**IEEE P802.15**

**Wireless Personal Area Networks**

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# Annex Q

(informative)

Deep learning for OCC receiver

## Q.1. Convolution Neural Network for LED detection with mobility effect.

A neural network (NN) is deployed at the receiver for accurately detecting the LED in both static and mobile conditions. An LED array is detected as a single LED in the existing literature. However, each LED in an LED array can be detected using the proposed NN technique. The NN can classify large image datasets with remarkable characteristics in several spatial layers and automatically learn from data through backpropagation.



Figure xxx. Training architecture of neural network-based stripe pattern reformation.

Background lights and neighboring LEDs can create noise and interference in the image sensor, respectively. On the other hand, interference occurs if a LED light source unexpectedly appears inside the image sensor FOV. In particular, after detection, several frames are captured and analyzed. If the stripe pattern of a specific area is changed in the subsequent frames, it is recognized as the source LED. Otherwise, it is categorized as the interfering LED and subsequently filters out from the image frame.



Figure xxx. Flow diagram of proposed neural network technique.

The neural network mainly operated based on the feature extraction technique of the stripe pattern. However, the given flow diagram shows the training and testing procedure and checks the similarity of each iteration. In every iteration, the relative position of the stripe is changed by checking the similarity with the reference pattern. Figure xxx illustrates the entire flow diagram of the proposed neural network.

## Q.2. Support Vector Machine (SVM) classifier

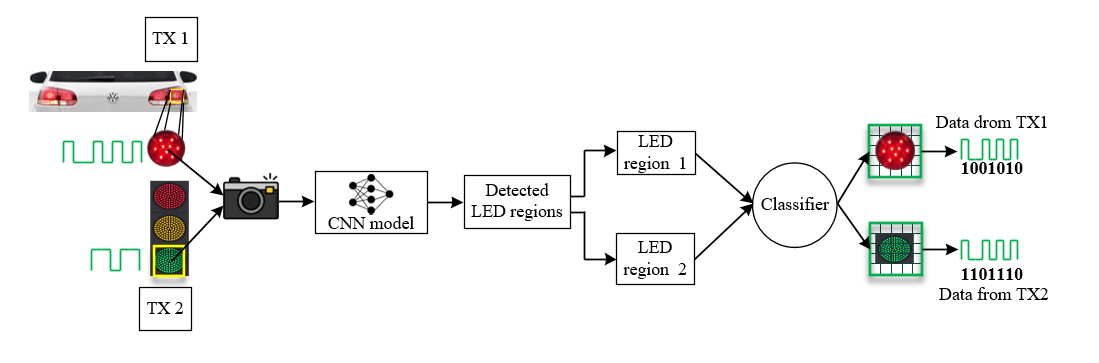


Figure xxx. The architecture of the accurate data transmitting LED detection scheme

In Fig. xxx, the block diagram delineates the overall architecture of the accurate data transmitting LED detection scheme. On the transmitter side, numerous LED regions were present. The LED optical signal was modulated by modulation at a frequency level between 2–4 kHz before sending to the receiver to attenuate the flickering issue in a significant margin. Concerning the transmitting LEDs and other sources of interference, they are not modulated in that particular frequency. The image sensor captured the projection of all these light-emitting sources. Interference sources were dispelled when a trained CNN model was used. All the possible LED sources were detected and segmented using image processing techniques. Due to the rolling shutter effect of the CMOS-based image sensor, each image frame gets striated of white and black shade. Afterward, necessary geometrical features have been extracted to classify and recognize accurate data transmitting regions from the range of all possible regions.

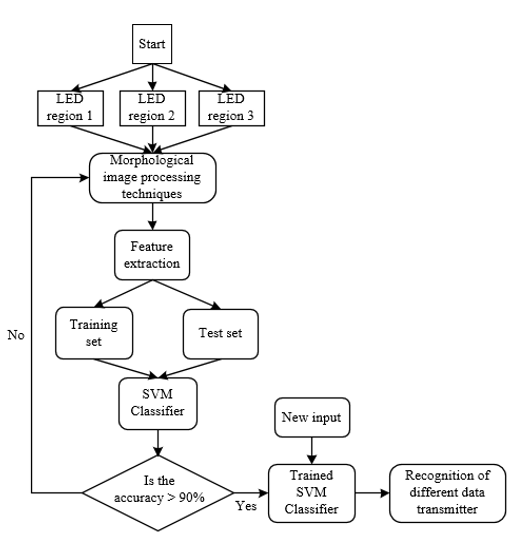


Figure xxx. Classifier structure

In Figure xxx, the detected LED regions with bounding boxes are the output of the CNN. The bounding box LED objects are then processed employing several image processing techniques. At first, each LED image is converted into a grayscale format to specify the distinct pixel intensity values of the stripes generated in the image sensor. Next, a kernel full of ones is used to reduce the shape of the projected stripes by removing small anomalies near the stripe boundaries. To make the receiver an intelligent and robust retrieval system, the system needs to recognize accurate LEDs separately as quickly as possible. Therefore, the selection of features is very important. The extraction of appropriate features is very challenging since the objects are almost the same. LED objects of the same type can have a different shape, stripe pattern based on the communication distance, camera frame rate, and mark and space frequency. To analyze the different geometrical shapes, computation of the features from the contour line has been considered significant distinguishable features. Contours are the outline that is designed using the edges of the object to represent the shape. They contain some geometrical attributes that are effective in recognizing and segmenting objects. However, before performing feature extraction, a closing operation is applied to the selected regions to combine all the neighboring stripes. The contour is drawn on the shape by combined stripes.