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Determining the Occupancy of Vehicle Parking Areas by Deep Learning

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Abstract—Parking a vehicle in heavy traffic situations leads to prolonged driving time, deterioration of traffic flow and therefore environmental pollution when searching for free space. Although the sensor systems in the indoor parking lots are beneficial, these systems cannot be applied to outdoor spaces. In this study, a deep learning application was developed which classifies the occupancy status of the parking spaces in outdoor parking areas. High accuracy rates were obtained in this application where transfer learning was performed using ResNet model.

Keywords—Deep Learning, Parking Lot, PKLot, CNRPark, ResNet

I. INTRODUCTION

In everyday life, it is common for almost everyone to go from one place to another with their private vehicle. Today, in the indoor parking areas, occupancy detection is made with the help of sensors and signs. Signboards indicating how many spaces are available on each floor in the parking lot are also being used. This made everybody's life easier. This work is aimed to increase the comfort in daily life by providing the same comfort and technology in outdoor spaces.

In recent years, studies have increased to determine occupancy of the car park areas. Infrared, ultrasonic and RFID sensors are used for parking area occupancy detection. However, there are various difficulties in the application of these methods to open spaces due to the varying environmental conditions. Among the solutions applicable to open spaces, microwave radar, GPS can be counted. These methods are not preferred because they are costly in implementation and sustainability[1].

Using wireless sensor networks Jihoon [2] studied this problem and developed a prototype using Google Maps and achieved good results. In general, hardware implementation in large scale outdoor car parks is difficult in such approaches. But using cameras and image processing is cost effective because there are already security cameras mounted in both streets and indoor parking areas. From one of the computer vision approaches, Ichihashi [3] have made a classifier using fuzzy c-means clustering and hyperparameter tuning by particle swarm optimization. Their system has reached a detection rate of 99.6 % for outdoor environments. Tschentscher used Support Vector Machines and DoG features to classify parking lots and reached from 92.33% to 99.96%, depending on the parking row's distance [4]. Recently, Kabak and Turgut have presented methods to detect vacant parking spaces using aerial images with SVM-based classification[5]. Raj also used image processing to solve this problem. They used Canny Edge detector to extract features from image in a particular slot, and the LUV bases colour variation detection. After extracting features all of them are given to Random Forest classifier to classify each slot into vacant or occupied and achieved 98.31% accuracy[6].

Deep learning is a solution that can be developed both in terms of applicability to open spaces and in terms of sustainability and cost. Moreover, these methods give higher accuracy results than traditional methods. Using Convolutional Neural Networks, Hoang developed their own neural network. First, they integrated a convolutional spatial transformer network (STN) to crop the local image area adaptively according to vehicle size and parking displacement. After that in order to solve inter-object occlusion problems, they've grouped 3 neighboring spaces as a unit. By implementing these methods they've reached 99.25% accuracy[7].

Another way to use CNNs is using pre-trained networks. Guiseppe, working on deep Learning with evolutionary neural networks, achieved 98% results using mLeNet and mAlexNet [8]. Mauro and his colleagues have correctly classified with VGG16 model 97.58%, AlexNet model 97.27% and GoogleNet model 99.52%[9]. Akıncı has classified with 99.9% accuracy using MobileNet model[10]. Valipour [11] also used VGGNet architecture and obtained 99.9% accuracy and made a user application for it. Ng [12] focused on application than the accuracy percentages. They didn't mention the accuracy rates but made a survey about whether this kind of application is useful or not. They also used Guiseppe's CNN training method. When looking at these studies, a high degree of accuracy was obtained in the classifications made with pre-trained models.

II. METHOD

Deep learning is a system that started to be used in 2010, it does not work with big data sets in a single layer, but in many layers, it can calculate the parameters that need to be defined in machine learning, and can evaluate with better parameters.

A. Convolutional Neural Networks

Convolutional Neural Networks has become a network structure frequently used in the past decade in areas such as

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image processing and sound processing. The most useful aspect of CNNs is to reduce the number of parameters in ANN. The most important assumption about problems solved by CNN should not have features that are spatially dependent. In other words, we do not need to pay attention to where the faces are in the pictures, for example in a face recognition application. Another important aspect of CNN is to achieve abstract features when the input spreads to deeper layers. For example, in image classification, edges can be detected in the first layers, and then simpler shapes are detected in the second layers, and higher level features such as the face in the next layers are revealed [13].

B. *Deep Learning Network Structures*

The deep learning network structure, which was first introduced by LeCun et al. with a gradient-based approach, was named LeNet [14] (1998). In the following years, ImageNet Large Scale Visual Recognition Competition (ILSVRC) started to be organized and AlexNet (2012) [15] Inception (2014) [16], ResNet (2016) [17] became winners in this contest in the relevant years. VGGNet [18] became runner up in the same competition in 2014. The MobileNet [19] architecture was designed by a group of researchers at Google and showed that such neural networks work very efficiently on mobile devices. In the literature, training was done with the other models except ResNet on the data sets used in this study. For this reason, ResNet, which has not been studied before, was chosen in this study.

***Resnet*:** Resnet is now an abbreviation of residual neural networks. With its first place in the ILSVRC competition in 2016, the 152-tier ResNet has the deepest network feature ever run on ImageNet and has 8 parameters less than VGG Net. This plays an important role in training faster. The Resnet model shows that there is a maximum threshold for depth in the conventional convolutional neural network model. As deep networks begin to converge, a distortion problem arises: as the network depth increases, accuracy reaches saturation and then drops rapidly. This model addresses the training error that increases as the network deepens.

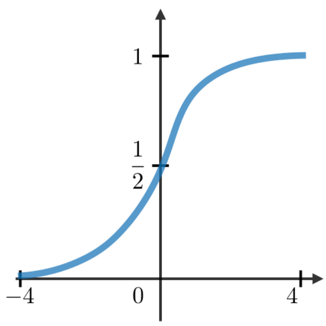

Fig. 1. Sigmoid Activation Function

One of the problems that ResNet solves is the vanishing gradient. Derivative values in the range [-4 +4] of a sigmoid activation function as in Fig. 1 produce significant values but in other regions the derivative values are very small and converge to 0. If the output of the activation function always produces "0" output, weights cannot be updated with the back propagation algorithm, so no learning is performed.

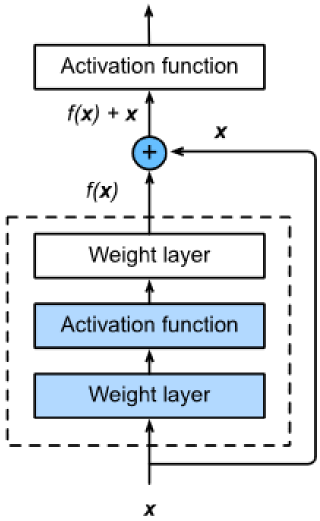

Fig. 2. ResNet Network Structure

It solves this problem as follows: As seen in Fig. 2, it adds and activates the output of the previous activation function f(x), with the input of the current activation function (x). Thus, it generates a value even if the result of the activation function of the layer before it f(x) is zero. This is a structure built on transferring the previous activation value to the output even in conditions where learning stops at the convolution outputs.

C. *Data Sets*

The datasets used are PKLot [20] and CNRPark [21] datasets that are shared as open source to support researchers' development activities. PKLot from these data sets consists of more than 700,000 parking lot views, viewed in three different weather conditions: sunny, cloudy and rainy. CNRPark, on the other hand, consists of two different cameras, approximately 13,000 parking lot images recorded under different day and light conditions. The parking lot images in both data sets are labeled to be empty or occupied. Occupied slots from these datasets can be seen in Fig. 3 and free slots can be seen in Fig. 4. In this study, a group was formed by selecting random images from the PKLot data set, and the CNRPark set was used without segmentation. For the neural network training, the images in these data sets are divided into training, verification and testing shown as in Table 1.

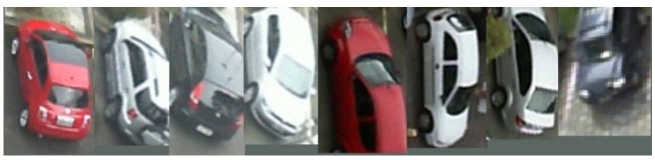

Fig. 3. Images of occupied parking lots

Fig. 4. Images of free parking lots

TABLE I. IMAGE NUMBERS IN DATA SETS

	TRAIN	VALIDATION	TEST
PKLOT	17160	5040	2244
CNRPARK	10066	3240	2518

D. *Transfer Learning*

Learning transfer is to use the knowledge learned to solve a particular problem, but in another area. It is almost impossible to perform in standard computer processors due to the training of some models, the complexity of the model or the size of the data set. That's why graphic processing units are needed. As a result of trainings that last for days or weeks, these trained models can be used in various ways to solve different problems. This process is called transfer learning. In this study, it was aimed to train only the last layer of ResNet Model and to use its trained weights on ImageNet dataset with transfer learning method.

III. RESULTS AND RECOMMENDATIONS

Images from CNRPark and PKLot datasets were trained using the ResNet50 model. Since the input layer of ResNet model takes 224x224 resolution images, the images in the dataset have been converted to this size. The last layer is average pooling layer and two categories of softmax layer are added for classification. The stochastic gradient descent optimization algorithm was selected and the learning coefficient was chosen as a decreasing function. The hardware which accessed through Google Colab consists of an Intel Xeon processor with two cores @ 2.3 GHz and 13 GB of RAM. NVIDIA Tesla K80 (GK210 chipset) is equipped with 12 GB RAM, 2496 CUDA core at 560 MHz. Keras library was used in the application. Training accuracy charts are given below. Training accuracy using CNRPark database can be seen in Fig. 5, and with PKLot database training results is in Fig. 6.

The trained models were tested by cross-test method. In this method, the network is first trained with one data set and then tested with the other. The results are given in Table 2.

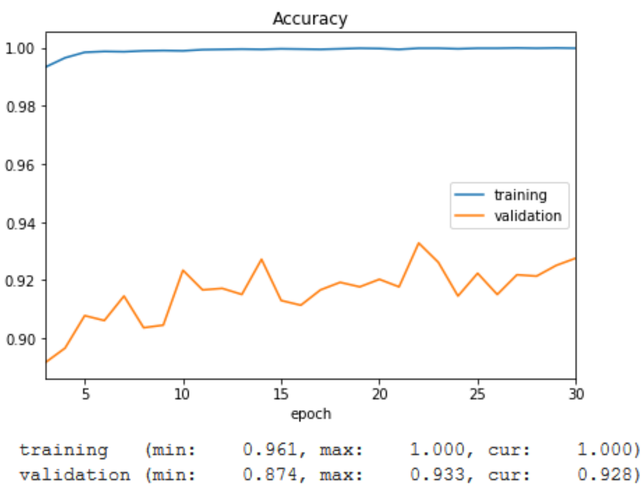

Fig. 5. Training accuracy with CNRPark database

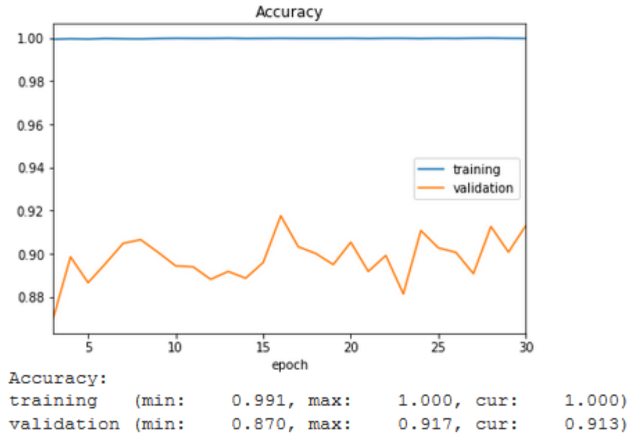

Fig. 6. Training accuracy with PKLot database

TABLE II. TEST ACCURACIES

TRAINING SET	TEST SET	
	CNRPARK	PKLOT
PKLOT	97,36%	99,82%
CNRPARK	99,52%	99,28%

IV. CONCLUSIONS

A study was carried out to solve the parking problem, which is a problem that we face almost every day in our daily lives, with cameras that will be placed in outdoor parking areas. In this study, training has been carried out with the ResNet model, unlike the studies that use deep learning method. Using the ResNet model, the accuracy rate obtained in previous studies was achieved.

In deep convolutional neural networks, the model is thought to give better results as the depth of the network increases, but in practice this is not the case. As the depth of the network increases, accuracy reaches saturation and then quickly decreases. The ResNet model provides an advantage over other models, as it optimizes the learning error that increases as the network gets deeper and provides faster training.

In future studies, it is considered a mobile application that informs the drivers by checking the free parking spaces from real-time video images.

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