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Automatic Car Damage detection by Hybrid Deep Learning Multi Label Classification

P. Ebby Darney

Associate Professor, Department of Electrical and Electronics Engineering, RajaRajeswari College of Engineering, Bangalore, India

E-mail: darney.pebby@gmail.com

Abstract

Automating image-based automobile insurance claims processing is a significant opportunity. In this research work, car damage categorization that is aided by the hybrid convolutional neural network approach is addressed and hence the deep learning-based strategies are applied. Insurance firms may leverage this paper's design and implementation of an automobile damage classification/detection pipeline to streamline car insurance claim policy. Using deep convolutional networks to detect car damage is now possible because of recent improvements in the artificial intelligence sector, mainly due to less computation time and higher accuracy with a hybrid transformation deep learning algorithm. In this paper, multiclass classification proposed to categorize the car damage parts such as broken headlight/taillight, glass fragments, damaged bonnet etc. are compiled into the proposed dataset. This model has been pre-trained on a wide-ranging and benchmark dataset due to the dataset's limited size to minimize overfitting and to understand more common properties of the dataset. To increase the overall proposed model's performance, the CNN feature extraction model is trained with Resnet architecture with the coco car damage detection datasets and reaches a higher accuracy of 90.82%, which is much better than the previous findings on the comparable test sets.

Keywords: Car damage, deep learning, assessment process, CNN, convolutional auto encoder, SVM.

1. Introduction

The raw data is abstracted into a high-dimensional representation in deep learning by creating complicated neural network architecture with many layers to extract the deep features of the image in order to begin, neural networks focused on vector processing. For example, a

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profound system, abstracts car damage or fracture in body parts with the dense layers formation in deep learning approach [1, 2] using a biased weight vector to characterize the original data. The problem with this deep learning framework is that it includes too many neural nodes and a considerable amount of computation that relies on the hardware's capabilities. Moreover, using a one-dimensional vector to analyse a picture may result in losing its spatial structure and local correlation [3-6].

During the traffic accident scenes, the video images captured frame by frame can be taken for the further feature extraction process. The car's body damage that includes injury to the features of the car such as glass fracture, broken mirror etc. are allotted a very minimum claim in insurance policy. Therefore, the proposed algorithm must be set, to extract the features in deep and provide accurate compensation for the appropriate harm. The efficiency of the proposed model is improved by the following approaches;

(1) Construct more filters with convolution layers

(2) Use max pooling layers to minimize the dimensions of the space

The feature engineering of car damaged images on the road traffic collision must depend on people's past knowledge and expertise, and corresponding extraction approaches may be built for these specific activities to accomplish perfect outcomes [8]. Figure 1 shows car images from benchmark dataset which are available in kaggle.

Figure 1. Car images from Stanford dataset (available at kaggle)

Claims leakage costs the auto insurance business a lot of money nowadays. If all the industries followed best practices, the actual claim payment made would be precisely the same as the amount that should be paid. Such impacts have been minimized via visual examination and confirmation. However, they slow down the claim procedure. But a few start-ups, have reduced the claim processing time such as motor insurance claim must be processed within an hour. Road traffic incidents are a great source of information for feature learning of glass fractures [9-12].

Nowadays, the car showrooms deal insurance policies with new customers. Nevertheless, claim leakage is a manual validation of business shares that differs from location to location to achieve ideal insurance claim processing standards [13]. This is simply a waste of management time, leading to inefficiency in the process. Most commonly, the claim amount is paid towards various parts of the damaged car. But this research work classifies the car damage detection and identifies the part accurately in an effective manner. Besides, this work can help satisfy both customers and the insurance dealers systematically [14, 15].

2. Research Article Structure

The rest of the research work is organized as following sections; section 3 summarizes previous researches that categorize automotive damage. Section 4 presents the recommended process for assessing automobile damage automatically. Section 5 discusses several performance metrics. The last portion of this paper summarizes the research study.

3. Preliminaries

Researchers Ying Li and Chitra Dorai (2007) have established an easy technique for analysing slight damage to a vehicle, claiming that the model does not need training. Insurance architecture automatically uses advanced image analysis and pattern recognition technology to detect and classify car damage. Demonstrating the system's potential requires the construction of a prototype that compares before and after photographs to identify visually observable damage [16].

In Srimal Jayewardene's (2013) method, 3D Computer-Aided Design (CAD) model of the vehicle under consideration is used to determine how it would seem if it had not been damaged. However, they could not generate such 3D models and instead turned to cutting-edge computer vision technologies like Convolutional Neural Networks (CNN). Content has proved to be a powerful tool when it comes to object identification. As a result of utilizing photos taken at the scene of an accident to identify the extent of a vehicle's damage, insurance claims may be processed more quickly. Customers who make the most of this feature will also find it more convenient. Customers can be satisfied with insurance claims by processing their input image from their smartphone, irrespective of the damaged part. However, finding a solution to this problem is still challenging because of several considerations [17].

A multiple number of models have been proposed that monitored the actual road condition through various video streams by arranging several camera setups to improve the efficacy. The YOLO algorithm was used by Du et al. to identify and categorize pavement distress in a dataset of around 45k road photos from benchmark dataset. The photographs in the dataset were taken with an industrial high-resolution camera [18], while the present study relies on images taken using a more affordable phone.

Transfer learning is a well-known method that has shown success in minimal labelled data. Hamdan et al. proposed a feature extracted from the source identification with liveness module used for the target task's feature extraction network [19]. The ImageNet transfer learning algorithm can work efficiently with less number of label and minimize the overfitting problem through predefined values in CNN.

To classify a density pavement distress in 22 distinct U.S. pavement sections, Majidifard et al. employed top view images from both top-down and wide-view perspective. Unfortunately, only around 7k photos were included in the dataset. For an image processing-based classification assignment, an ideal number of tagged pictures required are roughly 5k to provide excellent results [20].

Jaywardena et al. devised a model to compare the picture of a scratched car to the “3D” CAD model of a ground truth vehicle image with the aid of detecting mechanism of car damage. The damaged vehicle at specific geographic location may also be assessed using satellite imagery [17].

4. Proposed Method

4.1 Convolution Neural Network

The first step is to initialize the trained CNN randomly. It is proposed that the design of a CNN should have ten layers: convolutional, pooling, and a fully linked layer. In each convolutional layer, there are 16 5-by-5-pixel filters. Convolutional layers employ RELU non-linearity. There are around 423K weights in the network as a whole. Each layer includes dropout, which enhances generalization [21-23].

4.2 Convolutional Auto Encoder

When training data is sparse, the convolutional filters are more efficient than other encoder type algorithm. The primary goal of an convolutional auto encoder learning approach is to learn the distribution of input data to extract functional features from a batch of unlabelled data. The proposed tool contains various input redundancies with sufficient essential data points for different categorization (multiclass) purpose. There are many trainable parameters in a fully linked autoencoder, notably in the case of pictures. Because of sparse connections and weight sharing, Convolutional AutoEncoders (CAE) are superior because they employ fewer parameters [24-28]. Unsupervised layers are piled on top of one other to construct the hierarchical structure of CAE. It is possible to train each layer on its own, with the previous layer's output serving as an input for the next. Finally, a cross-entropy objective function is used to back-propagate and fine-tune the whole set of layers. According to the results, the Resnet can provide more details about similar images present in the car damage image dataset.

4.3 Dataset description

A trained CNN is created using both the original and the enhanced coco car damage detection datasets. To prevent local minima and improve network stability, unsupervised initialization is preferable. For example, Stanford's automobile dataset provided unlabelled photos for slightly damaged series. Rotation and flip adjustments were added to the dataset to make it seem more significant. To classify these photographs, it is believed that learning about car-specific traits would be helpful. To fine-tune the layers, a lower learning rate is used [29].

4.4 Classification by SVM with normalized dataset

While some information is exclusive to specific domains, some knowledge might be anticipated to be shared throughout multiple contexts, which may boost performance in the target domain or activity. However, brute-force transfer may fail in circumstances when the source and destination domains are unrelated. This might lead to a decrease in performance. CNN models built using the Imagenet dataset are used as an example. The transfer is expected to be correct since the Imagenet dataset includes an automobile as an object. This was tested using different pre-trained models. The input photos of vehicle damage are in each network and extract feature vectors. These characteristics can't exist without the linear classifier being trained. Linear classifiers such as SVM and Softmax were tested. All epoch procedures contains relu activation function and final classification with SVM and softmax activation function. The Softmax classifier uses the "Adam" optimization algorithm and cross-entropy loss. The proposed model has been initially trained with 50 epochs in order to get higher accuracy but it obtained only 49% identified accuracy level. Later, it was trained with 100 epochs and then the classification model reached the highest accuracy than other traditional models. It is also possible to train linear classifiers using enhanced feature sets to improve generalization [30].

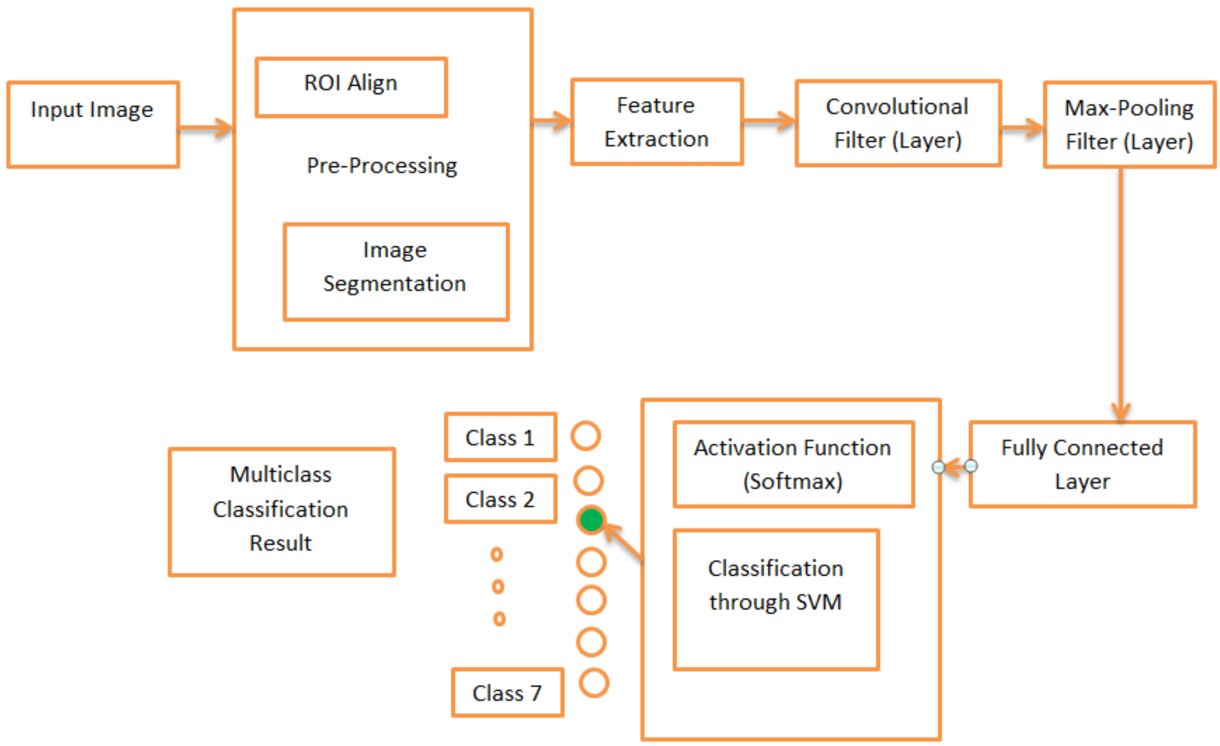

Figure 2. Block diagram of the proposed framework for car damage detection

4.5 Activation Function

Models that forecast multinomial probabilities employ the softmax function to activate the output layer. The activation function of softmax is also utilized for multi-class classification situations when class membership is needed on more than two class labels. In most circumstances, the data augmentations improve performance. Experimental test has showed that the Softmax activation function performs better than the other activation function such as relu, leaky relu and tanh; and it trains more efficiently. It is possible to classify every picture into one of the following categories: bumpers damaged, doors damaged, glass fragmented, head and tail lamps damaged. Since the computer does not comprehend certain kinds of data, it must turn it into numerical data with various class (1- 7) which is shown in the figure 2.

5. Experimental Tests

Coco car damage detection dataset is a publicly accessible dataset for the categorization of automotive damage which is produced and available in kaggle platform and has various images pertaining to different forms of damage to the vehicle which is shown in figure 3. This proposed research work has examined seven categories of damages named with 7 classes (multiclass) classification that are widely noticed;

1. Bumper / Fender pend,
2. Two side Door pend,
3. Glass fragment,
4. Headlamp smash,
5. Tail lamp broken,
6. Bonnet broken and
7. Small pends

Figure 3. Detected damage area and classified results

Images that don't show any signs of deterioration are also collected. Annotations were added manually to the photographs that were found on the internet. The dataset is described in Table 1.

In Table 1, Resnet is found to perform well in detecting the damage section of the car. The detector identifies the damaged area of the car and an algorithm trained on a damaged dataset classifies the proposed part's damage once it has been identified and localized. The photos accumulated over time, expands the dataset and improves the system's accuracy. The performance metrics such as accuracy, precision, recall, F1 measure, and false detection rate are measured to find the overall efficacy of the model. The proposed multiclass classifier provides a significantly lower false detection rate than other algorithms.

Table 1. Performance calculation for the proposed model

Model		Accuracy	Precision	Recall	F1 Measure	False detection rate
SVM(Pre-trained)		75%	72%	68%	72%	0.9%
CNN (Pre-trained)		82.76%	81.67%	86.9%	89.45%	0.61%
Proposed hybrid Multiclass CNN	Resnet	90.82%	91.18%	94.88%	90.09%	0.08%
	Inception	90.76%	74.67	87.9%	87.45%	0.7%

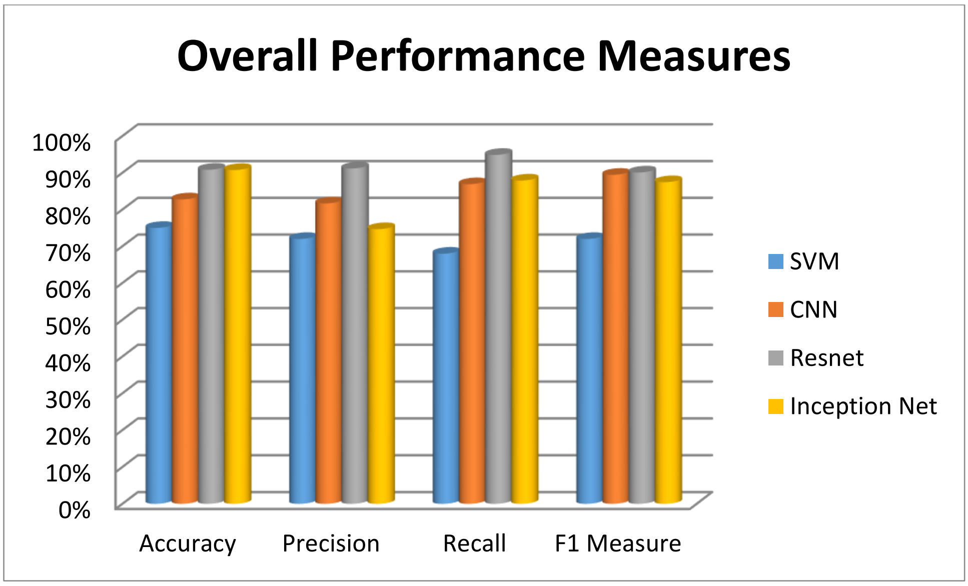

Figure 4. Performance chart of various models

The current proposed hybrid CNN approach with Resnet accuracy is found to be very accurate in training "coco car damage detection" dataset for identifying the damage as shown in figure 4.

The results obtained are positive, and common patterns can be discovered across all forms of damage, despite the very modest size of the dataset. Increasing the amount of dataset is all that is needed to improve the accuracy further. An extensive dataset of photographs provided by customers will help to increase the pipeline's capacity to identify the damage. In addition, it will enable the network to learn more essential characteristics that generalize well to inter-class changes over time, as long as saving the images are maintained.

6. Conclusion

A deep learning-based approach to automotive damage categorization is presented in this study. Since there is no publicly accessible dataset, photographs from the web were collected and manually annotated to build a new dataset. Deep learning-based approaches, including convolutional filters through auto encoders were tested in this experiment. Damage costs for different cars are classified and assessed using CNN with SVM classification which is found to be the most accurate method. This proposed architecture can be improved with the inclusive organization of more car parts to obtain better precision. Features learned from an extensive training set are shown to be better. Joint features may be derived from video, audio, and accelerometer data using feature extractors and new innovative ideas can be implemented further. The deep feature extraction methods can be performed well in sequential classifiers. There is a wide range of inputs from video and audio streams to accelerometer data streams, and a wide range of outputs. Sequential anomaly detection and classification framework may then be used to these characteristics. Based on this work, it is observed that, a larger dataset would enhance the system's performance and can be used in more dynamic real-world circumstances.

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Author's biography

P. Ebby Darney is working as an Associate Professor in the Department of Electrical and Electronics Engineering, RajaRajeswari College of Engineering, Bangalore, India. His area of research includes Image Processing, Artificial Intelligence, Control Systems, Radio Networks, and cloud computing.