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CNN BASED SMART PARKING SYSTEM

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Abstract: In the modern era, the problem of parking is also growing because of the growth in the number of vehicles. From the closing decade, numerous researches took place intending to broaden a perfect automated parking slot occupancy detection. There is an auto mechanism that can park vehicles automatically but it is required to detect which parking slot is available and which one is busy. It is proposed to design and implement a parking space detection using image processing. Images are captured when a car enters or leaves the parking slot. Computer vision techniques are used to infer the state of the parking slot given the data collected from the database. This project presents an approach for a real-time parking space classification based on Convolutional Neural Networks (CNN) using the Mask R-CNN framework. The training process has been done using MR-CNN and the output is a pickled model used for predictions to detect vacant and occupied parking slots. The system checks a defined area whether a parking slot (bounding boxes defined at initialization of the system) is containing a car or not (occupied or vacant). The proposed system indicates the great potential of this method to provide a low-cost and reliable solution to the PG (Parking Guidance) systems in outdoor environments.

Keywords: Convolution Neural Network, Parking Guidance

1.INTRODUCTION

Parking space is limited, as the number of cars increases, parking cars in the parking slot can be a daunting task. As a result, it takes a certain amount of time to find a parking space, traffic slows down, and traffic jams occur. The situation of finding a parking slot and the congestion of the parking slot is because the information on the available parking slots is not immediately available to those who are looking for a parking slot. The existing system [10,12] is based on either manual tracking or a sensor-based system. As we all know, manual tracking leads to output with low efficiency. Even though a sensor-based system has a good accuracy level it is prone to environmental factors so it is not reliable.

Therefore, different approaches have been used to develop parking management systems such as wireless sensor network systems and vision systems. This project introduces new methods run deep learning and PC-based to solve the problem of finding parking spaces in Metro City. This process has two phases. In the first stage, information such as capacity, free space, length, and width of parking space is immediately obtained from the parking space through image processing techniques and a neural network-based decision-making system in the mall, and this information is saved on the PC. In the second phase, it indicates the availability, occupied and total number of parking spaces. So, by adopting this technique it is ensured that there are no significantly outstaying vehicles due to improved enforcement methods.

2.PROPOSED MODEL

Convolutional neural network (CNN):

The main purpose of this project is to demonstrate the development of a low cost visual-based parking system that can be used to determine the location of available parking spaces and provide feedback on available locations. The core task is to train classification criteria from magnetic signals. First, the characteristics of the magnetic signal are analyzed and the characteristic variables of the fluctuating signal are calculated. Second, the classification rules are trained using the distance discrimination method, and the training data are pre-classified examples. Finally, the parking detection algorithm is designed based on classification criteria. The main theme of this project is based on **convolutional neural network (CNN)** which includes image recognition and processing which is optimized to process pixel data and it is basic building blocks for the computer vision task of image segmentation (CNN segmentation) [20].

MASK R-CNN – Architecture :

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Mask R CNN is a convolution neural network (CNN) that is at the forefront of image and instance segmentation. Mask RCNN was developed on top of Faster RCNN, a Region Based Convolution Neural Network [21] .Mask R-CNN works on the concept of image segmentation i.e Image segmentation is the process of dividing a digital image into multiple segments (pixel sets, also known as image objects). This segmentation is used to find objects and boundaries (lines, curves, etc.) [21]

Mask RCNN was created with Faster RCNN. Faster RCNN has two outputs for each candidate object, a class label and a bounding box offset, while Mask RCNN is the addition of a third branch that outputs the object mask [18,19]. The additional mask output, unlike the class and box output, requires a much finer spatial layout of the object to be extracted. Mask RCNN is an extension of Faster RCNN that works in parallel with the existing bounding box detection branch by adding a branch for predicting object masks (regions of interest).

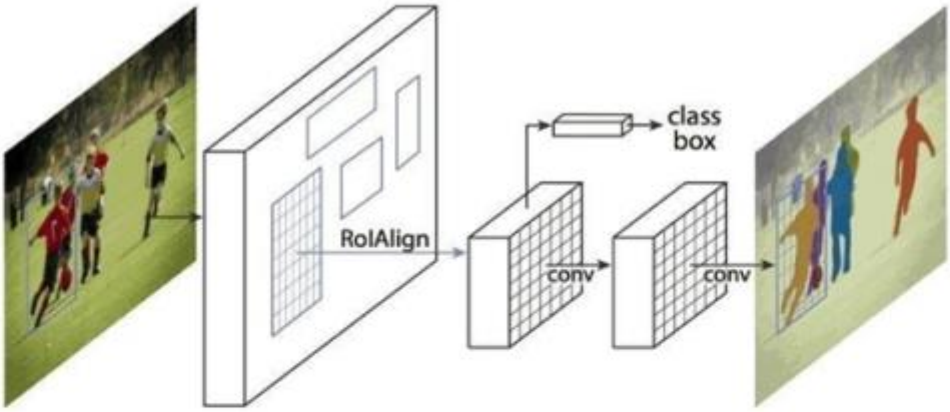

Fig 2 Mask R CNN Object Detection

CAR OCCUPANCY DETECTION USING MASK R-CNN :

If you can track the movement of a car in the image, you can identify the parked car that indicates the location of the parking space in the image. The task of identifying parking spaces in an image is called parking space detection [22]. Implementation of state-of-the-art object recognition and computer vision models based on AI research. The mask RCNN model is initialized from the model zoo. The exact name of the model is "mask_rcnn_R_50_FPN_3x".Pyramid Network Feature Extraction and uses the standard Faster RCNN architecture. The input to the object detection model is an image of the parking lot, and the output is a set of bounding boxes for each object and its categories. In this case, there is only one object. The bounding box is represented as (x1, y1, x2, y2). Where (x1, y1) is the upper left point of the box and (x2, y2) is the lower right point.

The Car Space Tracking algorithm takes the car mask RCNN-based bounding boxes detected by the model as input and compares them to the list of cars currently being tracked [22].As shown in Equation 1, the intersection over union (IOU) ratio is used to compare two bounding boxes. The IoU of two different boxes with no overlap will be 0. Their IoU increases as the amount of overlap increases. If the car is stationary, the IoU of the car's bounding box is high in consecutive frames, and if it is greater than the predefined threshold (IoU threshold), the counter of that bounding box is incremented. If the counter reaches a predefined target (frame threshold), i.e. The car will stop for a predefined time and the location will be marked as a parking space. If the input bounding box does not match any of the boxes in the list, it is a new car and will be added to the list of tracked cars

After comparing each car in the list, if the bounding box of the tracked car does not match any input, the car is not stationary and will be removed from the list of tracked cars.

$$IoU\,(Box1,\ Box2) = \frac{Intersection\_Area\ (Box1\ ,\ Box2)}{Union\_Area\ (Box1,\ \ Box2)} \qquad (1)$$

As the car moves, the IoU with the previous bounding box will decrease over time and will not be able to reach the frame threshold. The higher the IoU threshold, the more sensitive the algorithm is to small changes in the position of the bounding box. This can detect redundant bounding boxes in the same parking lot. Also, the IoU threshold should be

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high enough to ignore the intersection of adjacent parking spaces. Empirical observations show that IoU thresholds in the range of 0.350.5 gave the best results [22].

3.PROPOSED ALGORITHM

```
Input: pickle model, deploy video file, gray video and preprocessing video
Output: The actual output of vacancy and free space status = {}; Feature values holding each frame and them
          corresponding confidence of  IoU  result status = ” ”, actual values of the feature.
          while all the values and confidences of each predictions
          do
           status[confidence(i)] = confidence
           status[label(i)] = label (IoU)
           i ← i + 1
          end while
          if status[confidence0] > status[confidence1] then
result status = status[label0_IoU]
else
          result status = status[label1_IoU]
          end if
   return result status
```

Step 1:

- The system works on the fact that the video of the parking spot will represent a fixed parking lot.
- The system analyzes the parking lot after every few frames.
- A frame represents the state of the parking spot at a precise moment.
- The system works on live feed or on a recorded video

Step 2: Video Acquisition

- The image is from a parking video stored on a local workstation.
- Using OpenCV libraries, the video is read and generates frames to perform the predictions .

Step 3: Parking Slots

- The first frame of the footage (or a frame that contains mostly occupied parking spots) is used to define what a parking spot is in that current frame when the program starts.
- This technique of defining a parking spot on one frame relies on the fact that the camera will not move during the whole process of prediction and logically the parking lot does not move, only the cars are moving in or out of the different defined parking spots.
- The user clicks on the two corners of the parking space (upper left corner and lower right corner) to define the spot.

Step 4 : Prediction and classification

- After the training phase, the generated Mask CNN model comes along with pickle data containing the different label of a spot (vacant or occupied)
- This file defines the type of input allowed by the model and the protocol followed to produce the output.

4.IMPLEMENTATION AND DISCUSSION

DESCRIPTION

In this project, several processes are conducted to detect parking space. Those processes are gray conversion, filtering automatic marking of coordinate points and selection of the bounding box of each car as the detected object. The process carried out at the parking space detection stage can be seen in Fig.

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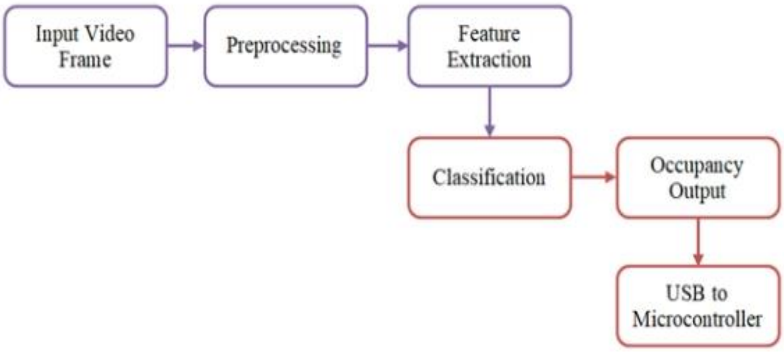

Fig.4 Proposed System Block Diagram

DATASET:

Two datasets are needed in this research. First are images of the parking area [22] from the stage of marking the area and a video from CCTV record to detect parking space availability in the parking area. The datasets that will be used are images and videos from CCTV located in the outdoor parking area. In this project, data training that we used to detect parking space is CNRPark published in 2016[22]. This dataset contains images of the outdoor parking area that are already segmented and labeled. In this dataset, each image size is 150 ×150 pixels. Data collected from CNRPark and CCTV will be used to detect parking areas automatically and detect parking space availability. The size of data testing used to capture all corners of the parking area is 1000 × 750 pixels for CNRPark [23]and 1920 × 1080 pixels for video from CCTV on the parking area at Informatics Department ITS.

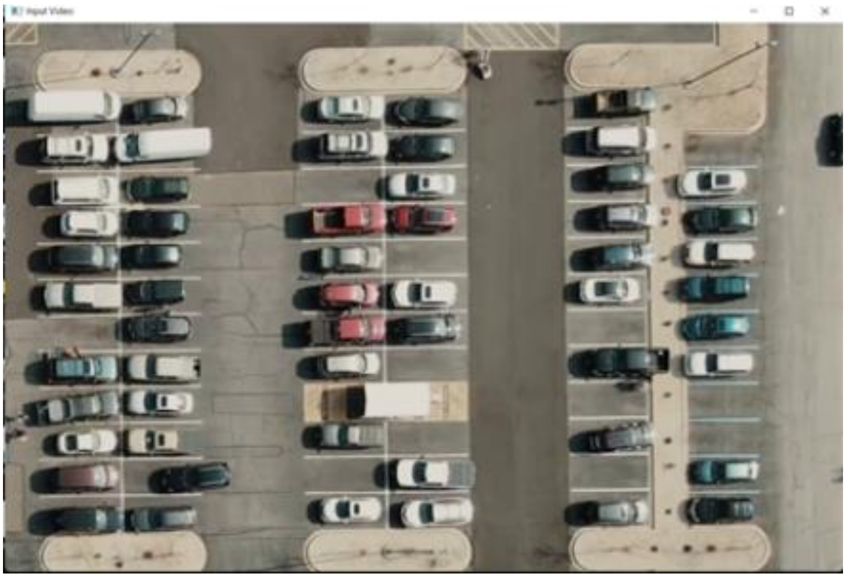

Fig.5 Input Video from CNRPark Dataset

CNRPark dataset [23] contains 1000 images taken from 5 angles of different parking areas in sunny, cloudy, and rainy days in the morning, afternoon, and night. In our project, data for videos are taken from CCTV in the parking area at the Informatics Department. It consists of 1 video with a total duration of 2 minutes taken from 1 angle of the parking area with good light conditions in our project.

PREPROCESSING:

The preprocessing framework is a contrast improvement method by putting an RGB image. The purpose of increasing contrast is to solve bad lighting problems. Contrast increasing method that has been done successfully solved low contrast problems and light distortion. Increasing exposure can show less exposed areas, but at the same time, areas that are well exposed can become overexposed.

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GRAY SCALE CONVERSION:

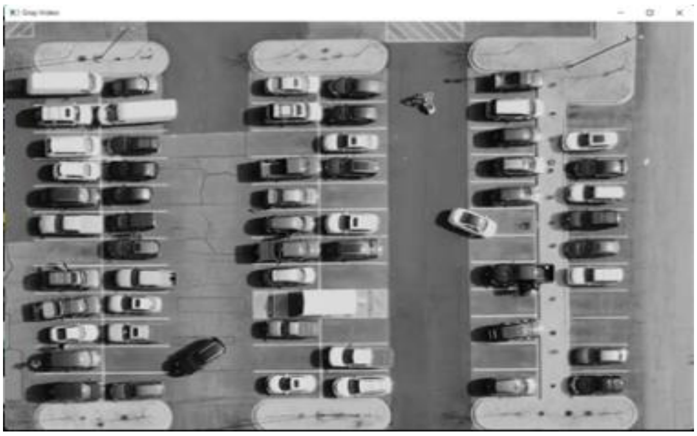

Fig.6 Gray Scale Conversion

In the phase of increasing contrast, the input image is combined with the image itself with other exposures to reduce complexity. So the input video is converted from RGB into Grayscale conversion to minimize complexity.

BLUR REMOVED VIDEO:

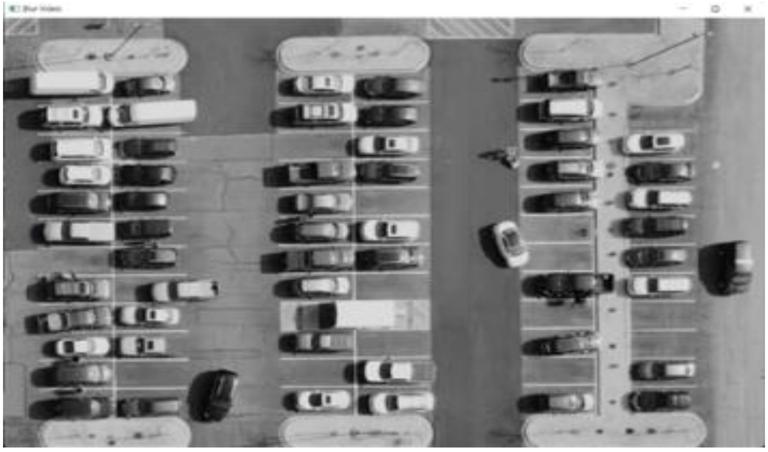

Fig.7 Blur Removed Input Video

The problem is that images with other exposure settings are not available for frame rate issues. This is because the photo was taken only once and there are no more photos with different exposures.

THRESHOLD OUTPUT

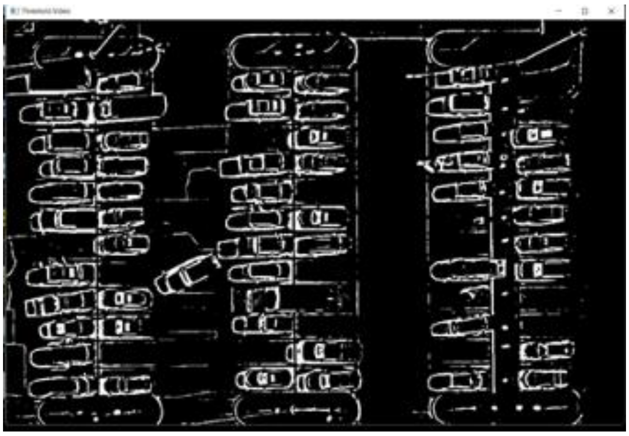

Fig.8 Threshold Output of Input Video

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Pixels that are underexposed are assigned a small weight value, and pixels that are well exposed are assigned a large weight value. Landscape lighting and weight matrix results are positively correlated with the threshold output. Pixels with good exposure are given high weight values to maintain contrast (very bright areas).

THRESHOLD MEDIAN FILTERED VIDEO

Fig.9 Threshold Median Filtered video of Input Video

Filtered optimization is needed to get a noise free estimation illumination scene map on input video. It will be done with a Median filter from the threshold output. The figure shows the Median filtered output for the threshold video output.

PREPROCESSED OUTPUT

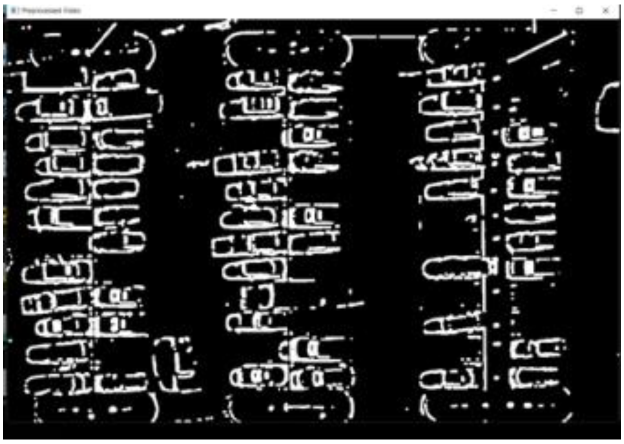

Fig.10 Preprocessed Output

In contrast to images taken with different exposures, the problem related to image enhancement can be overcome properly so that it is highly correlated between the two images. The transformation logarithm is applied to the gray value so that it becomes even broader, and Second Derivative performed to sharpen the outlines in the image. This process's results are converted into binary images and entered into the CNN. The research's deficiencies are that the researcher does not explain how the system can detect each empty or filled parking space.

PARKING SPACE DETECTION

The selection was made by taking an image of a parking area filled with cars and meeting all criteria. Obtained object detection results consisting of several classes in each image. The car object class is selected and used for further analysis. Each image consists of more than one car object (only the parking area filled with cars). Car object detection results can have obstacles in different environments. In high lighting conditions, there will be an inaccurate detection of car objects due to the reflection of sunlight. ROI's Ground Truth (GT) data and the number of cars are made from the pre-selected dataset images. The obtained area became the focus of the detection of car objects in each image.

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Fig.11 Vehicle Detection and Occupancy Output

The result of parking space detection is in the form of a boundary box for each object in the camera. Fig. 11 is an example of the results of the detection of parking spaces for each object in the input image. The results of the parking space detection analysis with the highest IoU value will be references for the next analysis in each of the test scenarios conducted. The bounding box used to cut the image caught by CCTV to determine the status of parking space availability.This project developed an automatically detecting the availability of vacant parking spaces through video data analysis in the outdoor parking area. The object detection technique detects parking spaces through the proposed approach. This system has two main stages, the first stage is marking the parking position on the image of a parking lot. We propose a Preprocessed Mask R-CNN to mark the parking position on the input image of a full parking lot.

5.CONCLUSION

The system being implemented above is much cheaper than those based on sensors as the hardware required decreases by a drastic amount. The system works on the concept of computer vision and helps the user identify the lane where a parking spot is empty which is all a user needs as whenever the user enters the lane the empty space is clearly visible.

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