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Enhanced Method of Detecting Wearing of Helmets in Traffic Using HOG-Sobel and Decision Tree Method

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Abstract: The disregard for road safety by those operating two-wheeled vehicles frequently leads to accidents and fatalities. Numerous nations have implemented a compulsory requirement for individuals to wear helmets when operating two-wheeled vehicles. If the riders do not wear helmets, they face an accident. This will lead to dangerous head or brain injury due to riding without protection. For this reason, we constructed a model based on HoG-Sobel fusion approach and a decision tree method to identify precisely the presence of a helmet on a person depicted in a picture. In this work, the author engages in the process of capturing photographs and subsequently extracting their attributes through the utilization of image processing techniques. Next, a model is constructed via machine learning techniques based on the aforementioned retrieved attributes. In this analysis, a comparison is conducted on several image processing and classification algorithms utilized for the given dataset. To enforce this requirement, a system has been constructed utilizing Tensorflow and Keras within the domain of computer vision. The decision tree classifier achieved the highest accuracy as compared to various classification models that were examined. This technique appears to be effective to ascertain whether individuals operating two-wheeled vehicles use a helmet for head protection. The use of helmets, designed to preserve human life will be impacted.

Keywords: *Helmet Detection, Decision Tree, HOG-Sobel, Classification, Machine Learning*

1. Introduction

Traffic accidents have increased dramatically in the last few decades. Every year, a large number of individuals fall victim to vehicle accidents. The bulk of all accidents are road incidents involving two-wheelers. The governing bodies have implemented numerous regulations, although only some individuals adhere to them. Ensuring proper helmet utilization is important in upholding safety standards. Following the Motor Vehicles Act of 1988, helmet use is mandatory, and neglect may result in a penalty. It is important to adhere to legal regulations mandating the use of helmets, as they safeguard the well-being of riders throughout the act of driving. A system for recognizing and categorizing helmets in photographs is the focus of this investigation. The helmet is essential for those engaged in riding activities and for many professionals and athletes in different occupational fields. This research mainly focused on helmet identification in an image using classification approach from machine learning domain.

Authors in paper [1] proposed a method where motorcyclists can be automatically clustered together and K − NN classifier used to remove motorcycling objects and determine if they are wearing helmets. In paper [2], researchers used a multi-layer perception classifier to detect cashless cyclists using Hough-transformation and feature extraction with unidirectional gradient histogram descriptors. In [3], Kalman filter method used to detect objects accurately. The cam shift technique employed for tracking the moving objects effectively. Similarly color pixel information of helmets has captured to identify the location of helmet of the motorcyclist. This proposed work aim is to protect and streamline unprotected motorcyclists by identifying helmet. In addition, the licence plate is retrieved so that it may be used to issue tickets for traffic violations. The technology employs machine learning and image processing to identify helmet-less motorcyclists.

The system in [4] identifies moving objects in the vicinity of public roadways by using videos of traffic as input. A machine learning classifier determines if the moving object is a two-wheeled vehicle. If it is a two-wheeled vehicle, a second classifier determines whether the rider doesn't wear a helmet. A Histogram of Oriented Gradient (HOG) was extracted from a paper by researchers [3]. Based on the extracted HOG features then trained with SVM classifier, and color feature recognition used for safety head-wear detection. The authors in paper [5] extracted the image data using a circular Hough transform and an oriented gradient histogram plot. After that, the results of other techniques compared with those of the Multilayer Perceptron classifier. You Only Look Once Method (YOLOv4) is employed to analyze helmet detection and violation of traffic rules [6].

In the literature, it is observed that there is a lack of a standard dataset to work on the automatic detection of

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helmets on two-wheeler riders. Most researchers used Support Vector Machine (SVM) classifier [3], Convolutional Neural Networks (CNN) [7], and deep learning techniques in [8] [9], but very few studies employed decision tree models to identify helmets. Hence, the proposed work started with the collection and creation of a dataset and proposed an enhanced method of detecting the wearing of helmets in traffic using a combined hog-sobel and decision tree method.

The aim is to construct a proposed model that can precisely identify the presence of a helmet on a person depicted in a picture. This work starts with the process of data collection and subsequently extracting their attributes through the utilization of image processing techniques. Next, a model is constructed via machine learning techniques based on the retrieved attributes. In this analysis, a comparison is conducted on several image processing and classification algorithms utilized for the given dataset.

The remaining part of paper is categorized into four sections: proposed methodology adopted for detecting helmets described in section 2. The experiments and its outcomes discussed in section

3. The section 4 provides conclusions and its future scope.

2. Proposed Methodology

The aim of this endeavor is to produce a model that correctly detects whether the individual in the picture has worn their helmet. In this work, the author engages in the process of data collection and subsequently extracting their attributes through the utilization of image processing techniques. Next, a model is constructed via machine learning techniques based on the retrieved attributes. In this analysis, a comparison is conducted on several image processing and classification algorithms utilized for the given dataset. The methodology adopted for the helmet detection comprises three steps, as depicted in Figure 1:

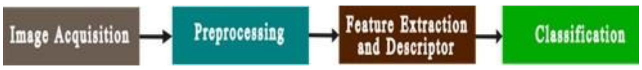

Fig 1. Overview of proposed system

Dataset preparation and preprocessing

This work's dataset contains photographs of individuals with and without helmets. Images without a helmet were gathered from the Kaggle mask dataset and the internet. Here, 66 images without helmets and 57 images with helmets are utilized. The proposed system tested based on helmet dataset. For training system, sample image data are required in two categories namely with helmet images and without helmet images. To perform experiments, with helmet images dataset prepared using Google search engine with creative license image and proper authentication. Further, without helmet images dataset prepared by collecting face mask detection dataset wherein images with face mask collected by Ashish Jangra [10] and without face mask images were from CelebFace dataset created by Jessica Li [11] taken from standard Kaggle dataset repository. These images are distributed as 80% in training and 20% in testing for the experimental evaluations. We extracted features namely HoG, Sobel, LBP, GLCM and Gabor of each image for the training as well as testing dataset and stored in feature maps.

It is required for preprocessing to clean or noise free images for further processing of feature extraction. Initially, color images are transformed into uniform color using gray scale algorithm. Further, gray scale image is converted in binary pattern by using Ostu thresholding procedure. Images from the dataset were converted from RGB to grayscale. The threshold function transforms the image into an image with two intensities. In the Otsu Threshold procedure, the threshold value is determined automatically. It analyzes the histogram and determines an optimal threshold value centered between the extreme values. Images with Sobel and canny edge detection are stored separately. Histogram of Oriented Gradients (HOG) is a technique utilized for extracting parameters from data images in the dataset. The image is divided into cells, and the intensity values are calculated. Using the Pythagorean theorem, the total size and direction of the gradient is calculated by the center pixel and the difference between the cells above and below the selected cell and the cells to the left and right of the selected cell. Each cell is further subdivided into local units for normalization. It extracts sum of individual values squared, and its square root value implemented further alogwith the local variation of the intensity gradients used to capture these blocks' histograms. Additionally, HOG images are stored separately. Sample images after pre-processing as presented in Figure 2.

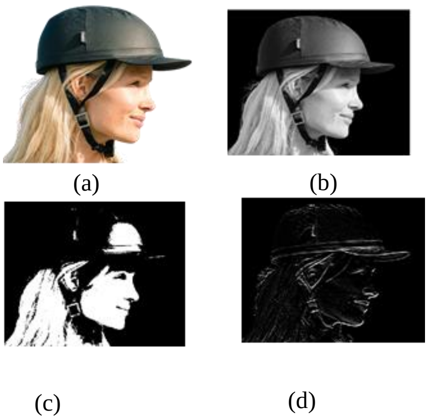

Fig 2. The Sample images used in experiments (a) Original RGB Image, (b) Grayscale Image, (C) Binary Image and (d) Sobel Image after pre-processing.

2.1. Extracting features

In this step, three features are extracted as mentioned below:

2.1.1. Local Binary Pattern (LBP)

This is a descriptor which represents texture. By dividing an image into cells, it computes the intensity values for each pixel. The binary pattern result defines the image's local texture. It calculates each pixel's LBP values [13], followed by a histogram calculation. This histogram is used to preserve the image's local texture. Visualized feature extracted for sample image depicted in Figure 3.

(a) (b)

Fig 3. Visualized feature extracted sample image (a) LBP visualization feature map, (b) HOG visualization cell size 16 × 16

i. LBP Histogram: This feature encodes an image's local texture by calculating the histogram of LBP values at each pixel.

ii. LBP Probability: This feature represents the local texture of an image by computing the probability of LBP values at each pixel.

iii. LBP Energy: This feature depicts the local texture of an image by calculating the energy of each pixel's LBP value.

2.2.2 Gray Level Co-occurrence Matrix (GLCM)

As a descriptor of texture, GLCM determines the possibility that two neighbor pixels have the same gray level value relying on their proximity [12].

i. Dissimilarity: The degree to which two particles differ.

ii. Correlation: Quantification of the degree to which two pixels are correlated. If two pixels with the same value are located far apart, this indicates a weak correlation between them. It is a measurement of the correlation intensity between two pixels, which can aid in identifying image patterns.

iii. Energy: It is calculated by analyzing the frequency with which two pixels with the same value appear in various relative positions within an image.

iv. Contrast: The difference between two pixels in an image

v. Homogeneity: It is a metric that quantifies the similarity between two pixels.

2.2.3 Gabor

An example of a linear filter used in image processing is the Gabor filter [13]. An input image is convolved with a Gabor kernel, an isotropic Gaussian envelope modulated by a sinusoidal plane wave, for them to function. Edge detection, texture analysis, and feature extraction frequently employ Gabor filters.

i. Energy measures the energy of image edges

ii. Entropy measures the randomness of image edges.

2.2. Classification

Four different classification models used in experimental evaluations are: Support Vector System (SVM), K-Nearest Neighbor (K-NN), Random Forest and Decision Tree.

i. SVM employed for classification which basically adopts supervised learning strategy. It generates a hyperplane after arranging the observations within a space of higher dimensions. The plane separates the data elements into distinct categories. The hyper plane is a dividing line that creates the most significant possible separation between the two classes. SVM is also used to solve classification problems that are not linear. There are different kernels in SVM namely the Radial Basis Function, polynomial, sigmoid, and Gaussian distributions. The kernel analyzes the data and produces details that may be applied when labeling the data [14].

ii. K-NN is classification-based supervised machine learning strategy. It identifies the K-nearest neighbors of a given data point and predicts the category the data point belongs to. It selects K-neighbors based on the calculated distance between two new data points.

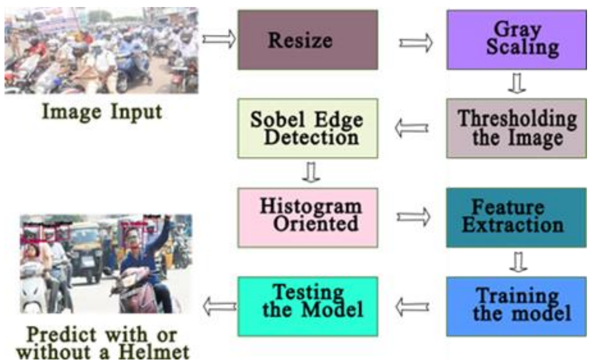

Fig 4. System architecture of proposed methodology

In addition, the class of new data points is determined by recording which class has the most neighbors.

iii. Random Forest is the technique used in ensembles. Creating a prediction by constructing a collection of decision trees and combining their results. The method randomly selects characteristics from the dataset and then constructs decision trees using them. Predictions are made using the output of these trees.

iv. Decision Tree is also an example of a guided machine learning classifier. The classifier has a tree-like structure. Its internal nodes contain the characteristics of a dataset, its branches contain the decision criteria, and its leaf nodes contain the result. Decision nodes are used to make any decision and can have multiple branches. The results of these decisions are leaf nodes, which contain no additional branches.

Figure 4 represents building the model to recognize the helmet using the proposed methodology. Initially, the image is taken from the created dataset. This input image has undergone the preprocessing steps like resizing gray scaling. Then, the threshold image is further used to extract the features for Sobel edge detection and Histogram Oriented Gradient (HOG). Similarly, features of all the images from the given dataset are stored in the feature library. Finally, 80% of the dataset is allocated for training, while 20% is reserved for testing to predict accuracy and precision with or without a helmet.

3. Results and Discussion

The dataset used for experiments contains images of individuals with and without helmets. Images without helmets were gathered from the Kaggle mask dataset and images with helmets were collected online. Here, 66 images without helmets and 57 images with helmets are utilized.

Model Training: The proportion of the training and validation sets in the dataset is 80 - 20.The training process involves utilizing a set of group size 32. With callbacks for model check pointing, learning rate schedule, and early termination, the training is carried out across 20 epochs. Table 1 summarizes the results for Helmet Detection using different classification models.

Table 1. Accuracy for Different Classification Models

Classification Model Name	**Features**	**Accuracy**
SVM	HoG	0.56
	Sobel	0.56
	HoG and Sobel	0.56
K-NN	HoG	0.52
	Sobel	0.56
	HoG and Sobel	0.52
Random Forest	HoG	0.52
	Sobel	0.56
	HoG and Sobel	0.6
Decision Tree	HoG	0.68
	Sobel	0.52
	HoG and Sobel	0.72

According to Table 1, the decision tree classifier was found to have a maximum accuracy of 72% and appears to be effective in this role. The Random Forest classifier achieved an accuracy of 60%, which is slightly lower than Decision tree but still relatively good. SVM, and K-NN classifiers obtained an accuracy of 56%, 52% respectively.

3.1. Accuracy Score

The assessment of a classification model's performance is known as accuracy. The computation involves dividing the number of precise predictions the algorithm makes by the number of forecasts. Solely, it fails to depict the model's performance accurately. A confusion matrix is prevalent in assessing a classification model's performance. It takes the shape of a matrix. A particular dataset's observed and forecasted categories are organized in tabular format. The matrix elements represent the count of data points accurately classified, inaccurately categorized, and left unclassified. The confusion matrix of K-NN displayed in Figure 5. Mathematical representation of evaluation measures comprising recall, precision, F1-score,and accuracy are computed using equations 1-4 [15] with the help of the confusion matrix which are later used to estimate the effectiveness of the model.

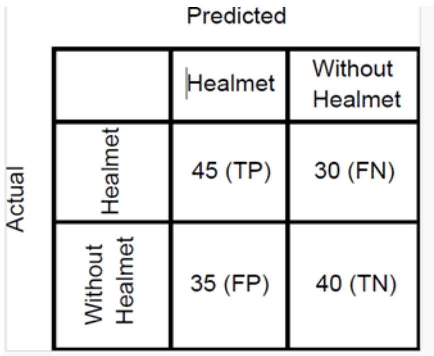

Fig 5. Confusion Matrix of K-NN

The current paper provides a comprehensive analysis of the classification performance by utilizing a classification report. Table 2 displays the combined outcome of various accuracy measures, including F1-score, recall, and precision for the decision tree classification model. The receiver function curve (ROC) shows the accuracy of classification in Figure 6. A curve exhibits both the true positive (TP) rate, false positive ratio (FP). The TP is the percentage of reliably identified positive cases. The false positive rate in research is the ratio of false positives to negative predictions.

Table 2. Classification Report for Decision Tree Classifier

	Precision	Recall	F1-score	support
0	0.55	0.92	0.76	12
1	0.88	0.54	0.67	13
Accuracy	-	-	0.72	25
Macro avg	0.76	0.73	0.71	25
Weighted avg	0.77	0.72	0.71	25

$$Recall = \frac{TP}{TP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

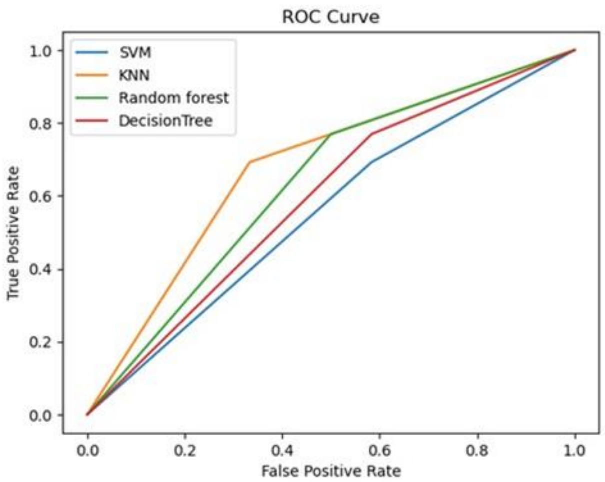

Fig 6. ROC Curve- HoG with Sobel model

4. Conclusion

This research investigates many image processing approaches, including Sobel, Canny edge detection, Histogram of Oriented Gradients (HOG), and a fusion approach that integrates both HOG-Sobel methods. The Canny and Sobel edge detection algorithms have similar degrees of accuracy. This study intends to examine the usefulness of these techniques in helmet identification. A variety of classifiers, including SVM, K − NN, random forest, and decision tree were employed in this research. Among the several classifiers that were assessed, it was found that the Decision Tree classifier demonstrated the most superior degree of accuracy. Implementing the model on a designated traffic camera is suggested as a future phase of this research. Furthermore, with the identification of helmets worn by motorcyclists, there will be a pursuit of implementing vehicle number identification. The inclusion of this supplementary feature will facilitate the identification and localization of those who engage in the violation of traffic restrictions. Moreover, it is possible to determine the persons adhering to legal norms to distribute information and enhance public awareness efficiently.

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