degree are calculated. For a gradient computation, first gray scale image is filtered to obtain '*x*' and '*y'* derivatives of pixels. After calculating '*x*, *y'* derivatives (*Ix* and*Iy*), the magnitude and orientation of the gradient is also computed:
$|G| = \sqrt{Ix^2 + Iy^2}$ And $\Theta = arctan\frac{Ix}{Iy}$

Then image is split to local area called *cell area*, which is composed of 16×16 pixel square. Each pixel calculates a weighted vote for an edge orientation histogram channel based on the orientation of the gradient element centered on it, and the votes are accumulated into orientation bins over local spatial regions that we call *cells*. Cell can be either rectangular or radial. In the next step an edge histogram is built using edge degree and the strength calculated in the previous step. Gradient strength vary over the wide range of owing to local variations in illumination and foreground-background contrast, so effective local contrast normalization turns out to be essential for good performance. Different normalization schemes are evaluated and most of them are based on grouping cells into larger spatial blocks and contrast normalizing each block separately. Normalization introduces better invariance to illumination, shadowing, and edge contrast. It is performed by accumulating a measure of local histogram *energy* over local groups of cells that we call *blocks.* The result is used to normalize each cell in the block. Typically each individual cell is shared between several blocks, but its normalization is block dependent and thus different. The final descriptor is then the vector of all components of the normalized cell responses from all of the blocks in the detection window.

## 6. Experiment Result

The human detection is constructed via a method for classifying individual images region. It is divided into training and testing phases is used to make a binary classifier which gives human or non-human decisions for input image windows. The testing phase uses the classifier to perform a dense multi-scale scan reporting human decisions at each location of the testing images. The overview of training and testing phases is provided in figure (1).

There are several notable findings in this work. HOG is affected by gradient quality, the choice of number of bins, normalization method and so on. In order to improve the performance, strong edge information is needed. Also gradient should be calculated at the finest available scale in pyramid layer when HOG can give fine orientations on the other hand, strong local contrast normalization produces good result. Overlapping cells sizes are an important component in raising accuracy. The overlapping scheme makes each cell normalized several times with respect to different local supports. In processing, each cell appears four times with different normalizations. The cell size has an impact on the quantity of information. For pedestrian detection, the cell size which approximates human part-template size gives the better performance, such as detection rate raise from 83.45% (8×8 cell) to 98.26% (16×16 cell) in training data set.

## 7. Conclusion

This work has described a complete framework for the problem of detecting objects in images and videos. The proposed approach builds upon ideas in machine learning, computer vision and image processing to provide a general, easy to use and fast method for pedestrian detection. Our main contribution is the development of robust images feature sets for object detection tasks. And also proposed feature set based on well normalized grids of gradient orientation histograms. These features provide some invariance to shifts in object location and changes in shape and good resistance to changes in illumination and shadowing, background clutter and camera view point. For increasing detection rate, capturing fine detail with unsmoothed gradients and fine orientation voting, strong normalized and overlapping blocks are used. The descriptors do not involve any arbitrary thresholding of edges and they are relatively fast to compute.

Our analysis and experiments show that it is possible to inexpensively estimate features at a dense set of scales by extrapolating computations carried out expensively, that is improved detection accuracy has been accompanied by decreased computational costs. And the system has moderate memory consumption.

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