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Visual Landscape Assessment with the Use of Cloud Vision API: Antalya Case

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ABSTRACT

Quantifying and mapping visual character of an area is complex because of their intangibility. But landscape visual character can be captured using indicators derived from several theory-based concepts related to landscape perception. One of the main methods to capture is to take photographs of a region and evaluate it by an expert group. However, manual content analysis and classification of large numbers of photographs can be time consuming. Therefore, an efficient tools such as Google Vision API image classification service can be used to fasten the process. The API can detect and classify multiple objects including the location of each object within the image and assign labels to images and quickly classify them into millions of predefined categories. This study compares previous landscape visual character analysis techniques and develops a method for automating content analysis of photographs with the use of an online machine learning algorithm. For this purpose, 60 photographs regarding to Antalya City evaluated by Google Vision API image classification service. At this stage, the method of evaluating the photos and capabilities for perceived landscape visual features of the API has been examined. According to the results, the API has been identified 3 main titles in landscape visual character assessment process as naturality, perceptibility and recreation value. As a result. a number of procedural recommendations for further evaluation were developed, and the advantages and disadvantages of this new evaluation technique have been discussed.

Keywords: Antalya, Machine Learning, Visual Landscape Analysis, Visual Perception.

INTRODUCTION

Landscape that constitutes the intersection between human and nature is a concept which is dealt with in many areas and in different dimensions. A balanced relationship between nature and human is possible only by defining landscapes and the elements that create the landscape. For this purpose, some analyzes and assessments are made. One of the methods used in defining landscapes and revealing their potential is "Visual Landscape Assessment".

In recent years, studies on visual landscape assessment have gained acceleration. According to Palmer and Hoffman (2001), it is among the aims of visual landscape assessment to determine the changes occurring on landscape characters, to determine the sensitivity of landscapes by determining the current situation, to create inventory in planning, design and resource management issues [1-2].

In addition to this, there are many studies that reveal the visual perceptions of users, decision makers or experts about visual landscape and visual landscape assessment. The studies mainly focus on the various key frames such as accessibility, balance, diversity, harmony, identity, openness, order, proportion, visibility, water, etc [3-19]. Key frames can be classified as various titles such as Naturalness, Harmony, Perceptibility, Land type & Land use, Recreation Value, Landscape Aesthetic [19].

Cloud Vision API allows developers to easily integrate vision detection features within applications, including image labeling, face and landmark detection, optical character recognition (OCR), and tagging of explicit content. The Vision API can detect and extract information about entities in an image, across a broad group of categories. Cloud Vision API returns the analyzed data as labels. Labels can identify general objects, locations, activities, animal species, products, and more. If you need targeted custom labels, Cloud AutoML Vision allows you to train a custom machine learning model to classify images and are returned only in English [20].

These are some of the excellent use-cases on which Vision API performs seamlessly. It can integrate any tasks
into softwares within very less amount of time and provides support for a wide range of languages like Go, C#, Java, PHP, Node.js, Python, and Ruby [21].
For the study, new software called "GPA 1.0" which has been developed by the use of Python software and Google Vision API. The software identifies the labels and their likelihoods from the processed photo and brings them together into the predetermined key frame groups. Software creates a percentage of 0 to 100 for every key frame.
60 photographs of Antalya City were evaluated for visual landscape assessment by the developed software and a landscape architect expert group. By this, a developed method for automating content analysis of photographs with the use of an online machine learning algorithm and previous landscape visual character analysis techniques has been compared and the advantages and disadvantages of this new evaluation technique have been discussed.

METHOD OF RESEARCH

For the study, previous studies and methods of visual landscape analysis were examined for detecting key frames and titles which have been used in evaluating photographs.

Antalya city center and districts have been selected as study area. 60 photographs were selected randomly from the study area, regardless of the image size, shooting distance and content. The photographs which were used in the study were given in Figure 1.

The photographs were evaluated by the GPA 1.0 software in order to determine the label outputs. By the first evaluation 320 labels have been detected. These labels were natural features such as Forest, Nature, Vegetation, Coast, Hill, Plain, Island, Cove, Beach, Mountain, etc. but also they were cultural features such as Rural Area, Cityscape, Ruins, Highway, State Park, Walkway, Historic Site, Port, Outdoor Recreation, Leisure, Tourism Attraction, etc. Even in some cases labels were proper names such as Hadrian's Gate, Kaleiçi or Karaalioğlu.

These labels were grouped under 3 main titles and 10 main key frames. These are;
- Naturalness (Natural Vegetation, Water Bodies, and Perceptibility of Landscape),
- Perceptibility (Diversity in Landscape, Open Orientation, and Existence of distinctive elements),
- Recreation Value (Presence of unique elements, Presence of focal points, Existence of cultural elements, and Presence of touristic sub-structure).

These photographs were evaluated by a group of 10 experts who were landscape architects and worked on the subject of visual landscape assessment. In this evaluation five point Likert scale which is used to allow the individual to express how much they agree or disagree with a particular statement scale, was used during the evaluation.
A Likert scale assumes that the strength/intensity of an attitude is linear, i.e. on a continuum from strongly agree to strongly disagree, and makes the assumption that attitudes can be measured [22]. Expert group evaluated "Strongly Agree" as (5), "Agree" as (4) "Undecided" as (3),

"Disagree" as (2) and "Strongly Disagree" as (1) for each key frame in every photograph.
In the next stage, the values given by the expert group were averaged and the key frame in each photograph was assigned a value between 1 and 5.
The photographs were evaluated again by the GPA 1.0 software in order to calculate the key frame values in five point Likert scale as the expert group.
In this evaluation, software gathers labels and their likelihoods values and collects the data under predetermined key frame groups. GPA 1.0 calculated that average number of labels that gathers in key frames are 3,22. For this, the software has adapted itself to take into evaluation the 3 labels with the highest values and exclude the rest to avoid reducing the average value for key frames.
At the same time software calculated the average values as all key frames has been built as 3 label structure and created a decision value even they have only one label in a key frame. Output sample for GPA 1.0 software for Picture 1 is given in Table 1.

Table 1: Output sample for GPA 1.0 software

	Picture 1			
	Labels	**Likelihood**	**Ave.**	**Decision**
Natural Vegetation	Tree	0,60	0,20	**1**
Water Bodies	Coast	0,88	0,83	**5**
	Sea	0,85		
	Water Body	0,75		
Diversity in Landscape	Coastal Land.	0,77	0,63	**4**
	Hill	0,57		
	Rock	0,54		
Perceptibility of Landscape	Sky	0,82	0,74	**4**
	Horizon	0,80		
	Landscape	0,61		
Open orientation	Kaleiçi	0,99	0,93	**5**
	Uzun Çarşı	0,92		
	Karaalioğlu	0,87		
Existence of distinctive elements	Cityscape	0,74	0,47	**2**
	Street	0,68		
Presence of unique elements	Harbor	0,88	0,74	**4**
	Shore	0,84		
	Landmark	0,50		
Presence of focal points	Bay	0,78	0,64	**4**
	Marina	0,60		
	Beach	0,53		
Existence of Cultural Elements	Town	0,91	0,53	**3**
	Boat	0,68		
Presence of Touristic Sub-structure	Tourism	0,82	0,72	**4**
	Vacation	0,80		
	Travel	0,55		

Assessments by expert group and developed software have been compared in every key frame of pictures as they are the same values or not. Key frames that were compatible and incompatible with the responses of the expert group were identified and possible causes were questioned.

RESULT AND DISCUSSION

The photographs were evaluated by the expert group and GPA 1.0 software in five point Likert scale. Calculated average and standard deviation values of Expert group and GPA 1.0 software evaluations are given in Table 2.

Table 2: Average and Standard Deviation Values of Expert Group and GPA 1.0 software

	Expert Group		**GPA 1.0**	
	Ave.	**Dev.**	**Ave.**	**Dev.**
Natural Vegetation	**2,85**	1,56	**2,92**	1,54
Water Bodies	2,83	1,98	2,80	1,96
Diversity in Landscape	2,37	1,46	2,25	1,40
Perceptibility of Landscape	2,77	**1,19**	2,83	1,27
Open Orientation	**2,95**	1,63	**3,72**	**1,25**
Existence of Distinctive Elements	2,33	**1,30**	2,05	**1,26**
Presence of Unique Elements	2,20	1,48	2,10	1,34
Presence of Focal Points	2,48	**1,28**	2,52	**1,24**
Existence of Cultural Elements	**3,52**	1,67	**3,30**	1,77
Presence of Touristic Sub-structure	2,53	1,38	2,65	1,31
TOTAL VALUE	**2,68**	**1,55**	**2,71**	**1,54**

Highest values for both expert group evaluation and GPA 1.0 software were Natural Vegetation, Open Orientation and Existence of Cultural Elements. This shows that photographs that have been selected were mainly evaluated within the same score range.

Lowest values for standard deviation for expert group evaluation were Perceptibility of Landscape, Existence of Distinctive Elements and Presence of Focal Points. Lowest values for standard deviation for GPA 1.0 software were Presence of Focal Points, Open Orientation and Existence of Distinctive Elements. This results show that these key frames were evaluated as close score ranges.

Expert group and GPA 1.0 software evaluations were brought together to see their consistency. Consistency assessment was based on having the same values for each key frame in photographs.

In order to find the relationships in terms of key frames, consistency numbers, differences and standard deviation values have been examined (Table 3).

Table 3: Consistency Numbers, Differences and Standard Deviation Values for Key Frames

	Num.	**Dif.**	**Dev.**	**(%)**
Natural Vegetation	52	-4	0,96	86,67
Water Bodies	**59**	**2**	**0,26**	**98,33**
Diversity in Landscape	52	7	0,61	86,67
Perceptibility of Landscape	44	-4	1,14	73,33
Open Orientation	**38**	**-46**	**1,44**	**63,33**
Existence of Distinctive Elements	44	17	1,05	73,33
Presence of Unique Elements	40	-6	1,35	66,67
Presence of Focal Points	46	-2	1,11	76,67
Existence of Cultural Elements	50	13	0,95	83,33
Presence of Touristic Sub-structure	48	-7	0,66	80,00
TOTAL VALUE	**473**	**-18**	**1,05**	**78,83**

The Naturalness title which has Natural Vegetation, Water Bodies and Diversity in Landscape key frames, has higher consistency ration than the other ones. Expert group and GPA 1.0 software have estimated the same values in almost every photograph related to water surfaces. Only in P57 there was 2 points of difference as expert group detected the water surfaces more accurate than the software.

The lowest consistency ratio is in Perceptibility title. In this, Perceptibility of Landscape and Existence of Distinctive Elements has 44 equal values in evaluation. Withal with lowest value in key frame in terms of compatibility is Open Orientation. This key frame has a difference as -46. This shows that software has given higher values than expert group with a deviation of 1,44 in total. This can be explained as the software was more successful in defining the locations in the photographs compared to the expert group.

Existences of Distinctive Elements and Existence of Cultural Elements key frames have a higher value in expert group evaluation**.** This can also be explained as the expert group was more successful in defining the distinctive and cultural elements in the photographs compared to the GPA 1.0 software.

In total, minimum value of consistency is 4 key frames in P57 and maximum value is 10 key frames in P46 and P50 in 60 photographs (Table 3). Highest ratios of consistencies are in 7, 8 and 9 key frames with 51 photographs (% 85).

Table 3: Consistency of Expert Group and GPA 1.0 software

	Picture Code	Num.	(%)
4	P57	1	1,67
5	P51, P53	2	3,33
6	P20, P41, P49, P55	4	6,67
7	P7, P8, P10, P21, P24, P26, P27, P28, Pp29, P37, P48	11	18,33
8	P1, P4, P5, P9, P11, P13, P14, P17, P22, P25, P32, P34, P38, P39, P40, P42, P43, P44, P47, P52, P54, P59	**22**	**36,67**
9	P2, P3, P6, P12, P15, P16, P18, P19, P23, P30, P31, P33, P35, P36, P45, P56, P58, P60	18	30,00
10	P46, P50	2	3,33

P57 coded picture (Figure 2) had the same values in Natural Vegetation (3), Diversity in Landscape (4), Presence of Focal Points (4) and Presence of Touristic Sub-structure (3) and had lower values in all other key frames by the GPA 1.0 software evaluation. Also this photograph is the only one which Water Bodies key frame is not in the same value in the evaluations. The software could not detect the water body in this photograph during the analysis as the part where the water spills and accumulates, is not visible.



Figure 2: P57coded Photograph.

P57 coded photograph has unique distinctive and cultural elements for Antalya city and the Turkish people. This place is the most famous and most beautiful entrance and exit way of Antalya. Also there is a unique monument belonging to Republic of Turkey's founder, Mustafa Kemal Ataturk. Expert Group evaluated this picture as its historical and social values too. But the GPA 1.0 software works on labels which are generated by the Google Cloud Vision API. And there are no label properties in initial assessment which are directly related to cultural features as this importance.

P46 coded photograph (Figure 3) is from Olympus, Antalya. This area is a popular holiday destination for tourists. This photograph had the same values for every key frame. It had an evaluation value for both expert group and GPA 1.0 software in Natural Vegetation as 5, Water Bodies as 5, Diversity in Landscape as 5, Perceptibility of Landscape as 4, Open Orientation as 5, Existence of Distinctive Elements as 4, Presence of Unique Elements as 3, Presence of Focal Points as 4, Existence of Cultural Elements as 1 and Presence of Touristic Sub-structure as 4. This photograph had a total evaluation value as 40.



Figure 3: P46 coded Photograph.

P50 coded photograph (Figure 4) is from Ulupınar, Antalya. This area is a popular restaurant and dining area for local people and tourists. This photograph had the same values for every key frame. It had an evaluation value for both expert group and GPA 1.0 software in Natural Vegetation as 5, Water Bodies as 5, Diversity in Landscape as 2, Perceptibility of Landscape as 2, Open Orientation as 5, Existence of Distinctive Elements as 3, Presence of Unique Elements as 1, Presence of Focal Points as 3, Existence of Cultural Elements as 1 and Presence of Touristic Sub-structure as 2. This photograph had a total evaluation value as 29.



Figure 4: P50 coded Photograph.

The software cannot be as precise as the expert group in areas with significant cultural values or designated as protected areas. Also some features cannot be recognized by the API if the image quality is poor or the objects are too far away. In particular, there are key frames that the expert group can estimate based on experience and previous knowledge, the software does not give any label value. However, the software has identified features that cannot be determined by the expert group. Especially in the Open Orientation key frame, the software provided more accurate results than expert group. Also in this study, expert group ignored cultural properties such as roads, tunnels or arch bridges if they don't have a historical value.

One of the most important advantages of the software is the processing time of photos. This study focused on 60 individual photographs. The software processing time for all photographs is only 2 minute and 48 seconds. But the evaluation period of all photographs of one of the expert group member took an average of 2 days. This takes a long time, even if the number is only 60 photographs and 10 experts. In addition, sometimes local people, users and experts are consulted in this type of studies. In such cases, the software will prevent loss of time and money.

The biggest problem of the software is the need for internet connection. The software should be linked to Google Vision in the evaluation process. In addition, if the number of photographs exceeds a certain number in the analysis, the type of pricing by Google rises.

No key frames could be developed for Perceptibility, Land Type / Land Use Type and Landscape Aesthetic titles during label output stage. Google Vision API could not create labels for key frames such as aesthetic, attraction, complexity, clarity, excitement, rhythm, etc.. This could be considered as a major inadequacy for the software. Also, it is not possible to interfere with software decisions or enrich the contents of the list obtained with Label returns in the hidden layer of the API. However, it is inevitable that there will be developments in this regard in the future.

As a result, both evaluation techniques have advantages and disadvantages, and it should be decided which method to use according to the study area and its properties.

CONCLUSION AND RECOMMENDATIONS

Technological advances in artificial intelligence and artificial neural networks have begun to offer great opportunities for the landscape architecture as in every profession. Innovative approaches are important for a profession which acts in the balance of ecology, aesthetics and economy.

Especially the prepared database feature in Google Cloud Vision API is developing day by day and is starting to give more efficient results. But it is still a code. API cannot understand human emotions and senses. Therefore, software may be inadequate in some cases. Instead of seeing such problems as a difficulty, it should be considered it as an opportunity.

GPA 1.0 software is an innovative approach for Visual Landscape Assessment procedure. It is in the process of trial and is still being developed. The 90.56% success in determining the natural title with the first version of the software proves that such software and techniques will be used more in the future.

In the light of the data obtained with the first study, further studies including public participation are required. In particular, it is necessary to conduct a study on whether the details can be determined in areas with the same structural characteristics. It should be linked to the responses of experts, public and local users, and software updates should be made to improve their compliance with these responses.

Figure 1: Photographs used during the research.



REFERENCES

[1] J.R. Palmer, E. Hoffman, Rating Reality and Representation Validity in Scenic Landscape Assessments, Landscape and Urban Planning 54 (2001), pp.149-161.

[2] F. Asur, H. Alphan, Görsel Peyzaj Kalite Değerlendirmesi ve Alan Kullanım Planlamasına Olan Etkileri, Yüzüncü Yıl Üniversitesi Tarım Bilimleri Dergisi, 28(1) (2018), pp.117-125.

[3] J.L. Nasar, Visual Preferences in Urban Street Scenes: A Cross Cultural Comparison Between Japan and the United States, Environmental Aethetics: Theory, Researchand Applications (Ed. Nasar, J.L.), (1992), Cambridge University Press, New York.

[4] G.R. Clay, T.C. Daniel, Scenic Landscape Assesssment: The Effects of Land Management Jurisdiction on Public Perception of Scenic Beauty, Landscape and Urban Planning, 49 (2000), pp. 1-13.

[5] T.C. Daniel, Whiter Scenic Beauty? Visual Landscape Quality Assessment in the 21st Century, Landscape Urban and Planning, 54 (2001), pp. 267-281.

[6] M. Arriaza, J.F. Canas-Ortega, J.A. Canas-Madueno, P. RuizAviles, Assessing the Visual Quality of Rural Landscapes. Lanscapeand Urban Planning, 69 (2004), pp.115-125.

[7] J. He, J.Y. Tsou, Y. Xue, B. Chow, A Visual Landscape Assessment Approach for High-Density Urban Development, In Computer Aided Architectural Design Futures, (2005), pp.125-134.

[8] C. Acar, B.Ç. Kurdoğlu, O. Kurdoğlu, H. Acar, Public Preferences for Visual Quality and Management in the Kaçkar Mountains National Park (Turkey), International Journal of Sustainabe Development and World Ecology, 13 (2006), pp.499-512.

[9] W.E. Dramstad, M.S. Tveit, W.J. Fjellstad, G.L.A. Fry, Relationships Between Visual Landscape Preferences and Map-Based Indicators of Landscape Structure, Landscape and Urban Planning, 78 (2006), pp.465-474.

[10] M. Roth, Validating the Use of Internet Survey Techniques in Visual Landscape Assessment-An Empirical Study From Germany, Landscape and Urban Planning, 78(3) (2001), pp.179-192.

[11] Y. Wu, I. Bishop, H. Hossain, V. Sposito, Using GIS in landscape visual quality assessment. Applied GIS, 2(3) (2006), pp.1-20.

[12] Z. Bulut, H. Yılmaz, Determination of Landscape Beauties Through Visual Quality Assessment Method: A Case Study for Kemaliye (Erzincan/Turkey), Environmental Monitoring and Assessment, 141(1-3) (2007), pp.121-129.

[13] C. Acar, Ç. Sakıcı, Assessing Landscape Perception of Urban Rocky Habitats, Building and Environment, 43 (2008), pp.1153-1170.

[14] H. Tüfekçioğlu Kuğu, Tarihsel Çevrede Görsel Peyzaj Kalite Değerlendirmesi İstanbul Yedikule Örneği, İstanbul Teknik Üniversitesi Fen Bilimleri Enstitüsü Peyzaj Mimarlığı Anabilim Dalı, Yüksek Lisans Tezi, (2008).

[15] A.Y. Çağlayan Kaptanoğlu, Peyzajın Görsel Analizinde Grafik Düşünme Süreci ve Soyutlama, İstanbul Üniversitesi Orman Fakültesi Dergisi, 58(2) (2008).

[16] O. Uzun, H. Müderrisoğlu, Visual Landscape Quality in Landscape Planning: Examples of Kars and Ardahan Cities in Turkey. African Journal of Agricultural Research, 6(6) (2011), pp.1627-1638.

[17] A. Caf, Bingöl-Erzurum Karayolu Güzergâhının Görsel Kalite Analizi, Atatürk Üniversitesi Fen Bilimleri Enstitüsü Peyzaj Mimarlığı Ana Bilim Dalı, Yüksek Lisans Tezi, (2014).

[18] J. Huang, Landscape Visual Quality Assessment in Washtenaw County, MI. School of Natural Resources and Environment University of Michigan, 18(1) (2014).

[19] A. Benliay, O. Soydan, M. Kayku, Aspendos-Sillyon-Perge Bisiklet Güzergahı Örneğinde Peyzaj Görsel Kalitesi ve Peyzaj Özelliklerinin Değerlendirilmesi Artium, 3(1) (2015).

[20] T. Kiper, A. Korkut, T. Üstün Topal, Görsel Peyzaj Kalite Değerlendirmesi: Kıyıköy Örneği, KSÜ Doğa Bilimleri Dergisi, 20(3) (2017), pp.258-269.

[21] Google Cloud API. Documantation AI & Machine Learning Products, (2019), https://cloud.google.com/vision/docs/labels

[22] DataCamp, Tutorials, (2019), https://www.datacamp.com/community/tutorials/beginner-guide-google-vision-api

[23] S. Mcleod, Likert Scale Definition, Examples and Analysis, (2019), https://www.simplypsychology.org/likert-scale.html