ACCIDENT AVOIDANCE

PEDESTRIAN DETECTION

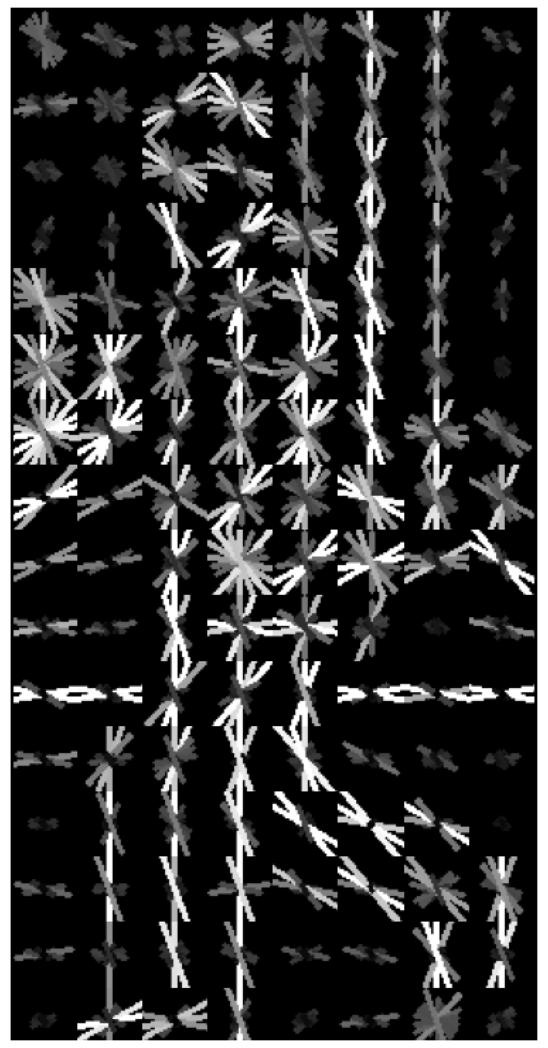
By: Donny Weintz, Aditya Mallepalli, Aakarsh Rai, Jianing Wang, Preetham Yerragudi

Mentors: Edward J. Delp, Carla B. Zoltowski, Fengqing M. Zhu

OVERVIEW

Pedestrian detection is a critical component in crash avoidance systems, with applications in autonomous vehicles and advanced driver assistance systems. This project aims to develop a pedestrian detection model leveraging Support Vector Machines (SVM) with Histogram of Oriented Gradients (HOG) descriptors in Python. Additionally, we aim to develop a mechanism to guide the direction of steering for autonomous vehicles in near crash situations.

Sample Pedestrian



Sample pedestrian represented by Histograms of Oriented Gradients

HISTOGRAM OF ORIENTED GRADIENTS

Histograms of Oriented Gradients (HOG) is a feature descriptor that captures edge orientations for object detection, often used in pedestrian detection. HOG divides an image into small cells, calculates gradients within each cell, and organizes these gradients into orientation-based histograms. Each pixel contributes to the histogram according to its gradient's angle and magnitude, capturing local edge patterns.

To improve stability, cells are grouped into overlapping blocks, with histograms normalized to minimize lighting effects. These combined histograms form a feature vector representing the image's structure, which, when used with a classifier like SVM, helps detect objects by emphasizing shape and edges while ignoring minor lighting changes.

SLIDING WINDOW + POST PROCESSING

After training an SVM on a dataset with 10,000+ images, we employed a sliding window technique by scanning each image at varying scales and locations to capture potential pedestrian features. The SVM is run through each iteration of this process, classifying a portion of the image as either containing a pedestrian or not.

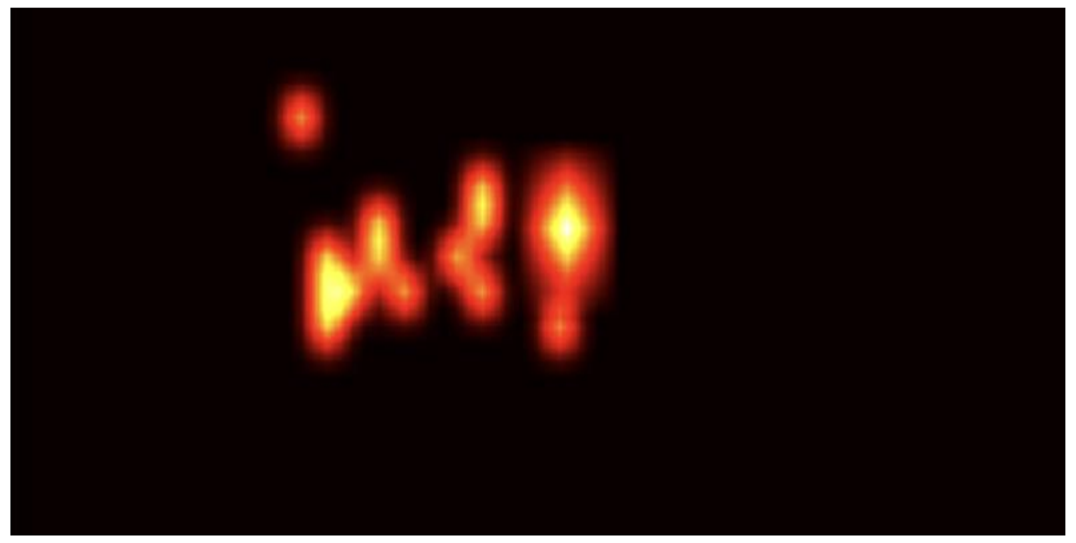
We refined this detection process with color filtering to reduce false positives by targeting hues most associated with vegetation and tree features and applying a threshold for the distance from the hyperplane.

Applying Non-Maximum Suppression further reduced overlapping bounding boxes, ensuring that only the highest-confidence detections remained. To maximize detection accuracy, we applied slight shifts to bounding box coordinates to make our model more resilient to misalignments in the window operation.

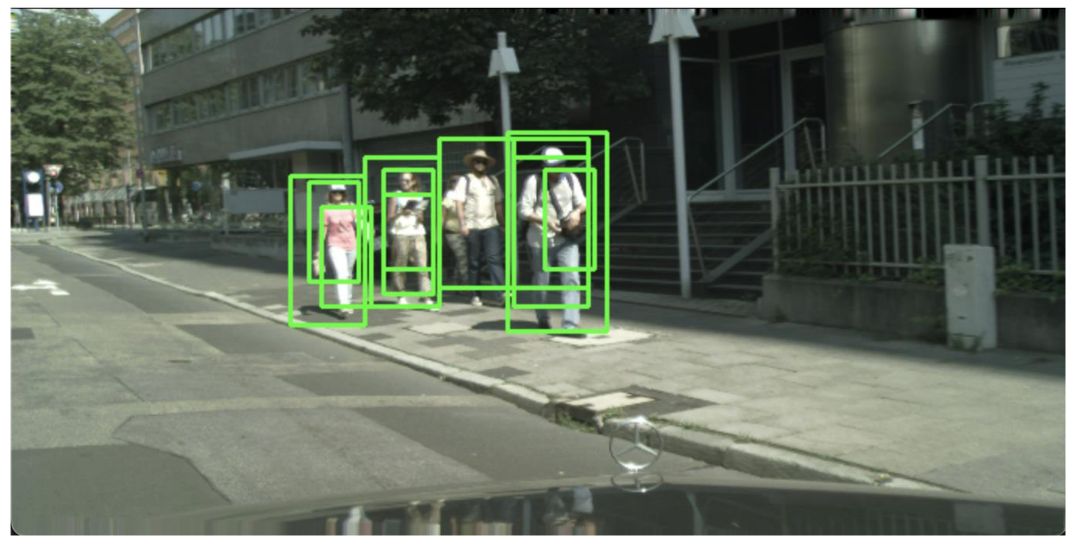
To further refine our pedestrian detection algorithm, we incorporated heatmaps to visualize and merge detection responses across sliding windows. The heatmap aggregates detections over multiple overlapping windows.

Using our optimized sliding window and SVM algorithm, we tested the model on a sample of 1,000+ additional images from the dataset, achieving a ~90% pedestrian detection rate. This high accuracy proves the effectiveness of our HOG and SVM model when combined with post-processing techniques such as NMS and color filtering.

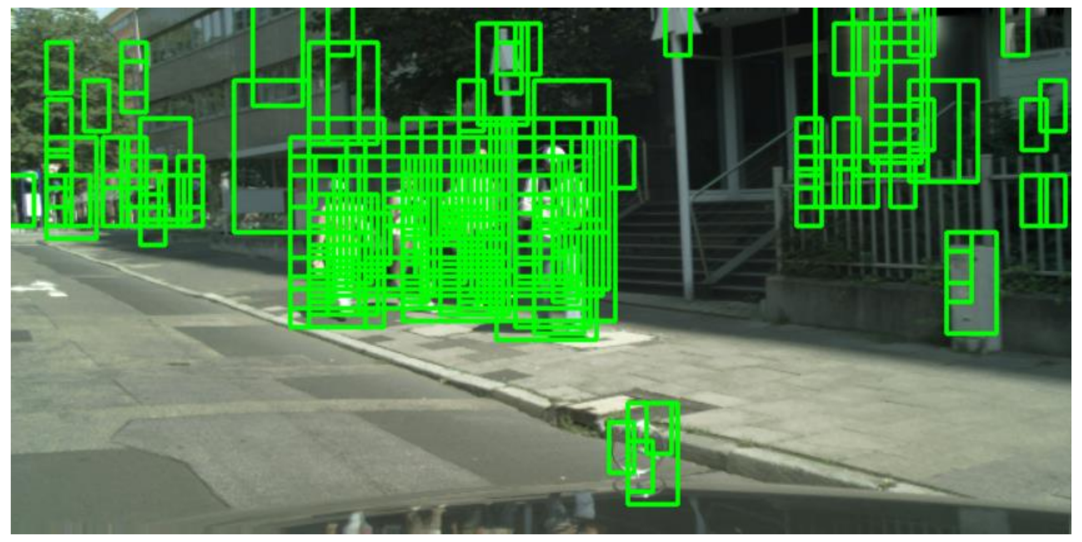
Our results demonstrate that this approach not only improves detection accuracy but also reduces redundant or overlapping detections. Using our improved detection, we aim to develop an algorithm for finding the optimal direction for a vehicle to follow to avoid pedestrians.



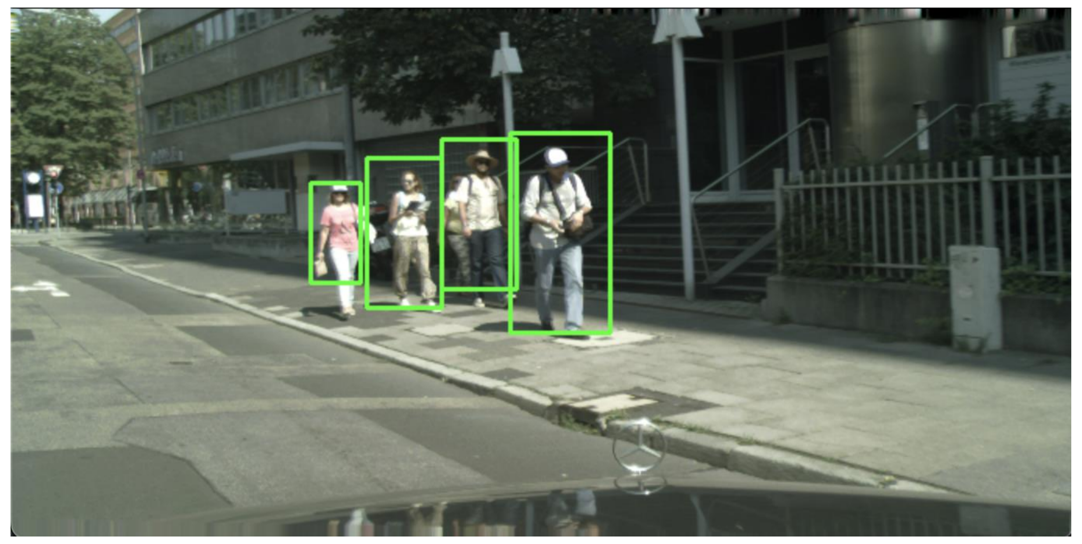
Heatmap



Filtered and thresholded without Non-Max Suppression



No color filters or thresholding



Final Output with Non-Max Suppression

REFERENCES

M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele, “The Cityscapes Dataset for Semantic Urban Scene Understanding,” in Proc. of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

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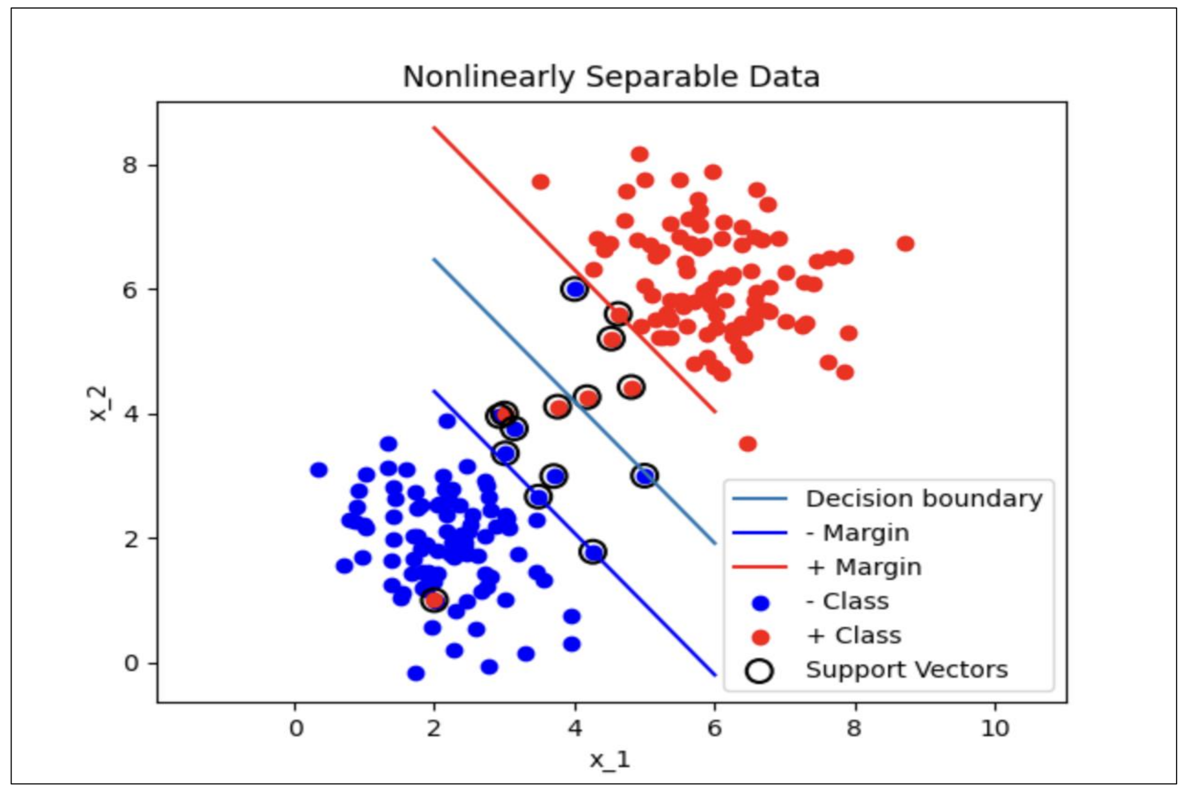
SOFT MARGIN SVM



The graph above shows a soft margin SVM implementation for a nonlinearly separable 2-dimensional dataset.

SUPPORT VECTOR MACHINE

Support Vector Machines (SVMs) are a computational tool used for classification and regression. They work by finding the best possible boundary, known as a hyperplane, to separate data points belonging to different classes. This boundary is chosen to maximize the margin between itself and the closest points from each class, which are the support vectors. A larger margin helps the model generalize better, making it more robust to new data points.

When data isn't linearly separable–can’t be divided by a straight line–SVMs use a kernel trick. This transforms data into a higher-dimensional space, allowing the SVM to create a clear separation even if it requires bending or curving the boundary.

When using HOG features in combination with SVMs, we can create a classifier that takes in a list of multi-dimensional features and classify it as either a pedestrian or not a pedestrian.