**CHAPTER 1**

**INTRODUCTION**

**1.1 OVERVIEW**

In today's world we deal with more images from capturing images in mobile phones to the Google Image search. All most all people would have used or using the images in one part of their life or other. Despite this overflow of visual information, humans are extremely good at remembering thousands of pictures along with some of their visual details. But not all images are equal in memory. Some stitch to our minds, and other are forgotten. Currently ,there is only an optimality in text searchers but the predictability of which part of an image is memorable is not in extensive use.

**1.2 OBJECTIVES**

* The focus of the project is to predict how memorable an image will be using Computer vision techniques and Visual Memory Schema.
* To serve the purpose of enhancing the human understandability, diagnose memory problems, for effective retrieval of image search, Computer Graphics and summarization of Big data images and videos etc .
* We will understand that memorability is a stable property of an image that is shared across different viewers.
* A database is introduced with the 2222 photographs from the SUN database ,2222 photos as target images and 8220 photos as filler images with pre computed features and annotations.
* We then analyze image features and labels that contribute to making an image memorable, and train a predictor based on global image descriptors.
* We finally find that predicting image memorability is a task that can be addressed with current computer vision techniques.

**1.3 PROBLEM STATEMENT**

The focus is of the project is predicting how memorable an image will be? using Computer vision techniques and Visual Memory Schema to serve the purpose of enhancing the human understandability, diagnose memory problems, for effective retrieval of image search, Computer Graphics and summarization of Big data images and videos etc...

We understand that memorability is a stable property of an image that is shared across different viewers. A database is introduced with the measured probability that each picture will be remembered after a single view. We then analyze image features and labels that contribute to making an image memorable, and train a predictor based on global image descriptors .We finally find that predicting image memorability is a task that can be addressed with current computer vision techniques.

**1.4 NEED FOR THE SYSTEM**

* To serve the purpose of enhancing the human understandability.
* To diagnose memory problems.
* To retrieve the images for effective retrieval of image on searching.
* To Compute Graphics and summarize Big data images and videos etc
* To understand that memorability is a stable property of an image that is shared across different viewers.

**1.5 CHALLENGES**

* The dataset is not available as easy to download.
* More complex computations are involved.
* Images that are non-semantics are not effective on retrieval.
* Images with low quality will results in degradation of performance.

**1.6 ORGANIZATION OF THE REPORT**

In this report, Chapter 2 gives the background on interactive discussion of related works. Chapter 3 describes the overall system design, algorithm and detailed description about each module and sub-modules. Chapter 4 describes the implementation of the proposed framework, results of the experiments conducted and performance evaluation.

**CHAPTER 2**

**LITERATURE SURVEY**

**2.1 FEATURE EXTRACTION**

E. Tulving in his work, “Organization of memory” best describes how memories play an important role in learning. The work emphasises more on how the memories form the essential component to define ourselves [1]

**2.2 CONSISTENCY ANALYSIS**

T. F. Brady et’al on their work “A review of visual memory capacity: Beyond individual items and toward structured representations” illustrates the human memory capacity for visual information absorption and retrieval of images from the memory.[2]

L. Standing et’al on their work “Verbal-pictorial transformations in recognition memory” performed two experiments during which subjects learned either footage or descriptions of footage of images and they’re then tested for recognition with either pictures or descriptions, altogether four mixtures. Recognition was best within the Picture-Picture condition, intermediate within the Picture-Word and Word-Word conditions which failed to take issue significantly, and worst within the Word-Picture condition. the additional variety of errors accessorial by dynamical to a metamorphosis condition (Picture-Word or Word-Picture) from the corresponding non-transformation condition (Picture-Picture or Word-Word respectively), was constant in either case. A model for recognition memory is projected that postulates that each pictorial stimuli and descriptive verbal stimuli are encoded in a very pictorial (or functionally equivalent) kind to that later transformations could also be applied by the experimental task. This model uses 2 parameters: a coffee background level related to pictorial secret writing and storage, and the next background level related to creating a verbal-pictorial transformation (or vice versa). The model is supported by a re-analysis of the information of Jenkins, Neale, and Deno (1967) and by the information of the 2 gift experiments. a further question, the chance of twin process of verbal and pictorial stimuli, was examined by using each footage and descriptions at the same time within the learning session and/or the take a look at the session. proof suggesting stereophonic operation was obtained in 3 out of 5 experimental conditions.[3]

**2.3 WHAT MAKES AN IMAGE MEMORABLE:**

P. Isola et’al on the work “Understanding the intrinsic memorability of images,” in conference on Neural information processing Systems, explained how the images exhibit the intrinsic property. Artists, advertisers, and photographers square measure habitually given with the task of making a picture can bear in mind ,whereas it's going to seem to be image memorability is only subjective, recent work shows that it's not associate degree paradoxical phenomenon: variation in memorability of pictures is consistent across subjects, suggesting that some pictures square measure in and of itself a lot of unforgettable than others, freelance of a subjects' contexts and biases. During this paper work, they tend to use the publically offered memorability dataset of Isola et al., and increased the article and scene annotations with explainable spatial, content, and they tend to used a feature-selection theme with fascinating explaining-away properties to work out a compact set of attributes that characterizes the memorability of any person image. They discover that pictures of fogbound areas containing folks with visible faces square measure unforgettable, whereas pictures of vistas and peaceful scenes don't seem to be. Contrary to fashionable belief, uncommon or esthetical pleasing scenes don't tend to be extremely unforgettable. This work represents one in all the primary tries at understanding intrinsic image memorability, and opens a replacement domain of investigation at the interface between human knowledge and pc vision. [4]

**2.4 WHAT CLASSES OF IMAGE PREDICT MEMORABILITY**

Z. Bylinskii et’al work on “Intrinsic and extrinsic effects on image memorability” ,explains how the intrinsic and extrinsic effects on image memorability. Previous studies have known that pictures carry the attribute of memorability, a prophetical worth of whether or not a unique image are going to be later remembered or forgotten. Here the work has a tendency to investigate the interaction between intrinsic and foreign factors that have an effect on image memorability. Firstly, they discovered that intrinsic variations in memorability exist at a finer-grained scale than antecedent documented. Secondly, they checked 2 foreign factors: image context and observer behaviour. Building on previous findings that pictures that area unit distinct with regard to their context area unit higher remembered, they proposed associate degree information-theoretic model of .Their model mechanically predicted amendments in the context change of the memorability of natural pictures. Additionally to context, they studied a second foreign factor: wherever associate degree observer appearance whereas memorizing a picture. It seems that eye movements give extra info which will predict whether or not or not a picture are going to be remembered, on a trial-by-trial basis. [5]

**2.5 MEMORABILITY MAP**

A. Oliva et’al work on “A holistic representation of the spatial envelope”, explains how to model the shape of the scene using a holistic representation of the spatial envelope. In this paper, their work tend to propose a process model of the popularity of universe scenes that bypasses the segmentation and also the process of individual objects or regions. The procedure relies on a awfully low dimensional illustration of the scene, that their work tend to term the abstraction Envelope their work tend to propose a collection of sensory activity dimensions(naturalness, openness, roughness, expansion, ruggedness) that represent the dominant abstraction structure of a scene. Then, their work tend to show that these dimensions is also dependably calculable exploitation spectral and coarsely localized info. The model generates a multidimensional area during which scenes sharing membership in linguistics classes (e.g., streets, highways, coasts) are projected closed along. The performance of the abstraction envelope model shows that specific info regarding object form or identity isn't a demand for scene categorization which modelling a holistic illustration of the scene informs regarding its probable linguistics class. [6]

**CHAPTER 3**

**DESIGN AND IMPLEMENTATION**

This chapter discusses the design of the system followed by implementation details. Initially the overall methodology is discussed followed by the implementation details for each of the modules in the system.

**3.1 SYSTEM ARCHITECTURE**

The system in Figure 3.1 aims at classifying the images based on memorable scores using visual memory schema. Image pre-processing is done to improve the image data. This method includes image color enhancement and image data augmentation. Then the transformed image is sent to traffic detection capsule network. Capsule network is implemented to overcome the disadvantages of convolution network. Capsule network involves four major steps. Input layer, primary capsule layer, traffic signcaps layer, output layer. Each layer takes the responsibility of carrying the encoded images and calculating the probablity of every image. Capsule network outputs the probablity of the layer. The probablity then subclassify using 9 main classes. The classification is handled by convolutinal network. Convolution network involves necessary layers to improve the performance of the system.

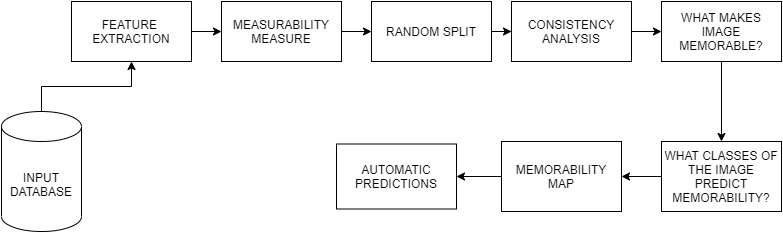


FIG 3.1 SYSTEM DESIGN

**3.2 LIST OF MODULES**

1. Feature Extraction and Memorability Measure
2. Split of Train and Testing data
3. Consistency Analysis
   1. Image Consistency
   2. Human Consistency
4. What Makes an Image Memorable?
   1. Color and Simple Image Feature Analysis
   2. Non Semantics Object Statistics
5. What Classes of an Image Predict Memorability?
6. Memorability Map Visual Memorability Map
7. Automatic Predictions

**3.2.1 FEATURE EXTRACTION AND MEMORABILITY MEASURE**

The aim is to compute the memorability measure and extract the features from the database. The input of the database is feed in matrix form consisting of images of 2222 photographs from the SUN database ,2222 photos as target images and 8220 photos as filler images with pre computed features and annotations.

We then, load the images and ignore the Texture Images for Feature extraction. Then, we compute the Memorability Measure to know the number of repeat images seen and Number of Filler images seen.

The aim of feature extraction is to improve the interpretability or perception of information in images for human viewers, or to provide `better' input for other automated image processing techniques.

**INPUT :**

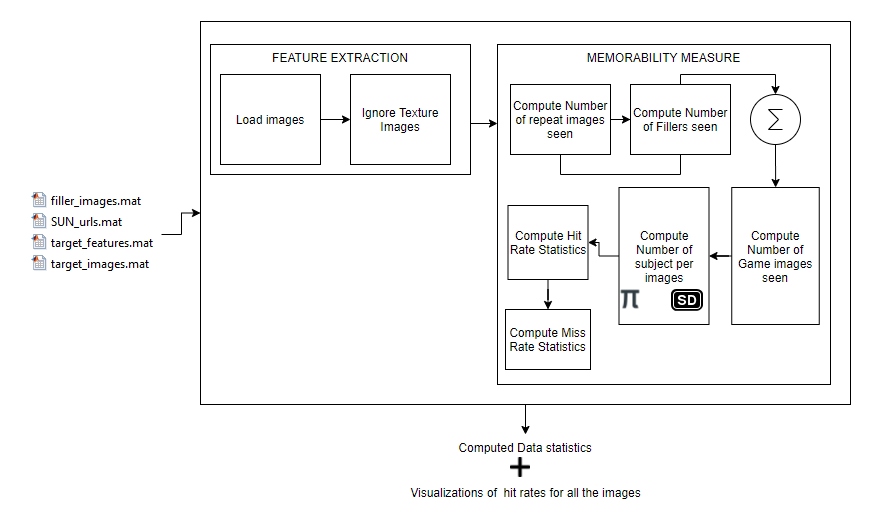
Database in matrix form consisting of images of 2222 photographs from the SUN database ,2222 photos as target images and 8220 photos as filler images with pre computed features and annotations.

**OUTPUT:**

Computed Memorability Score and Visualizations.

**INFERENCE:**

**Thus, memorability scores are a good measure of correct memories.**



3.2.1 FEATURE EXTRACTION AND MEASURING MEMORABILITY

**3.2.2 RANDOM SPLITS**

**INPUT :**

Database in matrix form consisting of images of 2222 photographs from the SUN database ,2222 photos as target images and 8220 photos as filler images with pre computed features and annotations.

**OUTPUT:**

Splited training and testing data in matrix format

  
3.2.2 RANDOM SPLITS

**PSEUDOCODE FOR RANDOM SPLITS**

Step 1**:** Input the database in matrix form consisting of images of 2222 photographs from the SUN database ,2222 photos as target images and 8220 photos as filler images with pre computed features and annotations.

Step 2 :Generate many random splits.

Step 3: Get the target detection vector and Ignore the texture images.

Step 4: Split Half subject Hit Rate Ratio.

Step 5 : Split the target detection Vectors into training and testing Hit Rate Ratios.

Step 6: Output consists of Splited training and testing data in matrix format.

**3.2.3 CONSISTENCY ANALYSIS**

**INPUT :**

Splited training and testing images for analysis of consistency model.

**OUTPUT:**

The percent of times that these images were remembered by an independent set of participants.

**INFERENCE:**

**Analysis shows how high human-to-human memorability consistency can be. Thus, our data has enough consistency that it should be possible to predict image memorability**

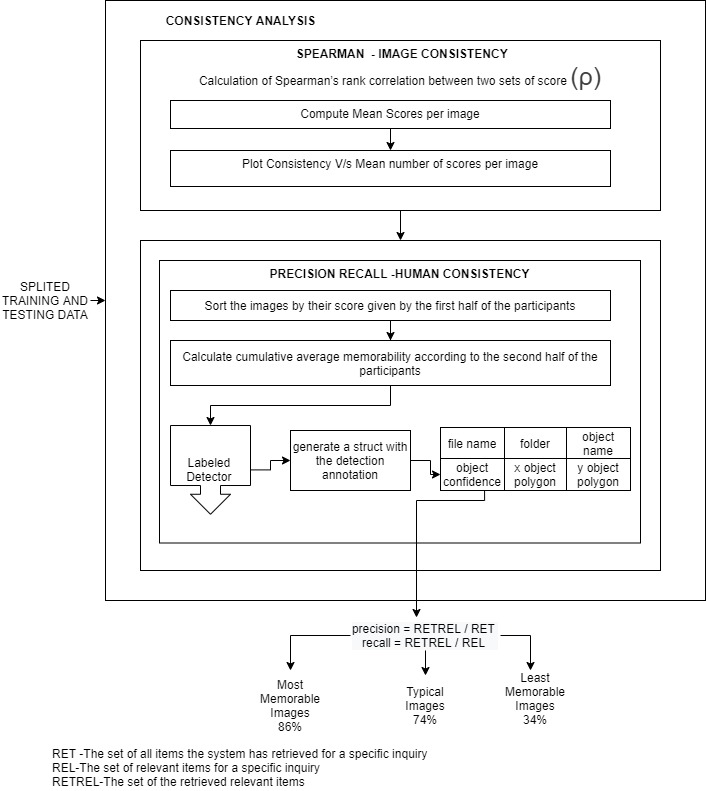
****

Fig 3.2.3 CONSISTENCY ANALYSIS

**PSEUDOCODE FOR CONSISTENCY ANALYSIS**

Step 1: Input the Splited training and testing images for analysis of consistency model.

Step 2 : Compute the Spearman's Rank Correlation for image Consistency analysis

* 1. Compute Mean Scores per Images
  2. Compute Consistency of Image

Step 3: Compute Precision Recall for Human Consistency Analysis

* 1. Sort the images by their score given by the first half of the participants
  2. Calculate the cumulative average memorability according to the second half of the participants
  3. Use the Object detector function to generate the structure with the detection annotation.
  4. Get the object Confidence and compute the precision Recall.

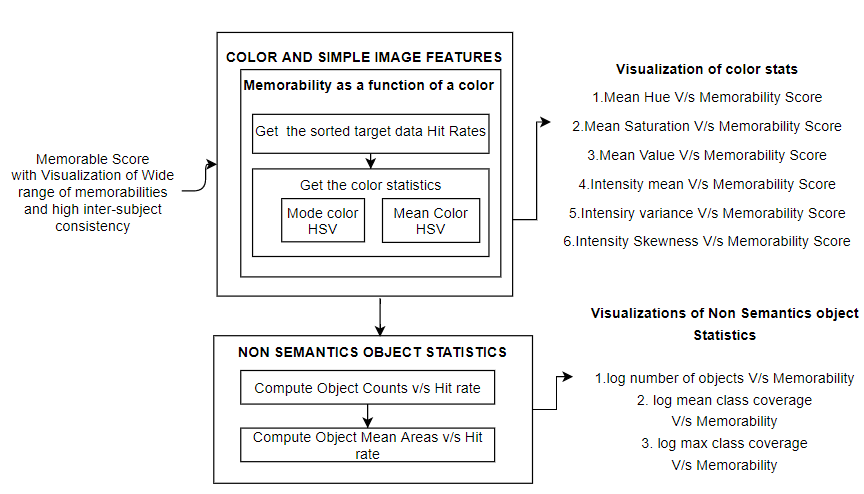
**3.2.4 WHAT MAKES IMAGE MEMORABLE?**

**INPUT** : Memorable Score with Visualization of Wide range of memorabilities and high inter subject consistency.

**OUTPUT:** Visualizations of Color Statistics and Non Schematics Object Statistics.

**INFERENCE: Do such statistics predict memorability?**

**Simple image features, as well as non-semantic object statistics, do not correlate strongly with memorability score.**

Fig 3.2.4 WHAT MAKES IMAGE MEMORABLE?

**PSEUDOCODE FOR WHAT MAKES IMAGE MEMORABLE?**

Step 1: Input the system with Memorable Score with Visualization of Wide range of memorabilities and high inter subject consistency

Step 2: Color and Simple image feature analysis using memorability as a function of a color

1. Get the sorted target data Hit Rates
2. Get the color Statistics
   * + - 1. Compute Mode Color Histogram Vector
         2. Compute Mean Color Histogram Vector

Step 3: Compute the Non-Semantics Object Statistics

* + - * 1. Compute Object Counts V/s Hit Rate
        2. Compute Object mean Area V/s Hit Rate

Output:

Visualizations of Color Statistics and Non Schematics Object Statistics

**Do such statistics predict memorability? Simple image features, as well as non-semantic object statistics, do not correlate strongly with memorability score.**

**3.2.5 WHAT CLASSES OF IMAGE PREDICT MEMORABILITY?**

**INPUT**:

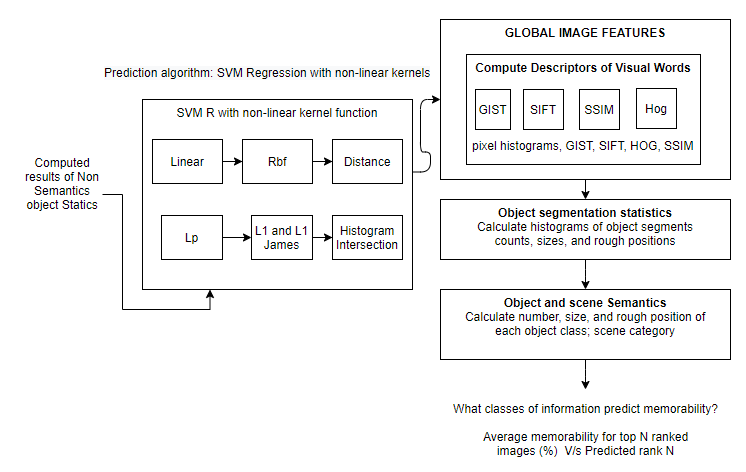
Computed results of Non Semantics Object Statistics.

**OUTPUT:**

Average memorability for top N ranked images(%) V/s Predicted Rank N.

**INFERENCE :**

Thus, analysis of object semantic regressions demonstrate that if a system knows which objects an image contains, it is able to predict memorability with a performance not too far from human consistency. Semantic images contribute for image memorability.



3.2.5 WHAT CLASSES OF IMAGE PREDICT MEMORABILITY?

**PSEUDOCODE FOR WHAT CLASSES OF IMAGE PREDICT MEMORABILITY?**

Step 1: Input the system with Computed results of Non Semantics Object Statistics.

Step 2: Use Prediction algorithm for effective correlation with memorability score

* 1. Calculate Support Vector Machine Regression with Non-linear Kernel Functions.
  2. Use the computation of kernel functions with global image features

a) Compute Descriptors of Visual words.

Step 3: Calculate histograms of object segments, count, sizes and rough positions for object segmentation statistics.

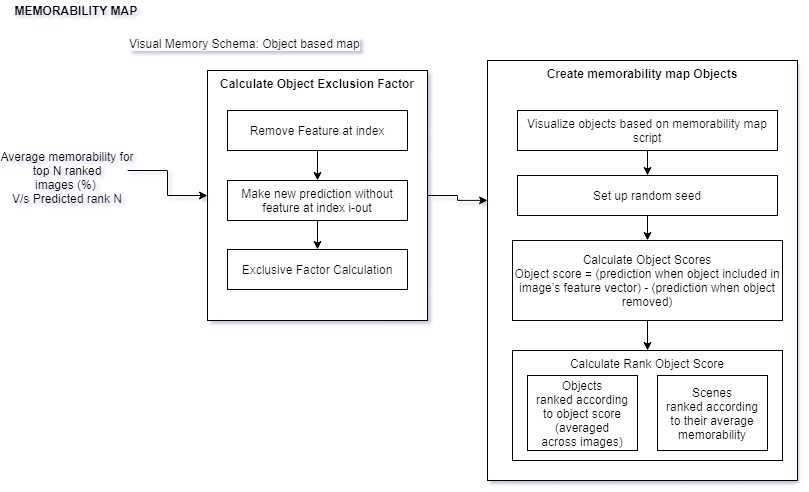
Step 4: Calculate number size and rough position of each object class scene category.

**3.2.6 MEMORABILITY MAP**

**INPUT:** Average memorability for top ranked images (%) V/s Predicted rank N

**OUPUT:** Visualizations of Objects ranked according to object score (averaged across image),Scenes ranked according to their average memorability.

**INFERENCE: It helps to visualize what content makes an image memorable?**



**3.2.6 MEMORABILITY MAP**

**PSEUDOCODE FOR MEMORABILITY MAP**

Step 1: Input the system with the Average memorability for top ranked images (%) V/s Predicted rank N.

Step 2:Calculate the object exclusion Factor

a. Remove the feature at index

b. Make the new prediction without features

c. Get the Exclusive Factor Calculation

Step 3 :Create Memorability map objects

a. Visualize objects based on memorability map

Step 4: Calculate Object Scores

Step 5 : Calculate Rank Object Scores

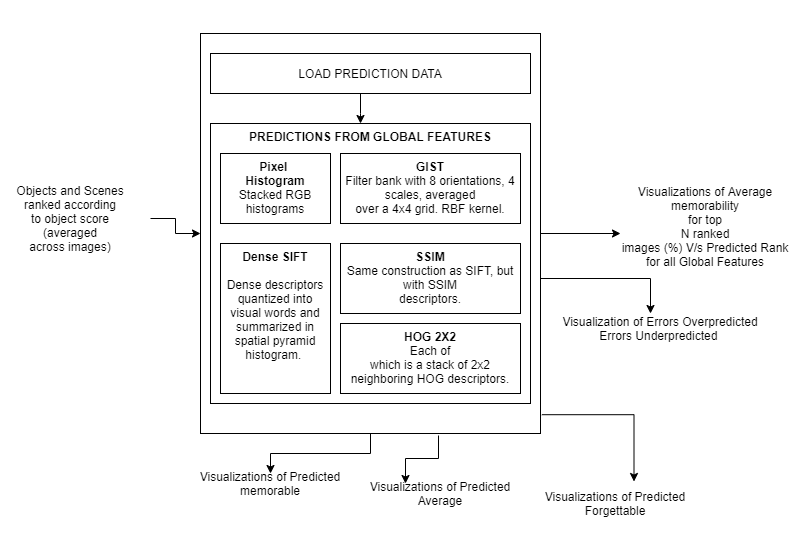
**3.2.7 AUTOMATIC PREDICTIONS**

**INPUT:**

Objects and scenes ranked according to the object score.

**OUTPUT:**

1. Visualizations of Average memorability for top N ranked Images V/s Predicted Rank for all global features.
2. Visualization of Predicted
   1. Memorable
   2. Average
   3. Forgettable
3. Visualization of Errors Over Predicted and Errors Under Predicted



3.2.7 AUTOMATIC PREDICTIONS

Step 1: Input the system with the object and scenes ranked according to the object score.

Step 2: Load the Prediction Data using Prediction function.

Step 3: Make Predictions from the Global Features using the following:

* 1. Pixel Histograms
  2. GIST
  3. Dense SIFT
  4. SSIM
  5. HOG 2x2

**CHAPTER 4**

**RESULT ANALYSIS AND DISCUSSION**

**4.1 EXPERIMENTAL SETUP**

* The IMAGE datasets: Database: 2222 photographs from SUN database:
  + Includes target and filler images.
  + Pre computed features and annotations
  + Memorability measurements from "Memory Game“.
* Computing features of new images, predicting their memorability, and replicating the results of Design.
* C,C++,Scripts, .mat for Coding.
* MatLab Software for results and plotting.
* Windows OS.

**4.2 TEST CASES**

* Natural Scene Images
* Outdoor Images
* Indoor Images
* Focused Images

We feed the system with the combination of the images and test for its accurate predictability.

**4.3 EXPERIMENTAL RESULTS**

The images are first augmented and then sent to detection and classification process.

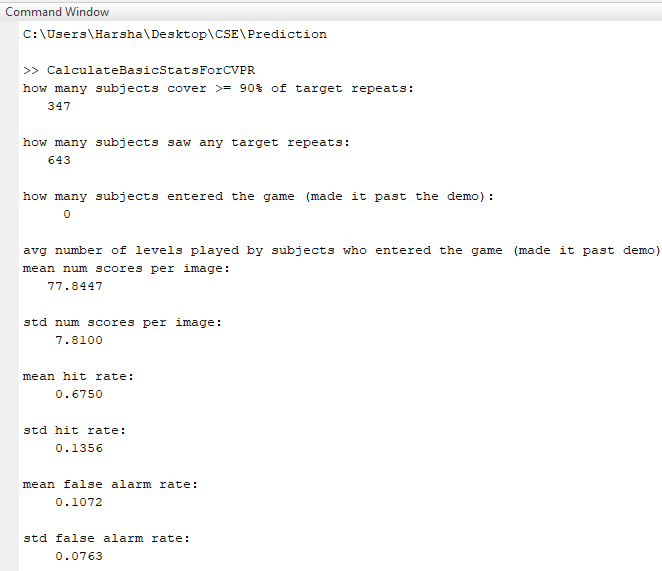


FIG 4.3.1 FEATURE EXTRACTION AND MEASURING MEMORABILITY

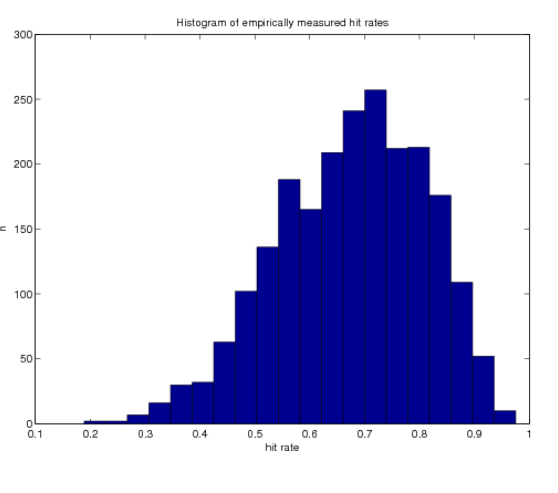


FIG 4.3.2 HISTOGRAM FOR FEATURE EXTRACTION AND MEASURING MEMORABILITY

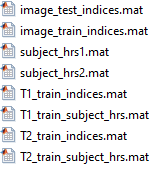


FIG 4.3.2 RANDOM SPLIT



FIG 4.3.3 DATABASE SAMPLE SET AFTER SPLIT

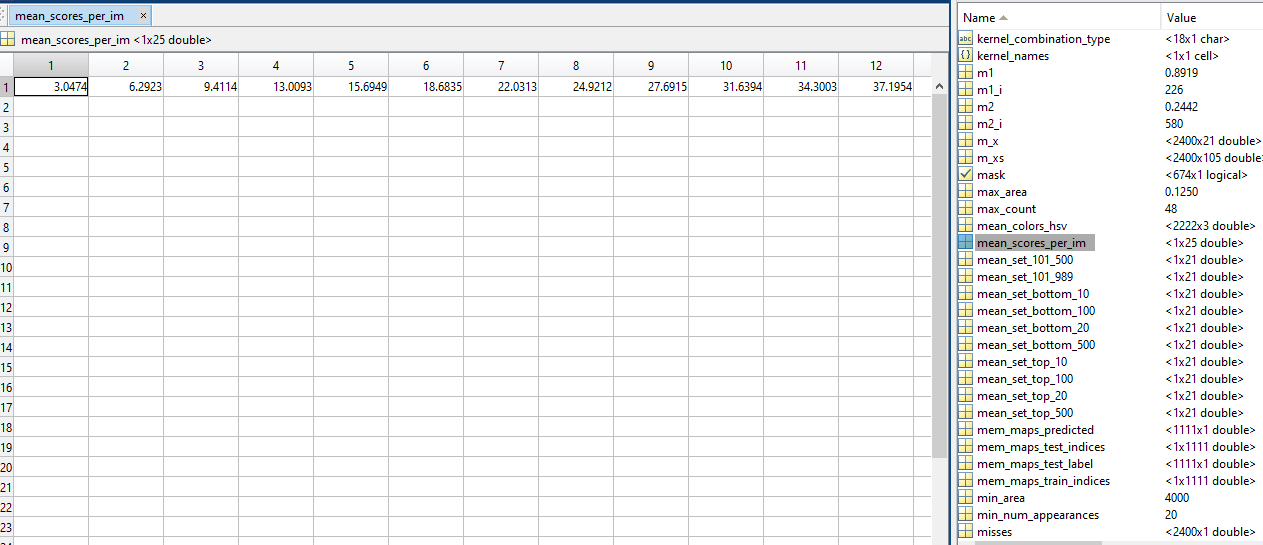


FIG 4.3.4 CONSISTENCY ANALYSIS

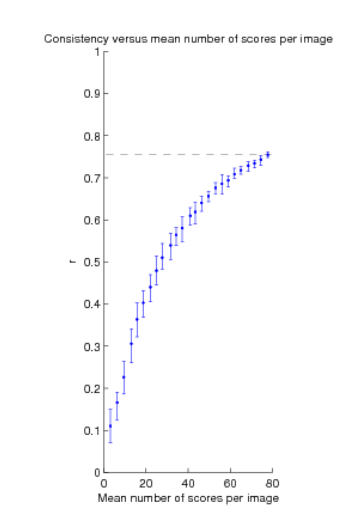


FIG 4.3.5 PLOT OF CONSISTENCY ANALYSIS

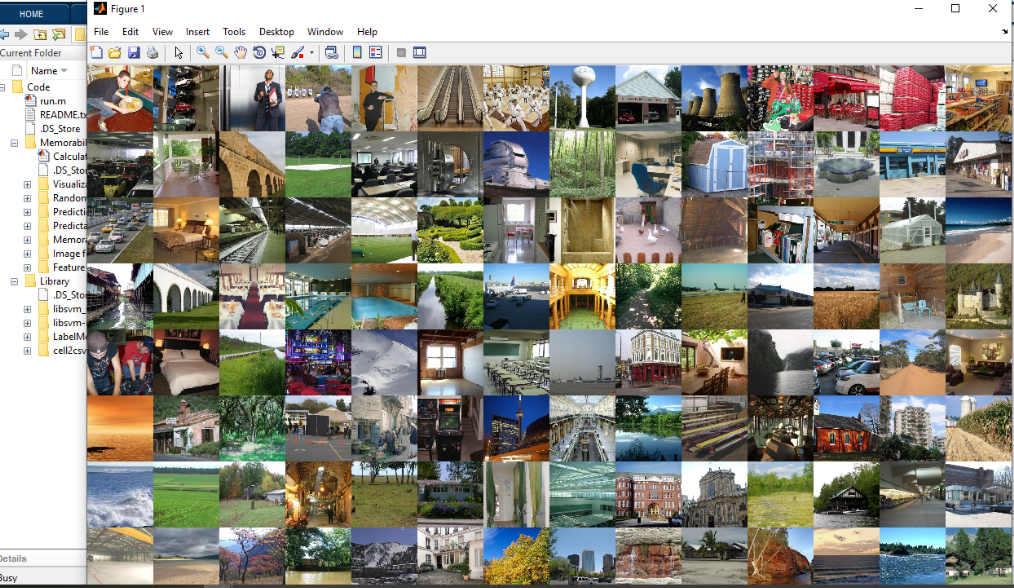
****

FIG 4.3.6 DATABASE ENTIRE SET SORTED BY HR

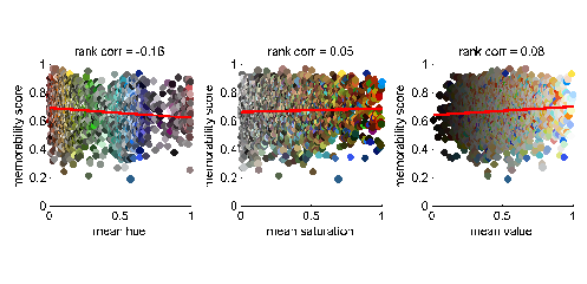
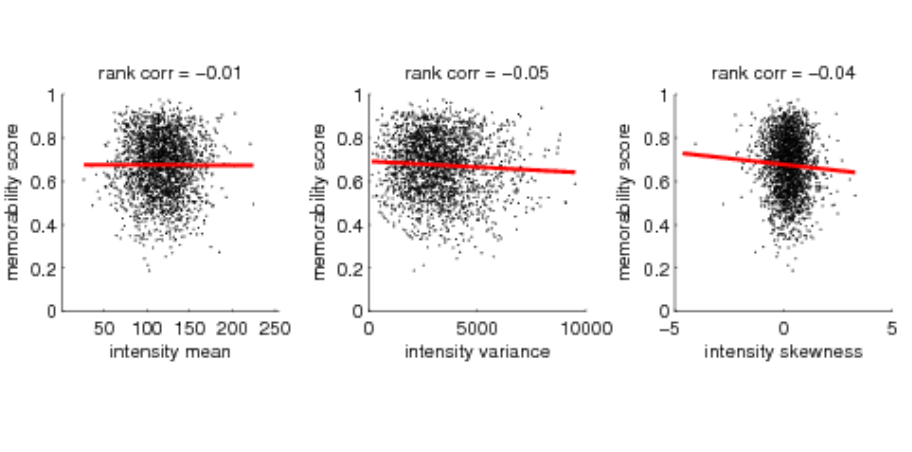
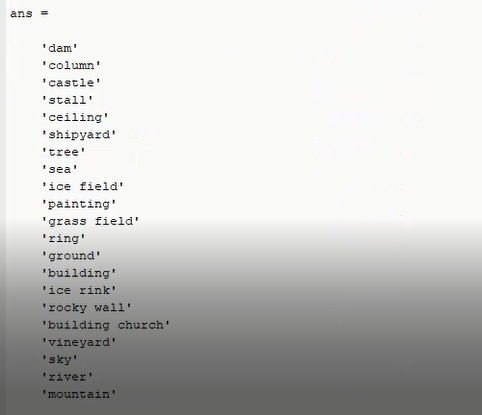


FIG 4.3.7 VISUALIZATION OF COLOR STATS

 FIG 4.3.7 VISUALIZATION OF COLOR STATS



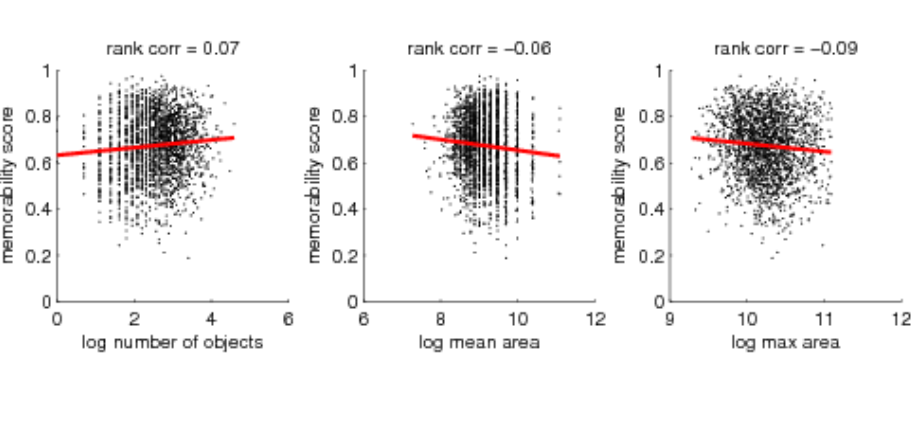
 FIG 4.3.8 NON SEMANTICS OBJECT STATS



FIG 4.3.9 OBJECT SCORE V/S OBJECT FREQUENCY

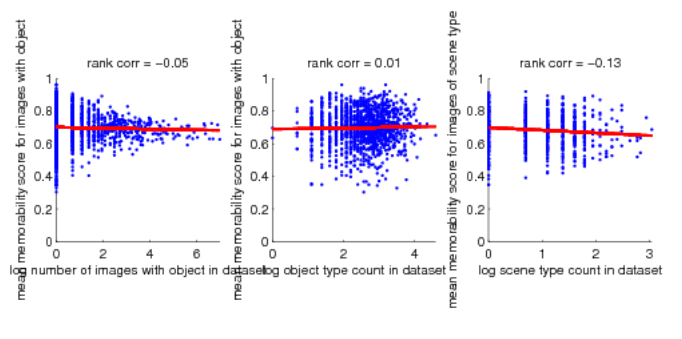


FIG 4.3.10 LOG NUMBER OF IMAGES V/S MEAN MEMORBILITY SCORE FOR IMAGES WITH OBJECT SCORE

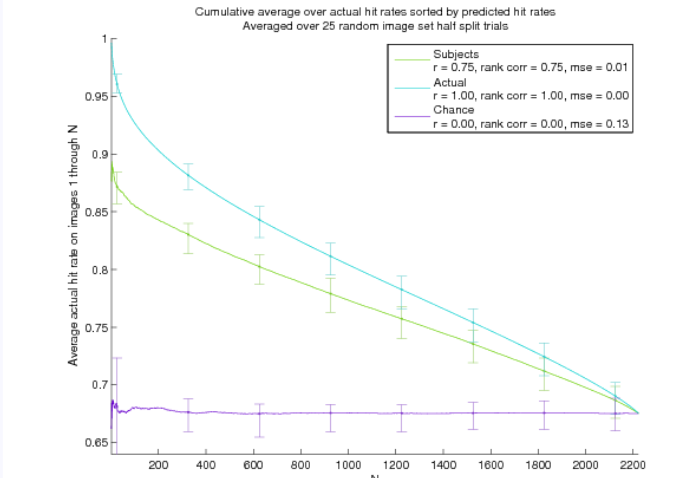


FIG 4.3.11 AVERAGE MEMORABILITY FOR TOP N RANKED IMAGES (%) V/S AVERAGE MEMORABILITY FOR TOP N RANKED IMAGES

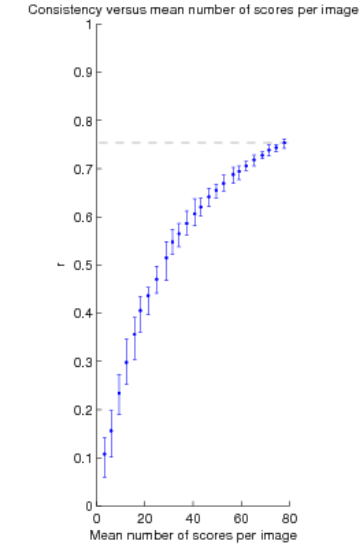


FIG 4.3.12 CONSISTENCY V/S MEAN NO.OF SCORES/IMAGE

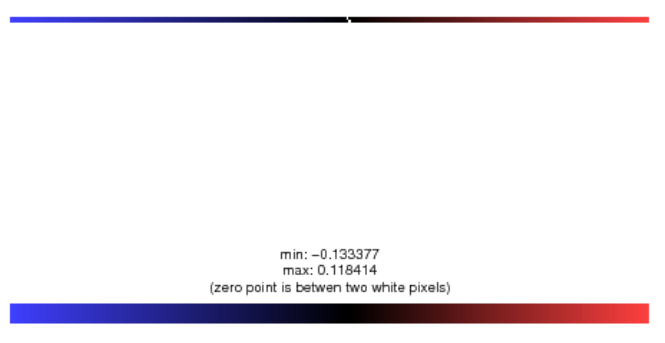


FIG 4.3.13 MEMORABILITY MAP COLOR SCALE



FIG 4.3.13 PREDICTED AS HIGHLY MEMORABLE 91%



FIG 4.3.14 PREDICTED AS MOST MEMORABLE 87%





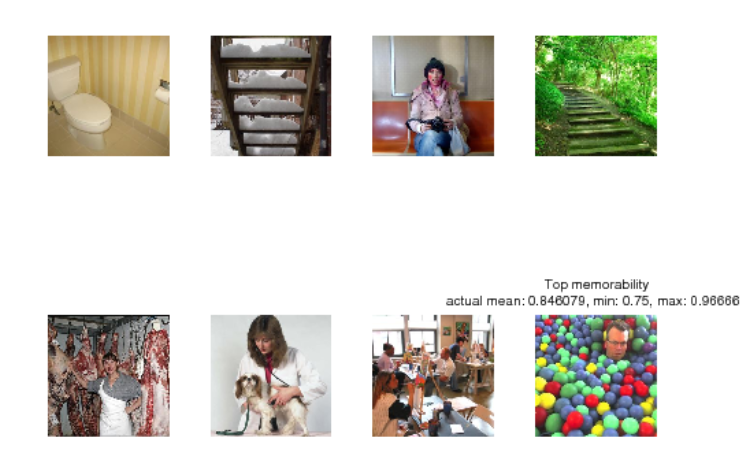
FIG 4.3.15 PREDICTED AS TYPICAL MEMORABILITY 68%

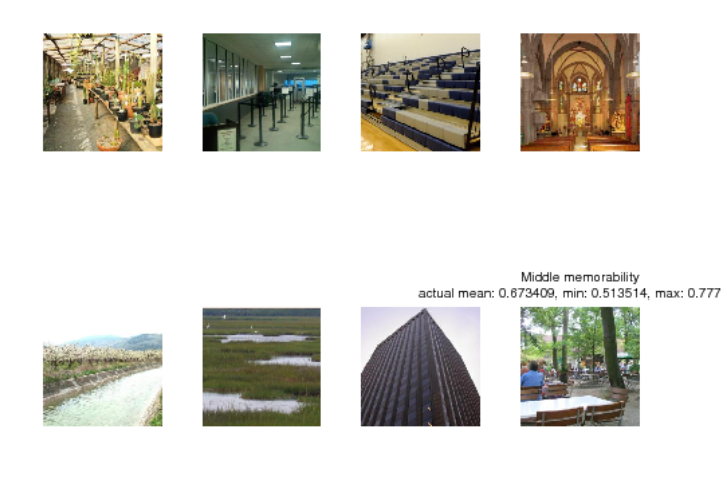


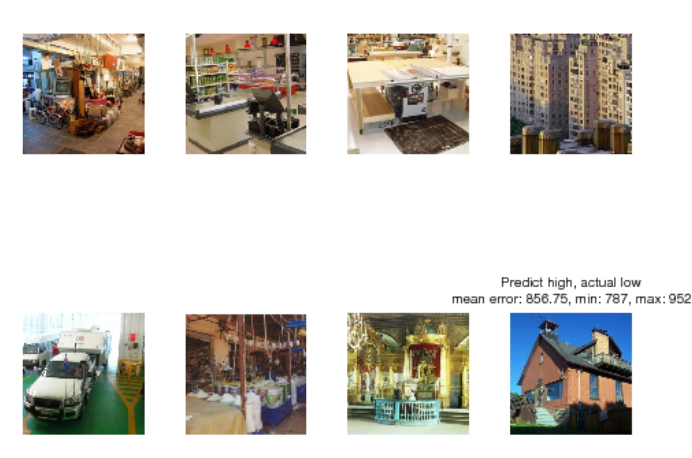
FIG 4.3.16 PREDICTED AS UNMEMORABLE 55%



FIG 4.3.17 PREDICTED AS LEAST MEMORABLE 52%





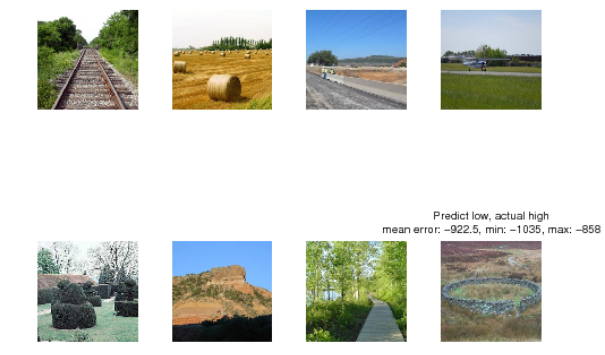


FIG 4.3.18 PREDICTED IMAGES

**4.4 EVALUATION METRICS**

1.Memorability = probability of correctly detecting a repeat after a single view of an image in a long stream.

2. Object score = (prediction when object included in image’s feature vector) - (prediction when object removed)

3. Hit Rate = Number of Images chosen correctly as remembered by observers ÷ Total number of their occurrences as a repeat image.

4. False Alarm Rate (FAR) = False Hits of an Image ÷ Total number of its occurrences as a second-stage-filler (i.e. non-repeat) image.

5. Spearman linear correlation coefficient c denoted as ρ2D 

6. Mutual information (MI) criterion, denoted as IA,B



7. A confidence scale allows us to produce ROC curves that provided us with a sensitivity measure of the experiment.

8.Precision = RETREL / RET

9. recall = RETREL / REL

10. RET -The set of all items the system has retrieved for a specific inquiry

11. REL-The set of relevant items for a specific inquiry

12. RETREL-The set of the retrieved relevant items

**5.1 CONCLUSION**

Making memorable photos is a challenging task in viewing and taking pictures, and is often presented as an obscure concept that is difficult to measure. Surprisingly, there has never been a previous attempt to measure this asset systematically in photo collections, and using computer viewing techniques to extract memory automatically. Scaling auto-image formats is an active domain for research many applications. For example, image memory can be used to extract, from a collection of images, those that can be most memorable viewers. This can be used to select image images, covers, user-friendly connectors, etc.

In this project we have shown that predicting image memory is a task that can be targeted at current computer viewing techniques. We rated the memory uses a restricted test setting to obtain a reasonable quantity: define the image monument rate as the viewer's chances of receiving a duplicate of image within photo streams. We have shown that there is a great balance between different viewers, and that some images are more memorable than others or no common items (such as relatives or famous reminders).

This work is the first attempt to measure the useful quality of each image. In the work to come it will be interesting to investigate the relationship between image memory and other steps such as object value, creativity, and image quality.

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