THE EFFECT OF LEARNING STYLE ON SKIN TEMPERATURE USING VARK MODEL AND DECISION TREE

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ABSTRACT

Learning is an everyday aspect of human lives, so it's rational and logical to understand how learning could be more efficient. Learning style is an interesting topic in knowledge management hence, attracting researchers and educators alike. Different models of learning styles exist. However, this study uses the VARK model, which is a learning style method constructed based on human sensory modality. Previous studies used the VARK model to understand learning styles, however, these studies used the questionnaire as a tool for data collection, which is flawed because of the errors that could arise from verification, and also time consuming. A previous study used the blood pressure and heart rate for a similar study, however, the study strongly suggested the use of other physiological factors for more accuracy and reliability. This study proposes the use of the skin temperature to have a more precise response during the learning process in other for understanding the individual preferred learning style. This study created 4 learning style experiments, with each experiment representing a learning style in the VARK model. Sensory modality is associated with skin temperature, which is why the VARK model is the appropriate fit for this study. Random run tests and one-way ANOVA are statistical analysis used in this study.

Keywords: Skin temperature, Physiological signal, Decision Tree, WEKA, Visual, Kinesthetic, Aural, Tactile

1. INTRODUCTION

Human beings are emotional creatures that function with a lot of emotions. According to Tyng et al. (2017) emotions either enhance or diminish the ability of learning and memory retention, depending on the emotions involved [1]. Many studies have shown the relationship between cognitive activities and emotion, such as attention, reasoning, memory and problem solving [2-5]. It's safe to assume that the state of mind (emotions) plays an essential role in learning. According to a study by Vytal and Hamann (2010), physiological signals are used to monitor the human state of mind, which involves the hemodynamic of the central nervous system (CNS) activities [6]; another study by Li and Chen (2006) further proves that the autonomic nervous system including heart rate, skin temperature, blood pulse, and respiration changes based on the human state of mind [7]. A study by Lee et al. (2005) used temperature to identify cognitive activities in the process of visual stimuli. The study shows that when people are engaged in an activity their skin temperature goes up [8]. A study by Laconesi (2010) shows a physical representation of human emotions using physiological signals with the help of wearable smart devices [9]. Learning style is gaining much more attention recently. Different terms are used to define learning style; definitions are associated with multiple factors, such as cognitive style, sensory preference, and personality types, which is used interchangeably, and in other aspects, mentioned differently [10]. Moayyeri defined learning style as "a biologically and developmentally imposed set of personal characteristics that make the same teaching and learning methods effective for some and ineffective for others" [11]. Educators have agreed that each individual has their own type of learning style. This makes it important for educators and administrators to know the accurate learning styles of their students. Acquiring knowledge of different learning styles will help in understanding the best way to teach the students, thus helping every person reach their potential [12]. According to Wu et al. (2014) analyzing the human state of mind in learning is a very crucial factor because emotions are very critical during cognitive activities such as learning [13].

Different learning styles models exist based on different aspects and factors. Dr. Neil Fleming, an educator, neurologist, and researcher created the VARK model in 1987: the model was created based on individual learning through modality preference. The Barbe VAK model which is a foundation of the Fleming VARK model was missing the reading/writing learning component, which was later introduced by the VARK model. The VARK is created on the foundation of Neuron-Linguistic Programming [14]. The VARK model classified learning into four classes: Visual, Aural, Reading and Writing, and Kinesthetic learning style respectively. The VARK model was chosen as the learning style in this study because it has a more successful learning style and renders more positive results. Because of its dynamic nature, it can be done on different multiple settings, which include classroom, labs and clinical environmental settings. Compared to other learning styles the VARK model provides more functionality, and provides more room for people with different demographics to apply for learning.

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Despite numerous research studies on emotions and physiological moments, there are not many studies that have undertaken to understand the relationship between the learning style and physiological signals [15-16]:

Skin temperature has been used by previous studies to identify cognitive activities and their relationship with emotions. A study by McFarland (1985) revealed that an individual state of mind affects the skin temperature. The study used two different unknown music as a stimulus for the participants. They deemed one music to be positive for evoking calm positive emotions. They believed that other music evokes negative emotions. During the experience of negative emotions, the skin temperature decreases, and during the positive emotions, the skin temperature increases [17]. Several studies [18-19] have also conducted similar researches. The result also showed that the skin temperature tends to increases during happy calm moments: these researches show clear links between skin temperature and cognitive activities. Learning is best when the state of mind is calm, happy and positive. Previous studies have used skin temperatures to understand emotions [20-21]. However, despite their association with cognitive actions, there have been no studies between the skin temperatures on VARK learning styles as of late. This study chose the skin temperature method because of its relationship with the Autonomous Nervous System (ANS).

Machine learning is part of artificial intelligence used as a data analysis method to understand patterns between input data and result output. Machine learning makes a classification decision with minimal intervention. The machine learning algorithm observes data (train data) and understands that the pattern can be further implemented into new data [22]. There are three types of machine learning: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is comprised of an algorithm that involves a pre-defined outcome grouping, known as classes. They predict the classes from a set of data that are independent variables. Supervised learning maps the train data input and output, and it keeps training until it finds an accurately predicted pattern. Unsupervised learning does not need data to predict classes, it uses them instantly such as clustering the population of different groups for a specific intervention. Reinforcement learning is applied when the machine trains itself using trial and error; the machine trains based on their experience. There are different machine learning algorithms. Some mentioned worthy algorithms include Navies Bayes classifier, K means clustering algorithm, Support Vector Machine algorithm, and Decision tree algorithm. For this study, we will use the decision tree algorithm. The decision tree is the simplest and most useful machine learning structure. A decision tree is a map of outcomes of a series of related choices. It allows data to weigh scenarios against one another based on certain rules [23]. The decision tree was named after the algorithm visual representation of the rules and classes which are like a tree. The decision tree is made up of rules, classes, and attributes. In this study, the classes are the four learning styles; the attributes are the data and the rules will be the pattern between the data and classes [24]. The decision tree is implemented in this study because of its relevance and the noticeable pattern makes it easier to comprehend. The decision tree doesn't require much-sophisticated computation. Decision trees provide a clear suggestion of which fields are most important for prediction or classification. [25-26]. The C4/5 algorithm is a decision tree algorithm that was developed by Ross Quinian. It extends the ID3 algorithm. It uses the decision tree algorithm for classification technique, known as a statistical classifier. The reason for choosing the J48 decision tree classifier for this study is because of its efficiency and construct. In 2008, the algorithm became popular after its best ranking in the top 10 algorithms in data mining pre-eminent paper published by springer LNCS in 2008 [27]. The J48 decision tree analysis method has been used by previous studies associated with machine learning, physiological signals, and social science. This supported the choice of using the algorithm for this study [28-29]

Many previous studies have been done on the VARK learning style for different purposes about cognitive activities, such as concentration attention [30-32]. These previous studies used only the VARK questionnaire as a tool for data collection. Even though the questionnaire tool is simple to analyze and understand, it takes time to record and analyze. Also, it is susceptible to inaccuracies that could arise from human bias or conscious inaccurate answers by participants. Inaccurate or delay in data collection could affect the overall reliability of the results and classification results. It is very important during the learning style study that accurate real-time data should be used. Human temperature cannot be manipulated consciously, which makes it a perfect fit in this study. This study intends to understand the effect of human skin temperature during learning through their preferred learning style medium. Hence, it could be used as an attribute for the VARK Learning style.

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2. METHODOLOGY

Table 1 shows the statistical data of the participants use for this study.

Table.1 Connecting time of proposed device

Number of participants	50
Male	31
Female	19
Age Range	18-36

2.1 Questionnaire and Sorting chart

The VARK questionnaire is used to understand the learning style of the student. The questionnaire is the tool used for the VARK method data collection, which had been adopted from the Fleming online VARK assessment.

The questionnaire has 16 questions, and every question has 4 options to choose from. Each option represents a single learning style, and the question is about how people will tackle real-time scenarios that might happen in their day-to-day lives. The beauty of the VARK questionnaire is that it is easy to analyze by using the sorting chart, and the most dominant option chosen is considered the learning style of that individual [33].

Table 2 below displays 3 questions in the VARK questionnaire; the actual questionnaire has 16 questions in total. However, the purpose of figure 2 is to show the reader the nature of the questions and not the whole questionnaire.

Table.2 Connecting time of proposed device

Number	Questions
1	I need to find the way to a shop that a friend has recommended. I would: a. Find out where the shop is in relation to somewhere I know b. Ask my friend to tell me the directions. c. Write down the street directions I need to remember. d. Use a map.
2	A website has a video showing how to make a special graph or chart. There is a person speaking, some lists and words describing what to do and some diagrams. I would learn most from: a. Seeing the diagrams. b. Listening. c. Reading the words. d. Watching the actions.
3	I want to find out more about a tour that I am going on. I would: a. Look at details about the highlights and activities on the tour. b. Use a map and see where the places are. c. Read about the tour on the itinerary. d. Talk with the person who planned the tour or others who are going on the tour.

Sorting Chart

Question	a category	b category	c category	d category
1	K	A	R	V
2	V	A	R	K
3	K	V	R	A
4	K	A	V	R

Figure.1 VARK questionnaire sorting chart

Figure 1 represents the sample of the sorting chart used to analyze the VARK questionnaire (Figure 1). The participant is required to choose an answer for every question. After the completion of the questionnaire, the options are analyzed using the sorting chart. For instance, if the participant's answer to number 1 is option "b", it means the participant prefers the aural method way for solving the issue for the scenario, it is counted as one "A". If the participant's answer to number 2 is option "a", meaning the participant prefers the visual method for the scenario, and it is counted as one "V", and so on. The highest counted learning style option selected by the participant is considered the learning style of that user.

Table 3 displays the total number of participants that answered. The table shows the number of participants belonging to each individual learning style of the whole study.

Table.3 Study VARK questionnaire outcome

Learning Style	Number of Participants
Visual Learning Style	10
Kinesthetic Learning Style	8
Aural learning Style	11
Read and Write learning Style	11
Total	40

2.2 Physiological Data Collection

Thermal infrared thermometer: The laser infrared thermometer was used to collect the skin temperature. Many studies have been carried out with the infrared thermometer, the equipment is endorsed by the medical bodies and agency [34]. The mercury thermometer wasn't fit for this study because it spent an amount of equilibrating time in temperature with the contacted tissue, also it requires physical contact with the participants, which isn't appropriately hygienic. According to a study by Sara et al. (2016), an infrared laser thermometer is a promising tool. The study was fully backed and approved by the Careggi University Hospital Ethical Committee [35].

The temporal artery in the forehead was used for the measurement of the skin temperature, it is the most suitable part when using an infrared temporal thermometer. The temporal; thermometer is the least disruptive and comfortable in manner to measure the body temperature. The infrared sensor is placed close to the forehead of the participant and it detects the heat temperature radiating from the forehead of the participant. The normal range of forehead temperature is 31.0 degrees C to 35.6 degrees C [36]. The ambient temperature is also important in this study, the ambient temperature is the air temperature in the environment where the experiment is conducted. The ambient temperature needs to be maintained because its fluctuation can affect body temperature as well. The ambient temperature, the appropriate range of ambient temperature is about 60 to 75 degrees Fahrenheit or 15 to 25 degrees Celsius. The air conditioner thermostat is a perfect instrument to be used as a room temperature regulator [37]. The air condition ambient thermometer sensor is used to measure the ambient temperature of the room, the air-condition automatically restart or halt itself if the ambient temperature is above or below the preset degree Celsius. During the exercise the air condition room was set to 23 degrees Celsius, in other words, the room temperature during the experiment is 23 degrees Celsius.

Experiment Design

Before the start of the experiment, the infrared thermometer has to be calibrated for an accurate result. The infrared thermometer is cleaned base on the UK acceptable guide [38]. The sensor is cleaned with a damp cloth to remove dust and debris because these could affect the accuracy of the thermometer. The accuracy of the temperature can be checked by comparing it to another stable temperature. The thermometer is held in the center of the room, not close to any surface nor wall. When the reading of the infrared thermometer is equal, or 0-1 degree Celsius less or more, than the ambient temperature, it's considered to be working accurately [39]. The infrared thermometer was calibrated, ready, and working.

The experiment is designed to personate the four learning styles based on the VARK model. Each experiment is set to represent a given learning style. The temperature of the participants is recorded before the experiment was recorded as the pre-test. In addition, further different types of temperatures were collected during the four experiments. Every participant in this study will individually go through every single experiment, and their temperature will be collected throughout the process. The experiment designs are as follows;

Aural Setting

Aural experiment is designed to connect with the participants who are good when grasping information through audio instruction, known as aural learners. The aural learners study best via the use of music, sound and also rhythm beats [40]. The experiment is designed to give more strength to aural activities: an audio clip was played to the participant, and during the process their temperature was collected. Questions were asked on the audio to measure their understanding.

Visual Setting

The visual experiment is set to use visualization techniques as props. Visual learners are very good in understanding lectures when there are visual aids such as graphs, pictures, and diagrams available [41]. Video clips with no sounds with slides are used during the visual experiment on the participants, and during the process, the temperature is collected.

Kinesthetic Setting

The kinesthetic experiment is designed to create an active engagement. The experiment is designed for the participant who will be physically engaged with the lesson. The kinesthetic learners learn best when they are engaged in the study. They get confused and bored easily when there is no opportunity for being actively engaged with the lesson. For this experiment, an origami was chosen. Origami uses the motor activity of participants: it fully needs precise action and concentration from participants who showcase great motor skill [42]

Read and Write Settings

Reading and writing are the most common learning skills in today's world; it is known as traditional learning for self-development. Learners who like to read and write perform at their best when they can do more activities related to reading and writing [40]. In this experiment, a comprehensive passage was given to the participants to read and write on open-ended questions. During this experiment, the temperature from the participant was collected as data.

Skin temperature collection

Skin temperature is affected by the environmental temperature [43] that's why in this study a stable and carefully controlled room temperature was observed as the environmental temperature. The non-contact infrared laser thermometer was used to take the temperature. The temperature was taken 5 different times, with each time representing a giving stage. However, because of the temperature slightly changing every second or millisecond, the temperature was recorded progressively at 30 seconds during each experiment in this case. The temperature is recorded on every slight change, and at the end of the 30 seconds an average is taken to showcase the temperature of that stage. There are 5 Stages in the skin Default, Visual, Aural, Verbal and Kinesthetic respectively.

Table 4 shows the collected skin temperature data recorded before and during the experiment, also the temperature gain and drop during each experiment .The variables listed on the table are explained below;

Note: Table 4 data are recorded and measured by degree Celsius (o C), the negative value (-) signifies the drop of a temperature.

Table.4 Collected Skin temperature sample

Quest	Pretest	K Exp	K t_diff	V Exp	V t_diff	A Exp	A t_diff	R Exp	R t_diff
K	33.4	34.5	1.1	34.1	0.7	33.2	0.2	33.1	-0.3
A	33.0	31.3	1.7	32.2	0.8	32.0	1.0	32.5	-0.5
A	35.2	36.2	1.0	35.5	0.3	35.3	0.1	35.6	0.4
V	34.4	34.7	0.3	35.4	1.0	35.2	0.8	33.9	-0.5
A	33.2	33.3	0.1	33.4	0.2	33.2	0.0	33.0	-0.2
V	34.9	34.9	0.0	35.2	0.3	35.2	0.3	38.4	3.5
K	33.4	33.9	0.5	33.4	0.0	33.9	0.5	36.9	3.5
V	34.6	35.4	0.8	35.6	1.0	35.4	0.8	31.0	-3.6
R	35.2	35.4	0.2	35.9	0.7	35.2	0.0	35.6	0.4
R	32.1	32.4	0.3	32.5	0.4	32.2	0.1	33.0	0.9
R	34.4	34.5	0.1	34.6	0.2	34.7	0.3	33.0	-1.4
V	34.4	35.4	1.0	34.8	0.4	34.6	0.2	34.7	0.3
K	33.2	33.6	0.4	35.6	2.4	33.6	0.4	33.4	0.2
R	34.9	35.3	0.4	35.2	0.3	38.3	3.4	35.8	0.9
A	32.2	32.5	0.3	32.5	0.3	32.5	0.3	33.2	1.0
R	33.4	33.4	0.0	33.6	0.2	36.1	2.7	36.4	3.0
R	34.5	34.8	0.3	34.7	0.2	34.7	0.2	35.6	1.1
R	34.0	34.3	0.3	34.5	0.5	34.6	0.6	33.1	-1.1
A	33.0	34.3	1.3	33.2	0.2	33.3	0.3	33.2	0.2
K	32.4	32.5	0.1	32.3	0.1	33.6	1.2	32.0	-0.4
V	33.0	33.8	0.8	34.3	1.3	33.2	0.2	34.1	1.1
V	34.7	35.0	0.3	34.5	0.2	34.6	0.1	34.5	-0.2

Quest =VARK Questionnaire Result of the participant

Pretest= Temperature recorded before the experiment started.

KExp= Temperature recorded during the kinesthetic experiment.

Kt_diff = the temperature drop/gain during the kinesthetic experiment, (K Exp.).

V Exp= Temperature recorded during the visual experiment.

Vt_diff = the temperature drop/gain during the visual experiment (V Exp.).

AExp= Temperature recorded during the aural experiment

At_diff = the temperature recorded during the aural experiment. (A Exp.).

R Exp= Temperature taking during the reading and writing experiment

R t_diff = the temperature drop/gain during the reading and writing experiment (R Exp.).

3. RESULT AND ANALYSIS

3.1 Statistical Data Analysis

Run Test Data Randomization

The run test was carried out to prove the authenticity of the data collected. The run test is a procedure that will prove that the data are random, even though it is from an occurrence of similar events. Although each participant undergoes the same experiment, every participant has a different individualistic temperature reading with no bias. The run test will be carried out to prove the randomness that will look through the order of occurrence, and show whether or not the order is within a dichotomous variable, and if the order of observation is random or not. The temperature of the student that was collected during the pre-testing will be the variable tested with the run randomness method to prove its authenticity.

Null Hypothesis: The order of the collected data are random but within an acceptable range.

Alternative Hypothesis: The order or the collected data are not random but predesign.

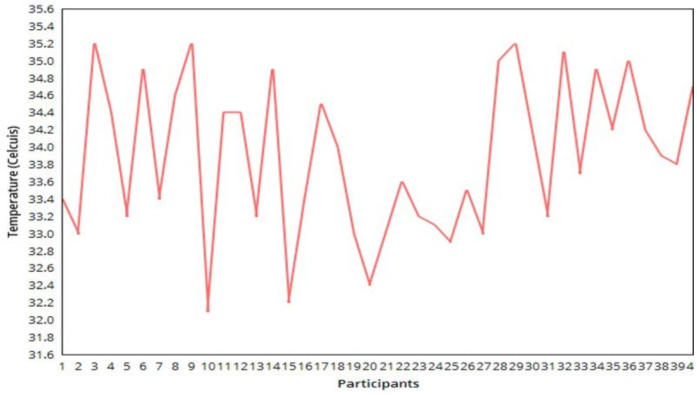


Figure.2 Statistical Data Graphical Representation

Figure 2 is a graphical representation of the participants' temperature which are of random but within the acceptable range, that are used in this study.

Table 5 shows the result output of the Run test variance. Below are the explanation of equations, values and variable used.

Table.5 Run test variance result

R	N1	N 0	N	E(R)	Var(R)	StDev(R)	Z	P-Value
\ 19	20	20	40	40	9.7	3.1	6.7	0.0001

$$E(R) = N + \frac{2(N0N1)}{N} \quad (1)$$

Equation 1 is the mathematical representation of finding the expected value, which is the calculation of the sum of all possible values, multiplied by the probability of its occurrence. Where:
'N'= the total number of observations. The total number of participants in the experiment.
'N1'= the number of participant's whose temperature data are above the mean average
'N0' = the number of participant's whose temperature data are below the mean average
'R' = the total number of run observations. Run observation is the successful switch of between N1 and N0 in a dataset.

$$Var(R) = \frac{2N0N1(2N0N1-N)}{N2(N-1)} \quad (2)$$

Equation 2 is the mathematical representation of finding the variance of the count value Var(R). Where:
The variables of equation (2) are the same as the variable of equation (1).

$$StDev(R) = \sqrt{Var(R)} \quad (3)$$

Equation 3 is the mathematical representation of finding the Standard deviation of the variance (StDev (R). Where:
Var(R) = variance of the count value

$$Z = \frac{R-E(R)}{StDev(R)} \quad (4)$$

Equation 4 is the mathematical representation of the standardization of the data (Z). Data, standardization is the process of putting different variables on the same scale where variables are the same as that of the equation above.
P-value= will be calculated returning the normal distribution for the specified mean and standard deviation. (z)

One Way ANOVA

The one-way ANOVA is a method of analysis that compares the means of two or more independent groups, to understand the possibility of statistical evidence in population data which might cause the difference between the subgroups [44]. In this study, the one-way ANOVA is employed because there are four individual groups of learning styles, which are classified base on the result of the Questionnaire. One-way ANOVA is used on the pretest data (temperature) collected from the participants

Hypothesis H0 is the null hypothesis, it states the temperature of all the participants are affected uniformly in every learning style experience,

Hypothesis H1 is the alternate hypothesis, state the individual's temperature isn't affected uniformly in every learning style experiment. The participant skin temperatures aren't all uniformly effected in every learning style experiment. This will also support the hypothesis that a person's temperature is affected differently during different learning style.

The alpha level is represented as α which is a threshold value used for understanding if the test statistics are important. The alpha value corresponds with the probability, it ranges from 0-1 [45]: in this research 0.05 was chosen.

α=0.05

Degree of freedom (DF) is the number of independent values that could fluctuate in a method without breaking any constraints [46]. The degree of freedom is classified into three:

- The degree within (DFWithin),
- The degree between (DFBetween)
- The degree total (DFTotal).

Table 6 contains the resulting output of the one way ANOVA. Below is the explanation of equations, values, and variables used in table 6.

Table.6 One Way ANOVA Output

	Sum of square(SS)	Degree of freedom (DF)	Mean Square(Ms)	F Value
Between	57.7	3.0	19.2	4.1
Within	175.4	37.0	4.7	
Total	232.7	39.0		

Figure 8 contains the resulting output of the one way ANOVA. Below is the explanation of equations, values, and variables used in figure 8.

Number of groups classified groups (a) = 4
Total number of the participant (N) =40
DFBetween = Number of groups classified groups -1= 3
DFWithin =Total number of the participant- DFBetween =37
DFTotal = Total number of the participant -1=39

Finding the critical value is a certain point on the test method. It is used to accept or reject the null hypothesis. When F is greater than the critical value, then the null hypothesis will be rejected [47]. To find the critical value we will use degrees of freedom within (DFWithin) and degree of freedom between (DFBetween) on the F distribution table, also the significant value (alpha) of 0.05.

(DFBetween, DFWithin)
(3, 37)
The critical value using the F table is =2.858.
Hypothesis H0 = f < 2.858

Hypothesis H1= f >2.858

To find the F value, the value of the Sum of square between (SSBetween), Sum of square within (SSWithin), Mean Square between (MsBetween) and Mean Square within (MsWithin) have to be calculated

$$\text{SSBetween} = \frac{\Sigma(\Sigma ai)^2}{n} - \frac{T^2}{N} \quad (5)$$

Equation 5 is the mathematical representation of finding the sum of square between where:

Σ (Σai) ^{2} = It's the summation of all the temperature difference in individual group, squared and then added together

n = number of participants that belong to the 4 learning style groups weren't the same, to find the aggregate of the n, the mean of the number of participant was used which is 10.

T=Total sum of the temperature difference in every group added together

N= number of the whole participant which is 40

$$\text{SSWithin} = \Sigma y^2 - \frac{\Sigma(\Sigma ai)^2}{n} \quad (6)$$

Equation 6 is the mathematical representation of finding the sum of square within where:

Σy2= means squaring of each individual value and adding them to each other.

Σ (Σai) ^{2} and **n** are the same variable as that of equation 5

$$\text{SSTotal} = \Sigma y^2 - \frac{T^2}{N} \quad (7)$$

Equation 7 is the mathematical representation of finding the sum of square total where:

All the variables in this equation are the same as identified as the previous equations above.

$$\text{MsBetween} = \frac{SSBetween}{DFBetween} \quad (8)$$

Equation 8 is the mathematical representation of finding the mean square between

$$\text{MsWithin} = \frac{SSwithin}{DFwithin} \quad (9)$$

Equation 9 is the mathematical representation of finding the mean square within

$$F = \frac{\text{MsBetween}}{\text{MsWithin}} \quad (10)$$

Equation 10 is the mathematical representation of finding the F.
F=4.1.
F is greater than the critical value, which means Hypothesis H0 is rejected.

3.2 Machine Learning Analysis

This section will highlight the analysis of the data collected. This section classifies the collected data (skin temperature) using the decision tree method. It will highlight the relationship between and individual preferred learning styles and their change of temperature.

WEKA Analysis Tool

The Waikato Environment for Knowledge Analysis (WEKA) tool is a free machine learning software that was developed by the University of Waikato, New Zealand. The free software is licensed under the GNU General Public License that is widely used for research studies, education and other industrial activities [48]. The software is equipped with a machine-learning algorithm such as the decision tree used in this study. WEKA has been used to analyze data on research studies that involve human physiological signals and bioinformatics such as research on data mining on bioinformatics [49].

The C4/5 algorithm is a decision tree algorithm that was developed from Ross Quinian. It is an extension of the ID3 algorithm [50]. The decision tree generated by the algorithm can be used for classification, thus the classifier is known as a statistical classifier. The reason for choosing the J48 decision tree classifier is because of its efficiency and construct. In 2008 the algorithm became popular after its #1 ranking in the top 10 algorithms in data mining pre-eminent paper published by Springer LNCS in 2008. Previous studies on topics that were associated with computer science illustrated that the human physiological signals and human bio have been analyzed by the J48 decision tree. This supported the choice of using the algorithm for this study [51-52].

Decision Tree Visualizers

The data which consists of the questionnaire result, the questionnaire collected data and the experiment collected data (see Table 3) were used as the decision tree attributes. The decision tree algorithm will find the pattern between the learning style classes and the temperature collected.

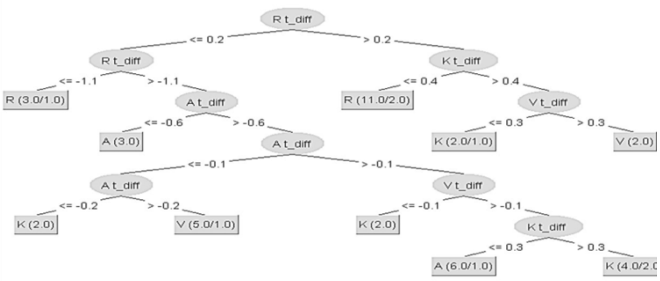


Figure.3 Decision Tree Visualizer

Figure 3 showcase the Decision tree visualizer using the j48 classifier, the tree is created using the combination of decision rules and conditions. In this process, the input attributes recorded in Figure 5 are fed into the classifier.

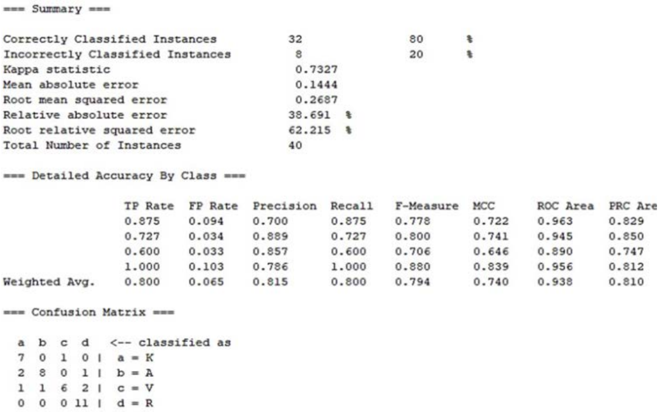
From the data collected the nodes are recognized by the capacity to classify the data. Information entropy is used to compute the additional gain of each attribute in this study. The attribute with the highest information gain is chosen as the internal nodes for each computational round. The classification decision rule is the regulation that an attribute abides before going to the next stage. Figure 9 shows a total of 10 rules for the classification to the four classes in total. Figure 10 shows the representation of different classification rules

Table 7 showcase the classification rule that explain the input attributes relationship with the possible outcome. For example, the first rule shows, if the participant temperature gain in the read and write experiment is greater than 0.2 degree Celsius and the temperature gain the kinesthetic experiment is anything less than 0.4 degree Celsius, and the participant outcome class is read and write. The second rule shows if the participant temperature gained in the read and write experiment is greater than 0.2 degree then Celsius and the temperature gained in the kinesthetic experiment is higher than 0.4 degree, thus Celsius as instances is considered a visual outcome. The classification goes on and so on.

Table.7 One Way ANOVA Output

Rule	Classification Result
IF (Rt_diff > 0.2) AND (Kt-diff<= 0.4)	Read and Write Learner
IF (Rt_diff > 0.2) AND (Kt-diff> 0.4) AND (Kt-diff> 0.3)	Visual Learner
IF (Rt_diff > 0.2) AND (Kt-diff> 0.4) AND (Kt-diff<=0.3)	Kinesthetic learner
IF (Rt_diff <= 0.2) AND (Rt-diff<= 1.1)	Read and Write Learner
IF (Rt_diff <= 0.2) AND (Rt-diff > 1.1) AND (At-diff <=0.6)	Aural Learner
IF (Rt_diff <= 0.2) AND (Rt-diff > 1.1) AND (At-diff >0.6) AND (At-diff <=0.1)AND (At-diff <=0.2)	Kinesthetic Learner
IF (Rt_diff <= 0.2) AND (Rt-diff > 1.1) AND (At-diff >0.6) AND (At-diff <=0.1)AND (At-diff >0.2)	Visual Learner
IF (Rt_diff <= 0.2) AND (Rt-diff > 1.1) AND (At-diff >0.6) AND (At-diff >0.1) AND (Vt-diff <=0.1)	Kinesthetic Learner
IF (Rt_diff <= 0.2) AND (Rt-diff > 1.1) AND (At-diff >0.6) AND (At-diff >0.1) AND (Vt-diff >0.1) AND (Kt-diff >0.3)	Kinesthetic Learner
IF (Rt_diff <= 0.2) AND (Rt-diff > 1.1) AND (At-diff >0.6) AND (At-diff >0.1) AND (Vt-diff >0.1) AND (Kt-diff<=0.3)	Aural Learner

3.3 Accuracy and Reliability Assessment



```
=== Summary ===

Correctly Classified Instances          32               80      %
Incorrectly Classified Instances         8               20      %
Kappa statistic                          0.7327
Mean absolute error                      0.1444
Root mean squared error                  0.2687
Relative absolute error                 38.691  %
Root relative squared error             62.215  %
Total Number of Instances               40

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Are
                 0.875    0.094    0.700      0.875    0.778      0.722    0.963     0.829
                 0.727    0.034    0.889      0.727    0.800      0.741    0.945     0.850
                 0.600    0.033    0.857      0.600    0.706      0.646    0.890     0.747
                 1.000    0.103    0.786      1.000    0.880      0.839    0.956     0.812
Weighted Avg.    0.800    0.065    0.815      0.800    0.794      0.740    0.938     0.810

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
  7  0  1  0 |  a = K
  2  8  0  1 |  b = A
  1  1  6  2 |  c = V
  0  0  0 11 |  d = R
```

Figure.4 Decision Rule (WEKA tool)

Figure 4 shows the window image of the WEKA J48 decision tree classifier summary result, a total of 40 instances were used for the model training and testing altogether. 8 instances were used for the model training and 32 instances were used for model testing. The model shows the accuracy of 80% which are the correctly identified instances, and 20% incorrect accuracy. The WEKA classifier also supports the result accuracy by the confusion matrix method. The confusion matrix section in figure 5 shows each class's statistical accuracy as being calculated independently, which means each class is independent of each other. The number of instances means the number of participant data used for the model classification. True Positive Rate (TP Rate), False Positive Rate (FP Rate), Precision, Recall-Measure, MCC, ROC Area, PRC Area.

The true positive Rate (TP Rate), is the percentage of participants whose questionnaire outcome is the same as their learning style experiment which signifies that they had much temperature gain. A high percentage of the TP rate means a high hypothesis accuracy.

The False-positive Rate (FP Rate), is the percentage of the participants whose learning style questionnaire outcome is not the same with the learning styles experiment that had the most gain on their temperature. A higher percentage of FP rate means a lower accuracy of the hypothesis.

False Negative Rate (FN Rate), is the percentage of students whose most gain in the experiment is the same as any outcomes except for their preferred chosen outcomes. A high FN rate percentage means a low accuracy of the hypothesis.

$$\text{Precision} = \frac{TP\ Rate}{TP\ Rate+FP\ Rate} \quad (11)$$

Equation 11 is the mathematical representation of the precision which is known as the positive predictive value. It is the proportion of the relevant instances within the collected instances. The precision is calculated by dividing the true positive rate by the summation of the true positive rate and false positive. Where
TP Rate= True Positive Rate
FP Rate= False Positive Rate
FN Rate= False Negative Rate

$$\text{Recall}=\frac{\text{TP Rate}}{\text{TP Rate +FN Rate}} \quad (12)$$

Equation 12 is the mathematical representation of the recall value which is also known as the sensitivity of the system, and recall is the percentage of the result that is rightfully classified by the algorithm. The recall is calculated by the true positive rate divided by the true positive rate and false negative.

$$\text{FMeasure}= \left(\frac{2}{recall^{-1}+precision^{-1}}\right) = 2.\left(\frac{\text{precision .recall}}{\text{precision+recall}}\right) \quad (13)$$

Equation 13 is the mathematical representation of the F measure which is also known as the f score, it is dependent on the precision and recall of the system to compute the score.

$$\left(\frac{\text{TP Rate}*\text{TN Rate} - \text{FP Rate} * \text{FN Rate}}{\sqrt{(TP\ Rate+FP\ Rate)(TP\ Rate+FN\ Rate)(TN\ Rate+FP\ Rate)(TN\ Rate+FN\ Rate)}}\right) \quad (14)$$

Equation 14 is the mathematical representation of the F measure whereas Matthews's correlation coefficient (MCC) is used in machine learning as a measure of the quality of the accuracy for the class classification.

4. DISCUSSION

4.1 Statistical Data Analysis

Run Test Analysis

The run test was applied for the insurance of reliability and integrity of the data collected which is the temperature of the participants. The run test proves that the data collected are of the natural formulation by a similar occurrence or similar events. When the p-value is calculated in the run test analysis, the p-value happens to be less than 5 %, which means the data are independently connected. This proves that the participant's data are individualistic with no hidden patterns or bias when collecting it.

One-way ANOVA

Using the one-way ANOVA on the data collected in all the experiments proves the temperature of the participants are not uniformly affected the same way during every experimental stage. Since the decision rule states "if f > 2.802 the null hypothesis will be invalid ", F is 4.1 which makes it higher than the critical value, therefore rejecting the hypothesis H0.

4.2 Decision Tree Analysis

The WEKA tool was used to analyze the questionnaire data and the collected temperature data. The result of the classification shows 80% of correctly classified instances, and 20% incorrect instances. Using the confusion matrix in fig 5 it can be affirmed that there is 32 instances where the most temperature gain was the same as the participant questionnaire outcome. The roc curve method was used to test the reliability classification result, with the average total of Area under the curve of 0.97945 in a total of all the four classes. The percentage error method was used to prove the accuracy error. Based on a collected train data, the confusion matrix enables the graphic representation of the algorithm performance, in this case, the decision tree. In this process, the number of correct and incorrect predictions is identified in each class separately. The confusion matrix in figure 11, shows the correctly classified machine learning. The confusion matrix shows 6 visual learners correctly classified from their temperature, and 4 incorrectly classified. The decision tree correctly classified 7 kinesthetic learners and 1 kinesthetic learner was incorrectly classified. The confusion matrix shows 8 aural learners were correctly classified and 3 were incorrectly classified. The confusion matrix shows 11 reading and writing learners were correctly classified and none were incorrectly classified.

E=Error
Corrected defined instance = 32
Total Number of instance= 40

$$PE = \left|\frac{Corrected\ Defined\ Instances - Total\ Numbers\ of\ Instances}{Total\ Numbers\ of\ Instances}\right| * 100\% \quad (16)$$

$$PE = \left|\frac{32-40}{40}\right| * 100\%$$

E=20%
Accuracy is the deduction on Error from 100, Therefore 100-20
80%.

Equation 16 is the mathematical representation showcasing the percentage error formula, which is used to calculate the accuracy of the decision outcomes.

This study shows that the learning styles have an effect on the skin temperature, just like with other physiological signals such as the heart rate and blood pressure. Unlike heart rate and blood pressure, the skin temperature provided a slight change. The skin temperature is more sensitive to change compared to the heart rate and blood pressure, and also other external factors have had to be considered such as the ambient temperature. The skin temperature is faster and easier to collect than the heart rate. However, it's more susceptible to errors and other factors. At the end the result shows that the skin temperature could also be used as an attribute used for the VARK learning style, just as the heart rate and blood pressure.

4.3 Implication of Study

The human temperature is an important measurement of human cognitive actions. This study can be used as a foundation for other studies that intend on building the relationship between the human physiological signals (temperature) and learning style. Further studies could help understand other models of learning style and intelligence that also has an effect on the human physiological signals.

5. CONCLUSION

This study suggests the use of temperature data for the classification of the VARK learning style. The temperature tends to rise higher when an individual is more involved in learning, which can be said to be their preferred learning style. This study is intended to correct the issue that has arisen through the use of questionnaires as the only tool for data collection. The C4/5 decision tree algorithm was used for the classification of classes which is based on the 4 VARK learning class. The proposed attribute classification achieved an accuracy of 80%. The classification accuracy shows that the temperature attribute can be used to classify a learning style that is proper for personalized learning development as further study.

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