Facial Expression to Analyze Human Mindset

Taiba Al Salmi¹, Emdad Hossain², Sallam Fageeri³ and Alaa Al-Obaidi⁴

^{1,2,3} Department of Information Systems
 ⁴Department of Mathematical and Physics Science
 ^{1,2,3} College of Economics, Management and Information Systems, University of Nizwa
 ⁴College of Arts and Sciences
 ^{1,2,3,4} Nizwa, Sultanate of Oman
 {¹8560797@uofn.edu.om}, {²emdad.hossain, ³sallam, ⁴alaamohammed @unizwa.edu.om}

Abstract—This paper, describe the experiment used to analyze human mindset through facial expression. The experiment was scripted through the free software Weka. The sample dataset (20 records) from Miami University Deception Detection (MU3D) database. Both (M5P and RepTree) methods tested related to training set and 10-fold cross-validation. These two methods are applicable to use with numeric classes. The analysis of M5P tree presented higher correlation related to REPTree, besides minor errors, and higher number of rules. Moreover, the elapsed time for processing is same in both methods. This specifies that the M5P and REPTree are models were suitable for predicting and extracting features.

Keywords-Facial expression; State of Mind; Mindset; Micro expression; Weka

1. INTRODUCTION

Social relationships are such an integral part of a person's life that one cannot live without others. Our emotions are the indicator of the state of mind. State of mind is "a person's emotional state: mood" [1]. Generally, in this paper, we use facial expressions to analyses human mindset. Dr. Paul Ekman (the author of research called Lie to Me) found seven facial expressions that are mostly realized, like surprise, fear, disgust, anger, happiness, sadness, and contempt [2]. Data mining is the process of automatically searching vast amounts of data for patterns and trends that go beyond simple analysis. It involves the use of powerful mathematical algorithms to divide the data and assess the future events. The effort in this research Is the experiments that can provide us clear picture regarding extracting features from dataset [3]. The significance of this work lies in the use of data mining trees to get results that are useful for analyzing human mindset associated to facial expression.

2. LITERATURE REVIEW

Mind theory relates to the capability to distinguish independent mental states to oneself and others regularly to predict and clarify behavior [4]. How people be able to present their desire, belief, and intention [5]. Charles Darwin found the link between emotion and expressive actions has been largely strengthened. However, historically, all the researchers concerned, including Darwin and Ekman, have maintained a view that is far more distinct than the view in current literature [6]. Paul Sel, Evan F. Risko & Daniel Smilek, categorized mind-wandering as spontaneous and deliberate that can be held in trait level and state level. They found no study on trait-level with state-level of these two types of minds wandering [7]. Diana Alkire found that MRI investigations of mental state tested people without any interaction with others. This because there is no evidence prove that our mind is working different when we are in social communication or work the same when we think about others without interaction [8]. The two important discoveries related to human mind "the universality of facial expressions of emotion and the existence of micro expressions" (David and Hyi Sung 2011). Darwin was the first researcher who claims that emotions and their expressions were biologically inherent and adapted to nature and that phylogenetic parallels could be found in them [9]. A lot of studies performed by Tomkins, the significant discovery, universality of emotional facial expressions and the presence of micro expressions will assist individuals in a variety of careers that involve face-to-face experiences to enhance their ability to read others' emotions [10]. As each part of the face conveys a message of fear, of surprise, etc., therefore, if it is enhancing your intention must focus on the rapid facial signals and their distinctive messages [11]. According to a new study facial muscles can help in reading face features. The authors found, by looking at these slight variations in faces color, people can correctly recognize other's emotions up to 75% of the time. The researchers also created a computer algorithm that can classify human emotions up to 93.53% of the time [12]. These helps observers focusing their look on certain parts of the face. Overall, this study confirms the high importance of the eye and mouth area for successfully recognizing emotional expressions [13]. It was easier to classify positive emotions than negative emotions. More precisely, happiness, was the most easily understood emotion 97%. Anger 69% was the least recognized facial expression, while contempt showed the lowest recognition rate 53%. [14]. Marianna and Jan found the answer related the question "do people from different cultural backgrounds recognize and interpret facial expressions the same way?". The answer came from scientists that both yes and no could be. Yes, since the brain structure that specializes in recognizing faces is identical across cultures, when looking at other faces, we can all identify simple feelings. No, because culture affects how we act and how we think. They conclude their article that most of us have the global force to read feelings of other people. [15]. Saket S Kulkarni and his colleagues categorized image expression into neutral, angry, disgusted, frightened, sad, shocked, or happy. They be able to extract 15 parameters, eight real values depending on the distance calculated with a definite value, and

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seven binary parameters. They found the emotions of anger, disgust and fear showed lowest accuracy of classification which range from 65% to 75%, while happiness, sadness and surprise displayed high accuracy of classification more than 90%. They conclude that intelligent systems based on the Committee neural network provide a useful method for classifying image-based expressions [16]. When it comes to mind reading, the most popular channel to read and infer emotion is from a person's face [17]. Facial colors allow observers detect emotions because of network blood vessels [12]. The study found, normal people can detect other's feeling up to 95%, by looking to the face change color [18]. The brain has been shown to contain a map of other people's faces. It could justify why some people are better than others at identifying faces [19]. David A. Rosenbaum raised a question "Do we smile because we are happy, or we are happy because we smile?" [20]. According to the James-Lange principle, we smile as we hear that something is synonymous with good experiences, but the pleasure we feel is generated from the feedback derived from our movements at that moment [21]. To put it another way, this hypothesis argues that people have a bodily response to external stimuli, which is then interpreted as an emotional experience [22]. Charles Darwin's pointed that emotion expressions serve to prepare the organism for emotion-relevant action, he stressed the language of emotions' communicative value [23]. Emotionality is related to several psychological characteristics such as disposition, attitude, mood, and motivation. [24]. William James and Carl Lange suggested that emotions generally occur because of physiological reactions to events. While the James-Lange theory encompassed both facial and non-facial expressions, it indicated subsequent studies on the Facial Feedback Hypothesis, which concentrated only on facial expressions and their effect on emotional perception [25]. Facial Feedback Hypothesis suggested that facial feedback is essential to generate emotional experience [26]. Paul Ekman then defines "Emotions are a process, a particular kind of automatic appraisal influenced by our evolutionary and personal past, in which we sense that something important to our welfare is occurring, and a set of psychological changes and emotional behaviors begins to deal with the situation" [27]. Emotions "are states elicited by rewards and punishers, including changes in rewards and punishment". Different emotion can be described and classified according to whether the reinforcer is positive or negative, and by the reinforcement contingency[28]. Related the above resources found that most researcher focused on some signals in the faces of human being to get detect either one of the seven marks that can be easily detected like happy, sad etc. while there are ways that can help us to analyze mindset of human like talk experience, as that can give us some hints about what other people think while they are speaking and what are the signal appears in their faces during speech as well the anxious, accuracy that can detect to their faces. All of that can help in analyzing the state of mind during the speech. So, we can guess what others saying either truth or lies, positive or negative. By considering the stated weakness of related work, we are going to design our platform which will solve the identified issues. the details mechanism of the platform discussed in the methodology below.

3. MATERIAL AND METHODS

3.1 DATA GATHERING AND PREPARATION

The most important objective of data collection is ensuring that information is valuable, rich, and reliable data that collected for statistical analysis, so data-driven decisions can be made for research [29]. Data preparation goes through different steps until is getting ready to be useful and helpful to the researcher. Data preparations combine six processes, gathering the right data that are appropriate for the topic (see Fig 1) [29][30].



Fig1 Data preparation steps source: devopedia.org

3.2 FEATURE EXTRACTION

Feature extraction is a major role in image prepossessing that support extract collection of features that maximizes recognition performance while using the fewest number of components [31]. In order to achieve the goal of dimensionality reduction, it removes the significant feature subset from the original dataset using various criteria in order to reduce machine training time and space complexity. Feature extraction reduces the input data to a set of features, yet the resultant reduced representation retains the majority of the original data's essential information [32]. A critical stage in every face recognition system is feature extraction. Children's anxious fear biases were investigated. Children with anxiety issues were more likely to properly recognize disgust faces and avoid a reinforce paired with a disguised furious face, according to our findings. The also looked into the genes and environmental influences that contributed to these threat biases. The findings add to previous research that shows a relationship between anxiety in children and a preference for threatening information during information processing. They also support the significance of nurture

in the development of threat biases in general [33]. According to a new study, persons who are highly worried can identify changes in facial emotions faster than humans that are less nervous. Strongly anxious adults (Fig2 and Fig3), on the other hand, may experience more wrong decisions and repeat a cycle of conflict and miscommunication in their interactions by going to emotional assumptions [34].



Fig.2 Schematic of the face emotion recognition with the different expression [33]



 $Fig.3\ \underline{https://anxietypanichealth.com/2008/08/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/08/anxious-people-jump-to-emotional-conclusions/2008/anxious-people-people-people-people-people-people-people-people-people-people-people-people-people-people-people-people-people-people-people-peop$

3.3 WEKA

Weka stands for Waikato Environment for Knowledge Analysis is an open-source software that developed at the University of Waikato, New Zealand [35]. Weka contain tools for data prepressing, implementation of collection of machine learning algorithm [36], classification, regression, clustering, association rules, and visualization tools [37]. There are many classifiers in Weka that used to extract the result like Naïve Bayes, k-Nearest Neighbors and Support Vector Machines [38]. Decision tree is low chart like tree structure, where internal node represent test on attribute and branch shows result of test. It is very simple and easily understandable classifier. (M5p and RepTree) and build a model for each view of the data[39]. Then compare the result and see which view of the data results is the best. M5P is a binary decision trees model that combines three basic steps: tree construction, tree pruning, and tree smoothing[40][41]. Create the basic tree, which uses the standard deviation of the class values that reach a node as a measure of the error at that node and calculates the predicted error reduction because of evaluating each attribute at that node. After that, the property with the highest anticipated error

reduction is chosen [42]. RepTree is stands for Reduced Error Pruning Tree algorithm. It's a rapid decision tree learner that creates a decision/regression tree using information gain as the splitting criterion and prunes it with a reduced error pruning technique [43][44].

3.4 THE EXPERIMENT USE WEKA FEATURES (M5P AND REPTREE)

Pre-processing is one of the features that used to load the dataset (show in Fig 4). The screen shows the content in the current relation (that contain information about the dataset name, attributes: 13, instances:20 and the sum of weights: 20), the selected attribute details and the list of all attributes in the current running dataset. Also the KnowledgeFlow as shown in Fig 5) used in the experiment to benchmark and validate the obtained result which is presenting the identical result.



Fig. 4 Pre-processing Screen



Fig .5 Graphical view of KnowledgeFlow using REPTree and M5P

Selected attribute screen displays information about each attribute. As we go through the attribute found that all are numeric type. There are minimum, maximum, mean, and standard deviation for each attribute as well as separate visualization. By proceeding in the dataset that used in this work (sample dataset 20 records) from Miami University Deception Detection (MU3D) database, which is a free resource that contain 320 videos of targets. They individually telling truth and lies. The database contains eighty people (20 black f, 20 black m, 20 white f and 20 white m). Those people were recorded as they are speaking honestly and dishonestly about their social relationships. Each target recorded four different videos containing positive truth, negative truth, positive lie and negative lie. The codebook of MU3D provides information about each video like the length of video, trustworthiness rating, transcription of video and anxiety rating. Beside that it also contains information about target variables like attractive, age of the target, and race [45]. The database is designed in MS Excel by following the required format. The sample data again reformatted to make runnable using WEKA. It is in fact type of ASCII text file where set of attributes with required instance are described [46]. Fig4 above shows the process environment of the file in WEKA. Each field in the dataset has different Min, Max, Mean, and StdDev for each attribute. Graphical visualization can be done to all attributes as shown in Fig 6 below.



Fig. 6 Graphical visualization of processed attributes.

4. INTERPRETATION THE RESULT

Machine learning and data mining technologies are sometimes better suited to accurate interpretation than others. Data mining is the process of automatically searching vast amounts of data for patterns and trends that go beyond simple analysis. It involves the use of powerful mathematical algorithms to divide the data and assess the future events. For example, decision trees are user-friendly when it comes to explaining outcomes. Classification, estimation, and prediction may all be done with decision trees. The experiment that used in classification (M5P, REPTree) methods. As these methods are applicable that can apply in dataset where classes are numeric. The dataset was processed and analyse by the above two methods depend on test options using training set and 10-fold cross-validation in Weka. The sample dataset that used in this experiment contain 20 instances (10 males, 10 female). The summery result that returns from M5P was higher and more satisfaction than the result from REPTree as the below tables when we used training set test see Table1. In other hand, the output from RepTree by using test 10-fold cross-validation was higher and more reasonable than in M5P as in Table 2.

Summary	M5P	RepTree
Correlation coefficient	0.8897	0
Mean absolute error	0.0567	0.1029
Root mean squared error	0.0725	0.1442
Relative absolute error	55.0594 %	100%
Root relative squared error	50.2504 %	100%
Total Number of Instances	20	20

Table 1: Summery	(Evaluate on	training data)
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Table 2. Summery	(10 fold cross validation)	
1 able 2: Summery	(10-1010 cross-vandation)	

Summary	M5P	RepTree
Correlation coefficient	0.2433	0.176
Mean absolute error	0.1064	0.096
Root mean squared error	0.1431	0.1423
Relative absolute error	101.3764	91.5154
Root relative squared error	96.3171 %	95.7952%
Total Number of Instances	20	20



Fig .7 Graphical view of M5P (full training set & cross validation)



Fig .8 Graphical view of RepTree (full training set & cross validation)

Fig 7 and 8, represent the outcome from both (M5P and RepTree) as graphical view and data. Graphical view presents the two predictive rules of IF-THEN which formed based on the initial values of TruthProp, if greater than or equal 0.595 then the predicted value is 15. If TruthProp > 0.595, the predicted value is 5. The graph related to RepTree predicted one value that is 13.

5. CONCLUSION

Our emotions are the indicator of our mind. This research, study facial expressions to analyze human mindset to understanding the functioning of the human mind. To achieve our goal, we make an experiment that helped us to find the strong relation between mind and face features. Machine learning and data mining technologies are sometimes better suited to extracting features and accurate interpretation than others. For example, decision trees are user-friendly when it comes to explaining outcomes, for that we used Weka tools to extract features from dataset. The sample dataset used in this work contains (20 records). The dataset run in M5P and RepTree that implemented in Weka toolkit to extract features. We tested both methods related to training set and 10-fold cross-validation. Then we compared the result and found that both methods are applicable to use with numeric classes. The Correlation coefficient from M5P in both test (training set and 10-fold cross-validation) were 0.8897, 0.2433 respectively, while in RepTree 0, 0.176. The result from M5P has more reasonable than RepTree when we used training set test, while RepTree produced reasonable result than M5P when use 10-fold cross-validation. This specifies that the M5P and REPTree are models were suitable for predicting and extracting features.

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