Tourist Spot Recommendation from Images Based on Age Group and Location for Dubai using Deep Transfer Learning

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***Abstract*— Tourism is an important sector which can boost the economy of a country. Tourist recommender systems are used to provide recommendations to tourists based on their preferences. The prime challenge a tourist face while visiting tourist spots in a country is in determining a tourist spot to visit next that best suits their age. This paper proposes a deep learning-based system called TSR-Net that recommends next tourist spot from images of a tourist in Dubai by predicting the age group and the current tourist spot. TSR-Net uses two pretrained MobileNet models for this purpose. One MobileNet predicts the age group from the image and the other MobileNet identifies the current tourist spot from the image. Once the age group and the current tourist spot are identified the next suitable tourist spot is recommended to the tourist. The TSR-Net is applied to datasets to evaluate its performance on age group classification (AGC) and tourist spot detection (TSD). Results proveed that the proposed model achieved the best accuracy of 82% and 100% for AGC and TSD. The proposed model was also tested on a custom dataset and showed satisfactory results. The TSR-Net classifies a person into one of 3 age groups (less than 18, 18-45, more than 45), identifies 4 tourist spots in Dubai, UAE (Burj Khalifa, Burj Al Arab, Atlantis, Ain Dubai) and recommends 20 different places. Thus, the proposed model will help tourists visit appropriate places according to their age and present location.**

Keywords—Recommendation, Tourism, Pretrained models, MobileNet, Deep Learning

I. INTRODUCTION

Tourist industry denotes to a venture which includes non-permanent migration of any person or group of people to other places excluding the places where they live.It's among the significant sectors in this globe, and many countries economy rely on tourism.It's a vast industry, which has many different industries,for example:hotel business,transportation sector, and others.It's very important to understand that holiday business is correlated to movements to numerous places operated by collections of travel motivations, including business and fun. Tourism has numerous benefits, comprising economic gains for nations which extract large numbers of tourists due to the money they spend on both their actual stay and on local businesses. Additionally, it gives rise to jobs for those employed in the transportation and hospitality departments[1]. In the 20th and early 21st century arranging a trip would take a lot of hard work which included contacting hotel's for reservation, arranging transport and contacting tourist spot guides [2]. But, tourism sector has evolved in the current years which has caused the field to become more dynamic and user controlled.

Dubai is a popular tourist destination and tourism is one of the significant sources of income for the city. In 2018 Dubai was the fourth most explored city in the world [3].Tourism is among the main economic drivers of Dubai as to keep inflows of foreign currency to the emirates [4]. In 2017, the tourist industry generated $41 billion in GDP, or 4.6% of the total revenue, and supported 570,000 jobs, or 4.8% of all employment [5]. Between 2007 and 2017, the sector's GDP contribution increased by 138%. With the intention of bolstering the tourism portfolio, the UAE Cabinet approved the foundation of the "Emirates Tourism Council" in January 2021 [6].

Recommendations systems (RS) display the most appropriate goods, services, or other offerings to users by anticipating their interest in a good or service based on past behaviour and interactions between goods and users. RS have been used for recommending movies, music, course, literature, items, people, links, location, healthcare, agriculture and tourist spots. RS can be classified into 3 types: Content based, collaborative filtering based and Hybrid recommendations [7]. Content based RS provides recommendations based on the features of the objects and the user's profile. Collaborative recommender systems pile suggestions of objects or ratings, identify resemblance among the users on the basis of their views, and give rise to new recommendations based on inter-user comparisons. A hybrid RS combines the features of both content and collaborative approaches. There are several tourist recommender systems (TRS) developed in the recent past based on content based, collaborative filtering, context and hybrid models [8].

Tourist attractions cater to different needs of individuals like calm and relaxing environment, devotional, cultural, leisure and adventure. While visiting a country, travelers usually have a list of tourist attractions to be visited in that country. But, availability of transportation, travel time, and time spent at tourist attractions hinder tourists to visit many attractions. Often, tourist fail to have a clear idea regarding the worthy attractions to be visited according to their age and current location [9]. It should be noted that age is an important factor when it comes for visiting tourist spots as individuals in an age group have their own preferences and each individual is affected in different ways [10].

The tourist spot recommendation systems (TSRs) proposed in the literature did not provide tourist recommendation to a person who was already in a tourist spot and would like to know the next appropriate tourist spot to visit. Also, they did not consider the age of the person while providing the recommendation. Hence, this research presents a deep learning-based system called tourist spot recommendation network (TSR-Net) that can assist tourists by providing recommendation of the next tourist spot that could be visited provided their current location in the form of an image. Since Dubai is considered one of the finest tourist destinations, and is the world's 4^{th} most visited city , this work, deals with providing "the next tourist spot" recommendation for a tourist in Dubai. The process starts when a user inputs an image of a person standing in front of a tourist spot to the TSR-Net. The TSR-Net uses two pretrained models. The first pretrained model identifies the age group of the person and the second pretrained model identifies the current tourist spot where the person is. Depending on the outputs (age and current tourist spot) from the pretrained models, "the next tourist spot" recommendation is made. The recommendation will be the most appropriate tourist spot that the person might want to visit immediately. The two models are trained separately for two different purposes: The first model has been trained on facial images and upper body images of persons. The model is used to identify the age group of a person from the input image. While the second model has been trained on images of four famous tourist spots in Dubai, UAE like Burj Khalifa, Burj Al Arab, Atlantis and Ain Dubai. This model is used to identify the tourist spot from the input image. Though this work presents a primitive approach for TSR, it could be enhanced in future.

The organization of the paper is as follows: Related work is discussed in Section II. Data collection and preprocessing is given in Section III. The methodology is discussed in Section IV. Experimental setup, experiments and metrics are in Section V, Results and discussion are presented in Section VI and Conclusion is given in Section VII.

II. RELATED WORK

As the approach of our model dealt with recommending tourist spot based on age group classification and detecting tourist spots.So we had done a literature survey on the past tourist spot recommendation system and age group clssification.To recommend tourist spots with the help of machine learning algorithms [12] had implemented popularity-based,collaborative-based,nearby place weighted recommender system and these techniques provided a personalized and customized list of similar places with respect to places of interest to the users. In [13] Puri tourism recommendation method was deployed based on the SOM architect, and by profit management system and a complete contrast had been described among supervised and unsupervised machine learning technique for tourism recommendation in Puri. Authors of [14] have dealt with a prediction problem which revolves around historical visiting sequences of tourist's and used a supervised learning algorithms i.e Random forest.Performance of LambdaMART, Ranking SVM, ListNet and RankBoost was highlighted among which Random forest performed the best.Tour Recommendation System Based On Web Information and Gis has been presented in [15].Information recommendation and filtering techniques had been studied and proposed a route search system for tourist's which wasn't limited to suggest the path simply connecting several tourist spots,but also effeciently recommends the path with beautiful scenic sights. Mobile recommender systems in tourism has been discussed in [16].Systematic approach had been used to review the state-of-the-art in the field and ultimately they proposed a classification of mobile tourism recommendation sysytem. It also highlighted challenges and promising research directions with respect to mobile RSs employed in tourism.Traveler's recommendation system using data mining techniques had been developed in[17],need, interest, hobbies are to be specified by the user and then the model will give suggestions like best places to travel closer to his current location, points according to season, hotels, route based on his/her interest, so that a good holiday could be planned by the user without any further guidance..

To classify age groups using facial images [18] has highlighted the performance of 4 pretrained Convolutional Neural Networks (CNNs): InceptionV4, Resnet50, Resnet101 and squeeze 1_0. Images were resized to (224,224,3).Best training result was acquired by InceptionV4 which was 91.60%. Authors in [19] mainly concerned the estimation of facial attributes namely age and gender from images of face. They presented a robust face alignment technique which explicitly considered the uncertainties of facial feature detection with the help of deep belief networks and acquired an accuracy of 78.2%. The Label Distribution Learning (LDL) used as ground truth age label encoding is discussed in [20]. At first LDL used gaussian distribution concept to encode age label. Then, gaussian distribution distributed one true age to a class. Finally, Xception model was trained on IMDB and attained mean absolute error (MAE) of 3.628. Pretrained ResNet50 was used for automatic age estimation by CNN. It obtained an MAE of 4.49 [21].

In [22] Age estimation on low quality face images are done by Densenet and Xception are modified with Depth wise separable conditions convolutions for replacing original connected layers and their proposed model achieved MAE of 7.87. Authors of [23] compared training strategies such input normalization, data augmentation, and label distribution. A hierarchy of deep CNNs is evaluated, which initially classifies participants by gender before predicting age using distinct male and female age models. The accuracy of gender recognition was 98.7%, with an MAE of 4.1 years.

The goal of [24] was to build a model which matched up visuals and human input to propose vacation spots. The system searched a database for locations that share the required visual features based on the user's input of either a snapshot of the desired scenery or a keyword defining the location of interest. Recommendations for tourist destinations were generated by comparing the query against the representative tags or representative photos.

It could be noted from the literature that there has been no previous works on providing tourist spot recommendation based on age groups and current tourist spot where the person is standing. So, this research attempts to provide a solution to this problem by providing appropriate recommendations based on age group and current tourist spot from images.

III. DATASET

A. *Data Collection*

The images for this study are collected manually and organized into two datasets. The first dataset is the age group dataset which contains images collected from online resources and from UTK face dataset [25]. The second dataset is the tourist spot dataset which contains images taken from online resources.

The age group dataset consisted of 15,039 images of people divided into 3 age groups (classes) as follows: Minor (Class 0. It comprised of images of people whose age is below 18), Adult (Class 1. It comprised of images of people whose age is between 18 and 45) and Senior (Class 2. It comprised of images of people whose age is above 45). Table I shows the number of images in each class. Out of 15,039 images 8,500 images are collected from internet sources and the rest are images from UTK face dataset. Fig.1 shows few images from the dataset. The dataset has been split in the ratio of 80:10:10 for training, testing and validation.

The tourist spot dataset comprised of 4,000 images of tourist spots like Ain Dubai (Class 0), Atlantis (Class 1), Burj Al Arab (Class 2) and Burj Khalifa (Class 3). Table II shows the total number of images in each class. Few images are taken from online resources and some are taken manually by the authors. The images in the tourist spot dataset has been split in the ratio of 80:20 for training and testing. Fig. 2 provides an overview of images from the dataset.

In order to evaluate the recommendations generated by the TSR-Net for a particular age group and tourist spot, we collected a custom test dataset which included people of the above mentioned age groups standing in front of any one of the 4 above mentioned tourist spots. Fig. 3 shows few images from the custom test dataset.

Fig.1. Sample images from the age group dataset

Fig.2. Sample images from the tourist spot dataset

Fig.3. Sample images from the custom test dataset

TABLE I. AGE GROUP DATASET – DISTRIBUTION OF IMAGES

Class	**Age Group**	**Age**	**Number of images**
Class 0	Minor	Below 18	3630
Class 1	Adult	18 to 45	7206
Class 2	Senior	Above 45	4203

TABLE 11. TOURIST SPOT DATASET – DISTRIBUTION OF IMAGES

Class	**Tourist spot**	**Number of images**
Class 0	Ain Dubai	840
Class 1	Atlantis	1132
Class 2	Burj Al Arab	1078
Class 3	Burj Khalifa	950

B. *Data Preprocessing*

Preprocessing is the essential stage for any image processing system. The images from both the dataset were preprocessed using the Adobe Lightroom software. The images from the dataset are initially resized according to the requirements of the pretrained models. The region of interest (face/tourist spot) is then extracted from the images. This is followed by removal of text and watermarks from the images and brightness of each image is increased. Fig.4 shows the original and preprocessed images from the age group dataset and the tourist spot dataset respectively.

Fig.4. Sample images before (left) and after (right) preprocessing

IV. METHODOLODY

This work presents the TSR-Net model which will recommend a tourist spot based on a person's age group and current tourist spot where the person is standing. The TSR-Net comprises of two sub-systems: the age group classification (AGC) sub-system and the tourist spot detection (TSD) sub-system. The AGC and TSD sub-systems work in tandem to provide the final recommendation. The pretrained MobileNet deep learning model is used by the AGC and TSD sub-systems. During the training phase, the

AGC sub-system is trained on the age group dataset in order to enable the system to classify the image of a person into one of three age groups. Similarly, during the training stage, the TSD sub-system is trained using the tourist spot dataset in order to enable the system to identify the tourist spot from the input image. During the testing phase, when a query image of a person in front of a tourist spot is input to the TSR-Net, it is processed by the AGC sub-system and the TSD sub-system. The AGC sub-system predicts the age of the person in the image and the TSD sub-system identifies the tourist spot. The age and the tourist spot information predicted by the sub-systems are then fed to a tourist spot recommender module which provides the necessary tourist spot recommendation to the person. Fig. 5 and Fig. 6 show the training and testing phases of the TSR-Net Model. The following subsections detail the various modules of the proposed model.

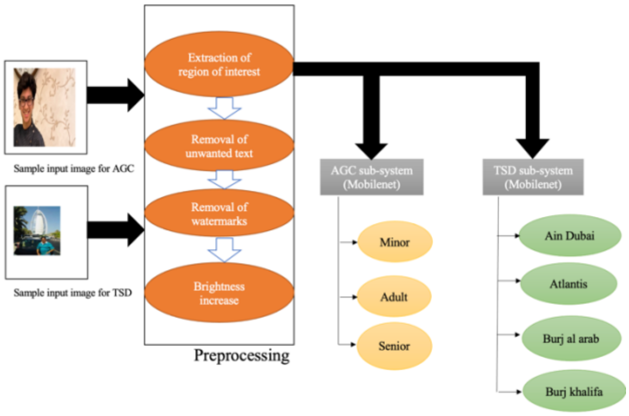

Fig.5. Training phase of TSR-Net

A. *Age group classification and tourist spot detection sub-systems*

As mentioned earlier, the age group classification and tourist spot recommendation sub-systems use a pretrained MobileNet model for predicting the age group and identifying the tourist spot. A pretrained model is one which is already trained on a huge dataset to solve a specific problem. Transfer learning is a technique of using a pretrained model for solving another related problem. This section explains the MobileNet model in detail.

The MobileNet is a deep convolutional neural network (CNN) introduced by Google in the year 2017 [26] which was primarily created to benefit mobile applications. The size of MobileNet is 16 MB with 4.3 million parameters. MobileNet uses depthwise separable convolutions which includes depthwise convolution and 1x1 point wise convolution. This lowers the number of parameters and increases the efficiency of the model. The depthwise convolutions apply a filter to every input channel. The pointwise convolution combines the feature maps to create a new feature map.

The MobileNet architecture initially has a convolutional layer followed by a depthwise convolutional layers. In a depthwise separable convolutional layer, the 3 x 3 depthwise convolution layer and the 1 x 1 pointwise convolutional layer are succeeded by a batch normalization and ReLu [27]. The depthwise convolution handles down sampling using strides. After the final convolutional layer an average pooling layer with kernel size of 7 x 7 is present. This is followed by a fully connected layer with 1024 nodes. In a fully connected layer, a node receives it's input from all the nodes of the previous layer.Finally, the output layer succeeds the fully connected layer. The original output layer of the MobileNet had 1000 nodes and softmax activation function. Table III shows Resource per layer type.

TABLE III. RESOURCE PER LAYER TYPE

Type	**Parameters**
Conv 1 x 1	74.59%
Conv DW 3 x 3	1.06%
Conv 3 x 3	0.02%
Fully Connected	24.33%

B. *Tourist Spot Recommender*

The output from the age group classification and the tourist spot identification sub-systems are fed to the tourist spot recommender. Based on the age group and the current tourist spot, the TSR outputs an appropriate tourist spot as recommendation to the user. Table IV shows the recommendations provided with respect to an age group and current tourist spot by TSR-Net. The recommendations in Table 3 is obtained after conducting survey by the authors in Dubai, UAE.

TABLE IV. TOURIST SPOT RECOMMENDATIONS

TOURIST SPOT/AGE GROUP	**Below 18**	**18 to 45**	**Above 45**
AIN DUBAI	• Rock republic climbing walls	• The green planet • Hysteria Haunted house	• Big bus Dubai sight • Aquarium Dubai mall
ATLANTIS	• Aquaventure water park	• Ski Dubai • Thrillzone Lasertag	• Lost chambers aquarium
BURJ AL ARAB	• Virtual worlds gaming	• RIB Speed boat sight • IMG World • Ferrari world	• Cruise dinner
BURJ KHALIFA	• Global village	• Dessert Safari • Dubai frame • Bollywood Park	• DXB museum

C. *Model Training*

The MobileNet model pretrained on ImageNet was used in this work. In order to finetune the model on the age group dataset and the tourist spot dataset, the last 10 layers of the model was set as trainable while the other initial layers of the model were frozen. Two fully connected dense layers were added on top of the model. The first dense layer had 1024 nodes, ReLu activation function and 0.2 dropout. The second dense layer had X nodes and softmax activation function. X denotes the number of classes. For the age group classification task, X was set as 3 and for the tourist spot detection task, X was set as 4. Adam optimizer was used as it is faster and the learning rate was set as 0.0001. The model was trained for 70 epochs for age group classification and tourist spot detection.

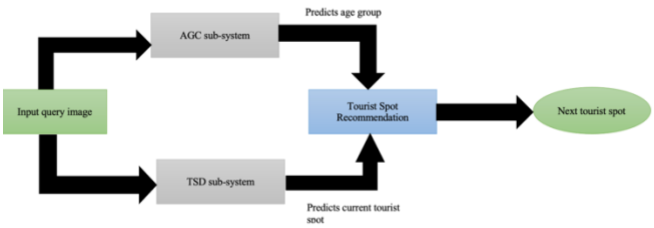

Fig.6. Testing phase of TSR-Net

V. IMPEMENTATION, EXPERIMENTS AND METRICS

A. *Implementation*

The TSR-Net was implemented using Tensorflow with Python 3.7.13 and Google Colaboratory (CoLab) Pro which is an interactive Jupyter development notebook. In addition, numpy, scikit, pandas, warnings, glob, random and matplotlib libraries were used. A Tesla T4 GPU was used to run the programs.

B. *Experiments Conducted*

Experiments were conducted on 5 other pretrained CNNs to identify the best model for age group classification and tourist spot detection. The pretrained models used in the experiments are:EfficientNetB0 [28],EffecientNetB1[28], NasNetMobile [29], EffecientNetB2V2 [30] and DenseNet121 [31]

C. *Metrics*

All the models are evaluated using the following metrics.

*a) Accuracy:*It is calculated by dividing the number of correct predictions by the total number of predictions and is given by equation 1.

$$\text{Accuracy} = \frac{\text{Correct predictions}}{\text{Total predictions}} \quad (1)$$

*b) Precision:*It is defined as the number of instances that are true positives over all the examples that were predicted to fall into a particular class and is given by equation 2.

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}} \quad (2)$$

*c) Recall:*It is defined as the number of instances that are true positives over all the examples that truly belong to a particular class and is given by equation 3.

$$Recall = \frac{True\ positives}{True\ positives + False\ negatives} \quad (3)$$

*d) F1 score:*It combines both precision and recall into a single measure and is given by equation 4.

$$F1\ score = \frac{2 * Precission * Recall}{Precision + Recall} \quad (4)$$

VI. RESULTS AND DISCUSSION

A. *Performance analysis of AGC sub-system*

Table V shows the accuracy, precision, recall and F1 score of the various models for the age group classification task. It could be seen from the table that the MobileNet model obtained the best testing accuracy, precision, recall and F1 score of 0.82, 0.82, 0.80 and 0.80 respectively. The EfficientNetB2 model achieved an accuracy of 0.81, and precision, recall and F1 score of 0.80. EfficientNetB1 and DenseNet121 exhibited the same performance for accuracy and F1 score of 0.80 and 0.79 respectively. EfficientNetB0 achieved an accuracy of 0.79 while the worst results were obtained by NasNetMobile with an accuracy of 0.73.

B. *Performance analysis of TSD sub-system*

Table VI shows the accuracy, precision, recall and F1 score of all the pretrained models on the tourist spot dataset. It could be seen from the table that the MobileNet achieved an accuracy of 1.0 and precision, recall and F1 score of 0.99. The EfficientNetB0, EfficientNetB1 and EfficientNetB2 exhibited an accuracy of 0.99. DenseNet121 attained an accuracy of 0.98 and NasNetMobile model had the least accuracy of 0.91.

TABLE V. RESULTS FOR AGE GROUP CLASSIFICATION

Models	**Accuracy**	**Precision**	**Recall**	**F1 score**
MobileNet	0.82	0.82	0.80	0.80
EfficientNetB0	0.79	0.80	0.79	0.78
NasNetMobile	0.73	0.77	0.69	0.72
EfficientNetB1	0.80	0.80	0.79	0.79
Densenet121	0.80	0.81	0.78	0.79
EfficientNetB2	0.81	0.80	0.80	0.80

TABLE VI. RESULTS FOR TOURIST SPOT CLASSIFICATION

Models	**Accuracy**	**Precision**	**Recall**	**F1 score**
MobileNet	1.00	0.99	0.99	0.99
EfficientNetB0	0.99	0.99	0.99	0.99
NasNetMobile	0.91	0.95	0.96	0.95
EfficientNetB1	0.99	0.99	0.99	0.99
Densenet121	0.98	0.98	0.98	0.98
EfficientNetB2	0.99	0.99	0.98	0.98

Thus, it could be seen from Table V and Table VI that the MobileNet is able to perform better than the other models for both age group classification and tourist spot identification.MobileNet achieved an accuracy of 1.00 for TSD which proved that it's architecture with fewer parameters and less processing has enabled it to achieve the best performance.

C. *Performance analysis on the custom dataset*

The performance of the TSR-Net on the custom dataset was also evaluated. Figure 7 shows a sample query input image and the corresponding recommendation provided by the TSR-Net. Thus, the results prove that the proposed methodology can achieve higher accuracy in detecting the age group of a person along with the current tourist spot and provide an appropriate recommendation. As MobileNet is a lightweight model and is optimized for resource constrained environments, the TSR-Net could be implemented in mobile devices as well.

Fig.7. Sample input image (top) from the custom dataset and the corresponding recommendation (bottom) provided by TSR-Net.

VII. CONCLUSION

This work introduced the TSR-Net which could recommend tourist spots to travelers in Dubai based on the age group and current tourist spot. This was achieved by the age group classification and tourist spot detection sub-systems which used a pretrained MobileNet model. Experimental results show that the model is able to provide appropriate recommendations for query input images. The proposed model can act as a word of mouth and help tourists to identify a tourist spot according to their age and current location. In future, the model could be extended by considering more age group classes, more tourist spots in the world and it could provide tourist a path navigator and traffic free route. The proposed work could also be extended to provide gender specific recommendations.

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