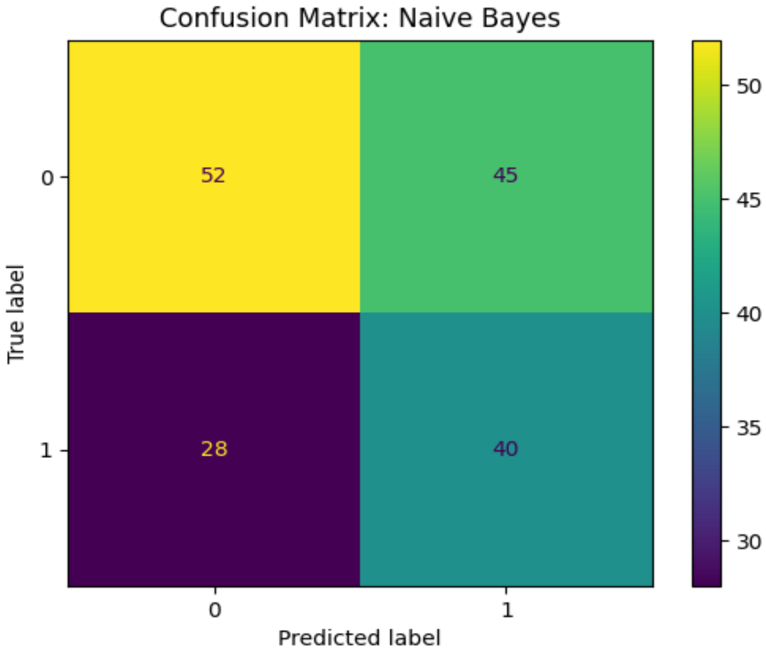


**Figure 11: Confusion Matrix for Naïve Bayes**

The Figure 11 confusion matrix for model represents higher misclassification rates.

**Table 1: Classification Report**

| Classifier | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Random Forest | 0.84 | 0.89 | 0.71 | 0.79 |
| Logistic Regression | 0.81 | 0.81 | 0.69 | 0.75 |
| Decision Tree | 0.82 | 0.83 | 0.72 | 0.77 |
| Support Vector Machine | 0.78 | 0.85 | 0.57 | 0.68 |
| Naïve Bayes | 0.56 | 0.47 | 0.59 | 0.52 |

The table 1 results collectively demonstrate that:

- There are strong correlations between respiration quality and EEG frequency bands.
- Anxiety states produce an increase in human beta activity and dysrhythmic respiration.
- Relaxation states exhibit elevated alpha power and stable respiration.
- Classifiers of machine learning effectively classify emotional states.
- The best classification performance (84% accurate) is achieved by Random Forest.

Those results provide strong evidence for the proposed respiratory-informed EEG emotional state prediction framework.

### *4.2* Discussion

After comparing five different machine learning models, the Random Forest (RF) classifier stands out as the best performer. It achieved the highest accuracy, correctly predicting 84% of the cases. It also had the highest precision at 89%, meaning it was very careful and made very few false positive errors. Its recall, which measures how well it identified actual positive cases, was strong at 71%. Most importantly, Random Forest achieved the highest F1 Score (0.79), balancing precision and recall, making it the most reliable and well-rounded model.

The Decision Tree (DT) model came in as a close second. It also performed well across all metrics, especially in recall (72%), and is easier to interpret. However, it was slightly behind Random Forest in terms of overall accuracy and F1 Score.

On other hand, Naive Bayes (NB) model performed the worst. It had the lowest accuracy and F1 Score, meaning it made more mistakes and was less dependable for this task.

Thus, Random Forest (RF) is the most accurate, reliable and balanced model among the ones tested, making it the best choice for predicting outcomes in this scenario.

The combination of yogic practices and NLP appears to positively influence emotional regulation, as reflected in improved physiological markers and emotional state classifications.

## 5. Conclusion

This study provides evidence that targeted yogic practices can modulate emotional states, as captured by

EEG and respiration data, and that machine learning classifiers can effectively distinguish emotional states pre- and post-intervention. The study concludes that incorporating Kriya yogic practices, specifically pranayama and physical postures, has a significant positive impact on students' emotional and physiological well-being. By analyzing changes in respiration patterns and EEG brain wave activity, it showed that students experienced reduced anxiety and improved relaxation after participating in the yoga sessions. The Random Forest model further validated these findings, achieving 84% accuracy in classifying emotional states.

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