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ROZPOZNÁVANIE EMOCIONÁLNEHO STAVU POUŽÍVATEĽA POMOCOU INTELIGENTNÝCH RIADIACICH SYSTÉMOV

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Abstract

Abstract goes here

Dedication

To mum and dad

Declaration

I declare that..

Acknowledgements

I want to thank...

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Introduction

> ”Smiles are probably the most underrated facial expressions, much more complicated than most people realize. There are dozens of smiles, each differing in appearance and in the message expressed.”
>
> - Paul Ekman

Emotions are at the core of the human experience, albeit very hard to define, recognize and name, even in yourself. They are, by definition different from person to person, in diverse cultures and upbringings. Our perception of emotions and their classification has evolved in recent years. Various authors has tried to divide our emotional states into basic categories such as Ekman’s Anger, Fear, Disgust, Happiness, Sadness and Surprise. However, recent work by psychologists and historians alike show, that a more complex look at emotions might be needed.

Emotional recognition changes with time. In 12th century, bards looked at yawning not as a sign of boredom or tiredness, but as a sign of a hidden and deep love. Early Christians recognized an emotion called ”accidie”, a lethargy and despair brought about by flying demons. Boredom, as such was first really felt by the Victorians as a response to the new ideas of leisure time and self-improvement. Among the psychologist, there is a standing question whether some cultures feel some hard to define emotions more strongly, because they bothered to name them as separate kinds. For example the Russian ”toska”, a longing with nothing to long for, as coined by Vladimir Nabokov. Recent developments of cognitive science tell us, that emotions are not just simple reflexes, but inherently complex and elastic systems of response towards both the biologies that we’ve inherited and the cultures, that we live in now. They are not just simple chemistry, but a cognitive phenomena, not shaped only by our body functions, but also our thought process, concepts and language. The neuroscientist Lisa Feldman Barrett studies this dynamic relationship between words and emotions. She argues, that when a person learns a new word for an emotion, they also learn to feel and recognize it (Barrett, 2007). There is a historicity to emotions, they have changed in history, often times very dramatically, in response to new cultural expectations, religious beliefs, new ideas about gender, age, ethnicity, economical and political ideologies.

There is a push to increase our emotional intelligence. Emotions are so powerful, that in past, they were sometimes thought to be a cause of illness. In 17th century, there was a student attending the Swiss university in Basel. He came afflicted with fever, heart palpitations, skin sores on his body and was close to dying. When they sent him back home to die, he started getting better and by the time, he returned to his hometown, he almost entirely recovered. In 1688, Johannes Hoffer, medical doctor, learnt of this case and many like it and coined the term for a severe homesickness as ”nostalgia”. Last confirmed death by nostalgia was an American soldier fighting during the First World War in France. In early 20th century, this feeling has morphed more into a longing for lost time, instead of homesickness and downgraded in severity. Nowadays, our culture celebrates happiness, as it is said to make us a better workers, parents and partners. However, in 16th century, this position was filled by sadness, as is evident by self-help books from that period, which tried to encourage sadness in readers by giving them lists of reasons to be disappointed.

In order to study both basic emotions and their mixtures in the complex variety, we need appropriate detection and classification tools and techniques. Over the years, many psychologists and computer scientist collaborated to create a set of markers and techniques recognizing them. We will discuss several of them and compare their usefulness, reliability and practicality. These methods most often try to detect basic emotions such as the seven basic emotions (Ekman, 1992) or a 12-point Affect Circumplex model (Yik et al., 2011).

Figure 1: Six primary emotions

1. Emotion classification

Emotion classification is a contested issue in emotion research and in affective science. The two fundamental viewpoints of affective scientists' approach are:

1. Emotions as discrete and fundamentally different constructs
2. Emotions as fluid and characterized on a dimensional basis in groupings

Various categorizations of emotions also vary in description how emotions relate to each other.

1.1. Discrete models of emotions

Discrete emotion theory claims that there is a small number of core affects. This number can vary depending on the proponent, for example Silvan Tomkins considered nine basic emotions. Six, that came evolutionarily earlier, interest-excitement, enjoyment-joy, surprise-startle, distress-anguish, anger-rage, fear-terror, once that evolved later, shame-humiliation and finally disgust and dissmell, which he later took back. In the paired affects, the first of the pair is the mild manifestation and the second the more intense. (Tomkins, 1962), (Tomkins, 1963). This model is somewhat controversial nowadays among affective theorists, especially over Tomkins' firm insistence that there were nine and only nine, biologically based affects. He also argued, that these affects are quite discreet (in contrast to the more muddled and complex emotions) and that they shared a common biological heritage with what Darwin called emotions in animals (Darwin et al., 1998). They also differ from Freudian drives in lacking an object.

Similarly, Carroll Izard delineated 12 discrete emotions: interest, joy, surprise, sadness, anger, disgust, contempt, self-hostility, fear, shame, shyness and guild. He measured these via his Differential Emotion Scale (Boyle et al., 2015). Among other contributors to this theory, such as John Watson, Edwin Newman and Ross Buck, Paul Ekman performed a series of cross-cultural studies with Carrol Izard and reported that there are at least six emotions, that people across the world produce and are able to recognize. This was further evidenced when researchers approached the people of New Guinea with no previous exposure to Westerners nor their culture. When they showed them pictures of people expressing six core emotions, subjects could in fact point out the different emotions and distinguish between them (Ekman et al., 1971).

1.2. Dimensional models of emotions

There are various theoretical and practical reasons for which some researchers define emotions according to one or more dimensions. Dimensional models are an attempt to conceptualize human emotions by defining where they lie in two or three dimensions. Most incorporate valence and arousal or intensity dimensions. In contrast to theories of basic emotion, which propose that different emotions arise from separate neural systems, dimensional models suggest that a common and interconnected neurophysiological system is responsible for all affective states. (Posner et al., 2005)

In 1897, Wilhelm Max Wundt proposed, that emotions can be described by three dimensions: "pleasurable versus unpleasurable", "arousing versus subduing" and "strain versus relaxation" (Wundt, 2017). Later, Harold Schlosberg named three dimension, "pleasantness–unpleasantness", "attention–rejection" and "level of activation" (Schlosberg, 1954).

Another model, called the circumplex model, was developed by James Russell. This model suggest that emotions are distributed in a two-dimensional circular space, containing both arousal and valence dimensions. The vertical axis represents arousal, horizontal axis valence and the center of the circle represents a neutral valence and medium level of arousal.(Russell, 1980).

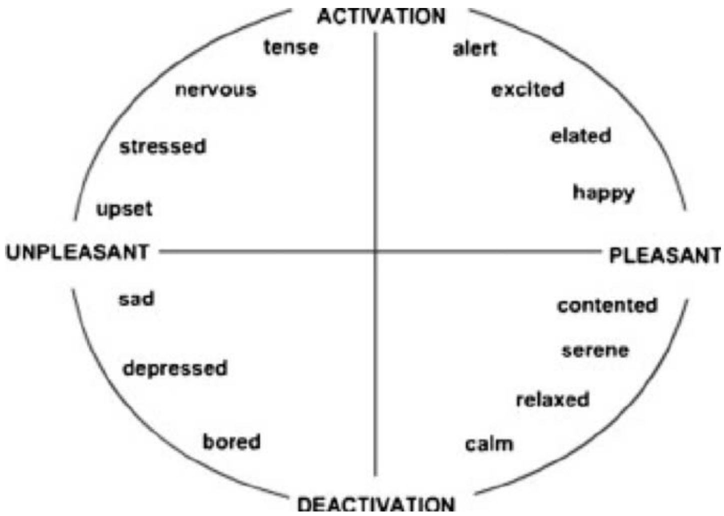
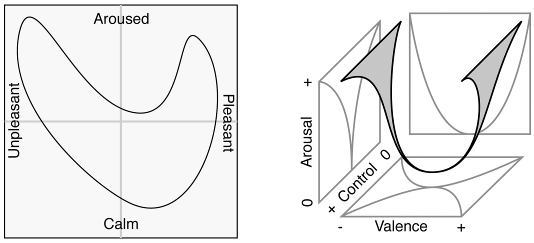


Figure 1.1: A. Russell's (1980) circumplex model of affect

This model was later modified by Russel and Lisa Feldman Barret, which they described as representative of core affect, which are the most elementary feelings that need not be directed toward anything. Different prototypical emotional episodes, or clear emotions that are evoked or directed by specific objects, can be plotted on the circumplex, according to their levels of arousal and pleasure (Russell et al., 1999).

Another model of emotion appeared in 1992. This two-dimensional model consists of vectors, that point in two directions. The vector model assumes that there is always an underlying arousal dimension and that valence determines the direction in which a particular emotion lies.



(a) 2D representation (b) 3D representation

Figure 1.2: Vector model of emotions

The positive activation – negative activation (PANA) was originally created in 1985 by David Watson and Auke Tellegen. It suggests that positive and negative affect are two separate systems. Like in the vector model, states of higher arousal tend to be defined by their valence and states of lower arousal tend to be more neutral in term of valence. In the PANA model, the vertical axis represents low to high positive affect and the horizontal axis represents low to high negative affect. The dimensions of valence and arousal lay at a 45-degree rotation over these axes (Watson et al., 1985).

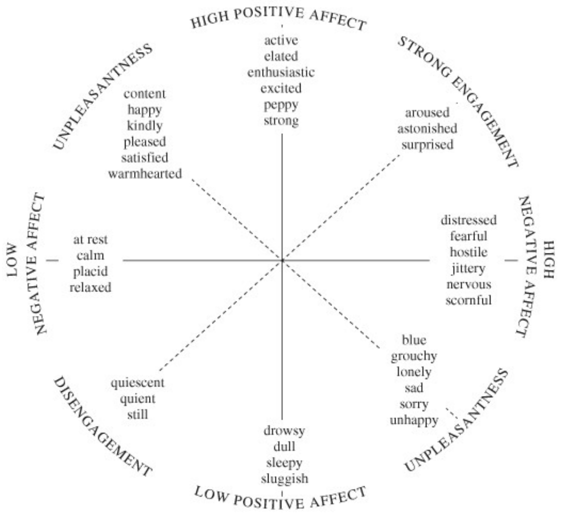


Figure 1.3: Consensual (PANA) model of emotion

In 1980, Robert Plutchik constructed a wheel of emotions. This model is a hybrid of both basic-complex categories and dimensional theories. Emotions are arranged in concentric circles, with the more basic emotions on the inner circles, while the outer circles are occupied by complex emotions. Notably, outer circles are also formed by blending the inner circle emotions. Plutchik suggested 8 primary contrasting pairs of emotions. Joy/sadness, anger/fear, trust/disgust and surprise/anticipation. Like colors, primary emotions can be expressed at different intensities and can mix with one another to form different emotions (Plutchik, 1988).

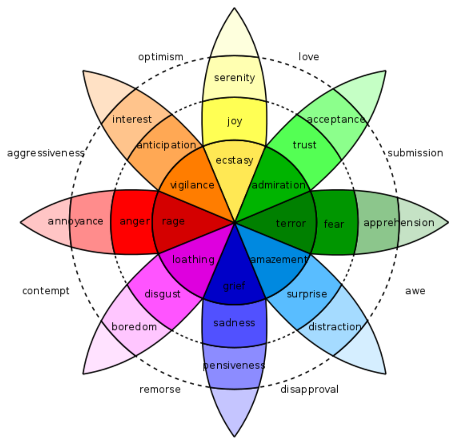


Figure 1.4: Plutchik's wheel of emotions

The PAD emotional state model was developed by Albert Mehrabian and James A. Russel. It uses three numerical dimensions, **P**leasure, **A**rousal, and **D**ominance to represent all emotions (Mehrabian, 1980). Initially it's use was in a theory of environmental psychology, the core idea being that physical environments influence people through their emotional impact (Mehrabian et al., 1974). Subsequently it was used by Peter Lang to propose a physiological theory of emotion (J. Lang et al., 1990). Furthermore, it was also used by Russel to develop a theory of emotional episodes (Russell, 2003). The Pleasure-Displeasure Scale measures how pleasant an emotion may be. Anger and fear are, for instance, unpleasant emotions and thus score high on the displeasure. Contrarily, joy is a pleasant emotion. The Arousal-Nonarousal Scale measures the intensity of emotion. For instance while both anger and rage are unpleasant emotions, rage is much more intense than anger. Boredom, while also an unpleasant state, has a low arousal volume. Lastly, the Dominance-Submissiveness Scale shows the dominant nature of the emotion. While both fear and anger are unpleasant emotions, anger is dominant, but fear is a submissive emotion (Mehrabian, 1980). A more

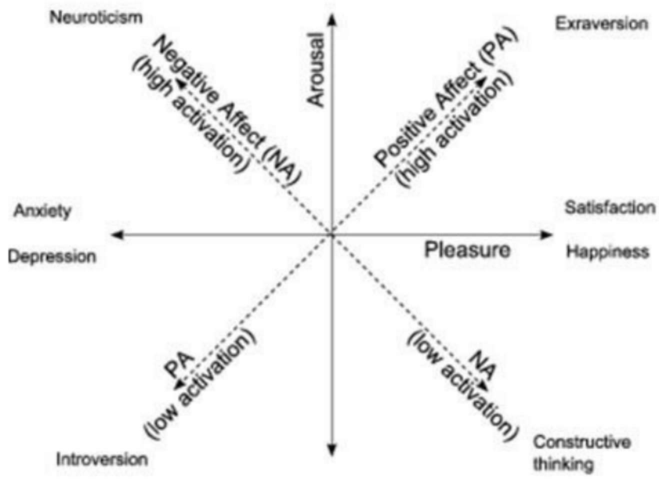


Figure 1.5: PAD emotional state model

abbreviated version of the PAD model has also been used in organizational studies where the emotions towards specific entities or products are measured. It uses just 4 values for each dimension, providing only 64 values for emotions (Ashkanasy et al., 2008).

An example of three-dimensional models, the Lövheim cube of emotion was presented where the signal substances (dopamine, noradrenaline and serotonin) form the axes of a coordinate system, and the eight basic emotions according to Tomkins are placed in the eight corners. As shown on the figure below, anger is produced by the combination of low serotonin, high dopamine and high noradrenaline. Conversely joy is a product of high serotonin, high dopamine and low noradrenaline. Since none of the axis is identical to valence [1], the cube seems somewhat rotated when compared to other models (Lövheim, 2012).

Most recently Cowen and Kelter, researchers from University of California, Berkeley introduced a statistically derived taxonomy of emotion. (Cowen et al., 2017)

[1] pleasantness

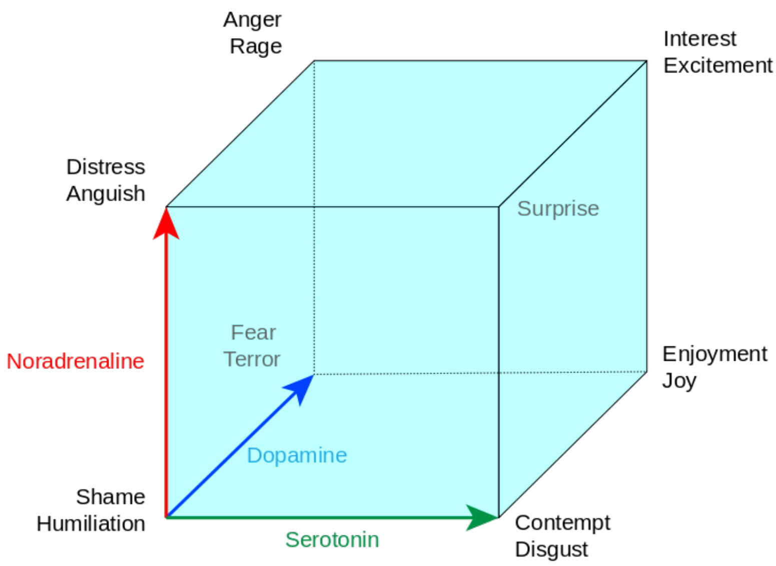


Figure 1.6: Lövheim cube of emotion

> Across self-report methods, we find that the [2185] videos [selected and shown to volunteer subjects] reliably elicit 27 distinct varieties of reported emotional experience. Further analyses revealed that categorical labels such as amusement better capture reports of subjective experience than commonly measured affective dimensions (e.g., valence and arousal). Although reported emotional experiences are represented within a semantic space best captured by categorical labels, the boundaries between categories of emotion are fuzzy rather than discrete. By analyzing the distribution of reported emotional states we uncover gradients of emotion—from anxiety to fear to horror to disgust, calmness to aesthetic appreciation to awe, and others—that correspond to smooth variation in affective dimensions such as valence and dominance. Reported emotional states occupy a complex, high-dimensional categorical space

More dimensional models of emotion have been developed, though there are just a few that remain as the dominant models currently accepted by most (Rubin et al., 2009). There have been observed great cultural differences in the way in which emotions are valued, expressed and regulated. The social norms for emotions, like the frequency with or circumstances in which they are expressed also vary drastically in diverse cultures. An important piece of evidence that disputes the universality of emotions is language. Emotions such as the schadenfreude [2] in German and saudade[3] in Portuguese are commonly expressed in emotions in their respective languages, but lack an English equivalent. Thus it is reasonable in our research to scale back on the complex, culturally influenced emotions and focus on the more primal, basic emotions, that may be more quantifiable by studying the physiological markers and responses in subjects.

[2]The experience of pleasure, joy, or self-satisfaction that comes from learning of or witnessing the troubles, failures, or humiliation of another.

[3]Deep emotional state of nostalgic or profound melancholic longing for an absent something or someone that one loves.

1.3. Physiological responses of emotions

In order for us to be able to detect and recognize emotions from the data samples, we need to asses which physiological effects of emotions we want to capture. Therefore, we need to divide our standard basic emotions depending on the combination of kinds and intensity of effects they have on human body. There is a difficulty with dealing with physiological markers of emotions in that not all emotions do perceivably alter the physiology of the subjects. That is the reason, why we need to supplement this data with the facial expressions or, as we have tried to confirm, ocular movements.

Anger is one of the emotions with more pronounced physiological signs. It comes along with faster and deeper breathing (Philippot et al., 2010), increased heart rate, blood pressure, perspiration and tensing of muscles. Fear, on the other hand, shares most of the surface physiological marks with anger, such as the accelerating breathing rate, heart rate and muscle tension, but facial expression and body language are vastly different. Even deeper markers, like the cortisol levels differ after subjecting a person to these stressors (Moons et al., 2010). Joy, sadness, disgust and surprise are similar to each other in their difficulty to asses using pure physiological markers and therefore requiring additional information, usually in form of facial expression.

1.4. Current approaches in detecting and classifying emotions

As we've described motion recognition is an important object of studies in today's psychology, with many potential uses and applications. Correctly assessing and recognizing subject's emotion can lead to better understanding it's motivation and inner working. Data gained through methods described below can be used to assess the effectiveness of marketing, comprehensibility of lectures, usability of user interfaces, measure of impact of psychological therapy, etc. Previous implementations of emotion recognition technology often have had a multitude of disadvantages, which prohibited it's daily and widespread usage. Therefore, we have set upon creating a solution, that is modular, reasonable to wear for prolonged durations of time and still maintains a degree of reliability in captured data. We can do so by using an array of data resources, that complement each other, diminishing their disadvantages and reinforcing confidence.

One particularly rich resource for data on human emotions is the brain. In 2015 a group of researchers in India published a paper on a system using EEG signals as input, Independent Component Analysis [4], Kernel Destiny Estimation [5] and an Artificial Neural Network to transform the inputs into meaningful outputs. They observed better results for clustering of EEG and ECG data stream (Lahane et al., 2015). Similar approach was taken by researchers in China. Main difference in their approach is that they first applied EMD [6] strategy to split EEG signals into a series of intrinsic mode functions, which were then fed as

[4] A statistical procedure used for splitting up a set of mixed signals into its sources

[5] A method used for feature extraction of signals by computing density estimate using kernel-smoothing method

[6] Empirical Mode Decomposition

sample entropies and as feature vectors into SVN[7] classifier for testing and training. With this approach, they claim to have reached accuracy levels of 94.98% for binary-class tasks and 93.20% for the multi-class task on DEAP database (Zhang et al., 2016). Also in 2016, researchers from the Duke University, North Carolina demonstrated an emotional recognition technique using functional MRI with results, that brain-based models may, in future, allow us deeper understanding and assessing emotional status in clinical settings, particularly in individuals incapable of providing self-report of their own emotional experience (Kragel et al., 2016). These techniques are, however, impossible to replicate on greater scale and in the context of a classroom, or other commonplace environment.

Another indicator of the subject's emotional state is heartbeat. Research published in May 2013 in International Journal of Engineering Trends and Technology shown compelling data gathering by means of ECG[8] and shown differences in ECG signal in subjects in chosen emotional states. [9] (Shalini et al., 2013). More complex approach was taken by researchers at University of Calabria in collaboration with Washington State University. Instead of applying a single or a few sensors to study physiological states, they used a whole BSN[10] Such networks can include accelerometers, gyroscopes, pressure sensors for body movements and applied forces, skin/chest electrodes (for electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), and electrical impedance plethysmography (EIP)), (PPG) sensors, microphones (for voice, ambient, and heart sounds), scalp-placed electrodes for electroencephalogram (EEG) (Gravina et al., 2016). Albeit they were not focusing primarily on emotion recognition, this survey shows consequential advancement in the state-of-the-art body data collection, especially in the data fusion techniques. Similar approach using a variety of sensors and data sources was also taken by Mosciano et al., 2017 to reasonably accurately classify the two dimensions of affect both normal and simulated critical working conditions.

An interesting approach to emotion detection and classification is based upon speech patterns and variations and are better suited for emotions, which are otherwise hard to physiologically measure, such as sadness and joy. One study shows, that speech signal and feature distances of letters and words vary depending on the mood and emotional state of the subject. The study was done upon the sample size of 30 people, however, researchers point out, that for getting better accuracy, one should consider the data collected from one person rather than considering the data from a group of people (Davletcharova et al., 2015).

In terms of evaluating arousal, respiration-based emotion recognition shows promise. A study in China showed, that using respiration data to evaluate valence and arousal levels of Russel theory, they reached classification accuracy of valence and arousal at 73.06% and 80.78%, respectively (Zhang et al., 2017). When compared to other studies using ECG or EEG data, the accuracy of valence levels are not exceptional, however the classification accuracy of arousal better than most other approaches.

[7] Support Vector Machine
[8] Electrocardiography
[9] This study was limited to joy, sadness, fear and anger
[10] Body Sensor Network, specialized Wireless Sensor Network applied to the whole human body.

A study on thermal behavior of anger, disgust, fear, joy and sadness was carried out in 2016. When an emotion occurs a change in facial temperature appears due to the blood flow that the body emits through blood vessels in the subcutaneous area (Ioannou et al., 2014). For example, research focused on the emotion of joy, in other words, when a subject is smiling, it has been found that the temperature of the nose and forehead decreases during this event (Salazar-Lopez et al., 2015). Biomedical thermal images of the facial expressions of 44 subjects were captured experiencing the five studied emotions, with results of this test at 89.9% success rate (Cruz-Albarran et al., 2017).

Another novel approach was experimented with by researchers from American University of Sharjah, United Arab Emirates. They have created a software touch keyboard, that was installed on Android smartphones, which then have been collecting sensor data while users were typing on the keyboard. As they have been typing, he or she were prompted to indicate their current emotional state, which then tagged the sensor data collected for the particular user. Afterwards the data was classified by multiple machine learning algorithms to find the best classification method. Based on ROC[11] and Precision-Recall curves, it was concluded that both J48 and Multi-response linear regression performed well. This system demonstrates that it is possible to enable emotion recognition on mobile phones using built-in sensors (Zualkernan et al., 2017). More research is, nevertheless, needed to precisely ascertain the accuracy and applicability of such solution in common practice.

One approach seems to be very promising, especially due to it's implementation in commercial solutions and services. That approach is based on facial expression evaluation and it is used by a wide variety of software vendors and research institutions. One such research has used Microsoft Kinect for 3D face modeling with a goal to computationally recognize facial expressions of seven basic emotional states: neutral, joy, surprise, anger, sadness, fear and disgust. The subjects of the experiment were six men aged 26-50 years, told to mimic expressions shown on the screen. Researchers used nearest neighbor classifier (3-NN) and two-layer neural network classifier (MLP) with 7 neurons in the hidden layer with output accuracy rate of 96% for random division of data and 73% for "natural" division of data (Tarnowski et al., 2017).

1.4.1 Emotion recognition APIs and SDKs used in commercial environment

There are two questions, that remains unanswered. Is our current method of selecting impulses the correct one? Are we rating approaches the right way? In research mentioned above, there are mainly two types of referential data. One is based on self-identifying emotions, the other on using previously assorted categories of pictures or impulses. As we've mentioned before, self-identifying emotions is a hard task for most people and it is the task, that we aim to solve. Also, is the methodology we use, to personally evaluate emotions the correct one? We usually refer to the previous evaluations, that trace back to psychologist and we take their emotion assessments at face value. It might be wise, that we should ignore previous results and rather try to classify and categorize emotions from ground up and

[11]Receiver Operating Characteristic

later compare them with historical data. Finally, most of the researches delving into face expression-based emotion recognition declare their statistics based upon the success rate of recognizing simple expressions, not emotions themselves.

2. Data gathering methodology

2.1. Hardware

2.2. Software

3. Data evaluation

4. Results

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