An affective classification approach for detecting emotions evoked in static food images

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Dedication

I dedicate this work to my parents without their support, unconditional love,prayers and motivation i would not be able to acheived this. Thankyou for always pushing me to get better. Secondly to my siblings for motivating me through out the life and believing in me.

Certificate of Originality

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any degree or diploma at National University of Sciences & Technology (NUST) School of Electrical Engineering & Computer Science (SEECS) or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at NUST SEECS or elsewhere, is explicitly acknowledged in the thesis.

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Abstract

To make machine emotionally intelligent and to have affective decision making, emotion is one of the basic human attribute which is used in affective classification . In this research work food images are used to evoke emotions by using principle of art features(emphasis, gradation, variety, symmetry, movement and harmony). These features are extracted from the images to form a feature vector and as a result a food-emotion model is created. Emotional labels to these images are associated with help of valence arousal psychological model. Three classifiers SVM(Support Vector Machine), MLP (Multi-layer Perceptron) and Naive Bayes are used to form a classification model. This classification approach help in forming a 4-label and 3-label model which associate emotional attribute Happy, Relax,Stress and Boring in the food images. With the help of these results decision making become more related to human attribute of emotion. Among all models, 3-label model give accuracy of 58%.

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I admire all of my cousins and friends who never give up their support to me in all aspects of life. Their motivation and kindness help me in accomplishment of my goals.

Yusra Tahir

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Chapter 1

Introduction

Emotions plays vital role in our lives for rational decision making. Love, joy, fear and hatred are most basic emotions, but they are the fundamentals of other emotions that are derived from them. Emotions tell us how an individual feel or behave toward the situation. They are one of the basic human attributes and human make decision on basis of how they feel (pleasure or displeasure) toward the things or situation. The psychological response by emotions is very helpful in decision making. Both the rational thinking and emotions work parallel in human nature sometimes one of them overcome the another one. According to some research, computers become more intelligent and the lack of similarities between humans and machines can be overcome in a better way if emotional aspects is induce in them [41]. Also some theories [43] show how affecting computing affect the process of decision making.

Affective computing is helpful,as technology is becoming more significant in human interactions and people mostly rely on the machines on daily basis. So we have to develop such machines which perform like humans. Most of the machines are performing task of decision making like human but it doesnt possess some of the attributes of human which can affect the decision. Affective computing is different as it will let machines think emotionally like humans. Machines are built upon mimicking the human attributes. Affective computing mainly add attribute of emotion and feel toward a task or decision. Affective computing systems address the emotional domain; they can help users to understands machine at a deeper level, which results in feels which are more like a human relationship. Affective computing also applies to many wearable devices (mobile computing). E-learning programs could automatically detect difficulty faced by learner and offer additional explanations or information. E-therapy could help deliver psychological health services on line and be effective similar to one to one person counseling. Thus it has many significant roles in making decisions which result in that we get model like human or we can say machine as human. By making machines emotionally intelligent it is easier for machines to behave like humans beings; it results in more effective for communication and interaction with people [35].

Food and emotion are very much correlated with each other. Our daily life intake of food is dependent on the individuals mood while on the other hand our mood have a great influence over the choice of our food to eat [21]. Food image is an important concept as The image of food is directly linked to attracting tourists for trying out that food. Several studies [39, 25, 47] have confirmed that people prefer to eat food which looks good in pictures because that way they are sure of the end results of individuals toward the food. In a study [13] it is concluded that children response positively toward their favorite food or beverages. Another study [5] shows the correlation exist between liking food and emotional response toward the food.

Computer science and cognitive science are interconnected. Combination of cognitive sciences and computer science is main feature for implementation of affective computing. There implementation results in models which has become similar to the result of decision making made by human. Moreover the psychological response of emotions will be used in this research which is one of the main attribute of cognitive science. Furthermore we will use the image classification techniques which help in extracting such feature vectors which have psychology theories attributes. So by combing the both domain we can check the influence of classification techniques on the human attributes like emotions etc. Without the feature of psychology in machines it will lack the closeness of machine toward human mood. So highly linked relation is seen between the both attributes and they make decision making more accurate and close to real world.

The challenges faced during implementation are many as we know that emotions are a variable attribute it varies from one person to other. Two people can feel toward same thing differently and response toward things can also vary from person to person.Emotions change with time. They are based on external situation and inner feelings.Human brain is very complex when it comes to emotions. We may like one particular thing at a particular time but later on hate it. If one person feel some emotion of joy for a food item it is not necessary that all individuals will have the same emotion towards that food item. This all is interconnected with emotions.So classifying things on basis of variability is difficult in itself. The challenges discussed in [38] are robustness, cross-cultural issues, standardization and ethical, legal and social implications. In this paper [26]the author discuss challenges of emotions during the research phase. Mainly the challenges are due to the dataset which includes quantity and quality of dataset and compatibility with other datasets. [16] shows challenges faced in instant messaging due to emotions.These challenges listed were discussed includes emotions continuum, different user having different dynamic and emotions misclassification.

Emotion image classification is a new promising field and has a great influence on the daily decision making tasks. Our main focus is on Affective image classification using principle of art features [48] and rating features (palatability, desirability) of a survey on data set of food images [3]. In our work we had identify the emotions associated with the food images using principle of art features like emphasis, symmetry etc.Labels of the image had been taken from valence arousal psychological model. Different classifiers (Naive Bayes, SVM and MLP) were implemented to train the model on basis of which emotion classification had done. Testing of dataset is also done among which different results had been concluded.With the help of these models we have indicated the emotion associated with the static food images. Following is the list of contributions in our research:

- Principle of art theory implementation for images feature vectors extraction
- Label assigning through valence-arousal psychological model
- Formation of emotion classification model for food images

In this work research, we have further illustrated the literature review in Section 2 in which we discuss the related work of affective computing, affective image classification, emotion classification, food emotion theory and rating features. The proposed methodology with implementation details is described in Section 3 and 4 respectively. The results detailed are illustrated in Section 5, followed by discussion and conclusion in Section 6 and 7 respectively.

Chapter 2

Related Work

Affective computing is new and currently evolving field and its application can be done in many domains. Affective computing is implemented in computer vision domain. Use of emotions can result in better life decisions and task performances. Using computer vision techniques and emotions based techniques most of the applications are for video games, social media analysis, mental health, facial recognition and devices where emotional communication are used.

The applications of affective computing are now becoming very common. It has become a great influence in fields of computer vision and graphics, medical and many other domains like social media analysis etc. In domain of computer vision and graphics such games are being made which have human attribute factors and facial recognition applications are made which have the emotion recognition features in it. It is also becoming promising field in medical in such way that many research on basis of emotion attribute is being done on mental health domain which include affect and response over depression, anxiety or stress. E-learning domain is also adopting the affective computing techniques for their student teacher interactions. It is also helpful in social media analysis as effect of person mood on the post and comments being made. So affective computing is becoming a part of many computer science domains and had a positive influence on the result of better and rational decision making.

2.0.1 Affective Computing

Previously research work on affective computing in computer vision domain is done for many applications as video games different colors can be used to extract emotions [14]. Similarly work on emotions effect on games [4] in which emotionally movements in digital games is extracted. Social media also play an important role on making decision on basis of our emotions so mostly research work on emotion analysis on text data of different social media site has been conducted. Following are few of the papers on that domain [45] in which Flicker dataset is used to see the influence of emotions on individual. Similarly in one of the research work the twitter data is used for identifying the user which are affected with depression using emotions [19]. In one of the researches the emotion analysis have been done on the basis of picture shared by user and the response (comment) of other users (friend) on it has been done [46].

Moreover some of the research is also be done on using the devices in our daily life task with help in decision making on the basis of emotion. Similarly vehicle are daily used in our lives so applications that are emotionally intelligent are becoming common. In this research [34, 33] emotions control the vehicle-learning is also one of the progressing field and also have a significant effect of using affective computing in it. In this [17] research paper the facial expressions of the teachers and students is captured which is further used for identifying the difficulties faced by students during learning and effect of teaching strategies on them.

2.0.2 Affective Image Classification

Affective image classification consist of such models that act as emotionally intelligent system using emotions as a basic attribute. Affective Classification in images is used by extracting low-level features that are element of art theory like color, textures etc [27] for making emotion detection models. These features classify the emotions in by using affective images. A similar approach [48] in which instead of element of art theory, the high level features that are principles of art theory, including symmetry, variety etc. are used for the emotion classification of images. From both the research stated above it was concluded that principles of art features give effective result in emotion based classification of images. We will use the similar approach in our research work by implementing the principle of art features in food images and using that features for classification of emotions in food. Moreover, in a research [44] affective image classification using SVM is done. Furthermore, for affective classification in facial expressions recognition many research [36, 42] are done,in which the facial pictures are used to extract emotions from them for intelligently making of decisions.

2.0.3 Emotion Classification

Emotion classification consist of such models which can distinguish between different emotions. Similar to the classification approach, emotion classification is also used to performs classify data set into different category but in it emotional aspects are involved for classifications. The approach is used to extract or classify emotions from all type of objects either video or images [8, 18] and this method is also used to recognize the speakers emotional speech [9]. Furthermore reader-emotion classification is also done in one of the research work [24]. Social media has a large emotion related content so to distinguish between emotions present in social media this [28] research work was done.

2.0.4 Food emotion theory

Food and emotions are interrelated. In a survey [1] shows the food-related lifestyles and their cross-cultural differences and shows the influence of food on human. The emotion-based influence on food is also due to present of nutritional characteristics of food products when buying a product or choosing a new food item [2]. Recently, emotional experience of an individual are measured by the help of neuron-physiology methods. A study related to this method [6] is used to measure emotion experienced while performing food related activities like cooking or tasting. All of the research work stated above state the psychological aspect in food and emotion relation; that a simple emotion evaluation technique tells emotional response of human towards foods.

2.0.5 Rating Features

Rating features are basically used in subjective studies for measuring influence of factors on human nature. In affective computing for images of food these features are rated to check the emotional affect when an individual view a food image.

These features influence arousal level, due to which food consumption is influenced. The experimental results in [32] shows that palatability of food is induce by arousal which result in an intake of less palatable and healthier food. Similarly, other factors like age, gender, and weight have great influence on food consumption. This research work [31] considers three variables: valence, arousal, and familiarity and illustrate the significance of theses variables on the factors stated above.

Positive valence is related to food product likeness [15]. Likeness rating is a important factor for a market success of food product. Moreover emotional attribute induced by choosing a food can provide more information which can not only be induce from likeness. Simply its mean that likeness of product can evoke emotion for determining food choice. A study considers this aspect for likeness of sweet tastes.The results for it shows that likeness extract positive emotions for sweet food items [20].

The feeling of pleasure (valence) and arousal are strongly related with each other. For this food images are used with emotion evaluation approach. Relevant studies using high-calorie food images [29] and cigarette images in natural settings [7] shows the pleasure effect which also evoke more craving for them. Furthermore, food items having positive or neutral valence and different levels of complexity induce emotion, as well as have influence on physiological factors like heart rate and levels of blood glucose [37]. The study state that complexity in meals result in less craving.Moreover, sad moods can effect person mood in such a way that individual intake of unhealthy food in increased, particularly in people which are addicted to food [12]. There are many prove in the literature which state that different factors evoke emotional attribute in food.

Latterly the rating features and food relation is discussed. However, these features are also used in different intensive other than food. As in one of the study,a reading experiment [10] tells the relationship present between paragraphs complexity and arousal level. This level is associated with how attractive and interesting the paragraph is. Similarly in another research it is stated that structural complexity have significant effect of arousal when viewing television. The results of this study show faster time of reaction for complex arousing television messages [22]. With complexity, familiarity is also correlated to the level of arousal while listening to music [40]. All these research work illustrate that different factors contribute towards emotional arousal.

Chapter 3

Proposed Approach

For emotion based classification on static food images we implemented different models for classification. These models are than tested and validated to evaluate models. The models include features set vectors extracted from image dataset on basis of different art theory. The classifiers used are SVM, Naive and MLP. Our implementation method include 4 Principle of Art models on basis of different feature vectors set on basis of principle of art theory.

3.0.1 Rating features details

Rating features are the features on basis of which survey is done on the images and shows such factors which have influence on human nature. The features define the characteristics present in the images. These features are further used in Section 4 for implementation of models. Following are the details about the features:

1. **Arousal.** is used for in sense of awareness of surroundings. Arousal is related to intake of food in such a way as people's response more to emotional arousal and anxiety rather than hunger toward the food item.

2. **Valence.** as used in psychology for attractiveness in objects. In food images the presentation of food product, colors and eye catching food items give valence attribute.

3. **Palatability.** means pleasure toward the food item. In food palatable food increase the intake.For rating this factor, questions like how palatable is this food for you general? and similar questions were used [3].

4. **Desirability.** is used to represent the craving of the food. In on-line survey such question was asked for rating this attribute.How much you will like to eat this food right now if it was in front of you? [3].

5. **Complexity.** represents the dishes in which multiple food items are present and due to the presence of complexity it is difficult to distinguish between different items.

6. **Recognizable.** food items which are common and human intake on daily basis.

7. **Familiarity.** is the known food items which are simple and used in daily routine.

3.0.2 Principle of art features details

Principle of art are different art attributes in an image. In our research we used these principle to extract art based features from food images. These features implementation is done by using concept implemented by [48]. Following are the principle of art features that are used in our work:

3.0.2.1 Symmetry

is used for extraction of balance in image present around the image axis. Symmetry can be detected by matching of images features with one another. For balance of image,key points are detected, moreover axis of symmetry is found and than the resultant image gave symmetry details and its magnitude. Mirror and rotational symmetry are used in our dataset. Scale-invariant feature transform (SIFT) is an algorithm to detect the key points in the image. Following images show key points detection and result how many key points were found. 226 key points found in Figure 3.1.

1. **Mirror symmetry:** For detection of mirror reflection we use lookup table to generate the SIFT descriptor for image mirror version. The output results into a SIFT descriptor vector about the y-axis and total number of matches. Among which the match pairs for symmetry features are extracted. We use linear Hough Transform for

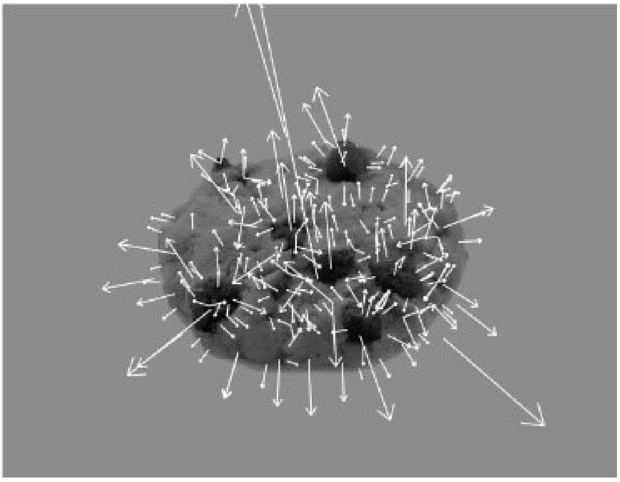

Figure 3.1: Key points details extracted using SIFT descriptor

symmetry axis points detection. For the implementation of linear hough transform the procedure is that firstly we determine the maximum radii. Secondly,initialize Hough vote space and convert x and y to polar coordinates having its origin at image center point. Finally blur the image and find maxima. After implementation of linear hough transform reject matches that are not symmetrical and having varying scale. Furthermore reject the irrelevant points and get the final results. Magnitude details for the dominant mirror symmetric axis for this images is 0.117044. Mirror symmetry is shown in Figure 3.2

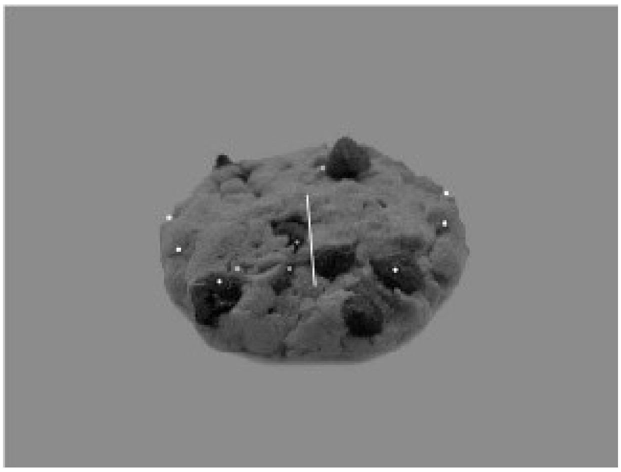

Figure 3.2: Mirror symmetry of an image

2. **Rotational symmetry:** Unlike mirror symmetry detection, detecting rotational symmetry is simply matching the features against each other. Firstly a pair of point vectors are identified and finally extracting the dominant centers for rotational symmetry. We reject the points having different scale and irrelevant matches. Lastly finding magnitude details is symmetry magnitude of dominant center. This image results into 6 rotationally symmetric matches, symmetry strength = 0.11303 as shown in Figure 3.3

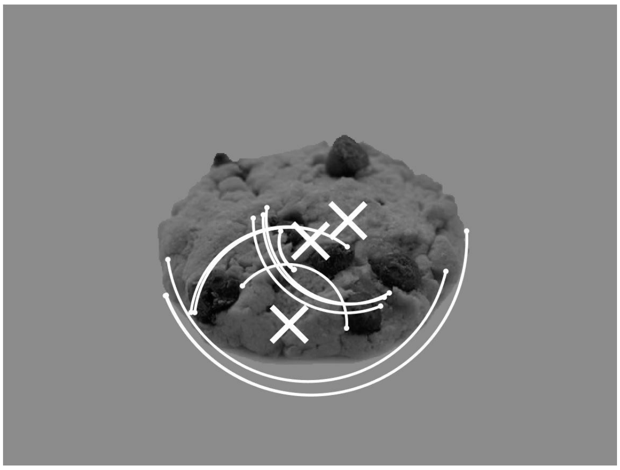

Figure 3.3: Rotational symmetry of an image

3.0.2.2 Emphasis

is used for extraction of portion that is dominant in the image. It differentiate elements present in image and determine the focused rate of a image with the help of Graph-Based Visual saliency map and RFA score.

1. **Saliency map:** Graph-Based Visual Saliency is use for implementation of the GBVS map for an image. Following steps are used for computing saliency map. Firstly extract raw feature maps from image and then calculate activation maps from feature maps and then that activation map is normalized. Calculating average and sum of feature channels and finally blur the image for better results as shown in Figure 3.4

Figure 3.4: Resultant blurred image for emphasis

2. **RFA (Rate of focused attention):** After we get saliency map, we get threshold mask of the image. We needed it for calculating RFA that is the focus rate of the image. The last step is to use formula to calculate RFA.The formula is shown in Figure 3.5.

$$RFA(i) = \frac{\sum_{x=1}^{Wid} \sum_{y=1}^{Hei} Saliency(x,y) Mask_i(x,y)}{\sum_{x=1}^{Wid} \sum_{y=1}^{Hei} Saliency(x,y)}$$

Figure 3.5: RFA(Rate of focused attention) formula

3.0.2.3 Harmony

is a visual satisfying effect by combination of elements in images. It is used for extraction of harmonious details from images on basis of extraction of hue and gradient direction from it.Figure 3.6 shows the hue portion from the HSV image. Moreover 3.7 shows the gradient of the hue image.

3.0.2.4 Variety

is used for combining images colors.We used im2c function which annotates image pixels with color names. A color image is given as an input which results in the probability for

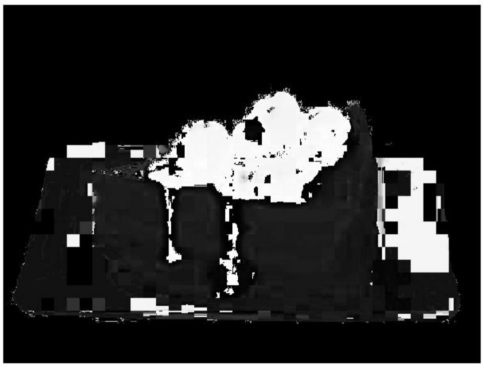

Figure 3.6: Hue value of the image for harmony calculation

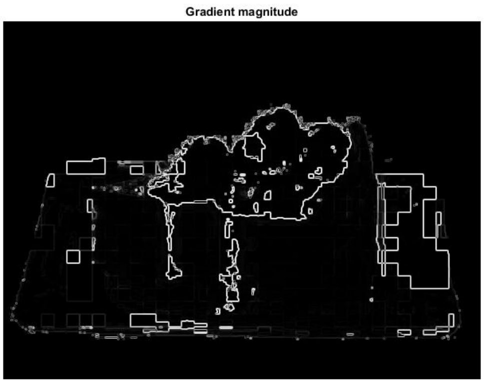

Figure 3.7: Harmony details as image gradient

eleven color (black, blue, brown, gray, green, orange, pink, purple, red, white, yellow) in image. The mapping of images from RGB values to 11 color names (w2c.mat) has been learn from Google images (2500). Output vector for the function is as follow [0.0007 0 0.1108 0.0559 0.0005 0.0000 0.0119 0.0011 0.0896 0.7157 0.0138 0.0236] Figure show 3.8 the orignal image and its bar chart is shown in Figure 3.9.

3.0.2.5 Movement

is used for creating look and feel of actions on the image. In this step we use gaze selection and eye scan path for human eye movement. Gaze vector is extracted from gaze selec-

Figure 3.8: Original Image used for variety calculation

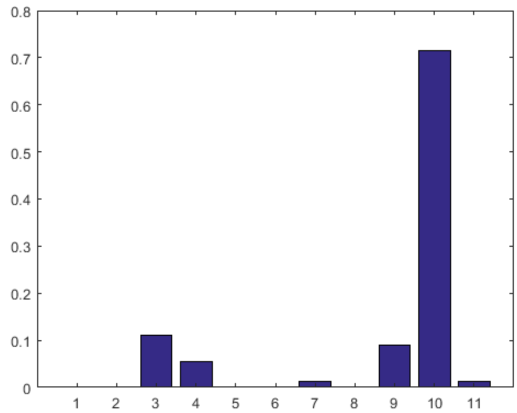

Figure 3.9: Histogram of 11 colors of image

tion.Visual data is represented as an ensemble of small images. Kurtosis maximization is use to indicate the Super Gaussian Component (SGC). Response map is extracted from SGC.Based on the response map, we locate fixation point by winner-takes all (WTA) principle. Gram-Schmidt orthogonal method is applied to avoid convergence. Along with this a saliency map can be calculated using selected fixations or the response maps.Output will be the gaze vector. [-0.2349 -0.4174 -0.5984 0.4884 -1.3728 -0.2030 0.3347 -0.3834 -0.3997 0.6686].The scan of image is shown in 3.10

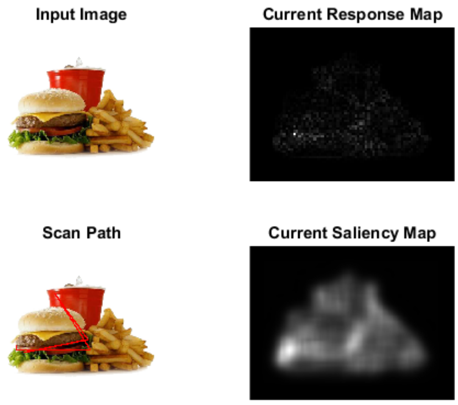

Figure 3.10: Eye Scan movement and saliency map details for implementation of movement feature

3.0.2.6 Gradation

is combination of elements by using a gradual changes series. For implementation of gradation we get image gradient in x and y direction, calculate window inherent variation and window total variation. Moreover we calculate the relative gradation and absolute gradation of the image. Following piece of code is used for calculation of gradation and Figure 3.11 show the gradation formula.

[Gx, Gy] = imgradientxy(V);

[Dx,Dy,Lx,Ly] = getMatrix(V,Gx,Gy);

RT = RT + Dx(i,j)/(Lx(i,j)+0.1) + Dy(i,j)/(Ly(i,j)+0.1);

$$RG = \sum_p RTV(p) = \sum_p \left(\frac{D_x(p)}{L_x(p) + \varepsilon} + \frac{D_y(p)}{L_y(p) + \varepsilon} \right),$$

Figure 3.11: Gradation formula

Each of these art features give a different attribute details from the image, resulting in a feature vector which have cognitive science features in it for emotion classification of food images as illustrated in section 4 .

Chapter 4

Implementation Details

In this section we will discuss the implementation details done to achieve our proposed solution. We implement some of the machine learning classifiers on our dataset for making machine emotionally intelligent and than performed evaluation analysis on them. The classifiers used are SVM, Naive and MLP. We extract features from image dataset by using principle of art theories. From the food-images dataset we extracted the features on basis of principle of art features and rating factors on which the emotion classification can be done.

4.0.1 Dataset

Dataset used for implementation of food-emotion model is food-pics. This dataset contains total 568 food images which fall into multiple categories like fruit, vegetable, chocolate, fish, meat, and nut. It also contain details of images characteristics such as RGB values, brightness, contrast, moreover norm complexity and spatial frequency details are also given. Furthermore the dataset also have macro nutrients details that are fat, carbohydrate, protein, and calories. Few of the food item and dataset properties is shown in Figure 4.1 and Table 4.0.1 respectively .

This dataset also have rating features for images on basis of survey done. The rating features mentioned in survey are recognizability, familiarity, palatability, valence, arousal, complexity, and craving. Furthermore these labels rating is divided on basis of gender (male/female) and diet (Omnivore/vegetarian). Other factors like familiarity and recognizability was rated on questionnaire as (yes/no) and (easy /difficult) respectively.For the

Table 4.1: Dataset properties

No. of images	Categories	Macro nutrient	Characteristics
568	Fruit	Fat	RGB
	Vegetable	Carbohydrates	Brightness
	Chocolate	Protein	Contrast
	Fish	Calories	Norm complexity
	Meat		Spatial Freq
	Nut		

Figure 4.1: Few of the Dataset Samples used in research

remaining factors evaluation the VAS (Visual analogue scale) was used. In VAS complexity was rated between very little to very high while valence as very negative to very positive. Lastly the factors palatability, desirability and arousal was rated between not at all to extremely. The evaluation scale used was from 0-100.The rating against each food picture considered to be an average rating of 49 participants [3].

Secondly, for assigning the emotion labels to this dataset the valence arousal model is used. For this dataset, the rating scale used for survey is between $[0 - 100]$.For assigning of labels to the images, we normalize the rating features between $[-1, 1]$ so that it can be plotted it on the valence-arousal model as shown in Figure 4.2. Four basic emotions(happy, stress, boring and relax) are assign to the images with the help of this plot.This data set is further used for emotion classification.

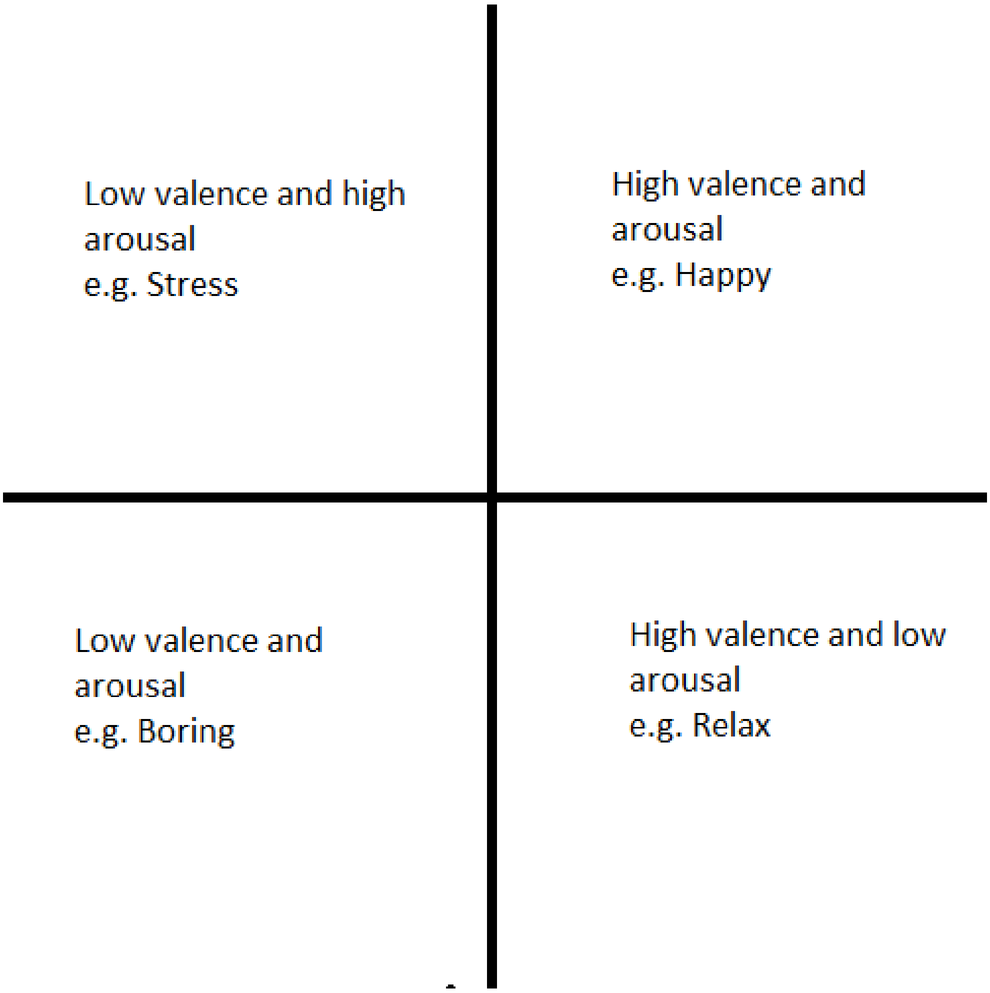

Figure 4.2: Valence-Arousal plot for assigning emotion label on images

4.0.2 Rating Model

In this model($\mathbb{M}_{Rating_{4-class}}$) we have a feature vector on basis of rating factors of a survey done [3]. We used this model for assigning label as discussed in 4.0.1. The feature vector is of size 7 (seven) which contain rating features for the attributes (recognizability, familiarity, valence, arousal, complexity, palatability and craving). In our dataset total 6 data points have label "stress" which is effecting the overall accuracy. We recreated a model with 3 labels by extracting the instances of label stress and form a 3-label rating model($\mathbb{M}_{Rating_{3-class}}$). Three of the classifiers that are SVM, MLP and Naive Bayes were implemented on basis of these feature vector.

4.0.3 Principle of art Model

For art model, we have a first model $\mathbb{M}_{Art_{4-class}}$ in which principle of art features emphasis, symmetry, movement, harmony, variety, and gradation are use to extract feature vectors from the dataset. The feature vector is of size 6. Table 4.4 show the feature vector details of $\mathbb{M}_{Art_{4-class}}$.

Moreover, the $\mathbb{M}_{Art_{4-class}}$ has total six data points with label "stress" which is affecting the overall prediction accuracy of our proposed model. For solving this issue , we recreate a model with three labels($\mathbb{M}_{Art_{3-class}}$).3-label model don't have the stress label.

Furthermore, to increase prediction accuracy we recreate the $\mathbb{M}_{Art_{4-class}}$ as $\mathbb{M}_{Art-mapped_{4-class}}$. For the new model we form a correlation matrix with $\mathbb{M}_{Rating}$ model features and $\mathbb{M}_{Art_{4-class}}$ features. We select the maximum value from each $\mathbb{M}_{Rating}$ against $\mathbb{M}_{Art_{4-class}}$ to create new model as $\mathbb{M}_{Art-mapped_{4-class}}$. Correlation matrix is shown in Table 4.3.

Table 4.2: Mapping of rating features with $\mathbb{M}_{Art_{4-class}}$.This table show feature vector for the $\mathbb{M}_{Art-mapped_{4-class}}$

$\mathbb{M}_{Rating_{4-class}}$	$\mathbb{M}_{Art1_{4-class}}$
Recognizability	Variety
Familiarity	Emphasis and Harmony
Valence	Variety
Arousal	Harmony
Complexity	Gradation
Palatability	Symmetry
Craving	Harmony and Symmetry

Table 4.2 shows the detail of the new $\mathbb{M}_{Art-mapping_{4-class}}$. We used normalized dataset for $\mathbb{M}_{Art-mapped_{4-class}}$ then check accuracy from the implementation of 10-fold cross-validation

Table 4.3: Correlation matrix of Rating features in $\mathbb{M}_{Rating}$ and $\mathbb{M}_{Art_{4-class}}$ on basis of which $\mathbb{M}_{Art-mapped_{4-class}}$ is formed.

	recognize	familiar	valence	arousal	complex	palatable	craving
Symmetry	0.01	-0.009	0.10	0.22	0.26	**0.14**	**0.20**
Movement	-0.03	-0.05	-0.008	-0.06	-0.01	-0.04	-0.07
Emphasis	0.07	**0.08**	0.11	0.13	0.07	0.08	0.12
Gradation	-0.09	-0.10	0.04	0.09	**0.37**	0.03	0.06
Variety	**0.10**	**0.08**	**0.14**	0.16	0.15	0.10	0.15
Harmony	-0.02	-0.001	0.09	**0.26**	0.34	0.13	**0.20**

on the dataset as shown in Table 4.5. Whereas from cross-validation dataset we infer that dataset distribution is not even and it should be shuffle so that accuracy of classifiers can be improve. To improve the predictions result we use the shuffled dataset. Similarly, we also create the mapped model with three labels as $\mathbb{M}_{Art-mapped_{3-class}}$ due to insufficient data points for stress label.

Table 4.4: Feature vector details for the implementation of $\mathbb{M}_{Art_{4-class}}$

Principle of art features	Values
Symmetry	Average of mirror and rotational Symmetry Strength
Movement	Sum of Gaze vector from gaze selection
Emphasis	RFA (Rate of focused attention) score
Gradation	Pixel-wise windowed total variation
Variety	Skewness of pixel amount of basic 11 colors
Harmony	Average of hue color pixels and their gradient

4.0.4 Evaluation Metrics

For the result evaluation of models we use confusion matrix which is use to tell the details about the performances about our implemented emotion based models. In addition to this, we also calculate accuracy, misclassification rate of our models. Statistic evaluation

Table 4.5: 10-fold cross validation

Iteration	MLP	SVM	Naive Bayes
1	38.59	38.50	33.33
2	45.61	40.35	42.10
3	40.35	43.80	43.80
4	49.10	42.10	38.50
5	64.90	64.90	64.90
6	52.63	50.80	45.60
7	66.66	64.90	57.80
8	63.10	52.60	63.15
9	42.10	40.35	38.59
10	36.36	36.36	41.81
Average	**50**	**47.46**	**47**

for models include true positive (Recall) rate(correctly identified classes), precision rate (predictive rate for positive values), F1-score is the support for simple and robust model. Furthermore for result analysis the support is also calculated which is used to indicate total correct instances present in the model. Lastly mean squared error(MSE) use for illustrating the difference of result and predicted values for the evaluation of our proposed models.

4.0.5 Tool and Technologies

In our research work we use MATLAB for extraction of features vectors details from images. The principle of art features were extracted from the images using it. The details features vectors were stored in file. Afterward we used Python programming language for implementation of the classifiers that are SVM, MLP and Naive Bayes and used it also for calculating the accuracy results of the models implemented.

Chapter 5

Results

In our research,the data for food-emotion model is distributed in such a way that 60 % is used for training set, 20 % for validation set and test set. Secondly, outliers are removed form the dataset which we calculated quartile 1 and 3 and find upper and lower bound to extract outliers values from our dataset. Normalizing and shuffling of feature vectors are performed to increase the prediction result for our models.

Three classifiers that are SVM, MLP and Naive Bayes are used for training the food-emotion based models. In this chapter detailed result of rating($\mathbb{M}_{Rating_{4-class}}$ and $\mathbb{M}_{Rating_{3-class}}$) and art models($\mathbb{ART}_{4-Class}$, $\mathbb{ART}_{3-Class}$, $\mathbb{ART}_{4-Class-mapped}$, and $\mathbb{ART}_{3-Class-mapped}$.) are given.

5.0.1 Rating Model

The 4-class confusion matrix for ($\mathbb{M}_{Rating_{4-class}}$ is shown in Table 5.4. We used the test set model to evaluate the accuracy of models.

Emotions	Happy	Relax	Stress	Boring
Happy	**23(20.17)**	1(0.87)	0(0.0)	0(0.0)
Relax	2(1.75)	**34(29.82)**	0(0.0)	1(0.87)
Stress	0(0.0)	0(0.0)	**1(0.87)**	0(0.0)
Boring	1(0.87)	0(0.0)	0(0.0)	**51(44.73)**
Total	26(22.80)	35(30.70)	1(0.87)	52(45.61)

Table 5.1: Error Analysis: Confusion matrix for $\mathbb{M}_{Rating_{4-class}}$

Its accuracy and misclassification rate is 0.956 and 0,04 respectively. A 3-label confusion matrix for $\mathbb{M}_{Rating_{3-class}}$ excluding the stress label is shown in Table 5.5.

Emotions	Happy	Relax	Boring
Happy	**23(20.53)**	1(0.89)	0(0.0)
Relax	1(0.89)	**34(30.35)**	1(0.89)
Boring	1(0.89)	0(0.0)	**51(45.53)**
Total	25(22.32)	35(31.25)	52(46.42)

Table 5.2: Error Analysis: Confusion Matrix for $\mathbb{M}_{Rating_{3-class}}$

It shows the accuracy rate of 96 %. The mean squared error for 4-class and 3-class models are 2.175 and 2.00 respectively. Overall statistics analysis of $\mathbb{M}_{Rating_{4-class}}$ and $\mathbb{M}_{Rating_{3-class}}$ is shown in Table 5.3

For these models MLP give the better result as compared to SVM and Naive Bayes. SVM with decision function one vs rest was used and it gives 81.57 % and 92.1 % accuracy on validation set and test set respectively. For MLP classifier with one hidden layer the accuracy was 93.8 %. In validation procedure we added two hidden layer and changing learning rate from constant to adaptive as a result of this our accuracy increase to 94.73 %. Test dataset gave accuracy of 95.6%. Furthermore we use Gaussian and Bernoulli for naive Bayes on validation dataset. Upon which 94.73 % and 77.19 % accuracy was achieved from Bernoullis and Gaussian respectively. On test set Bernoulli method gave accuracy of 93.85 % for Naive Bayes Classifier. Figure 5.1 shows the classifiers comparison for model1.

Table 5.3: Statistics details about 4 and 3-labels $\mathbb{M}_{Rating}$

	$\mathbb{M}_{Rating_{4-class}}$				$\mathbb{M}_{Rating_{3-class}}$			
	Prec.	Rec.	F1	Support	Prec.	Rec.	F1	Support
Happy	0.88	0.95	0.91	24	0.92	0.95	0.93	24
Relax	0.97	0.91	0.94	37	0.97	0.94	0.95	36
Stress	1	1	1	1	-	-	-	-
Boring	0.98	0.98	0.98	52	0.98	0.98	0.98	52

* Notes This table shows the details of recall, precision, f1-score and support for 2 models.

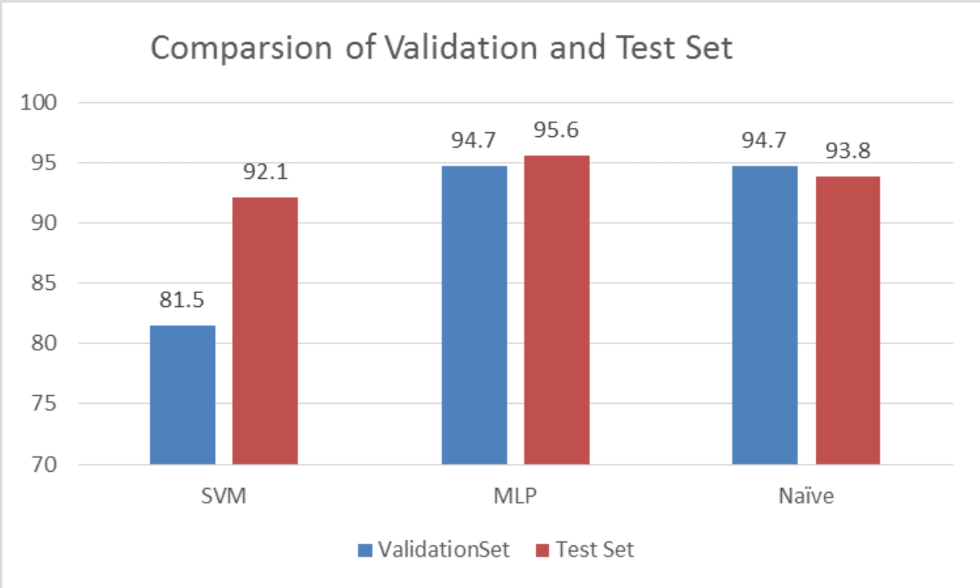

Figure 5.1: Validation and Test set comparison for ($\mathbb{M}_{Rating_{4-class}}$)

5.0.2 Principle of art model

Table 5.4: Error Analysis: Confusion Matrix for the model $\mathbb{M}_{Art_{4-class}}$.

	Target Emotion			
Emotion	Happy	Relax	Stress	Boring
Happy	**17 (14.91)**	5 (4.38)	0 (0.00)	2 (1.75)
Relax	10 (8.77)	**12 (10.52)**	1(0.87)	14 (12.28)
Stress	1 (0.87)	0 (0.00)	**0 (0.00)**	0 (0.00)
Boring	11 (9.64)	18 (15.78)	2(1.75)	**21 (18.42)**
Total Error	22 (19.29)	23 (20.17)	3 (2.63)	16 (14.03)

* Note. Values are numbers of errors (with % in brackets). Correct predictions are in bold. Target emotions denote the four emotion conditions employed in this model.

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In this evaluation we give the details results of $\mathbb{M}_{Art_{4-class}}$, $\mathbb{M}_{Art_{3-class}}$,$\mathbb{M}_{Art-mapped_{4-class}}$ and $\mathbb{M}_{Art-mapped_{3-class}}$.

The 4-class confusion matrix of our result for $\mathbb{M}_{Art_{4-class}}$ is shown in Table 5.4. We

Table 5.5: Error Analysis: Confusion Matrix for the model $\mathbb{M}_{Art_{3-class}}$

	Target Emotion		
Emotions	Happy	Relax	Boring
Happy	**17(15.17)**	6(5.35)	1(0.89)
Relax	10(8.92)	**16(14.28)**	10 (8.92)
Boring	11(9.82)	22(19.64)	**19(16.96)**
Total	21(18.75)	28(25.00)	11(9.82)

* Note. Values are numbers of errors (with % in brackets).Correct predictions are in bold. Target emotions denote the three emotion conditions employed in this model.

used the Naive Bayes model for calculation of the accuracy of $\mathbb{M}_{Art_{4-class}}$ for which the matrix shows a total of 64 and 50 errors and correct predictions respectively. Its accuracy and misclassification rate is 0.43 and 0.56 respectively. Moreover for $\mathbb{M}_{Art_{3-class}}$ a 3-label confusion matrix as shown in Table 5.5 is given. The matrix shows a total of 60 errors and 52 correct predictions.The $\mathbb{M}_{Art_{3-class}}$ gave 46% accuracy. The mean squared error for 4-class is 25.5 and 3-class models gave 25.6. Table 5.8 shows the detailed statistics of Art models.

Table 5.6: Error Analysis: Confusion Matrix for the model $\mathbb{M}_{Art-mapped_{4-class}}$

	Target Emotion			
Emotions	Happy	Relax	Stress	Boring
Happy	**13(11.40)**	21(18.42)	0(0.00)	0(0.00)
Relax	3(2.63)	**47(41.22)**	0(0.00)	2(1.75)
Stress	0(0.00)	1(0,87)	**0(0.00)**	0(0.00)
Boring	2(1.75)	21(18.42)	0(0.00)	**4(3.50)**
Total	5(4.38)	43(37.71)	0(0.00)	2(1.75)

* Note. Values are numbers of errors (with % in brackets). Correct predictions are in bold. Target emotions denote the four emotion conditions employed in this model.

Similarly the 4-class confusion matrix for model $\mathbb{M}_{Art-mapped_{4-class}}$ is shown in Table 5.6. To evaluate the accuracy of this model we used the test set for which the confusion matrix

Table 5.7: Error Analysis: Confusion Matrix for the model $\mathbb{M}_{Art-mapped_{3-class}}$

	Target Emotion		
Emotions	Happy	Relax	Boring
Happy	**13(11.60)**	21(18.75)	0(0.00)
Relax	2(1.78)	**49(43.75)**	1(0.89)
Boring	2(1.78)	21(18.75)	**3(2.67)**
Total	4(3.57)	42(37.5)	1(0.89)

* Note. Values are numbers of errors (with % in brackets). Correct predictions are in bold. Target emotions denote the three emotion conditions employed in this model.

gives 50 errors and 64 correct predictions. Its give 56% accuracy and 43% misclassification. Secondly for $\mathbb{M}_{Art-mapped_{3-class}}$ a 3-label confusion matrix is shown in Table 5.7. This matrix results in 47 and 65 errors and correct predictions respectively. The mean squared error for 4-class models is 19.92 while 3-class models gives 20.00. Table 5.9 shows the detailed statistics of Art mapped models.

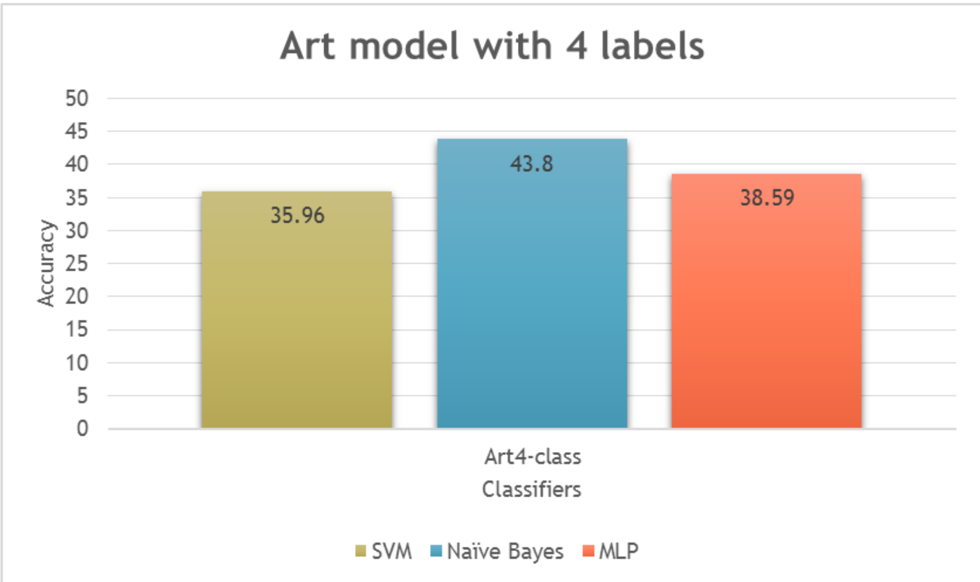

Figure 5.2: $\mathbb{M}_{Art_{4-class}}$

For model $\mathbb{M}_{Art_{4-class}}$ we used SVM and it gives 57.8% accuracy on validation set and

35.96% on the test set. Secondly, we test it on MLP classifier with one hidden layer the accuracy was 42.10%. We validated by adding 5 hidden layers as a result of this our accuracy increase to 62.28%. The accuracy for test set is 38.59 %. Thirdly, we use Gaussian and Bernoulli naive Bayes for validating the dataset. Upon which later gave 22.86% accuracy and former Gaussian gives accuracy of 44.34%. The Gaussian method have higher accuracy as compared to Bernoulli so we tested it on Gaussian method which resulted in an accuracy of 43.8% for Nave Bayes Classifier as shown in figure 5.2. Furthermore, we tested for $\mathbb{M}_{Art_{3-class}}$, its accuracy for SVM is 36.6% and Naive Bayes gives 46.42% accuracy. While MLP gave an accuracy of 42.85%. Detailed comparison for this model is given in Figure 5.3.

$\mathbb{M}_{Art-mapped_{4-class}}$ gave the accuracy for different classifier as stated below. SVM validated as assigning C=5 for which the result of validation set and test set were 48.2% and 56.1% accuracy respectively. Similarly, MLP was validated from adding 4 hidden layers and the accuracy was 47.3% whereas 55.26% accuracy was on test dataset. The Gaussian method of naive Bayes gave an accuracy of 47.3% on validation set. Furthermore 49.12% accuracy on the test set was achieved. The overall results for classifier comparison is shown in figure 5.4.

$\mathbb{M}_{Art-mapped_{3-class}}$ accuracy for SVM become 58.03%. Whereas for Naive Bayes and MLP the accuracy of a model is 49.1% and 56.25% respectively. The overall accuracy of 3-class model against each classifier is shown in Figure 5.5.

Table 5.8: Statistics details about all $\mathbb{M}_{Art_{4-class}}$ and $\mathbb{M}_{Art_{3-class}}$

	$\mathbb{M}_{Art_{4-class}}$				$\mathbb{M}_{Art_{3-class}}$			
	Prec.	Rec.	F1	Support	Prec.	Rec.	F1	Support
Happy	0.43	0.70	0.53	24	0.44	0.70	0.54	24
Relax	0.34	0.32	0.33	37	0.36	0.44	0.40	36
Stress	0	0	infinity	1	-	-	-	-
Boring	0.56	0.40	0.47	52	0.63	0.36	0.46	52

* Notes This table shows the details of recall, precision, f1-score and support for all the 3 models.

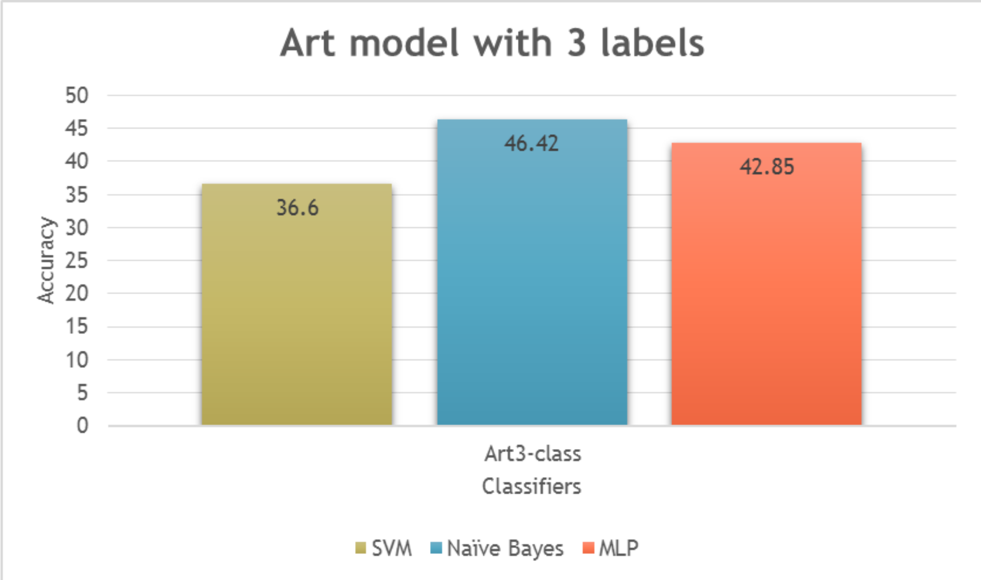

Figure 5.3: $\mathbb{M}_{Art_{3-class}}$

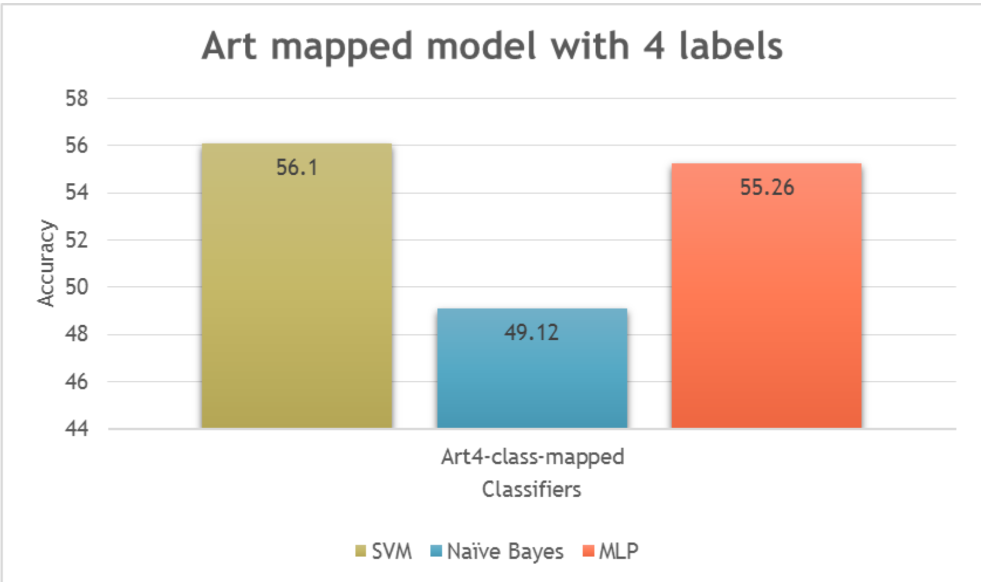

Figure 5.4: $\mathbb{M}_{Art-mapped_{4-class}}$

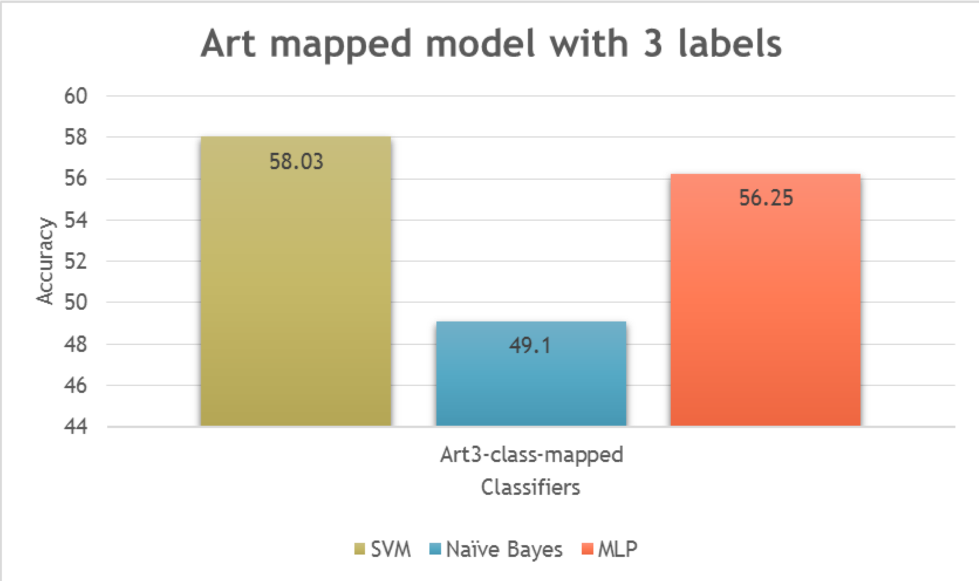

Figure 5.5: $\mathbb{M}_{Art-mapped_{3-class}}$

Table 5.9: Statistics details about all $\mathbb{M}_{Art-mapped_{4-class}}$ and $\mathbb{M}_{Art-mapped_{3-class}}$

	$\mathbb{M}_{Art-mapped_{4-class}}$				$\mathbb{M}_{Art-mapped_{3-class}}$			
	Prec.	Rec.	F1	Support	Prec.	Rec.	F1	Support
Happy	0.72	0.38	0.50	34	0.76	0.38	0.51	34
Relax	0.52	0.90	0.66	52	0.54	0.94	0.69	52
Stress	0	0	infinity	1	-	-	-	-
Boring	0.66	0.14	0.23	27	0.75	0.12	0.21	26

* Notes This table shows the details of recall, precision, f1-score and support for all the 3 models.

Chapter 6

Discussion

For decision making, Emotions ia an extremely important attribute in humans. Existing decision making models lacks human emotional attributes as previously affective techniques were not present for machine learning. The objective of this research work is to make models emotionally intelligent for decision making. Affective computing is an interdisciplinary research which consist of cognitive sciences and computing which is helpful in measuring emotions present in images. For this research work food images is used on which affective method is used for extraction of emotions which shows that food intake is totally dependent on individual mood. These different food type will be helpful to evoke emotions in them.

Food & emotion relationship tells us about the individual emotional response toward the food item. Intake of food provide good mood and healthy lifestyle to the humans. Food images having emotional prescriptive is helpful in affective emotion classification. This study describe that emotion classifications models can be formed to induce emotional attribute in foods by using of affective classification. The outcome of this research work illustrate that emotion based models can be used for identifying emotions present in food images. Emotion in food can makes an individual addictive towards the intake of it. This will gave human a emotional affection with intake of food.

Our dataset images lacks labels related to emotions which are required for implementation of classifier for machine learning. For assigning labels to the images of food present in emotion classification models, valence and arousal values were used. These features are helpful for assigning 4 basic emotions (Happy,Relax,Boring,Stress) attribute to the food images. Emotions labels are achieved by plotting on the valence arousal model. This 2-dimensional model is considered to be one of the basic and common model for assigning the emotional attributes. Moreover the rating details for label assigning task was obtained by the survey done [3] on food dataset. High and low valence arousal values are used in one of the study [20]. These values are helpful in assigning the emotional attribute to food.

Food images are important.Our dataset contain details about image basic characteristics, nutrient details and rating done on basis of a survey. The food images which are part of the dataset are highly addictive and demanded by the individuals. One major limitation of the study is that the small dataset is used. This is one of the reason that final accuracy of our models achieved was only 58%. Furthermore,in our data total of six (6) data points are present who has emotion label assigned as "stress". To overcome this problem we created a 3-label model by excluding the label stress with the help of which prediction result for our models increases. Furthermore,for achievement of better prediction result the data size should be increased. Dataset can be increase in number by adding similar images that are the part of food-pics dataset. These images should also have valence and arousal values so emotion label according to our food-emotion based implementation approach can be applied.

Principle of art features play an important role in expressing emotions in food images. The art theory features are related to emotion and psychological attributes of humans [48].The art features extracted for implementation of affective image classification models are robust due to the reason that they are closely related to emotions. The method used for implementation is similar to research done by [48]. However, our dataset differ from it.Our dataset contains food images while in [48] the author use IAPS (International affective pictures system) which is psychological emotion evoking dataset. In [29],food-emotion related methodology is used. This work show to evoke emotion in food we have to use non-food images as parallel to food images to extract emotions from them. So for food image the Open Library of Affective Foods (OLAF) [30] and for non food images [23] is simultaneously used.

This research can be further applied either on different dataset which are different from the one used in this research work or other emotion theories like color theory etc. can be utilize in feature extraction for emotions in images.Different approach used for emotion labeling can be used to assign labels.Size of dataset can be increased to get the better prediction results These two dataset [29] and [11] can be used for increasing the dataset. This research proposed such food-emotion decision making model which measure emotions evoked in images of food. These emotions based features of images are extracted by using principle of art theory attributes. Through this study the computer and psychological domain is interlinked in such a way that decision making models have become more emotionally intelligent.

Chapter 7

Conclusion

For this research work, our proposed solution is used to extract art features based on principles-of-art features for image emotion classification implementation,which are used to predict emotions in images of food. This food-emotion model is favorable in detection of emotions in images of food and because of presence of emotion attribute the machine become emotionally intelligent for decision making tasks.

On basis of different feature set for each art model,we illustrate that among different emotion based models implemented which one is favorable to evoke emotions in food images. The results performed on affective image classification models shows that among performance of four models ,a $\mathbb{M}_{Art-mapped_{3-class}}$ gave best prediction results. This model gave total accuracy of 58% on the test data and the emotion detection done by this model is based on 3 labels(Happy, Relax and Boring). ($\mathbb{M}_{Rating_{3-class}}$) give better accuracy of 96% as the features used in is of participant rating instead of image features and ground truth is also extracted from the same model.So the former model ,that is the art mapped model, is recommended due to having features vector related to emotional attributes.

The application of art features for emotion detection is promising and potentially strong for future research.Similarly our approach can be applied to a different set of data and form models which become emotionally intelligent for decision making.

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