Innovative Multi-Feature Based Weather Classification for Supervised Learning in Multiclass Environments

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Abstract

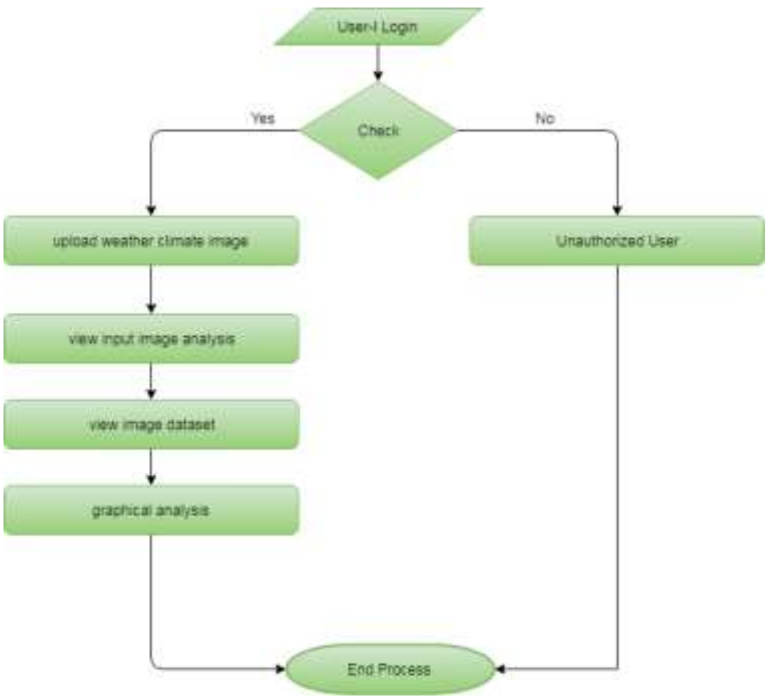
Highway traffic accidents have devastating consequences, leading to significant loss of lives and property. However, one promising solution to reduce these accidents lies in the implementation of advanced driver assistance systems (ADAS). These systems have proven to be effective in enhancing road safety. A critical component for these ADAS is the ability to perceive and understand complex traffic scenes under various weather conditions, as this valuable information can greatly improve their performance. Different weather conditions present unique challenges, particularly in terms of visibility, and specialized approaches are needed to address these challenges effectively. By tailoring the ADAS algorithms based on weather categories, we can enhance visibility and expand the application of these systems further. Among the weather conditions that significantly impact traffic safety are rainy days, dark nights, overcast and rainy nights, foggy days, and other situations with poor visibility. Most current vision-based driver assistance systems are optimized to function well under favorable weather conditions. To address the issue of poor visibility in bad weather situations, a multi-class weather classification method is proposed. This method relies on multiple weather features and supervised learning techniques. First, visual features are extracted from multi-traffic scene images. These features are then represented as an eight-dimensional feature matrix, capturing the crucial characteristics of the scene. Next, the supervised learning algorithms are employed to train classifiers, enabling the system to recognize different weather conditions accurately. The analysis of the proposed method shows promising results. The extracted features effectively describe the image semantics, and the trained classifiers demonstrate high recognition accuracy and adaptability. This lays the foundation for enhancing anterior vehicle detection during nighttime illumination changes and improving the driver's field of vision on foggy days. By integrating this multi-class weather classification method into ADAS, there will be a significant improvement in road safety, especially during challenging weather conditions. This advancement will have a positive impact on reducing traffic accidents and protecting the lives of motorists and pedestrians alike.

1. Introduction

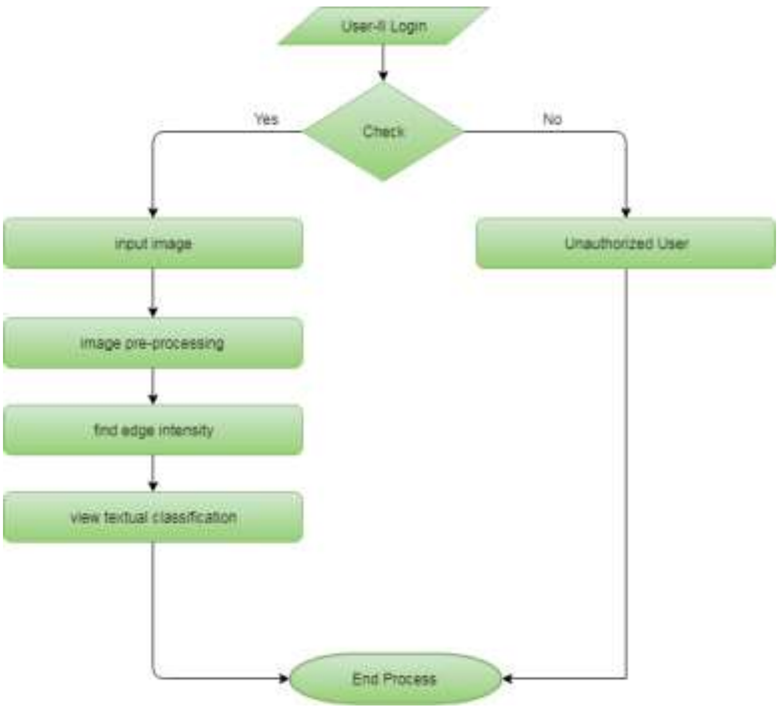
In recent years, significant research has been made as an attempt to deal with the weather classification problem. However, the existing works still have some limitations. The weather identification was initially carried out in the road detection system, but only the relatively single rain [2, 3], fog [4, 5, 6] weather conditions were identified. Most of the weather images used to train this classifier were captured by In-Vehicle Multipurpose Cameras, which in the car on the highway, but these captured images are fixed and share a set of similar features, which implies the classifier cannot be generalized for the images with different backgrounds and viewpoints [7]. Practically, domain specific engineered features play an important role in building a weather classification model. Most recent works [8] have utilized sky and shadow to constitute weather specific features for weather classification model. Lu et al. [9] presented a two-class weather classification framework that classified images based on SVM and five weather-specific features such as sky, haze, contrast, reflection and shadow. Zhang et al. [10] proposed a method to label images with four weather conditions including sunny, cloudy, and snowy and haze. They trained a SVM as weather classifier which combined the global and local features. Martin et al. [11] estimated weather conditions by extracting five features of images (such as brightness, contrast, sharpness, saturation, and hue) and training a classifier base on SVM. Recently, CNN is one of the most advanced and very widely used classification models in image classification. Krichevsky et al. [12] proposed a particular CNN structure called AlexNet and obtained the champion of the ILSVRC-2012 ImageNet challenge. Elhoseiny et al. [1] proposed a method to label the image as either sunny or cloudy based on AlexNet. Lu et al. [13] performed a similar series of experiments to extend their work of two-class weather recognition based on [12]. The study by Zhu [14] offered a comprehensive empirical analysis of the four class weather classification algorithms through fine-tuning the Google Net. Di Lin et al. [15] proposed a deep learning framework named the region selection and concurrency model (RSCM) which used regional cues to identify the weather category. Different from these methods, we extracted six well-chosen weather-specific features to represent different weather types and fused data-driven CNNs feature to train classification models.

3. Proposed System

In this work, firstly, owing to classify multi-traffic scene road images, underlying visual features (color features, texture features, edge features) are extracted from multi-traffic scene images, and then the features expressed as eight-dimensions feature matrix. The traffic scene classification problem is becoming the supervised learning problem. Secondly, BP neural network, support vector machine, probabilistic neural network, S_Kohonen network and extreme learning machine algorithms are used to train classifiers. In order to achieve weather images automatic classification, the main steps are shown in Fig. 1



(a)



(b)

Figure 4.1: Proposed system workflow diagram.

According to the facts, training and testing of proposed model involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1]. Convolution layer as is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$.

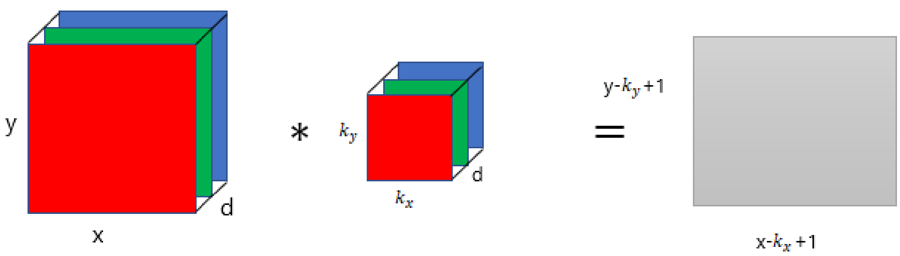
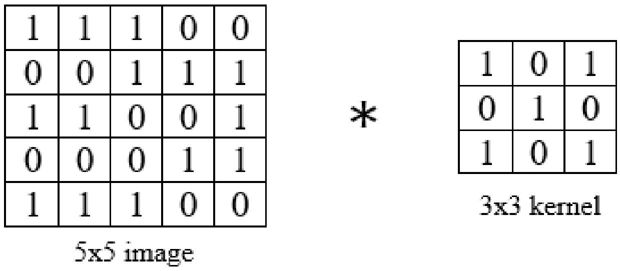
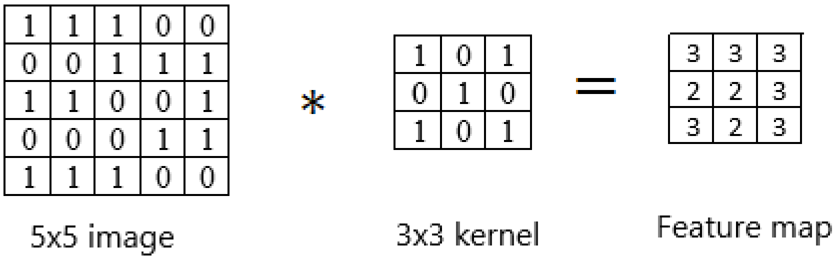


Fig. 2: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.



(a)



(b)

Fig. 3: Example of convolution layer process (a) an image with size $\mathbf{5} \times \mathbf{5}$ is convolving with $\mathbf{3} \times \mathbf{3}$ kernel (b) Convolved feature map

ReLU layer: Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

Max pooing layer: This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

Softmax classifier: Generally, as seen in the above picture softmax function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

4.Results and Discussion

```
image_dataset = load_image_files("C:\\complete project SVM\\train")

clf = CNN()

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)
```

```
print('accuracy is :',accuracy_score(y_test,y_pred))

#accuracy is : 0.6333333333333333

print("Classification report for - \n{}:\n{}\n".format(

   clf, metrics.classification_report(y_test, y_pred)))

'''

 precision    recall  f1-score   support

         0       0.50      0.85      0.63        13

         1       0.89      0.53      0.67        15

         2       0.74      0.70      0.72        20

         3       0.50      0.42      0.45        12


  micro avg       0.63      0.63      0.63        60

  macro avg       0.66      0.62      0.62        60

weighted avg       0.68      0.63      0.63        60

'''
```

5. Conclusion

This work implemented a comprehensive approach to address the challenge of image classification within the context of accident scenarios. It orchestrates a series of essential tasks, encompassing image preprocessing, feature extraction, and machine learning model training, to effectively categorize images associated with different types of accidents. This project offered valuable insights and achievements in several critical areas of image analysis and classification. One of the primary accomplishments lies in its adeptness at feature extraction. By distilling meaningful features from images, such as grayscale representations, blurred versions, contour maps, and Gaussian-filtered renditions, it effectively transforms raw image data into a format that is amenable to machine learning analysis. This initial phase is pivotal as it equips the models with relevant and discriminative information. Furthermore, this demonstrates a versatile approach by employing various machine learning techniques. It employs SVM and Naive Bayes algorithms to establish classification models. These models are meticulously trained using labeled image datasets, enabling them to discern and recognize patterns indicative of distinct accident types. Additionally, the inclusion of CNNs underscores the potential of deep learning in tackling intricate image recognition challenges. The CNN model's definition and training underscore its applicability in this context. Finally, single image prediction adds a practical dimension to its functionality. This feature facilitates swift assessments of individual images, a capability of paramount importance in real-time applications where rapid evaluation of accidents or other image-related scenarios is imperative.

References

[1] M. Elhoseiny, S. Huang and A. Elgammal, "Weather classification with deep convolutional neural networks," in 2015 IEEE International Conference on Image Processing (ICIP), pp. 3349–3353, Quebec City, QC, Canada (2015) [doi:10.1109/icip.2015.7351424].

[2] A. Cord and N. Gimonet, "Detecting Unfocused Raindrops: In-Vehicle Multipurpose Cameras," IEEE Robotics & Automation Magazine. 21 (1), 49-56 (2014) [doi:10.1109/mra.2013.2287451].

[3] Andreas Kuehnle, "Method and system for weather condition detection with image-based road characterization," May 7 2013, US Patent 8, 436, 902.

[4] M. Pavlic, G. Rigoll and S. Ilic, "Classification of images in fog and fog-free scenes for use in vehicles," 2013 IEEE Intelligent Vehicles Symposium (IV). 481 - 486 (2013) [doi:10.1109/ivs.2013.6629514].

[5] R. Belaroussi and D. Gruyer, "Convergence of a Traffic Signs-Based Fog Density Model," 2015 IEEE 18th International Conference on Intelligent Transportation Systems, pp. 783–787, Las Palmas, Spain (2015) [doi:10.1109/itsc.2015.132].

[6] Mario Pavlic, "Method for fog detection," July 5 2016, US Patent 9, 384, 401.

[7] J. Villarreal Guerra et al., "Weather Classification: A new multi-class dataset, data augmentation approach and comprehensive evaluations of Convolutional Neural Networks," 2018 NASA/ESA Conference on Adaptive Hardware and Systems (AHS), Edinburgh, UK (2018) [doi:10.1109/ahs.2018.8541482].

[8] Zhiqiang Li et al 2020 IOP Conf. Ser.: Earth Environ. Sci. 558 042038

[9] C. Lu et al., "Two-Class Weather Classification," 2014 IEEE Conference on Computer Vision and Pattern Recognition, pp. 3718–3725, Columbus, OH, USA (2014) [doi:10.1109/cvpr.2014.475].

[10] Z. Zhang and H. Ma, "Multi-class weather classification on single images," 2015 IEEE International Conference on Image Processing (ICIP), pp. 4396–4400, Quebec City, QC, Canada (2015) [doi:10.1109/icip.2015.7351637].

[11] M. Roser and F. Moosmann, "Classification of weather situations on single color images," 2008 IEEE Intelligent Vehicles Symposium, pp. 798–803, Eindhoven, Netherlands (2008) [doi:10.1109/ivs.2008.4621205].

[12] A. Krizhevsky, I. Sutskever and G. Hinton, "ImageNet classification with deep convolutional neural networks," Communications of the ACM. 60 (6), 84-90 (2017) [doi:10.1145/3065386].

[13] C. Lu et al., "Two-Class Weather Classification," IEEE Transactions on Pattern Analysis and Machine Intelligence, 39 (12), 2510-2524 (2017) [doi: 10.1109/tpami.2016.2640295].

[14] Z. Zhu et al., "Extreme Weather Recognition Using Convolutional Neural Networks," 2016 IEEE International Symposium on Multimedia (ISM), pp. 621-625, San Jose, CA, USA (2016) [doi:10.1109/ism.2016.0133].

[15] D. Lin et al., "RSCM: Region Selection and Concurrency Model for Multi-Class Weather Recognition," IEEE Transactions on Image Processing. 26 (9), 4154 - 4167 (2017) [doi:10.1109/tip.2017.2695883].