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# Deep Fuzzy Ontology for Travel User Interest Discovery Based on Visual Shared Data in Social Networks

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***Abstract*: In the present research, a novel system for travel interest discovery from visual shared data through social networks is discussed. The proposed Deep Fuzzy System is based on neural features extracted from well-known CNN architecture. GoogleNet to learn the inference system based on fuzzy ontology. Deep fuzzy ontology is a new framework that includes essentially two phases. The first consists of image conceptualization by existing objects found in shared images. In the second phase, we use the concepts issued from ImageNet classes to design our Tree-based ontology for travel interest discovery.To evaluate our deep fuzzy CNN ontology system, we construct a new database of visual shared data on Facebook coming from Sudanese citizens. Our proposed system has shown a very impressive result for travel Sudanese user's interest.**

***Keywords***: CNN architectures, social networks, social visual information, user interest, fuzzy ontology, deep fuzzy ontology.

## I. Introduction

Social networks are simulated environments through which opinions, preferences, and interests are expressed by users. Through the shared information from Facebook, Twitter, LinkedIn citizens, interest can be easily understood [1].
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, analyzed 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 analyzing the deep visual features of shared data to predict user interest. There are different modalities of user profiling, explicit like likes, ranks, and favorites, and implicit like: textual and visual. Figure 1 shows that.

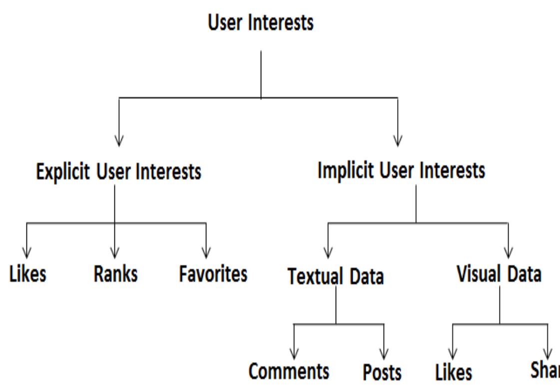



**Figure 1.** An overview of user profiling through social networks

The most proposed works [2 - 3] depend a lot on textual data to analyze social networks and to avoid the visual data, due to the lack or the limitation of available social images analysis systems. Our proposed system is a novel framework to detect travel user interest from social network images.
In this paper, we focus on deep fuzzy ontology classification based on discovering user interests through visual data shared in social networks.
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. One of the hottest research trends in this area is 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 and multiple semantic relations.
The study follows the structure explained below:
The initial part provides a brief note of certain papers from the literature concentrating on using CNN architecture and ontology inference for user interest discovery. Then, we will illustrate our proposed approach by giving details of each

phase of our system including the visual object recognition based on GoogleNet and VGG'19 CNN designs and the constructed fuzzy ontology to predict the user is interested in travel based on his shared visual data. In section three, the light is shed on exhibiting experimental work organizations to assess the system under treatment. Specifications of the innovated established database of Sudanese Facebook accounts will be given. Lastly, a comparison of CNN architectures by using ontology and fuzzy ontology for the discovery of travel user interest. Furthermore, the concluded results of the new database will also be discussed.

## II. State of the art

Many recent studies have suggested various approaches for articulating user's identity from textual or visual data that are posted and shared through social networks, analysis this data to detect some users' preferences or interests, or some soft biometrics information, 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.

There are many works on analyzing, detecting and discover the user's attributes, interests through social networks using textual and visual data.

### *A. Object recognition based approaches*

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 7years [4]. It is capable of classifying images correctly. 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 [1] Convolutional neural networks and neural networks are almost the same as the special type of automatic feeding networks. Models are made to simulate the action of the visual cortex. 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 performs very well in visual recognition tasks.

#### *1) Handcrafted methods*

A group of models proposed was capable of capturing social activities from a photograph as well as being able to categorize photographs in a sensible method. This effort grabbed attention to group photography where there are some people. Subsequently, the question emerged was: How social trends or urban tribes can be determined for those who appear in a group photo? [5]. In 2015, Serra et al. [6] proposed a CRF model that predicting the fashionability of the user's photographs. Data collected from a social website, the model exhibits a beautiful fashionable image that can be utilized to analyze trends in fashion in cities or worldwide, also can be used for outfit recommendation that enhances today's user experience of the current society. In 2018, Aodha et al. [7] have proposed a framework for teaching that can be considered as defining feedback with the ability to be interpreted. The framework indicates the way learners integrate this extra feature while learning. It also automatically generates explanations that highlight the image parts it is also responsible for labeling classes. The textual data is very limited, whereas the social visual one is conversational and has wide content. Consequently, the method of the current study identifies the interest of users travel from the social image (using scene understanding concept) with no need to present any textual data.

#### *2) Neural network-based approaches*

In 2016, Guo et al. [8] studied the challenges and applications from recent research papers in deep learning algorithms. The study covered methods in computer vision like detection of objects classifying an image, image retrieval and semantic segmentation it also gives a brief note.

In 2017 Lazzez et al. [9] Create a new framework to infer user characteristics from social media images that they post and share, especially gender, age, race and smile. In 2017. Lazzez et al. [10] invented an innovative framework that extracts the user's soft biometric data, particularly age, gender, race, and smile. In 2017, Wang et al. [11] Suggested mechanical techniques based on convolutional neural networks to infer geolocation, their method succeeds in the 144k fashion and the Pinterest-based dataset. This finding indicates that these mechanical techniques can be used in other people's features such as clothing style, physical features, and accessories. In 2017, Li et al. [12] Graph Neural Network (GNN) which is an approach for identifying images situation and estimating the correct verb with the assistant of a role-noun pair, relying on a benchmark dataset imSitu, 4.5% accuracy improvement was achieved on a metric. In 2017, Ombabi et al. [2] A suggested an effective approach that provides a summary of the interests of Twitter users based on their social textual data, they have focused on five categories of daily life that can be formulated as travel, food, sports, religion, fashion, and their ways of discovering the topic users are interested in. They have used pre-trained Word2Vec for text pre-processing and Support Vector Machine classifiers for classification. In 2013, Lovato et al. [13] presented an image classification framework based on image characteristics obtained from unsupervised deep learning algorithms. They used a novel database collected from Sina microblog, containing 5000 social images, applied their framework to online social networking images and obtained 89.7accuracy.

CNN is completely data-driven, and therefore more accurate in representing training samples and able to discover feature patterns that manual properties fail to describe.

### *B. Crisp ontology*

The technique based on the use of semantic roles from ADESSE to dig out the semantic relations between concepts was in 2011, where J. Ochoa proposed the approach of ontology learning from monetary written pieces depends on the conclusion of semantic relations and natural language texts, presented an automatic method of getting knowledge from texts.[14]. In 2014, Girshick et al. [15] the intelligent recommendation system counting on Jeju travel ontology recommended the holiday-maker, the use of properties, travel ontology relationship and also responsible for detecting individual preference and determine the traveler location on the AI map. In 2017, Yassin et al. [1]

A travel user interest discovery system built on CNN, GoogleNet and VGG'19 designs and an ontological prediction system designed from new databases of shared images are proposed in Sudanese Facebook accounts. Their approach demonstrated that GoogleNet architecture improved performance compared to VGG'19. In 2018, Lazzez et al. [16] the author proposed an innovative structure to predict user interest from visual data on Facebook based on a deep neural approach to building ontology. The proposed framework achieved an accuracy of .80 to categorize user interests.

## III. Fuzzy ontology for knowledge discovery

Most proposed works and applications use the ontology to discover the user interest and there are no fuzzy ontology systems or methods proposed to detect user interest, which is our contribution.

*Table 1.* Topics of interest's categories in the state of the art

| Study | Datatype | Topics |
|---|---|---|
| [2] | Tweets | Travel, food, sports, religion, and fashion. |
| [5] | Group Images | Social subculture or urban tribe. |
| [6] | Images | Fashionability |
| [10] | Images | Biometrics information, specifica age, gender, race, and smile. |
| [16] | Images | Travel, food, sports, religion, and fashion. |
| [28] | Tweets | Sport, finance, health, movies, ar digital. |

To discover user interests in social networks, it is apparent that some of the studies centralized in texts, links, clicks, Metadata, and social hints. Such methods are heavily based on textual content and cannot apply as long as the side texts are not available. Then essentially still text-based. Some works concentrate on images or photos to analyzing, detecting, and discover the user's attributes from social networks, some of these using ontology and no fuzzy ontology methods proposed to detect user interest. Our work proposed a novel framework to detect travel interest from social network images used a fuzzy ontology Prediction System (visual data).

## IV. Problem definition

This paper concentrates focus on the analysis of social images which is a well-known sort of media within social networking. Figures10 and11 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 analyze social images from images that users shared on their Facebook accounts.

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

## V. Deep fuzzy ontology travel interest system (DFOTIS)

In this paper, A new deep fuzzy ontology framework is proposed that describes the discovery of travel user interests based on Sudanese images on Facebook. This system is called (Deep Fuzzy Ontology Travel Interest System (DFOTIS)) Focused on using CNN architectures, FiRE fuzzy ontology. Figure 2 shows the (DFOTIS), 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 architecture to give the top N 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 (Table 2 shows travel interest categories ) 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.

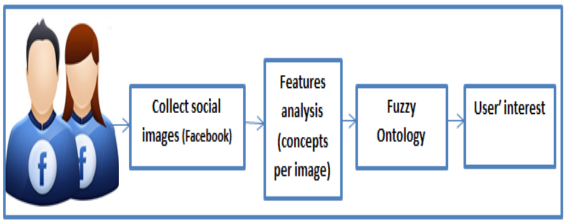



**Figure 2.** Overview of the proposed system

*Table 2.* Travel interest categories

| | | |
|---|---|---|
| Nature | Food | Architecture |
| Art | Holydays | Events |
| History | DIY& Crafts | Celebrities |

*A. New Social Database Sudanese Facebook accounts Data collection*

Currently, creating data sets like ImageNet that contain a large number of images, especially social images within social networking sites across the Internet, is an important issue. One of the challenges addressed in social network analysis is the concept of social data collection available on the social network Facebook.

A social photo visual database was created with 120 Sudanese Facebook accounts, with 25 social photos 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. Table 3 shows how many images per class. Figure 3 shows Image samples from some topics of interest on Sudanese DB, Samples from the datasets for training and testing are shown in Figure 4 (a) and Figure 4 (a).

*Table 3.* Travel interest Topics in Sudanese Facebook DB

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

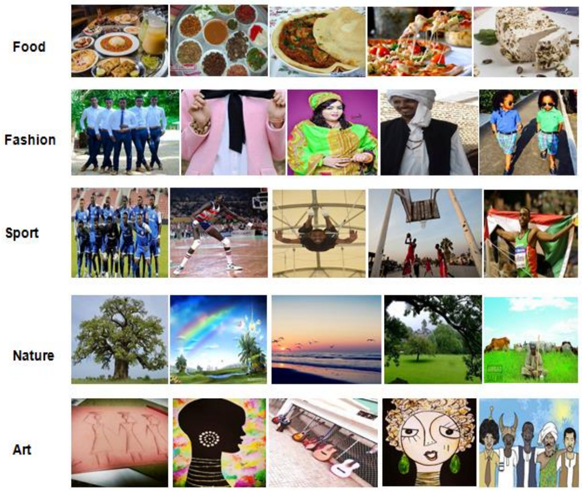



**Figure 3.** Image samples from some topic of interests on Sudanese DB

(a) (b)

**Figure 4.** (a) and (b). Samples of images from training and testing sets of Sudanese DB

*B. The concept of visual Classification using Deep Learning based on neural network structures (CNN)*

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 7years. 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 [1].

Convolutional Neural Networks and ordinary Neural Networks are nearly alike with the specific sort of feed-forward networks. The models were merely designed to stimulate visual cortex actions.

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 Pretrained CNN models with Caffe to extract visual features, then we use the softmax classifier.

In this work, we applied two models that were previously trained on ImageNet Large Scale Visual Recognition (ILSVRC) dataset.

*1) VGG'19 Architecture*

The VGG19 [17], 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.

*2) GoogleNet Architecture*

The GoogleNet [18] 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.

Table 4 illustrates a comparison between the main CNN architectures based on the numbers of layers, filters, and parameters for GoogleNet and VGG'19 architectures.

*Table 4.* CNN's Architecture comparison

| **Architecture Features** | **GoogleNet** | **VGG19** |
|---|---|---|
| Input Image | 224*224*3 | 224*224*3 |
| ConvLayer | 22 Convlayers | 16 Convlayers |
| 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 |

*C. Ontology construction*

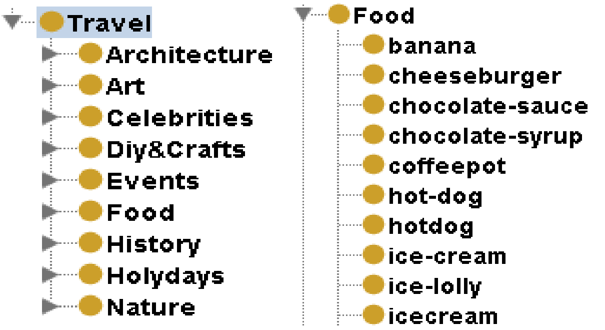
User interest ontology is constructed based on the images' objects extracted from the Sudanese Facebook database, besides, to apply a unified database as inputs to CNN models to identify objects to extract database objects that will be concepts in the ontology.

Protégé-OWL 4.3 is used to build an ontology, which is a free open source platform that provides equipment for creating domain models and applications of a knowledge base nature with ontology. For the object recognition, we used pre-trained CNN GoogleNet, [19] architectures stage outputs as input to ontology. To create this user ontology, researchers start by identifying the travel interest categories through describing the consequent ontological classes as illustrated in Table 2. were divided into nine classes, Nature, Food, Architecture, Art, Holidays, Events, History, Celebrities, DIY and Crafts, figure 5(a) show the ontology 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, figure 5(b) illustrate images concepts(sub-classes), 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 [19] CNN architectures on Sudanese social images. The development of ontology seems to be both an art and a deep understanding of engineering processes [20, 21]. Figures 6,7 and 8 show travel ontology construction.

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 Facebook accounts.

To assess our ontology, a novel database of shared photos was created in Sudanese Facebook accounts.



(a) (b)

**Figure 5.** (a). Users interests ontology-based CNN architectures, (b) images concepts(sub-classes), obtained by CNN architectures

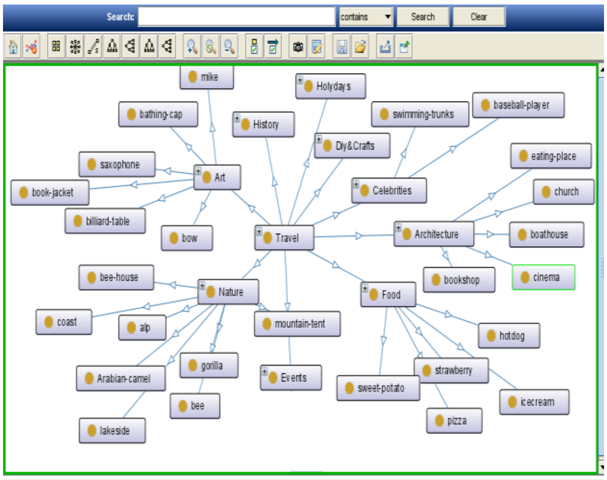



**Figure 6.** Proposed users interest ontology (super-class and sub-class)

*D. Proposed deep fuzzy ontology*

The Ontology building process is based on three sequential processes respectively known as Conceptualization, discovery, and inference. Figure 7 shows the process of building a fuzzy ontology.

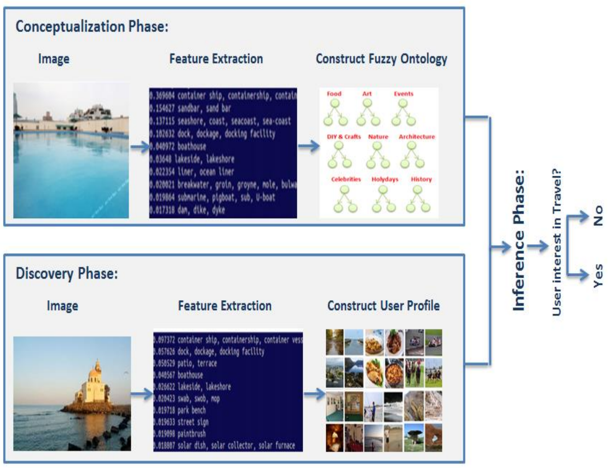



**Figure 7.** DFOTIS for user interest travel ontology

Conceptualization process for user interests fuzzy ontology prediction system construction. At this process Pre-trained, CNN GoogleNet architecture enables 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, and 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 architecture directly detects 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. Reference [5] uses 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.

*E. Fuzzy ontology construction*

The fuzzy ontology includes a physical performance, formal labeling, classification definition, properties, concepts relation, data, entities that authenticate one domain, many domains, or all domains.

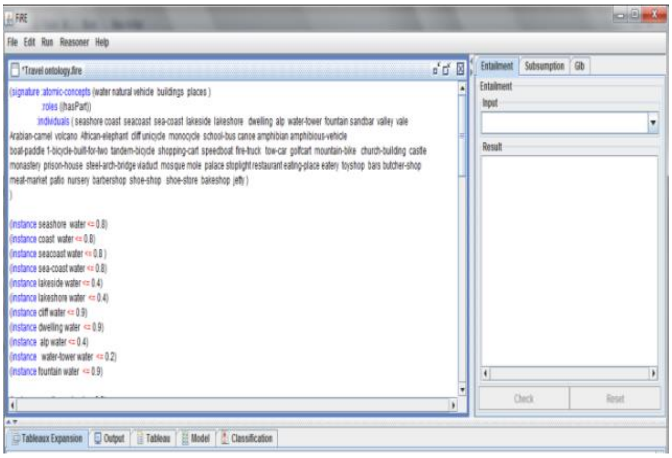


**Figure 8.** The design of rules and memberships for a fuzzy ontology

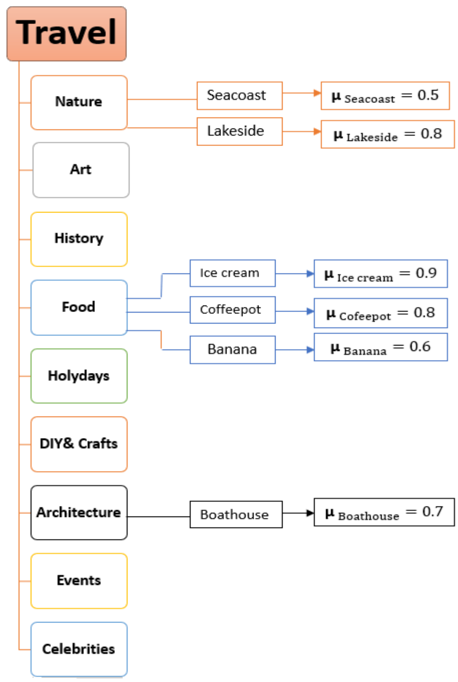



**Figure 9.** Example of fuzzy ontology with the membership function

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. FiRE is research software based on the fKD-SHIN. Currently, support on broader ideas enclosure for fuzzy description logics is implemented, to extend its expressiveness.

FiRE is a prototype JAVA implementation of a fuzzy algorithm for an expressive fuzzy DL language. Figure 8 shows the FiRE user interface and figure 9 shows a fuzzy ontology with membership function.

## VI. Experimental study

### A. Training databases

In this research, the ImageNet database [22] (which is a popular dataset for detection and classification) is adopted and we use constructing a visual social images database contains Sudanese Facebook accounts (as mentioned in figure 3 and figure 4) to make it suitable for Sudanese society, this dataset contains images for the task of detection and classification. Figure 10 shows samples of the ImageNet dataset.

**Figure 10.** Examples of images from ImageNet [22]

### B. Experimental results

The results are implemented in 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, and Java toolbox software to get final results. This section deals with explaining the experimental outcomes extracted by the chosen methodologies. As mentioned above, the experiment has been conducted on travel user interest discovery. Our experimental has 120 Sudanese Facebook accounts (for training) and comprises 25 images per account, 60 Sudanese Facebook accounts for testing (25 images per account) 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 others but all results very close to user interest in travel. To evaluate our framework performance, we apply five evaluation measures criteria. Figures 11 and 12, illustrate the confusion matrixes obtained when we achieve our method on the Sudanese Facebook accounts database.

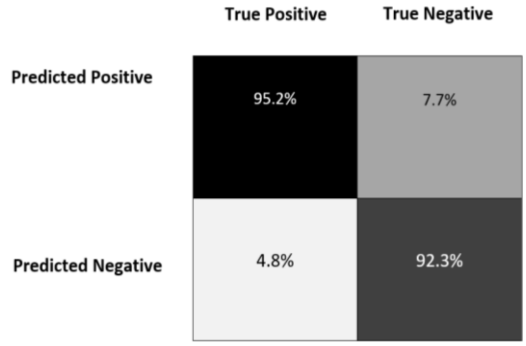



**Figure 11.** Confusion Matrix for Travel Interests Classification using GoogleNet on the Sudanese Database.

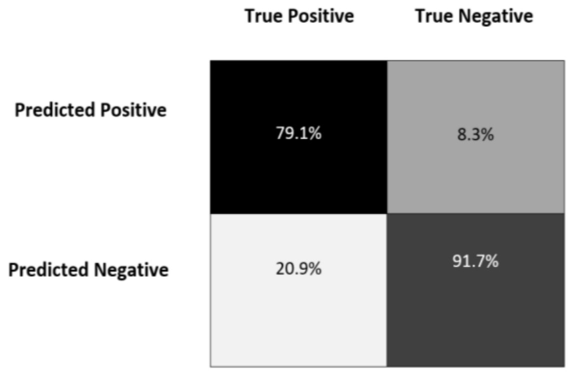



**Figure 12.** Confusion matrix for classifying travel interests using [19] architecture on the Sudanese database.

Table 5 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 taxonomic performance and improvement compared to [19]. Table 6 shows the accuracy of the travel interest classification for our approach to the Sudanese user account on Facebook using ontology and table 7 shows the accuracy of the travel interest classification of our approach to the Sudanese user account on Facebook using fuzzy ontology.

Table 5. The Accuracy assessment measures the values from the obtained confusion matrix.

| Sudanese DB | DFOTIS | [19] |
|---|---|---|
| Accuracy (ACC) | .93 | .87 |
| Specificity (SP) | .97 | .86 |
| Precision (PRE) | .95 | .80 |
| False positive rate (FPR) | .03 | .14 |
| Error Rate (ERR) | .06 | .13 |

Accuracy (ACC) = TP+TN/ (TP+TN+FN+FP) (1)
Specificity (SP) = TN/ (TN+FP) (2)
Precision (PRE) = TP/ (TP+FP) (3)
False positive rate (FPR) =FP/(TN+FP) (4)
Error Rate (ERR) = FP+FN/ (TP+TN+FN+FP) (5)

*Table 6.* Accuracy classify travel interests of our approach on a Sudanese user's Facebook account using ontology

| | DFOTIS | [19] |
|---|---|---|
| Sudanese DB | .82 | .79 |

*Table 7.* Accuracy classify travel interests of our approach on a Sudanese user's Facebook account using fuzzy ontology

| | DFOTIS | [19] |
|---|---|---|
| Sudanese DB | .93 | .87 |

As previously stated in the results section in(Table4), A classification rates of 82% has been achieved and 79% users correspondingly GoogleNet and [19] CNN architectures on Sudanese Facebook users using ontology and in (Table 6) classification rates of 93% and 87% using respectively GoogleNet and [19] CNN architectures on Sudanese Facebook users 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 [19].

*C. Discussion*

In this section of the discussion, we will try to discuss the performance of DFOTIS based on the content of the images and give some examples of misclassification and true classification. We examine our proposed system by illustrating the travel users' interest’s focused on nine categories according to the number of shared images by them on Facebook. From table 7, we found that DFOTIS is the most for users' interest prediction with high accuracy in the travel user interests, The reason for misclassification is, the users which have shared images processed by computer programs are more likely to change the output class to any other class.

Figures 13 and 14 illustrate random examples of true and false results that our system classified.

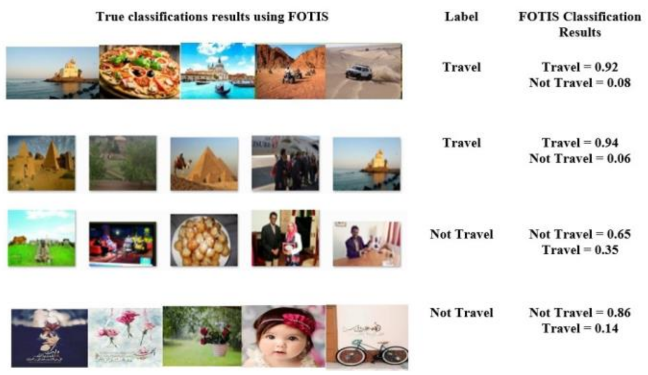



**Figure 13.** Random examples of true classifications

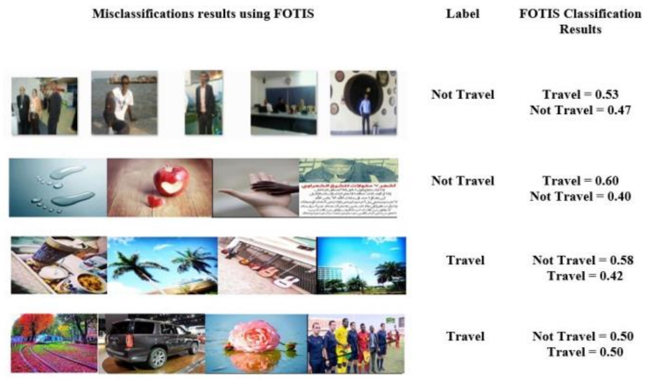



**Figure 14.** Random examples of false classifications

## VII. Conclusion

To understand user trends to efficiently extract information about their preferences on a specific topic such as travel, the system is necessary as is the case in many recommendation systems. Given the shared group data for social media like Facebook, the research relied on understanding whether the user was interested in the topic of travel. To achieve this, a proposal was made for a travel interest rating system created on CNN architectures to identify visual objects from Facebook posting and a fuzzy ontology prediction system constructed by a well-known ImageNet database. The proposed system might be expanded to include more topics of interest to the user such as sports, food, fashion, etc. At present, the researchers are dealing with a more inclusive database of social photography. With larger training, data may help improve recognition performance especially in people interesting.

More attention is given to the fuzzy ontology approach as it is assumed that it might generate worthy outcomes that can reveal more about user interest such as sports, culture, food, fashion, religion, and political opinion, we running our approach using Sudanese Facebook accounts database also it is recommended to use other Sudanese social images database. 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.

## Acknowledgment

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