Brain Cognitive Performance Identification for Student Learning in Classroom

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Introduction:

This study focuses on the critical role of cognitive performance and attention ability in a student's academic success. It highlights the influence of factors like meditation and parental expectations on a student's intelligence quotient. The study suggests that parental involvement through direct communication can enhance a student's cognitive abilities. Additionally, stress is identified as a common issue affecting students' learning performance. The study notes that most individuals have a limited attention span of 45-50 minutes, and exceeding this without breaks is found to increase stress levels, which can negatively affect a student's cognitive performance, concentration, and overall mental health. This can be prevented by taking breaks during study sessions to refresh the mind and reduce stress. It cites evidence from experiments indicating that breaks can improve cognitive performance, reduce stress, and boost creativity. The study also mentions the positive impact of short naps on academic focus and productivity, supported by EEG wave activity measurements. However, the study acknowledges that different students have varying abilities to maintain focus during study sessions. Therefore, to support itself the study employs as well as emphasizes on electroencephalography (EEG) signals and decision tree analysis based on neuroscience criteria to determine cognitive performance.

Literature Review:

The literature review explores studies that estimate cognitive performance's impact on academic learning. The results indicate that cognitive skill instruction had a positive effect on students, improving cognitive performance and test scores. The review touches on the application of neuroscience in assessing cognitive performance. Decision trees are suggested as an effective way to classify brain signals collected during activities like imagination, providing a straightforward and automated approach. Although the primarily focuses on cognitive performance in students and academic learning, this study seeks to offer a more real-time measurement of learning ability during study sessions. It advocates for the use of decision trees as a quick and intuitive method to compute and classify performance indicators based on neurological theories, offering a potential breakthrough in understanding, and enhancing cognitive performance during study sessions.

Proposed Methodology:

1. **Brain Cognitive Performance:**
   Cognitive performance, linked to Theta and Alpha brain signals, which depend on memory demand and can be measured by the average attention and relaxation levels. Neuroscience criteria classify cognitive performance on a scale highlighting:
   - 20-30 as low,

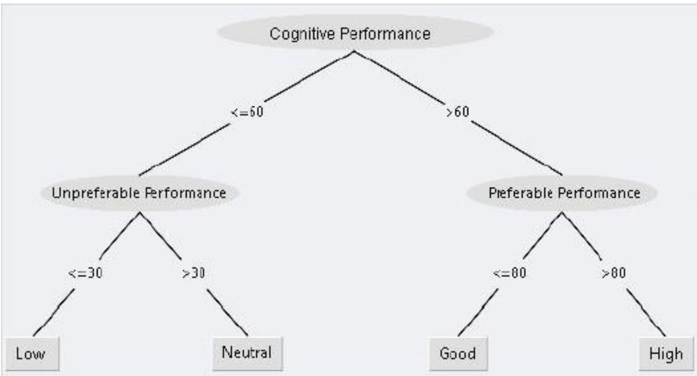
- 40-60 as neutral,
- 60-80 as good, and
- 80-100 as high.

Values below neutral warrant a mental break before 45 minutes. The study uses four 10-minute detection periods within a 45-minute classroom session, including 30-second breaks, to assess cognitive performance.

$$Cognitive\ Performance = \frac{Attention_{Avg.} + Relaxation_{Avg.}}{2}$$

2. **Brainwaves Detection:**
This study uses the NeuroSky Mindwave mobile EEG device and the Neurosky Experimentor app to measure attention and relaxation levels in the classroom. Attention reflects focus and learning effectiveness on a 0 to 100 scale, while relaxation indicates mental calmness and meditation, also on a 0 to 100 scale. The equipment helps monitor cognitive states during learning.

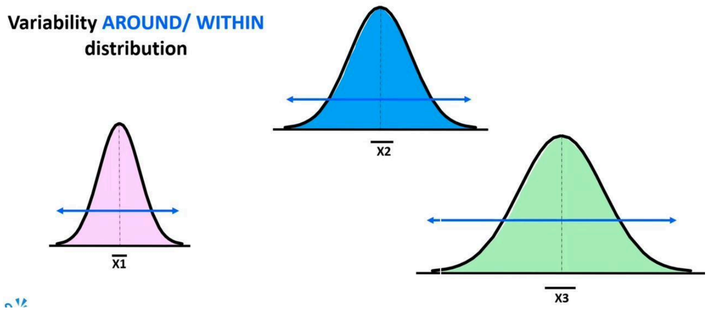
3. **Data Classification:**
For decision-making this study employs a decision tree, a popular classification and machine learning tool which uses conditional factors to create a flowchart-like structure with decision nodes (square symbols), chance nodes (circle symbols), and end nodes. The sequence from the root (top) to the leaf (bottom) represents the classification rule or the decision-making process. Nodes are categorized into three types: decision nodes, which control decisions based on multiple conditions; chance nodes, which represent outcome probabilities; and end nodes, providing the final decision outcome. Typically, the decision making is applied through a general form such as condition 1-n and outcomes. The study uses relative scales of attention and relaxation as inputs to assess cognitive performance, making the methodology interpretable and reliable, aligning with neuroscience criteria.



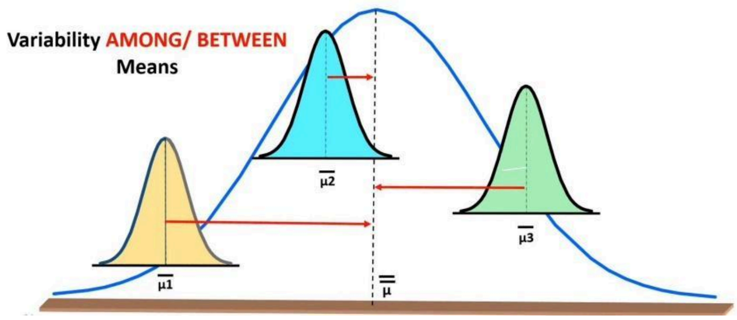
4. **Experimental Results:**
An experiment was conducted in May 2018 in a 45 minutes mathematics classroom in Chiang Rai, Thailand, involving 10 participants aged 18-20, split evenly between male and female students. The experiment measured attention and relaxation levels of the participants over four periods using EEG performance data, with the aim of investigating how prolonged focus on studying affects cognitive performance. The

study used a statistical method known as ANOVA: Single Factor to analyse the data and test the initial hypothesis that students' cognitive performance would decrease over time.

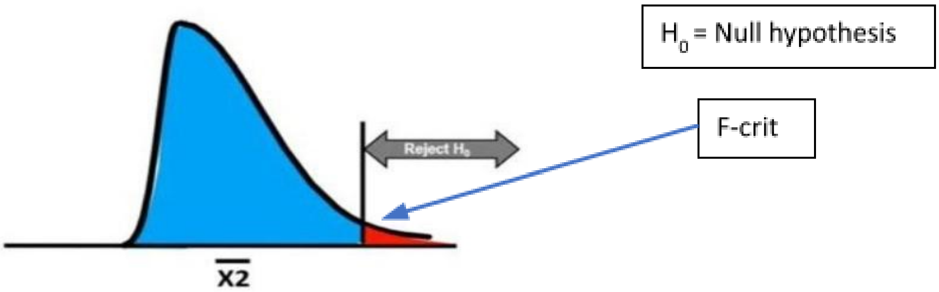
- **ANOVA(Analysis of Variance):** is calculated to find whether the null hypothesis is supported or not. **SS:** Sum of squares between the source. **MS:** Mean sum of squares between the source.
- **Null hypothesis:** states that all group means are equal.
- **P-value:** The p-value indicates the probability of obtaining the observed results if the null hypothesis is true.
- **P-value < Alpha (usually 0.05):** You reject the null hypothesis and
- **P-value > Alpha:** You fail to reject the null hypothesis.
- **Within Variance:** shows the spread in the variances of different groups in case there is a offset in the mean value.



- **In Between Variance:** shows the distance of individual means of each group from the common mean of all the groups.



- **F-value:** It assess whether the means of three or more groups are statistically different from each other. It is obtained by dividing the between-group variance by the within-group variance.



F value: Variance Between/Variance Within

F-crit: is the part of the variance shown by the degrees of freedom.

F-crit: Numerator Degrees of Freedom/Denominator Degrees of Freedom

Numerator Degrees of Freedom: Total sample value - 1
Denominator Degrees of Freedom: Total no. of values - Total sample values

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	893.97	3	297.99	7.48	0.00052	2.87
Within Groups	1435.03	36	39.86			
Total	2329.00	39				

- The results revealed a highly significant difference in the data (P<0.001), leading to the rejection of the null hypothesis, confirming that cognitive performance does change during extended study sessions and tends to slightly decrease over time. It categorized cognitive performance into two types: "unpreferable" performance (low and neutral) and "preferable" performance (good and high), with neutral being considered a common state conducive to learning. In the experiment, only two students exhibited low cognitive performance during the experiment, suggesting they needed a mental break before the class ended. The rest of the students maintained a neutral or higher level of performance, even though extended studying made them more prone to lower performance. In order to cross validate the decision tree the performance is calculated by 10 times and the accuracy of the experiment is found to be 87%. The error margin of 13% occurs due to other factors in the class affecting the students such as noise and class atmosphere.

Student No.	Gender	Cognitive Performance Levels			
		1st Period	2nd Period	3rd Period	4th Period
1	Male	Good	Neutral	Neutral	Neutral
2	Male	Good	Neutral	Low	Low
3	Male	Neutral	Neutral	Neutral	Neutral
4	Male	Good	Neutral	Neutral	Neutral
5	Male	Neutral	Neutral	Neutral	Neutral
6	Female	Good	Good	Neutral	Neutral
7	Female	Good	Neutral	Neutral	Neutral
8	Female	Good	Neutral	Neutral	Neutral
9	Female	Neutral	Neutral	Low	Low
10	Female	Neutral	Neutral	Neutral	Neutral

Conclusion:

Therefore, the study explores the use of neuroscience criteria to precisely define students' cognitive performance levels. Employing a decision tree algorithm, it was determined that individual cognitive performance levels may experience slight changes and declines with prolonged learning. The results, with an 87% accuracy rate, demonstrate reliability and ease of interpretation. The study's findings have practical implications, suggesting that they can aid in class and learning management by identifying students who may require a mental break.