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Development of Deep Neural Networks Framework for Travel User Interest Discovery from Visual Shared sData in Social Networks (Case Study Facebook, Sudan)

تطوير إطار عمل من الشبكات العصبية العميقة لاكتشاف اهتمامات رحلات المستخدمين من خلال البيانات المرئية في الشبكات الاجتماعية

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Dissertation

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DECLARATION

I hereby declare that this thesis is the result of my own investigation, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole for any other degrees at Sudan University of Science and Technology or other institutions.

Fatima Mohamed Yassin Mostafa

Signature **Fatima Mohamed Yassin Mostafa** Date **8/8/2022**

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ABSTRACT

Social networks are virtual environments where users express their opinions, preferences and interests. All shared information in Social Networks like Facebook, Twitter, LinkedIn can be very useful to understand citizen's interest. This study aims to discover the travel user's interests through the shared social images. The most proposed works depend a lot on textual data to analyse social networks and avoid the visual data especially in Facebook, due to the lack or the limitation of available social images analysis systems. Our proposed system is a novel framework to detect travel user's interests from their posted and shared images in Facebook network. The two research questions are (1) what the current models of image analysis are used to discover the user's interests in social networks especially in Facebook, and (2), how may those models be improved or select the best of them to discover the user's interests. In terms of methods, deep neural network approaches were used. First we proposed a comparison between approaches based on Feedforward learning of Convolutional Neural Network (CNN) architectures GoogleNet and VGG'19 trained on Places365 Dataset for visual object Recognition. Once objects are recognized in images, we proposed a Deep Ontology Travel User Interest System (DOTUIS) based decision system for travel users interest prediction, our approaches based on CNN, GoogleNet and VGG'19 architectures can facilitate the interest of travel topic make it easy to discover is the users interest in travel or not, the GoogleNet architecture leading to a better performance and improving the classification accuracy than VGG'19 and in order to evaluate our Deep Neural approach, we have constructed a new database of shared images in Sudanese and Tunisian Facebook accounts. Our approaches have shown a promising result on Sudanese Facebook accounts database. Second, we proposed Deep Fuzzy Ontology Travel User Interest System (DFOTUIS) based on CNN, GoogleNet and VGG'19 architectures, and our proposed system has shown a very impressive result for travel Sudanese user's interest. Both proposed ontologies are tested and evaluated on collected Sudanese Database. The Deep fuzzy ontology system (DFOTUIS) performs well than the crisp inference system (DOTUIS). Based on the profile outputted from the deep fuzzy ontology we proposed an Intelligent Recommendation System for Travellers' Preferences (IRSTP).

مستخلص البحث

الشبكات الإجتماعية هي عبارة عن بيئة إفتراضية حيث يتبادل المستخدمون أراءهم، تفضيلاتهم واهتماماتهم. جميع المعلومات التي يتم مشاركتها في الشبكات الإجتماعية من فيس بوك وتويتر وغيرها يمكن ان تكون مفيدة في فهم إهتمامات المجتمعات. هذه الدراسة تهدف الي اكتشاف إهتمامات المستخدمين بالرحلات وذلك من خلال الصور التي تتم مشاركتها. تعتمد معظم الأعمال المقترحة على البيانات النصية في تحليل بيانات الشبكات الإجتماعية خصوصاً في الفيس بوك وبسبب نقص او محدودية أنظمة تحليل بيانات الصور في الشبكات الإجتماعية، نظامنا المقترح يمثل إطار عمل جديد لاكتشاف إهتمامات المستخدمين بالرحلات من خلال صورهم التي تمت مشاركتها على شبكة الفيس بوك. يحاول البحث الإجابة على سؤالين هما: (1) ماهي النماذج المستخدمة حالياً في تحليل الصور لإكتشاف إهتمامات مستخدمي الشبكات الإجتماعية خصوصاً في الفيس بوك؟، (2) كيف يمكن تحسين هذه النماذج أو اختيار أفضلها لاكتشاف إهتمامات المستخدمين. فيما يتعلق بمنهج البحث، تم استخدام نماذج التعلم العميق في الشبكات العصبية. أولاً تم عمل مقارنة بين نماذج شبكات عصبية ذات تغذية أمامية وهي GoogleNet, VGG’19 تم تدريبهما على قاعدة بيانات Places365 للتعرف البصري على الأشياء وبمجرد تعرفهما على الصور تم عمل نظام (DOTUIS) يعتمد على Crisp Ontology من أجل التنبؤ باهتمامات المستخدمين، وبما أنه التعرف على اهتمام المستخدم أمر صعب لكن النماذج المعتمدة على الشبكات العصبية سهلت هذا الأمر واكتشفت ما إذا كان المستخدم مهتم بالرحلات ام لا؟ كما أن النموذج GoogleNet قدم نتائج أفضل من النموذج VGG’19 ، ولتقييم عمل النموذج تم بناء قاعدة بيانات مكونة من حسابات فيس بوك سودانية وأخرى تونسية، النظام اعطى نتائج أفضل عندما طُبق على قاعدة بيانات الفيس بوك السودانية. ثانياً تم عمل نظام (DFOTUIS) يعتمد على Fuzzy Ontology مع نموذج الشبكات العصبية الذي أعطى نتائج أفضل على قاعدة بيانات الفيس بوك السودانية. تم مقارنة نتائج النظامين DOTUIS و DFOTUIS حيث أعطى النظام الثاني نتائج أفضل بكثير من النظام الأول، واستندنا على هذه الأنطولوجي في بناء تطبيق إرشاد رحلات مبني على إهتمامات وتفضيلات المستخدمين.

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LIST OF ABBREVIATIONS

CNN	Convolutional neural network
WOL	Web Ontology Language
DOTUIS	Deep Ontology Travel User Interest System
DFOTUIS	Deep Fuzzy Ontology Travel User Interest System
IRSTP	Intelligent Recommendation System for Traveller’s Preferences

LIST OF PUBLICATIONS

1- Yassin, F.M., Lazzez, O., Ouarda, W. and Alimi, A.M., 2017, November. Travel user interest discovery from visual shared data in social networks. In 2017 Sudan Conference on Computer Science and Information Technology (SCCSIT) (pp. 1-7). IEEE.

2- Yassin, F.M., Ouarda, W. and Alimi, A.M., 2020, September. Deep fuzzy ontology for travel user interest discovery based on visual shared data in social networks. In International Journal of Computer Information Systems and Industrial Management Applications (IJCISIM) ISSN 2150-7988 Volume 12 (2020) (pp. 330-338).

3- Yassin, F.M., Ouarda, W. and Alimi, A.M., 2021, Fuzzy Ontology as a Basis for Recommendation Systems for Traveler's Preference. Multimedia Tools and Applications (2022) 81:6599–6631.

CHAPTER ONE INTRODUCTION

1.1 Overview

Social networks are virtual environments where users express their opinions, preferences and interests. All shared information in Social Networks like Facebook, Twitter, LinkedIn can be very useful to understand citizen's interest. The visual shared data in social networks can express many latent knowledge about user' interests in such topic. Due to grown photo-taking devices and social media, social networks have become a precious resource for the acquisition of visual information.

Moreover, the visual data which is shared in social networks reveals many hidden pieces of knowledge about the interests of the users such as travel interest. Hence, user interest has become an inevitable domain of previous work. As the literature shows, "user interest" has emerged as a key element in the domain as a result of large data being shared daily by the users. This data can be accessed, analysed to discover concealed information about human needs and preferences.

An analysis of socially shared data can be applied to generate the user's interest profile by analysing the deep visual features of shared data to predict the user interests. As is shown in Figure 1.1, there are different modalities of user profiling, explicit like likes, ranks, and favourites, and implicit like: textual and visual.

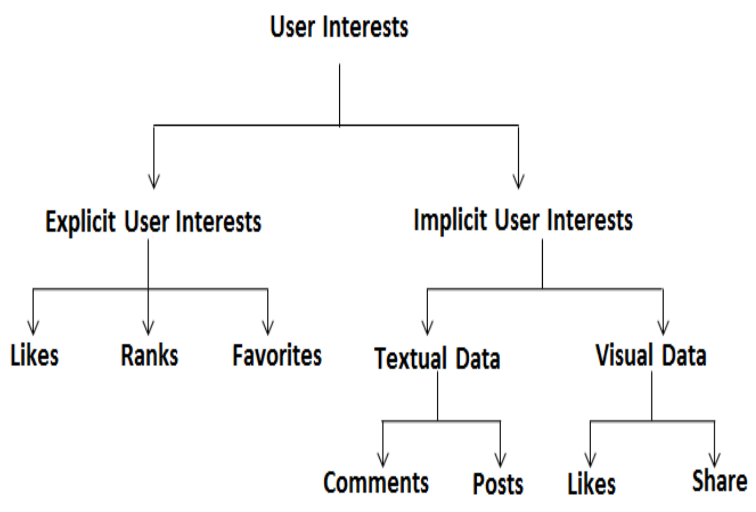

Figure 1.1 User Profiling through Social Networks

In this work, we proposed that images associated with individuals in social network especially in Facebook network can provide the travel interest and preferences of those individuals. User interest has become a required field in literature due to the huge data shared everyday by citizen which may be analysed to discover a hidden knowledge about human preferences for a personalized recommender system in several topics like sport, travel, food, culture, shopping, etc. In this work, we focus only on one topic of interest and the most important in the social networks which is travel. Also, we focus on deep ontology classification system based on discovering user interests through visual data shared in social networks especially Facebook network.

Our work concentrates focus on the analysis of social images which is a well-known sort of media within social networking. Figure 1.2 represent images from a variety of Facebook accounts. Researchers tried to investigate the interests of people according to their social photography activities. The main focus was on the issue of how we can find out the social culture of these users who are interested especially in the take a travel interest topic, to capture travel characteristics, we should utilize the modern development in computer vision and learning machine including detection and recognition of objects and we show that it is possible to analyse social images from images that users shared and posted on their Facebook accounts.

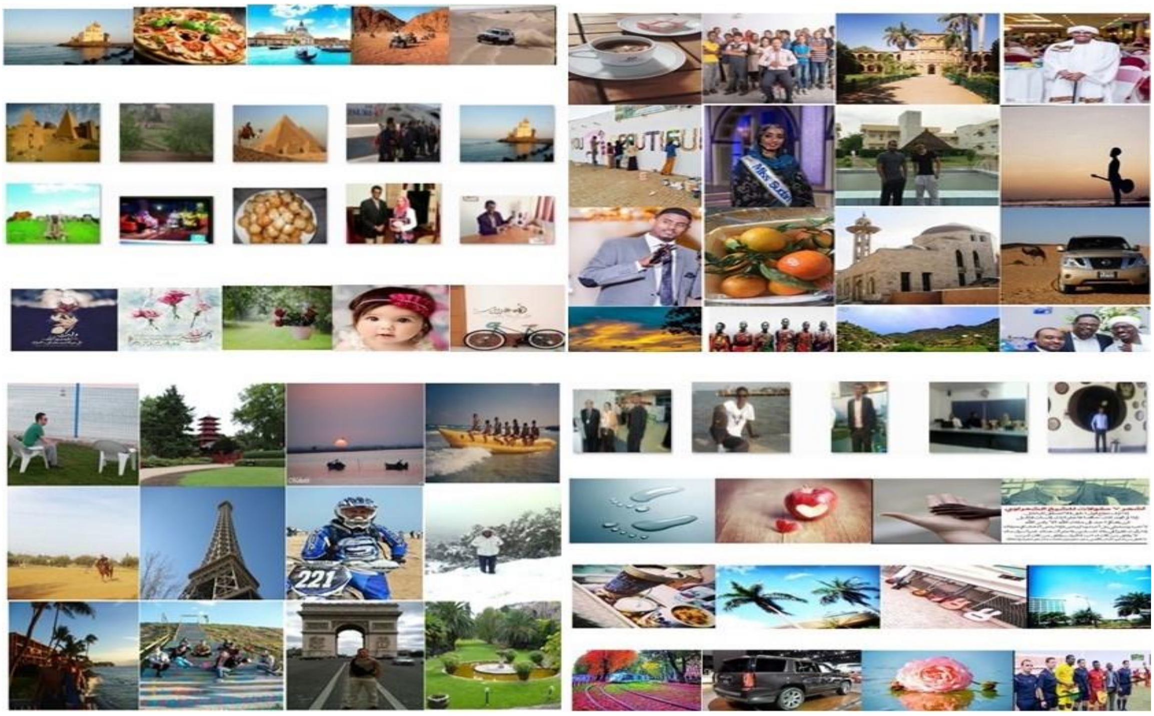

Figure 1.2 Example of Facebook Images

In this work, we suggest that individuals' interests and preferences information can be provided by the photos they shared and posted in Facebook network. Analysing users' interests is continuously growing field and, as enormous data are daily shared, inherent information can be discovered. This can be used as personalized recommending system for several issues such as food, shopping, sport, travel, clothing, culture, health, etc.

Different recommendation systems require intensively understanding users' tendencies to provide reliable information about their preferences on a specified issue such as travel. Visual information which is shared in social networks could be useful for individuals in terms of suggesting many spots and/or activities tailored according to their own taste and interest. The task for recommender systems, therefore, is to produce suggestions derived from accumulating user's data such as interests and location (Ravi and Vairavasundaram, 2016).

Recommender system is defined as a software product that recommends the most convenient piece, location or product that matches the user's preference (Itoga et al., 2018). Recommender systems (RSs) have holistically been identified as specialist systems which are utilized in order to recommend goods or services to the users (Itoga et al., 2018) (Noguera et al., 2012). Figure 1.3 shows the generic recommendation system environment.

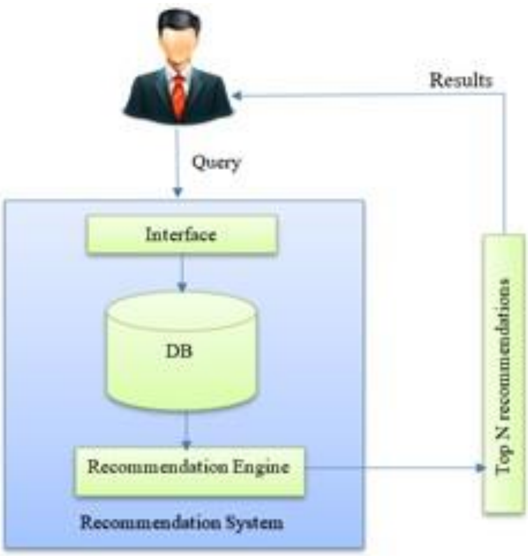

Figure 1.3 Generic Recommendation System Environment

The present study also proposed a simple personalized travel recommendation system. This system appears as a photo recommending the travel specified by the user using recommender system initiated by the interest. As holiday-makers go to unfamiliar places, it seems that they have no clue about travel destinations, restaurants and cafes, natural sites, monuments and events nearby their existing location. In that case, the system of the present study will use the current location (city) of the user and immediately recommends activities with their locations, such as sports to do, based on the interests of users.

It is easy to interact with travellers through the "Travel Recommendation System" where they demand their interest. Afterwards, the application looks into the preferences and finds out the results that come with those interests. As many users might be aware of the travel locations, restaurants and cafes, nature spots, events and art now, they can go on with the process.

1.2 Problem Statement and Motivation

Today the analysis of social data which can be: Textual or Visual. Most proposed works (Qiu and Cho, 2006); (Wen and Lin, 2010); (Kim et al., 2012);(Wang et al., 2013); (Hong et al., 2013);(Kosinski et al., 2013);(Ombabi et al., 2017) depend a lot on textual data to analyse social networks and there are not several works on analysis of visual data (images) especially travel images and also specially in Sudanese Facebook network, due to the lack or the limitation of available Facebook images analysis systems and some works using ontology and no fuzzy ontology methods proposed to detect travel user interest, our proposed system is a novel framework to detect travel user interest from images that shared and posted in Sudanese Facebook network.

With the development of CNN's architectures for image classification, we have intended to analyse visual data using this robust representation of images based on deep convolutional neural networks. In our work, we will study the effectiveness of CNN architectures for travel user interest discovery based on crisp ontology and fuzzy ontology. Our system can be very useful for a recommendation system of travel like trip advisor.

1.3 Research Questions

To construct a system for discover the travel user's interests through the huge number of social images shared and posted in Facebook accounts and use the user profile to create recommendation system for travel, this thesis concentrates on two main research questions:

1) RQ1: what the current models of image analysis are used to discover the user's interests in social network especially in Facebook?

In this research question, the researcher aims to explore the limitations and weak points of current approaches that may potentially challenge the user's interest detection.

2) RQ2: how may those models be improved or select the best of them to discover the user's interests?

In this research question, the researcher seeks to address how to improve the limitations and weak points of the current approaches through the design of approach that could lead to improve the process of travel user interest's detection in Facebook network.

1.4 Aim and Objectives

The main contribution of our work presents a novel framework to detect travel interest from social network images used prediction system. Using optical item recognition architectures from shared illustrated information, Sudanese and Tunisian Facebook accounts, we have collected a dataset from a variety of Facebook accounts. We intended to study the effectiveness of deep Convolutional Neural Networks (CNNs), GoogleNet, and VGG'19 architectures for features extraction to discover travel user interests based on crisp ontology and fuzzy ontology prediction systems. Our approach may be useful for obtaining a travel interest recommendation or advisor system.

The main objective of this work is to investigate the travel interest of people according to their social images based Deep Learning architectures, which can be achieved by:

- Proposed a comparison between approaches based on Feedforward learning of Convolutional Neural Network (CNN) architectures GoogleNet and VGG'19 trained on ImageNet and Places 365 Dataset for visual object Recognition and select the best approach of them.
- Proposed Deep Ontology Travel User Interest System (DOTUIS) for travel users interests prediction (is user interest in travel or not?).
- In order to evaluate our Deep Neural approach, we have constructed two datasets of shared images in Sudanese and Tunisian Facebook accounts.
- Proposed Deep Fuzzy Ontology Travel User Interest System (DFOTUIS) for travel user's interests.

- In order to evaluate our Deep Fuzzy Neural approach, we have constructed datasets of shared images in Sudanese Facebook accounts.
- Proposed a comparison between DOTUIS and DFOTUIS to determine the better performance.
- Proposed an Intelligent Recommendation System for Travellers' Preferences (IRSTP).

1.5 Methods

The researcher used the following list of technologies and tools:

- Caffe under the operating system Linux Ubuntu to run CNN models.
- Protégé Wol2 API version 4.1 to create the ontology.
- FIRE API to create Fuzzy ontology.
- Java toolbox software to get final results.

The app (IRSTP) is created on a web technology through using:

- Angular JS framework
- Java script
- Visual Studio
- Firebase Google cloud database
- CSS and html

1.6 Structure of the Thesis

In the present chapter, the overview about the social network analysis, problem and motivation, research questions, objectives and methods illustrated. While the next paragraphs will describe the organization of the remaining chapters as follows:

Chapter 2 Overview

This chapter presents an overview of related research on visual analysis of social networks including (1) user interest discovery, (2) user profiling, Hand crafted methods, Neural network-based approaches and crisp ontology and (3) related work on recommendation systems.

Chapter 3 Methodology

This chapter, explains the proposed systems (crisp and fuzzy ontology) for user's interest's discovery in more details including models and phases, data collection (Training and Testing databases) and finally we present ethical considerations for this thesis.

Chapter 4 Results and Discussions

This chapter will present the experimental results of our proposed systems (crisp and fuzzy ontology) to travel user interest discovery and application to travel recommendation system.

Chapter 5 Conclusion

This chapter presents the main thesis findings, important results, recommendations for future works and limitation need to be covered.

CHAPTER TWO OVERVIEW

2.1 Related Work on User Interest Discovery

Many works have been proposed to discover user's interests, and many studies have suggested various approaches for articulating user's identity from textual or visual data that are shared through social networks, analysis this data to detect some users' preferences or interests, or some soft biometrics information, discover the user's attributes, infer the geographic location, fashionability, users' sentiments, social subculture or urban tribe, discover user opinions and others. In this section, we presented some of the recent works.

In a study conducted by (Qiu and Cho, 2006), users' interests through search on the web from their search history. To attain this objective, three datasets were used: users' click history, pages sets that seem consistent with the queries that they perform and the Topic-Sensitive PageRank values for each page. (Li et al., 2008) to detect users' interests from the visited locations.

Furthermore, (Wang et al., 2009), suggested a model baptized Argo for users' interests, relying on contextual data to examine discovery of photo-based interests. Nevertheless, they applied tools for standalone image annotation to convert images into textualized tags and consequently derive interests from tags.

Another users' interests' model was proposed by (White et al., 2009), depending on contextual information involving social, historic, task, collection and user's interaction.

A new approach to infer users' interests depending on social connections and interactions was proposed by (Wen and Lin, 2010) ;(Wang et al., 2013). This model combines both text and link of interests sharing to information such as "follow", "tweet", "mention" and "comment".

(Kim et al., 2012), illustrated users' interests by topic distribution and reading standard to provide an innovative representation of the content of the web. Similarly, (Hong et al., 2013) have analysing data on Twitter such as hash tags, followers and tweets, different types of users' interests.

Also, personal photos were subject to a study conducted by (Feng and Qian, 2013); (Feng and Qian, 2014) where these photos associated to photos' texts and comments to deduce users' interests.

Another study in the same perspective was conducted by (Xin et al., 2015), which adopted a User Image Latent Space Model to depict users' interests by associating them to image contents. The researchers were able to infer the underlying interests and users' distribution over them. Thus, they could, by underlining users' interests, organize image contents into four-stage graded structure: themes, semantic regions, visual words and pixels. Therefore, the experiment based upon 180K (about 183723) photos associated to 227 FLICKR users among whom each has approximately 800 images, including themes such as cars, birds, people, etc.

Moreover, (Zhou et al., 2016) have provided an original prototype visual user interest profile, which undertook to seize users' interests depending on image analysis that users seemed to like the most. Thanks to deep-learning, they managed to specify subsequent recommendations and status personalization by extracting a visual user's interests' profile. They used a hotel booking system to establish their technique.

Another new framework is proposed by (Lazzez et al., 2016), which attempted to extract the users' attributes depending on social networks pictures previously posted and then shared. The attributes they depicted included gender, age, race and smile. Also, (Lazzez et al., 2016) they presented a novel framework to extract the user' soft biometrics information from Social Visual Data.

The previous works exposed here focused on texts, links, clicks metadata and social clues, apart from the last studies by Zhou and Lazzez. The approached adopted depended significantly on textual information and could not be applied when there were no side texts. The utilization of only textual data could become extremely limited when the social visual data is generally conversational and rich in content. Thus, the approach immediately distinguishes the users' interests from social images depending on scene understanding concept and doesn't entail the existence of any textual data.

2.2 Related Work on User Profiling

User profiling is typically either knowledge-based or behaviour-based. Knowledge-based approaches engineer static models of users and dynamically match users to the closest model. Questionnaires and interviews are often employed to obtain this user knowledge. Behaviour-based approaches use the user's behaviour as a model, commonly using machine-learning techniques to discover useful patterns in the behaviour. Behavioural logging is employed to obtain the data necessary from which to extract patterns (Middleton et al., 2004). Different current research have proposed several methods for depicting users' profile from textual or visual information which are dispatched and shared via social networks and by analysing these data, some users' tendencies, preferences and interests can be inferred, or other soft biometrics data could permit geographic location specification. Other aspects could also be depicted such as fashion tendencies, sentiments, social subculture, urban or tribal relevance besides opinions and personal views. Such recent studies are exposed in this part.

The user profiling approach used by most recommender systems is behaviour-based, commonly using a binary class model to represent what users find interesting and uninteresting. Machine-learning techniques are then used to find potential items of interest in respect to the binary model.

(Middleton et al., 2004) explore a novel ontological approach to user profiling within recommender systems, working on the problem of recommending on-line academic research papers. Using two experimental systems, Quickstep and Foxtrot. Adapted Approach for User Profiling in a Recommendation System, Application to Industrial Diagnosis. This tool provides diagnostic documents for industrial operators based on collaborative filtering that operates on users' preferences and similar responses.

2.2.1 Object recognition-based approaches

The object detection is one of the current and most looked-for areas in visual recognition. We can state as an example the use for nearly seven years of Convolutional Neural Networks (CNNs) in visual recognition (Jia et al., 2014). Images can accordingly be categorized in an appropriate way. It was also proved that the accuracy has significantly improved; besides, the use of tough layers strings as an incentive for using CNN architectures. Moreover, to clarify the appearance of objects in image, several filters have been utilized with input image. Considered as the special kind of automatic feeding networks, Convolutional neural networks and neural networks are nearly identical.

The models are furthermore utilized to stimulate the act of the visual cortex. The distinguishing aspects of CNN from others are the convolutional layers and the pooling layers, which could enable the network to execute the properties of certain images. These can perform extremely perfectly in visual recognition operations.

2.2.1.1 Hand crafted methods

Several suggested models can depict social activities thanks to a photograph, besides being able to identify photographs in a functional manner. This possibility caught attention to regroup photography that covers many individuals. Consequently, the question raised was: how can social tendencies or urban tribes be specified for individuals who appear in a group photo? (Murillo, 2012).

However, (Simo et al., 2015) suggested CRF model that can forecast fashion's tendencies of users' photographs. The model exposes, depending on data collected from a social website, a magnificent fashionable image that can be used to analyse fashion trends in certain cities or all over the world, as well as to fit in recommendation that reinforce up-to-date users' experience of today's society.

A teaching framework was proposed by (Mac et al., 2018), that can be looked for as specifying interpretable feedback. This framework shows that learners assimilate this additional feature during their learning. Moreover, it can create explanations, highlighting image bits and can also label classes. It also indicated that textual data is extremely constrained while the social visual information is conversational, having rich content.

Subsequently, the present study method detects the users' interests for travel depending on social image (using scene understanding concept) without requiring textual data.

2.2.1.2 Neural network-based approaches

The study conducted by (Guo et al., 2016), concentrated on encounters and applications of deep learning algorithms treated in current research papers. The study has surveyed computer vision methods such as objects detection, image categorizing and retrieval, semantic segmentation and brief notes giving.

A novel framework was created by (Lazzez et al., 2016) used to deduce users' characteristics depending on posted and shared social media images, in particular, gender, age, race, smile. And invented an innovative framework that extracts the user's soft biometric from shared social data.

(Wang et al., 2018), mechanical techniques based on convolutional neural networks to deduce the geographic location, and this method was effective in 144K fashion and the Pinterest-based dataset. These results show that the mechanical techniques can be utilized with other's people features like clothing style, physical features and accessories.

On the other hand, (Li et al., 2017) focused on Graph Neural Network (GNN), which represents a method for identifying images situation and find out the correct verb thanks to role-noun pairs, depending on a benchmark dataset imSitu, 4.5% accuracy enhancement was accomplished in a metric.

(Ombabi et al., 2017) proposed an efficient method providing a brief of Twitter's users' interests, depending on their social textual information. Five everyday life categories were underlined as travel, food, sports, religion, fashion, beside the way that users' interests are revealed. For text pre-processing, pre-trained Wrod2Vec is used while for categorization, Support Vector Machine is used. In the same perspective.

(Lovato et al, 2013) suggested an image classification framework concentrating on image characteristics extracted from unsupervised deep learning algorithms. Up-to-date database gathered from Sina microblog was used, including 5000 social images. The framework was applied to an online social networking image and, thus, gained 89.7 of accuracy.

Because CNN are totally data-driven, they are extremely accurate in representing training samples and quite capable to disclose patterns features, otherwise cannot be described by manual properties.

2.2.2 Crisp ontology

An ontology is a conceptualisation of a domain into a human-understandable, but machine-readable format consisting of entities, attributes, relationships, and axioms (Guarino et al., 1995). Ontologies can provide a rich conceptualisation of the working domain of an organisation, representing the main concepts and relationships of the work activities (Middleton et al., 2004).

(Ochoa et al., 2011) proposed the technique that depends on using semantic roles from ADESSE to find out the semantic relations between concepts. This technique was carried out as an approach of ontology learning from monetary written pieces, relying on the findings of semantic relations and natural language texts, provided as an automatic approach of extracting knowledge from texts.

(Girshick et al., 2014) applied an intelligent recommendation system counting on Jeju travel ontology that commanded the holiday-maker. Individual preferences were detected by using properties and travel ontology relationship and, consequently, can determine the traveller location on the AI map.

In the same perspective, (Lazzez et al., 2018), have suggested an original structure for predicting users' interests, based on visual data on Facebook via deep neural approach for building ontology. However, the suggested framework has accomplished a .80 of accuracy when categorizing users' interests.

Below (table 2.1) shows the topics of user interests according to some works.

Table 2.1 Topics of Interest's Categories in Some Related Work

Study	Datatype	Topics
(Ombabi et al., 2017)	Tweets	Travel, food, sports, religion, and fashion.
(Murillo et al., 2012)	Group Images	Social subculture or urban tribe.
(Simo et al., 2015)	Images	Fashionability
(Lazzez et al., 2017)	Images	Biometrics information, specifically age, gender, race, and smile.
(Lazzez et al., 2018)	Images	Travel, food, sports, religion, and fashion.
(Jun and Peng, 2013)	Tweets	Sport, finance, health, movies, and digital.

2.3 Related Work on Recommendation System

The EEG application is based on an automatic music recommendation system that utilizes a deep artificial neural network (Itoga et al., 2018) which is constructed three rankings of deep neural network structures (named RDNN1 to RDNN3) and applied them to EEG according to music recommendation system. RDNN2 demonstrated competence when it comes to nDCG performance.

Other research works obtain travel user interest based to his/her past time history in a single city, (Memon et al., 2015) recommended a new method for locating places for tourists according to their time and their interest. The experiment outcomes show that the travel recommendations method which is based on tourist time is capable of predicting tourist location recommendation whether for famous places or new places.

(Subramaniyaswamy et al., 2015) Proposed techniques used to forecast demographic data (tourist locations) and present travel recommendations to users. This method mines the user interests from the available users contributed photos of places that they share on different websites

(Choi et al., 2009) This research proposed intellectual systems of recommendations generated from Jeju's travel ontology. The anticipated system could possibly recommend to the traveller more intelligent data utilizing properties and relationships of trip ontology and assist them to predict confusion of streets or attractions. The system is accountable for articulating tailored attractions and plotting spots of tourists as visualization data with a map.

(Choi et al., 2006) Research shows in the Travel Ontology of Semantic Web-based Recommendation Systems, the OWL is used to create the travel Ontology, while preference profile creates the Metadata.

(Cao et al., 2010) Constructed the traveller's recommendation system according to the existing tags and photos with analogous GPS locations. They collected a database of geographic tagging by collecting more than one million Flickr photos with GPS records from Flickr.

(Subramaniyaswamy et al., 2015) Suggested an application that assists users to locate touristic destination that might appeal to them to visit or a location from obtainable shared images of the location which are reachable online on sites that share images. The study illustrates techniques utilized to extract demographic data and offer user recommendation to travellers. Furthermore, "algorithm adaboost" is defined to categorize information and "Bayesian Learning model" is described to forecast preferred spots for a tourist according to their interests.

Additionally, a few recommender systems go with the interests of the traveller, looks into the previous history of a traveller for places then evaluates the places with high rates reviews for other holiday-makers too in order to offer a proposed menu of suggestions. This can be done through the usage of machinery to evaluate different interests and resemblances between different user profile and streaming information. Relative factors, for example, the current geographical position of the user could also be taken into account for offering suggestions (Noguera et al., 2012). Rationalization competence of the menu of proposals is further offered by a few systems (e.g., Jannach et al., 2010). Most users' recommendation systems are short of the points of personal suitability, being interactive, and being adaptive.

The approach followed in this research offer points of preference according to the user interests. The system still requires the traveller's assistance to construct their trip suggestions manually. A few investigations have tried to sort out the problem of automaticity when providing and planning travel service, however, the dilemma of e-mechanized trip arrangement is still novice and needs deep digging. It can be considered as a fresh matter in which social data, along with users' contexts can be deployed in order to resolve the matter.

(Wang et al., 2013) proposed algorithms that create recommendations based on four factors: a) past user behavior (visited places), b) the location of each venue, c) the social relationships among the users, and d) the similarity between users. The proposed algorithms outperform traditional recommendation algorithms and other approaches that try to exploit location-based social networks (LBSN) information. Proposed two algorithms for recommending new venues to users in LBSNs. Unlike traditional approaches, the algorithms do not solely rely on past user preferences, but they also exploit the social relations of the network and the geographical location of the venues. (Sarwat et al., 2014) This paper proposed a location-aware recommender system that uses location-based ratings to produce recommendations, exploits user rating locations through user partitioning, a technique that influences recommendations with ratings spatially close to querying users in a manner that maximizes system scalability while not sacrificing recommendation quality, exploits item locations using travel penalty, a technique that favors recommendation candidates closer in travel distance to querying users in a way that avoids exhaustive access to all spatial items. (Logesh et al., 2019) Developed a Personalized Context-Aware Hybrid Travel Recommender System (PCAHTRS) by incorporating user's contextual information. The proposed PCAHTRS is evaluated on the real-time large-scale datasets of Yelp and TripAdvisor. (Kesorn et al., 2017) in 2017 proposed a tourism RS that is based on its recommendations on data dynamically aggregated and extrapolated from the Facebook check-in data. This paper demonstrate the usefulness of the data available on Facebook through the example studies involving attraction recommendations, and adapting the user model to improve recommendation quality in the tourism domain. (Dhaware et al., 2020), in 2020, E-Tourism Recommendation system aim to help the tourist for selecting a destination, present a technique known as User Location Vector for identifying the implicit relationship between Users and their Point of Interest. Traditional recommender systems do not consider spatial properties or preferences of users and challenge faced by the travel recommendation system is to mainly exploit the existing relationship between a user and their Point of Interest and hence recommend appropriate places of attraction and some works in their future work, they recommended to include the identification of communities and the incorporation of venue or places categories in the recommendation approaches, this is the points our work treat it, detect the user interest from their social images in term of user profile and use this profile to help users to selecting the travel places or destination.

2.4 Discussion

Currently, the visual features-based users' interests discovery process has been proposed for a long time, and there is an insufficient significant advancement in ways that the challenge has been tackled. Using the opportunity offered by the Convolutional Neural Network architectures.

(You et al., 2015) train the AlexNet architecture on the users' shared images to extract the most relevant visual features. Then, an image-level similarity is applied to propagate the label information, within a set of provided social images. This similarity allows to classify the category level knowledge for all of shared images.

In the same context, the authors in confirm that users' interests classification and prediction are based on the visual features distribution for each shared image.

In addition, (Yang et al., 2015) use Siamese architecture to extract the visual features from social favourite images. These extracted visual features are classified to discover users' hidden visual interests. Moreover, the authors apply, at first, the distance metric learning method to obtain the similarity information from obtained visual features and in a second time, the derived distance metric to minimize the most important personal topic of interest. Based on Flickr social network.

The authors in (Monay et al., 2005) discover users' interests from their shared personal images. They proposed a user's image latent space model to jointly model users' interests and image content. By inferring the latent interests and user's distribution over them, they can discover what users are interested in.

Furthermore, (Yang el al., 2017) proposed a novel deep learning framework for users' interest's discovery based on the social visual data analysis in the context of hotel booking system demonstrator recommendation.

CHAPTER THREE METHODOLOGY

3.1 The Concept of Machine Learning and Classification

Machine learning is a branch of artificial intelligence that include a broad ranging of methods which employ various statistical and optimization techniques to provide decision making by learning complex patterns in a population from a sample set of data. There are two types of learning these types are: supervised learning, and unsupervised learning. In the supervised learning, the learning of the machine is controlled, and the data will be normally divided into learning set and testing set. Both of input and target output are given to train a function, and a learning model is trained so that the output of the function can be predicted at a least cost. The common supervised machine-learning methods include Artificial Neural Network (ANN), K-Nearest Neighbour (KNN), Decision tree (DT), Support Vector Machine (SVM), Bayesian Networks (BNs), and the Hidden Markov Model (HMM). In unsupervised learning, no target or label is given in sample data. Unsupervised Learning methods are designed to summarize the key features of the data and to form the natural clusters of input patterns given a particular cost function. The most famous unsupervised learning methods include k-means clustering, hierarchical clustering, and self-organizing map. Unsupervised learning is hard to evaluate, because it does not controlled, therefore, does not have labelled data for testing.

Classification is a broad ranging research field which includes many decision-theoretic approaches for identifying data. A datum described numerically through a vector (x1, x2 ...xn) where n is the number of attributes (features).

Therefore, each piece of data can be treated as one point in an n dimensional space, and belongs to one class or multi classes. All classification algorithms normally employ two steps, training and testing. Characteristic properties of data calculated through the analysis of labelled training data will be applied to classify unlabelled testing data.

Many classification algorithms available, such as the nearest neighbour (NN) algorithm, neural network, decision tree, Bayesian network, and support vector machine (SVM) In general, it is hard to say which classification algorithm is better than others, we can only say one classification algorithm is better than others for a specific problem. The CNN technique is one of classification algorithms, is very simple, highly efficient and effective in the field of pattern recognition, text categorization, object recognition etc.

With the growth of computer technology we have a chance to improve image interpretation using computer capabilities. Visual information from social networks provides one of the more important sources of information for a variety of applications. Many researchers had worked on this field. The main objective of this work is to apply the different CNN classification algorithms and evaluate the effectiveness of CNN to find which one is more accurate.

3.2 The Concept of Image Processing

Image analysis is the extraction of meaningful information from images using digital image processing techniques, Image analysis tasks can be as simple as reading bar coded tags or as sophisticated as identifying a person from their gait or face.

Human visual cortex is an excellent image analysis apparatus, especially for extracting higher-level information, and for many applications such as medicine, security, and remote sensing human analysts still cannot be replaced by computers. For this reason, many important image analysis tools such as edge detectors and neural networks are inspired by human visual perception models.

Digital image processing is the use of a digital computer to process digital images through an algorithm.

3.3 The Concept of Convolutional Neural Networks

A neural network is a network or circuit of neurons, or in a modern sense, an artificial neural network, composed of artificial neurons or nodes (Hopfield, 1982). Thus a neural network is either a biological neural network, made up of real biological neurons, or an artificial neural network, for solving artificial intelligence (AI) problems. The connections of the biological neuron are modelled as weights. A positive weight reflects an excitatory connection, while negative values mean inhibitory connections. All inputs are modified by a weight and summed. This activity is referred to as a linear combination. Finally, an activation function controls the amplitude of the output. For example, an acceptable range of output is usually between 0 and 1, or it could be -1 and 1.

These artificial networks may be used for predictive modelling, adaptive control and applications where they can be trained via a dataset. Self-learning resulting from experience can occur within networks, which can derive conclusions from a complex and seemingly unrelated set of information.

Object detection becomes an attractive topic in visual recognition area. Convolutional Neural Networks (CNNs) have been widely used in visual recognition (Krizhevsky et al., 2012). It had a high capability in correctly classifying images. The researchers show an extremely improvement on the accuracy. The motivation to use of the CNN architecture consists to the high robustness of the cascading of layers based on multiple filters applied on the input images to provide a high-level representation of objects in image.

In fact, Convolutional Neural Networks are very similar to ordinary Neural Networks, its special type of feed-forward networks. These models are designed to emulate the behaviour of a visual cortex. CNNs have special layers called convolutional layers and pooling layers that allow the network to encode certain images properties. It performs very well on visual recognition tasks and does not require handcrafted image features.

The concept of visual classification using deep learning based on neural network architectures, one of the most desirable and recent areas in visual recognition is object detection. For instance, Convolutional Neural Networks (CNN's) were serving in visual recognition for nearly 7 years. It is capable of classifying images accurately. The researchers found that accuracy has substantially improved. The strong series of layers played as an incentive for using CNN architecture. Furthermore, to make the objects very clear in the image, many filters have been used on the input image. Next figure shows an example of object detection.

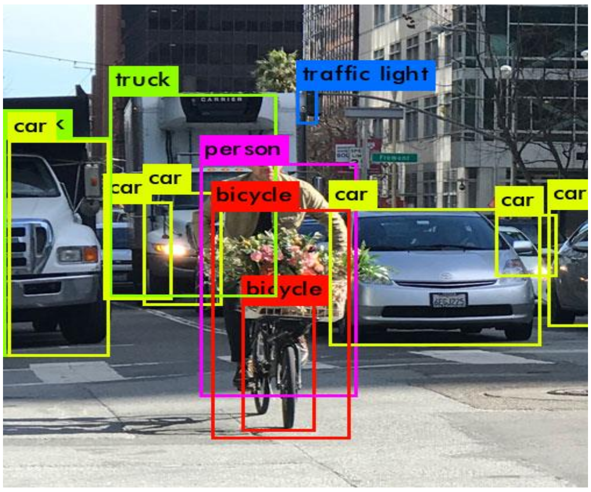

Figure 3.1 Example of Object Detection

3.4 CNN Models

CNN has many models that can be used by the researcher. In this work, we applied two models that were previously trained on ImageNet Large Scale Visual Recognition (ILSVRC) dataset.

We used architectures based on three main types of layers: the convolutional layer, the pooling layer, and the fully connected layer:

Convolutional layers and Pooling layers are layers that distinguish each other from CNN, and these layers enable the network to perform the properties of some images. It works perfectly on visual recognition tasks and does not require handcrafted image features. We use Pre-trained CNN models with Caffe to extract visual features, then we use the softmax classifier.

1) VGG'19 Architecture

The VGG19 (Simonyan and Zisserman, 2014), is famous for its simplicity, deploying just 3x3 convolutional layers, stacked on the top of each other, within an expanding depth. The max-pooling handles a minimized volume size. Two fully connected layers, each of which has 4,096 nodes, are then traced by a softmax classifier, as is shown in Figure 3.2.

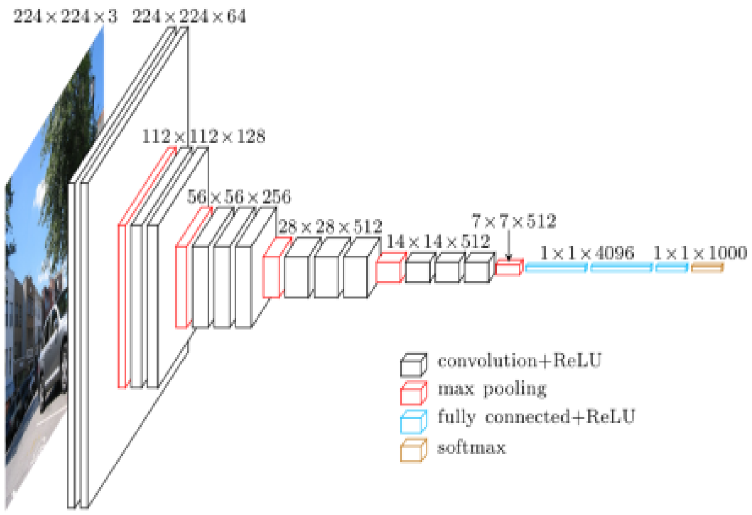

Figure 3.2 VGG'19 Architecture

2) GoogleNet Architecture

The GoogleNet (Szegedy et al., 2015) is composed of an average pooling layer with 5x5 filter size and stride 3, a 1x1 convolutional layer with 128 filters to reduce dimension and rectify linear activation, a fully connected layer with 1024 units and a resolved linear activation, as is shown in Figure 3.3.

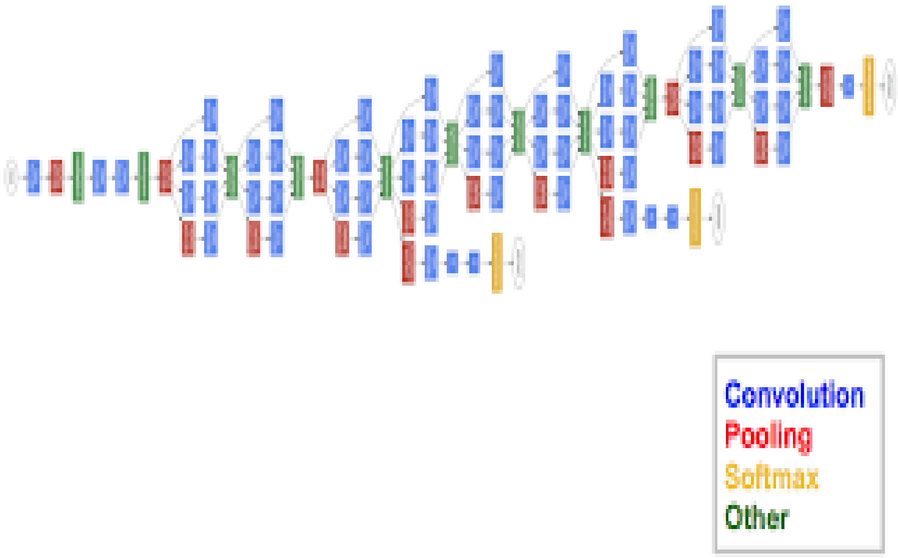

Figure 3.3 GoogleNet Architecture

Table 3.1 illustrates a comparison between the main CNNs architectures based on the numbers of layers, filters, and parameters for GoogleNet and VGG'19 architectures.

Table 3.1 CNN's Architectures Comparison

Architecture Features	**GoogleNet**	**VGG'19**
Input Image	224*224*3	224*224*3
Conv Layer	22 Conv Layers	16 Conv Layers
Pooling Layer	max pooling	5max pooling
FC	No	3 FC
Size of kernels	20 (1*1) (3*3) (5*5)	(3*3) (2*2)
Parameters	4M	140M

Convolutional neural networks start with an input layer (pictures) followed by a sequence of convolutional layers, pooling layers and ReLU layers, finally ends with high-level reasoning in the neural network that are fully-connected layers. Any conv Layer followed by activation functions (ReLU layer), applies the non-saturating activation function.

f (x) = max (0, x). It increases the nonlinear properties of the decision function and of the overall network. Features extraction is in convolutional, pooling and ReLU layers, VGG 19 and GoogleNet architectures are the feedforward learning in CNN that extract a 4096-dimensional feature vector from each image using the Caffe implementation of the CNN. Features are computed by feedforward a mean-subtracted 224_224 RGB, fully connected layers used as classifier, their activations can hence be computed with a matrix multiplication followed by a bias offset. In this case, the convolution formula becomes:

$$y_{ijk} = \sum_{uvp} w_{uvpk} x_{i+u, j+v, p}$$

3.5 Proposed Systems

A wide range of methods that can be used and researchers have actually free hands to choose from them and find a workable combination that can lead to improvement through the process of detect user interest. In this work we proposed three systems:

3.5.1 Deep Ontology Visual User Interest System (DOTUIS)

By applying a deep-learning for scene understanding (Places365) using CNN architectures, build a visual knowledge that can be used to train algorithms that require huge amounts of data. The trends of travel interest discovery from visual data consist of the recognition of object in images. For this reason, we have adopted feedforward learning in CNN well known architectures, GoogleNet and VGG'19 (CNN models run using Caffe under the operating system Linux Ubuntu). The user travel interest prediction was made by an ontology inference that contains concepts from ImageNet and Paces 365 databases.

The DOTUIS system developed, as shown in figure 3.4, depends on two crucial stages. The first one is the training process for user's interest's ontology Prediction

System Construction and, the second is the testing process for user's interests prediction, by using visual object recognition architectures from visual data shared via the Sudanese and Tunisian accounts on Facebook.

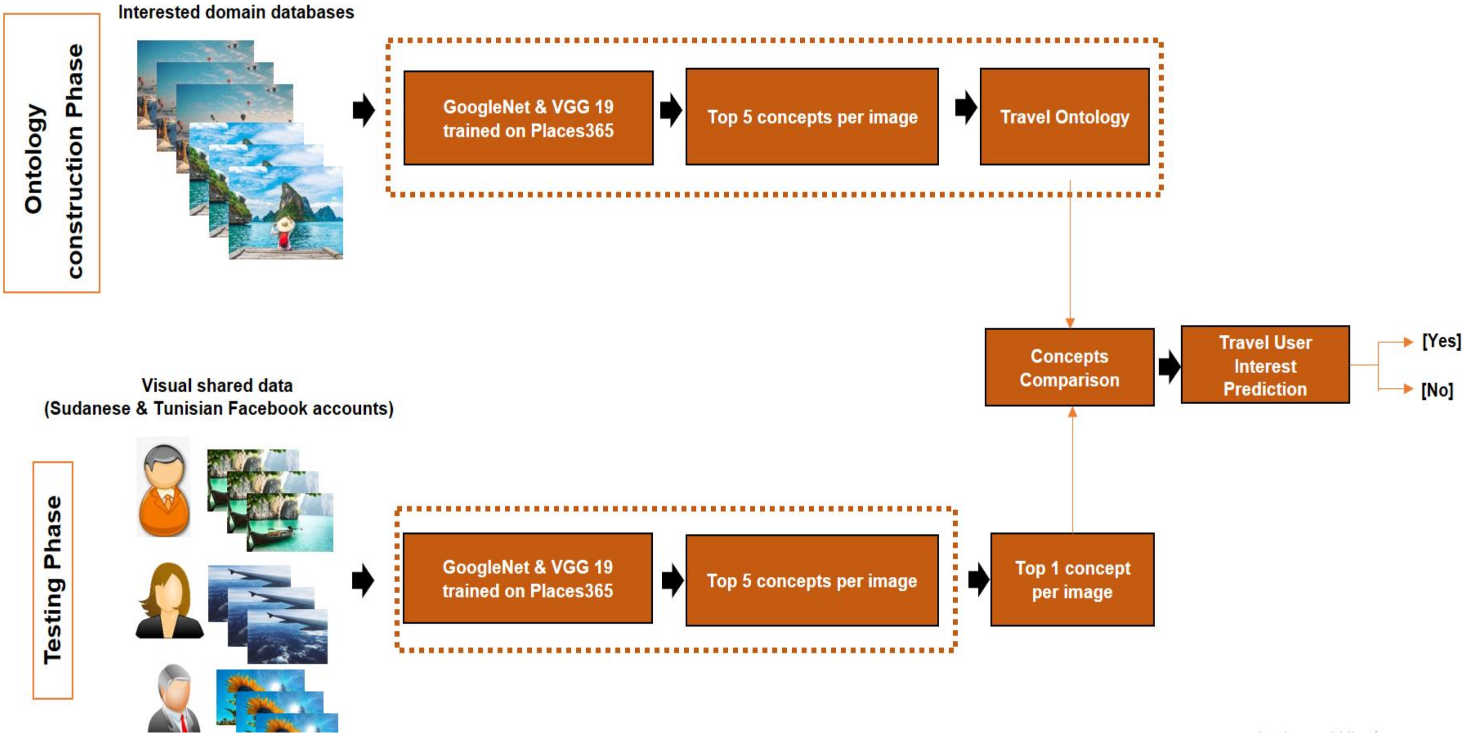

Figure 3.4 Deep Ontology Travel User Interest System (DOTUIS)

Caffe Overview

Caffe is a deep learning framework developed by the Berkeley Vision and Learning Center (BVLC).There are 4 steps in training a CNN using Caffe:

Step 1 - Data preparation: In this step, we clean the images and store them in a format that can be used by Caffe. We will write a Python script that will handle both image pre-processing and storage.

Step 2 - Model definition: In this step, we choose a CNN architecture and we define its parameters in a configuration file with extension .prototxt.

Step 3 - Solver definition: The solver is responsible for model optimization. We define the solver parameters in a configuration file with extension .prototxt.

Step 4 - Model training: We train the model by executing one Caffe command from the terminal. After training the model, we will get the trained model in a file with extension .caffemodel.

After the training phase, we will use the .caffemodel trained model to make predictions of new unseen data. We will write a Python script to this.

Ontology construction

We construct user interest ontology by using social images database as input to CNN models for objects recognition to extract the database' objects that will be the concepts in the ontology. Protégé-OWL 4.3 is used to build the ontology, is a free, open-source platform that provides tools to construct domain models and knowledge-based applications with ontologies. For the object recognition, we used pre-trained CNN GoogleNet and VGG'19 architectures phase outputs as input to ontology. To create this user ontology, researchers start by identifying the travel interest categories through describing the consequent ontological classes, were divided into nine classes, Nature, Food, Architecture, Art, Holidays, Events, History, Celebrities, DIY & Crafts. Figure 3.5 and Figure 3.6 illustrate the ontology classes and sub classes, each class has many concepts. A class in ontology referred to as a category or concept related to the travel domain, each class subsumed by each other class (class hierarchy) and define the concept of super-class and sub-class obtained by CNN architectures, as the input of our ontology.

The end nodes in our ontology represent the classes (concepts) of ImageNet that we have obtained by using GoogleNet and VGG'19 CNN architectures on Sudanese and Tunisian Facebook images.

The development of ontology seems to be both an art and a deep understanding of engineering processes (De et al., 2009); (De et al., 2012).

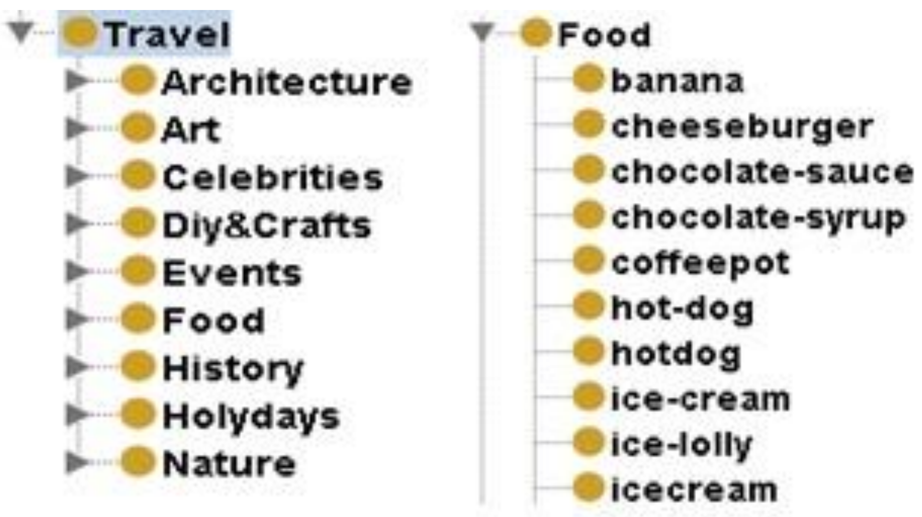

Figure 3.5(a) Nine Ontology Categories Using Owl (b) Examples of Sub Classes of Food Category

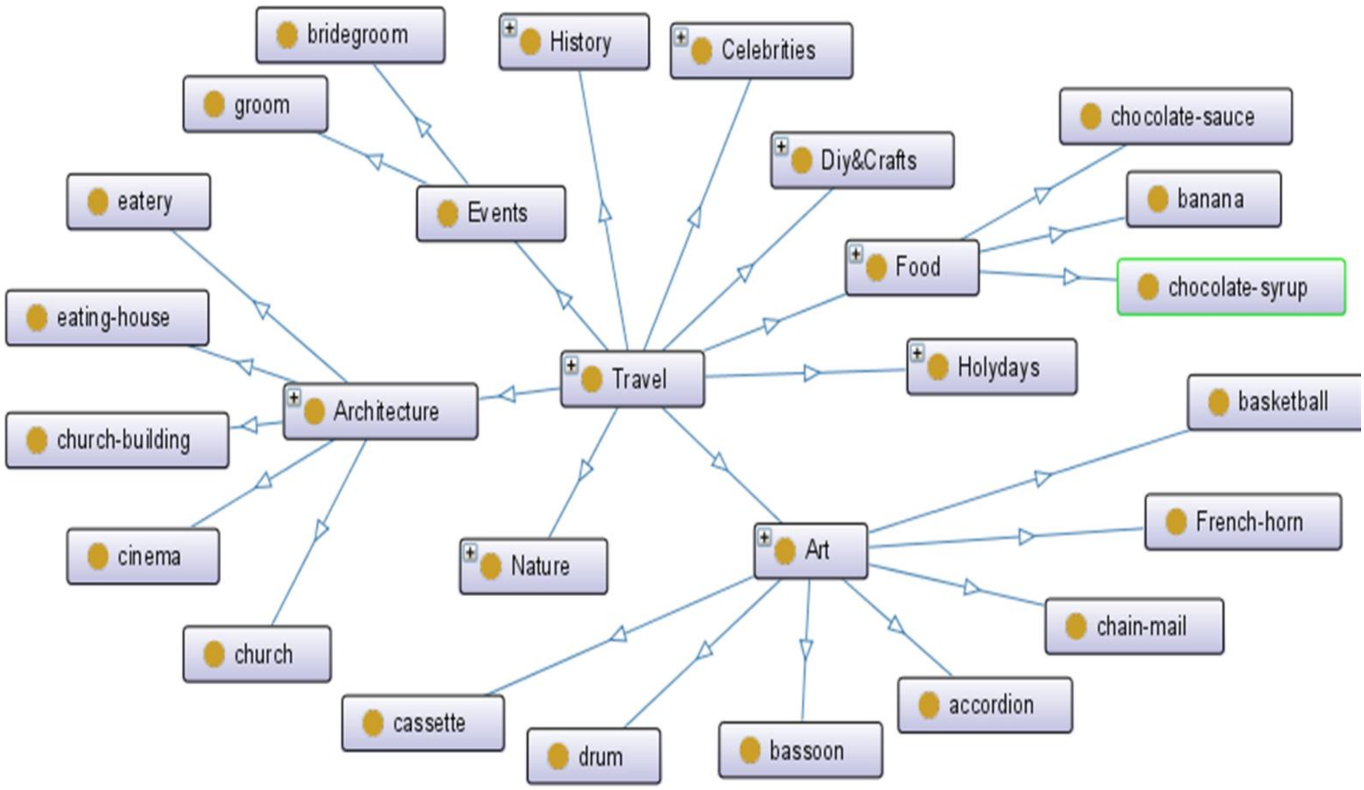

Figure 3.6 Ontology Using OWL API

The important or necessity of chose 9 interest categories is, this nine categories can represent the travel topic when the user images contains all this categories or contains a large part of it. And these categories are considered from the Facebook generic topics.

We use constructed ontology inference for travel user interest prediction, or to predict if the user is interested in the topic of travel or not? Based on his/ her shared visual data in there Facebook accounts. To assess our ontology, a novel database of shared photos was created in Tunisian and Sudanese Facebook accounts.

User interest ontology is constructed based on the images' objects extracted from the Sudanese and Tunisian Facebook database, besides, to apply a unified database as inputs to CNN models to identify objects to extract database objects that will be concepts in the ontology.

3.5.2 Deep Fuzzy Ontology Travel User Interest System (DFOTUIS)

Most proposed works and applications use the crisp ontology to discover the travel user interest and there are no fuzzy ontology systems or methods proposed to detect travel user interest.

One of the hottest research trends in this area is fuzzy ontology learning from social network images, which is considered to be an important activity to promote social network image analysis. Knowledge acquisition from images is a process that has already been considered part of the ontology learning process. The approach presented in this work it works not only with one user interest topic but also with multiple user interest topics.

By applying deep learning, using CNN designs, feedforward learning in CNN, CNN cognitive engineering, GoogleNet, and VGG'19 have been adopted. Exploring the interest of the travel user was carried out by the inference of fuzzy ontology which comprises some concepts of ImageNet databases.

A new deep fuzzy ontology framework is proposed that describes the discovery of travel user interests based on only Sudanese images on Facebook. This system is called (Deep Fuzzy Ontology Travel User Interest System (DFOTUIS)) Focused on using CNN architectures and FiRE fuzzy ontology.

Proposed architecture based on fuzzy ontology as illustrated in the next figure, copes with the uncertainty of detected objects obtained from the crisp ontology already developed in (Segalin et al., 2017). In fact, we compute for each image the membership of each detected concept.

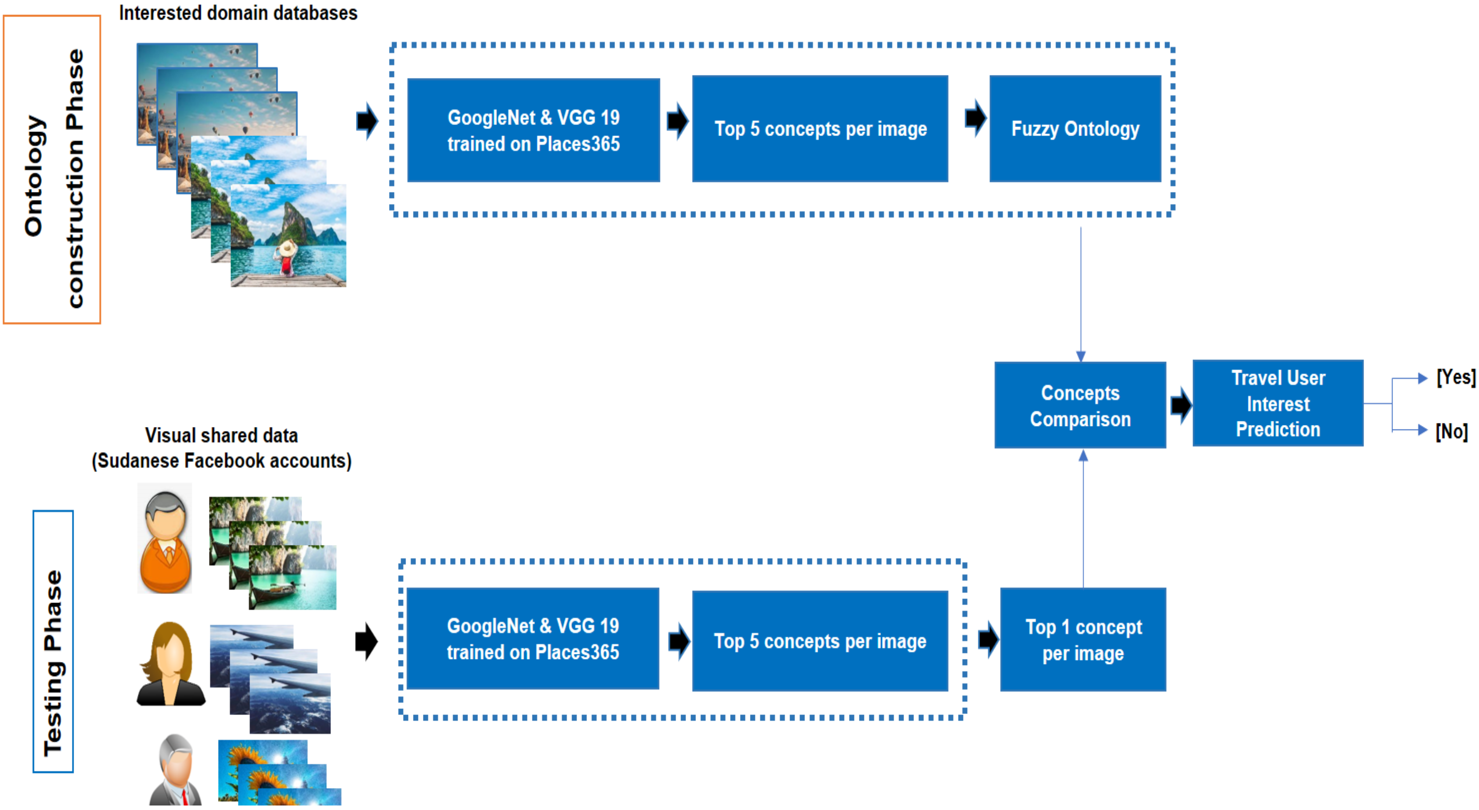

Figure 3.7 Deep Fuzzy Ontology Travel User Interest System (DFOTUIS)

first, we have constructed a visual social images database(Sudanese Facebook images) which consists of illustrations so that it detects the user travel interests, images Features analysis has been done using CNN architectures to give the top five concepts represent the image, and using FiRE fuzzy ontology to identify the relations between concepts, matching of concepts for images classification to nine classes or categories (Nature, Food, Architecture, Art, Holidays, Events, History, Celebrities, DIY & Crafts) under travel topic to construct the classes that are usually associated with our topic to check if, or if not, the user is interested in travel.

The Ontology building process is based on three sequential processes respectively known as conceptualization, discovery, and inference. Figure 3.8 shows the process of building a fuzzy ontology.

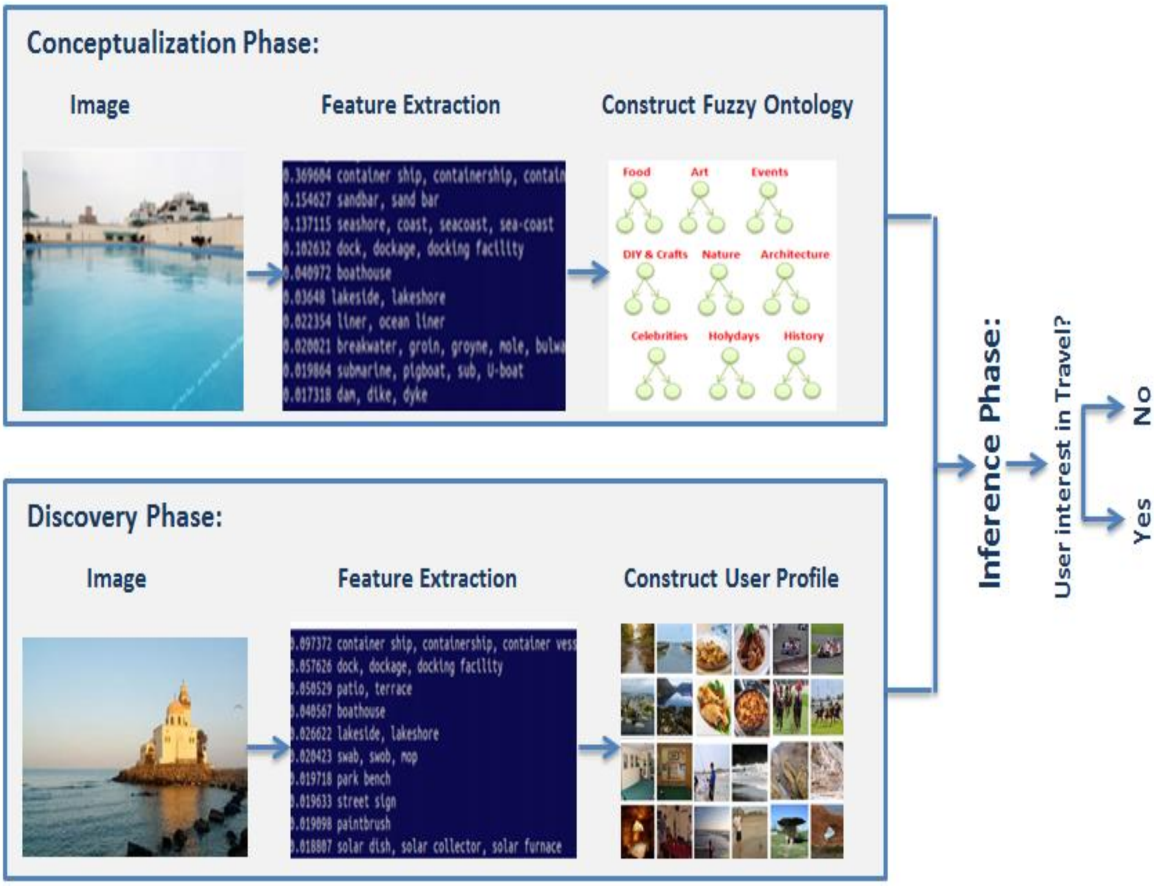

Figure 3.8 DFOTUIS for User Interest Travel Ontology

Conceptualization process for user interest's fuzzy ontology prediction system construction. At this process Pre-trained, CNN GoogleNet and VGG'19 architectures enable the automatic extraction of the top five concepts. CNN outputs are used as inputs to the current fuzzy ontology and have been split into nine classes, Nature, Food, Architecture, Art, Holidays, Events, History, Celebrities, DIY & Crafts. After that we found the relations between concepts to construct the classes that are usually associated with our topic. Discovery process, our approach based on CNN, GoogleNet and VGG'19 architectures directly detect travel users' interests from social images using the scene understanding concepts which do not call for any textual information. Inference process for user interest's prediction using visual object recognition architecture from visual shared data in user' Facebook accounts. (Murillo et al, 2012) used an approach that is more similar to ours. The authors use it to learn semantic relations from the documents of Spanish natural language related to the financial domain. We present in figure 3.9 some examples of concepts' membership functions (values).

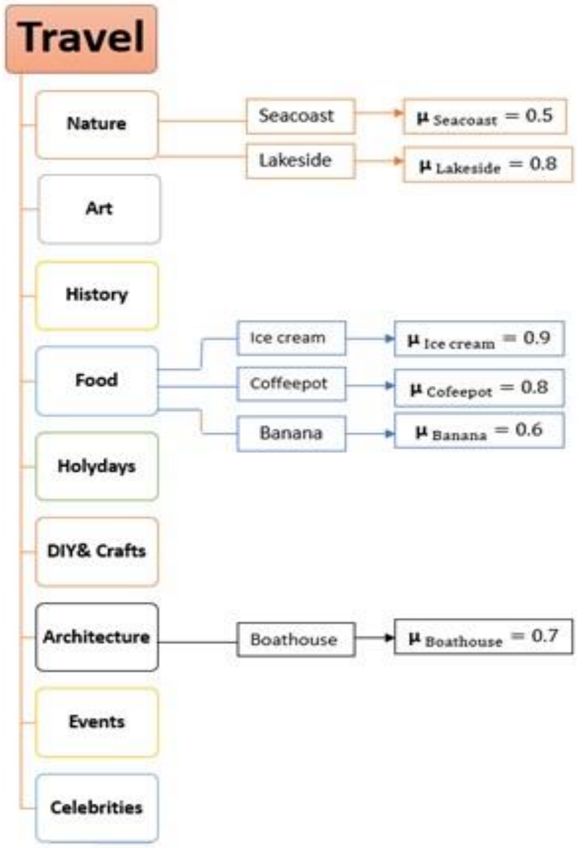

Figure 3.9 Fuzzy Ontology with the Membership Function

In this work, we used the FIRE API for fuzzy ontology representation. In particular, we deploy FIRE, with its annotation properties, for encoding fuzzy ontology representation. Next figure explain the fuzzy ontology with a membership and FIRE interface.

```
Axioms

Assertions:336
        tench instanceOf Nature >= 0.2
        Tinca-tinca instanceOf Nature >= 0.2
        frican-elephant instanceOf Nature >= 0.4
        Loxodonta-Africana instanceOf Nature >= 0.4
        volcano instanceOf Nature >= 0.8
        seashore instanceOf Nature >= 0.9
        coast instanceOf Nature >= 0.9
        seacoast instanceOf Nature >= 0.9
        sea-coast instanceOf Nature >= 0.9
        fountain instanceOf Nature >= 0.8
        lakeside instanceOf Nature >= 0.4
        lakeshore instanceOf Nature >= 0.4
        apiary instanceOf Nature >= 0.1
        bee-house instanceOf Nature >= 0.1
        ping-pong-ball instanceOf Nature >= 0.1
```

Figure 3.10 Design of Rules and Memberships for a Fuzzy Ontology Using FIRE

FiRE permits the users to build up a fuzzy knowledge base, based on the description logic Knowledge Representation System Specification (KRSS) which is expanded to cater for the fuzzy element. Furthermore, despite entailment and subsumption, it provides the user with enriched, by the fuzzy element, inference procedures. Fuzzy entailment queries ask whether an individual participates in a concept to a specific degree.

The travel Ontology is made by FIRE, the highest class is Travel as the zone for building the Travel Ontology and concepts named Nature, Food, Architecture, Art, Holydays, Events, History, DIY & Crafts and Celebrities are selected as the subclass.

Our aim is to build a deep fuzzy ontology travel user interest system (DFOTUIS) that can handle uncertainties in rules or in system parameters.

We define the basic metrics for the size of the travel users' interest ontology on various aspects. The size of our ontology is defined as follows:

– Size of Ontology= 2485

– Size of Ontology (topic = Food) = 425

– Size of Ontology (topic = Nature) = 630

– Size of Ontology (topic = Art) = 500

– Size of Ontology (topic = Holydays) = 148

– Size of Ontology (topic = Architecture) = 213

– Size of Ontology (topic = Celebrities) = 190

– Size of Ontology (topic = Events) = 68

– Size of Ontology (topic = DIY and Crafts) = 202

– Size of Ontology (topic = History) = 109

3.5.3 Intelligent Recommendation System for Travellers' Preferences (IRSTP)

To recommend the travel based on the user interest, this application runs as a web application and to develop this application, there are a few necessary procedures such as data collection, building dataset, and Deep Convolutional Neural Networks (CNN) architecture execution, GoogleNet for travel user interest discovery based on deep fuzzy ontology in order to create the user profile and using this user profile to find the recommended travel. The property of our model is that it can be used the user interest (profile) in our recommendation system. We developed a simple recommendation system that is based on user interest discovery using Deep Convolutional Neural Networks (CNN) architecture, fuzzy ontology and Java technologies. Figure 3.11 presents the framework of the suggested application based on three transformations.

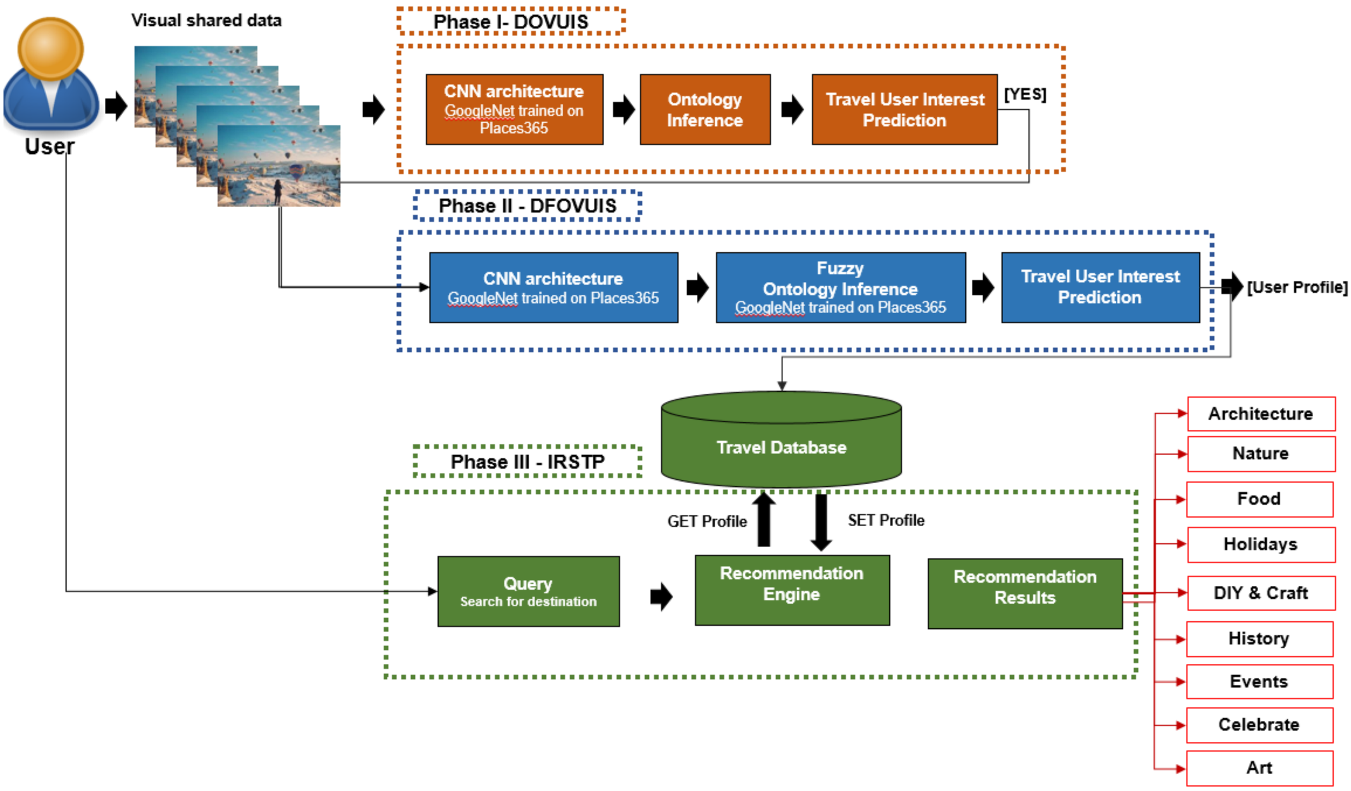

Figure 3.11 Architecture of the Proposed Intelligent Recommendation System for Travellers' Preferences (IRSTP)

This work studies the problem of recommending Sudanese travel places to users who participate in Facebook. There are more studies on recommender systems working with textual and visual data in social networks but there are very few approaches that exploit the user interests especially in Facebook and in Sudanese Facebook network. In this work, we proposed approach that create recommendations based on user's interest. To design our recommendation approach we study the concepts or categories that represent travel topic and detect the relation between these categories and concepts discovered in users images to specify if user interest in travel or not? In term of user profile. After that we build our recommendation system based on this user's interest.

Our application takes the user profile and based on his / her profile, we recommend the places, food, Nature, Events, Art and Architecture when the user sends a request.

Additionally, if the database contains reachable user's data on his/her interests or location, and if a user is new to the application, the user gives his / her request. (See appendix C).

The proposed Intelligent Recommendation System for Travellers' Preferences (IRSTP). The Use case diagram illustrated the relationship between actors and functions deployed on the IRSTP and the proposed system is illustrated over the presented class diagram given in figure 3.12.

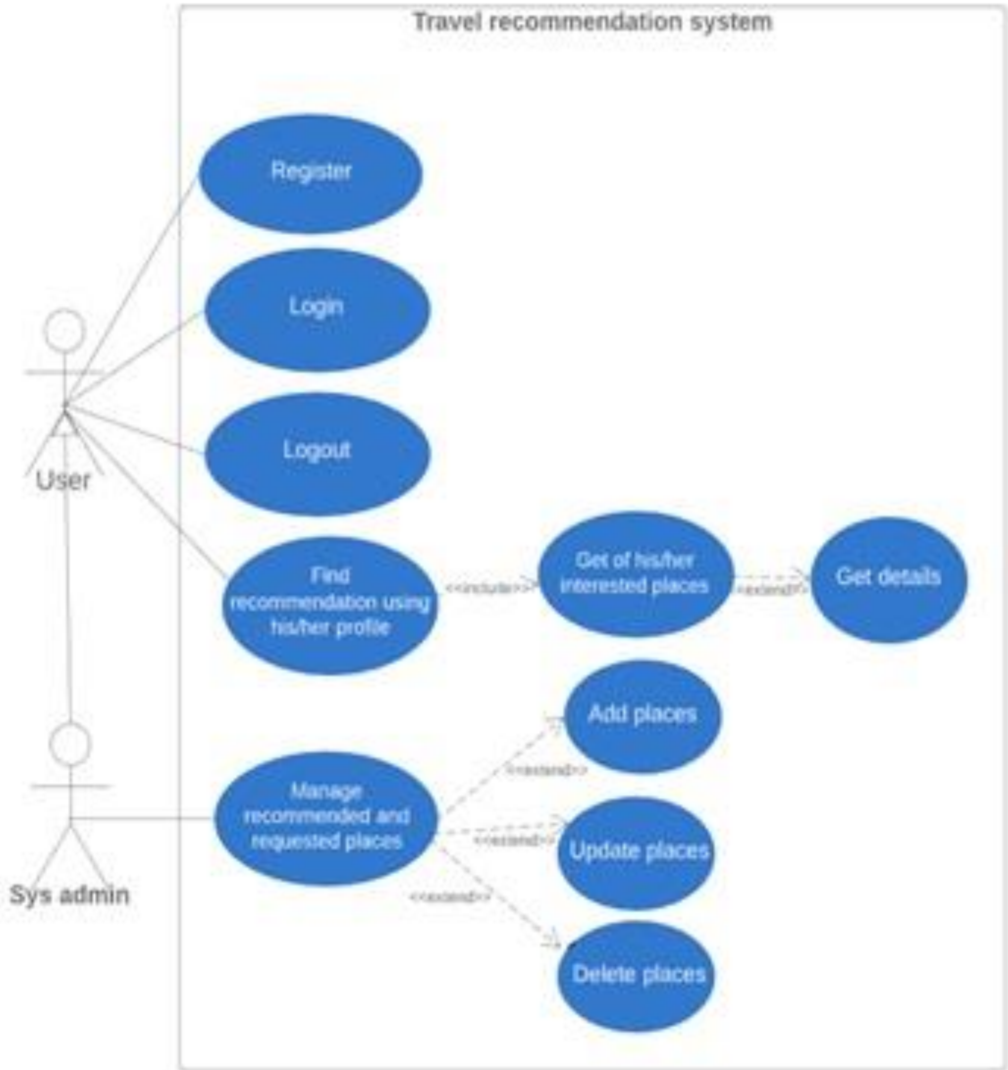

Figure 3.12 UML Diagrams of the Developed IRSTP Recommendation System Web Application

3.6 Data Collection and Analysis

3.6.1 Training Databases

In our work we adopt the ImageNet and Paces 365 databases. ImageNet is a popular dataset for detection and classification. This dataset contains millions of images for the task of detection and classification. Figure 3.13 shows samples of ImageNet dataset.

It's important novel tool for detecting the scene from images. Places 365 have 1,803,460 training images. The validation set has 50 images per class and the test set has 900 images per class. Note that the experiments in this work are reported on Places365. Places365 classifier is an algorithm trained using the deep learning framework Caffe, and it classifies images as a particular location, such as a castle, hotel room, nursery or even a landscape tag such as a glacier or hot spring. This algorithm is particularly useful in travel and real applications. Figure 3.14 shows some images from places365.

Figure 3.13 Some Images from ImageNet Dataset

Figure 3.14 Some Images from Places365, Contains Three Macro-classes: Indoor, Nature, and Urban

3.6.2 New Social Databases of Tunisian and Sudanese Facebook accounts

One of the challenges addressed in social network analysis is the concept of social data collection available on the social networks.

- In (DOTUIS) we construct two visual social images databases, this social data consists of images that users are posted and shared with friends in Facebook accounts, contain 80 Sudanese DB from Facebook accounts, 9 social images per user. We collect this data manually; we have contacted 80 users. Also, we construct Tunisian DB in our work from Facebook accounts that contains 80 users include 9 social images per user; the samples of the datasets are shown in the following figures.

Figure 3.15 Samples of Images from Sudanese Travel DB

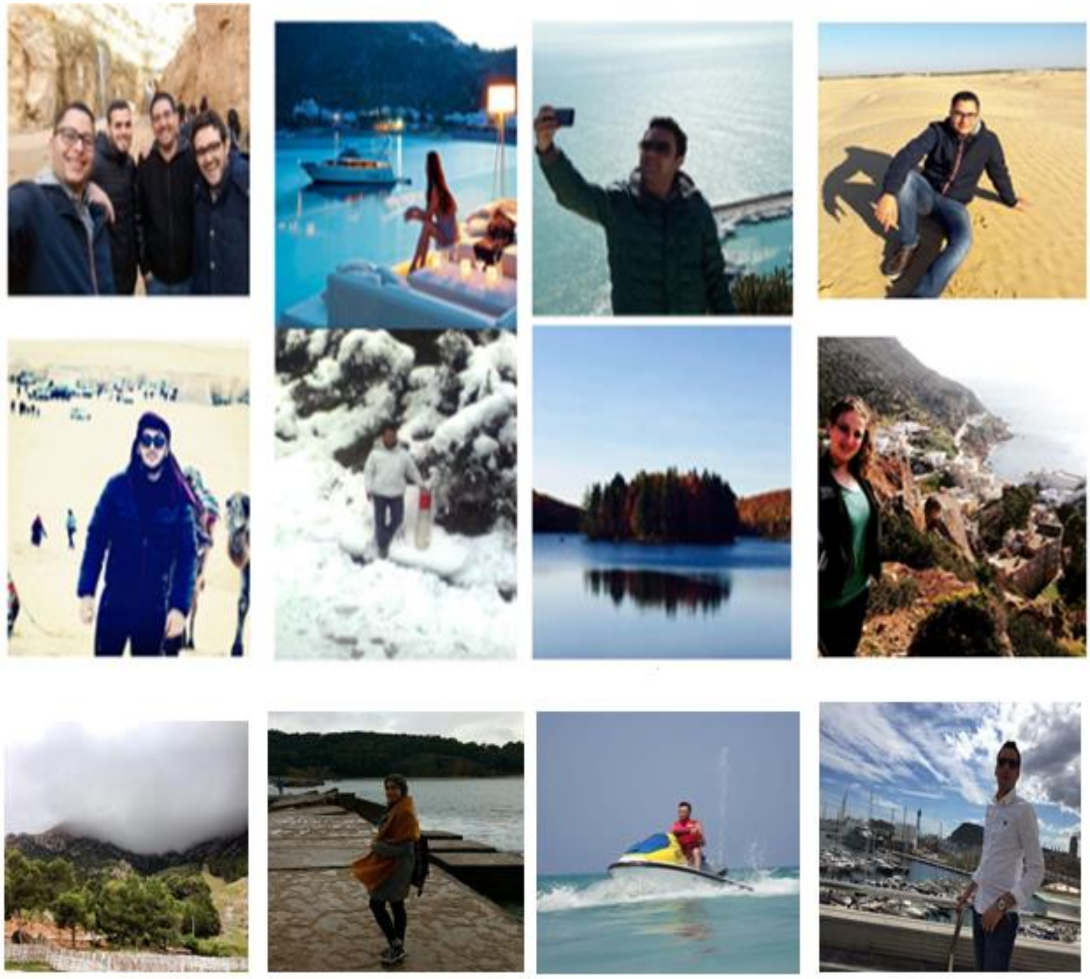

Figure 3.16 Samples of Images from Tunisian Travel DB

- In (DFOTUIS), our social database was increased to 120 Sudanese Facebook accounts, with 25 social images per user. Data collected manually; 120 users connected. Every image we have in our database has a resolution of 800*600, and many topics as mentioned in our database like Food, Clothes, Sport, etc. as is shown in Figure 3.17.

Figure 3.17 Sudanese Facebook Database

Table 3.2 shows how many images per class (Travel Interest Topics in Sudanese Facebook DB) and figure 3.18 shows Image samples from some topics of interest on Sudanese Facebook DB.

Table 3.2 Travel Interest Topics in Sudanese Facebook DB

Topic	Number of images
Food	425
Fashion	290
Nature	630
Sport	200
Art	500
Others	955

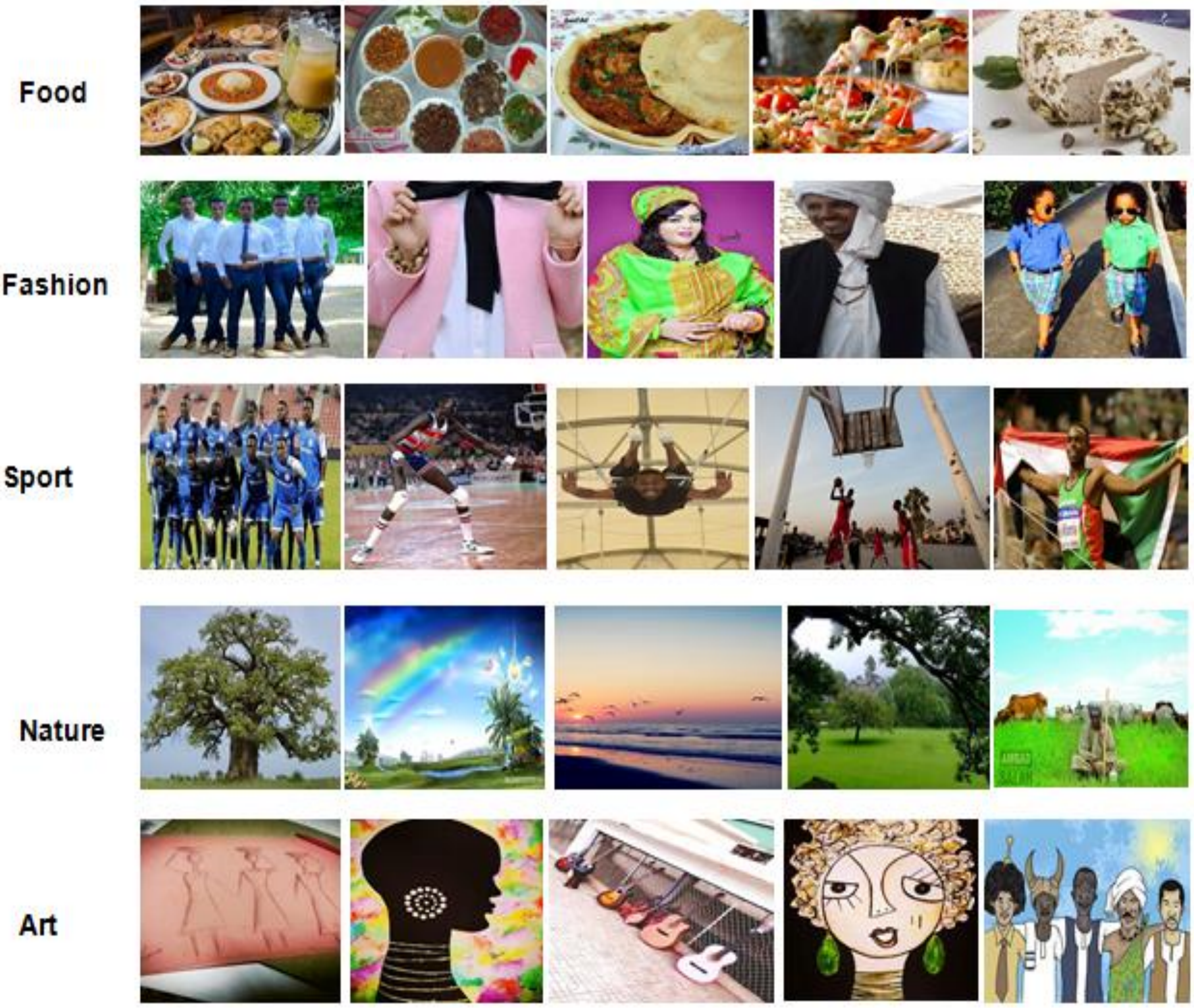

Figure 3.18 Image Samples from Some Topics of Interests on Sudanese DB

Samples of training information are gathered from Sudanese Facebook accounts. Another set of data that is used by the application is testing data in order to anticipate the user interest (profile). This data is regarded as the ultimate input for suggesting the desired travel places. The obtained data follow the format of .jpg. The First collected data is stored in the Training database, and the second collected data is stored in the testing database. Samples from the datasets for training and testing are shown in next Figures.

Figure 3.19 Samples of images from training set of Sudanese DB

Figure 3.20 Samples of images from testing set of Sudanese DB

3.7 Ethical Considerations

All data collected after users accepting to give their posted and shared images in their Facebook accounts. Moreover, the users were informed that he or she could retreat at any time. The data collected are confidential throughout the study and did not disclose or mixing with any other data. Finally, this project is in accordance with the guidelines of the Sudan University of Science and Technology.

CHAPTER FOUR RESULTS AND DISCUSSIONS

This chapter presents the experimental results and implementation based on the data collected and analyzed in the previous chapter.

There are three scenarios for extracting Facebook images to detect user interests and once obtained, used to construct a user profile for recommendations, One for train data and create ontology, second for test data and user interest prediction and third for user profile and recommendation system. All scenarios shown in the next Algorithms.

Algorithm 1 Create ontology

Input: 25 images per Facebook account (80 accounts for train).
Output: ontology representation.
1: Images Features analysis using CNN architectures.
2: Result: top five concepts for each image.
3: Select top 1 concept for each image.
4: Using FiRE fuzzy ontology to identify the relations between concepts to construct Travel ontology.
5: Classify images into nine categories.
6: Define level of categories with membership value.

Algorithm 2 User interest prediction

Input: 25 images per user (60 accounts for test).
Output: User Interest.
1: Images Features analysis using CNN architectures.
2: Result: top five concepts for each image.
3: Select top 1 concept for each image.
4: Comparison between top 1 and step 6 in Algorithm 1.
5: If all classified images or apart of them represent travel.
6: Return Yes (user interest in travel).
7: Else
8: Return No (user not interest in travel).
9: Create users profiles.

Algorithm 3 Recommender System

Input: User Interest categories from Algorithm 2 step 6.
Output: Recommender travel places.
1: Create Sudanese travel database (consist travel places and information about this places like locations, telephone numbers and time of services).
2: Create users database from users who interest in travel (user profiles (Algorithm 2 step 9)).
3: User login to the APP.
4: If user implies to users in test data (have a profile contains his/her interest categories) our system automatically generate recommender travel places based on his/her interests.
5: Else

6: Also our system recommender the user.
7: End

4.1 Experimental Results for DOTUIS

As the results achieved by the CNNs models trained on ImageNet and places365 to discover the user interest in travel is lead to a better performance and improving the places classification to discover the places and find is the user interest in travel or not. Other thing the results vary from model to other but all results very close to user preferences or interest in travel topic. Next figures explain the confusion matrixes.

Confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data. Confusion matrix is simple to understand.

Classification accuracy:

$$(TP + TN) / (TP + TN + FP + FN)$$

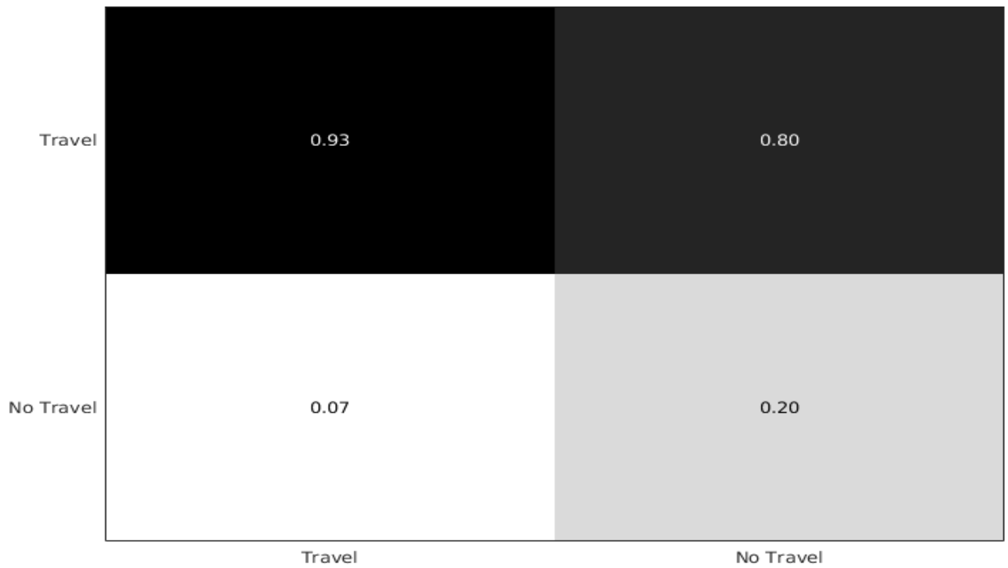

Figure 4.1 Confusion Matrix of Travel Interest classification Using GoogleNet Architecture on Sudanese DB.

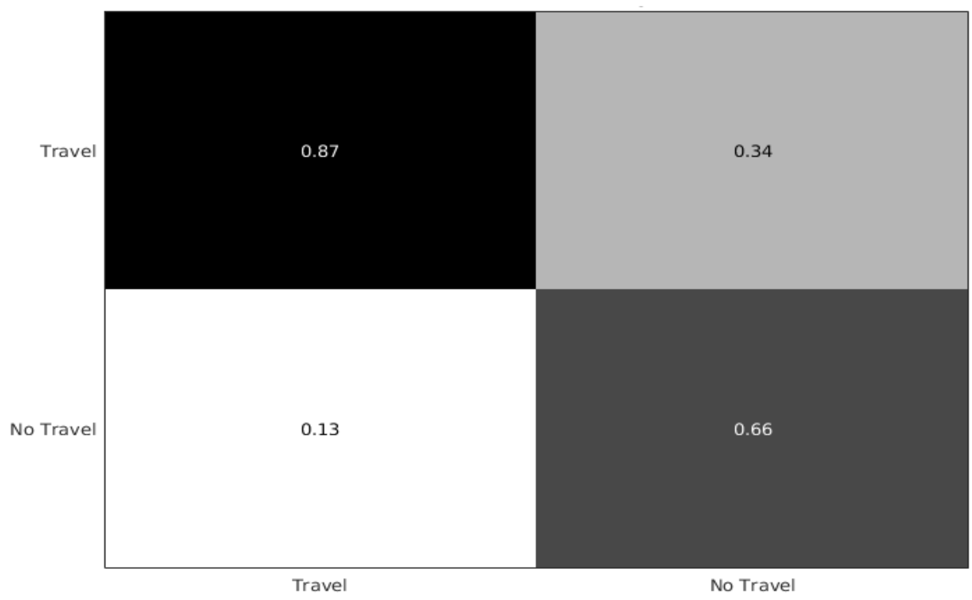

Figure 4.2 Confusion Matrix of Travel Interest classification Using VGG’19 Architecture on Sudanese DB.

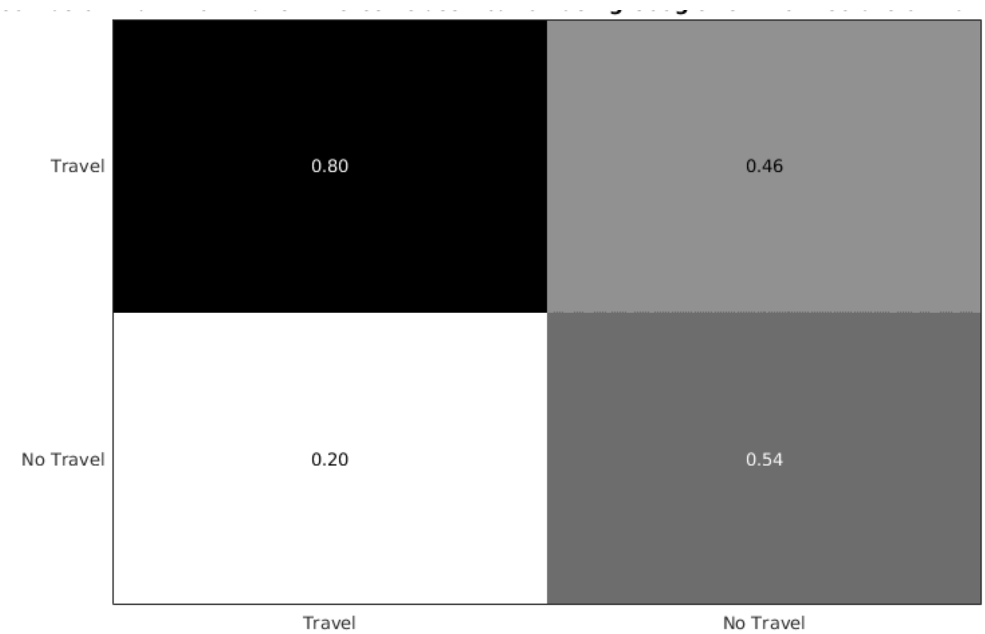

Figure 4.3 Confusion Matrix of Travel Interest classification Using GoogleNet Architecture on Tunisian DB.

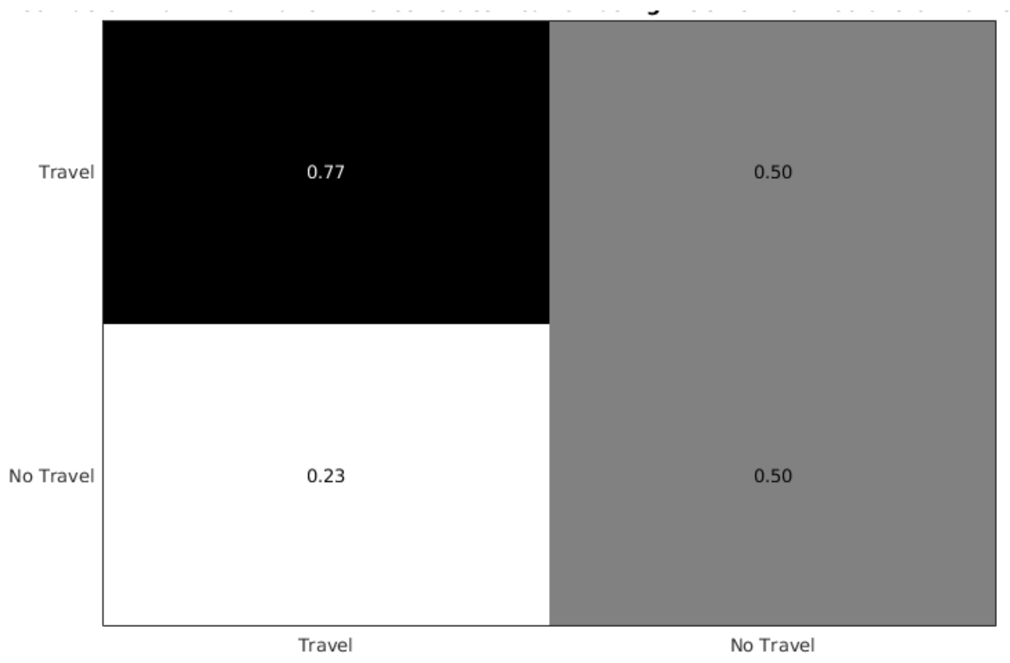

Figure 4.4 Confusion Matrix of Travel Interest classification Using VGG'19 Architecture on Tunisian DB.

Table 4.1 Accuracy of Travel Interest Classification of our approaches on Sudanese and Tunisian user’s Facebook Account

	GoogleNet	**VGG’19**
Sudanese DB	93%	87%
Tunisian DB	80%	77%

As mentioned in the previous results (TABLE 4.1), We achieve classification rates of 93% and 87% using respectively GoogleNet and VGG’19 CNN architectures on Sudanese Facebook database and classification rates of 80% and 77% using respectively GoogleNet and VGG’19 CNN architectures on Tunisian Facebook database, our approaches based on CNN, GoogleNet and VGG’19 architectures can facilitate the interest of travel topic make it easy to discover is the user interest in travel or not, other thing the GoogleNet architecture leading to a better performance and improving the classification accuracy than VGG’19.

4.2 Experimental Results for DFOTUIS

In this experiment we increase the number of Sudanese Facebook accounts to 120 user accounts, 25 images per account, 60 Sudanese Facebook accounts for training and 60 Sudanese Facebook accounts for testing. These accounts have been manually collected, obtaining a total amount of concepts or classes using the CNN models trained on ImageNet to build a fuzzy ontology-based decision system for travel user interest prediction. The results lead to better performance. Another key feature of our approach is that its results vary from model to other but all results very close to user interest in travel. Figures 4.5 and 4.6, illustrate the confusion matrixes obtained when we achieve our method on only Sudanese Facebook accounts database.

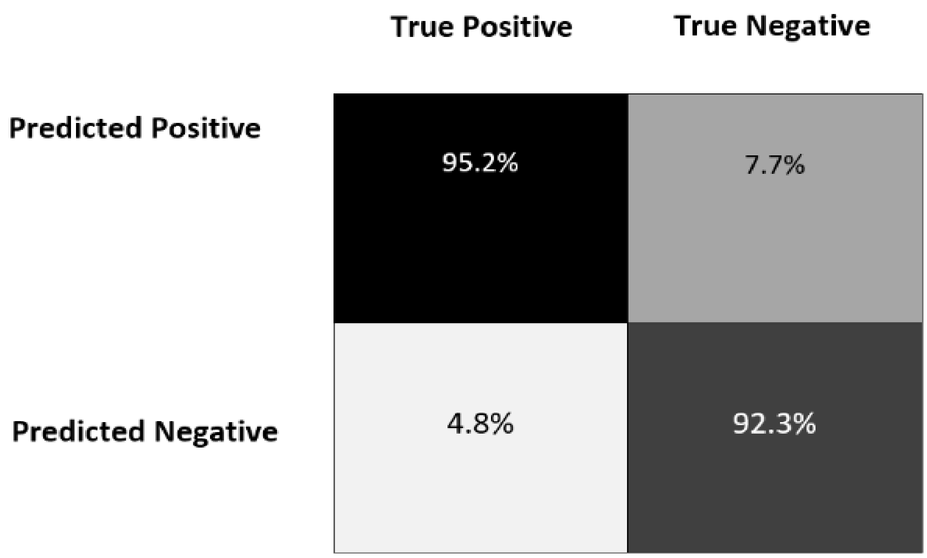

Figure 4.5 Confusion Matrix for Travel Interests Classification using GoogleNet Architecture on Sudanese Facebook DB

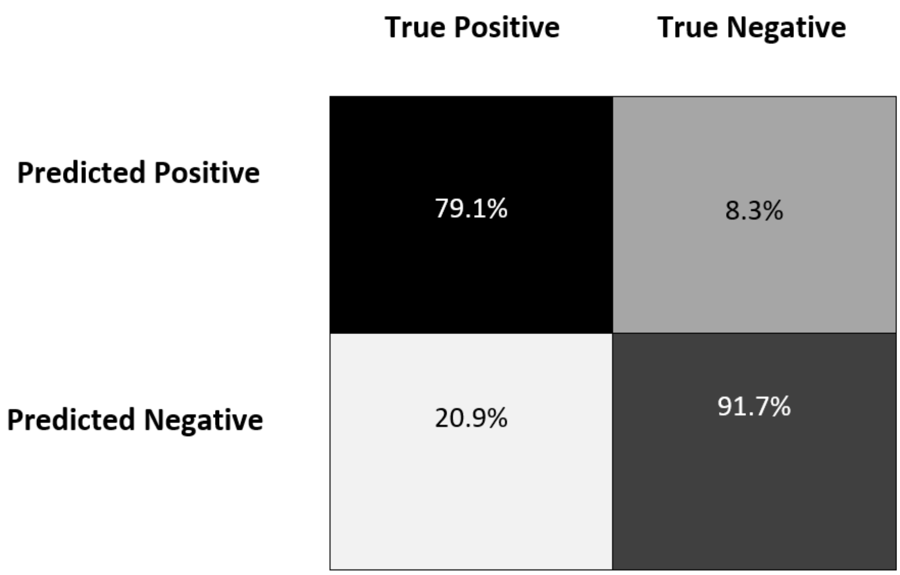

Figure 4.6 Confusion Matrix for Travel Interests Classification using VGG'19 Architecture on Sudanese Facebook DB

Evaluation metrics adopted within DL tasks play a crucial role in achieving the optimized classifier. They are utilized within a usual data classification procedure through two main stages: training and testing. It is utilized to optimize the classification algorithm during the training stage. This means that the evaluation metric is utilized to discriminate and select the optimized solution, e.g., as a discriminator, which can generate an extra-accurate forecast of upcoming evaluations related to a specific classifier. For the time being, the evaluation metric is utilized to measure the efficiency of the created classifier, e.g. as an evaluator, within the model testing stage using hidden data. As given in Eq. 20, TN and TP are defined as the number of negative and positive instances, respectively, which are successfully classified. In addition, FN and FP are defined as the number of misclassified positive and negative instances respectively (Alzubaidi et al., 2021). Next, some of the most well-known evaluation metrics are used below:

$$\text{Accuracy (ACC)} = TP + TN/(TP + TN + FN + FP) \quad (1)$$

$$\text{Specificity (SP)} = TN/(TN + FP) \quad (2)$$

$$\text{Precision (PRE)} = TP/(TP + FP) \quad (3)$$

$$\text{False positive rate (FPR)} = FP/(TN + FP) \quad (4)$$

$$\text{Error Rate (ERR)} = FP + FN/(TP + TN + FN + FP) \quad (5)$$

To evaluate our framework performance, we apply five evaluation measures criteria. Table 4.2 provides measures of calculated values that can be obtained from the confusion matrix applied to evaluate the performance of the specified approach. Calculated values for these metrics demonstrate that GoogleNet architecture may generate better performance and improvement compared to VGG'19. Table 4.3 shows the accuracy of the travel interest classification for our approach to the Sudanese user account on Facebook using ontology and table 4.4 shows the accuracy of the travel interest classification of our approach to the Sudanese user account on Facebook using fuzzy ontology.

Table 4.2 The Accuracy Assessment Measures the Values from the Obtained Confusion Matrix

Sudanese DB	**DFOTUIS(GoogleNet)**	**DFOTUIS(VGG'19)**
Accuracy (ACC)	.93	.87
Specificity (SP)	.97	.86
Precision (PRE)	.95	.80
False positive rate (FPR)	.03	.14
Error Rate (ERR)	.06	.13

Table 4.3 Accuracy Classify Travel Interests of our Approach on a Sudanese Facebook DB Using Ontology

	DOTUIS(GoogleNet)	**DOTUIS(VGG'19)**
Sudanese DB	.82	.79

Table 4.4 Accuracy Classify Travel Interests of our Approach on a Sudanese Facebook DB Using Fuzzy Ontology

	DFOTUIS(GoogleNet)	**DFOTUIS(VGG'19)**
Sudanese DB	.93	.87

As previously stated in the results section in(Table 4.3), A classification rates of 82% has been achieved and 79% users correspondingly GoogleNet and VGG'19 CNN architectures on Sudanese Facebook DB using ontology and in (Table 4.4) classification rates of 93% and 87% using respectively GoogleNet and VGG'19 CNN architectures on Sudanese Facebook DB using fuzzy ontology, the travel user interest discovery is a challenging exercise then our approaches can facilitate and pave the way for us to find out whether, or not, the user is interested in traveling.

The GoogleNet architecture using a fuzzy ontology could result in better function than using ontology and improving the classification accuracy than VGG'19.

4.3 Discussion

In this section of the discussion, we will try to discuss the performance of DFOTUIS based on the content of the images and give some examples of misclassification and true classification. Next Figures illustrate random examples of true and false results that our system classified.

We examine our proposed system by illustrating the travel users' interest's focused on nine categories according to the number of shared and posted images by them on their Facebook accounts. From table 4.4, we found that DFOTUIS is the most for users' interest prediction with high accuracy in the travel user interests.

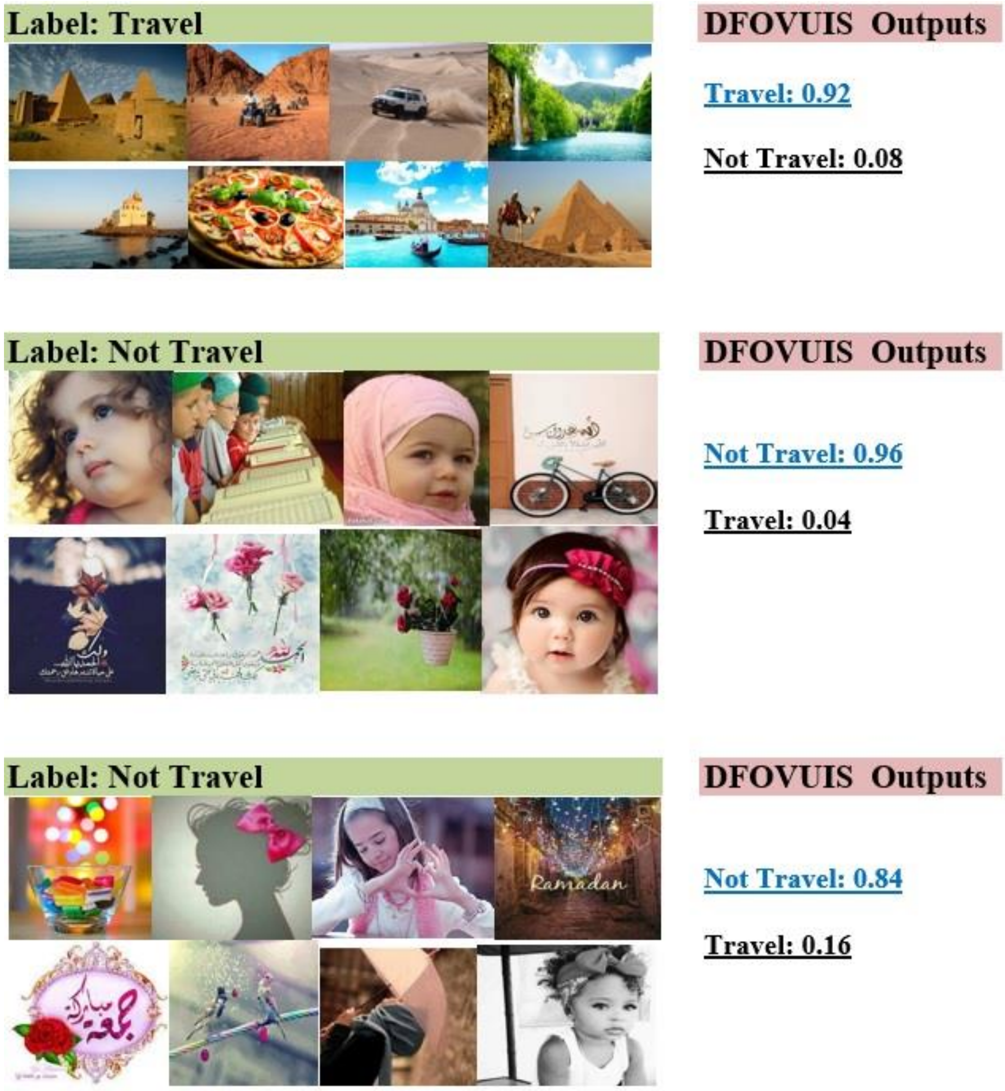

Figure 4.7 Random Examples of True Classifications

Figure 4.8 Random Examples of False Classifications

The reason for misclassification is, the users which have shared or posted images processed by computer programs are more likely to change the output class to any other class.

Another reason some concepts appear only in the testing and not existed in the training set. For example the six image of the first user in figure 4.8 has sunglasses concept and this is wrong classification also there are some image has wrong classification.

4.4 Experimental Results for IRSTP

We have previously indicated that the experiment was carried out in order to find out users' interest in travelling. In this experiment, we focused on 140 Sudanese Facebook accounts, 80 Facebook users for training, contained 25 images per each user, 60 Facebook users for the test, each user contained 25 images. In order to assess the performance of our framework, we adopt accuracy assessment measure. Figure 4.9 show the confusion matrix that we obtained by applying our approach on the database of the Sudanese Facebook DB.

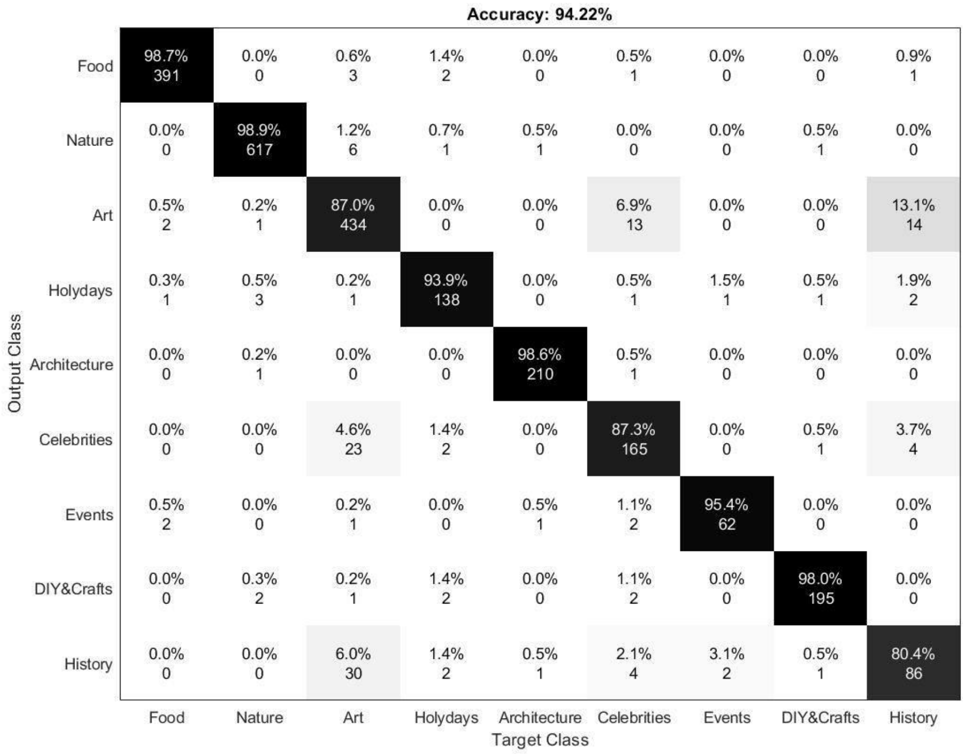

Figure 4.9 Confusion Matrix for Travel Interest Categories Classification using our system on Sudanese Facebook DB

Table 4.5 Precision of Traveler Interest Sorting out of the Study's Application on Sudanese Facebook DB

	DFOTUIS(GoogleNet)
Sudanese DB	94.22%

Table 4.5 classification rates are of 94.22% applied to Facebook's Sudanese DB. The detection of travel users' interest is a tough task; thus, our methods can make it easier and enables us to discover whether the users are interested in travelling or not. Better function can be gained due to our approach using fuzzy ontology than using crisp ontology and improving the accuracy of categorization than VGG'19. Random of correct and false results examples that are classified by our system shown in Figure 4.10 and Figure 4.11.

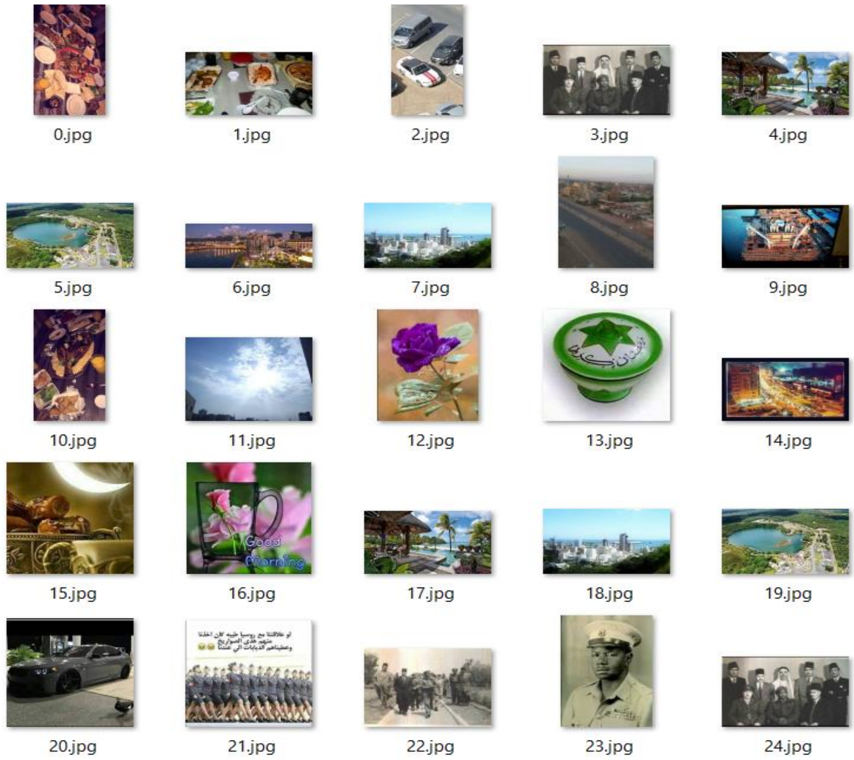

Figure 4.10 Examples of Correct Classification and Labeling

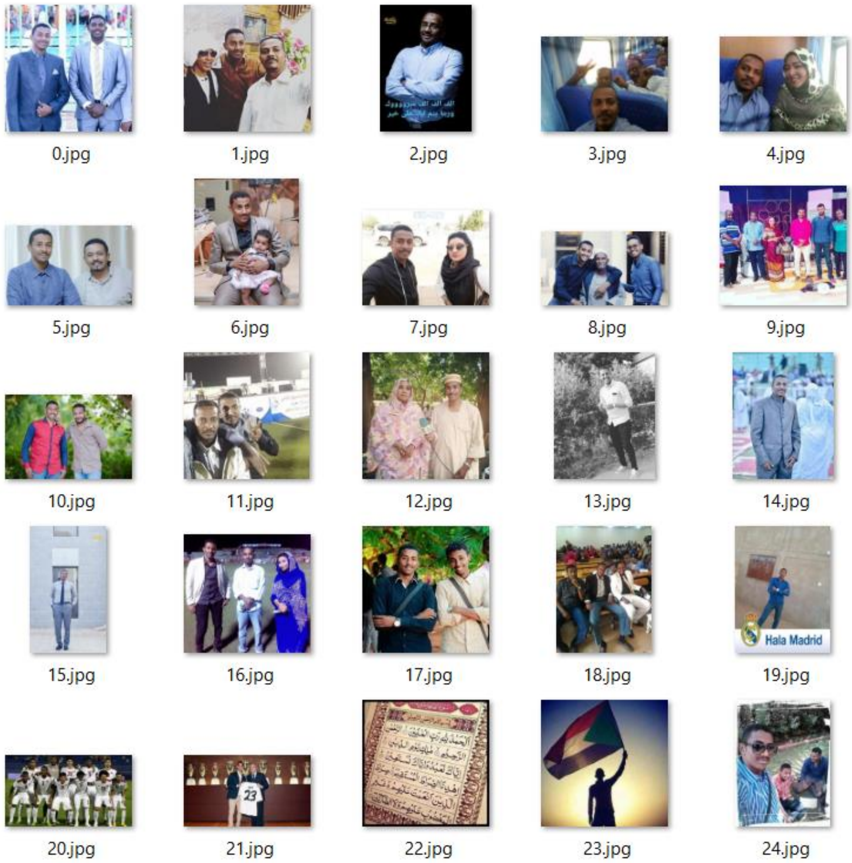

Figure 4.11 Examples of Disagreement

Table 4.6 represents the travel categories interests classified by our approach DFOTUIS CNN model and explain the prediction of the travel user's interests. We have passed 60 Sudanese Facebook social images (25 images per user) as a test of population sampling data as input to the CNN algorithm. As illustrated in the table, our approach DFOTUIS using GoogleNet CNN algorithm and using fuzzy ontology classified or predicted if the user interest in travel or not based on the travel concepts, here we have nine travel concepts (Nature, Food, Architecture, Art, Holydays, Events, History, DIY and Crafts and Celebrities). The travel interest is taken with the values yes or no. The colour green means that the model or algorithm is anticipated accurately through the algorithm (that means user is interested in travel) whereas the red colour says that predicted wrongly by the model or algorithm (means user is not interested in travel). For example, user 11 is investigated as a sample case to the CNN algorithm, our approach predicted Art, food and Architecture, which is correct because that categories represent a travel concept in our DFOTUIS.

Table 4.6 Results Predicted by the DFOTUIS

Users	**DFOTUIS(GoogleNet)**	**Travel User Interest?**
User 1	Nature & Architecture	Yes
User 2	Art & Nature	Yes
Users 3 to 9	--------	No
User10	Art	Yes
User 11	Art & Food & Architecture	Yes
User 12	Nature & Architecture & DIY & Crafts& Food	Yes
Users 13 to 17	--------	No
User 18	Art & Nature & Architecture & Holydays	Yes
Users 19 to 24	-------------	No
User 25	Food &Nature & Architecture & DIY & Crafts	Yes
User 26	-------------	No
User 27	Food &Nature	Yes
Users 28,29	-------------	No
User 30	Art & Nature	Yes
User 31	Art & DIY & Crafts	Yes
Users 32 to 36	--------------	No
User 37	Food &Nature& Art& Holydays	Yes
User 38	---------------	No
User 39	Art & History	Yes
Users 40 to 60	---------------	No

Figure 4.12 shows the common travel interest categories when we apply our DFOTUIS on Sudanese social images (Facebook) and Figure 4.13 show Example of users' profiles.

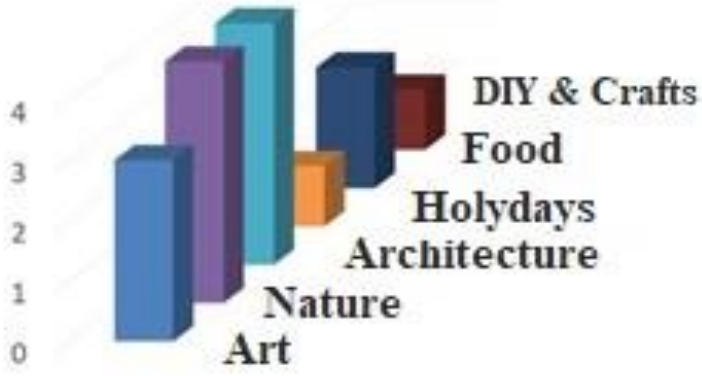

Figure 4.12 Common Travel Interests Categories in Sudanese Facebook DB

User 1 Nature & Architecture (Esra Mohamed, Wad Medni)
User 2 art & Nature (Omer Abdelraheem , Kassala)
User 10 Art (Yaser Ali, Khartoum)
User 11 Art & food & Architecture (Ali Ahmed, Khartoum)
User 12 Nature & Architecture & DIY & Crafts (Mona Adel, Khartoum)
User 18 Art & Nature & Architecture & Holydays (Alaa Bdereldeen, Khartoum)
User 25 food & Nature & Architecture & DIY & Crafts (Mohamed Elbager, Khartoum)
User 27 food & Nature (TagEldeen Fares, Khartoum)
user 30 Art & Nature & DIY & Crafts (Hala Omer,Khartoum)
user 31 Art & DIY & Crafts (Gaida Taher, Khartoum)
user 37 food & Nature & Art & Holydays (Tahani Ahmed, Khartoum)
user 39 Art & History (Daffalah Alhahi, Wad Medni)

Figure 4.13 Example of users' profiles

CHAPTER FIVE CONCLUSION

5.1 Introduction

Understanding user’s behaviour to provide an efficient knowledge about their preferences in a specific topic like Travel, has become a very required by several recommendation systems.

To do this, we have proposed a Travel Interest Classification system based on CNN architectures for visual object recognition from images shared in Facebook with a Fuzzy Ontology Prediction System constructed by two well-known database ImageNet and Places365. The proposed system can be extended for other user interest topics like sport, food, fashion, etc.

We running our approach using Sudanese Facebook accounts database (population of 140 accounts). Moreover, researchers will attempt to use their suggested user profiling to build a recommendation system, to recommend the travel, when the user has to be aware of the travel places, eating houses, nature, events, art, etc.

The results showed that the CNN architectures achieve a high performance of travel prediction when we know the user’s interest, this point provides our application better quality to response.

To assess our ontology, we use accuracy as measurement, and it gives us a better performance. And to evaluate our recommendation system, the system was presented to a group of people including Facebook users the feedback it’s very positive.

5.2 Important Results

In this study, the researcher aimed to discover the travel user’s interests through the huge number of social images shared and posted in Facebook accounts. We running our approach using Sudanese Facebook database.

The researcher proposed and implemented a new system that has consists of two components: a fuzzy ontology prediction system and travel recommendation app.

Through Fuzzy ontology prediction system, the researcher discovery travel users interest (if user interest in travel or not?) to create users’ profiles, whilst the travel recommendation app component aimed to use their interested user profiling to build a simple recommendation system, to recommend the travel, when the user has to be aware of the travel places, eating houses, nature, events, art, etc.

Based on the results of showing that our system achieves a high performance of travel prediction when we know the user's interest, this point provides our application better quality to response, the findings of this study indicate that our system can be very useful for a recommendation system of travel like trip advisor.

5.3 Recommendations and Future Work

- Dealing with a more inclusive database of social images, with larger training, data may help improve recognition performance especially in people interesting.
- Expand the research to be further improved, giving more accurate results that cater for other different Sudanese interests such as sports, shopping, fashion or culture, … etc.
- Concerns, the system will be extended to real time travel recommendation system.
- Extending the implementation of app component to support Android.

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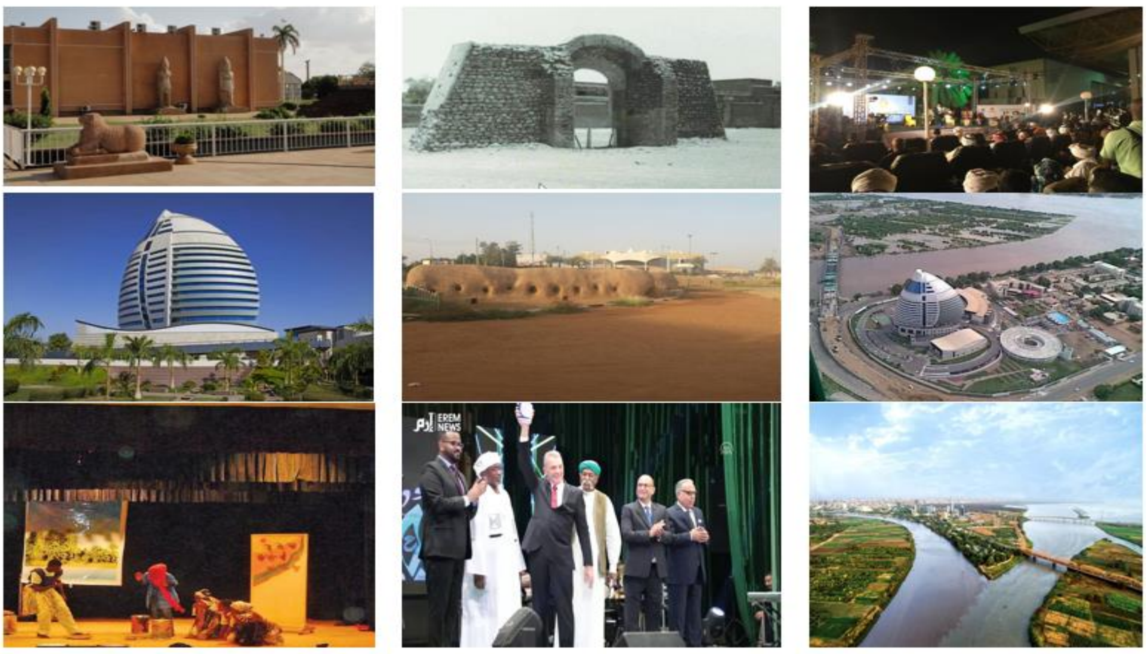
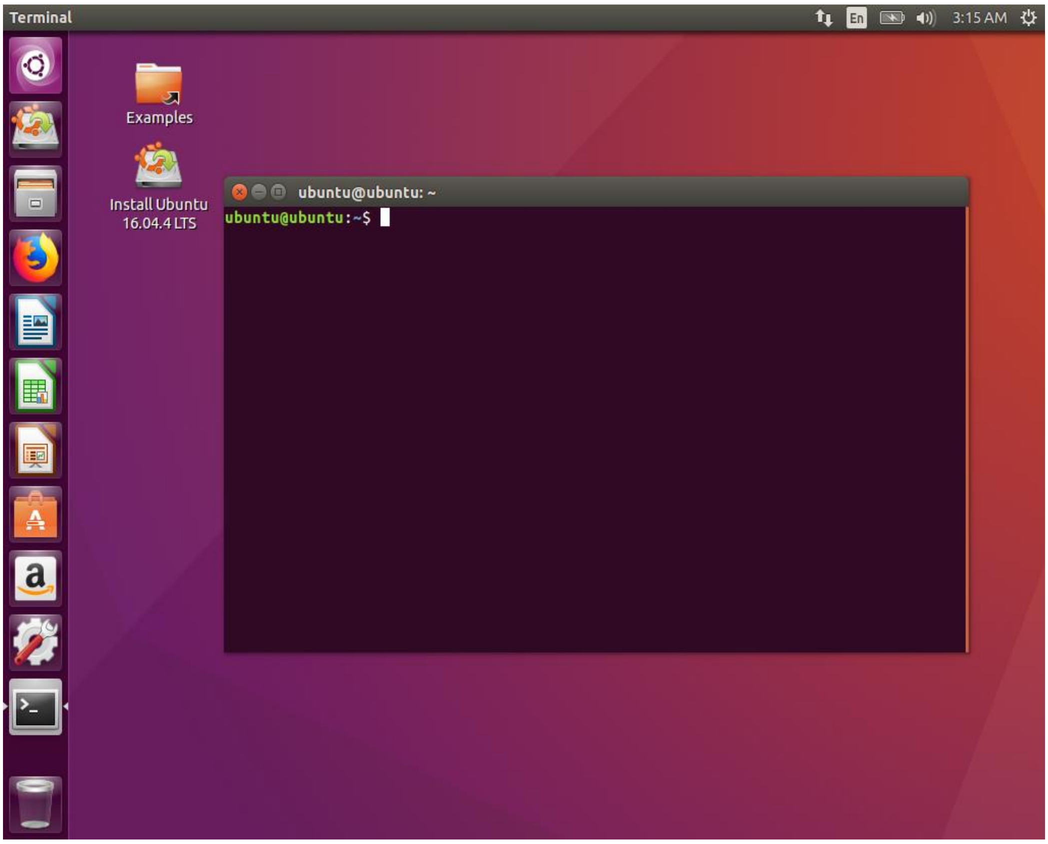
APPENDIX A

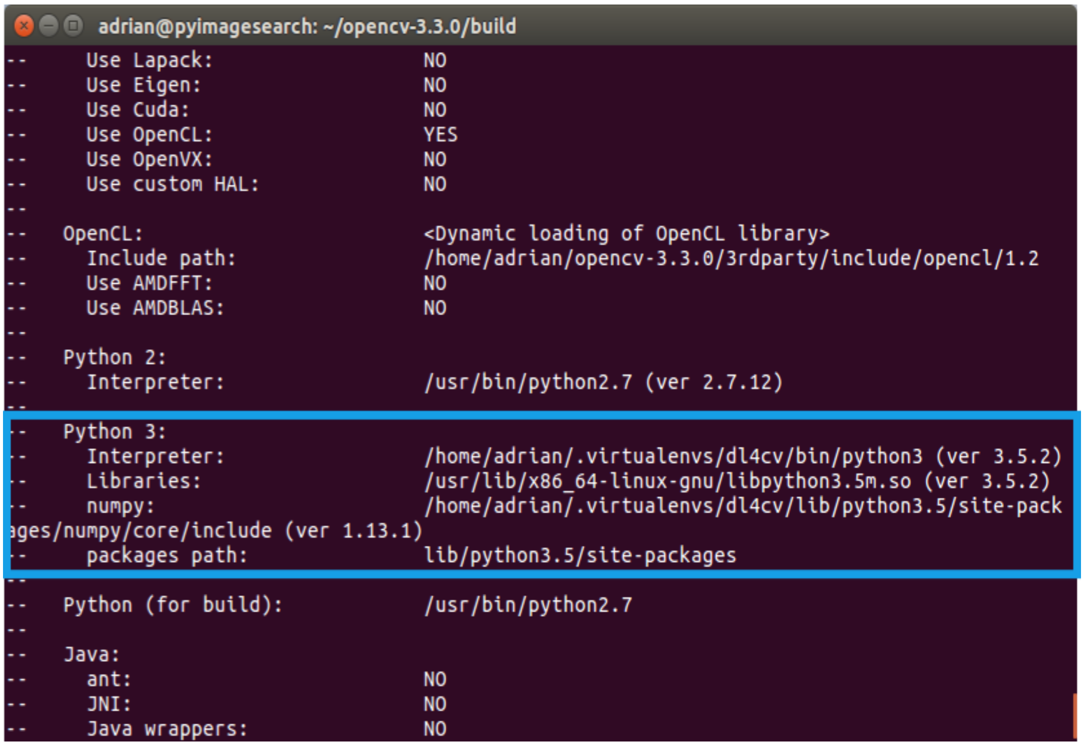
This appendix contains some photos used in TRSTP



APPENDIX B

This appendix contains caffe configuration





```
adrian@pyimagesearch: ~/opencv-3.3.0/build
--     Use Lapack:                  NO
--     Use Eigen:                   NO
--     Use Cuda:                    NO
--     Use OpenCL:                  YES
--     Use OpenVX:                  NO
--     Use custom HAL:              NO
--
--   OpenCL:                        <Dynamic loading of OpenCL library>
--     Include path:                /home/adrian/opencv-3.3.0/3rdparty/include/opencl/1.2
--     Use AMDFFT:                  NO
--     Use AMDBLAS:                 NO
--
--   Python 2:
--     Interpreter:                 /usr/bin/python2.7 (ver 2.7.12)
--
--   Python 3:
--     Interpreter:                 /home/adrian/.virtualenvs/dl4cv/bin/python3 (ver 3.5.2)
--     Libraries:                   /usr/lib/x86_64-linux-gnu/libpython3.5m.so (ver 3.5.2)
--     numpy:                       /home/adrian/.virtualenvs/dl4cv/lib/python3.5/site-pack
ages/numpy/core/include (ver 1.13.1)
--     packages path:               lib/python3.5/site-packages
--
--   Python (for build):            /usr/bin/python2.7
--
--   Java:
--     ant:                         NO
--     JNI:                         NO
--     Java wrappers:               NO
```

APPENDIX C

An App for Recommendation System (TRSTP)

Searching online for travel destinations, restaurants and cafes, natural zones, different events or art gallery could waste a lot of time. This process does not provide relevant results when the user in specific location. If we are aware of the user's interests or preferences, the user has to be supplied by the nearby and preferred locations of holiday destinations. Recently, analyzing user's interests or preferences to identify their favourite travel spots has stood out, especially if we are to deal with deployment of traveller's recommendation systems

The last step is building simple the recommendation system derived from the profile of the user's that had been predicted by DFOTUIS.

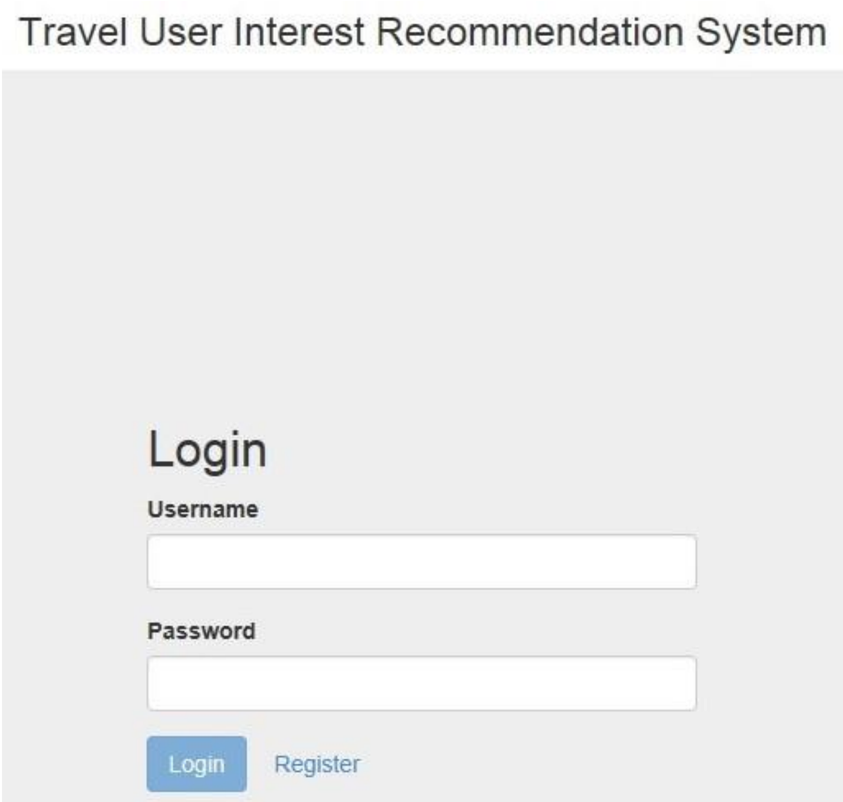
Travel Recommendation System is a web Application for finding user response based on user request and profile provided by the deep learning classification algorithm. Convolution neural networks model, especially GoogleNet helps us achieve a maximum precision compared to other models. Hence, this application is handy, even for those who are searching about travel in some cities in Sudan (here we achieved two cities, wad Medani and Khartoum) and they are not aware of the places of travel.

Travel Recommendation System makes the advantage of a couple of datasets. Firstly, Travel dataset and secondly the user interest dataset. The Travel dataset is composed from travel places, eating houses, nature, events and art, and some attributes such as travel places name, address, phone numbers, services time and some photos and logos for these places. Those qualities are thought to be the necessary fields for suggesting the interested places. The user interest dataset consists of what user interested based on user profiling. This user profiling determines how our recommendation system response to user request. If the user implies to users that take as the sample in our work, then we knew his/her interests otherwise our recommendation system gives the user a result. Trial findings that emerged from the suggested system indicate that the present method is able to achieve a function of a high standard. From the experimental data (Sudanese Facebook DB), our recommendation system is very useful as advisor system of travel interest.

Travel Places Examples

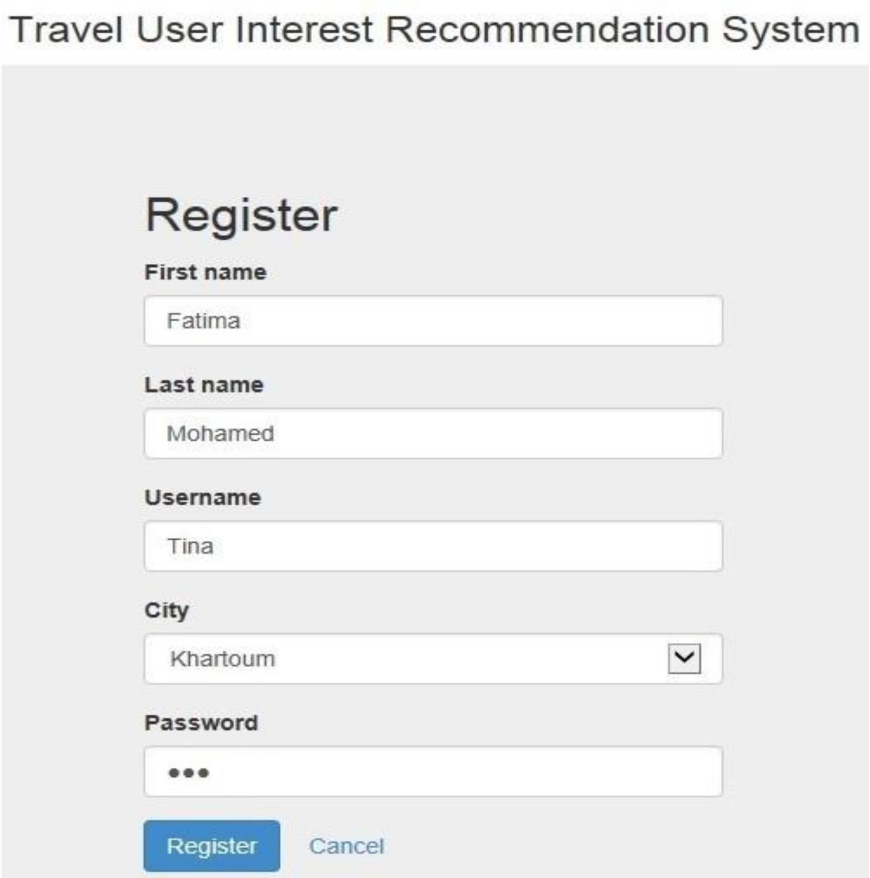
The traveller could interact with user recommendation system through a travel Recommendation website Application. The Recommender system is handy to the user in terms of providing them with their interested request.

The following illustration presents the interfaces of the study system. The system's execution begins with login screen with two options are provided to users: Login and Register, as shown in the next figure.

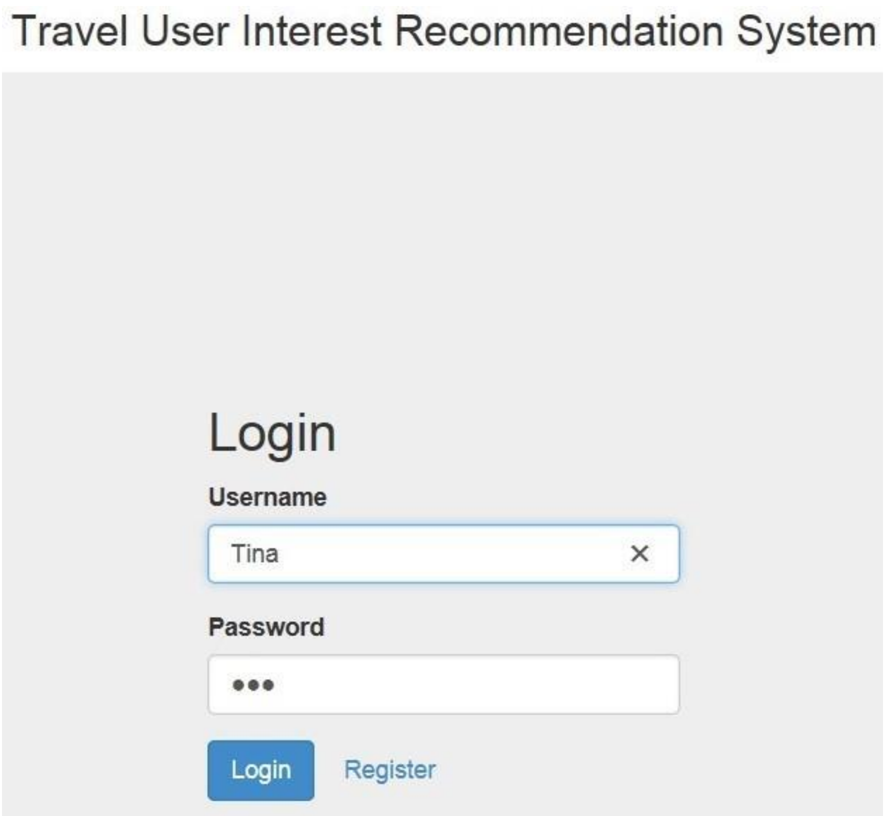


The App Login Interface

Furthermore, If the user has already registered, then the right information is used to login (Username and Password), whilst if user has not an account must go to register, as is shown in the next figure and fill the basic information such first name, last name, username, city and password.

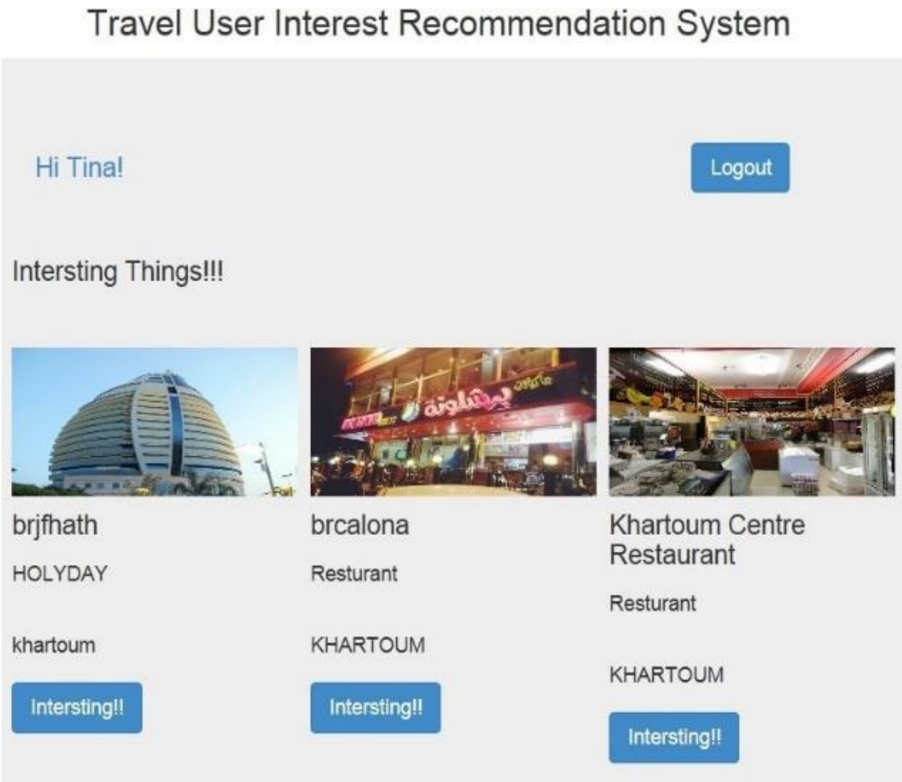


App Registration Interface

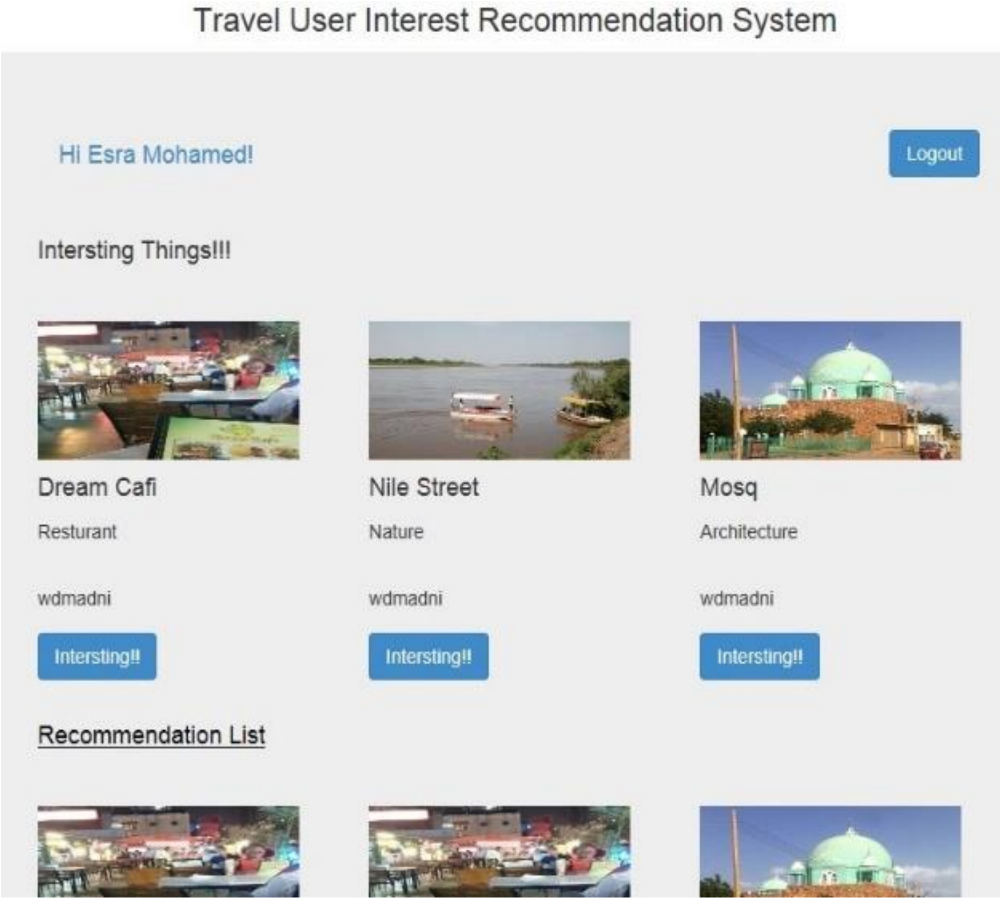


Login after Registration

In addition, once the user has successfully login, the app shows the user interests generated by our system which are compatible with the user preferences as is shown in the next figures, in addition, the app provides the user travel information that includes travel locations, restaurants and cafes, natural spots, social events and art galleries.



App User Interest Results



Another User Interest Results

APPENDIX D

This appendix contains sample of CNN models results under caffe environment

GoogleNet Model

GoogleNet found.

mean-subtracted values: [('B', 104.0069879317889), ('G', 116.66876761696767), ('R', 122.6789143406786)]

0

TravelDatabase/0/0.jpg

predicted class is: 970

output label: n09193705 alp

probabilities and labels:

[(0.1767024, 'n09193705 alp'), (0.16914949, 'n03781244 monastery'), (0.13882723, 'n04604644 worm fence, snake fence, snake-rail fence, Virginia fence'), (0.11631308, 'n09468604 valley, vale'), (0.085744746, 'n09332890 lakeside, lakeshore')]

TravelDatabase/0/1.jpg

predicted class is: 853

output label: n04417672 thatch, thatched roof

probabilities and labels:

[(0.24023975, 'n04417672 thatch, thatched roof'), (0.18327774, 'n02793495 barn'), (0.18275571, 'n02437312 Arabian camel, dromedary, Camelus dromedarius'), (0.10795407, 'n09472597 volcano'), (0.068556204, 'n03792972 mountain tent')]

TravelDatabase/0/2.jpg

predicted class is: 627

output label: n03670208 limousine, limo

probabilities and labels:

[(0.18672217, 'n03670208 limousine, limo'), (0.16311954, 'n02690373 airliner'), (0.097124763, 'n02701002 ambulance'), (0.095062979, 'n02917067 bullet train, bullet'), (0.072418593, 'n03769881 minibus')]

TravelDatabase/0/3.jpg

predicted class is: 437

output label: n02814860 beacon, lighthouse, beacon light, pharos

probabilities and labels:

[(0.42977732, 'n02814860 beacon, lighthouse, beacon light, pharos'), (0.10170016, 'n02894605 breakwater, groin, groyne, mole, bulwark, seawall, jetty'), (0.087403454, 'n02825657 bell cote, bell cot'), (0.082046971, 'n03781244 monastery'), (0.074236378, 'n09399592 promontory, headland, head, foreland')]

TravelDatabase/0/4.jpg

predicted class is: 470

output label: n02948072 candle, taper, wax light

probabilities and labels:

[(0.9483549, 'n02948072 candle, taper, wax light'), (0.042192798, "n03590841 jack-o'-lantern"), (0.0024236068, 'n03729826 matchstick'), (0.00072789658, 'n07720875 bell pepper'), (0.00039182851, 'n03637318 lampshade, lamp shade')]

TravelDatabase/0/5.jpg

predicted class is: 147

output label: n02066245 grey whale, gray whale, devilfish, Eschrichtius gibbosus, Eschrichtius robustus

probabilities and labels:

[(0.1573977, 'n02066245 grey whale, gray whale, devilfish, Eschrichtius gibbosus, Eschrichtius robustus'), (0.1298331, 'n02071294 killer whale, killer, orca, grampus, sea wolf, Orcinus orca'), (0.073117405, 'n02077923 sea lion'), (0.055534597, 'n09428293 seashore, coast, seacoast, sea-coast'), (0.045711543, 'n02074367 dugong, Dugong dugon')]

TravelDatabase/0/6.jpg

predicted class is: 976

output label: n09399592 promontory, headland, head, foreland

probabilities and labels:

[(0.51148444, 'n09399592 promontory, headland, head, foreland'), (0.2763336, 'n09428293 seashore, coast, seacoast, sea-coast'), (0.14602797, 'n09332890 lakeside, lakeshore'), (0.044213668, 'n09421951 sandbar, sand bar'), (0.0089613404, 'n09246464 cliff, drop, drop-off')]

TravelDatabase/0/7.jpg

predicted class is: 743

output label: n04005630 prison, prison house

probabilities and labels:

[(0.29396921, 'n04005630 prison, prison house'), (0.28711888, 'n03877845 palace'), (0.099864632, 'n09332890 lakeside, lakeshore'), (0.081708401, 'n03781244 monastery'), (0.076563388, 'n03899768 patio, terrace')]

TravelDatabase/0/8.jpg

predicted class is: 580

output label: n03457902 greenhouse, nursery, glasshouse

probabilities and labels:

[(0.48198345, 'n03457902 greenhouse, nursery, glasshouse'), (0.46981052, 'n02793495 barn'), (0.016991546, 'n02859443 boathouse'), (0.0090251574, 'n03776460 mobile home, manufactured home'), (0.0086726658, 'n03697007 lumbermill, sawmill')]

VGG19 Model

Vgg found.

mean-subtracted values: [('B', 104.0069879317889), ('G', 116.66876761696767), ('R', 122.6789143406786)]

0

TravelDatabase/0/0.jpg

predicted class is: 978

output label: n09428293 seashore, coast, seacoast, sea-coast

probabilities and labels:

[(0.44021863, 'n09428293 seashore, coast, seacoast, sea-coast'), (0.31360295, 'n09421951 sandbar, sand bar'), (0.034388307, 'n09399592 promontory, headland, head, foreland'), (0.019737829, 'n04251144 snorkel'), (0.019298097, 'n01498041 stingray')]

TravelDatabase/0/1.jpg

predicted class is: 838

output label: n04357314 sunscreen, sunblock, sun blocker

probabilities and labels:

[(0.076107413, 'n04357314 sunscreen, sunblock, sun blocker'), (0.055053744, 'n04162706 seat belt, seatbelt'), (0.046646819, 'n07615774 ice lolly, lolly, lollipop, popsicle'), (0.039444771, 'n04356056 sunglasses, dark glasses, shades'), (0.037183255, 'n03814639 neck brace')]

TravelDatabase/0/2.jpg

predicted class is: 976

output label: n09399592 promontory, headland, head, foreland

probabilities and labels:

[(0.14426883, 'n09399592 promontory, headland, head, foreland'), (0.10199457, 'n04136333 sarong'), (0.084631406, 'n09428293 seashore, coast, seacoast, sea-coast'), (0.05567798, 'n09421951 sandbar, sand bar'), (0.054237317, 'n04357314 sunscreen, sunblock, sun blocker')]

TravelDatabase/0/3.jpg

predicted class is: 808

output label: n04259630 sombrero

probabilities and labels:

[(0.1518683, 'n04259630 sombrero'), (0.086838573, 'n04355933 sunglass'), (0.056268334, 'n03000684 chain saw, chainsaw'), (0.050592821, 'n02412080 ram, tup'), (0.044276159, 'n03124170 cowboy hat, ten-gallon hat')]

2

TravelDatabase/1/0.jpg

predicted class is: 975

output label: n09332890 lakeside, lakeshore

probabilities and labels:

[(0.22645825, 'n09332890 lakeside, lakeshore'), (0.11296132, 'n03891251 park bench'), (0.066608518, 'n02894605 breakwater, groin, groyne, mole, bulwark, seawall, jetty'), (0.034559008, 'n04604644 worm fence, snake fence, snake-rail fence, Virginia fence'), (0.028170958, 'n03594734 jean, blue jean, denim')]

TravelDatabase/1/1.jpg

predicted class is: 391

output label: n02536864 coho, cohoe, coho salmon, blue jack, silver salmon, Oncorhynchus kisutch

probabilities and labels:

[(0.15841359, 'n02536864 coho, cohoe, coho salmon, blue jack, silver salmon, Oncorhynchus kisutch'), (0.12892415, 'n09399592 promontory, headland, head, foreland'), (0.099525437, 'n09332890 lakeside, lakeshore'), (0.064670779, 'n02841315 binoculars, field glasses, opera glasses'), (0.054442368, 'n04067472 reel')]

TravelDatabase/1/2.jpg

predicted class is: 890

output label: n04540053 volleyball

probabilities and labels:

[(0.029218633, 'n04540053 volleyball'), (0.029075578, 'n03773504 missile'), (0.027246686, 'n03733281 maze, labyrinth'), (0.024460495, 'n09835506 ballplayer, baseball player'), (0.021694485, 'n03930313 picket fence, paling')]

TravelDatabase/1/3.jpg

predicted class is: 977

output label: n09421951 sandbar, sand bar

probabilities and labels:

[(0.087009676, 'n09421951 sandbar, sand bar'), (0.077064656, 'n09428293 seashore, coast, seacoast, sea-coast'), (0.058260728, 'n04208210 shovel'), (0.041634403, 'n04371430 swimming trunks, bathing trunks'), (0.038033124, 'n04357314 sunscreen, sunblock, sun blocker')]

3

TravelDatabase/2/0.jpg

predicted class is: 474

output label: n02963159 cardigan

probabilities and labels:

[(0.26577866, 'n02963159 cardigan'), (0.049367759, 'n03000247 chain mail, ring mail, mail, chain armor, chain armour, ring armor, ring armour'), (0.029687919, 'n06785654 crossword puzzle, crossword'), (0.028947189, 'n04356056 sunglasses, dark glasses, shades'), (0.022990754, 'n03770439 miniskirt, mini')]

TravelDatabase/2/1.jpg

predicted class is: 832

output label: n04346328 stupa, tope

probabilities and labels:

[(0.29758781, 'n04346328 stupa, tope'), (0.20382968, 'n03929855 pickelhaube'), (0.083252572, 'n04141076 sax, saxophone'), (0.046548322, 'n04429376 throne'), (0.03251987, 'n03877845 palace')]

TravelDatabase/2/2.jpg

predicted class is: 880

output label: n04509417 unicycle, monocycle

probabilities and labels:

[(0.53082287, 'n04509417 unicycle, monocycle'), (0.17672753, 'n03733281 maze, labyrinth'), (0.051711176, 'n09421951 sandbar, sand bar'), (0.028289944, 'n09428293 seashore, coast, seacoast, sea-coast'), (0.022858424, 'n01665541 leatherback turtle, leatherback, leathery turtle, Dermochelys coriacea')]

TravelDatabase/2/3.jpg

predicted class is: 500

output label: n03042490 cliff dwelling

probabilities and labels:

[(0.78830439, 'n03042490 cliff dwelling'), (0.11002955, 'n09246464 cliff, drop, drop-off'), (0.031397503, 'n09468604 valley, vale'), (0.012087696, 'n09193705 alp'), (0.005805722, 'n03160309 dam, dike, dyke')]

4

TravelDatabase/3/0.jpg

predicted class is: 920

output label: n06874185 traffic light, traffic signal, stoplight

probabilities and labels:

[(0.31251577, 'n06874185 traffic light, traffic signal, stoplight'), (0.089973986, 'n03355925 flagpole, flagstaff'), (0.058135293, 'n02930766 cab, hack, taxi, taxicab'), (0.057690036, 'n04146614 school bus'), (0.052382104, 'n06794110 street sign')]

TravelDatabase/3/1.jpg

predicted class is: 977

output label: n09421951 sandbar, sand bar

probabilities and labels:

[(0.2771534, 'n09421951 sandbar, sand bar'), (0.10535329, 'n09428293 seashore, coast, seacoast, sea-coast'), (0.096779406, 'n04136333 sarong'), (0.026338248, 'n04371430 swimming trunks, bathing trunks'), (0.019781284, 'n09332890 lakeside, lakeshore')]

TravelDatabase/3/2.jpg

predicted class is: 913

output label: n04606251 wreck

probabilities and labels:

[(0.323457, 'n04606251 wreck'), (0.26075432, 'n09428293 seashore, coast, seacoast, sea-coast'), (0.07837034, 'n03947888 pirate, pirate ship'), (0.060208507, 'n09421951 sandbar, sand bar'), (0.059569914, 'n09332890 lakeside, lakeshore')]

TravelDatabase/3/3.jpg

predicted class is: 442

output label: n02825657 bell cote, bell cot

probabilities and labels:

[(0.33440584, 'n02825657 bell cote, bell cot'), (0.19862381, 'n03028079 church, church building'), (0.067463599, 'n02843684 birdhouse'), (0.050001066, 'n04346328 stupa, tope'), (0.034543715, 'n03355925 flagpole, flagstaff')]

5

TravelDatabase/4/0.jpg

predicted class is: 652

output label: n03763968 military uniform

probabilities and labels:

[(0.11104539, 'n03763968 military uniform'), (0.05261533, 'n04479046 trench coat'), (0.045647144, 'n04350905 suit, suit of clothes'), (0.035270654, 'n03888257 parachute, chute'), (0.025597792, 'n02088094 Afghan hound, Afghan')]

TravelDatabase/4/1.jpg

predicted class is: 842

output label: n04371430 swimming trunks, bathing trunks

probabilities and labels:

[(0.11346598, 'n04371430 swimming trunks, bathing trunks'), (0.089899987, 'n09421951 sandbar, sand bar'), (0.075113215, 'n04251144 snorkel'), (0.070739098, 'n09332890 lakeside, lakeshore'), (0.056518897, 'n04136333 sarong')]

TravelDatabase/4/2.jpg

predicted class is: 792

output label: n04208210 shovel

probabilities and labels:

[(0.11223428, 'n04208210 shovel'), (0.039658178, 'n04228054 ski'), (0.033248428, 'n09193705 alp'), (0.026871607, 'n04252077 snowmobile'), (0.024497159, 'n04229816 ski mask')]

TravelDatabase/4/3.jpg

predicted class is: 792

output label: n04208210 shovel

probabilities and labels:

[(0.31490871, 'n04208210 shovel'), (0.23356944, 'n04228054 ski'), (0.062038779, 'n04252077 snowmobile'), (0.047264963, 'n03218198 dogsled, dog sled, dog sleigh'), (0.031538658, 'n02860847 bobsled, bobsleigh, bob')]

7

TravelDatabase/0/0.jpg

predicted class is: 873

output label: n04486054 triumphal arch

probabilities and labels:

[(0.34364197, 'n04486054 triumphal arch'), (0.1105811, 'n02825657 bell cote, bell cot'), (0.095992833, 'n03933933 pier'), (0.049775857, 'n04562935 water tower'), (0.045799442, 'n03837869 obelisk')]

TravelDatabase/0/1.jpg

predicted class is: 698

output label: n03877845 palace

probabilities and labels:

[(0.58508581, 'n03877845 palace'), (0.16216595, 'n03781244 monastery'), (0.071550123, 'n04486054 triumphal arch'), (0.037959162, 'n02980441 castle'), (0.024685521, 'n03837869 obelisk')]

TravelDatabase/0/2.jpg

predicted class is: 832

output label: n04346328 stupa, tope

probabilities and labels:

[(0.32801992, 'n04346328 stupa, tope'), (0.098618299, 'n09428293 seashore, coast, seacoast, sea-coast'), (0.066820048, 'n03877845 palace'), (0.065521851, 'n03837869 obelisk'), (0.024202626, 'n09421951 sandbar, sand bar')]

TravelDatabase/0/3.jpg

predicted class is: 873

output label: n04486054 triumphal arch

probabilities and labels:

[(0.99954176, 'n04486054 triumphal arch'), (0.0003215725, 'n03903868 pedestal, plinth, footstall'), (5.6082037e-05, 'n03837869 obelisk'), (4.712072e-05, 'n02825657 bell cote, bell cot'), (9.0005942e-06, 'n03877845 palace')]

APPENDIX E

Java code (Protégé wol ontology)

```
package testowl;


import java.io.File;
import java.net.URI;
import java.net.URL;
import java.util.Arrays;
import java.util.Set;
import java.util.Vector;

import javax.swing.JOptionPane;
import javax.swing.JScrollPane;
import javax.swing.JTable;
import javax.swing.table.DefaultTableModel;

import org.semanticweb.HermiT.Reasoner;
import org.semanticweb.owlapi.apibinding.OWLManager;
import org.semanticweb.owlapi.model.IRI;
import org.semanticweb.owlapi.model.OWLAnnotationSubject;
import org.semanticweb.owlapi.model.OWLClass;
import org.semanticweb.owlapi.model.OWLDataFactory;
import org.semanticweb.owlapi.model.OWLEntity;
import org.semanticweb.owlapi.model.OWLIndividual;
import org.semanticweb.owlapi.model.OWLNamedIndividual;
import org.semanticweb.owlapi.model.OWLOntology;
import org.semanticweb.owlapi.model.OWLOntologyCreationException;
import org.semanticweb.owlapi.model.OWLOntologyManager;
import org.semanticweb.owlapi.reasoner.NodeSet;
import org.semanticweb.owlapi.reasoner.OWLReasoner;
import org.semanticweb.owlapi.reasoner.OWLReasonerFactory;
import org.semanticweb.owlapi.reasoner.structural.StructuralReasonerFactory;
import org.semanticweb.owlapi.util.OWLEntityRemover;



public class myclass {
	static OWLOntology myOntology ;
	static OWLDataFactory df ;
	static OWLOntologyManager manager ;
	static IRI ontologyIRI ;
	static File file = new File("C:/travel.owl");
	private OWLOntologyManager manager2;
   private static OWLOntology ontology;
   private static OWLDataFactory factory;
   private static Reasoner reasoner;
```

```
    private OWLEntityRemover remover;
    private static URL url;
   private static URI uri;
       public static IRI fileURI = IRI.create(file);
       static OWLReasonerFactory reasonerFactory = new StructuralReasonerFactory();

       @SuppressWarnings({ "deprecation", "null" })
public static void main(String args[]) throws OWLOntologyCreationException {

              manager = OWLManager.createOWLOntologyManager();
              myOntology = manager.loadOntology(fileURI);
              ontologyIRI = IRI.create("the IRI of the onology");
              df = manager.getOWLDataFactory();
             // System.out.println("whaaaaaat"+myOntology.getAnnotations());
              String classes[]=new String[myOntology.getClassesInSignature().size()];
              int y=0;
                 for (OWLClass cls : myOntology.getClassesInSignature())
{
                 classes[y]=cls.getIRI().getShortForm();

                    System.out.println("My class is : " + cls.getIRI().getShortForm());
                    System.out.println("The IRI of my class is : "+ cls);
                    System.out.println("----------------------");

                    OWLReasoner reasoner =
reasonerFactory.createReasoner(myOntology);
                    NodeSet<OWLNamedIndividual> instances = reasoner.getInstances(cls,
true);
                    System.out.println("The Individuals of my class : "+classes[y]);
                 y++;
                  //  for (OWLNamedIndividual i : instances.getFlattened()) {
                    //      System.out.println(i.getIRI().getFragment());            }

                 }
     String user[][]=new String[][]{
 {"drugstore", "beer_garden","beer_hall"
,"drugstore,patio","jewelry_shop","pharmacy","discotheque","office"},
 {"museum","server_room","beach","pharmacy","beauty_salon","nursery","volleyball_
court","childs_room","boat_deck"},
 {"beer_hall","lecture_room","patio","jewelry_shop","alley","amusement_arcade"},
 {"delicatessen","sauna","science_museum","nursery","kindergarden_classroom","whea
t_field","medina"},
 {"hangar","classroom","discotheque","office","dining_hall","ice_cream_parlor","scien
ce_museum,bedroom","train_interior"},
 {"medina","pharmacy","playground","office","amphitheater","music_studio","dining_h
all","village","plaza",},
 {"science_museum","reception","arena","conference_room","courtyard","conference_r
oom","mansion","stage","church"},
 {"candy_store","nursing_home","car_interior","dorm_room","baseball_field","train_int
erior","bus_interior","rice_paddy","department_store"},
 {"crevasse","drugstore","beauty_salon","ice_cream_parlor","kindergarden_classroom",
"basement","restaurant_kitchen","mansion","gift_shop"},
```

```
 {"restaurant","reception","lagoon","science_museum","conference_center","science_m
useum","pharmacy","yard","office"},
 {"canyon","temple","bar","pavilion","shoe_shop","lawn","gas_station","art_gallery","k
itchen"},
 {"desert","train_interior","beauty_salon","village","plaza","patio","shopping_mall","m
ausoleum","beauty_salon"},
 {"library","art_school","mountain_snowy","playground","water_tower","heliport","pon
d","art_school","clothing_store"},
 {"department_store","laundromat","locker_room","ice_cream_parlor","porch","bow_w
indow","train_interior","butchers_shop","airplane_cabin"},
 {"beer_garden","airport_terminal","dressing_room","clothing_store","bowling_alley","
museum","nursing_home","restaurant","candy_store"},
 {"canal","fountain","sandbox","operating_room","clothing_store","marsh","harbor","ic
e_floe","balcony"},
 {"desert_road","beer_hall","chemistry_lab","office_cubicles","conference_center","rop
e_bridge","desert_road","construction_site","forest_path"},
 {"porch","veterinarians_office","stage","burial_chamber","rock_arch","mausoleum","a
quarium","arch","shower"},
 {"shower","mansion","beer_garden","pub","playground","kindergarden_classroom","fi
eld","laundromat","conference_center"},
 {"clean_room","junkyard","clothing_store","server_room","museum","corn_field","sh
ower","beauty_salon","candy_store"},
 {"volleyball_court","clothing_store","sky","field","medina","cemetery","natural_histor
y_museum","sandbox"},
 {"General_store","shed","industrial_area","cliff","playroom","wave","lighthouse","cam
psite","landing_deck"},
             };
                //  for (int i=0;)
            //  int count=0;
              int UserNumber=0;
              String row="";
             int UserIndex=0;
              boolean[] ismatch = new boolean[22];
              Arrays.fill(ismatch, false);

              Object[][] rows3 = {
            {"userNumber","ismatched"}
         };
           for(int u=0;u<user.length;u++){
            int count=0;
             for(int z=0;z<user[u].length;z++){
             for(int i=0;i<classes.length;i++){

             if(classes[i].equals(user[u][z]))
             count++;
             }
             }
           UserNumber++;
             if(count>1){
            ismatch[u]=true;
                    // UserIndex =UserNumber;
             }
```

```
            }
         // System.out.println(row);
           // Object[][] rows = {
           //    {element,symbol,atomicNumber,atomicMass,valence}
           // };
//           String[] value_split = row.split("[user::yes]");
//           String [] match=row.split(":noo");
//     //     String []matchY=row.split(":yess");
//        System.out.println("ASDASD"+match[9]);
//           for(int m=0;m<value_split.length;m++){
//             System.out.print(value_split[m]);
//
//           }
           int []userIdex={1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22};

           Object[] cols = {
             "userNumber","isMatch"
           };
           DefaultTableModel model = new DefaultTableModel(
             new Object[]{ "userNumber","isMatch"},
             0);
           for(int i=0;i<21;i++){


                model.insertRow(i,  new Object[]{userIdex[i],ismatch[i]});



             }

           JTable table = new JTable(model);
           JOptionPane.showMessageDialog(null, new JScrollPane(table));


              for (OWLClass c : myOntology.getClassesInSignature()) {
                 if (c.getIRI().getFragment().equals("Places")){
                 //  System.out.println("ASDAS");
                 //    NodeSet<OWLNamedIndividual> instances = reasoner.getInstances(c,
false);
                  //   System.out.println("ASDYYY"+instances);
                   //  System.out.println("$%$#%$%"+c.getIRI().getFragment());
                 //    for (OWLNamedIndividual i : instances.getFlattened()) {
                   //      System.out.println(i.getIRI().getFragment());
                    // }
                 }
              }
      //     System.out.println("all classes "+OWLEntity.getIRI().getShortForm());

                          }}
```

APPENDIX F

FIRE Result

No errors found.

Concepts

top = null
bottom = null
TOP = null
BOTTOM = null
TOP = null
BOTTOM = null
top = null
bottom = null
Nature = null
Food = null
Architecture = null
Art = null
Holydays = null
Events = null
History = null
DIY&Crafts = null
Celebrities = null

Roles

ROLE:hasPart-DOMAIN:null-RANGE:null-TRANS:false-INVERSE:Inv_hasPart-PARENT:null-CHILDS:null
ROLE:Inv_hasPart-DOMAIN:null-RANGE:null-TRANS:false-INVERSE:hasPart-PARENT:null-CHILDS:null

Individuals

tench
Tinca-tinca
frican-elephant
Loxodonta-Africana
volcano
seashore
coast
seacoast
sea-coast
fountain
lakeside
lakeshore
apiary
bee-house
ping-pong
ball
crayfish
crawfish

crawdad
crawdaddy
valley
vale
sandbar
sand-bar
cliff
drop
drop-off
pier
parachute
chute
golfcart
golf-cart
vase
panpipe
pandean-pipe
syrinx
spoonbill
water-buffalo
water-ox
Asiatic-buffalo
Bubalus-bubalis
barrow
garden-cart
lawn-cart
wheelbarrow
breakwater
groin
groyne
mole
bulwark
seawall
jetty
bighorn
bighorn-sheep
cimarron
Rocky-Mountain-bighorn
Rocky-Mountain-sheep
Ovis-Canadensis
mountain-bike
all-terrain-bike
off-roader
sandal
macaque
dugong
Dugong-dugon
chimpanzee
chimp
Pan-troglodytes
broccoli
vale-broccoli

monarch
monarch-butterfly
milkweed-butterfly
Danaus-plexippus
alp
leatherback-turtle
leatherback
leathery-turtle
Dermochelys-coriacea
starfish
sea-star
hay
Windsor-tie
lion
king-of-beasts
Panthera-leo
ear
spike
capitulum
conch
paintbrush
Arabian-camel
dromedary
Camelus-dromedarius
swimming-trunks
bathing-trunks
promontory
headland
head
foreland
daisy
papillon
hartebeest
wool
woolen
gazelle
liner
ocean-liner
Bedlington-terrier
Python-sebae
rock-python
rock-snake
killer-whale
killer
orca
grampus
sea-wolf
Orcinus-orca
ram
tup
space-shuttle
rapeseed

platypus
duckbill
duckbilled-platypus
duck-billed-platypus
Ornithorhynchus-anatinus
hummingbird
Angora
Angora-rabbit
ground-beetle
carabid-beetle
lawn-mower
mower
oscilloscope
scope
cathode-ray-oscilloscope
CRO
bubble
geyser
trifle
shower-curtain
West-Highland-white-terrier
stupa
tope
gondola
chambered-nautilus
pearly-nautilus
nautilus
menu
spatula
pool-table
billiard-table
snooker-table
chocolate-sauce
chocolate-syrup
plate
whiskey-jug
butcher-shop
meat-market
bagel
beigel
potpie
coho
cohoe
coho-salmon
blue-jack
silver-salmon
Oncorhynchus-kisutch
pizza
pizza-pie
coffeepot
ice-cream
icecream

rotisserie
espresso
custard-apple
coffee-mug
confectionery
confectionary
candy-store
dining-table
board
banana
cleaver
meat-cleaver
chopper
ice-lolly
lolly
lollipop
popsicle
teapot
goblet
wooden-spoon
pomegranate
spaghetti-squash
eggnog
honeycomb
pineapple
ananas
beer-glass
pretzel
fig
cheeseburger'
lab-coat
laboratory-coat
prison
prison-house
megalith
megalithic-structure
restaurant
eating-house
eating-place
eatery
stage
shoe-shop
shoe-store
palace
cash-machine
cash-dispenser
automated-teller-machine
automatic-teller-machine
automated-teller
automatic-teller
ATM
cinema

movie-theater
movie-theatre
movie-house
picture-palace
photocopier
mosque
speedboat
park-bench
water-tower
greenhouse
nursery
glasshouse
bakery
bakeshop
bakehouse
grocery-store
grocery
food-market
market
theater-curtain
theatre-curtain
barn
barbershop
abacus
bookstore
bookstall
bookshop
castle
fireboat
home-theater
home-theatre
picket-fence
paling
electric-locomotive
wardrobe
closet
press
mailbox
letter-box
cliff-dwelling
toaster
desk
refrigerator
icebox
studio-couch
day-bed
monastery
toy-shop
viaduct
church
church-building
dam

dike
dyke
comic-book
croquet-ball
crossword-puzzle
crossword
jigsaw-puzzle
football-helmet
bow
ballplayer
baseball-player
soccer-ball
puck
hockey-puck
ping-pong-ball
marimba
xylophone
library
drum
membranophone
tympan
rugby-ball
electric-guitar
harmonica
whistle
mouth-organ
harp
mouth-harp
sax
saxophone
pick
plectrum
plectron
banjo
volleyball
violin
fiddle
punching-bag
punch-bag
punching-ball
punchball
grand-piano
grand
basketball
Christmas-stocking
schooner
tray
canoe
Crock-Pot
wallet
billfold
notecase

pocketbook
brass
memorial-tablet
plaque
paddle
boat-paddle
altar

Axioms

Assertions:336

tench instanceOf Nature >= 0.2
Tinca-tinca instanceOf Nature >= 0.2
frican-elephant instanceOf Nature >= 0.4
Loxodonta-Africana instanceOf Nature >= 0.4
volcano instanceOf Nature >= 0.8
seashore instanceOf Nature >= 0.9
coast instanceOf Nature >= 0.9
seacoast instanceOf Nature >= 0.9
sea-coast instanceOf Nature >= 0.9
fountain instanceOf Nature >= 0.8
lakeside instanceOf Nature >= 0.4
lakeshore instanceOf Nature >= 0.4
apiary instanceOf Nature >= 0.1
bee-house instanceOf Nature >= 0.1
ping-pong-ball instanceOf Nature >= 0.1
crayfish instanceOf Nature >= 0.3
crawfish instanceOf Nature >= 0.3
crawdad instanceOf Nature >= 0.3
crawdaddy instanceOf Nature >= 0.3
valley instanceOf Nature >= 0.7
vale instanceOf Nature >= 0.7
sandbar instanceOf Nature >= 0.8
sand-bar instanceOf Nature >= 0.6
cliff instanceOf Nature >= 0.3
drop instanceOf Nature >= 0.2
drop-off instanceOf Nature >= 0.2
pier instanceOf Nature >= 0.5
parachute instanceOf Nature >= 0.6
chute instanceOf Nature >= 0.6
golfcart instanceOf Nature >= 0.2
golf-cart instanceOf Nature >= 0.2
vase instanceOf Nature >= 0.5
panpipe instanceOf Nature >= 0.3
pandean-pipe instanceOf Nature >= 0.3
syrinx instanceOf Nature >= 0.3
spoonbill instanceOf Nature >= 0.7
water-buffalo instanceOf Nature >= 0.3
water-ox instanceOf Nature >= 0.3
Asiatic-buffalo instanceOf Nature >= 0.3
Bubalus-bubalis instanceOf Nature >= 0.3
barrow instanceOf Nature >= 0.7

garden-cart instanceOf Nature >= 0.7
lawn-cart instanceOf Nature >= 0.7
wheelbarrow instanceOf Nature >= 0.7
breakwater instanceOf Nature >= 0.8
groin instanceOf Nature >= 0.8
groyne instanceOf Nature >= 0.8
mole instanceOf Nature >= 0.8
bulwark instanceOf Nature >= 0.8
seawall instanceOf Nature >= 0.8
jetty instanceOf Nature >= 0.8
bighorn instanceOf Nature >= 0.1
bighorn-sheep instanceOf Nature >= 0.1
cimarron instanceOf Nature >= 0.1
Rocky-Mountain-bighorn instanceOf Nature >= 0.1
Rocky-Mountain-sheep instanceOf Nature >= 0.1
Ovis-Canadensis instanceOf Nature >= 0.1
mountain-bike instanceOf Nature >= 0.1
all-terrain-bike instanceOf Nature >= 0.1
off-roader instanceOf Nature >= 0.1
sandal instanceOf Nature >= 0.6
macaque instanceOf Nature >= 0.6
dugong instanceOf Nature >= 0.1
Dugong-dugon instanceOf Nature >= 0.1
chimpanzee instanceOf Nature >= 0.3
chimp instanceOf Nature >= 0.3
Pan-troglodytes instanceOf Nature >= 0.3
broccoli instanceOf Nature >= 0.3
vale-broccoli instanceOf Nature >= 0.6
monarch instanceOf Nature >= 1.0
monarch-butterfly instanceOf Nature >= 1.0
milkweed-butterfly instanceOf Nature >= 1.0
Danaus-plexippus instanceOf Nature >= 1.0
alp instanceOf Nature >= 0.2
leatherback-turtle instanceOf Nature >= 0.1
leatherback instanceOf Nature >= 0.1
leathery-turtle instanceOf Nature >= 0.1
Dermochelys-coriacea instanceOf Nature >= 0.1
starfish instanceOf Nature >= 0.1
sea-star instanceOf Nature >= 0.1
hay instanceOf Nature >= 0.1
Windsor-tie instanceOf Nature >= 0.3
lion instanceOf Nature >= 0.1
king-of-beasts instanceOf Nature >= 0.1
Panthera-leo instanceOf Nature >= 0.1
ear instanceOf Nature >= 0.5
spike instanceOf Nature >= 0.5
capitulum instanceOf Nature >= 0.5
conch instanceOf Nature >= 0.5
paintbrush instanceOf Nature >= 0.1
Arabian-camel instanceOf Nature >= 1.0
dromedary instanceOf Nature >= 1.0
Camelus-dromedarius instanceOf Nature >= 1.0

swimming-trunks instanceOf Nature >= 0.1
bathing-trunks instanceOf Nature >= 0.1
promontory instanceOf Nature >= 0.7
headland instanceOf Nature >= 0.7
head instanceOf Nature >= 0.7
foreland instanceOf Nature >= 0.7
daisy instanceOf Nature >= 0.5
papillon instanceOf Nature >= 0.1
hartebeest instanceOf Nature >= 0.2
wool instanceOf Nature >= 0.2
woolen instanceOf Nature >= 0.2
gazelle instanceOf Nature >= 0.2
liner instanceOf Nature >= 0.9
ocean-liner instanceOf Nature >= 0.9
Bedlington-terrier instanceOf Nature >= 0.1
Python-sebae instanceOf Nature >= 0.2
rock-python instanceOf Nature >= 0.2
rock-snake instanceOf Nature >= 0.2
killer-whale instanceOf Nature >= 0.2
killer instanceOf Nature >= 0.2
orca instanceOf Nature >= 0.2
grampus instanceOf Nature >= 0.2
sea-wolf instanceOf Nature >= 0.2
Orcinus-orca instanceOf Nature >= 0.2
ram instanceOf Nature >= 0.5
tup instanceOf Nature >= 0.5
space-shuttle instanceOf Nature >= 0.1
rapeseed instanceOf Nature >= 0.1
platypus instanceOf Nature >= 0.4
duckbill instanceOf Nature >= 0.4
duckbilled-platypus instanceOf Nature >= 0.4
duck-billed-platypus instanceOf Nature >= 0.4
Ornithorhynchus-anatinus instanceOf Nature >= 0.4
hummingbird instanceOf Nature >= 0.3
Angora instanceOf Nature >= 0.9
Angora-rabbit instanceOf Nature >= 0.9
ground-beetle instanceOf Nature >= 0.2
carabid-beetle instanceOf Nature >= 0.2
lawn-mower instanceOf Nature >= 0.4
mower instanceOf Nature >= 0.4
oscilloscope instanceOf Nature >= 0.1
scope instanceOf Nature >= 0.1
cathode-ray-oscilloscope instanceOf Nature >= 0.1
CRO instanceOf Nature >= 0.1
bubble instanceOf Nature >= 0.2
geyser instanceOf Nature >= 0.8
trifle instanceOf Nature >= 0.2
shower-curtain instanceOf Nature >= 0.3
West-Highland-white-terrier instanceOf Nature >= 0.5
stupa instanceOf Nature >= 0.3
tope instanceOf Nature >= 0.3
gondola instanceOf Nature >= 1.0

chambered-nautilus instanceOf Nature >= 0.2
pearly-nautilus instanceOf Nature >= 0.2
nautilus instanceOf Nature >= 0.2
menu instanceOf Food >= 0.9
spatula instanceOf Food >= 0.6
pool-table instanceOf Food >= 0.1
billiard-table instanceOf Food >= 0.1
snooker-table instanceOf Food >= 0.1
chocolate-sauce instanceOf Food >= 1.0
chocolate-syrup instanceOf Food >= 1.0
plate instanceOf Food >= 0.7
whiskey-jug instanceOf Food >= 0.5
butcher-shop instanceOf Food >= 1.0
meat-market instanceOf Food >= 1.0
bagel instanceOf Food >= 0.4
beigel instanceOf Food >= 0.4
potpie instanceOf Food >= 0.3
coho instanceOf Food >= 0.2
cohoe instanceOf Food >= 0.2
coho-salmon instanceOf Food >= 0.2
blue-jack instanceOf Food >= 0.2
silver-salmon instanceOf Food >= 0.2
Oncorhynchus-kisutch instanceOf Food >= 0.2
pizza instanceOf Food >= 1.0
pizza-pie instanceOf Food >= 1.0
coffeepot instanceOf Food >= 0.3
ice-cream instanceOf Food >= 0.9
icecream instanceOf Food >= 0.9
rotisserie instanceOf Food >= 0.2
espresso instanceOf Food >= 0.8
custard-apple instanceOf Food >= 0.3
coffee-mug instanceOf Food >= 0.1
confectionery instanceOf Food >= 0.5
confectionary instanceOf Food >= 0.5
candy-store instanceOf Food >= 0.5
dining-table instanceOf Food >= 0.5
board instanceOf Food >= 0.5
banana instanceOf Food >= 0.3
cleaver instanceOf Food >= 0.1
meat-cleaver instanceOf Food >= 0.1
chopper instanceOf Food >= 0.1
ice-lolly instanceOf Food >= 0.4
lolly instanceOf Food >= 0.4
lollipop instanceOf Food >= 0.4
popsicle instanceOf Food >= 0.4
teapot instanceOf Food >= 0.1
goblet instanceOf Food >= 0.3
wooden-spoon instanceOf Food >= 0.3
pomegranate instanceOf Food >= 0.6
spaghetti-squash instanceOf Food >= 0.1
eggnog instanceOf Food >= 0.6
honeycomb instanceOf Food >= 0.5

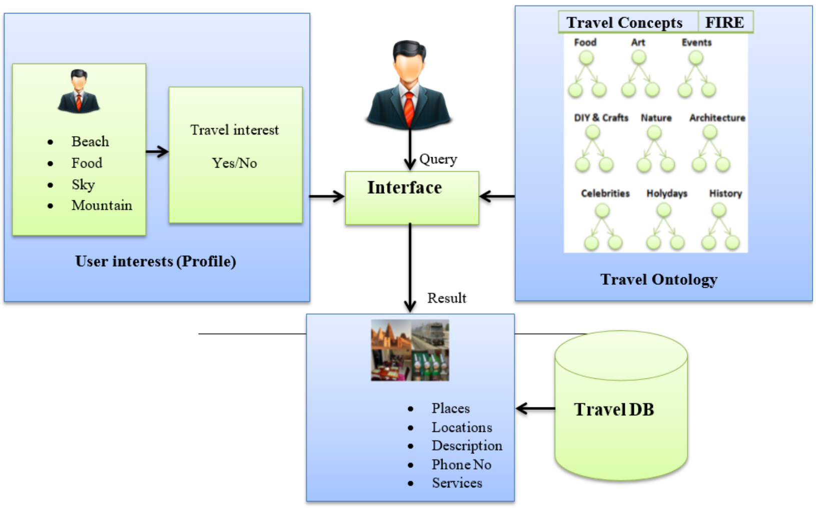
pineapple instanceOf Food >= 0.7
ananas instanceOf Food >= 0.7
beer-glass instanceOf Food >= 0.1
pretzel instanceOf Food >= 0.1
fig instanceOf Food >= 0.8
cheeseburger' instanceOf Food >= 0.2
lab-coat instanceOf Architecture >= 1.0
laboratory-coat instanceOf Architecture >= 1.0
prison instanceOf Architecture >= 0.6
prison-house instanceOf Architecture >= 0.6
megalith instanceOf Architecture >= 0.3
megalithic-structure instanceOf Architecture >= 0.3
restaurant instanceOf Architecture >= 0.8
eating-house instanceOf Architecture >= 0.8
eating-place instanceOf Architecture >= 0.8
eatery instanceOf Architecture >= 0.8
stage instanceOf Architecture >= 0.9
shoe-shop instanceOf Architecture >= 0.6
shoe-store instanceOf Architecture >= 0.6
palace instanceOf Architecture >= 1.0
cash-machine instanceOf Architecture >= 0.2
cash-dispenser instanceOf Architecture >= 0.2
automated-teller-machine instanceOf Architecture >= 0.2
automatic-teller-machine instanceOf Architecture >= 0.2
automated-teller instanceOf Architecture >= 0.2
automatic-teller instanceOf Architecture >= 0.2
ATM instanceOf Architecture >= 0.2
cinema instanceOf Architecture >= 0.2
movie-theater instanceOf Architecture >= 0.2
movie-theatre instanceOf Architecture >= 0.2
movie-house instanceOf Architecture >= 0.2
picture-palace instanceOf Architecture >= 0.2
photocopier instanceOf Architecture >= 0.2
mosque instanceOf Architecture >= 1.0
speedboat instanceOf Architecture >= 0.7
park-bench instanceOf Architecture >= 0.4
water-tower instanceOf Architecture >= 0.6
greenhouse instanceOf Architecture >= 0.3
nursery instanceOf Architecture >= 0.3
glasshouse instanceOf Architecture >= 0.3
bakery instanceOf Architecture >= 0.3
bakeshop instanceOf Architecture >= 0.3
bakehouse instanceOf Architecture >= 0.3
grocery-store instanceOf Architecture >= 0.2
grocery instanceOf Architecture >= 0.2
food-market instanceOf Architecture >= 0.2
market instanceOf Architecture >= 0.2
theater-curtain instanceOf Architecture >= 1.0
theatre-curtain instanceOf Architecture >= 1.0
barn instanceOf Architecture >= 0.6
barbershop instanceOf Architecture >= 0.4
abacus instanceOf Architecture >= 0.3

bookstore instanceOf Architecture >= 0.5
bookstall instanceOf Architecture >= 0.5
bookshop instanceOf Architecture >= 0.5
castle instanceOf Architecture >= 0.5
fireboat instanceOf Architecture >= 0.6
home-theater instanceOf Architecture >= 0.2
home-theatre instanceOf Architecture >= 0.2
picket-fence instanceOf Architecture >= 0.1
paling instanceOf Architecture >= 0.1
electric-locomotive instanceOf Architecture >= 0.8
wardrobe instanceOf Architecture >= 0.6
closet instanceOf Architecture >= 0.6
press instanceOf Architecture >= 0.6
mailbox instanceOf Architecture >= 0.1
letter-box instanceOf Architecture >= 0.1
cliff-dwelling instanceOf Architecture >= 0.3
toaster instanceOf Architecture >= 0.1
desk instanceOf Architecture >= 0.1
refrigerator instanceOf Architecture >= 0.1
icebox instanceOf Architecture >= 0.1
studio-couch instanceOf Architecture >= 0.2
day-bed instanceOf Architecture >= 0.2
monastery instanceOf Architecture >= 0.4
toy-shop instanceOf Architecture >= 0.6
viaduct instanceOf Architecture >= 0.2
church instanceOf Architecture >= 0.1
church-building instanceOf Architecture >= 0.1
dam instanceOf Architecture >= 0.7
dike instanceOf Architecture >= 0.7
dyke instanceOf Architecture >= 0.7
comic-book instanceOf Art >= 0.3
croquet-ball instanceOf Art >= 0.5
crossword-puzzle instanceOf Art >= 0.3
crossword instanceOf Art >= 0.3
jigsaw-puzzle instanceOf Art >= 0.6
football-helmet instanceOf Art >= 1.0
bow instanceOf Art >= 0.8
ballplayer instanceOf Art >= 0.4
baseball-player instanceOf Art >= 0.4
soccer-ball instanceOf Art >= 0.9
puck instanceOf Art >= 0.9
hockey-puck instanceOf Art >= 0.9
ping-pong-ball instanceOf Art >= 0.7
marimba instanceOf Art >= 0.4
xylophone instanceOf Art >= 1.0
library instanceOf Art >= 0.2
drum instanceOf Art >= 0.1
membranophone instanceOf Art >= 0.1
tympan instanceOf Art >= 0.1
rugby-ball instanceOf Art >= 0.6
electric-guitar instanceOf Art >= 0.1
harmonica instanceOf Art >= 0.7

whistle instanceOf Art >= 0.2
mouth-organ instanceOf Art >= 0.7
harp instanceOf Art >= 0.7
mouth-harp instanceOf Art >= 0.7
sax instanceOf Art >= 0.2
saxophone instanceOf Art >= 0.2
pick instanceOf Art >= 0.4
plectrum instanceOf Art >= 0.4
plectron instanceOf Art >= 0.4
banjo instanceOf Art >= 0.1
volleyball instanceOf Art >= 0.2
violin instanceOf Art >= 0.3
fiddle instanceOf Art >= 0.3
punching-bag instanceOf Art >= 0.2
punch-bag instanceOf Art >= 0.2
punching-ball instanceOf Art >= 0.2
punchball instanceOf Art >= 0.2
grand-piano instanceOf Art >= 0.3
grand instanceOf Art >= 0.3
basketball instanceOf Art >= 0.3
Christmas-stocking instanceOf Events >= 0.4
schooner instanceOf DIY&Crafts >= 0.3
tray instanceOf DIY&Crafts >= 0.2
canoe instanceOf DIY&Crafts >= 0.5
Crock-Pot instanceOf DIY&Crafts >= 0.3
wallet instanceOf DIY&Crafts >= 0.3
billfold instanceOf DIY&Crafts >= 0.3
notecase instanceOf DIY&Crafts >= 0.3
pocketbook instanceOf DIY&Crafts >= 0.3
brass instanceOf DIY&Crafts >= 0.4
memorial-tablet instanceOf DIY&Crafts >= 0.4
plaque instanceOf DIY&Crafts >= 0.4
paddle instanceOf DIY&Crafts >= 0.1
boat-paddle instanceOf DIY&Crafts >= 0.1
altar instanceOf Celebrities >= 0.2

APPENDIX G

This appendix contains our Recommendation system overview



Recommendation

Photos from our Primitive ontology