# Simple Highway Traffic Accident Scene Classification with On-Vehicle Cameras

Azharul MD Islam[1], San Yeung[2]
Department of Computer Science
Missouri University of Science and Technology
syq3b[2],mi6df[1]@mst.edu

***Abstract*—With the ongoing development of self-driving (smart) vehicles, many of them are equipped with sensors (such as laser scanner) and cameras to help with road navigation. To accommodate automatic navigation techniques, many of them are equipped with powerful computing units too. In this paper, we propose a simple classification framework to classify highway traffic accident scenes with images captured by those on-vehicle cameras equipped on smart cars. The classification results can be used for traffic accident detection, accident impact prediction, and traffic emergency response management. We classify traffic accidents into three top categories–accident location, people involvement, and potential risk–using a variation of logistic regression methods. The traffic accident datasets are collected from the Internet, mainly extracted from video sequences of traffic accidents. The experimental results indicate that logistic regression methods are able to produce satisfactory classification results, with accuracy up to 95% in some categories. Experimental data also includes results from exploring various color space and parameter tuning. The results support our belief that an establishment of such classification framework help with better traffic info management. This project also offers many open challenges for future research, including the use of other classification schemes and feature space exploration. Combining the classification results with accident impact prediction to increase prediction accuracy would also pose as an interesting study topic.**

***Index Terms*—traffic accidents, traffic scene classification, classification, logistic regression**

## I. Introduction

In the literature world of traffic management, many work have been done on traffic obstacle detection, traffic anomaly detection and traffic pattern analysis for the road networks. For the many proposed approaches and frameworks, majority of them rely on the availability of probe vehicle location traces data or traffic surveillance video footage [6], [8]–[11], [14], [15]. For those proposed systems that utilize static road traffic images, most of them focus on detecting road types, pedestrian crossing, and vehicle types [1]–[3], [5]. However, with the emerging technologies of self-driving cars, it brings new light to the way we could do traffic scene classification.

For many self-driving cars, they are equipped with many sensors and cameras to help them to be capable of achieving autonomous driving and navigation. It is also standard for them to have been installed with powerful computing units and processors to handle the many computer vision and navigation algorithms. Imaging a scenario where a self-driving car is traveling on a highway and it witnessed the occurrence of an accident near it, we could utilize the accident images taken by that vehicle to infer some useful information to help us better handle the emergency situation. For example, we could detect whether the accident scene is happening at the shoulder area or confined to the lanes, or we could also detect whether there is any fire or any overturned vehicles. With the real-time images taken by the on-vehicle cameras and the processing units, we would be capable of running classification on the vehicle and send any important information back to the traffic management server or emergency roadside response server.

Because of this observation, it motivates us to propose a classification framework of highway traffic accident classification using real-time images taken from on-board vehicle cameras. Even though we limit our models to highway traffic accidents, the model can be adapted to the more complex urban traffic setting too. In our approach, we first categorized traffic accident scenes into three main categories, including accident location, people involvement, and potential risk. For each of the category, we then construct a binary classifier to perform the classification task. In a practical setting, there will be a computational flow among the classifiers such that the priorities of different traffic accident scene can be assigned and sent to the server accordingly. We use various logistic regression models to build the classifier, including the Bayesian logistic regression, dual logistic regression, kernel logistic regression, and the relevance vector regression models.

In our experiments, we evaluate the performance of all logistic regression models for each accident category and we also explore different color space. In addition, we also explore the effect of different parameter tuning for some of the logistic regression models. The experimental results indicated that using logistic regression models is able to classify traffic accident scene with low missed detection and low false alarm rates, even if we are using traffic scene images mostly extracted from highway accident videos obtained freely from the Internet. We believe that our proposed classification models are able to help with the emergency response for real-time traffic accidents, and the performance of our models will be increased once more real-time images are collected.

## II. Related Work

For related work, there are not many literature studies on traffic accident scene classification. We could classify related work into two generalization: traffic scene classification and traffic accident detection and analysis.

There are several literature work related to the area of traffic scene classification [1]–[5]. In [1], the authors propose a method to recognize traffic scenes especially those of different road types and the existence of commonly encountered objects, such as cars or pedestrian crossing. And in [2], the authors develop modules for understanding urban traffic scenes such as traffic signs and lights, crosswalks, and pedestrians. Finally, the authors in [3] present a generative model for multi-object traffic scene understanding with the interests to infer the scene layout (e.g., number and location of streets) as well as the 3D location and orientation of traffic cars from short video sequences captured onboard a driving vehicle. These work do not focus on understanding and classifying traffic accident scenes.

Another subset of the literature work focuses on classifying and detecting the types of vehicles or obstacles in traffic. For example, in [5], the authors present algorithms for vision-based detection and classification of vehicles in image sequences of traffic scenes used for the purpose of vehicle motion tracking. In [6], the authors propose a real-time automatic obstacle detection method based on traffic surveillance videos processing. The model is based on HOG (histogram of oriented-flow gradient) and SVM (the support vector machine). And in [7], the authors improve the performance of obstacle classification in ADAS (automatic driving assistance systems) by taking advantage of the sensor fusion technique with laser scanners and vehicle cameras. Although these methods can be used to detect accident vehicles, they are not adequate to classify more complex traffic accident scenes.

The final group of literature work focuses on traffic accident detection and analysis. The major types of dataset they used are probe data (such as GPS and trajectory data) and images from traffic videos [8]–[16]. In [8], the authors propose a traffic jam detection and classification framework based location traces data collected from probe vehicles. The traffic jam detector classifies jams into recurring and non-recurring jams, and the accident classifier determines upstream and downstream traffic patterns. The authors in [9] investigate a hybrid traffic incident detection model using logistic regression with a wavelet-based feature extraction process. Wavelet transformation is a powerful technique for feature extraction from data that are characterized by frequent additive white noise. Since this technique is well-known in the field of image process, we should consider this as a feature extraction tool for future research. In [14], the authors propose a traffic anomaly detection and classification algorithm that combines the spatiotemporal changes in the variability of microscopic traffic variables (relative speed, intervehicle time gap, and lane changing, etc.). Both major anomalies (leading to major disruption of traffic flow) and transient anomalies (slight deviation of traffic patterns) are classified. The authors hope that the alarms generated from the proposed detection and classification framework can serve as early warning signal where traffic should be more closely monitored. Finally, the authors in [16] proposed an approach to quantify the spatiotemporal impact of traffic incidents in order to predict when and how the travel time delays will occur in the road network due to traffic incidents. The traffic incidents are classified based on features such as time, location, and type of incident by analyzing archived incident data. Then, the impact of each incident case is modeled with those information in addition to its surrounding traffic pattern. Most of these work focus on traffic anomaly detection and traffic flow analysis with little emphasis on traffic accident classification and feature extraction. We hope that the results of our classification framework can be combined with those analysis systems to enhance their prediction and traffic analysis power.

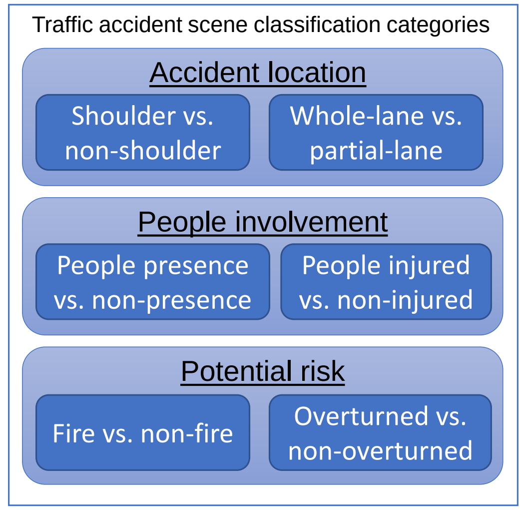


Fig. 1: A top level view of the traffic accident categories

## III. Methodology

### A. Category Definition

In this project, we used various logistic regression model to make classifications of different traffic accident scene. The traffic accident scenes are categorized into three top categories and the top level view is generalized by figure 2 :

1) Accident location
2) People involvement
3) Potential risk

For accident location, our goal is to infer the location type that an accident happens. It can be further divided into i) shoulder vs. non-shoulder and ii) whole-lane vs. partial lane. We would like to detect if the accident occurs at the shoulder or not because accidents that occurred and confined to shoulder area tend to not having a intense impact on traffic flow. On the other hand, we would still desire to learn other important info such as injury information. Secondly, we would like to know if the aftermath of an accident affects the entire lane or


Fig. 2: Sample images collected in this project

only partial of the lanes; accidents that affect the whole lane would be more serious than partial lane since vehicles would have no access to advance on highways.

For the people involvement category, we would want to detect whether the accident scene has people presence or not. If the scene contains people presence, then such image might need to be assigned a higher priority when it is sent to the servers of emergency response teams. In fact, we would also like to classify whether a scene contains signs of people injuries or not; however, insufficient amount of image data that we had tried to obtain forces us to postpone this component into future work.

Lastly, the potential risk category aims to classify i) fire vs. non-fire and ii) regular vehicles vs. overturned vehicles. It is important to correctly identify whether an accident scene contains fire or not because uncontrolled fire may cause explosion among crashed vehicles and further injuries. Similarly, we would like to detect whether the crashed vehicles are overturned or not because vehicles that are overturned in an accident are the signals of a seriously injured sign.

### *B. Classification Models*

In this paper, we employ different logistic regression models to perform classification for each category. For each logistic regression model, we model the world state as the response variable with respect to the training data as a Bernoulli distribution using the discriminative method:

$$Pr(w|\phi, \mathbf{x}) = Bern_w(sig[a])$$

where $a$ is the activation function in form of $\phi^T\mathbf{x}$ where $\phi$ is the parameters we want to estimate and $\mathbf{x}$ is the training dataset.

We decided to use several variation of logistic regression models to build classifiers for our datasets and they are the following:

- Logistic regression
  - Since it is not possible to obtain a closed form solution using the maximum likelihood method, we use the iterative non-linear optimization Newton method to estimate the parameters.
- Bayesian logistic regression
  - The Bayesian logistic regression model introduces prior information to avoid the overconfident issue in the simple logistic regression method. The parameter distribution with prior is represented as a normal distribution and the parameters are estimated using the Laplace approximation technique.
- Dual logistic regression
  - This model reparameterizes $\phi = \mathbf{x}\psi$ where $\psi$ is the parameter vector for each training example instead of per data dimension. It is an alternative method for when the size of data dimension is big.
- Dual bayesian logistic regression
  - This model introduces the prior variable into dual logistic regression method similar as the Bayesian logistic regression method.
- Kernel logistic regression
  - The goal of kernel logistic regression model is to make the computation more efficient by replacing the inner products in dual bayesian logistic regression model with a kernel function $k[\mathbf{x}, x_i]$. In our implementation, we use the Gaussian kernel function.
- Relevance vector regression
  - This model takes advantage of sparseness to combine with the kernel logistic regression model to further speed up computation. This is achieved by replacing $\psi$ with a t-distribution such that $Pr(\psi) = \prod Stud_\psi[0, 1, \nu]$

### *C. Computation Flow*

In the experiments of this paper, we train and inference a binary classifier for each category class, and the whole process can be run all at once or sequentially. However, in a practical situation, although a smart car is capable of inferencing all of the categories from the classifiers, sending all results to the server (of traffic management or emergency response center) might require extra human power to examine them and make decisions. Therefore, it is better to establish a computation flow as followed.

First, we run an image through the accident vs. non-accident classifier to determine the probability that the image captures an true accident scene. If the classification belongs to the accident class, then we could execute the accident location classifier, people involvement classifier, and the potential risk classifier simultaneously.

If an accident image is classified to be on the shoulder area, then we will send the relevant information (such as the presence of people) to the server if either fire or overturned vehicles are detected. Otherwise, the image can be sent to another server where further accident impact analysis can be done since it does not require immediate emergency response. On the other hand, if an accident image is classified as being whole-lane or partial lane, then all relevant information should be sent to the emergency response server since they may pose more serious risk and danger.

## IV. Evaluation

Most of the research works have been conducted based on the proprietary data set [13]. To the best of our knowledge, no data set is publicly available for highway accident. We have collected our own image dataset from static images and video samples gathered from the Internet for the evaluation purpose of our algorithm. All of our images have the dimension of $540 \times 304$ *px*. For the convenience of our experiment, we had to resized the images while reading them in Matlab. Table I shows the resizing factor in percentage for each of the regression methods. Since *Logistic regression* and *Bayesian logistic regression* methods are the slowest (in terms of training time), we had to resize the images into 5% of the original size. For rest of the methods, image size was reduced to 25% of the original size. Table II shows the number of images for each of the five classes. Since our data set is relatively small, we have used *stratified k-fold cross validation* in our experiment and set the value of $k$ equal to 10. *Stratified k-fold cross validation* randomly divides the data set into $k$ samples and splits them between testing and training set roughly equally. We ran each of the experiments 10 times and calculated the evaluation matrices *miss detection* and *false alarm* by taking the average. We discuss the experimental results in the following.

TABLE I: Image dimension for different methods

| Method | Resizing factor (%) |
|---|---|
| Logistic Regression | 5 |
| Bayesian Logistic Regression | 5 |
| Dual Logistic Regression | 25 |
| Dual Bayesian Logistic Regression | 25 |
| the Kernel Logistic Regression | 25 |
| Relevance Vector Logistic Regression | 25 |

### A. Accident / Not accident class

For this class, we show the results in figure 3. We can see that kernel logistic regression method (figure 3c) gives better results than other methods specially when the value of $\lambda$ equals 5. The experiments shown here were carried out in RGB colorspace. We do not report the results for other colorspaces since they do not show any significant improvement over RGB.

TABLE II: Data size for different classes

| Class No. | Class Name | No of Images |
|---|---|---|
| 1 | Accident | 149 |
| | Not accident | 549 |
| 2 | Fire | 41 |
| | Not fire | 117 |
| 3 | Vehicle overturned | 23 |
| | Vehicle not overturned | 78 |
| 4 | People present | 22 |
| | People not present | 16 |
| 5 | Shoulder | 23 |
| | Not shoulder | 38 |

| Color Space | Evaluation Metric | var_prior | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.0001 | 0.001 | 0.009 | 0.01 | 100 | 10000 |
| RGB | Miss Detection | 0.75851 | 0.4371 | 0.35994 | 0.53025 | 0 | 0 |
| | False Alarm | 0 | 0.10061 | 0.12361 | 0.071735 | 0.24149 | 0.24149 |
| Gradient | Miss Detection | 0 | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.24149 | 0.24149 | 0.24149 | 0.24149 | 0.24149 | 0.24149 |

(a) Dual Bayesian Logistic Regression

| Lambda | Evaluation Metric | var_prior | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 0.0001 | 0.001 | 0.005 | 0.009 | 0.01 | 100 | 10000 |
| | Miss Detection | 0.75851 | 0.5702 | 0.46497 | 0.34154 | 0.57948 | 0 | 0 |
| RGB | False Alarm | 0 | 0.061687 | 0.095161 | 0.11851 | 0.05806 | 0.24149 | 0.24149 |
| | Miss Detection | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Gradient | False Alarm | 0.24149 | 0.24149 | 0.24149 | 0.24149 | 0.24149 | 0.24149 | 0.24149 |

(b) Dual Logistic Regression

| Lambda | Evaluation Metric | var_prior | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.0001 | 1 | 100 | 1000 | 5000 | 10000 |
| | Miss Detection | 0 | 0.003252 | 0.001613 | 0.003226 | 0 | 0 |
| 0.0001 | False Alarm | 0.24149 | 0.24149 | 0.24149 | 0.24149 | 0.24149 | 0.24149 |
| | Miss Detection | 0.0032258 | 0.003252 | 0.001639 | 0 | 0 | 0 |
| 1 | False Alarm | 0.24149 | 0.24149 | 0.24149 | 0.24149 | 0.24149 | 0.24149 |
| | Miss Detection | 0.01129 | 0.020994 | 0.00973 | 0.019487 | 0.009704 | 0.006505 |
| 3 | False Alarm | 0.20746 | 0.19781 | 0.18313 | 0.17332 | 0.18638 | 0.201 |
| | Miss Detection | 0.016155 | 0.034003 | 0.042094 | 0.021074 | 0.017901 | 0.016208 |
| 5 | False Alarm | 0.14424 | 0.11491 | 0.10219 | 0.11348 | 0.13287 | 0.15066 |
| | Miss Detection | 0.014569 | 0.019434 | 0.017795 | 0.014622 | 0.008117 | 0.009704 |
| 10 | False Alarm | 0.19455 | 0.18802 | 0.17832 | 0.18318 | 0.19762 | 0.20584 |

(c) Kernel Logistic Regression

Fig. 3: Evaluation Results For Accident / Not accident Class

### B. Vehicle Overturned / Not overturned class

Figure 4 shows the experiment results for vehicle overturned / not overturned class. Here, both kernel logistic regression 4c and relevance vector logistic regression 4d methods shows best results when $\lambda$ varied between 5 to 10. Here, we also report only the results for RGB colorspace because others do not show any significant improvements over RGB.

### C. Fire / Not fire class

Here we report our experimental results for different colorspaces in figure 5. We have also the explored the Red channel separately to see if it improves the performance. Intuitively red channel should perform better for fire detection. But in our experiment, it does not have significant impact. The reason is probably our experimental data set is too small.

| Color Space | Evaluation Metric | var_prior | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.0001 | 0.001 | 0.009 | 0.01 | 100 | 10000 |
| RGB | Miss Detection | 0.087273 | 0.07 | 0.05 | 0.10727 | 0.22727 | 0.22727 |
| | False Alarm | 0.46 | 0.54273 | 0.62273 | 0.38 | 0 | 0 |
| Gradient | Miss Detection | 0.22727 | 0.22727 | 0.22727 | 0.22727 | 0.22727 | 0.22727 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 | 0 |

(a) Dual Bayesian Logistic Regression

| Lambda | Evaluation Metric | var_prior | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 0.00001 | 0.0001 | 0.001 | 0.005 | 0.009 | 0.01 | 100 | 10000 |
| RGB | Miss Detection | 0.20727 | 0.13727 | 0.08 | 0.04 | 0.05 | 0.02 | 0.22727 | 0.22727 |
| | False Alarm | 0.03 | 0.32 | 0.55273 | 0.61273 | 0.62273 | 0.69273 | 0 | 0 |
| Gradient | Miss Detection | 0.22727 | 0.22727 | 0.22727 | 0.22727 | 0.22727 | 0.22727 | 0.22727 | 0.22727 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

(b) Dual Logistic Regression

| Lambda | Evaluation Metric | var_prior | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.0001 | 1 | 100 | 1000 | 5000 | 10000 |
| 0.0001 | Miss Detection | 0.0090909 | 0.01 | 0.01 | 0.01 | 0.009091 | 0.01 |
| | False Alarm | 0.77273 | 0.77273 | 0.77273 | 0.77273 | 0.77273 | 0.77273 |
| 1 | Miss Detection | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| | False Alarm | 0.73364 | 0.72273 | 0.72273 | 0.72273 | 0.72364 | 0.72364 |
| 3 | Miss Detection | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| | False Alarm | 0.57455 | 0.49727 | 0.48545 | 0.49636 | 0.48545 | 0.48455 |
| 5 | Miss Detection | 0.03 | 0.058182 | 0.078182 | 0.09 | 0.079091 | 0.087273 |
| | False Alarm | 0.36727 | 0.18818 | 0.14909 | 0.11909 | 0.11818 | 0.11909 |
| 10 | Miss Detection | 0.1 | 0.098182 | 0.099091 | 0.1 | 0.1 | 0.10818 |
| | False Alarm | 0.06 | 0.05 | 0.08 | 0.07 | 0.062 | 0.05 |

(c) Kernel Logistic Regression

| Lambda | Evaluation Metric | nu | | | | |
|---|---|---|---|---|---|---|
| | | 0.1 | 5 | 100 | 500 | 1000 |
| 0.1 | Miss Detection | 0 | 0 | 0.01 | 0.01 | 0.01 |
| | False Alarm | 0.77273 | 0.77273 | 0.77273 | 0.77273 | 0.77273 |
| 1 | Miss Detection | 0 | 0.01 | 0 | 0 | 0.01 |
| | False Alarm | 0.72364 | 0.72273 | 0.72273 | 0.72273 | 0.72364 |
| 5 | Miss Detection | 0.049091 | 0.049091 | 0.059091 | 0.059091 | 0.059091 |
| | False Alarm | 0.24636 | 0.17 | 0.15818 | 0.16727 | 0.16909 |
| 10 | Miss Detection | 0.10818 | 0.10818 | 0.12 | 0.1 | 0.10909 |
| | False Alarm | 0.049091 | 0.06 | 0.05 | 0.06 | 0.059091 |
| 100 | Miss Detection | 0.22727 | 0.22727 | 0.22727 | 0.22727 | 0.22727 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 |
| 1000 | Miss Detection | 0.01 | 0.22727 | 0.22727 | 0.22727 | 0.22727 |
| | False Alarm | 0.77273 | 0 | 0 | 0 | 0 |

(d) Relevance Vector Logistic Regression

Fig. 4: Evaluation Results For vehicle overturned / Not overturned Class

### *D. People present / People not present class*

For this experiment 6, our data set is the smallest. So, the result is not as great as that in other classes. Here, kernel logistic regression method 6e for gradient and HSV colorspace shows the best result. On the other hand, relevance vector logistic regression method 6f shows similar good results for RGB, Gray scale, YCbCr and HSV colorspace.

### *E. Shoulder / Not shoulder class*

We show the results for shoulder / not shoulder class in figure 7. Here also kernel logistic regression and relevance vector logistic regression methods (figure 7e and 7f respectively) outperforms other methods. Kernel logistic regression method gives best result for *nu* equals 10 in RGB, Grayscale, YCbCr and HSV colorspace. On the otherhand, relevance vector logistic regression method performs best for $\lambda = 10$ in RGB, Gray scale, YCbCr and HSV colorspace.

## V. Discussion

The purpose of this section is to present some open challenges and future research directions for this project. First, we would like to discuss additional questions/queries that we would want to answer in the domain of traffic accident scene classification. In the accident location category, if an accident is classified as affecting partial lane, then one may also want to answer the question of which lanes are affected. Moreover, one may also want to know how many people and vehicles involved in the accident are present. To answer some of these questions, one may borrow some ideas from the area of image segmentation and use the labeling information to infer the answer.

As we mentioned earlier, there are additional scenes that we could classify in some categories but they are more difficult to achieve. For the people involvement category, one may further wish to know if the people involved in the accident display any signs of injury or not. However, this is often difficult to infer through classification because the injury signs are often difficult to be captured by static images, and it's difficult to obtain good dataset to perform training for this particular category also. Additionally, it is also of interests to know if the people involving still remain conscious. If people are unconscious, then the situation is much more serious and they would need immediate medical assistance and emergency aid. However, classifying whether the people present are conscious or not based one or a few static images is a difficult task. It is better to perform such detection via a serious of images depicting the real-time scene. Since a single vehicle may not be able to provide enough images in a serious, we may need to develop a detection approach that uses images captured by a set of vehicles that continuously pass by the accident scene.

There are still many open questions/challenges for this project. For example, one could explore with different classification methods to improve the performance. One potential model is to employ the multiclass (multinominal) logistic regression method. Using multiclass logistic regression, we would describe the posterior as a categorical distribution, with each category (such as fire vs. non-fire) treated as the categorical variable. This way, we do not have to train and inference multiple classifiers; instead, we would only need one classifier. During inference, we would still be able to induce the answers through the new single classifier. Other models worth considering may be the graph-based models or the convolution neural networks.

Besides considering different models, one could also explore different feature space and feature selection. In this paper, we use different color space to train our classifiers. Other image processing technique such as the wavelet transformation may also be explored. The factor of illumination condition may also be considered too. For example, it may be more difficult to perform classification at night using the images captured by the regular on-vehicle cameras.

## VI. Conclusion

The emerging technologies of self-driving cars is exciting and can inspire many practical and meaningful applications. Using the on-vehicle cameras equipped on smart cars, we are able to perform highway traffic accident classification using the real-time captured images using various logistic regression models. Through deliberate parameter tuning observed from empirical study in this paper, we conclude that the classification models are able to achieve low missed detection and false alarm rates, which is critical if we are sending real-time classification results to emergency response and traffic management control centers. We also believe that via successful deployment of more self-driving cars into the road network, we would be able to improve the accuracy of our models even further because we would be able to obtain more realistic images to be used for model training. In conclusion, we have presented an interesting classification problem in the domain of traffic accident analysis and many open questions could follow from it. One could investigate more related traffic accident scene queries, explore other classification models and feature space, and integrate the classification component with advance traffic pattern analysis in order to build a more complete and efficient intelligent transportation management system.

## References


[1] Ess, Andreas, et al. "Segmentation-Based Urban Traffic Scene Understanding." *BMVC*. Vol. 1. 2009.

[2] Franke, Uwe, and Armin Joos. "Real-time stereo vision for urban traffic scene understanding." *Intelligent Vehicles Symposium*, 2000. IV 2000. Proceedings of the IEEE. IEEE, 2000.

[3] Geiger, Andreas, et al. "3d traffic scene understanding from movable platforms." *IEEE transactions on pattern analysis and machine intelligence* 36.5 (2014): 1012-1025.

[4] Koller, Dieter, et al. "Towards robust automatic traffic scene analysis in real-time." *Pattern Recognition, 1994. Vol. 1-Conference A: Computer Vision & Image Processing., Proceedings of the 12th IAPR International Conference on*. Vol. 1. IEEE, 1994.

[5] Gupte, Surendra, et al. "Detection and classification of vehicles." *IEEE Transactions on intelligent transportation systems* 3.1 (2002): 37-47.

[6] Lan, Jinhui, et al. "Real-time automatic obstacle detection method for traffic surveillance in urban traffic." *Journal of Signal Processing Systems* 82.3 (2016): 357-371.

[7] Ponz, Aurelio, et al. "Laser Scanner and Camera Fusion for Automatic Obstacle Classification in ADAS Application." *International Conference on Smart Cities and Green ICT Systems*. Springer International Publishing, 2015.

[8] Xu, Bo, et al. "Real-time detection and classification of traffic jams from probe data." *Proceedings of the 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. ACM, 2016.

[9] Agarwal, Shaurya, Pushkin Kachroo, and Emma Regentova. "A hybrid model using logistic regression and wavelet transformation to detect traffic incidents." IATSS Research 40.1 (2016): 56-63.

[10] Shiau, Yau-Ren, et al. "The application of data mining technology to build a forecasting model for classification of road traffic accidents." Mathematical Problems in Engineering 2015 (2015).

[11] Gakis, Evangelos, Dionysios Kehagias, and Dimitrios Tzovaras. "Mining traffic data for road incidents detection." Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on. IEEE, 2014.

[12] Celikoglu, Hilmi Berk. "Dynamic classification of traffic flow patterns simulated by a switching multimode discrete cell transmission model." IEEE Transactions on Intelligent Transportation Systems 15.6 (2014): 2539-2550.

[13] Buch, Norbert, Sergio A. Velastin, and James Orwell. "A review of computer vision techniques for the analysis of urban traffic." IEEE Transactions on Intelligent Transportation Systems 12.3 (2011): 920-939.

[14] Barria, Javier A., and Suttipong Thajchayapong. "Detection and classification of traffic anomalies using microscopic traffic variables." IEEE Transactions on Intelligent Transportation Systems 12.3 (2011): 695-704.

[15] Sadek, Samy, et al. "A statistical framework for real-time traffic accident recognition." Journal of Signal and Information Processing 1.1 (2010): 77.

[16] Pan, Bei, et al. "Forecasting spatiotemporal impact of traffic incidents for next-generation navigation systems." Knowledge and Information Systems 45.1 (2015): 75-104.

| Evaluation Metric | Colorspace | | | | | |
|---|---|---|---|---|---|---|
| | RGB | Red | Gray | HSV | YCbCr | Gradient |
| Miss Detection | 0 | 0.0713 | 0.0508 | 0 | 0 | 0.05875 |
| False Alarm | 0.747 | 0.0525 | 0.0508 | 0.747 | 0.747 | 0.0521 |

(a) Logistic Regression for different colorspace

| Evaluation Metric | Colorspace | | | | | |
|---|---|---|---|---|---|---|
| | RGB | Red | Gray | HSV | YCbCr | Gradient |
| Miss Detection | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 |
| False Alarm | 0 | 0 | 0 | 0 | 0 | 0 |

(b) Dual Logistic Regression for different colorspace

| var_prior | Evaluation Metric | Colorspace | | | | | |
|---|---|---|---|---|---|---|---|
| | | RGB | Red | Gray | HSV | YCbCr | Gradient |
| 0.001 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.01 | Miss Detection | 0.215 | 0.253 | 0.253 | 0.195 | 0.235 | 0.253 |
| | False Alarm | 0.105 | 0 | 0 | 0.128 | 0.0187 | 0 |
| 0.1 | Miss Dete | 0.207 | 0.227 | 0.143 | 0.1295 | 0.247 | 0.2204 |
| | False Alar | 0.0654 | 0.065 | 0.222 | 0.287 | 0.0125 | 0.079 |
| 1 | Miss Detection | 0.0645 | 0.156 | 0.149 | 0.0129 | 0.176 | 0.22 |
| | False Alarm | 0.286 | 0.167 | 0.216 | 0.543 | 0.188 | 0.104 |
| 10 | Miss Detection | 0.045 | 0.039 | 0.04 | 0.0063 | 0.0637 | 0.0775 |
| | False Alarm | 0.707 | 0.378 | 0.55 | 0.6687 | 0.5975 | 0.0833 |
| 100 | Miss Detection | 0 | 0.0125 | 0.0195 | 0 | 0 | 0.0329 |
| | False Alarm | 0.746 | 0.594 | 0.617 | 0.7337 | 0.746 | 0.2237 |

(c) Bayesian Logistic Regression for different colorspace

| var_prior | Evaluation Metric | Colorspace | | | | | |
|---|---|---|---|---|---|---|---|
| | | RGB | Red | Gray | HSV | YCbCr | Gradient |
| 0.001 | Miss Detection | 0.253 | 0.143 | 0.0833 | 0.253 | 0.253 | 0.195 |
| | False Alarm | 0 | 0.259 | 0.377 | 0 | 0 | 0.0129 |
| 0.01 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.227 | 0.253 | 0.253 |
| | False Alarm | 0 | 0 | 0 | 0.073 | 0 | 0 |
| 0.1 | Miss Dete | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 |
| | False Alar | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 | 0 |
| 100 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 | 0 |

(d) Dual Bayesian Logistic Regression for different colorspace

**RGB**

| Lambda | Evaluation Metric | var_prior | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.0001 | 0.01 | 0.1 | 1 | 10 | 100 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 |
| 1 | Miss Detection | 0 | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.7337 | 0.721 | 0.7204 | 7204 | 7204 | 0.7208 |
| 10 | Miss Detection | 0.0387 | 0.0517 | 0.0329 | 0.0267 | 0.0263 | 0.025 |
| | False Alarm | 0.0192 | 0.0192 | 0.0192 | 0.02 | 0.0192 | 0.0263 |
| 100 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.247 | 0.247 | 0.169 |
| | False Alarm | 0 | 0 | 0.116 | 0.209 | 0.11 | 0.0645 |

**Red**

| Lambda | Evaluation Metric | var_prior | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.0001 | 0.01 | 0.1 | 1 | 10 | 100 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 |
| 1 | Miss Detection | 0 | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.7008 | 0.687 | 0.688 | 0.6629 | 0.676 | 0.661 |
| 10 | Miss Detection | 0.118 | 0.0979 | 0.103 | 0.0979 | 0.0983 | 0.0771 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 | 0.0192 |
| 100 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.233 | 0.247 | 0.253 |
| | False Alarm | 0 | 0 | 0.0775 | 0.312 | 0.292 | 0.065 |

**HSV**

| Lambda | Evaluation Metric | var_prior | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.0001 | 0.01 | 0.1 | 1 | 10 | 100 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 |
| 1 | Miss Detection | 0 | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.7337 | 0.7337 | 0.7337 | 0.7337 | 0.7337 | 0.727 |
| 10 | Miss Detection | 0.0529 | 0.0517 | 0.057 | 0.0521 | 0.065 | 0.0521 |
| | False Alarm | 0.0129 | 0.013 | 0.0125 | 0.0133 | 0.0133 | 0.0129 |
| 100 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.253 | 0.253 | 0.247 |
| | False Alarm | 0 | 0 | 0.007 | 0.103 | 0.124 | 0.129 |

**YCbCr**

| Lambda | Evaluation Metric | var_prior | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.0001 | 0.01 | 0.1 | 1 | 10 | 100 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 |
| 1 | Miss Detection | 0 | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.675 | 0.675 | 0.675 | 0.662 | 0.649 | 0.642 |
| 10 | Miss Detection | 0.155 | 0.143 | 0.149 | 0.163 | 0.0904 | 0.0663 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 | 0.045 |
| 100 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.253 | 0.24 | 0.247 |
| | False Alarm | 0 | 0 | 0 | 0.103 | 0.213 | 0.161 |

**Gray**

| Lambda | Evaluation Metric | var_prior | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.0001 | 0.01 | 0.1 | 1 | 10 | 100 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 |
| 1 | Miss Detection | 0 | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.687 | 0.689 | 0.688 | 0.675 | 0.674 | 0.663 |
| 10 | Miss Detection | 0.123 | 0.1175 | 0.1108 | 0.1104 | 0.0904 | 0.0792 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 | 0.0467 |
| 100 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.233 | 0.247 | 0.247 |
| | False Alarm | 0 | 0 | 0.0262 | 0.293 | 0.277 | 0.129 |

**Gradient**

| Lambda | Evaluation Metric | var_prior | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.0001 | 0.01 | 0.1 | 1 | 10 | 100 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 | 0.747 |
| 1 | Miss Detection | 0 | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.589 | 0.577 | 0.577 | 0.552 | 0.508 | 0.498 |
| 10 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.253 | 0.24 | 0.0775 |
| | False Alarm | 0 | 0 | 0 | 0.0642 | 0.123 | 0.143 |
| 100 | Miss Detection | 0.253 | 0.253 | 0.253 | 0.253 | 0.247 | 0.247 |
| | False Alarm | 0 | 0 | 0 | 0.0129 | 0.175 | 0.163 |

(e) Kernel Logistic Regression for different colorspace

Fig. 5: Evaluation Results For Fire / Not fire Class

| RGB | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.0001 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.387 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.72 | 0.02 | 0 |
| | Miss Dete | 0 | 0 | 0 | 0.0383 | 0.253 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.721 | 0.0321 | 0 |
| 1 | Miss Detection | 0 | 0 | 0 | 0.0387 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.721 | 0.02 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.025 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.72 | 0.0196 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.0325 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.734 | 0.0196 | 0 |

| Red | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.0001 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.188 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.688 | 0 | 0 |
| | Miss Dete | 0 | 0 | 0 | 0.181 | 0.253 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.688 | 0 | 0 |
| 1 | Miss Detection | 0 | 0 | 0 | 0.189 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.675 | 0 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.0967 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.675 | 0 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.112 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.675 | 0 | 0 |

| HSV | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.0001 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.0587 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.734 | 0.0133 | 0 |
| | Miss Dete | 0 | 0 | 0 | 0.052 | 0.253 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.7338 | 0.0133 | 0 |
| 1 | Miss Detection | 0 | 0 | 0 | 0.0517 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.734 | 0.0129 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.051 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.721 | 0.0263 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.0521 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.734 | 0.0133 | 0 |

| YCbCr | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.0001 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.247 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.674 | 0 | 0 |
| | Miss Dete | 0 | 0 | 0 | 0.253 | 0.253 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.676 | 0 | 0 |
| 1 | Miss Detection | 0 | 0 | 0 | 0.253 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.662 | 0 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.168 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.721 | 0 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.163 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.662 | 0 | 0 |

| Gray | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.0001 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.22 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.688 | 0 | 0 |
| | Miss Dete | 0 | 0 | 0 | 0.202 | 0.253 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.674 | 0 | 0 |
| 1 | Miss Detection | 0 | 0 | 0 | 0.212 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.662 | 0 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.124 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.675 | 0 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.0975 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.675 | 0 | 0 |

| Gradient | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.0001 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.253 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.611 | 0 | 0 |
| | Miss Dete | 0 | 0 | 0 | 0.253 | 0.253 |
| 0.1 | False Alar | 0.747 | 0.747 | 0.565 | 0 | 0 |
| 1 | Miss Detection | 0 | 0 | 0 | 0.253 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.546 | 0 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.253 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.539 | 0 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.253 | 0.253 |
| | False Alarm | 0.747 | 0.747 | 0.538 | 0 | 0 |

(f) Relevance Vector Logistic Regression for different colorspace

Fig. 5: Evaluation Results For Fire / Not fire Class (cont.)

| Evaluation Metric | Colorspace | | | | |
|---|---|---|---|---|---|
| | RGB | Gray | HSV | YCbCr | Gradient |
| Miss Detection | 0 | 0.158 | 0 | 0 | 0.142 |
| False Alarm | 0.4 | 0.233 | 0.4 | 0.4 | 0.208 |

(a) Logistic Regression for different colorspace

| Evaluation Metric | Colorspace | | | | |
|---|---|---|---|---|---|
| | RGB | Gray | HSV | YCbCr | Gradient |
| Miss Detection | 0 | 0 | 0 | 0 | 0.0583 |
| False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.375 |

(b) Dual Logistic Regression for different colorspace

| var_prior | Evaluation Metric | Colorspace | | | | |
|---|---|---|---|---|---|---|
| | | RGB | Gray | HSV | YCbCr | Gradient |
| 0.001 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 0.1 | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| | False Alar | 0.367 | 0.4 | 0.342 | 0.4 | 0.4 |
| 1 | Miss Detection | 0 | 0 | 0 | 0.033 | 0 |
| | False Alarm | 0.342 | 0.258 | 0.4 | 0.283 | 0.4 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.125 | 0.033 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.325 | 0.267 |
| 100 | Miss Detection | 0 | 0 | 0 | 0 | 0.0583 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.375 |

(c) Bayesian Logistic Regression for different colorspace

| var_prior | Evaluation Metric | Colorspace | | | | |
|---|---|---|---|---|---|---|
| | | RGB | Gray | HSV | YCbCr | Gradient |
| 0.001 | Miss Detection | 0.417 | 0.467 | 0.35 | 0.25 | 0.075 |
| | False Alarm | 0.15 | 0.1 | 0.217 | 0.25 | 0.325 |
| 0.01 | Miss Detection | 0.167 | 0.133 | 0 | 0.033 | 0.342 |
| | False Alarm | 0.317 | 0.367 | 0.4 | 0.367 | 0.2 |
| 0.1 | Miss Dete | 0 | 0.025 | 0 | 0 | 0 |
| | False Alar | 0.375 | 0.4 | 0.4 | 0.4 | 0.4 |
| 1 | Miss Detection | 0 | 0 | 0 | 0 | 0.067 |
| | False Alarm | 0.4 | 0.367 | 0.4 | 0.4 | 0.308 |
| 10 | Miss Detection | 0 | 0 | 0 | 0 | 0.067 |
| | False Alarm | 0.375 | 0.4 | 0.4 | 0.4 | 0.4 |
| 100 | Miss Detection | 0 | 0 | 0 | 0 | 0.033 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |

(d) Dual Bayesian Logistic Regression for different colorspace

RGB

| Lambda | Evaluation Metric | var_prior | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| 1 | False Alar | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Detection | 0.208 | 0.233 | 0.208 | 0.242 | 0.233 |
| 10 | False Alarm | 0.175 | 0.2 | 0.225 | 0.25 | 0.192 |
| | Miss Detection | 0 | 0 | 0 | 0 | 0.067 |
| 100 | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.283 |

Gray

| Lambda | Evaluation Metric | var_prior | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| 1 | False Alar | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Detection | 0.092 | 0.067 | 0.1 | 0.167 | 0.225 |
| 10 | False Alarm | 0.225 | 0.233 | 0.233 | 0.233 | 0.2 |
| | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| 100 | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |

YCbCr

| Lambda | Evaluation Metric | var_prior | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| 1 | False Alar | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Detection | 0.1 | 0.083 | 0 | 0.133 | 0.208 |
| 10 | False Alarm | 0.242 | 0.225 | 0.7204 | 0.242 | 0.225 |
| | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| 100 | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |

Gradient

| Lambda | Evaluation Metric | var_prior | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| 1 | False Alar | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0.033 | 0.092 |
| 10 | False Alarm | 0.4 | 0.4 | 0.4 | 0.292 | 0.267 |
| | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| 100 | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |

HSV

| Lambda | Evaluation Metric | var_prior | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| 1 | False Alar | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Detection | 0.133 | 0.125 | 0.092 | 0.117 | 0.108 |
| 10 | False Alarm | 0.25 | 0.292 | 0.275 | 0.283 | 0.283 |
| | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| 100 | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.342 |

(e) Kernel Logistic Regression for different colorspace

Fig. 6: Evaluation Results For People present / People not present Class

RGB

| nu | Evaluation Metric | lambda | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.2 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.217 | 0.4 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0.225 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.208 | 0.4 |
| | Miss Dete | 0 | 0 | 0 | 0.217 | 0 |
| 1 | False Alar | 0.4 | 0.4 | 0.4 | 0.167 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0.242 | 0 |
| 10 | False Alarm | 0.4 | 0.4 | 0.4 | 0.2 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0.217 | 0 |
| 100 | False Alarm | 0.4 | 0.4 | 0.4 | 0.2 | 0.4 |

Gray

| nu | Evaluation Metric | lambda | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.083 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.258 | 0.4 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0.092 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.283 | 0.4 |
| | Miss Dete | 0 | 0 | 0 | 0.1 | 0 |
| 1 | False Alar | 0.4 | 0.4 | 0.4 | 0.217 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0.092 | 0 |
| 10 | False Alarm | 0.4 | 0.4 | 0.4 | 0.225 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0.117 | 0 |
| 100 | False Alarm | 0.4 | 0.4 | 0.4 | 0.225 | 0.4 |

YCbCr

| nu | Evaluation Metric | lambda | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.058 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.233 | 0.4 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0.092 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.217 | 0.4 |
| | Miss Dete | 0 | 0 | 0 | 0.133 | 0 |
| 1 | False Alar | 0.4 | 0.4 | 0.4 | 0.225 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0.083 | 0 |
| 10 | False Alarm | 0.4 | 0.4 | 0.4 | 0.217 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0.125 | 0 |
| 100 | False Alarm | 0.4 | 0.4 | 0.4 | 0.225 | 0.4 |

Gradient

| nu | Evaluation Metric | lambda | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| 1 | False Alar | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| 10 | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| 100 | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |

HSV

| nu | Evaluation Metric | lambda | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.133 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.317 | 0.4 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Miss Dete | 0 | 0 | 0 | 0.125 | 0 |
| 1 | False Alar | 0.4 | 0.4 | 0.4 | 0.233 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0.092 | 0 |
| 10 | False Alarm | 0.4 | 0.4 | 0.4 | 0.233 | 0.4 |
| | Miss Detection | 0 | 0 | 0 | 0.125 | 0 |
| 100 | False Alarm | 0.4 | 0.4 | 0.4 | 0.267 | 0.4 |

(f) Relevance Vector Logistic Regression for different colorspace

Fig. 6: Evaluation Results For People present / People not present Class (cont.)

| Evaluation Metric | Colorspace | | | | |
|---|---|---|---|---|---|
| | RGB | Gray | HSV | YCbCr | Gradient |
| Miss Detection | 0 | 0.12 | 0 | 0 | 0.14 |
| False Alarm | 0.63 | 0.14 | 0.63 | 0.63 | 0.157 |

(a) Logistic Regression for different colorspace

| Evaluation Metric | Colorspace | | | | |
|---|---|---|---|---|---|
| | RGB | Gray | HSV | YCbCr | Gradient |
| Miss Detection | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 |
| False Alarm | 0 | 0 | 0 | 0 | 0 |

(b) Dual Logistic Regression for different colorspace

| var_prior | Evaluation Metric | Colorspace | | | | |
|---|---|---|---|---|---|---|
| | | RGB | Gray | HSV | YCbCr | Gradient |
| 0.001 | Miss Detection | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 |
| 0.01 | Miss Detection | 0.37 | 0.37 | 0.303 | 0.37 | 0.37 |
| | False Alarm | 0.017 | 0 | 0.16 | 0 | 0 |
| 0.1 | Miss Dete | 0.243 | 0.3 | 0.18 | 0.37 | 0.37 |
| | False Alar | 0.23 | 0.117 | 0.277 | 0 | 0 |
| 1 | Miss Detection | 0.143 | 0.193 | 0 | 0.14 | 0.353 |
| | False Alarm | 0.417 | 0.243 | 0.597 | 0.247 | 0.107 |
| 10 | Miss Detection | 0.053 | 0.0367 | 0 | 0.0567 | 0.12 |
| | False Alarm | 0.523 | 0.573 | 0.63 | 0.543 | 0.303 |
| 100 | Miss Detection | 0 | 0 | 0 | 0 | 0.02 |
| | False Alarm | 0.63 | 0.593 | 0.63 | 0.63 | 0.457 |

(c) Bayesian Logistic Regression for different colorspace

| var_prior | Evaluation Metric | Colorspace | | | | |
|---|---|---|---|---|---|---|
| | | RGB | Gray | HSV | YCbCr | Gradient |
| 0.001 | Miss Detection | 0.067 | 0.14 | 0 | 0.083 | 0.227 |
| | False Alarm | 0.497 | 0.387 | 0.63 | 0.513 | 0 |
| 0.01 | Miss Detection | 0.033 | 0 | 0.05 | 0.03 | 0.143 |
| | False Alarm | 0.53 | 0.63 | 0.547 | 0.563 | 0.31 |
| 0.1 | Miss Dete | 0.107 | 0.05 | 0.08 | 0 | 0.05 |
| | False Alar | 0.437 | 0.497 | 0.51 | 0.63 | 0.38 |
| 1 | Miss Detection | 0.19 | 0.05 | 0.067 | 0.197 | 0.09 |
| | False Alarm | 0.27 | 0.58 | 0.497 | 0.327 | 0.367 |
| 10 | Miss Detection | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 |
| 100 | Miss Detection | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 |
| | False Alarm | 0 | 0 | 0 | 0 | 0 |

(d) Dual Bayesian Logistic Regression for different colorspace

RGB

| Lambda | Evaluation Metric | var_prior | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 1 | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| | False Alar | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 10 | Miss Detection | 0.127 | 0.14 | 0.123 | 0.107 | 0.13 |
| | False Alarm | 0.137 | 0.157 | 0.123 | 0.12 | 0.127 |
| 100 | Miss Detection | 0.37 | 0.37 | 0.293 | 0.247 | 0.197 |
| | False Alarm | 0 | 0 | 0.037 | 0.083 | 0.07 |

YCbCr

| Lambda | Evaluation Metric | var_prior | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 1 | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| | False Alar | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 10 | Miss Detection | 0.21 | 0.23 | 0.193 | 0.213 | 0.21 |
| | False Alarm | 0.073 | 0.057 | 0.053 | 0.073 | 0.107 |
| 100 | Miss Detection | 0.37 | 0.37 | 0.37 | 0.297 | 0.283 |
| | False Alarm | 0 | 0 | 0 | 0.03 | 0.1 |

HSV

| Lambda | Evaluation Metric | var_prior | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 1 | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| | False Alar | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 10 | Miss Detection | 0.14 | 0.127 | 0.11 | 0.123 | 0.087 |
| | False Alarm | 0.073 | 0.157 | 0.107 | 0.05 | 0.103 |

Gray

| Lambda | Evaluation Metric | var_prior | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 1 | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| | False Alar | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 10 | Miss Detection | 0.19 | 0.18 | 0.157 | 0.197 | 0.177 |
| | False Alarm | 0.083 | 0.053 | 0.067 | 0.07 | 0.053 |
| 100 | Miss Detection | 0.37 | 0.37 | 0.353 | 0.24 | 0.22 |
| | False Alarm | 0 | 0 | 0.02 | 0.107 | 0.087 |

Gradient

| Lambda | Evaluation Metric | var_prior | | | | |
|---|---|---|---|---|---|---|
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0 | 0 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| 1 | Miss Dete | 0 | 0 | 0 | 0 | 0 |
| | False Alar | 0.597 | 0.63 | 0.597 | 0.593 | 0.593 |
| 10 | Miss Detection | 0.37 | 0.37 | 0.303 | 0.16 | 0.167 |
| | False Alarm | 0 | 0 | 0 | 0.033 | 0.053 |
| 100 | Miss Detection | 0.37 | 0.37 | 0.37 | 0.37 | 0.283 |
| | False Alarm | 0 | 0 | 0 | 0.017 | 0.067 |

(e) Kernel Logistic Regression for different colorspace

Fig. 7: Evaluation Results For Shoulder / Not shoulder Class

| RGB | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.107 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.12 | 0 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0.13 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.137 | 0 |
| 1 | Miss Dete | 0 | 0 | 0 | 0.1 | 0.37 |
| | False Alar | 0.63 | 0.63 | 0.63 | 0.157 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.123 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.157 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.127 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.117 | 0 |

| Gray | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.197 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.07 | 0 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0.157 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.057 | 0 |
| 1 | Miss Dete | 0 | 0 | 0 | 0.197 | 0.37 |
| | False Alar | 0.63 | 0.63 | 0.63 | 0.07 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.16 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.053 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.173 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.093 | 0 |

| YCbCr | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.193 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.083 | 0 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0.193 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.033 | 0 |
| 1 | Miss Dete | 0 | 0 | 0 | 0.21 | 0.37 |
| | False Alar | 0.63 | 0.63 | 0.63 | 0.05 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.207 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.09 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.193 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.05 | 0 |

| Gradient | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.37 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0 | 0 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0.37 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.597 | 0 | 0 |
| 1 | Miss Dete | 0 | 0 | 0 | 0.37 | 0.37 |
| | False Alar | 0.63 | 0.63 | 0.597 | 0 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.317 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.593 | 0 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.33 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.597 | 0 | 0 |

| HSV | | | | | | |
|---|---|---|---|---|---|---|
| nu | Evaluation Metric | lambda | | | | |
| | | 0.01 | 0.1 | 1 | 10 | 100 |
| 0.01 | Miss Detection | 0 | 0 | 0 | 0.123 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.053 | 0 |
| 0.1 | Miss Detection | 0 | 0 | 0 | 0.16 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.09 | 0 |
| 1 | Miss Dete | 0 | 0 | 0 | 0.157 | 0.37 |
| | False Alar | 0.63 | 0.63 | 0.63 | 0.05 | 0 |
| 10 | Miss Detection | 0 | 0 | 0 | 0.14 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.09 | 0 |
| 100 | Miss Detection | 0 | 0 | 0 | 0.16 | 0.37 |
| | False Alarm | 0.63 | 0.63 | 0.63 | 0.097 | 0 |

(f) Relevance Vector Logistic Regression for different colorspace

Fig. 7: Evaluation Results For Shoulder / Not shoulder Class (cont.)