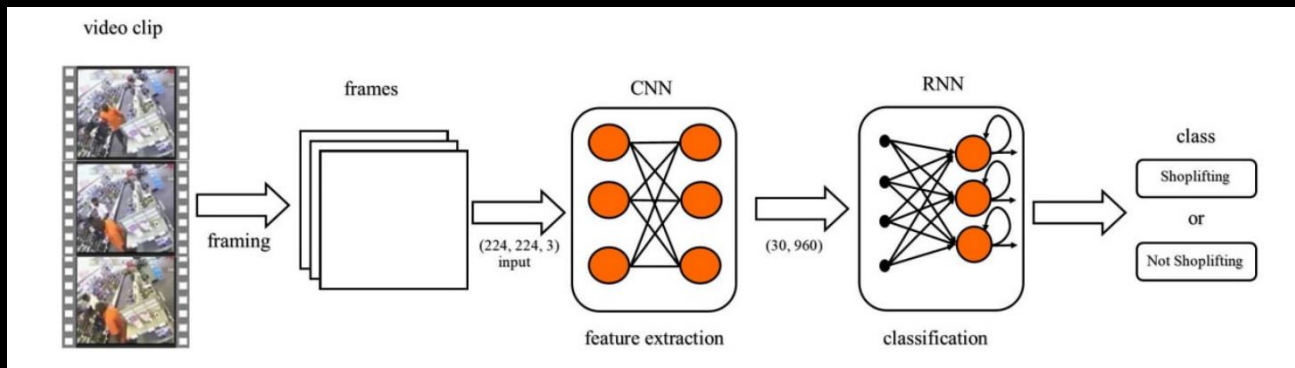


# **Paper Two summary**

Detection of Shoplifting on  
Video Using a Hybrid  
Network

- In this paper, we used a video classification method that extracted the features from each frame by a **CNN** and passed the sequence to a **separate GRU convolutional neural network**. The convolutional neural network was used as a feature extractor so we obtained a sequence of feature vectors.
- Feature extraction consists of determining the most relevant characteristics of images and assigning labels to them. In image classification, the decisive step is to analyze the properties of the image features and numerical features into classes. In other words, the image is classified according to its content. The efficiency of a classification model and the degree of classification accuracy mainly depend on the numerical properties of the different image features that represent these classification models. In recent years, many feature extraction methods have been developed; each method has advantages and disadvantages.
- At the second stage of data preprocessing, work was performed on the data. The video fragments were labelled into classes (**Class 1: cases with shoplifting and Class 0: normal customer behavior**). Processing was also performed before the feature extraction by resizing the image to a **size of  $224 \times 224$  pixels** and dividing the video into frames. As each video fragment was **3 s long by 10 frames/second**, this provided sequences of **30 frames**. The dataset was divided into training and test sets (**1302 training and 558 test sets**).
- neural network **MobileNetV3Large** preprepared on the ImageNet-1k dataset. 4: We created, trained, and tested a recurrent neural network with layers of gated recurrent nodes. The features extracted by the convolutional network MobileNetV3Large from each image of the labeled sequences of frames of video fragments were delivered for training in a recurrent network with gated nodes



## Results

Batch Size	Iterations	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Test Accuracy
4	228	99.34	0.026	90.28	0.407	90.14
8	114	98.02	0.066	92.84	0.247	91.27
16	57	99.34	0.027	90.79	0.326	92.11
32	29	98.57	0.051	90.79	0.302	92.83
64	15	99.45	0.015	93.09	0.338	93.19

