Distracted Driver Detection

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I. Problem Statement

Distracted driving is a global public health concern that is largely preventable. According to a study [1] conducted by NCBI-NIH, Govt. of India, as much as 44.7% of motor vehicle collisions were due to the use of mobile phones alone. Other forms of distraction include adjusting ones hair, looking in the rearview mirror for a prolonged time, peeking outside windows and others.

In this project, we aim to detect such distracted drivers from among a set of actions portrayed in each sample of the image dataset provided as part of an already-concluded Kaggle competition [2].

II. Literature Review

Distraction can be broadly categorized into three types: visual (eg. taking ones eyes off the road), cognitive (eg. taking ones mind off driving) and manual (eg. taking ones hands off the steering wheel). The focus of this project is on manual distractions. In order to process images corresponding to this specific problem, CNNs (Convolutional Neural Networks) have been tested [2] as the most state-of-art technique and has led to efficient performance on visual recognition.

Another popular model that has been used is VGGNet, which is a pre-trained deep CNN. In 2017, Abouelnaga et al. [3] created a new dataset similar to StateFarms dataset for distracted driver detection. Authors preprocessed the images by applying skin, face and hand segmentation and proposed the solution using weighted ensemble of five different CNNs.

For the specific distracted driver detection task, most of the top teams on Kaggle Leaderboard have tried [2] ResNet and Inception models; then ensembled different models.

III. Database Details

The dataset consists of 100k images among which 79k (unlabelled) are for testing and 22k labelled images are for training. For our project, we shall divide the labelled images as 70% for training and 30% for testing. *Table 1* gives a concise description of the dataset.

Link: Kaggle Distracted Driver Challenge

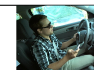
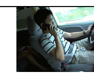
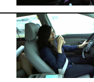
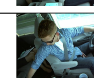
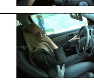
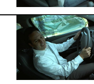
Class Symbol	Class Name	Number of Training Images	Sample Class Image
C0	Normal Driving	2490	
C1	Texting (right)	2268	
C2	Talking on the phone (right)	2318	
C3	Texting (left)	2347	
C4	Talking on the phone (left)	2327	
C5	Operating the radio	2313	
C6	Drinking	2326	
C7	Reaching behind	2003	
C8	Hair and Makeup	1912	
C9	Talking to passenger	2130	

Table 1: Class labels alongwith their description, count and sample image

IV. Work Done

A. Preprocessing

The training dataset consists of imbalanced class samples and images with different illumination. This is addressed by manually removing some of the images from training data. The illumination is handled by using histogram equalization.

B. Feature engineering

- Intensity value
- Histogram value
- Haar wavelets
- Histogram of Oriented Gradient (HOG)
- Local Binary Pattern (LBP)

We used these features individually and in conjunction to train and test our data using different models.

C. *Classifiers*

For the classification we use the following classifiers along with the features mentioned in above section.

- Gaussian Naive Bayes (GNB)
- Logistic Regression (LR)
- Support Vector Machine (SVM)

V. RESULTS

The images in both datasets were used for five different features - intensity values of each pixel, histogram of the image, HOG on the image, Haar wavelet decomposition on the image and LBP on the image. Following are the set of test accuracies obtained for different classifiers:

Classifier	**Accuracy (%)**				
	Intensity	**Histogram**	**HOG**	**Haar**	**LBP**
Naive Bayes (NB)	49.69	19.34	75.4	54.11	19.15
Logistic Regression (LR)	97.39	21.77	93.46	19.01	97.48
Support Vector Machine (SVM)	61.75	22.32	95.92	99.39	16.46

Table 2: Accuracy on different features

The results for different classifiers using different features were uploaded on Kaggle and the following multi-class logarithmic loss scores were obtained as summarised below:

Classifier	Feature	Kaggle Score
LR	**HOG**	**2.01986**
SVM	Wavelet	2.59980
LR	HOG + LBP	5.57286

Table 3: Kaggle scores for classifier-feature combinations

ROC curve and Confusion Matrix for best score on Kaggle, as highlighted above:

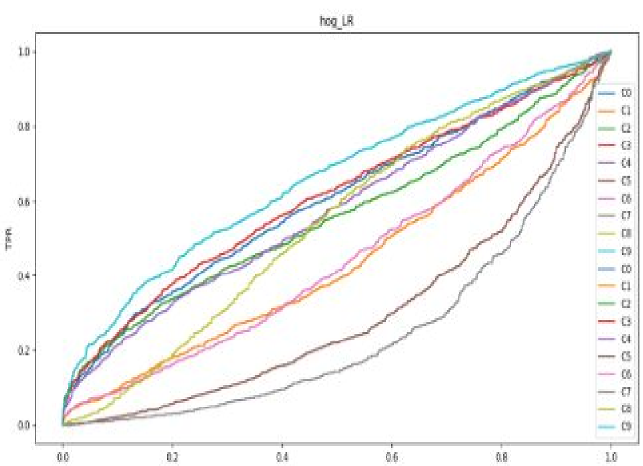


Figure 1. ROC Curve

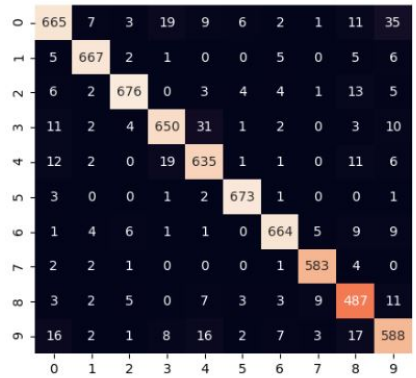


Figure 2. Confusion Matrix

VI. FUTURE WORK

In the next phase of our project, we plan to implement the following:

- Segment the person alongwith the action from each image and then train the classifier. This should increase the classification accuracy as we ignore irrelevant segemnts in the image like the view outside the window, interior of the car etc.
- Implement GIST as a feature
- Adaboost model for classification
- Bagging model for classification
- Deep learning models for classification

REFERENCES

[1] Natasa Zatezalo, Mete Erdogan, and Robert S Green. Road traffic injuries and fatalities among drivers distracted by mobile devices. *Journal of emergencies, trauma, and shock*, 11(3):175, 2018.

[2] https://www.kaggle.com/c/state-farm-distracted-driver-detection/.

[3] Yehya Abouelnaga, Hesham M Eraqi, and Mohamed N Moustafa. Real-time distracted driver posture classification. *arXiv preprint arXiv:1706.09498*, 2017.