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Deep Learning using Spatial Distances, Normalized Coordinates, Scaling and Visual Words for Large Datasets

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Abstract

Image Retrieval has become popular and crucial task and the number of digital images on (web servers) amplified, it became increasingly very difficult to classify and track images. Many methods have been used to make image exploration effective and reliable, such as search based on the file name, image tagging, etc. but none have proved a good idea to work in real scenario. Our proposed methodology applies deep learning using spatial distances, normalized coordinates, scaling and visual words for large data sets for retrieval of images with highest accuracy. The proposed methodology has three basic steps: the first is Content Analysis. The image is passed through coarser intervolving phase, second is CNN, third is RGB color evaluation, fourth is Retrieved feature vectors and fifth is results derivation. Proposed methodology was applied on the three famous datasets namely, Cifar-100, FTVL and Fashion. Experiments conducted on these datasets have shown outstanding results.

Key Words: *Spatial Distances, Deep learning, Normalized Coordinates CNN, Artificial Neural Network, Computer Vision.*

Introduction:

Webservers became popular and the number of digital images on (web servers) amplified, it became increasingly very difficult to classify and track images. Many methods have been used to make image exploration effective and reliable, such as search based on the file name, image tagging, etc., but none have proved a good idea to work in real scenario. T Kato first used the term CBIR in 1992 when he described automatic color and shape-based image retrieval. From that day on, image searching has entered a new era and a lot of work in statistics, pattern recognition and Computer vision has been done to make CBIR more effective and profitable.

With increasingly growing demand for image retrieval, CBIR is attracting increasing interest from oftware designers and researchers in making it more powerful and reliable. The dimensions of the image retrieval applications as well as image databases are growing. As a result, increasingly refine algorithms and methods are presence contracted to meet complex requirements and CBIR's demanding. Content-Based Image Retrieval is extensively used in much research, governments, businesses, and other areas. Described below are some of its applications.

- Medical Science [32]
- Medical Imaging [32]
- Education [38]
- Multimedia [38]
- Remote Sensing [37]
- Crime Prevention [39]
- Management of Earth Resources [40]

CBIR introduces the image search concept through image as search query and extracting from the images database which are identical to searched image in content. The image features contain, or one of their combinations, color, texture, and shape. Texture features and Color features are like human experience, so these features are called high level features. On the other hand, shapes are low level feature because of shape is structural. Performance issues include retrieval time, recall and better precision consistency, and semantic difference. Both problems are highly dependent on which method is used for features extraction. An efficient method of extraction of the features produces successful results. It was observed that shape is the most powerful among all features because it recognizes the shapes existing in an image. “Relevance feedback” is another method used to enhance user experiences, or to collect interactive images. In short, all features have their own benefits and functions, and their individual advantages and features can be jointly used by having a combination of these features.

Machine learning (ML) is a sub-domain of artificial intelligence (AI) that enables the computers to learn from data automatically and improve themselves without human assistance. It focuses primarily on designing computer algorithms to access data and allow it to train on its own [1]. This is done by inspecting the data and searching the patterns for better decisions. The aim of Machine learning is to enable systems to learn automatically without explicit programming. In this way, ML is different from traditional computational approaches in which rules for algorithms are explicitly programmed.

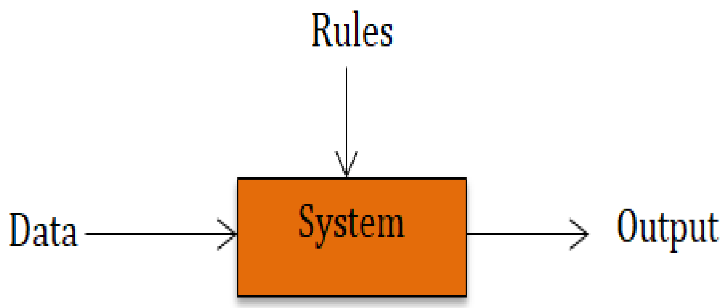

Fig. 1: Traditional Computing

In ML, algorithms are trained in finding the correlation between input and output and building the rule (figure 1.2). ML does not need humans during the learning process that uses statistical analysis to predict more accurate outcomes.

Fig. 2: Machine Learning Algorithms

Machine learning is being used in numerous applications today. Facebook's News Feed is one of the popular examples of ML. Each individual user's feed is customized. If a user continuously stops at the post of a specific friend or shares a post, News Feed would begin to show more updates from that friend than that friend's previous feeds. Behind the scenes, ML is using statistical and analytical tools to identify the patterns in user's data to fill the feed. When the user is no longer reading or liking or sharing that friend's posts, this new information will be added to News Feed.

Some other applications using ML include recommender systems, finance, robotics, and problem solving. The medical field is using ML in huge applications. It is also used to detect fraud and threats, in spam filtering and customized marketing.

Literature Review:

The Digital information division has improved the significantly in the recent year or so due to the use of digital media and the World-Wide-Web as platforms for the conversion and distribution of the digital-content. The digital images are one of the major and primacy individuals in the content based digital category present which is almost everywhere in the world where digital data is being share and used. Hosting and digital image sharing due to new technology and web server architecture become friendly for the end user.

Thus, as the webservers became popular and the number of digital-images on (web servers) amplified, it became increasingly very difficult to classify and track images. Many methods have been used to make image exploration effective and reliable, such as search based on the file name, image tagging, etc., but none have proved a good idea to work in real scenario. T Kato [41] first used the term CBIR in 1992 when he described automatic color and shape-based image retrieval. From that day on, image searching has entered a new era and a lot of work in statistics, pattern recognition and computer vision has been done to make CBIR more effective and profitable.

With increasingly growing demand for image retrieval, CBIR is attracting increasing interest from software designers and researchers in making it more powerful and reliable. The dimensions of the image retrieval applications as well as image databases are growing. As a result, increasingly refine algorithms and methods are presence contracted to meet complex requirements and CBIR's demanding.

Content-Based Image Retrieval is extensively used in much research, governments, businesses, and other areas. Medical Science [32], Medical Imaging [32], Education [38], Multimedia [38], Remote Sensing [37], Crime Prevention [39] and Management of Earth Resources [40] are some of its applications.

CBIR introduces the image search concept through image as search query and extracting from the images database which are identical to searched image in content. The image features contain, or one of their combinations, color, texture, and shape. Texture features and Color features are like human experience, so these features are called high level features. On the other hand, shapes are low level feature because of shape is structural. Performance issues include retrieval time, recall and better precision consistency, and semantic difference. Both problems are highly dependent on which method is used for features extraction. An efficient method of extraction of the features produces successful results. It was observed that shape is the most powerful among all features because it recognizes the shapes existing in an image. “Relevance feedback" is another method used to enhance user experiences, or to collect interactive images. In short, all features have their own benefits and functions, and their individual advantages and features can be jointly used by having a combination of these features.

Table 1: Categories of Image Retrieval Methods

	Color Based Feedback	**Shape Based Feedback**	**Relevance based Feedback**
Image-Retrieval Methods	Histogram Based Method	Combinational Shape Based method	Entropy
	Color Vector Quantization Based Method	Miscellaneous Shape Based Method	Kernel
	Color Indexing Schemes Based Method	Texture and Shape Based method	Statistical

In the last few years, there has been an emergence of research topics which are of immense importance and CBIR is one of them. After the concept emergence, initially the scientists and researchers focused on solving the problem of image retrieval based on its contents, particularly in cases where sets of millions of images need to be searched for finding the desired images. Existing image retrieval techniques have limitations which are always highlighted by the digital image's utilization and fast development of modern information technology infrastructure. This has resulted in the introduction of new image retrieval techniques and has created room for innovation and improvement. Researchers have explored newer vistas for developing more sophisticated image retrieval techniques to provide more effective and accurate results of image search based on image contents. In the literature review image retrieval techniques have been divided into three categories such as color, shape, and relevance feedback-based systems. A picture of this categorization is provided on the above table.

CBIR (Color Based Image Retrieval):

Color histogram is a smart technique for separating different portion of the image. It's commonly used since the early 1990's as a source of optimum image retrieval solution. However, in existing Web server models "Color Histogram Based" IR is not a "state-of-the-art" method. The need for effective and smarter methods of image retrieval has persistently surfaced due to the increasingly rising demand from web servers. However, even by the some known functional restrictions of the color histogram-based retrieval methods, it’s still being studied, and some of the operations in the variety of requests produce successful results.

As mentioned in [1], a "Color-edge Co-occurrence Histogram" pattern is used that is more specific on color edges and therefore makes it much easier to identify objects. This system, however, is proven non-resistant to “geometric” attacks and the lacks precision. If attempts are being made to resist this pattern to “geometric” attacks, and if the accuracy is increased, the method will produce even the better results.

It suggested the trademark and the logo retrieval system as mentioned in [2]. This method uses vector order statistics to produce more accurate representation of the colors on the edges of objects. Results showed accuracy of the retrieval but the little resistor above the algorithm once applied to tune it. This scheme has also shown zero resistance to geometric attacks and a problem is also the lack of precise usability. This scheme's adoption could rise if the usability increased, and this is also making manageable.

The method for retrieving the logo based on edge-gradient is detail discussed [3]. The suggested pattern operates with edged-gradients and has proven robust in the light of experimental results. This system, however, is not free from any critical shortcomings. Though this works will be best on gradient “image logos” it is not suitable for standard images. Similarly, in this technique the algorithm is not dynamically controllable. When it comes to image manipulation, geometric attacks are very important. Even this pattern is nonresistant to geometric attacks. The technique has minimal applicability and effectiveness for all these reasons.

A threshold-based scheme using gray level histograms was proposed in [5] that has proved very useful in multi-color images. Inceptions are more helpful in predicting the differences in color among items. This pattern also supports input parameter inception values, permitting application control to ask the algorithm to behave consequently as needed. It is non-resistant to geometrical attacks, and thus lacks strong usability. Only if its usability is enhanced and made to handle geometric attacks effectively as has been stated in the proposed techniques based on image decomposition and curve fitting can it become a better choice.

Article [6] applies statistical distribution to produce information with a view to rapid image retrieval. Experimental results have shown that the technique is simpler, more precise, and more resistant to scrambling and rotational attacks. Though the algorithm is robust, meanwhile it does not support dynamicity, it still lacks popularity.

The image retrieval technique for the block histogram was discussed in [7]. It operates on the concepts of the visual system of humans. Experimental findings indicated performance improvement over other approaches but without threshold help or control of dynamic change. It also has minimal uses, since it lacks resistance to geometric attacks. The future version of this method will expand its weaknesses and make it trust worthier with little more effort. For example, to enhance their functionality, the approach described in the proposed geometric attack resistance techniques can be integrated in it.

Article [41] presents a summary of techniques in four categories of CBIR. It presents the concept of Sequential Multiple Attribute Tree (SMAT). The tree is a multi-layer architecture in which the top layer depends on color; the second layer is based on size of cluster while the last one is based on spatial properties. The histogram refinement technique discussed in [10] detects the intensity value of the color pixel and separates the gray scale image on that basis. The image is then checked based on the result. There is, however, no provision in this algorithm for setting or managing color intensity. Authors may have enhanced the solution they suggested through making it resistant to geometric attacks.

The “block histogram image retrieval technique” listed in [36] applies on the human visual system theory and thus searches the image based on the visual weights assigned to the image blocks. Experimental findings showed improvement in efficiency over other approaches, but no threshold or dynamic change control support was also highlighted. There is a need for efforts to address these shortcomings which will also improve the technological applications.

The Content Based Image Retrieval technique detail discussed in [13] highlights the generation of local color-histogram that uses 5x5 neighboring pixel despicable and standard abnormality to estimate local mean histogram. This method works well on images with characteristics of broad texture but lacks power to work differently on characteristics of small texture size. It’s resistant to geometrical attacks and has good usability. This would have been more valuable if it had been dynamically controllable.

In Table 2 below, color-based image methods which make use of color histograms are discussed. In different ways, some of these techniques are defective in producing the best results but in exceptional circumstances, a number of these works. As mentioned earlier, image retrieval techniques based on histograms continue to be the focus of further study. Often, they are not flexible enough to cope with geometric attacks. Many techniques based on this logic suffer from out-of-control color histograms. Despite all the above-mentioned issues, they can provide very useful information if combined with other techniques.

Table 2: Color Histogram Based Image Retrieval Techniques

Sr.	Techniques / Algorithms	Pros	Cons	Conclusion
1	[1] Color edge co-occurrence-histogram	This will work better way on the object of edges	Nonresistant against geometric attacks.	Necessities to improve usability and geometric attacks.
2	[2] Logo & trademark retrieval	This will work better on small images and logo	Non-generic.	Only work on the logo images and very small images
3	[3] “Logo-retrieval based on edge gradient”	This will work better on logos and images gradient	Not appropriate for common images.	Deficiencies good practice of general images to become more flexible.
4	[4] Cloud image retrieval using (histograms)	Very robust and documented method for cloud-based image retrieval	Nonresistant-against geometric-attacks.	Enhancements desired to make the pattern more operational.
5	[5] (TBSB) Threshold based scheme based on grey level histograms	Better method which can control the infested domain at time of run	Nonresistant-against geometric-attacks & deficiencies good usability.	Best way using threshold managing the interested regions
6	[6] Fast image-retrieval	Effective image retrieval by support besides geometric attacks.	This will Support for dynamically alteration of algorithm	Very decent technique.
7	[7] Block (histogram-based image retrieval)	Works on values of generic and human-eye.	Nonresistant-against geometric-attacks and intricate.	Very decent technique.
8	[8] Color approximation technique	Only Works on low color regions & boundaries.	Non-generic.	Needs enhancements.
9	[9] Image retrieval using histogram-graph	Low overhead & light weight.	Nonresistant-against geometric-attacks.	Good method
10	[10] Histogram-refinement for image retrieval	Works only on color pixel intensity and gives auspicious results.	Color intensity metrics are not under user control.	Batter approach with fine results.
11	[11,12] Feature-Extraction technique	Will work only on the images and their different kinds of objects	Not manageable to set the attentive region.	Batter technique with most usability scenarios.

12	Local color histogram generation [13]	Works on localized histogram for improved accuracy.	Requires increased computations.	The idea is good, but implementation is not up to the mark.

Image Retrieval Techniques Using Color Vector Quantization

The quantization color-based method suggested for histogram generation as mentioned [14] works best on dark background images. However, there is no way of providing light context execution for images. If made robust against geometric attacks, this scheme can be more efficient. Another method as mentioned in [15] classification of images based on the viewer's pictorial consideration of the image. This method has been used in the mean color and the moment of regions cleverly to efficiently retrieve images. The proposed techniques based on curve fitting and image decomposition are quite suitable to enhance its capability.

[16] provides an image retrieval strategy based on the quantization of the vectors. In the presented scheme the relationship of pixels is captured when indexing images. It then makes effective use of this relationship in efficient retrieval. The robustness of the method and the quality of recovery are apparent by experimental results. But the above said algorithm cannot avoid common image attacks and is not changed without a large portion of the algorithms being rewritten owing to unattainability of dynamicity and generalization.

A novel approach for fast image retrieval is presented in [42]. It first generates a matrix from feature vectors, and then it composes a dictionary structure based on it. The technique can expand the dictionary of features for new features. It presents a total of 77 per cent for a given database.

As illustrated in Table 3 below, it describes methods for CBIR that allow use of color quantization. Although approximately of these didn't provide the batter outputs view but same few in similar applications are very good. These techniques can provide good description for different colors within an image. If they are combined with others, they can provide the best results for color features of image because no single algorithm is best for all types of images related to different domains.

Table 1: Illustrate the Quantization CBIR techniques

Sr.	**Techniques / Algorithms**	**Cons**	**Pros**	**Conclusion**
1	Image classification	Non generic.	Used color mean and region for efficient retrieval.	General images for supports are required

2	Novel color quantization technique [17]	Nonresistant against geometric attacks.	capable results are achieved and HSV domain targeted.	Another new approach for finding the right regions of the images
3	[14] Color-quantization approach	Not accurate results in those images have such background	Works best on images with dark backgrounds.	An average technique which requires improvements.
4	Classified Vector quantization [31]	Nonresistant against geometric attacks.	Providing color and threshold to look for images inside range.	Overall, a good technique.
5	[16] Vector-quantization approach	Nonresistant against geometric attacks.	Color used for pixel relationship to get the accur4ate retrieval	Very batter algorithm if it improves the functionality

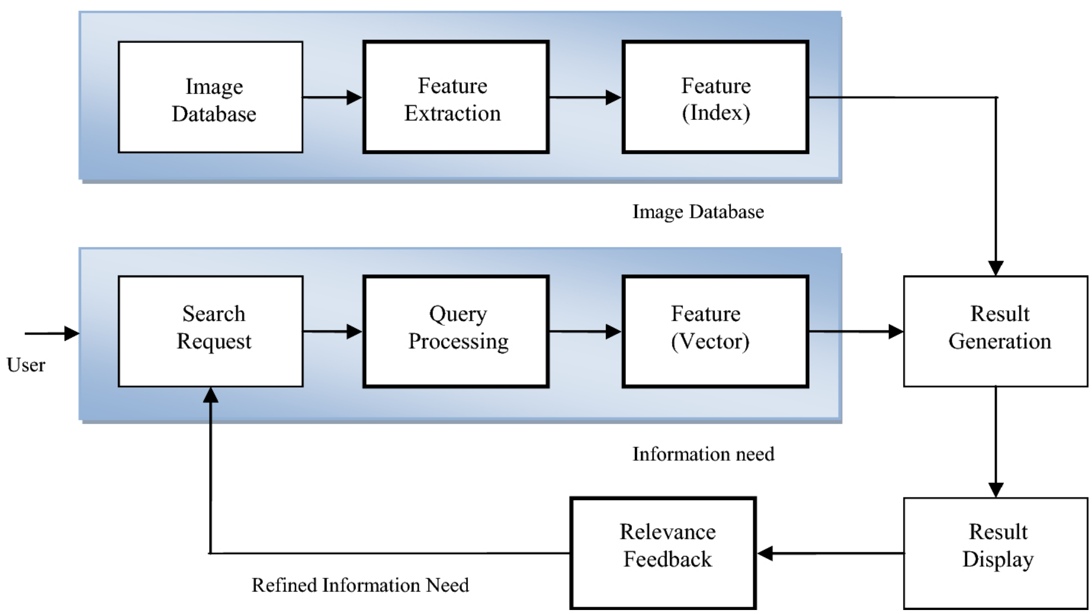

Fig. 3: Show All Information Retrieval Process in Indexing [43]

Image Retrieval Techniques" Using Color Image Indexing:

Image retrieval techniques" always based on the frequency layers of color indexing as mentioned in [19]. Image is indexed by using the color information present within its regions. This technique/method always focuses on lacks dynamicity and simplicity, resistance to geometric attacks and good use that make it less common.

Another approach as mention [20] regarding compact color which is used for the indexing and image retrieval. This algorithm focuses on effective, highly relevant retrieval but lacks resistance to geometric attacks and dynamically controllable parameters necessary to change the algorithm. If there were those add-ins, this algorithm might have performed much better.

An additional indexing scheme for color-based images is suggested in [21]. Color-correlograms are used to extract color spreading and spatial information within pixels. This proposed method has concentrated only on retrieval efficiency while ignoring the relevance, accuracy, resistance to geometric attacks and possibilities of running the same algorithm in different modes as needed.

Region-based indexing and Image segmentation technique suggested mention in [28] the tested by more than 10k test images in real world. Experimental findings have shown performance enhancement and have emphasized the fact that the algorithm could have been more usable if the system's dynamic parameters were given to control flow. Extraction for indexing images is discussed in [28] wavelet-based extraction feature. The author suggested the concept of wavelet architecture modeling image for the extraction of information relevant to color. Then this information is used for indexing and subsequent retrieval of the images. As with many other algorithms, non-resistance to geometric attacks, lack of accuracy and poor algorithm control according to requirement are its key shortcomings.

The color-based method is proposed for images indexing in the database. Considering the relation of objects in the image and computational difficulty, this solution is proposed. A 3D model represents a book of color codes. This technique is distortion resistant and can be modified based on three input parameters. However, this tuning must be done before running and cannot be modified when successively.

Using the wavelet quantization introduced in [30], enhanced image indexing technique is used to index images using their gray level information. Algorithms are tested against approximately 1000 image databases and show performance improvement but lacks resistance to geometric attacks and dynamic algorithm control which are the key improvements needed.

[35] As proposed, Wavelet-based indexing of images are used. Efficient exploration features interplanetary are mined, and color of keys are produced. In the image database these color keys are used to search for images. In finding images of similar color schemes and items this algorithm works well.

Table 4 below gives indexing-based image retrieval techniques. The image indexed using color information contemporary within image. Many of these techniques lack geometric attacks and dynamic algorithm control. CBIR based on indexing image, if not populated well, can severely decrease the performance of system. Not all these techniques deliver optimal outcomes, but some are able to produce very successful and consistent performance.

Table 2: Color Image Indexing Based Image Retrieval Techniques

Sr.	Techniques / Algorithms	Cons	Pros	Conclusion
1	New indexing technique [23]	Scaling and rotational attacks are not handled	Provides improved accuracy and efficiency.	Overall, a good technique.
2	Dynamic indexing [22]	There is no dynamic handing to tell which one index to usage.	improved searching changes, Index-based via multiple feat.	Batter approach for finding the image accurate results
3	Color [21] correlograms for extracting-index	Computational complexity.	Retrieval-efficiency.	results via less complexity.
4	Compact color descriptor [20]	Nonresistant against geometric attacks.	Binary descriptor and efficient results.	Improvement needed for geometric attacks.
5	Frequency layer indexing [19]	Not good for practical with complex images.	Performance and simplicity.	average method which requires improvements.
6	[26] Color-semantic indexing	geometric attacks. Nonresistant-against	Accurate results.	Room for improvement.
7	Gaussian mixture indexing [25]	Dynamically controlling the algorithm according to needs is lacking.	Works best on lossy images.	Fine approach.
8	Region based indexing [28]	Dynamic interaction is not possible.	Under use and deployed.	A good example of running implementation in production.
9	Color based indexing [30]	An increasing number of parameters will be required.	Takes input and works accordingly.	Very efficient approach.
10	Semantic indexing [24]	Not good for all images.	Caption based indexing with certain accuracy.	Not a very practical approach.
11	Wavelet based feature extraction for indexing [28]	No support for scaling attacks.	Improved accuracy.	Improvements needed for deployment.
12	Efficient indexing techniques [40,41]	Lacks support of attacks.	Improved efficiency.	Room for improvement.
13	Enhanced image indexing [30]	There is no user input combination.	Performance improvements.	Extensive requires for deployment
14	Wavelet based feature extraction for indexing [35]	Nonresistant against geometric attacks.	Efficient and accurate.	Need improvements for being a deployment candidate.

15	Local feature for indexing [33]	Non generic domain algorithm.	Vector based indexing increases efficiency.	Efficiency is good.
16	Color vector for indexing [31].	Distortion & lossy attacks are not impervious.	Efficient retrieval.	Need improvements.
17	Medical [32] Image-indexing	Non generic algorithm.	Works better on cancer images.	Not good for medical image-searching.
18	Multi resolution color indexing [34]	To manage multiple indexing for the same image extra load on server required	Improved accuracy.	Best for the corporate environment.

Hybrid Techniques for Shape Based Image Retrieval:

Each technique has some pros and cons. When two or more techniques are combined to cover the limitations of one by the other, they are categorized as hybrid techniques. These techniques are most effective because they can provide a good combination to resolve the targeted issues. The resulting techniques are more flexible and stronger to provide reliable and accurate results. Few hybrid image retrieval techniques based on shape are discussed in the following lines.

A technique is used to combine different features in [20]. In this study, it is proposed that combined features be used and that each feature of its own kind be taken advantage of, instead of using just one image retrieval function. With this approach, images could be clearly represented of all their aspects clarified. Experimental studies have clearly shown that integrating multiple features can better represent the image properties and result in efficient image retrieval across the entire process. But this set of features isn't dynamic because of which not all the techniques based on this concept have dynamics.

Another Honoring and Weight Assignment combined image recovery system is suggested in [22]. The proposed solution has an ability to assign weights to different features like texture, color, shape of objects and position. Weights are assigned automatically by the algorithm after calculating it from the test image directly without the user interaction. Weights will be assigned based on some parameters. Equations to calculate the weights are given in the article, so the weights are not fixed. The algorithm assigns greater weight to the color that has occupied a larger area of the image and so on for texture etc. Thus, images from different domains are more properly retrieved. Experimental results declare 92.8% accurate result to reveal the effectiveness of this technique. If weight assignment is associated with user input, further improvement could be achieved, and the user can decide which features are more significant.

Weights will then be assigned to the features accordingly started giving greater weight to the most important feature and so on. Thus, if a user wants to give importance to a specific object within several objects in an image, this will be considered to enhance the relevancy.

While searching for images, the retrieval system explicitly built for all kinds of medical images still has a combination aspect. Special image information is read from header "DICOM" and collective with the image features. Improvements in efficiency can be seen from the results of the studies. This algorithm could be further developed to make it work with non-DICOM images too. The hybrid techniques given in Table 3.5 below for shape-based image retrieval lack the best outputs.

Table 3: Image Retrieval Techniques Based on Combined Features.

Sr.	Techniques / Algorithms	Cons	Pros	Conclusion
1	Combined statistical information	Complexity and efficiency require the integration of statistical data degradation.	Incorporating statistical data for future searches.	Lack of good functionality but enhanced accuracy of the device.
2	Weight assignment & Honoring system	More complex.	Filter result of assigned weights can be giving good results	It operates well where it is appropriate to look for a choice of features.
3	Image Retrieval using mutual features	No dynamic feature selection.	Works best on the whole picture rather than relying on	Usability of the system needs improvements.
4	Search and Merge based retrieval	None.	Fine-designed methodology for effectively finding and combining search	Good way of handling the findings derived and reflecting them.
5	Combined features-based retrieval while filtering results	Slows down on extended feature vectors.	Good technique with filtered results.	Requires Enhancements to make the device more accessible.
6	Medical images retrieval by combined features	Dependent on DICOM format header.	Provides good retrieval results of medical images.	A working approach for medical images.
7	Irregular object-based retrieval	There are very complex artefacts in user-captured images. Additional Improvement is expected in algorithm.	Huge inspiration for complex systems. Works better amongst the same issue targeting techniques.	Overall, a very good technique.

Texture and shape features are very critical for a CBIR algorithm. The overall images retrieval accuracy mostly depends on these features. Image retrieval techniques based on texture and shape presented in Table 6 below are overall good to capture the correct texture and shape features from test images, but some have shortcomings that can be resolved to make the techniques more suitable for real use.

Table 4: Show the Texture and Shape Based CBIR techniques

Sr.	Techniques / Algorithms	Cons	Pros	Conclusion
1	Heterogeneous object shape retrieval	Images which are under attack not retrievable	Better Features extraction with evident results.	batter accuracy and efficiency with improved features extraction.
2	Shape based retrieval using Wavelets	Nonresistant against geometric attacks.	"Highlighted the potential" of research in this domain.	General motivational research. Need improvements.
3	Independent search for feature vector	Results are not calculated on huge datasets.	The main advantage of the strategy is independent search before combining the findings.	In general, a fresh approach to finding the correct images may be a strong candidate for execution.
4	Texture and shape-based retrieval	Implementation details are missing.	Extracts most details of images efficiently.	An average technique which requires improvements.
5	Leaf image retrieval technique	No information about attacks in such kind of results.	Promising accuracy is evident from test results.	Overall, a good, ranked technique.
6	Plant image retrieval by shapes	The figures are needed to enhance both are quite and low	Opened research opportunities for plant image retrieval.	Overall, a new direction of research but not very promising results.
7	Watermark based embedding and retrieval	Efficiency of the embedding of the watermark even before images are deployed.	Most advanced techniques with valuable benefits.	A most technological methodology and deserving of it. The overhead can be minimized to make the device more realistic and accessible.
8	Shape based retrieval for x- ray images	Specific to x-ray images.	With 90% precision, X-ray images are efficiently obtained.	Among one of the techniques graded highest for retrieval of x-ray images.

Materials and Methods:

This chapter discusses the proposed methodology. The chapter is divided into five sections. The first section provides a brief overview of methodology. The second section describes detailed content analysis. The third section discusses the CNN layers used to train the network.

The fourth section represents RGB coefficients mapping and spatial color information. The fifth and final section provides details about classification models used and indexing.

Proposed Methodology:

The proposed methodology applies deep learning using spatial distances, normalized coordinates, scaling and visual words for large data sets.

The proposed methodology has five basic steps:

1. Content Analysis
2. CNN
3. RGB color evaluation
4. Retrieved feature vectors
5. Results

Content Analysis:

The content analysis of this methodology consists of the following steps:

Coarser Intervolving:

Segmentation process is one of the most fundamental processes in image processing because the whole extraction and image retrieval process is based on it. Segmentation can be applied at a fine scale or coarse scale.

Coarser Scale: If the image is reduced, the image obtained after performing reduction is the image at the coarser level. Coarser details are available in the coarse scale image

Fine Scale: The original image is stated as the fine scale image.

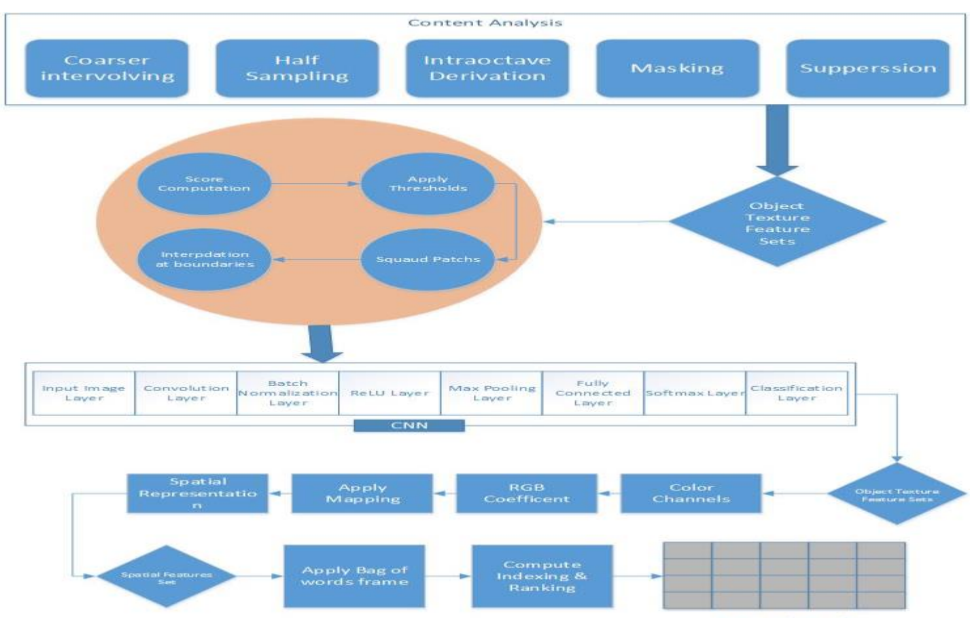

Fig. 4: Proposed Methodology

Thus, in the proposed architecture the image is first passed through coarser intervolving phase. Coarse scale segmentation is chosen because it involves discriminative and powerful features which provide great help in extracting useful features.

Half sampling:

The second step is to apply sampling to the images. The original image is half-sampled, i.e. half-sampling mechanism is applied on the original image. For an image pyramids usually scale spaces are used and they are divided into octaves. Half-sampling is helpful in the formation of octaves.

Intra Octave:

The pyramid layers consist of m intra-octaves y_i and m octaves x_i where i= {0,1,2…., m-1} and usually m=4. The original image is half-sampled gradually and octaves are formed as a result. Every intra-octave y_i is present between the two octaves.

To obtain the very first intra-octave y_0 the original image is down sampled by the 1.5 factor. Whereas the remaining intra-octave layers are obtained by applying successive half-sampling strategy. Thus, if scale is denoted by S, then

$$S\ (xi) = 2i \text{ and } S\ (yi) = 2i * 1.5.$$

Masking:

9-16 mask is used, and it demands nine consecutive pixels in a sixteen-pixel circle to be either brighter or darker as compared to the central pixel. Different mask shapes can be applied for key point detection. To identify the potential interest points the detector known as FAST 9-16 is separately applied on every octave and each intra-octave keeps the same threshold.

Suppression:

After applying mask, the next step is to apply suppression. Non-maxima suppression is applied on the points that belongs the regions obtained in the previous step.

- Objective texture feature sets
- Texture Feature Sets are obtained after performing the above steps.
- Score Computation and Threshold Application

First, in relation to its 8 neighboring FAST scores in the same layer, the point in question must satisfy the maximum requirement. The maximum T threshold that considers point as a corner is defined as score S.

Squad Patches:

After the computation of the scores these scores need to be lowered in above and below pyramid layers. Equal size patches are checked form inside and the length of the side is two pixels in that layer which is suspected as maximum.

Interpolation at Boundaries:

The layers in the neighbors have dissimilar discretization thus, interpolation mechanism is applied on the patch boundaries.

CNN:

Input Image Layer:

Image input layer inputs the image into the network and implements image normalization methods.

Convolution Layer:

This layer performs the operation named as "convolution". The convolutional layer can be applied on the results obtained from other layers in the CNN.

Batch Normalization Layer:

Batch normalization layer causes reduction in overfitting. I have applied this layer so that there will be less dropout. It means that less information will be lost.

ReLu Layer:

It stands for the Rectified Linear Unit. It is a linear function if the input is positive then it will give out the input as a result otherwise zero output.

Max Poling Layer:

It works on feature maps and reduces the spatial size.

Fully Connected Layer:

It is also called the output layer. Pooling and convolutional layer results are entered in fully connected layer.

Softmax Layer:

It is applied in CNN before the output layer and its number of nodes should be equal to number of nodes present in the output layer.

Classification Layer:

Cross entropy loss is computed by classification layer. It is calculated for classification problems with mutual exclusive classes.

RGB color Co-efficient and their Mapping:

In the color image there are three primary colors Red Green Blue (RGB) all the other colors are formed as the combination of these three colors. Color is also a feature of the image, and it contains very useful information for precise retrieval of the images. It is invariant to position which means it can deduct the color of the object present at any location of the image. So, the color co-efficient are deducted and they are mapped to get the most useful information about the image features.

Spatial Representation:

Spatial representation information is added because a bag of words does not have any spatial information which makes it weak classifier. To overcome this deficiency of Bow and precise retrieval of the images color-correlogram feature is used to also include spatial information.

Spatial Feature Sets:

After adding spatial information, the feature sets also containing the spatial information are obtained.

Bag of Words:

Bag of words also termed as Bag of visual words in image processing. This model is chosen for fast and accurate results. In this model the features extracted from the above phases are added and a bag of features is formed.

This model can only be used if the feature extraction process has already been applied on the image.

Codebook is a term just like the vocabulary term in Bag of Words model used for document classification. Codebook is the vocabulary containing the extracted features.

K means clustering is also applied for vector-quantization. The result of the BoW technique is the histogram of the features.

Indexing and Ranking:

After the histogram formation inverted index of the features is designed. For the ranked retrieval of the images by applying the matching mechanism between the query image and images present in the database.

Results:

The results retrieved from the above mechanism show a high precision rate and hence our methodology proved to be effective in precise retrieval.

Results and Discussion:

Data Sets:

In image retrieval tasks it is necessary to choose the data sets wisely. Datasets should be chosen by considering the fact which methodology is being performed, what is the domain and what methods are being used to make the CBIR systems that give precise results.

Cifar 100:

The dataset Cifar-100 is one of the large datasets which comprises 100 image classes and, in each class, have 600 images. And these images further split into the 500 training and every class has 100 tests. In Cifar 100 the 100 classes are assembled into 6 sub classes. Here we have the subclass including the 15 categories as aquarium, fish, bear, beer, beetle, bud, bowl, baby, beaver, bed, bicycle, bottle, boy, bridge, butterfly, and apple. Similarly, the second sub class includes the 5 categories named as camel, can, castle, caterpillar, and cattle. The third one sub class includes the categories named crocodile, crab, couch, cockroach, cloud, clock, chimpanzee, chair, fox, forest, flatfish, elephant, dolphin, and dinosaur. The three of the remaining sub classes are also categorized in a similar way.

FTVL:

The database of FTVL comprises 2612 images of fruits and vegetables. This includes the 15 types of categories with names of agata_potato, asterix_potato, cashew, fuji apple, honneydew_melon, diamond_peach, granny_smith_apple, kiwi, orange, spanish_pear, watermelon, plum, taiti_lime, onion and nectarine.

Fashion:

The dataset of fashion includes the images having items of 15 types of Blouses, Cloak, Coat, Jacket, jersey-tshirt, long dress, polo-sport shirt, long dress, polo-sport shirt, Robe, Shirt, short dress, Suit, Sweater, Undergarment, Uniform and vest-waistcoat.

Implementation and Results:

The following results are obtained by performing the proposed framework. We have applied the proposed methodology on Cifar 100, FTVL and Fashion datasets and the outstanding results have been obtained.

Cifar 100:

The results of applying proposed methodology on first 15 categories are shown in table 7and figure 5. The Bicycle category has the highest precision of 0.98 and Bottle has 0.96.

Table 7: Cifar 100 Categories 1-15 Precision.

Category	Precision

Apple	0.95
aquarium_fish	0.33
Baby	0.69
Bear	0.52
Beaver	0.47
Bed	0.69
Bee	0.61
Beetle	0.89
Bicycle	0.98
Bottle	0.96
Bowl	0.55
Boy	0.65
Bridge	0.49
Bus	0.55
Butterfly	0.22

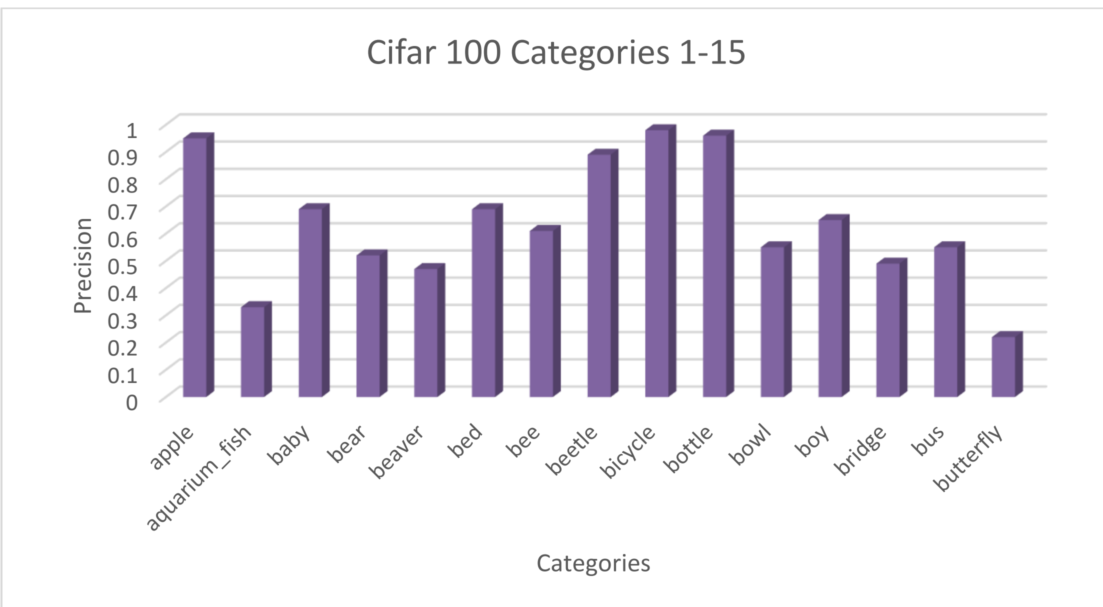

Fig. 5: Cifar 100 Categories 1-15 Precision

The categories of bicycle, bottle and apple are with the highest precision of 0.98, 0.96 and 0.95 respectively. Table 8 shows the precision of 16-20 categories.

Table 8: Cifar 100 Categories 16-20 Precision.

Categories	Precision
Camel	0.67
Can	0.88
Castle	0.7
Caterpillar	0.54
Cattle	0.88

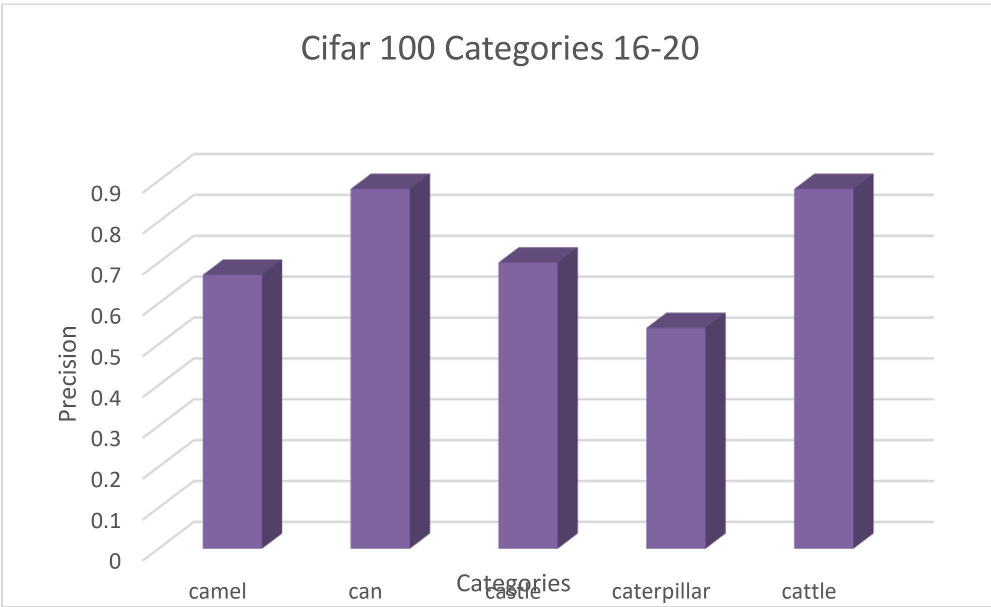

Fig. 6: Cifar 100 Categories 16-20 Precision.

This includes the categories of can, cattle and castle are with the highest precision having the values 0.88, 0.88 and 0.7 respectively. Table 9 and figure 7 shows the precision of 21-35 categories.

Table 9: Cifar 100 Categories 21-35 Precision

Categories	Precision
Chair	0.87
Chimpanzee	0.89
Clock	0.78
Cloud	0.98
Cockroach	0.97

Couch	0.39
Crab	0.76
Crocodile	0.5
Cup	0.97
Dinosaur	0.48
Dolphin	0.68
Elephant	0.6
Flatfish	0.48
Forest	0.8
Fox	0.89

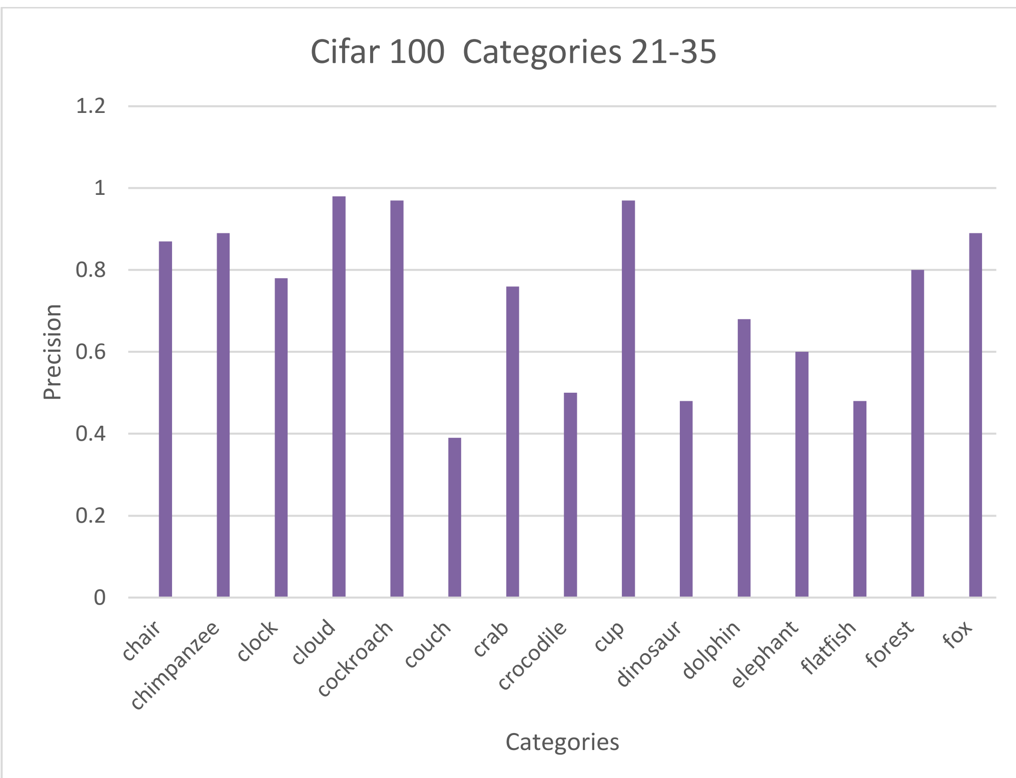

Figure 7: Cifar 100 Categories 21-35 Precision

The categories of cloud, cockroach and chimpanzee are with the highest precision of 0.98, 0.97 and 0.89 respectively and category couch is lowest precision of 0.39.

Fashion:

Table 10 and graph 8 depict the precision rates of Fashion dataset.

Table 10: Fashion Data set Precision

Category	Precision
Blouses	0.49
Cloak	0.79
Coat	0.99
Jacket	0.92
jersey-tshirt	0.87
long dress	0.89
polo-sport shirt	0.6
Robe	0.91
Shirt	0.59
short dress	0.8
Suit	0.98
Sweater	0.91
Undergarment	0.89
Uniform	0.93
vest-waistcoat	0.49

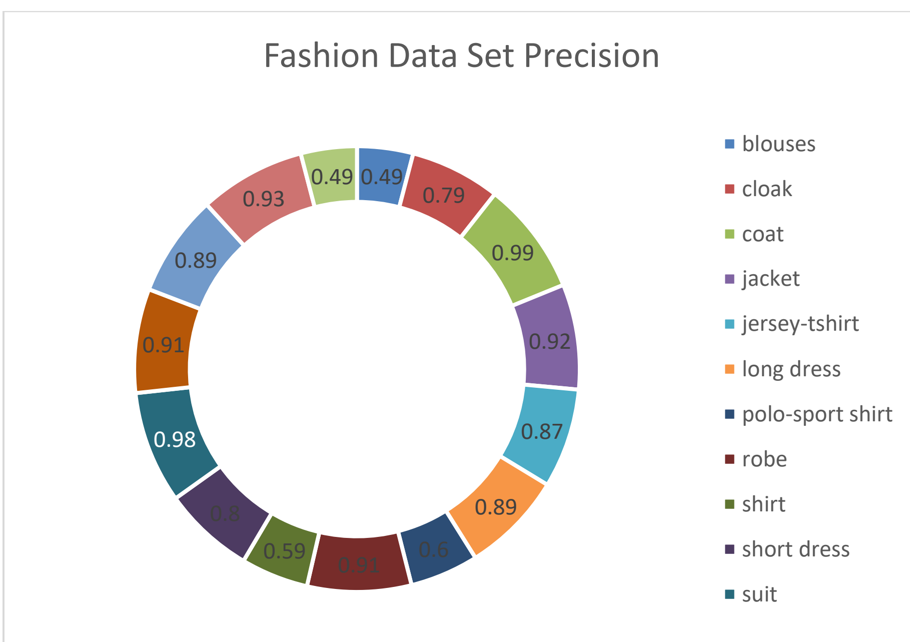

Fig. 8: Fashion Data set Precision.

It is comprised of the categories of coat, uniform and jacket are with the highest precision having the values 0.99, 0.93 and 0.92 respectively. The first category blouses and category vest-waistcoat have the lowest precision of 0.49.

Cifar-100:

The following table shows the cifar-100 categories precision rate from 36-50.

Table 11: Cifar-100 Categories 36-50 Precision.

Categories	Precision
Girl	0.4
Hamster	0.88
House	0.69
Kangaroo	0.58
Keyboard	0.87
Lamp	0.7
lawn_mower	0.91
Leopard	0.03
Lion	0.89
Lizard	0.66
Lobster	0.54
Man	0.61
maple_tree	0.88
Motorcycle	0.92
Mountain	0.69

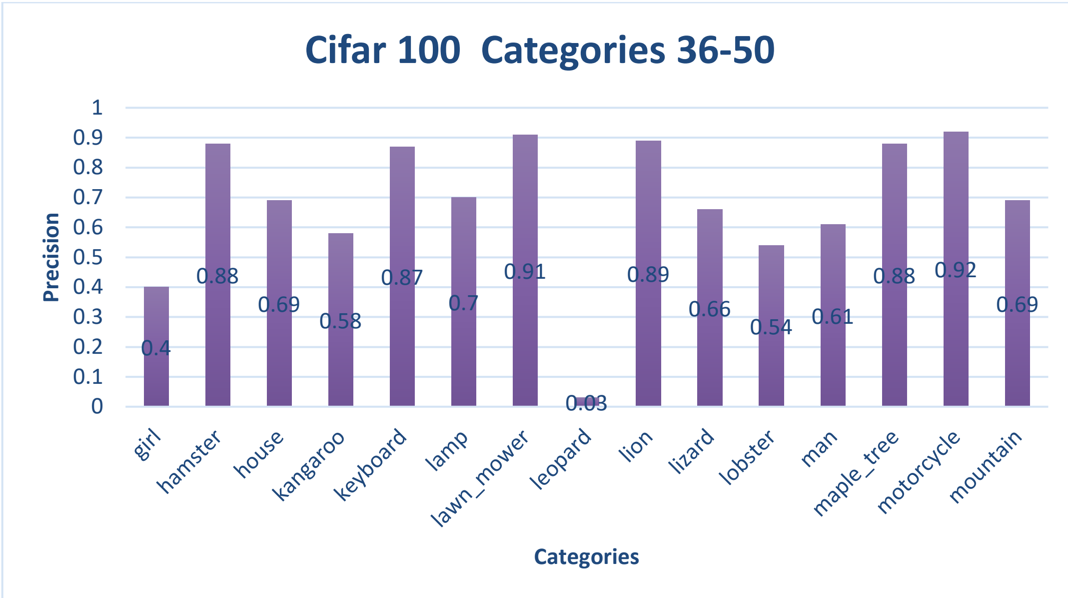

Fig. 9: Cifar-100 Categories 36-50 Precision.

The categories of motorcycles, lawnmower and lion are with the highest precision of 0.92, 0.91 and 0.89 respectively.

The following table shows the cifar-100 categories precision rate from 51-70.

Table 12: Cifar-100 Categories 51-70 Precision

Categories	**Precision**
Mouse	0.4
Mushroom	0.7
oak_tree	0.7
Orange	1
Orchid	0.7
Otter	0.3
palm_tree	0.45
Pear	0.75
pickup_truck	0.75
pine_tree	0.65
Plain	1
Plate	0.95
Poppy	0.75
Porcupine	0.85

Possum	0.5
Rabbit	0.55
Raccoon	0.45
Ray	0.59
Road	0.76
Rocket	0.64

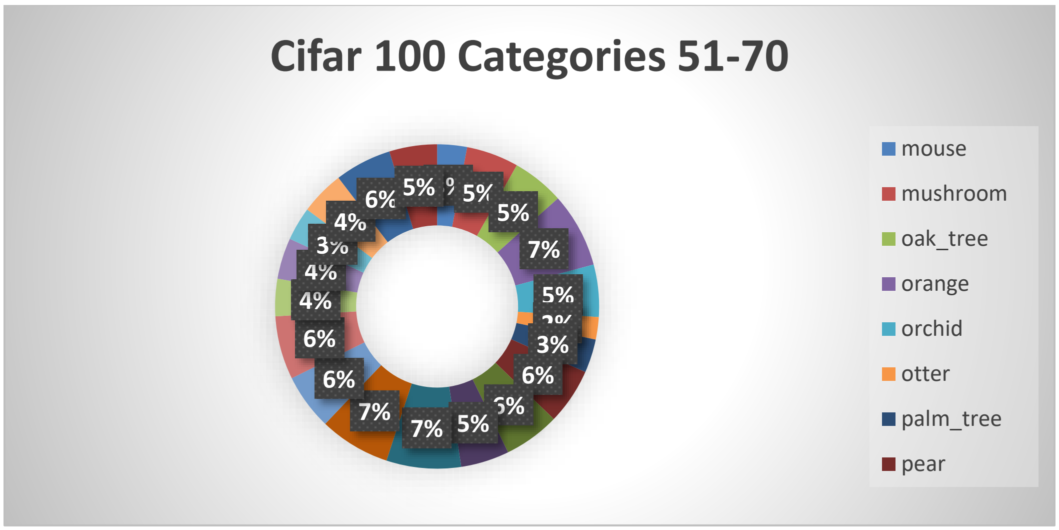

Fig. 10: Cifar-100 Categories 51-70 Precision

This includes the categories of orange, plate, porcupine, and jacket with the highest precision having the values 1, 0.95 and 0.85 respectively.

FTVL:

The following table shows the FTVL categories precision rate.

Table 13: FTVL Dataset Precision

Category	**Precision**
agata_potato	0.77
asterix_potato	0.82
Cashew	0.69
diamond_peach	0.72
fuji_apple	0.87
granny_smith_apple	0.63
honneydew_melon	0.79
Kiwi	0.67

Nectarine	0.8
Onion	0.74
Orange	0.84
Plum	0.65
spanish_pear	0.71
taiti_lime	0.86
Watermelon	0.66

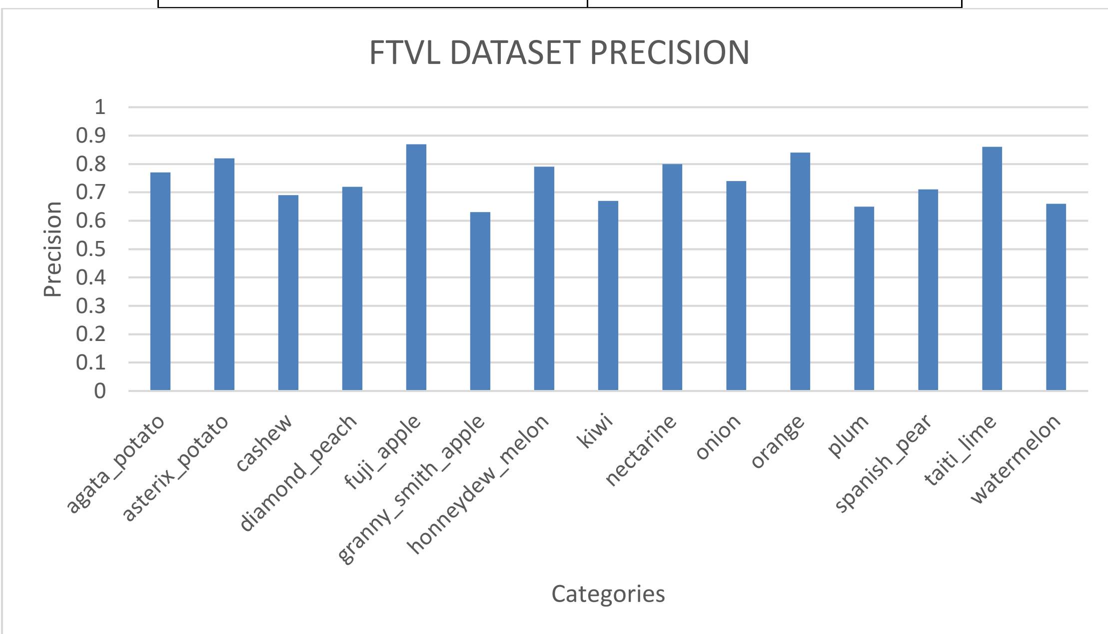

Figure 11: FTVL Dataset Precision

The categories of fuji_apple, taiti_lime and orange are with the highest precision of 0.87, 0.86 and 0.84 respectively.

Cifar 100:

The following table shows the cifar-100 categories precision rate from 71-100.

Table 13: Cifar-100 71-100 Categories Precision

Categories	**Precision**
Rose	0.88
Sea	0.7
Seal	0.39
Shark	0.68
Shrew	0.47
Skunk	0.73

Skyscraper	0.54
Snail	0.31
Snake	0.97
Spider	0.88
Squirrel	0.39
Streetcar	0.58
Sunflower	0.94
sweet_pepper	0.88
Table	0.49
Tank	0.37
Telephone	0.91
Television	0.97
Tiger	0.38
Tractor	0.68
Train	0.39
Trout	0.96
Tulip	0.49
Turtle	0.48
Wardrobe	0.93
Whale	0.59
willow_tree	0.67
Wolf	0.97
Woman	0.49
Worm	0.88

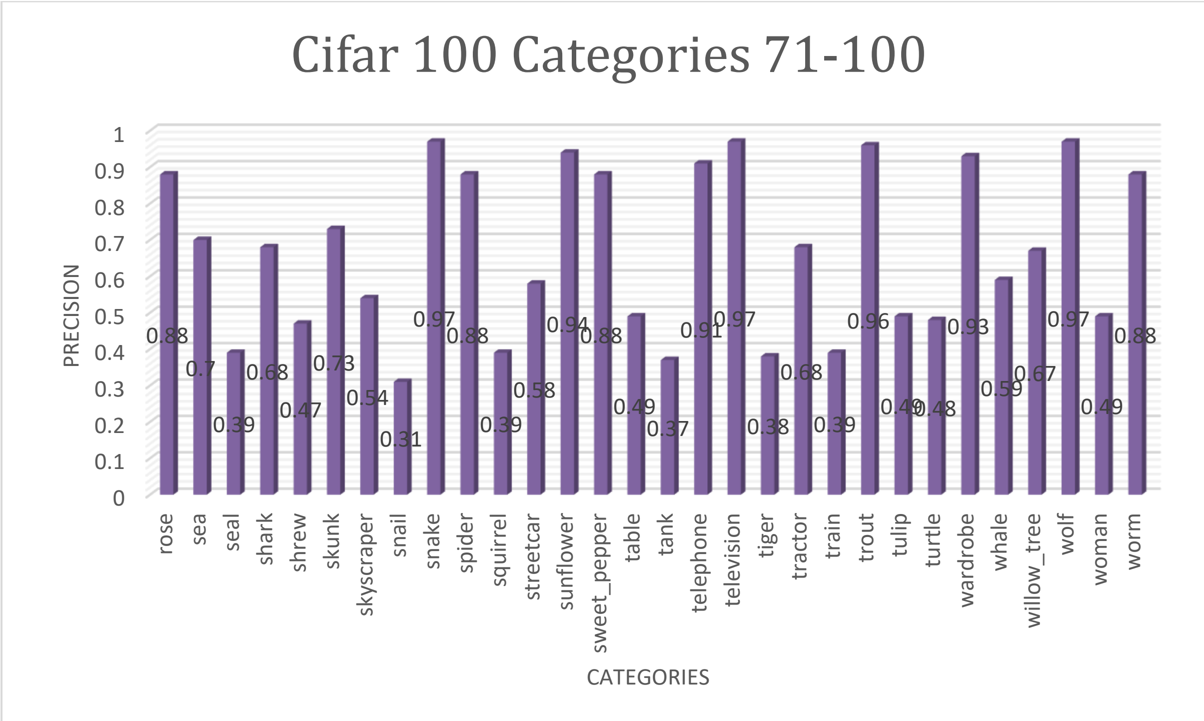

Fig. 12: Cifar-100 71-100 Categories Precision.

This includes the categories of television, trout and sunflower are with the highest precision having the values 0.97, 0.96 and 0.94 respectively.

Conclusion:

In this section discuss the research thesis. It contributes to analyzing the results and directing the future perspectives where we can amplify our thesis work. Many CBIR systems have evolved but the CBIR system which we have proposed gives precise results compared to the other CBIR systems. It performs in the finest way than others.

In the proposed technique we have used the MATLAB in which we have performed the entire methodology.

The datasets we have used in our methodology comprise Cifar-100 that is one of the large datasets which covers the 100 image classes and, in each class, have the 600 images. And these images further split into the 500 training and every class has 100 tests. In Cifar-100 the 100 classes are assembled into 6 sub classes.

The database of FTVL contains 2612 images of fruits and vegetables. This includes the 15 types of categories and in the dataset of Fashion includes the images having the items of 15 types.

Our work is based on the procedure such that initially we took the query image where we have employed the grey scale values and its color values. By manipulating both values we got the exceptional results as compare to the other techniques. The main contribution of the proposed methodology is that the fusion of the techniques we have used has not been used before in any methodology.

First, we implemented the intervolving, half sampling technique, then after suppression we applied thresholding and kernels. After its execution we retrieved the texture features. Similarly, with color images we applied color correlogram to get the features. After that we have integrated CNN with it and getting features from it, we put it into a bag of words and rank them. The results we got from it were very accurate and explicit. By fusing our technique with the other techniques, we can produce better results. We can make the CBIR system much better by making use of intensity values and color values by applying different strategies.

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