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Emotion-Based Painting Image Display System

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ABSTRACT
As mobile devices have tremendously developed, people can now get sensor data easily. These data are not only physical data such as temperature, humidity, gravity, acceleration, etc. but also human health data such as blood pressure, heart pulse rate, etc. With this information, Internet of Things (IoT) technology has provided many systems to support human health care. Systems for human health care support physical health care like checking blood pressure, pulse rate, etc. However, the demand for physical health care as well as mental health care is increasing. So, a system, which automatically recommends a painting to users based on their feeling, is proposed in this paper. Using a smartphone application, users take a self-portrait. Then, the application reads the user's facial expression, and obtains an Arousal-Valence (A.V.) emotion value. Also, the application has a database of paintings with A.V. value in advance. To create this database, we extracted many features from various paintings and estimated their A.V. value using regression analysis. When users reach home, the application detects it automatically using GPS information, and shows the painting that best suits the user's emotion, based on the extracted A.V. value. Thereby, users can get a feeling of relaxation by admiring the painting.

KEY WORDS: Aesthetic analysis, Arousal-Valence, Attributes of Paintings, Emotional care, Emotion of Paintings, Internet of Things

1 INTRODUCTION

NOWADAYS, people easily obtain various sensor data from mobile devices like mobile phones, tablet pc, etc. This has made Internet of Things (IoT) popular in our lives by making everything intelligent, such as smart-home, smart-car, smart health-care and etc. Especially, with people becoming health conscious, many health-care systems based on IoT are being developed. However, general health care applications provide only physical care, and a very few systems are available for mental health. With the need for good mental health as well as physical health increasing, the mental health care system becomes more important.

Therefore, we present a system that can deal with a user's emotion. The purpose of this system is to relax a user by showing a painting depending on their feeling using emotion value. Utilizing IoT, people can get matching paintings at home based on their emotions when they were outdoors. In detail, when users take a self-portrait at various times of a day using a smartphone, the system detects their emotion using their facial expression. In addition, the system has a database that consists of numerous paintings and their Arousal-Valence (A.V.) value. The paintings have been studied in advance for estimating emotion depending on the extracted features from paintings. We use machine learning for estimating emotion from any painting. Comparing the emotion of paintings and user's facial expression on A.V. coordinate, the system can recommend the most suitable painting to users. Finally, when the user come back home, the system detects it using GPS information from mobile device and shows the painting that can make the user relax and feel better. Consequently, the user can feel happier even before they enter the home by admiring the recommended paintings.

The main contributions of our study are as follows. First of all, we propose an emotional care application based on IoT technology for humans. GPS information is used to detect the user's location.

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Second, we suggest a high accuracy emotion prediction model based on paintings. To do this, the artistic features are defined and used, which are the physical features for predicting emotion of paintings. These artistic features are color combination, composition, symmetry, and rule-of-third. We use regression analysis method to obtain the features. We calculate the predictive accuracy and validated our emotion prediction model. Finally, we prove that our system relaxes the users and make them feel good by showing them recommended paintings based on their emotion by conducting user studies.

The rest of this paper is organized as follows. An overview of related works on IoT applications and extracting emotion from paintings are explained in Section 2. In Section 3, our system that automatically detects facial emotions and recommends paintings using GPS information is proposed. Next, we define artistic features that are related with emotion of paintings, and build a regression model in Section 4. In Section 5, we explain results of our experiment and evaluate them. Finally, we summarize our research and conclude our results and discuss future development.

2 RELATED WORK

AS humans can achieve sensor data easily by mobile devices now, IoT technology is rapidly proliferating as mobile devices are becoming indispensable. Thus, IoT technology is expanding to touch almost every aspect of our lives, and supports our well-being extensively. So, there are many studies that suggest IoT applications. Maurer et al. (2006), Wile et al. (2014) and Phan et al. (2015) suggested a health care application for measuring heart rate that provide personalized information for the users. Applications for fitness suggest personalized exercise plans to users based on the data obtained from fitness criteria such as walking distance, speed, and slope tracking through smartphone in Hassanalieragh et al. (2015)'s work. In spite of the increase of interest in physical health, only a few studies have been conducted to treat mental health and emotional issues. Lanata et al. (2015) suggested wearable monitoring system for human's mental health, and M. Nardelli et al. (2015) suggested recognizing emotion system depend on heart rate. These two works proposed monitoring mental system, but there is no recovery system when users are in bad mood. Therefore, in this paper, we aim to develop a system for emotional health care for users. To achieve this, we estimate emotion data from paintings and recommend paintings to users depending on their feelings. It helps users to keep track of their mental health, leading to a happier life.

Studies that predict emotions from photographs rather than paintings have been researched well by Datta et al. (2006), Machajdik et al. (2010), Joshi et al. (2011), and Zhao (2014). Furthermore, Shin et al. (2017) conducted a study to extract emotions from the video. For the production of the music video, the music and video were matched based on emotion. At this time, they divided the video into still shots and calculated the A.V. value of each picture image to extract the emotion. However only a few studies exist that predict emotion from given paintings like Icoglu et al. (2014). Yanulevskaya et al. (2008) extracted emotions from paintings through machine learning using Lab color value and Scale Invariant Feature Transform. They only used the physical features that can be directly obtained from the images. Kang et al. (2018) extracted emotional adjectives through a representative color combination in paintings. Moreover, Lee et al. (2016) mapped the emotional adjective to the Arousal-Valence model of Russell (1980) that can be easily applied to other emotional studies as well. Lee et al. (2016) and Kang et al. (2018) used artistic features for predicting emotions, but they considered only the color. Yanulevskaya et al. (2012) extracted artistic features from paintings, and estimated the positive-negative value from input paintings. However, they used only abstract paintings as input.

Previous researches tend to predict emotions from photographs or from abstract paintings. For prediction of emotions from a painting, only low-level features were used. With physical features, emotion is predictable, but the result can have higher accuracy only with artistic features. For this, we analyze artistic features including color combination, composition, symmetry, and rule-of-third that consist of combination of physical features. Based on these features, we suggest a highly accurate emotion prediction model.

3 DETECTION OF FACIAL EMOTION AND RECOMMENDATION OF A PAINTING FOR MENTAL HEALTH CARE

3.1 *System Overview*

THE system consists of outdoor part and indoor part. In this framework, users take a picture of their faces through smartphones. Figure 1 shows overview of our system application. The application will identify the users' emotions from their facial expression and convert that information into arousal-valence (A.V) value. When the users return home, the system will detect the users' arrival using GPS information from mobile device. Meanwhile, the application finds the best matched painting from a database which has many paintings with A.V value. This database is constructed by regression analysis which will be explained in Section 4. If the users are emotionally bad, the system shows them the paintings, which makes them feel better. If the users are already good, the system further improves their mood by showing them paintings depicting happiness. Hence,

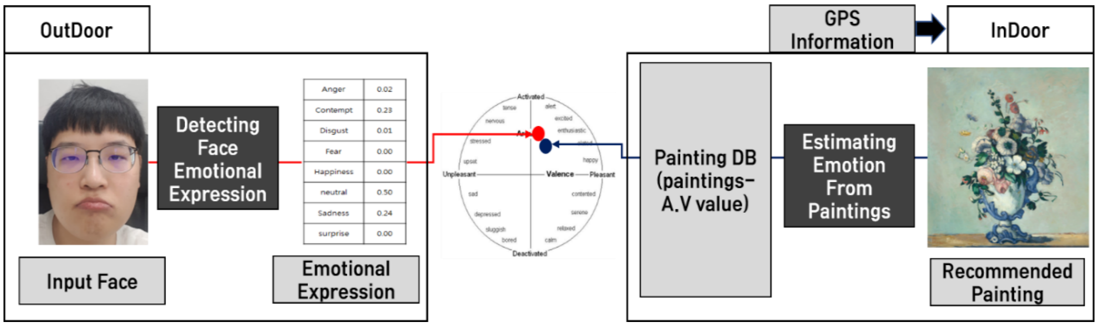


Figure 1. **System Flow of recommending painting to user (left flow is occurred outdoor. When user come back home, device detect it using GPS information, and right flow is occurred.)**

the users feel emotionally relieved and feel good. The following sections discuss each part in detail.

3.2 Function of Mobile Application in Detecting Facial Emotion (Outdoor Part)

Users' portraits must be taken using their smartphones when they want to know their current feeling. After the picture is obtained, the smartphone application recognizes the user's facial expressions and reads the user's feelings. Dachapally (2017)'s method was used for extracting the facial expression. This study had read emotions from 7 different emotions defined in the arousal-valence model. We consider all the 7 emotions and calculate the magnitude of emotion expressed in facial expressions. The emotions are listed below: anger, disgust, fear, happiness, neutral, sadness, surprise. Each emotion has an A.V value, according to Warriner et al. (2013)'s work.

The A.V values of each feeling is respectively as follows: (5.9, 2.5), (5.0, 3.32), (6.14, 2.93), (6.5, 8.48), (3.45, 5.5), (2.81, 2.4), (6.57, 7.44). Then, the system converted the A.V values of each emotion from the photo and sent them to the server. We calculated the A.V values with sum of rate of emotion. Figure 1 shows the result of detected facial expression from photo.

Figure 2(a) is a facial expression showing emotions of neutrality and sadness whose A.V value is (3.5994, 4.1228). Figure 2(b) shows emotions of neutrality and happiness whose A.V value is (5.402, 7.4072).

The emotion detected by the application can be renewed when they take a new portrait. The system calculates the A.V value of last taken picture. When the user returns home, application uses this A.V value to show the best matched painting.

Type of Emotion	Ratio of Emotion
Anger	0.02
Disgust	0.24
Fear	0.00
Happiness	0.00
Neutral	0.50
Sadness	0.24
Surprise	0.00

(a) Neutral, disgust and sadness

Type of Emotion	Ratio of Emotion
Anger	0.00
Disgust	0.00
Fear	0.00
Happiness	0.64
Neutral	0.36
Sadness	0.00
Surprise	0.00

(b) Neutral and happiness

Figure 2. **Result of Detecting Facial Expression. (Images are result of facial detection in mobile application. It shows best 3 emotions in large ratio order. The table shows the real data ratio of emotion from input image.)**

3.3 *Function of the System in Recommending Suitable Paintings (Indoor Part)*

To use this system, the users must register their home GPS information in the application in advance. The system continually updates the GPS information to check the user's current location. Finally, when the application detects the user to be at home through GPS data, it finds the painting which best matches with the A.V value of the latest facial expression from painting-A.V database.

We emphasize two things here. First, users will feel a sense of psychological stability when they see a painting that depicts their feel. Second, if the user's mood is bad, a positive image should be shown to make them feel better. In other words, the user's A.V value and the paintings (A.V values should match).

In this study, we used the Samsung Galaxy S8 smartphone and got the GPS information. Our smartphone application has been developed on Android platform. Also, if user have the other display device such as a digital frame, they can be provided by showing paintings from bigger screen than mobile phone. Figure 3 shows the example of showing paintings from a digital frame.

Figure 3. Showing by other display device (digital frame)

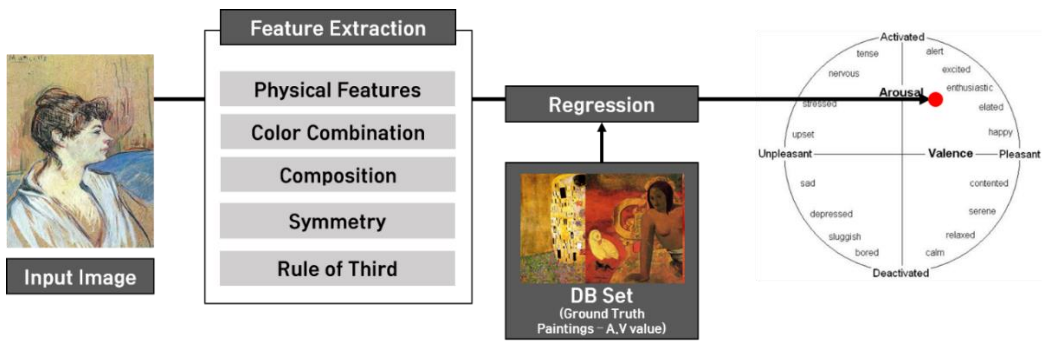


Figure 4. Estimating Flow for A.V Emotion Value from Input Image

4 EMOTION EXTRACTION FROM PAINTINGS

IN order to predict emotional values from paintings, we go through two steps in this study. One is the feature extraction, and the other is the regression. The feature extraction phase selects features associated with the given paintings and emotion. These features include the adjective models of color combination, a set of lines of drawings, and the shape of the structure such as symmetry and rule-of-third. The regression phase is divided into construction of the database set and the re-gression Model, which is used to analyze the painting. Then, several paintings of various impressionist painters were gathered and the database was compiled using A.V values through user study. Using the gathered ground-truth values, painting, and characteristic values, the regression model was constructed to estimate arousal-valence value. Figure 4 shows the system flow of estimation of emotion.

4.1 *Feature Extraction from Paintings*

4.1.1 Physical Features

In this research, the physical features used in Zujovic's et al. (2009) work, were used for regression. After changing the paintings to grayscale, the average of saturation and the brightness of image are obtained. Additionally, the wavelet is obtained from the paintings using Liu et al. (2007)'s method. Four features are obtained from the extracted wavelet such as low-horizontal, low-vertical, low diagonal, and average horizontal.

4.1.2 Color Combination

Color is the most important factor in estimating emotion from paintings, as it is an intuitive feature that appeals visually. So the color combination from the paintings are considered. For this, method of Lee et al. (2016) was modified. They predicted the emotions using the representative colors of the painting. To achieve this, they extracted a representative 3 color combination that are defined by

Kobayashi (1981). Warriner et al. (2013) defined 935 color combinations with emotional-adjectives. Lee et al. (2016) got the emotional adjectives from paintings using Warriner (2013)'s work, and then projected the emotional-adjectives into A.V coordinates. Their method for finding a representative 3-color combination from painting has been used in this study. For example, Figure 5 shows that the color scheme of "intimate" is determined for given input image by using Lee et al. (2016)'s method. Further, in this research, the physical features that are used in Zujovic et al. (2009)'s work for regression are also used in this research. After changing the paintings to grayscale, the average of saturation and brightness of all the images are obtained., The wavelet from the paintings are also obtained using Liu et al. (2007)'s method. The four features from extracted wavelet which are low-horizontal, low-vertical, low- diagonal, and average-horizontal are used in this research.When the 3 color combination that represents "intimate" Figure 6 is projected, (7.3, 2.9) in warm-cool/soft-hard coordinate and (5.8, 2.9) in clear-grayish/soft-hard coordinate can be obtained. In this study, the values of each coordinate system were defined as 1 to 9, and the value of "intimate" can be obtained as, (WC, SH, CG) = (7.3, 2.9, 5.8).

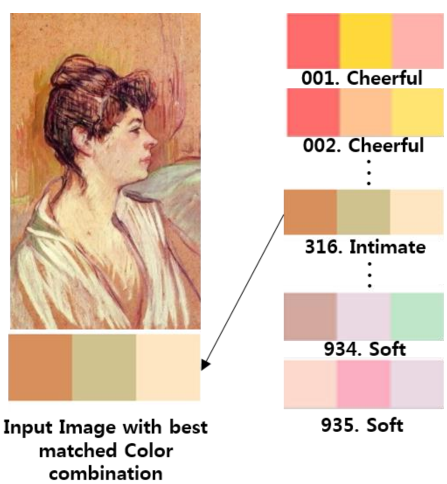


Figure 5. Overview of Extracting Color Combination Value.

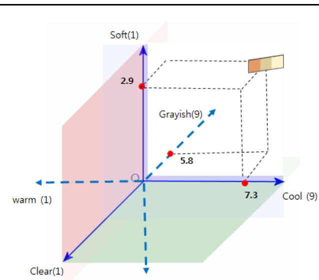
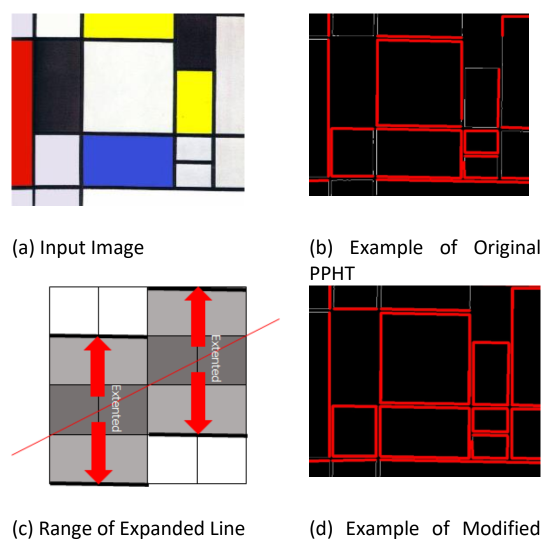


Figure 6. "Intimate" on the Color Image Scale of Kobayashi (1981).

4.1.3 Composition

From a given painting Figure 7(a), the straight lines are extracted as shown in Figure 7(a). Many lines were not extracted from a straight line of Mondrian's painting, as they had errors. The lines are not perfectly straight, but are perceived to be straight by observers. Thus, the existing linear extract range was increased and Progressive Probability Hough Transform (PPHT) was performed. As shown in Figure 7(c), it is defined as a single pixel from the reference pixel to form a straight line connecting all the lines. Figure 7(d) shows that the lines are extracted better using modified PPHT than by original PPHT algorithm Figure 7(a).

The value of lines was numberized Figure 7(d) after the lines were defined as perpendicular to the horizontal lines which were 0 to 30 degrees, diagonal lines which were 30 to 60 degrees, and vertical lines which were 60 to 90 degrees. Line Score was used as a feature for regression that is sum of intensity of pixels consisting of lines through, equation 1. In the equation, k denotes the 3 directions; horizontal, diagonal, vertical. To define the magnitude of the variation in the pixels across the entire image, the cumulative distribution function values based on the mean variation (μ_{total}) and the standard deviation (${\sigma^2}_{total}$) were defined as the pixel score. Figure 8 shows the extracted lines in paintings where the value of S_k in equation 1 is higher than threshold value.



(a) Input Image
(b) Example of Original PPHT
(c) Range of Expanded Line
(d) Example of Modified PPHT

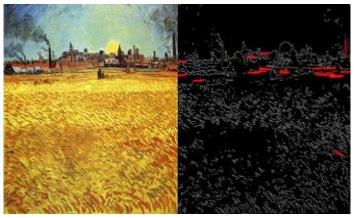
Figure 7. Modified PPHT – "Composition in red, yellow, blue and black", Pieter-Cornelis Mondriaan, 1921

$$S_k = \frac{\sum LineScore_k}{MaxRadius} \quad k \in \{V, D, H\}$$

$$LineSocre_k = \sum PixelScore$$

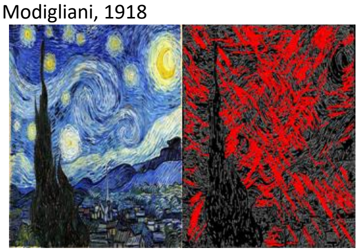
$$\text{MaxRadius} = \sqrt{width^2 + height^2}$$

$$PixelScore_i = CDF(\mu_{total}, \sigma^2{}_{total}, PixelGradieny_i) \quad (1)$$



(a) Image that has a relatively large horizontal intensity in database (0.782, 0.00, 0.046)- “Wheat field at sunset”, Vincent Van Gogh,1888

(b) Image that has a relatively large vertical intensity in database (0, 1.7892, 0.0539)- - “Woman with blue eyes”, Amedeo Modigliani, 1918



(c) Image that has a relatively large diagonal intensity in database (7.0393, 0.0404, 13.0451,)- “The Starry Night”, Vincent Van Gogh, 1889

Figure 8. Example of Extracting Composition Intensity

4.1.4 Symmetry

The basic symmetry defines the amount of equality based on the center. In paintings, this symmetry refers to visually similar objects or colors. The greater the symmetry, the more the viewers feel comfortable on viewing the paintings and vice versa. Symmetry consists of a visual element, and was calculated using two factors that could affect the visual effects. One is the symmetry based on color, and the other is the symmetry based on entropy.

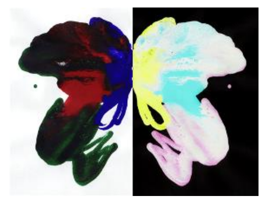
Color based Symmetry: For calculating symmetry based on color, it was defined that high-symmetry image has similar colors when the painting is divided either horizontally or vertically by half and vice versa For this purpose, based on the central axis, the degree of symmetry was measured by calculating the differences between the pixel values at the same distance. The decalcomania images, such as Figure 9 (a), are images with maximum symmetry, and Figure 9 (b) has the lowest symmetry.

Equation 2 gives the formula to calculate symmetry. P (x, y) represents the RGB value of the pixel in x and y positions, and the average of each channel was calculated. The larger the pixel values of the pixel in the same distance, the lower the symmetry, and the lower the pixel values, the greater the symmetry.

$$Sym_h = \sum_{x=0}^{height} \sum_{y=0}^{width/2} p\left(x, \frac{width}{2} - y\right) - p(x, \frac{width}{2} + y)$$

$$Sym_w = \sum_{x=0}^{\frac{height}{2}} \sum_{y=0}^{width} p\left(\frac{height}{2} - x, y\right) - p(\frac{height}{2} + x, y) \quad (2)$$

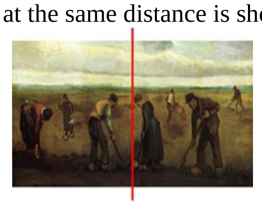
(a) Image that has maximum horizontal symmetry



(b)Image that has minimum horizontal symmetry

Figure 9. Assumed maximum and minimum symmetrical images

Figure 10 shows paintings with relatively large horizontal symmetry value and small value in our database based on the calculated result through the equation 2. Figure 10(a) has similar halves because the values of each color are similar to that of the vertical axis. Therefore, the horizontal symmetry is large, calculated as 0.0792. On the other hand, in Figure 10(b), the difference in luminance between the values at the same distance is shown.



(a) Image with relatively large symmetry (0.0792) - “Wheat Field with Cypresses”, Vincent Van Gogh, 1889

(b) Image with relatively small symmetry (0.4644)- “Head of a Peasant”, Vincent Van Gogh, 1884

Figure 10. Example of Color based Symmetry

Entropy based Symmetry: Color-based symmetry does not account for compositional factors because only color values are defined symmetrically. In order to measure and evaluate symmetry according to the overall structure, the symmetry based on entropy was derived.

To calculate this, Jensen - Shannon Diversity from Endres et al. (2003) was used. The higher the entropy, the higher the symmetry and the lower the entropy the lower the symmetry. The value M(n) of the equation 3 shows the calculation of structural symmetry. Since the results of the formula are distributed between 0.90 and 1.00, data was normalized from 0 to 10 to digitize them. H(x) is the enhancement of the entropy of each area according to the probability of color.

$$M_j(n) = \frac{\sum_{i=1}^{n} \Pi_i H(p_i)}{H_p}$$

$$\mathrm{H(x)} = -\sum_{x \epsilon X} p(x) log p(x) \tag{3}$$

(a) Input image

(b) Segment for horizontal symmetry

(c) Segment for vertical symmetry

Figure 11. **Entropy based Symmetry - "Poppy Field", Claude Monet, 1873.**

(a) Image with relatively high vertical symmetry (6.97) -"Waterloo Bridge in London", Claude Monet, 1902

(b) Image with relatively small vertical symmetry (2.11) - "Riverbank at LavaCourt", Claude Monet, 1879

Figure 12. **Example of Entropy based Symmetry**

Figure 11 demonstrates how to divide the given image. Figure 11(a) shows the input image. Figure 11(b) shows division of image for calculating vertical structural symmetry, and Figure 11(c) shows division of image for calculating horizontal structural symmetry. The value of Figure 11(b) is 3.49 and the value of Figure 10(c) is 7.59. In the case of Figure 11(b), the two sections differ in relation to each other. Therefore, symmetry is very low. Conversely, the two sections are very similar in Figure 11(c), and hence the value of symmetry is high. Figure 12 shows paintings that have high and low value of structural symmetry. As shown in Figure 12(a), left and right halves are similar, and the result is 6.97. On the other hand, in Figure 12(b), trees are found in the left half, near the centerline, while the right half is dissimilar. Hence, the value is 2.11.

4.1.5 Rule-of-Third

Position in the image is a feature that highlights the intention and the themes depicted by the image. Rule-of-third is a technique that can highlight the position. This is one of the most used techniques that provides stability of the image in photography or design. In this research, this rule is defined as a feature of stability. Rule-of-third divides the given image by four lines as shown in Figure 13. The object in the third point of each area is relatively stable. A systematic approach to application of rule-of–third was done in this research. The characteristic value of objects in one of the lines 1, 2, 3, and 4 was defined by the line and was calculated. For example, Figure 12 shows a flower on a horizontal line. Now, the rule-of-third must be used to calculate the values.

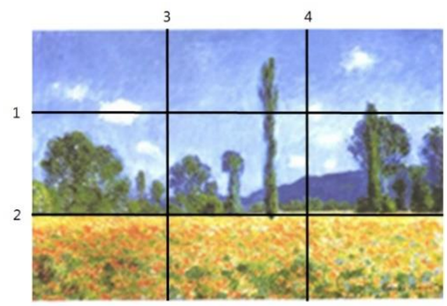
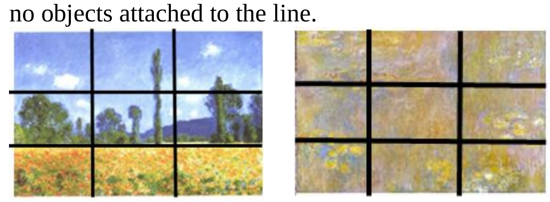


Figure 13. Rule-of-Third.**

Therefore, the structural similarity of each part of Figure 13, was compared. The method of calculating structural similarity is given in equation (4) of 3.2.3. The structural similarity of each part is different, meaning that the two spaces are divided into separate halves, which can be interpreted as follows. Based on line 1, line 2, line 3, and line 4, the structural symmetry of Figure 12 is respectively (7.12, 3.21, 4.17, 4.17). The smallest value, i.e. the least symmetrical value, is the equivalent value of rule-of-third. Because, the painting follows this characteristic based on the thumb rule. Figure 14(a) and Figure 14(b) show examples of large and small rule-of-third in the database. In the case of (a), the two sides have a fine layout of the flower beds and the sky, and the formation of a high profile is not the same, but in the case of (b), the whole picture has spread out, there are no objects attached to the line.



(a) Image with relatively large Rule-of-Third (3.21)- "Poppy Field in Giverny", Claude Monet, 1891

(b) Image with relatively small Rule-of-Third (8.32)- "Sea-Roses", Claude Monet, 1916

Figure 14. **Example of Rule-of-Third**

4.2 Regression Analysis

4.2.1 Data Collection

The paintings were collected such that they could be sorted out easily. Impressionist paintings, which clearly depict the color and the texture were collected. Modern art was also collected for the interpretation of social background of such arts. In the case of the 57 paintings that were collected, the arousal-valence value of each painting was calculated through the mechanical tune of Amazon Mechanical Turk (MTurk). Using the SD act, each score was collected from 1 to 9. This process was repeated 1,000 times for 57 chapters and approximately 90 arousal-valence values per paintings were collected, except redundant and unreliable data. Our database is listed in Appendix

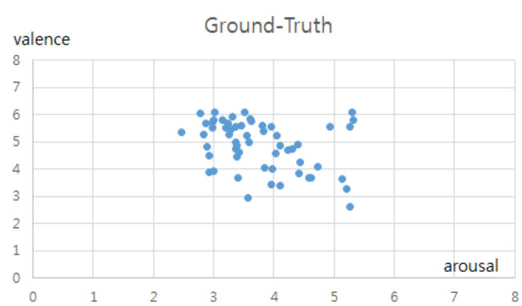
4.2.2 Linear Regression

The features used for regression are listed in Table 1. The equation (4) shows the regression model. x is the value between arousal and valence that range from 1 to 9, and a is the feature matrix. We find the minimum weight value and build the prediction model.

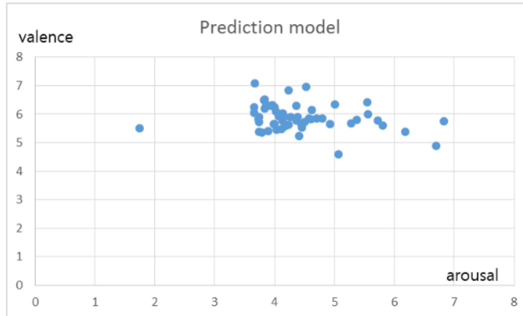
$$\min(\sum_{i=1}^{n}(x^i - \sum_{j=0}^{k} w_j\, a_j^i)^2 \qquad (4)$$

Table 1. Feature List for Regression

Type of Features	Feature name (# of features)
Physical value	Wavelet_LH, LV, LD, AH(4), AVE_saturation, brightness(2)
Color information	Warm-Cool, Soft-Hard, Clear-Grayish (3)
Composition	Vertical, Horizontal, Diagonal(3)
Symmetry	H_Symmetry_Color/Entropy(2), V_Symmetry_Color/Entropy(2)
Rule of Third	Rule-of-Third(1)



(a) Ground-Truth distribution



(b) Prediction distribution

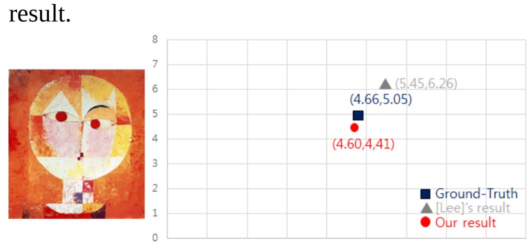
Figure 15. Regression Result

5 EXPERIMENTAL RESULTS

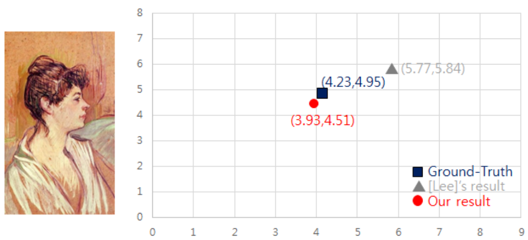
5.1 Estimating Emotion from Paintings

A computer with Intel Core i7, 16GB RAM, Windows 7 64 bit, Android SDK and Visual C++ were used to implement our system, especially for extracting the features and estimating the A.V value. For user-study, MTurk is used. Extracting features takes only 10 ms for each task, and building regression model takes less than 1 second. Therefore, A.V value can be found from input paintings in a second.

Using the 57 data set, linear regression was performed to predict the results. Figure 15(a) is the mean distribution of the A.V values obtained through MTurk with 57 data. Figure 15(b) is a distribution chart which is predicted and distributed with same 57 data. The predicted accuracy of arousal is 79.4% and the predicted accuracy of valence is 86.5%. Each correlation shown by (0.27, 0.54) validate the relevance of the features used in this study in predicting emotion. The forecast performance of valence is better than the predicted performance of arousal because, on average, there is not much change in valence, even though people scored the valence a lot. Other paintings were mapped into A.V coordinate through our predicting model. Figure 16 is the result of ground-truth, Lee et al. (2016)'s work, and our result.



(a) "Senecio", Paul Klee, 1922



(b) "Portrait of Marcelle", Toulouse Lautrec, 1893~1894

Figure 16. Arousal-Valence Estimation Result (red-G.T, blue –our result, grey – Lee et al. (2016)'s result)

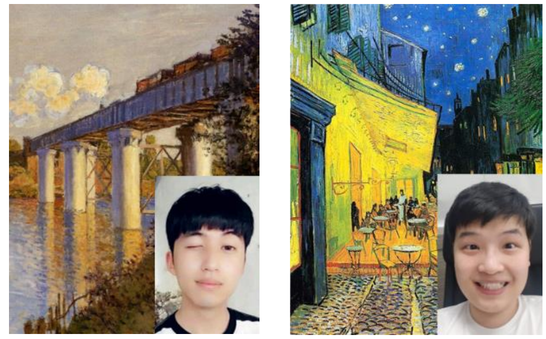
5.2 Recommending Paintings to Users

Provided the A.V value obtained from user's feelings, the system recommended the best suitable paintings to the user, making them feel better. To achieve this, the closest set on A.V coordinate was found through Euclidean distance. However, when the user is already bad, showing paintings of similar mood makes them feel worse. In this case, the opposite value of users' valence data is used. Figure 17 shows the recommended paintings to the user depending on their facial expression. Figure 17(a) shows user with negative facial expression and an image with a refreshing painting. Figure 17(a)'s valence is 4.1228 and the opposite of 4.1228 is 5.8772, because the range of A.V is 1 to 9. The recommended painting was Paul Cezanne's painting, and its A.V value is (3.74, 5.91). Figure 17(b) matches positive facial expression and paintings, and A.V value of the recommended painting is (5.01, 6.33).

(a) Sad face with painting ("Flowers in a Rococo Vase", Paul Cezanne, 1876)

(b) Happy face with painting ("The basin at Argenteuil", Claude Monet, 1872)

Figure 17. Results showing recommended paintings based on user's facial expression. (Shown on the top left is the input facial image.)



(a) Neutral face with painting ("Le Pont du chemin de fer a Argenteuil", Claude Monet, 1874)

(b) Happy face with painting ("Terrasse des Cafes an der Place du Forum in Arles am Abend, Vincent van Gogh, 1888)

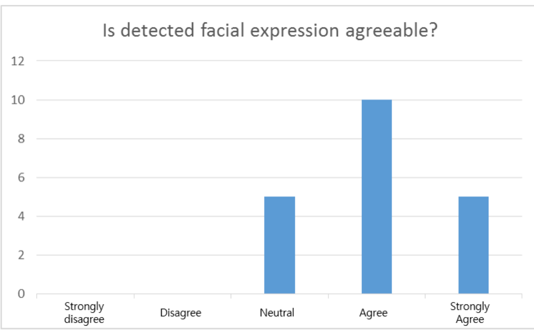
Figure 18. Another results.

Figure 18 is another matching results with face. The face of figure 18(a) get (3.896, 5.382) with 78% neutral, 15% disgust, and 7% happy emotion. Recommended painting is Monet's painting of which A.V. value is (3.70,5.31). The Euclidean distance of two A.V. value is about 0.21 that means they are very close on A.V. coordinate. Also Figure 18(b) gets 99.9% (it means 100%) happy emotion. The A.V. value of 18(b) is (6.5, 8.48), and its recommended painting is Gogh's painting with (5.54, 6.42). The distance of two contents is 2.27 that is relatively large than other distance. This example is limitation of our research, so it is discussed in Section 6 in detail.

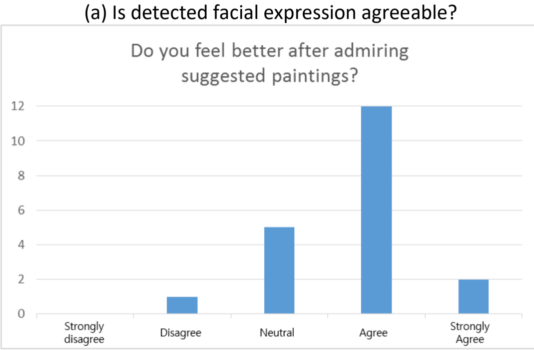
We supposed that the users take photograph by themselves and our system were put into use only after the users return home. But to obtain the user-study data, our application was installed at an office in a university. We pictured the users through the application and asked them to show their emotions and conducted an experiment at the office, for recommending a painting based on their mood, through the system. Participants consisted of 20 graduate students. Half of them are experienced in fine arts and the others were not. We evaluated their feelings and showed them the suggested paintings through our system and then inquired them about the following: (1) Is the detected facial expression agreeable? (2) Do you feel better after viewing the suggested paintings? (3) Do you think that the paintings suit your mood well? We used 5 scales for the answers. 5: strongly agree, 4: agree, 3: neutral, 2: disagree, and 1: strongly disagree.

Figure 19(a) shows the answers to question 1. The answers ranged from 3 to 5, and most people answered "agreeable". The average score was 4.00 which means the method used in detecting human's emotion based on facial expression is reliable. Figure 19(b) shows the answers to question 2. The answers ranged from 3 to 5, except one person. The average score was 3.75. 14 people agreed that the painting shown made them feel better. From this result, we can conclude that the recommended paintings make users feel better in most cases. Figure 19(c) shows the answers to question 3. The answers ranged from 2 to 5 and the average score was 3.35. The reason for the relatively low score is that the accuracy of the recommended picture's A.V value was low or the paintings in database cannot cover whole A.V. coordinate. So, some users did not agree that the recommended paintings suited well to their mood. Figure 18(b) is an example of failure matching. We have discussed this in Section 6 in detail, and have suggested a solution as future work.

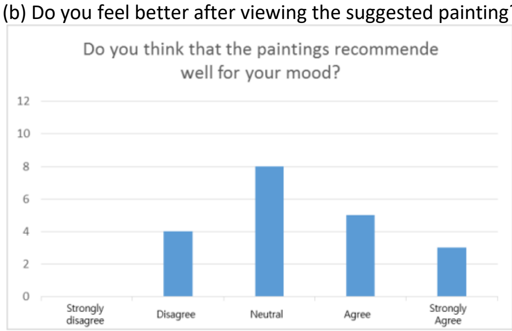
With validation in Section 5.1 and evaluation in Section 5.2, we can conclude that our system predicts the A.V value from paintings well, and suggests the best suitable paintings to users depending on their emotions.



(a) Is detected facial expression agreeable?



(b) Do you feel better after viewing the suggested painting?



(c) Do you think that the paintings well suited your mood?

Figure 19. **User Study Results**

6 CONCLUSION

IN this paper, we provided a system for emotional health-care of humans, through a mobile application. The users' emotions were decided based on their self-portrait. Then we matched these emotions with arousal-valence emotional coordination with paintings that are defined as the artistic features. These artistic features helped in improving the accuracy of the prediction. When the users felt bad, the suggested painting made them feel better. On the other hand, when the users were already happy, the system further improved their happiness.

Our research has the following contribution. First, it recognized the user's face and recommended a suitable painting. We used GPS information to locate the user. This helped the application show paintings automatically when the user arrived home. This can be defined as an emotional health-care for people using IoT. Second, various emotions were extracted from different paintings and various artistic features were used for high accuracy. The paintings were projected onto the A.V coordinate that can be used aesthetically. Finally, we calculated our predictive accuracy and validated our emotion prediction model based on user-study.

However, there is a limitation in predicting emotions. As we mentioned in figure 18(b), there is a problem with painting and facial emotion matching. The largest estimated arousal or valence value is about 7. In contrast, valence value of 100% happy face get 8.48. Range of database cannot cover whole facial expression.

To improve the results of this study, future work must be done, such as: First, it should be supplemented by adding features in use. The regression analysis model we used allowed higher number of features leading to better results. As the characteristics of paintings, texture and shape can be considered as well. In particular, the objects portrayed in the paintings can greatly affect the appeal of the paintings. If the sensitivity of the object portrayed in the painting is considered, the results can be predicted with more accuracy. There is a limitation to the reliability of the user-study. This study conducted a user questionnaire through MTurk. Since there are few experts of paintings in computer science field, a clear analysis of the quality of the painting was not carried out. If the study is performed utilizing aesthetics experts or an expert of paintings, a prediction with higher accuracy can be expected.

7 ACKNOWLEDGMENT

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9 APPENDIX

Index	Name of Painting, Painter
1	Senecio, Paul Klee
2	L'Arlesienne, Vincent van Gogh
3	Girl in front of Mirror, Piccaso
4	The Large Bathers, Renoir
5	Portrait of Marcelle, Lautrec
6	April, Denis
7	The Kiss, Klimt
8	Vairumati, Paul Gauguin
9	The Promenade, Claude Monet
10	La Creation de l'homme, Marc Chagal
11	Deer, Marie Laurencin
12	Women Sonando Evasion, Joan Miro
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14	Woman with Blue eyes, Amedeo Modigliani

Index	Name of Painting, Painter
15	Woman with a Fan, Piccaso
16	Nude Descending a Staircase No 2, Marcel Duchamp
17	Camille monet on a garden bench, Claude Monet
18	Jeune garcon au gilet rouge, Paul Cezanne
19	Young Girls at the Piano, Renoir
20	Torso, effect de soleil, Renoir
21	Le Moulin de la Galette, Renoir
22	Two Sisters, Renoir
23	The potato eaters, Vincent van Gogh
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25	Flowers in a Rococo Vase, Cezanne
26	Mixed Flowers in an Earthenware Pot, Renoir
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32	The bridge at argenteuil, Claude Monet
33	Poppy Field, Claude Monet
34	Cliffs of Les Petites-Dalles, Claude Monet
35	Garden at Sainte-Adresse, Claude Monet
36	The Garden at Argenteuil, Claude Monet
37	The Water-Lily Pond, Claude Monet
38	L'Estaque, Paul Cezanne
39	Die Brucke von Langlois in Arles mit Wascherinnen, Gogh
40	Terrasse des Cafes an der Place du Forum in Arles am Abend, Vincent van Gogh
41	Starry Night over the Rhone, Vincent van Gogh
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43	Wheat Field with Cypresses at the Haude Galline near Eygalieres, Vincent van Gogh
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47	Wheatfield with crows, Vincent van Gogh
48	The Sower, Vincent van Gogh
49	The woman in the atelier, Jaewoo Yoon
50	The still object of summer, Jaewoo Yoon
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52	The rose, Jewoo Yoon
53	The lying nude woman, Jaewoo Yoon
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55	The fall crop, Jaewoo Yoon
56	The night atelier, Jaewoo Yoon
57	The sunset of HongIsland, Jaewoo Yoon

10 NOTES ON CONTRIBUTORS

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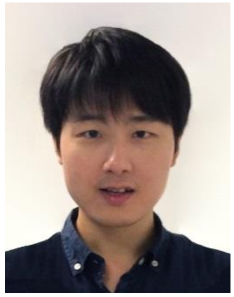

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