# AN ONTOLOGY-DRIVEN VEGETATION CLASSIFICATION FOR SEMANTIC-BASED IMAGE RETRIEVAL OF AERIAL PHOTOGRAPHY

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**ABSTRACT**

**The retrieval of images using semantic concepts is challenging and essential issue in watchword based search. The focus has been shifted from low-level feature extraction to human semantics in order to enhance the precision of content based image recovery framework. It is done to decrease the semantic gap between visual components and affluence of human semantics. This research provides an ontology-driven approach to train the system by modeling the human cognition that also conquers the constraints of a label based retrieval. In the proposed work, a properly characterised philosophy framework is used to drive image annotations that enable semantic retrieval of aerial photography. The concept of image semantics is exploited for the classification of vegetation and also to determine the qualitative semantics by using Allen's qualitative relations. Psychophysical evaluation is used to assess the effectiveness of the proposed approach. The outcomes of the different experiments are relatively favorable in terms of accuracy of relevant image retrieval.**

*Keywords: Semantic Image Retrieval, Vegetation Classification, Aerial Photography, Qualitative Semantics*

## 1. INTRODUCTION

Image recovery is the field of study concerned with looking the perusing computerized image form distinctive database gathering. Gathering images into (semantically) significant classes, utilising low-level visual components or features is still a testing and critical issue in substance based image recovery. A tremendous measure of data is out there. On the other hand, we cannot get or utilise the data unless it is sorted to permit productive browsing, beholding, and recovery. In the light of these groupings, for an image database, viable records can be manufactured [1, 2]. Human cognition focuses on how humans process information, by looking at the way people treat information that comes to them and their treatment that leads to responses. The main theme of this research is to build this cognition into a machine which can behave similarly to human behaviour. The system perceives like human cognition works.

Appropriately defined domain ontology provides the vocabulary for the annotation drives the extraction of automatically produced annotations and provides the conceptualization utilized in retrieval [14]. In the sequel, a comprehensive review of the relevant background in semantic image annotation and retrieval is presented. It is followed by a detailed description of the proposed ontology infrastructure, the ontology-based semantic analysis, and retrieval components. Experimental results in the domain of aerial images against both plain content-based and keyword-based retrieval will illustrate the contribution of this approach.

This area of study is very active in research since the 1970s [3]. Due to the availability of such digital content in abundance, image retrieval pulls in enthusiasm from specialists in the fields of image handling, mixed media, computerized libraries, remote detecting, space science, database applications and other related disciplines. Viable and quick recovery of an image was not simple, particularly, when the accumulations developed into terabytes. A viable image recovery framework needs to work on the gathering of image to recover the important image in view of the client question image which adjusts as nearly as would be prudent to human discernment and comprehension the inquiry image.

## 2. LITERATURE REVIEW

Low-level visual features such as color, texture, and shape, as well as higher-abstraction structural information, formed the content annotation metadata. Indexing was performed using the automatically extracted numerical descriptors, and retrieval was based on similarity measures that try to match the way humans perceive visual similarity. Four broad categories can be identified depending on the chosen content and indexing paradigm: query by example, iconic, textual and hybrid, respectively. The literature considers a huge number of diverse approaches for a variety of application domains.

An expert Bayesian network was presented by Mukashema et al. that implements as a novel object-based classification technique to extract coffee fields from very high resolution (VHR) imagery [4]. Theme is to disdeveloped and tested for ten agricultural zones of Rwanda using aerial orthophotos. A high resolution coffee map of Rwanda was produced by applying the automated method on 198 orthophotos and one Quick Bird image. At the startup, the spectral separatability was assessed between coffee and other major land cover classes. Then, the expert Bayesian network model is developed for one site and tested in other nine sites. Finally, the model parameters are implemented to all aerial orthophotos at national level and assessed using field and census validation data sets. A Bayesian system is just as helpful as this former information is dependable. Either an unnecessarily idealistic or skeptical desire of the nature of these earlier convictions will misshape the whole system and negate the outcomes. Another strategy for immediate features based image recovery was proposed by Bhattacharyya et al. [5]. The author developed an image database with low-level texture features from Gray Level Co-Occurrence Matrix. For testing the images, the decision tree is framed in the training stage.

Sohail S et al. presents an ontology-based image retrieval system from a corpus of characteristic scene images by conferring human cognition in the retrieval procedure, to address the issues of keyword-based image retrieval and substance based image retrieval through the utilization of subjective spatial representations over semantic image annotations [6]. The performance evaluation of the suggested framework has been carried out by comparing the semantically retrieved images, in view of queries and descriptions provided by users. A much-known approach in evaluating such systems is the "Psychophysical". Data has been collected to manoeuvre the proposed approach, which consists of manually classified 300 aerial images of vegetation. The Psychophysical was carried out by dividing 300 images into different groups and given to different users from various domains including IT Experts, Farmers, Agrarians, Students. Hence, every user was given a set of 30 images and had five images in each belonging to every category. Each one of these images was represented using 10 concepts.

Cristina S et al. proposed a measured framework that permitted us to offer distinctive arrangements in the Image CLEF 2013Plant Identification task [7]. An adaptable, particular framework is proposed which permits us to investigate and consolidate the outcomes in the wake of applying techniques, for example, image retrieval utilizing (LIRe), metadata grouping and innocent Bayes classification. Training gathering is very broad, covering an extensive number of animal varieties, keeping in mind the end goal to acquire precise results with this photograph annotation calculation. Henning S. et al. performed a study with multi temporal simultaneous C- and L-band polarimetric SAR data to assess the crop classification accuracy for different modes [8]. Kadir A. developed a method for leaf classification. This method incorporates shape, vein, colour, and texture like features and uses PNN as a classifier [9]. Fourier descriptors, slimness ratio, roundness ratio, and dispersion are used to speak to shape highlights. Shading minutes that comprise of mean, standard deviation, and sticks are utilised to speak to shading. Twelve composition elements are separated from lacunary. Larranaga A. et al. has assessed, from an operational viewpoint, regardless of whether the consolidation of spring SAR perceptions into an order plan in light of one multispectral summer scene gave upgraded crop characterization [10]. Effective procurement of information is significantly more probable from SAR sensors than from optical sensors due to a couple of chances for without cloud optical acquisitions. This is the essential reason for the utilization of SAR images to characterize diverse products . The outcomes showed an increment in exactness when SAR information was incorporated into a multispectral order plan. Enhancements were slight, and the incorporation of two SAR scenes did not give extra advantages. In all the cases, correctness acquired utilizing just SAR information was lower than those who utilised the optical images, failing to reach more than 75%.

Isabel L. et al. investigated five different classification methods and their precision: (i) Parallelepiped (ii) Minimum Distance (iii) Mahalanob is Classifier Distance (iv) Spectral Angle Mapper (v) Maximum Likelihood using Quick Bird imagery [11]. This technique identifies whether remote identification provides the ability to perceive products adequately and agro-processing measures in a standard agricultural based district depicted by dry weather conditions. The minimum information was taken from the division of the satellite data for portrayal in order to survey pixel-article and pixel-item information. The results exhibited that challenge and pixel-article based examinations unmistakably manoeuvred pixel-based examinations, resulting in the exactness more than 85% in an extensive segment of the requests and highlighting the more likelihood of exact classifier.

All the techniques /approaches discussed used the low-level concept of the images to classify the vegetation in the image. They do not consider the high-level concepts of images except Sohail, S. [6], where image retrieval is based on the high-level semantics of the image and uses spatial relationships. The research framework provided details about semantic similarity and its different methods to compute similarity among different concepts. They were not applied in their work for image categorization and retrieval, but the relative effectiveness of their approach in regards to image segmentation and labeling can be used to retrieve an image on keyword-based retrieval method.

The classification of vegetation, based on different objects has been performed on high-resolution satellite images [12, 13]. However, the objects always have certain semantic relationships among them. In this research, these relationships are exploited and a knowledge-driven framework, using ontologies as the means for knowledge representation, is investigated for aerial image semantic retrieval for vegetation classification.

## 3. PROPOSED FRAMEWORK

An Ontology-Based Image Retrieval framework has been proposed to search in digital repositories.

### 3.1. SEMANTIC IMAGE DESCRIPTION

Keeping in view the goal of searching of the images in advanced vaults, we propose an Ontology-Based Image Retrieval Approach utilising Qualitative Semantic Image Descriptions, to enhance the accuracy of pursuit. Coordinating of RDF triples has been utilised rather than watchwords keeping in mind the end goal to focus on the setting of the hunting term.

### 3.2. PROPOSED FRAMEWORK

The proposed system is in parts: User Interface, Domain Ontology, and Images vault. In the framework shown in Figure 1, a user submits the RDF query through a user interface that expands the query's search. These questions have been sent to metaphysics, to perform the semantic coordinating on the inquiry looking terms. The inquiry result will be the images reference, originating from the cosmology. The real images will go to the ranker in the wake of contrasting and the images reference. The ranker figures out the priority among the images and positions them as per their significance scores. The resulting segments depict the points of interest of every part of the system.Figure 2 represents the proposed ontology-based image retrieval framework. The proposed methodology to perform semantic matching and searching in digital repositories is also provided. Finally, a dry run of the proposed methodology is provided by carrying out different experiments.

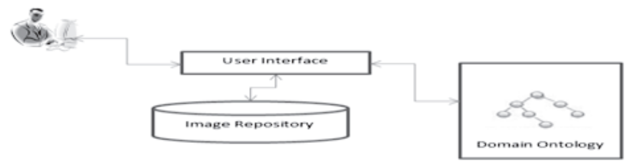


Figure 1: Generic Ontology-based Image Retrieval Process

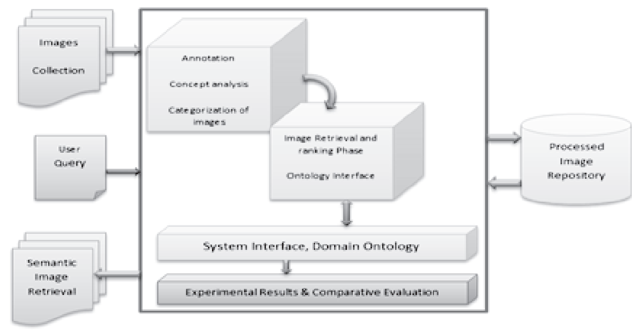


Figure 2: Proposed Ontology-based Image Retrieval Framework using Image Semantics

### 3.3. IMAGE ANNOTATION

An example of annotated aerial image is presented in Figure 3, which contains the concepts present in an image that is being used to measure the frequency of each concept. The whole annotation process is performed manually by using psychophysical evaluation, in which the objects and their relationships are identified for more comprehensive analysis of the image semantics. In result of this evaluation, we annotated the image in a better way that ultimately leads to a more accurate classification of vegetation images.

### 3.4 ONTOLOGY FORMULATION

An ontology-based image retrieval framework to carry out searching is proposed. In the framework, thematic similarity approach is used in order to capture the context-aware meanings of the concepts.

The ontology model is formulated using the open source Protégé (version 4.3) as RDF Triple. The concepts, identified through annotation in the previous step, were implemented through 10 classes (Barren Land, Road, Vegetation, Terraces, Tree, Rock, Crop, Building, Forest, and Water) as objects & subjects and their relationships were mapped as the predicates. We employ searching on metadata (in the form of triples) instead of keywords to concentrate on concepts and their relationships together in the following SPARQL query.

## 4. RESULTS AND DISCUSSION

The user interface of the prototype system and the workflow of the end-user are described. Users are able to specify queries by selecting the triples from the UI. The system should be simple and easy to use, so the user interface of the prototype system is designed similar to the Google search engine. In addition, results should be ranked according to the degree of relevance to the user query to enable users to focus on the top ranked, more relevant results to the query rather than on the less relevant results.

Figure 4 shows the psychophysical evaluation where the x-axis represents the concepts and a y-axis represents the frequency of occurrence of each concept. In order to assess the statistical relationship, the T-test is applied, presented in Figure 5 and Figure 6. It is distributed on a curve based on the number of degrees of freedom (df). It confirmed the hypothesis. A significant difference between psychophysical evaluations and semantic image retrieval is found. By applying T-test, it is seen that the hypothesis is correct.

```
PREFIX ns: <http://www.semanticweb.org/ontologie/Ontologyaerial.owl#>
SELECT  ?img ?catag
        where
{?image ns:hasCatogeory ?catag.}
```

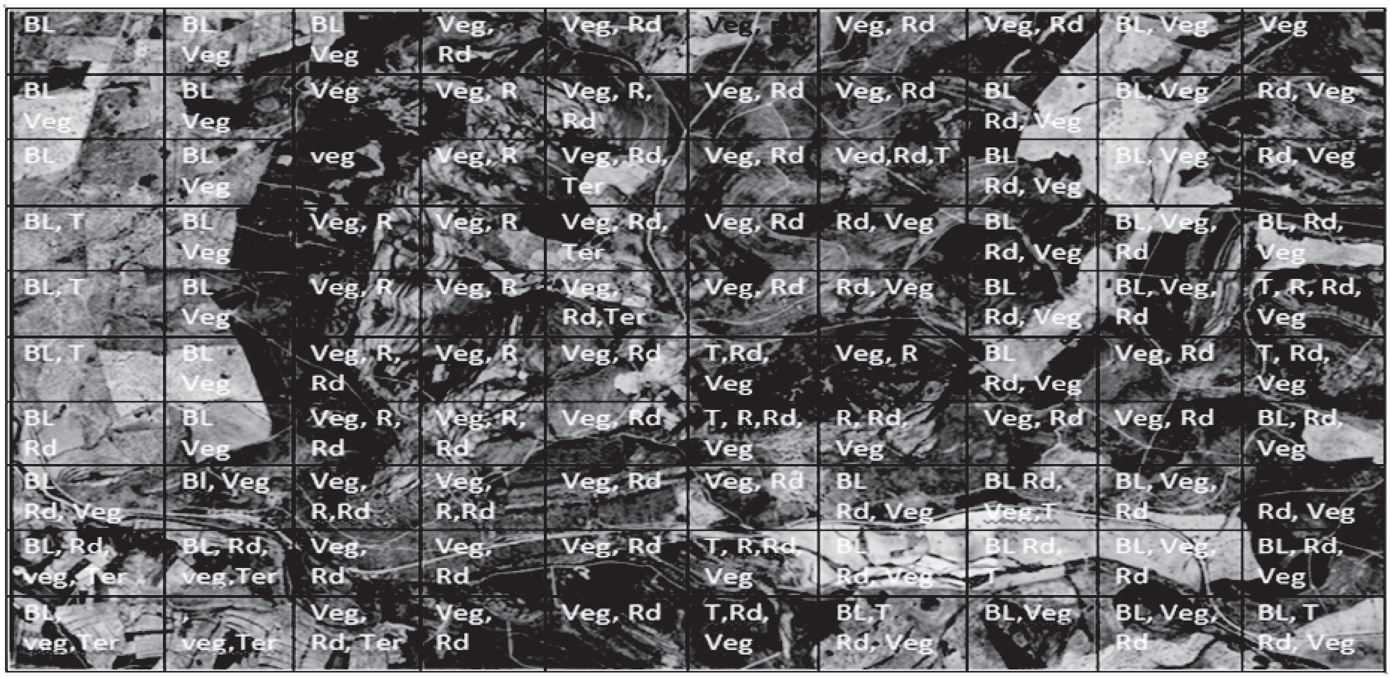


Figure 3: An example of annotated aerial image representing concepts and their respective frequencies

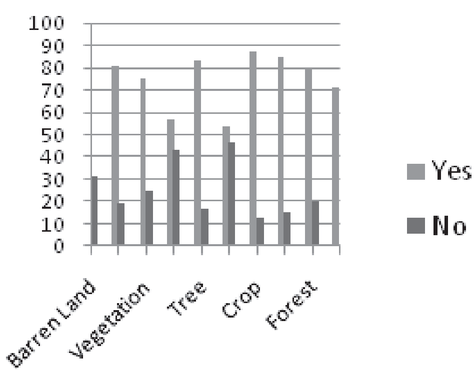


Figure 4 (a): psychophysical analysis

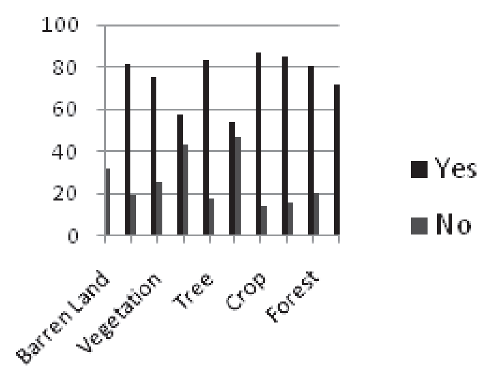


Figure 4 (b): SPARQL Query results

t-Test: Paired Two Sample for Means

| | Variable 1 | Variable 2 |
|---|---|---|
| Mean | 73.875 | 94.375 |
| Variance | 162.125 | 4.839286 |
| Observations | 8 | 8 |
| Pearson Correlation | 0.675138 | |
| Hypothesized Mean Difference | 0 | |
| df | 7 | |
| t Stat | -5.10227 | |
| P(T<=t) one-tail | 0.000698 | |
| t Critical one-tail | 1.894579 | |
| P(T<=t) two-tail | 0.001396 | |
| t Critical two-tail | 2.364624 | |

Figure 5: T-test on analysis

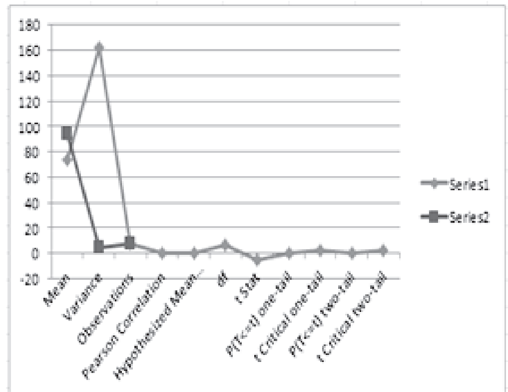


Figure 6: Graph for T-test

## 5. CONCLUSION

The image retrieval is based on high-level features and descriptive characteristics of an image. In this research, both semantic and qualitative semantic relations are exploited to model the human cognition for vegetation classification of aerial photography. The image annotations are used to understand the image semantics clearly.. For this purpose, concepts, categories, and auxiliary characteristics have extracted via human cognition. Further, these characteristics are validated by presenting a framework based on psychophysical evaluation to retrieve the relevant images, accurately. However, the presented framework does not consider incomplete RDF triples that can also contain useful information which may enhance the accuracy of the retrieved images.

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