# Research Diary

## Open-air Off-street Vehicle Parking Management System for IITH using Deep Neural Network

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Smart parking solution aims to output real-time parking occupancy information. It helps to reduce parking bay search time, traffic, fuel consumption, and thereby vehicular emissions with increased road safety. A computer vision-based solution using camera video data is the most reliable and rational since it allows monitoring of the entire open-air parking area at once. A real-time parking solution (cloud-based, server processing, or onboard processing) helps bring the occupancy information to the end-user.

It comes with many challenges such as viewing angles, lighting conditions, model optimization, reducing inference time, and many more real-world challenges. Also, the earlier research works focus on day-time data and do not discuss the night data. So, in this work, we perform experiments on real-time 24-hour data from an input camera video source mounted to monitor parking at IIT Hyderabad (IITH) parking lot.

The IITH parking dataset contains 24 hours of video data recorded at the IIT Hyderabad open-air parking area. We capture the video data using a Hikvision Exir mini bullet network camera at 20 frames per second with 5MP resolution. We have installed the camera at the height of 25 meters on a seven-story institute building (Block-C). The camera angle is adjusted to capture the entire parking area with 91 parking bays, as shown in **Figure 21**. We manually annotate a single frame with polygon-shaped spatial regions to capture the perfect bay areas. We use the Labelme tool for manual annotation. We monitor the spatial regions of each bay marked in the parking area for the entire duration of the video. We observe that a 10-second interval could capture a complete parking behaviour, including the peak hour occupancy. Hence, we sample the 24-hour video data at one frame out of 20 frames per 10 seconds.

This data sampling resulted in 6 frames per minute and a total of 8640 frames (24hrs x 60minutes x 6 frames per minute). Further, as each frame consists of 91 spatial parking bays, we obtain a total of 786240 spatial regions (24hrs x 60minutes x six frames per minute x 91 bays per frame) for further processing. Finally, we manually inspect each of the cropped spatial regions and bucket them into the empty or occupied categories to train a supervised deep neural network.

The dataset consists of polygon-shaped bays cropped from a set of data frames sampled from the manually annotated live-camera feed video data. Polygon-shaped bays perfectly capture the viewpoint variations caused due to the input camera angle. However, the extra black areas add noise to the polygon-shaped bay data, as shown in **Figure 22**. They are not suitable for feature extraction and model training. Hence, it is necessary to remove the noise (black areas) by transforming the polygon-shaped bays into perfect rectangular data samples, as shown in **Figure 22**. We consider the perspective transform method for our preprocessing. Further, we use perspective transform on the original polygon bay points and the above-defined four points to obtain the transformation matrix. Finally, we apply the transformation matrix to the polygon-shaped parking bays to get the transformed rectangular bays, as shown in **Figure 22**.

Further, we use these transformed bays for our model training. We design a four-layered convolution neural network (CNN) architecture followed by two fully connected layers for the empty bay classification.

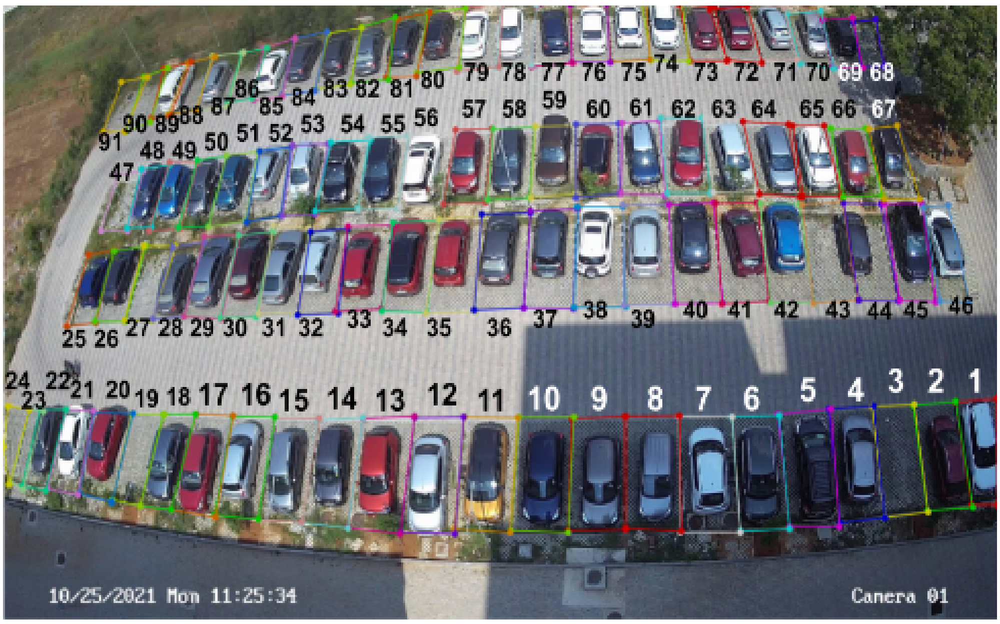


Figure 21: IITH (Block-C) parking lot

**Figure 23** shows the real-time occupancy performance and corresponding confusion matrices of day and night data. However, our proposed CNN model achieves an accuracy of 99.8% on test data, we observe an accuracy drop of ~ 3 - 7% while testing on real-time data. This is due to the effect of different lighting conditions (shadows).

We analyze the per-hour & per-bay parking occupancy using our proposed architecture, as shown in **Figure 24**. We observe a bell-shaped occupancy curve highlighting the peak hour occupancy, which matches the real-world scenario. the efficiency of the parking area.

Our proposed CNN model gave a test accuracy of 99.8%, one limitation is the accuracy drop of ~ 3 - 7% on real-time inference due to different lighting conditions of the day. Hence, in the future, we would like to apply semi-supervised learning algorithms to combine both less annotated and a large amount of unannotated parking data to improve real-time performance. Also, we plan to deploy the solution on edge hardware and provide real-time parking occupancy information to the IITH parking lot users.

**Reference:**

K. Naveen Kumar, Digvijay S. Pawar, and C. Krishna Mohan. "Open-air Off-street Vehicle Parking Management System Using Deep Neural Networks: A Case Study." In 2022 14th International Conference on COMmunication Systems & NETworkS (COMSNETS) ITS Workshop, pp. 800-805. IEEE, 2022.

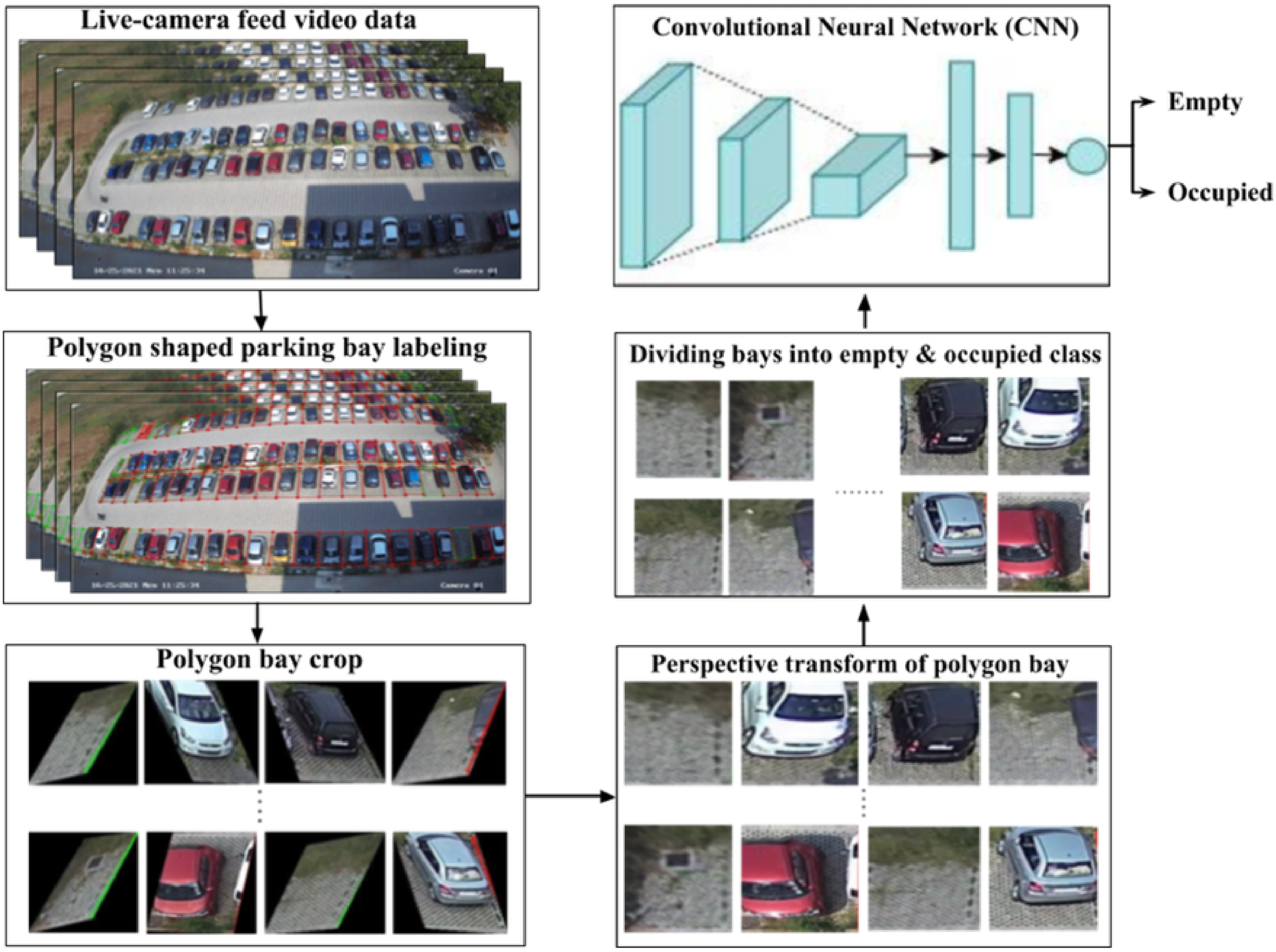


Figure 22: Block diagram of the proposed approach. We manually annotate the spatial bay regions of a single frame obtained from the live-camera feed video data and extract the polygon-shaped bays. Further, we apply the perspective transformation on polygon bays to remove noise and convert it into perfect rectangular samples. Finally, the samples are manually bucketed empty and occupied and sent into a deep neural network for model training.

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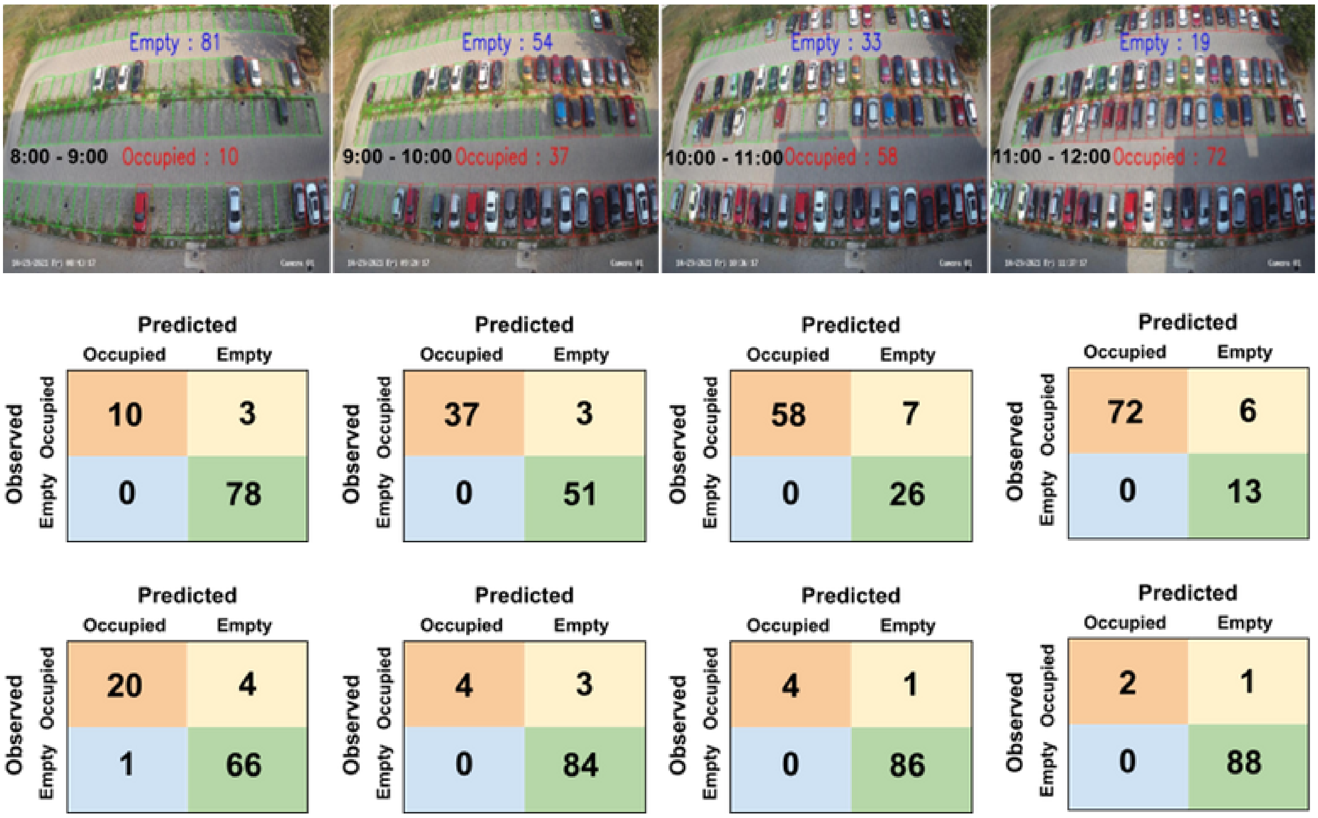


Figure 23: Day-time & Night-time occupancy analysis at regular time intervals and corresponding confusion matrices. Time is represented in the format hh:00:00.

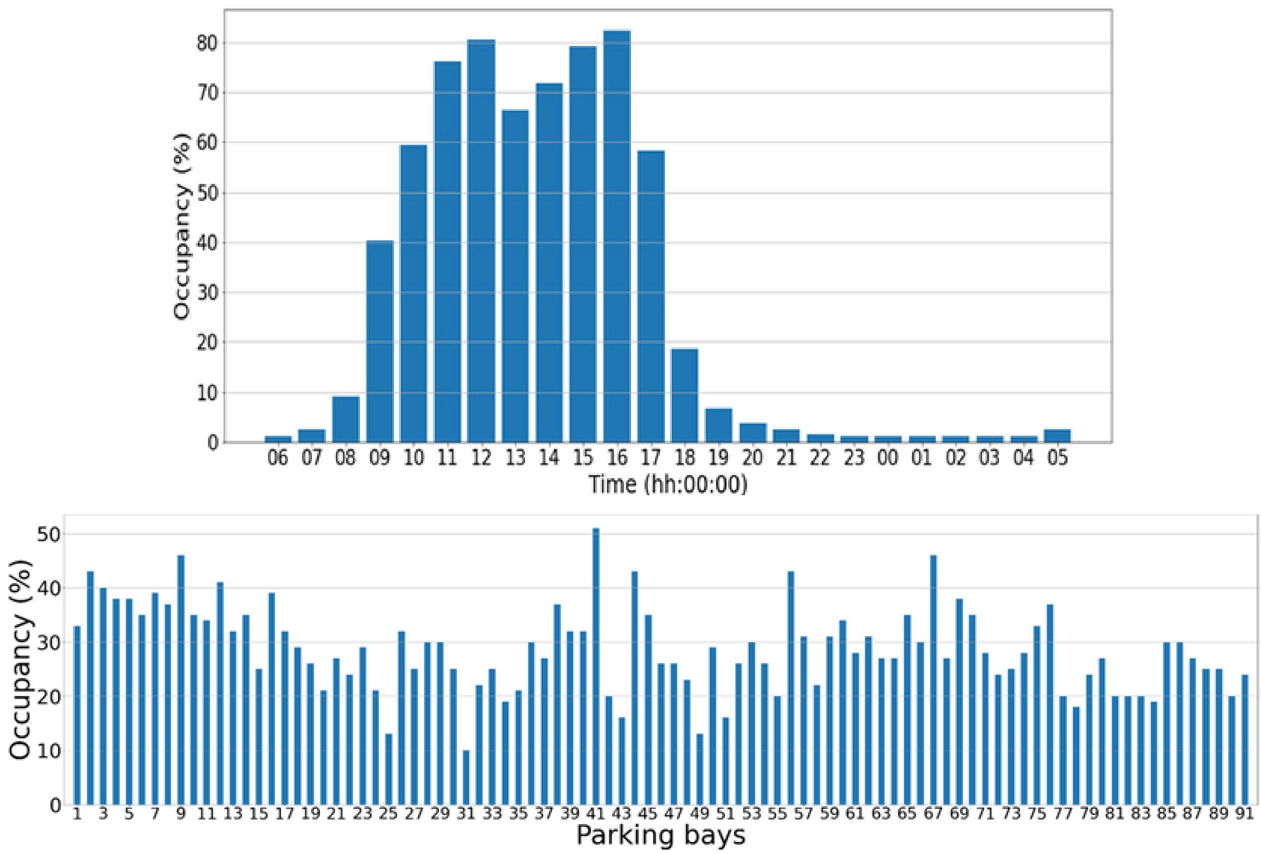


Figure 24: Per-hour & Per-bay occupancy analysis