Mood Detection through Aesthetic Assessment of Videos using Deep Learning

Shruti Vinit Asarkar[1], Prof Madhura V. Phatak[2]
Student[1], Assistant Professor[2]

Abstract: Human interaction and carrier of feelings among humans are accomplished mainly through five senses, such as: touch, smell, taste, audio, and Visual. Considering Visual sense, images and videos are important gradients in day-to-day life. It can elevate/depress mood of person. Video Aesthetics improves user satisfaction. In this study of mood detection, we are demonstrating an approach which is automatically assessed the aesthetics of videos, with emphasis on detecting mood of videos. With the rise popularity of DSLR camera, Mobile dual camera, the amount of Visual data available on the internet is expanding exponentially. Some of the videos and pictures are aesthetically pleasing and beautiful to human eyes. But there are some videos as well as photos which are uninteresting and of low-quality. This paper demonstrates a simple but powerful method to classify videos into pleasing and non pleasing categories. Further our aesthetic quality assessment will find the mood of aesthetically pleasing video (i.e. video representing a happy video or sad or fear, etc), that reflect on person's mood.

Keywords: Video aesthetics, Color preference, Color-Mood Analysis Deep Learning, DCNN.

1. Introduction

As the use of social media is growing rapidly, demand of images and videos is also increased. We people capturing, watching, sharing, computing, storing photos and videos and for appreciation we upload this photos and videos on social media. Appreciation of photos and Videos is totally based on 'Likes' given by people and 'Likes' depends on pleasingness of video and photos. Finding pleasing videos is very important, for wide applications such as in cinematography, to show beautiful high content videos, search and recommendation, UI Design, revenue generation in advertisement world, and Social Media Websites too.

Mood detection is an essential component. Mood detection applications can be discover in different domains. In this study of mood detection, we will detect the mood of videos and images with an aesthetic assessment of video. This assessment of videos will classify videos into pleasing and non-pleasing videos. Pleasing videos will helps to elevate the mood of the person.It is somewhat difficult task to automatically detecting mood from pleasing videos. This paper addresses this problem by considering LowLevel and HighLevel features of an image.

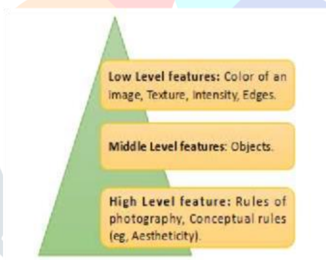
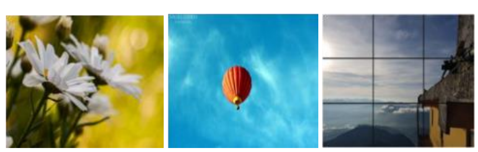


Figure 1. Visual Features of an image

A video is nothing but gathering images altogether. Images having some Visual features. Visual features are those which are directly affected a person's Visual perception. Low-Level features (Color of an image, Texture, Intensity Edges), MiddleLevel features (Objects), High-Level feature (Rules-of-Photography, Conceptual rules (eg, Aestheticism)). There are few rules of photography including, Depth of Field (Main focus on subject and background is blurred), Color Contrast (Also known to be Opposing colors), Rule of Thirds (Divide image into equal parts such that, they reveal primary composition elements near the intersecting line).



(a) (b) (c)

Figure 2. Example images for Rues of Photography. (a)Depth of field. (b) Color Contrast. (c) Rule of thirds

2. Color-Mood Analysis in Video:

Videos are important media that conveys human emotions. Color preference, content, motion of video is important component of Visual experience. This aspects affects a wide spectrum of human mood. Considering Color of videos, that sends "approach" signals(e.g. good colors of videos attract people to watch), and sometimes sends "avoid" signals(e.g. the color that creates irritation to eyes). There is a correlation between color and mood. Color-mood analysis is the study of Psychological and Cinematographic aspect, in which we have found studies about the color-mood association. According to [19], mood is far different concept than emotion. Emotions are for small period of time, whereas moods are usually longer period of time. Every color represents specific moods: Brighter warm colors, energizes viewer and make more alert. Whereas, dark cool shade color, tend to be soothing and relaxing. Color association is not made by single term of 'emotion'. For example, Red color shows Love, Passion, Violence, Danger, Anger, Power, etc. Instead not only Red color is a color, which is related Love, but the term called Love is also allied with red and violet colors combination. According to web survey, we have established association of color and mood as shown in following Table 1.

Table 1. Color Mood Association[23]

Color	Mood
Red	anger, passion, rage, desire, excitement, energy, speed, strength, power, heat, love, aggression, danger, fire, blood, war, violence
Pink	love, innocence, healthy, happy, content, romantic, charming, playfulness, soft, delicate, feminine
Yellow	wisdom, knowledge, relaxation, joy, happiness, optimism, idealism, imagination, hope, sunshine, summer, dishonesty, cowardice, betrayal, jealousy, covetousness, deceit, illness, hazard
Orange	humor, energy, balance, warmth, enthusiasm, vibrant, expansive, flamboyant
Green	healing, soothing, perseverance, tenacity, self-awareness, proud, unchanging nature, environment, healthy, good luck, renewal, youth, vigour, spring, generosity, fertility, jealousy, inexperience, envy
Blue	faith, spirituality, contentment, loyalty, fulfillment peace, tranquility, calm, stability, harmony, unity, trust, truth, confidence, conservatism, security, cleanliness, order, sky, water, cold, technology, depression
Purple/ Violet	erotic, royalty, nobility, spirituality, ceremony, mysterious, transformation, wisdom, enlightenment, cruelty, arrogance, mourning, power, sensitive, intimacy
Brown	materialistic, sensation, earth, home, outdoors, reliability, comfort, endurance, stability, simplicity
Black	No, power, sexuality, sophistication, formality, elegance, wealth, mystery, fear, anonymity, unhappiness, depth, style, evil, sadness, remorse, anger
White	Yes, protection, love, reverence, purity, simplicity, cleanliness, peace, humility, precision, innocence, youth, birth, winter, snow, good, sterility, marriage (Western cultures), death (Eastern cultures), cold, clinical, sterile
Silver	riches, glamorous, distinguished, earthy, natural, sleek, elegant, high-tech
Gold	precious, riches, extravagance. warm, wealth, prosperity, grandeur

3. Color Preference

For Visual experience, color preference is one of the important aspect. Color preference influences a wide diversity of human behaviors: buying assets, choosing cloths, designing websites, etc. Focusing on actual mechanisms that may be involved in humans, found sex differences, age differences, and cultural variation in how the brain process color information. According to studies, Color preference departs from person to person. In [21], authors made hypothesis about color preference is, color preferences might also vary according to sexual orientation. According to author, Females are more choosy about softer colors and are sensitive to pinks, reds, and yellows, while Male generally prefer bold colors and they are seems to be more sensitized to colors in the bluegreen light spectrum. Near about 45% male vote their favourite color as blue or shades of blue, whereas 24% women gave their vote to Blue and shades of Blue. Not only gender affects color preferences, it also varies by age group. As per mention in [20], adults mostly prefer blue color than that of Yellow. Sometimes cultural factors also implies for color preference. According to survey presented in [21], there is a tendency in Western cultures, pink color is preferred to dress baby girls and for Baby Boys Blue is preferred. Cross-Cultural research shed light on the issues by discovering how differed gender makes a differences in color preferences. According to [22], combinations of colors with same hues are generally preferred. Color preference in case of aesthetics, differs basically in terms of lightness contrast.

4. Aesthetics of Video

Video aesthetics is extracting beauty from Video. This Video aesthetic is very useful for betterment of user gratification in many good practices, like recommendations as well as search. Aesthetic assessment of videos is useful in many applications, including Cinematography, UI Design, Advertisement world, and Social Media Websites too [9]. The research which is already existed, has mainly addressing on building handcrafted features for estimation of video aesthetics. In the study of aesthetics assessment of video, we present a computational approach for appraise video aesthetics. In this framework, we will adopt Deep Learning to predict aesthetic quality. In this case, large number of features is evaluated.

5. Significance and Approaches for Video Aesthetic Assessment

Cinematography is an art of Visual storytelling. It inclues controlling what the viewer likes to sees as well as how the video is presented towards the viewer. Video appreciation is totally based on sincere compliments. And sincere compliments are totally depends on the Aesthetically Pleasing Videos. Video aesthetics plays important role in Advertisement world. Pleasing videos captures the attention of target audience. Aesthetic videos also increase the engagement with audience. In this era of digital world, videos have been a effective way to attract consumers towards product and as a result, popularity of video advertising has been increasing day by day. In the modern digital world, users are watching videos across a number of devices, like computers, smart phones and tablets. In recent years, there has been explosive growth in video on social media, like YouTube, Facebook, Instagram, Twitter, etc. On social media especially on YouTube, subscription and likes given by user contribute towards Aesthetically appealing videos that are catered mostly for Visually appealing factors (for example, nature films, travelogue, and advertisement).

There have been several researches focusing on aesthetics assessment of Videos. The aim is to automatically classify videos into pleasing and non-pleasing videos. The very first approach is that, clarifying a collection of features of videos that they assume to influence the aesthetic quality of frames of videos. Then design some MathematicalModels for extracting those video frames. Such handcrafting of features is not only tough but also it is inadequate to eliminate the full, and complex nature of video aesthetics. Therefore, it could produce less accurate assessment result.

Another remarkable approach is to automate the process of assessing the aesthetic video demands deep learning. Particularly, using the Deep-Convolutional-NeuralNetworks(DCNN),which is trained on a Large-Scale video dataset, by which more accurate video quality assessment result is obtained than the conventional approaches. This technique is based on automated feature representation generally perform well in terms of determining whether the given video is aesthetically pleasing or not.

6. Literature Survey on Deep Learning

Aesthetic assessment of videos can help people to pick out or filtrate beautiful or say pleasing videos from the crowd. Aesthetic evaluation is an abstract field. Aesthetic evaluation of videos includes some Visual features. Visual features are those which are directly affecting to a person's Visual appreciation. This Visual feature includes color, texture, shape, pixel-level feature, edge detection. Various properties or attributes of an image affect on the photo, like Low-level feature, Middle-level feature, High-level feature. Low-level features are a slight description of an image including color, texture, intensity, edges, etc. For aesthetic evaluation, there is a use of a Multi-Scene-DeepLearning-Model (MSDLM)[1]. This model includes 8-layers Deep-ConvolutionalNeural-Network(DCNN), from which 5-layers are of Convolutional, and other 3-layers are fully-connected layers. Here a novel deep neural network and pre-training strategy is adopted. Due to use of DCNN approach, the result for image aesthetic evaluation is increased and more accurate. In this work, AVA(Aesthetic Visual Analysis) and CHUKPQ datasets are used. AVA dataset consists 255,000 images[3]. This datasets (AVA and CUHKPQ) having a lot of noisy data. A lot of data noise is reduced from this dataset.

As the number of layers is increased, complexity is increased. In [2], to reduce the complexity of DCNN, Global Average Pooling (GAP) is used. Here two approaches are used, in which 1) With a GAP layer, it fine-tunes a standard CNN, 2) with individual GAP operations, reduce the dimensionality of convolution layers, and then extract global as well as local CNN codes. An experiment shows the comparable accuracy results within different methods. The accuracy of the GAP is 76.32%, which is maximum than other methods. The complexity of training and testing is substantially reduced. Also, GAP layer is used in producing CAMs(Class Activation Maps) for Visualizing location in photographs. This will contribute towards an aesthetic quality of photos. Image aesthetics may depend on objects as well as scenes. To forecast image aesthetics scores in [3], Deep Convolutional Neural Network is used. By directing the image aesthetics prediction as a regression problem, make improvements in an authorized CNN architecture, to classify both targets or objects and scene.

Aesthetic assessment can be done with handcrafted features extraction as well as with Deep Learning. To estimate the aesthetic image descriptor, previous Algorithms used different techniques such as SVM, Neural Network or Random Forest[4]. To assess image aesthetics, study and compare the selection of algorithm that used handcrafted features. By integrating all the features altogether and obtain performance similar to the model which is trained on learned CNN features, we can achieve more improvements in aesthetic assessment accuracy. For various tasks such as classification, regression, categories, feature elimination is performed. [5] uses the architecture of DCM (Deep Chatterjee's Machine) for image aesthetics assessment that leads to superior performance. By using DCM photos are classified in High-Quality-Image and Low-Quality-Image. For Binary rating prediction, accuracy is compared with a different method. For low-quality images, accuracy by using DCM is correctly identified with accuracy result as 76.80% and for a high-quality image, accuracy is 76.04%. Hence DCM shows excellent performance compared to another state of art model. [6] focuses on Deep Neural Network approach. This approach is used to estimate image aesthetics. Aim and the focus of this paper is more on automatic feature learning. To absorb effective aesthetic features, Convolutional-Neural-Network(CNN) is used. However, photo aesthetics depending on an union of a Local-Views(for example sharpness and noise levels of an image) and Global-Views(i.e.Rule of Thirds). To take parallel inputs from two columns, the DoubleColumn-Neural-Network architecture is developed. In this double column neural network, one of the columns takes a Global-View and another column takes the Local-View of the photo. These two-columns further clustered after some layers of transformation and then mapped to the Label-Layer. This double column approach is applied to the generic image aesthetic problem. For Content-Based aesthetics of images, an approach of network adaption is proposed. For network related approach, attributes associated with images such as a style of an image and semantic attributes are explored. By leveraging these two style and semantic attribute respectively, performance is boosted. The overall result shows DCNN(Double Column Neural Network) achieved more accuracy (72.9%) as compared to SCNN(Single Column Neural Network) for global input as well as local input. [7] aims to improve the accuracy of photo quality assessment. The main focus is on the classification of an image into high quality and low-quality image, aesthetic attributes identification; automatically extract the high-level features, using pre-trained DCNN. In [8], LowLevel features and HighLevel features are combined, because as we study psychology of Humans about photos, then we came to know, humans usually rate only a few silent regions in the photo. To integrate low-level Visual signals and high-level Visual signals Sparsity-Constrained-Graphlet-Ranking algorithm is used. For silent graphlets discovery, this framework integrates multiple Visual/ semantic features. For duplicating a human gaze shifting path, these discovered paths are connected into AVP(Actively Viewing Path). For learning the distribution of AVP from aesthetically pleasing training photographs, GMM is employed.

[9] aims to study the properties of videos from the aesthetics belief. A variety of features are designed, for videos. Furthermore, features performance is examined in this domain of video detection. The experiment in this paper shows, this set of features can be used to obtain, classification rate of High-Professional video and Amateur video. For Professional-Video-Classification as well as Amateur-Video-Classification, the rate of accuracy is 97.3% and professional video detection rate is 91.2%. This paper is more focused on video features, such as motion of camera as well as length of shot. For a Visual aesthetics impression, in [10] authors designed some low-level features. They observed that this low-level feature affects the aesthetics of videos. With low-level features, authors are using some high- level features. The high-level feature is those which includes Rules of Photography, Conceptual rules. This high-level feature is also affecting the aesthetics of videos. Generic architecture that explains in the paper is shown below:

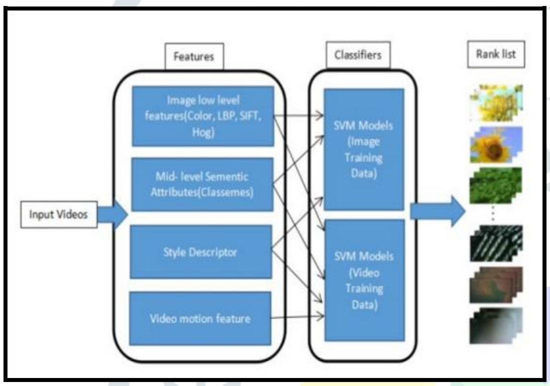


Figure 3. Generic Architecture for Video Aesthetics

As shown in the above figure, low-level image feature, Mid-Level-SemanticAttributes, Style-Descriptor, Video-Motion-Feature are extracted. To classify images and videos, SVM is used. Resultant will shows the ranking of image and videos according to aesthetic pleasingness. Similar to this summary of a literature survey is shown in the following Table II.

Table 2. Literature Survey

Sr. No	Papers refer (year of Publication)	Authors	Strong Points	Accuracy
[11]	Video_Aesthetic_Quality_Assessment_By_Combining_Semantically_Independent_and_Dependent_Features(2011)[11]	Chun-Yu Yang,Hsin-HoYeh and Chu-Song Chen	1. Assessing the Video aesthetic quality, for that combine Semantically independent as well as semantically dependent features. 2. Semantically independent features include Motion Space(MS), Hand Shaking(HS), Color Harmonic, Composition. Semantically-Dependent-Features include Motion-Direction-Entropy(MDE), Color-Saturation and Value, Lightness. 3. A result of these experiment shows, to differentiate the performance of an assessment between	Sementic-dependent: 69 ± 2.2%, Semantic-independen: 74 ± 1.5%

			SemanticallyIndependent-Features and Semantically-Dependent-Features, it can be notice that SemanticallyIndependent-Features exceed the Semantically-Dependent-Features in terms of aesthetic quality assessment	
[12]	Video_Aesthetic_Quality_Assessment_by_Temporal_Integration_of_Ph oto-and_MotionBased_Features(2013)[12]	Hsin-Ho Yeh, Chun-Yu Yang, MingSui Lee, &Chu-Song Chen	1. For obtaining the aesthetics standard of videos, a new method is presented in this paper. 2. Two processes are there, namely- for extracting the Aesthetic-Features from for every Frame in the video, this first method unites both photobased as well as motion-based Visual clues. 3. A Temporal-Order-Aware-Framework integrates Frame-BasedFeatures. This increases the evaluation accuracy. 4. Remarkable accuracy difference is the result of this paper.	On dataset, Telefoni on ca- 81.5 $\pm$ 1.9% $\pm$ And ADCC- 81.1 1.3%
[13]	Towards_a_Comprehensive_Computational_Model_for_Aesthetic_Assessment_of_Videos(2013)[13]	Subhabrata Bhattacharya, Behnaz Nojavanasghari, Tao Chen	1. Novel Aesthetic model is proposed, in which Psycho-Visual-Statistics are fragmented from numerous levels. 2. For evaluating the beauty of broadcast standard quality videos, this novel model is proposed. 3. Every video is dissociate into shots, and for each shot, uniformly keyframes are picked. 4. Features are selected at 3-levels, namely at Cells, then at Frames and then at Shots.	
[14]	A_Novel_Feature_Set_for_Video_Emotion_Recognition(2018)[14]	Shasha Moa, Jianwei Niua, Yiming Sua, Sajal K. Das	1. In this paper, survey of Social media is done. 2. Given approach in this paper is for effective feature extraction in Video affecting recognition system is built. 3. Performance of emotion recognitionis improved.	

[15]	Video_Aesthetic_Quality_Assessment_using_Kernel_Support_Vector_Machine_with_Isotropic_Gaussian_Sample_Uncertainty(KSVM-IGSU)(2016)[15]	Christos Tzelepis,Eftichia Mavridaki,Vasileios Mezaris, Ioannis Patras.	1. The KernelSVM-IsotropicGaussianSampleUncertainty(KSVM-iGSU), is an adjunct of the Kernel-SVM. This Kernel-SVM employs the unpredictability of data which is inputted, by which better classification results are obtained. 2. Video-Aesthetic-Quality Assessment Method integrating the characterizing every video as per the Rules-ofPhotography and Rules-of-Cinematography, with the use of methods of learning. Video representation's dilemma can be taken into consideration, with this learning method.	0.6814

Thus as given in Table 6.1, related work in the area of video aesthetics involves including video and approaches used include machine learning algorithms, deep learning methods and DCNN.

6.1. Research Gaps.

Earlier work concentrated on extracting the handcrafted image and video characteristics or collective Image-Descriptors to construct a Statistical-Model for assessing aesthetics. Although, the efficiency of the approach restricted by researchers' understanding of the aesthetic rules. Nowadays, researchers start to apply and use DeepLearning strategy in the Aesthetic assessment of Photos, Images as well as Videos.

Till now work on image aesthetic assessment is done, some researchers use handcrafted feature extraction technique or some prefer Deep Learning. But there have been few works on aesthetic assessment using video aesthetics by using Deep Learning. Almost all studies have been using, handcrafted feature extraction for aesthetic assessment of videos, which is not really accurate to rely on. Thus there is a need for mood detection through aesthetic assessment of videos using Deep Learning. Also here we are considering high-level features. Since this high-level features are unique for aesthetic sense.

7. Conclusion

In the study of mood detection of aesthetics video, we have reviewed advance deep learning techniques for video aesthetic assessment. In variance to handcrafted features that are expensive to design and have limited generalization capability, the essence of deep learning for video classification is to derive discriminate and robust feature representations from raw data through exploiting massive videos with an aim to achieve effective and efficient classification, which could hence serve as a fundamental component in video aesthetic assessment. This approach of assessment of videos is focusing on accuracy. In case of Deep Learning, accuracy is more than that of Handcrafted Feature Extraction mechanism. In Deep Learning our focus is on DCNN, for accuracy in the aesthetic assessment result. Here we are going to use, unique feature combination of color contrast (handcrafted extraction) and high-level features of Rule-ofThirds and Depth-of-Field for Mood Detection by assessing aesthetic Videos using Deep Learning.

References

[1] Weining Wang, Mingquan Zhao, Li Wang, Jiexiong Huang, Chengjia Cai, Xiangmin Xu, "A multiscene deep learning model for image aesthetic evaluation", (2016), ACM journal Image communication, Vol.47, Issue C, Pages 511-518.

[2] Magzhan Kairanbay, John See, Lai-Kuan Wong, Yong-Lian Hii, "Filling the GAPS: Reducing the Complexity of Networks for Multi-Attribute Image Aesthetic Prediction." (2017) IEEE International Conference on Image Processing.

[3] Simone Bianco, Luigi Celona, Paolo Napoletano, and Raimondo Schettini, "Predicting Image Aesthetics with Deep Learning", (2018) Springer international Journal.

[4] Michal Kucer, Alexander C. Loui, David W. Messinger, "Leveraging Expert Feature Knowledge for Predicting Image Aesthetics", (2018) IEEE Transactions on Image Processing, Vol. 27, No. 10.

[5] Zhangyang Wang, Ding Liu, Shiyu Chang, Florin Dolcos, Diane Beck, Thomas Huang, "Image Aesthetics Assessment using Deep Chatterjee's Machine" (2017) IEEE International Joint Conference on Neural Networks(IJCNN).

[6] Xin Lu, Zhe Lin, Hailin Jin, Jianchao Yang, and James. Z. Wang, "Rating Image Aesthetics Using Deep Learning", (2015) IEEE Transactions on Multimedia, Vol. 17, No. 11.

[7] Hui-Jin Lee, Ki-Sang Hong, Henry Kang, and Seungyong Lee, "Photo Aesthetics Analysis via DCNN Feature Encoding", (2017) IEEE Transactions on Multimedia, Vol. 19, No. 8.

[8] Luming Zhangy, Yue Gaoy, Chao Zhangz, Hanwang Zhangy, Qi Tian, Roger Zimmermann, "PerceptionGuided Multimodal Feature Fusion for Photo Aesthetics Assessment", (2014), Proceeding of the 22nd ACM international conference on Multimedia Pages 237-246.

[9] Yuzhen Niu and Feng Liu, "What Makes a Professional Video? A Computational Aesthetics Approach", July (2012) IEEE Transactions on Circuits and Systems for Video Technology, Vol. 22, issue:7

[10] Yanran Wang, Qi Dai, Rui Feng, Yu-Gang Jiang, "Beauty is Here: Evaluating Aesthetics in Videos Using Multimodal Features and Free Training Data", (2013), Proceeding of the 21st ACM international conference on Multimedia Pages 369-372.

[11] Chun-Yu Yang, Hsin-Ho Yeh and Chu-Song Chen, "Video Aesthetic quality assessment by combining semantically independent and dependent features", (2011) IEEE International conference on Acoustics, Speech, and Signal Processing(ICASSP).

[12] Hsin-Ho Yeh, Chun-Yu Yang, Ming-Sui Lee, and Chu-Song Chen, "Video Aesthetic Quality Assessment by Temporal Integration of Photo- and Motion-Based Features", Dec (2013) IEEE Transactions on Multimedia, Vol. 15, issue: 8

[13] Subhabrata Bhattacharya, Behnaz Nojavanasghari, Tao Chen, "Towards a Comprehensive Computational Model for Aesthetic Assessment of Videos", (2013), Proceeding of the 21st ACM international conference on Multimedia Pages 361-364.

[14] Shasha Moa, Jianwei Niua, Yiming Sua, Sajal K. Das, "A Novel Feature Set for Video Emotion Recognition", (2018) Neurocomputing 291, 11-20.

[15] Christos Tzelepis, Eftichia Mavridaki, Vasileios Mezaris, Ioannis Patras, "Video Aesthetic Quality Assessment using Kernel Support Vector Machine with Isotropic Gaussian Sample Uncertainty (KSVMIGSU)", (2016) IEEE International Conference on Image Processing (ICIP).

[16] Loris Nanni, Stefano Ghidoni, Sheryl Brahnam, "Handcrafted vs Non-Handcrafted Features for computer vision classification", (2017) Pattern Recognition 71, 158-172.

[17] Sanjay K. Kuanar, Rameswar Panda, Ananda S. Chowdhury, "Video key frame extraction through dynamic Delaunay clustering with a structural constraint", (2013) journal of Visual Communication and Image Representation, Vol. 24, issue: 7, Pages 1212-1227.

[18] Ritendra Datta, James Z. Wang, "ACQUINE: Aesthetic Quality Inference Engine –Real-time Automatic Rating of Photo Aesthetics", Proceedings of the ACM international conference on Multimedia information retrieval Pages 421-424.

[19] Cheng-Yu Wei,NevenkaDimitrova, Shih-Fu Chang, "Color-Mood Analysis of Films Based on Syntactic and Psychological Models", (2004) IEEE International Conference on Multimedia and Expo (ICME).

[20] Taylor, C., Schloss, K., Palmer, S.E. and Franklin, A., "Color preferences in infants and adults are different", (2013) Psychonomic bulletin & review, 20(5), pp.916-922.

[21] Lee Ellis, Christopher Ficek, "Color Preference according to gender and sexual orientation", Personality and Individual Differences. (2001) Dec 1;31(8):1375-9.

[22] Schloss, Karen B., and Stephen E. Palmer. "An ecological valence theory of human color preferences." Journal of Vision9.8 (2009): 358-358.

[23] https://nofilmschool.com/2016/06/watch-psychology-color-film