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# Intelligent Water Drop Algorithm based Relevant Image Fetching using Histogram and Annotation Features

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***Abstract*: Social media network increase trend of image collection at various platforms. Hence getting an relevant image as per query image or text is depend on retrieval algorithms. Number of researcher has proposed algorithms for fetching relevant images, but relevancy of those still need improvement. Hence proposed paper has utilized the Intelligent water Drop algorithm for initial clustering of images as per feature values. Clustering or relevancy of an image depends on visual feature histogram and annotation similarity. Here property of moving a water drop from one node to another in a water drop graph has increase the clustering accuracy of the work. Experiment was done on real dataset having five different group of image set with annotation. Result shows that proposed work has increase the retrieval relevancy accuracy as well as reduce the fetching of the images. This reduction of time was obtained by using the clustering structure of image dataset.***

***Keywords: Digital Image Processing, Information Extraction, feature extraction, Re-ranking.***

## I. INTRODUCTION

In the last few years, the ground of computer vision (CV) and Machine learning (ML) has widen its scale to address a variety of duties in Textile and Fashion manufacturing industry [1, 2]. An illustration of such type of classical duty is to take out visually related pictures from a huge picture record in reply to a question image given by customer. The increase of visual search brings forwards a variety of search engines TinEye, Flicker, Google as well as multimedia study paradigms [3,4].

This huge boost triggered the challenge of mining particular image amongst vast groups. Thus, image retrieval has become a vigorous ground of research [1]. Content Based Image Retrieval (CBIR) permits the consumers to convey his field interest by inserting a query picture that reproduce the semantics he/she is searching for. The record is then retrieved according to the inquiry content. For CBIR systems, the image properties of a picture are explained utilizing low-level characteristic signifier [2]. More particularly, the signifiers can be the shade, the quality and the shape types of the picture. These low-level characteristics interpret the visible content of the picture into statistical vectors that permit quantitative evaluation of the likeness between both pictures [3],[4],[5],[6],[7]. Though, there is a space between the semantic interest of the customer and the mined visual characteristic signifiers. For example, as shown in Figure 1, if the customer gives an image having a red apple as an inquiry, the retrieved pictures may include red flowers, red balloon or green fruit depending on the visual descriptor utilized by the CBIR. An additional inquiry in particular image retrieval comes out when the inquiry image have a number of objects. In fact, the recovered images may not be related to the exact objective meant by the customer. Lately, the several query retrieval systems has been projected in order to fill up this semantic gap, and improve the retrieval presentation [8]. For multiple query retrieval system, the customer expresses his attention via a collection of query images. This gives a more affluent perceptive of the customer high-level interest to the retrieval system and fills out the semantic gap with the low-level image function. Dissimilar to solo query based CBIR system where the gaps between the visual attribute descriptor of the inquiry image and the visual characteristic descriptor of every picture in the record are calculated and arranged in order to offer the nearly all related images to the customer, for multiple query image based CBIR systems, the dispute is how to calculate the gap between the collection of inquiry images and every image in the record in a way that improves the retrieval end results and reproduce the elevated semantic. The remaining research paper is prepared as follows. Section II explains color form. Section III shows histogram and picture retrieval. Section IV and Section V give aspects of color quantization and image query, equally. Section VI highlights trial results and finally, Section VII illustrates the generally end result of this document.

## II. RELATED WORK

Bhute and meshram (2013) [9] designed a new content based picture indexing and revival structure. In this occupation, utilize color, texture and form of inputs to facilitate the mending process. For improved mining, extract the color, texture and character information of input data normally using boundary detection which is widely utilized in sign processing and image firmness.

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In color characteristic removal scheme, image histogram and color correlogram are fast retrieval performs the antipole-tree system for indexing the descriptions. Finally histogram Euclidean division is executed to figure out the similarity amongst record and inquiry image.

Munje and kapgate (2014) [10] planned a new CBIR system. In CBIR system, the color and texture information's are extracted from inquiry images. The color characteristic is extracted by utilizing color instant and surface features are extracted by using gabor sort out system and wavelet convert. The information's are calculated for all pictures of inquiry and record images. Completely 15 characteristics for each image are determined, 6 color characteristic and enduring are texture element. Lastly according to the resemblance calculation the important images are taken out.

In [11] uses the visual contents of an image similar to worldwide features-color characteristic, shape feature, texture feature, and local features-spatial domain present to signify and index the image. CBIR method combines global and local features. In this paper worked on Haar Discrete Wavelet Transform (HDWT) for decaying an image into horizontal, vertical and diagonal region and Gray Level Co occurrence Matrix (GLCM) for feature extraction. Support Vector Machine (SVM) used, diverse calculations to recover the accuracy and implementation of recovery.

In [12] pictures resize according to the section of interest for the earlier recovery of pictures. Removing and eliminating difficult background will boost up further image processing. Very well-built discriminative power characteristic makes an important element in image and video recovery. Consequently, it is extremely significant to discover an effectual technique to calculate the directionality of an image, and tamura utilizes statistical calculation to compute statistical characteristic. And thus we mine texture characteristics and shape and fused these element vectors of tamura and form combinations for enhanced end result

Fu et al (2016) [13] projected the Convolution Neural Network (CNN) based deep characteristic mining techniques. The CBIR structure utilizes the direct Support Vector Machine (SVM) to arrange a hyper plane which can separate the relative images sets and dissimilar images sets to a huge degree. The couple of features from key image and each study image in the image dataset are known as information (input). The analysis images at that end are evaluated by the division amongst the couple features and the specialized hyper plane. Tests reveals that the intended system can significantly boost the implementation of CBIR for image revival undertakings.

Alsmadi (2017) [14] intended a novel resemblance system for CBIR utilizing mimetic approach. In this work, color, character and color texture information are extracted from question images. The shape characteristics are utilized to mine the belongings of the shape of the images. The texture features are mined by utilizing GLCM which is vigorous image statistical investigation approach. Then the likeness is calculated amongst the mined function and record feature by utilizing mimetic algorithm. Lastly the presentation of the work is examined.

In [15] writer attempted texture based image retrieval (TBIR) utilizing machine learning algorithms and their amalgamation including Faster Region based Convolution Neural Network (R-CNN), Adaptive Linear Binary Pattern (ALBP), Complete Local Oriented Statistical Information Booster (CLOSIB) Histogram of Oriented Gradients (HOG) and Half Complete Local Oriented Statistical Information Booster (HCLOSIB) for neighboring patch explanation of clothing. Their dataset is collected of 684 pictures of sizes that series between 480x360 and 1280x720 pixels gathered from 15 videos of YouTube. According to them R-CNN gained highest accurateness of around 85%. Job has also been done for detection of diverse form of dresses.

## III. PROPOSED METHODOLOGY

This section gives a complete explanation of proposed IRIWD (Image Retrieval By Intelligent Water Drop). Here fig. 1 shows steps of developing a ontology from the image database. Image set of features were extract and store in hierarchal structure where selection of cluster center were done by Intelligent Water Drop Algorithm. Two features were extract for developing of ontology from the image dataset first was annotation second was histogram. In other part of this section testing was perform where developed ontology gives an output as per input image and test query.

### A. Visual Content Processing

Input dataset may have different dimension image collection so transformation of all set of images in same Row-X-Column is prior requirement. As this work extract image visual features so all image matrix are of equal size. For annotation feature text pre-processing steps were apply such as conversion of string to words and then removal of stop words form the annotation.

### B. Feature Extraction

In this work two type of features were used for the image retrieval first was visual where histogram values were obtained. Here work has utilized B bins of histogram values. So image feature is counting of pixels range in [(1-B), (B+1 – 2B), ………(PB-M)], where M is max pixel limit and P is (M/B – 1). This can be understand as let image have 256 type of pixel values, now bins have values in range of [(0-15), (16-31), (32-47),………………….(250-255)]. Small feature set of sixteen values were produced with the image in form of visual content so comparison takes less time.

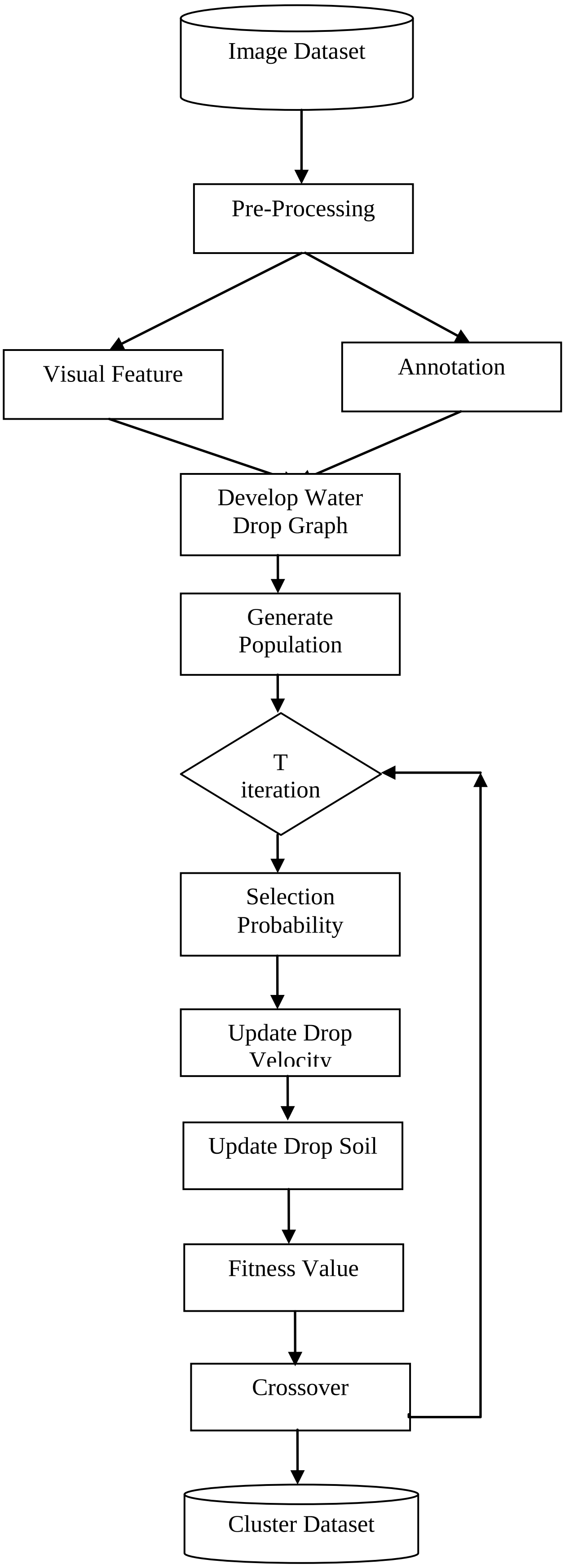



**Fig.1. Block diagram of proposed model.**

Further each annotation string is convert into set of words as per text pre-processing, so similar kind of image may have different set of words. This annotation increase searching accuracy. Hence feature set is collection of two type of data first is bins count and second was words from annotation.

Feature· [Bins Count, Annotations]

### A. IRIWD (Image Retrieval Intelligent Water Drop)

In this algorithm each image act as 'WATER DROP' where graph was develop having drop as node and feature difference as edge. This edge in the IWD algorithm s term as 'SOIL'. So a drop move form one node to other such that soil between nodes should be less as soil reduce the velocity of the moving drop. Hence as per similarity between the drops soil is less and cluster get form.

### B. Water Drop Graph

This is complete graph having N number of nodes where N is total number of images in the dataset. Hence WDG is NxN. Graph weight value in form of SOIL S was estimate for each edge between nodes. This value was obtain by the normalized value of annotation similarity and histogram distance of between nodes (Images).

$$Soil(i,j) = \frac{1}{Similarity(N_i, N_j) + \mathrm{Euclidian}(N_i, N_j) * \alpha} \quad \text{--Eq. } 1$$

Where α are normalization factor whose value range in 0.1 to 0.0001 as distance value by Euclidian is high so normalization is required for annotation factor.

### C. Static and Dynamic Parameter

In this step some of constant were initialize before the start of algorithm such as soil updating parameters $S_1 = 1$, $S_2 = .01$, and $S_3 = 1$, velocity updating parameters $V_1 = 1$, $V_2 = .01$, and $V_3 = 1$. Finally global and local soil constants $\beta_L$ and $\beta_G$ are initialize by 0.9. Values of constants may be vary as per algorithm requirement.

### D. Generate population

As population is collection of chromosomes where each chromosome is collection of cluster centers. Hence chromosome having set of image features which act as cluster center. To better understand this let image dataset have N number of images so one of possible solution is Chromo = $\{I_1, I_2, I_9, I_M\}$ where M is class of images. In similar way other set of M images were collect from dataset randomly. Hence population generation function can be written as:

**E.** P←Generate_Population(D, M, N)

### F. Selection Probability

This is probability of the drop to move from one of N-1 possible nodes. So this probability value SP is calculate as below:

$$\mathrm{SP}(i,j) = \frac{\mathrm{FS}(i,j)}{\sum_{k=1}^{N} \mathrm{FS}(i,k)}$$

$$\mathrm{FS}(i,j) = \frac{1}{\delta + \mathrm{GS}(i,k)}$$

$$\mathrm{GS}(i,j) = \begin{cases} \mathrm{soil}(i,j) & \text{if } \min(\mathrm{soil}(i, \text{all element}) > 0 \\ \mathrm{soil}(i,j) - \min(\mathrm{soil}(i, \text{all element}) & \text{otherwise} \end{cases}$$

### G. Update Velocity

Update velocity of the ith drop moving toward jth node by below formula:

$$V(t+1) = V(t) + \frac{V_1}{V_2 + V_3 * Soil(i,j)^2}$$

### H. Update Soil

Update velocity of the ith drop moving toward jth node by below formula:

$$\Delta S(i,j) = \frac{S_1}{S_2 + S_3 * T(t+1)^2}$$

$$T(t+1) = \frac{HD}{V(t+1)}$$

HD is heuristic durability a constant value range in 0-1.

$$Soil(i,j) = (1-\beta_L) * Soil(i,j) - \beta_L * \Delta S(i,j)$$

### I. Fitness Function

For finding the fitness value of the chromosome one need to compare the cluster fitness value. As work uses visual and annotation feature of the image so fitness value takes of them as input for each chromosome fitness value evaluation. Algorithm 1 shows the evaluation steps of fitness value from set of dataset images, as per population

Input: P, D // P: Pupulation, D: Dataset of N images
Output: Fitness
Loop 1:P
Loop 1:N
F[N,P]←Distance(Chromo[P], Feature[N])
EndLoop
Min←Minimum(F[N,:])
Fitness[P]←Sum(Min)
EndLoop

Where Distance is function that find difference in Bins count value of two images (Cluster center image, Input Image), while dissimilar words from the annotation were also increase this distance value. But as distance value of both feature is quit high so normalization of feature values were done by multiplying the Bins value with an constant range in [0.01 to 0.0001].

### J. Global Crossover

In this step of genetic algorithm crossover of the algorithm was done by selecting one common parent in all crossover with other set of chromosome. So selection of this common parent depends on fitness value. Here best fitness values chromosome act as common parent in all crossover operation. So other set of chromosome undergoes crossover by randomly replacing a cluster center as per common parent cluster center value in same position. So if best set of Chromo is $\{I_1, I_2, I_9, I_{22}\}$ and random position is two than $I_2$ is place in same position two of other parent chromosome. This replacement is done only if other parent do not have same cluster center in other positions of chromosome.

### K. Population Updation

As crossover changes the chromosomes of the population so retention of this chromosome depends on fitness value. This can be understand if child chromosome have good fitness value as compared to parent fitness value than new child was include in the population, otherwise parent chromosome will continue in population. Hence in all situation population size will never change from P number.

### L. Cluster Dataset

After T number of genetic algorithm iteration final update population was obtain. Best fitness value chromosome gives an set of cluster centers. Here all other images were clustered accordingly as per cluster center feature values.

### M. Testing Phase

Once dataset get grouped into cluster form than testing dataset will pass and evaluate the resultant ranked images. So each image from the testing dataset is pre-process first as done in learning phase, further similar visual, annotation features were also extract. Finally based on testing image feature cluster center feature values were compared and most matching cluster is select for the image ranking. Now each clustered image features were compared with testing image feature for final rank of images. This comparison was done by fitness function.

### N. Proposed Algorithm

Input: D // Dataset
Output: CD // Clustered Dataset

1. Loop 1:N
2. D←Image-Pre-Processing(D[n])
3. D←Text-Pre-Processing(D[n])
4. F←Feature-Extraction(D[N])
5. End Loop
6. WDG←Graph(N, F)
7. Initialize Static and Dynamic parameters
8. P←Generate-Population(D)
9. Loop 1:T // T: Number of iteration
10. SP←Selection Probability(WDG)
11. Loop 1:M
12. WDG←Update_Velocity(SP, WDG)
13. WDG←Update_Soil(SP, WDG)
14. End Loop
15. Fitness←Fitness-Function(P)
16. G←Best(Fitness)// G: Global
17. P←Crossover(G, P)
18. End Loop
19. Fitness←Fitness-Function(P)
20. G←Best(Fitness)// G: Global
21. CD←Cluster(G, D)

## IV. EXPERIMENT AND RESULT

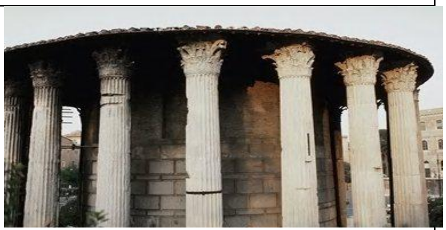
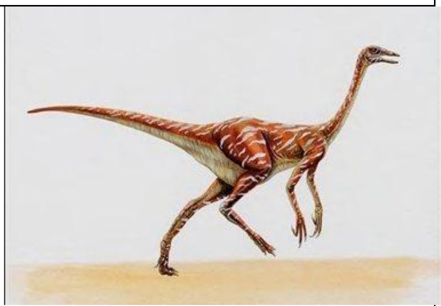
### A. Experimental Setup

Experiment was done on MATLAB platform where machine have configuration of 8GB Random Access memory, i5 processor. Results were evaluate on real dataset having 100 Images from 5 category [14]. Each category have 20 image in a set.

Detail description of dataset is shown in table 2.

| Feature | Description |
|---|---|
| Number of Images | 100 |
| Category | 5 |
| Dimension | 384x256 |
| Dimension | Three Dimension Color |

**Table –III: Sample Image with Category.**

| Category | Sample Image |
|---|---|
| Human |  |
| Building |  |
| Transport |  |
| Animal |  |
| Food |  |

### A. Evaluation Parameters

**Normalized Discounted Cumulative Gain (NDCG):** l is list of relevant and ir-relevant vector having 1/0 values for ith position. i range from 1 to P.

$$NDCG@P = Z_P \sum_{i=1}^{P} \frac{2^{l(i)} - 1}{\log(i+1)}$$

B. **Precision:** In this parameter all relevant images are divide by total number of ranked P images.

P = Sum(l) / P

C. **Execution Time (Seconds):** This is time required to fetch image from the dataset as per input testing image and annotation.

### D. Results

Table –IV: Precision Value Based Comparison of Proposed Model for top 18 images.

| Category | Previous Work | GA | IRIWD |
|---|---|---|---|
| Human | 0.5 | 0.861117 | 0.944444 |
| Building | 0.362856 | 0.525 | 0.584418 |
| Transport | 0.41667 | 0.58335 | 0.77778 |
| Animal | 0.447 | 0.8333 | 1 |
| Food | 0.5278 | 1 | 1 |

Above table 4 represent that accuracy of relevant image retrieval of proposed IRIWD model using IWD genetic algorithm was high as compared to previous approach. Here use of visual and annotation feature in cluster form increase this efficiency of work. In previous work [13] Harris feature reduce retrieval accuracy.

Table –V: NDCG@18 Value Based Comparison of Proposed Model.

| Category | Previous Work | GA | IRIWD |
|---|---|---|---|
| Human | 0.64646 | 0.898792 | 0.958853 |
| Building | 0.460468 | 0.60683 | 0.695542 |
| Transport | 0.576752 | 0.633327 | 0.787896 |
| Animal | 0.62359 | 0.889843 | 1 |
| Food | 0.668422 | | |

Above table 5 represent that NDCG value for top 18 resultant images and it was obtained that proposed IRIWD model using IWD genetic algorithm was high as compared to previous approach. Here use of visual and annotation feature in cluster form increase this relevancy of resultant ranked images. In previous work [13] corner feature point matching reduce this NDCG value.

Table –VI: Precision Value Based Comparison of Proposed Model for top 20.

| Category | Previous Work | GA | IRIWD |
|---|---|---|---|
| Human | 0.475 | 0.85 | 0.925 |
| Building | 0.275 | 0.525 | 0.575 |
| Transport | 0.375 | 0.575 | 0.775 |
| Animal | 0.425 | 0.75 | 1 |
| Food | 0.475 | 0.9 | 1 |

Above table 6 represent that accuracy of relevant image retrieval of proposed IRIWD model using IWD genetic algorithm was high as compared to previous approach. Here use of visual and annotation feature in cluster form increase this efficiency of work.

In previous work [13] harris feature reduce retrieval accuracy.

**Table –VII: NDCG@20 Value Based Comparison of Proposed Model.**

| Category | Previous Work | GA | IRIWD |
|---|---|---|---|
| Human | 0.620478 | 0.889222 | 0.945367 |
| Building | 0.433405 | 0.600128 | 0.666623 |
| Transport | 0.539146 | 0.624897 | 0.785294 |
| Animal | 0.58293 | 0.831823 | |
| Food | 0.624838 | 0.934797 | |

Above table 7 represent that NDCG value for top 18 resultant images and it was obtained that proposed IRIWD model using IWD genetic algorithm was high as compared to previous approach. Here use of visual and annotation feature in cluster form increase this relevancy of resultant ranked images. In previous work [13] corner feature point matching reduce this NDCG value.

**Table –VIII: Average Precision Value Based Comparison of Proposed Model.**

| Category | Previous Work | GA | IRIWD |
|---|---|---|---|
| Human | 0.4875 | 0.855558 | 0.934722 |
| Building | 0.318928 | 0.525 | 0.579709 |
| Transport | 0.395835 | 0.579175 | 0.77639 |
| Animal | 0.436 | 0.79165 | 1 |
| Food | 0.5014 | 0.95 | 1 |

Above table 8 shows average values for different top relevant image set, proposed IRIWD model using genetic algorithm was high as compared to previous approach. Here use of visual and annotation feature in cluster form increase this efficiency of work.

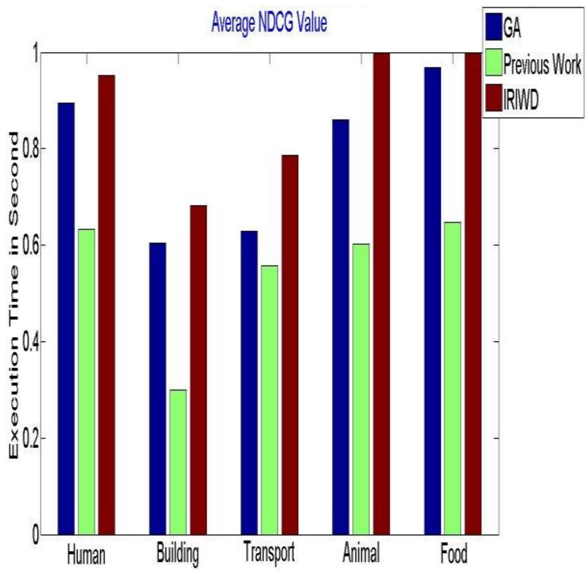



**Fig. 2. Average NDCG value Based Comparison.**

**Table –IX: Average Execution Time in Seconds Based Comparison of Proposed Model.**

| Category | Previous Work | GA | IRIWD |
|---|---|---|---|
| Human | 0.898 | 0.7781 | 0.7339 |
| Building | 0.8923 | 0.7922 | 0.7399 |
| Transport | 0.8103 | 0.7613 | 0.7269 |
| Animal | 0.8383 | 0.7838 | 0.7439 |
| Food | 0.8987 | 0.7938 | 0.7539 |

Above table 9 represent that execution time of relevant image retrieval of proposed IRWD model using IWD genetic algorithm was low as compared to previous approach. Here use of cluster structure for image fetching reduce this time.

## V. CONCLUSIONS

In the research of Image retrieval, there are a lot of achievements in image semantic feature, they can be applied to content-based image retrieval to analyze the transition between visual features and semantic features of the images. This paper has proposed a clustered structure to reduce the execution time of the algorithm for retrieval of relevant images. Here visual content histogram and annotation features were used by the proposed IRIWD model for finding the fitness value during clustering of images. Experiment was done on real dataset having different category images. Results were compared with previous existing approaches and it was obtained that proposed method has improved the NDCG value by 10.51%, while accuracy improved by 13.73%. In future one can involve other visual feature to increase this accuracy of work.

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