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An Approach for Estimating Damage of Cars During Accidents Using Deep Learning Techniques

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A B S T R A C T

Photo based totally car coverage processing is an important vicinity with large scope for automation. In this paper we do not forget the hassle of car damage classification, where a number of the kinds can be nice-granular. We explore deep learning-based techniques for this purpose. First of all, we attempt directly training a CNN. But, due to small set of labelled statistics, it does now not work nicely. Then, we discover the effect of domain-specific pre-schooling followed by using nice-tuning. Finally, we experiment with transfer getting to know and ensemble studying. Experimental results show that transfer learning works better than area particular excellent-tuning. We reap accuracy of 89. Five% with mixture of transfer and ensemble mastering.

Keywords: Deep Learning Techniques, Damage of Cars During Accidents

I. INTRODUCTION

Today, inside the vehicle coverage industry, a number of cash is wasted because of claims leakage. Claims leakage / Underwriting leakage is described because the distinction between the actual declare price made and the amount that ought to had been paid if all enterprise leading practices were carried out. Visible inspection and validation have been used to reduce such effects. But, they introduce delays in the claim processing. There were efforts by using some start-America to mitigate claim processing time. An automatic machine for the car coverage declare processing is a need of the hour.

In this paper, we employ Convolutional Neural network (CNN) based totally methods for type of car harm sorts. Specifically, we consider not unusual harm kinds together with bumper dent, door dent, glass shatter, head lamp damaged, tail lamp damaged, scratch and ruin. To the first-rate of our expertise, there may be no publicly to be had dataset for vehicle harm type. Therefore, we created our very own dataset by way of amassing snap shots from internet and manually annotating them. The class challenge is difficult due to factors which includes big inter-class similarity and slightly visible damages. We experimented with many techniques which includes without delay schooling a CNN, pre-training a CNN the usage of auto-encoder accompanied by pleasant-tuning, the usage of switch studying from massive CNNs trained on ImageNet and constructing an ensemble classifier on top of the set of pre-trained classifiers. We observe that transfer getting to know mixed with ensemble gaining knowledge of works the pleasant. We additionally devise a method to localize a specific harm type. Experimental consequences validate the effectiveness of our proposed solution.

II. RELATED WORKS

Deep getting to know has proven promising results in machine mastering applications. Mainly, CNNs carry out well for pc imaginative and prescient tasks including visible item reputation and detection. Application of CNNs to structural harm assessment has been studied in. The authors advocate a deep studying-based method for Structural fitness monitoring (SHM) to characterize the damage inside the form of cracks on a composite fabric. Unsupervised representation is hired and consequences were shown on a extensive range of loading situations with confined range of labeled training picture information. Maximum of the supervised techniques want large quantities of labeled records and compute resources. Unsupervised pre-training strategies

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inclusive of Autoencoders have been proven to enhance the generalization performance of the classifier in case of small quantity of categorized samples. For pictures, Convolutional automobile Encoders (CAE) have shown promising outcomes. A totally well-known method which has labored effectively in case of small labeled data is transfer gaining knowledge of. A network that's educated on a source assignment is used as a characteristic extractor for target project. There are numerous CNN models educated on ImageNet which can be to be had publicly along with VGG-sixteen, VGG-19, Alex internet [6], Inception,automobiles,Resnet. Transferable feature representation learned by using CNN minimizes the impact of over-becoming in case of a small classified set.

Traditional machine learning strategies have also been experimented for automated damage assessment. Jayawardena et al proposed a way for car scratch damage detection with the aid of registering 3D CAD model of undamaged vehicle (ground fact) at the picture of the damaged automobile. There has been tries to research damage in geographical regions the usage of satellite tv for pc pics to nice of our expertise, deep gaining knowledge of-based totally techniques have no longer been hired for automatic car damage classification, particularly for the first-class granular damage category.

III. DATASET DESCRIPTION

On account that there is no publicly available dataset for vehicle damage category, we created our personal dataset along with photos belonging to extraordinary kinds of vehicle damage. We bear in mind seven typically determined kinds of damage such as bumper dent, door dent, glass shatter, head lamp broken, tail lamp damaged,

Scratch and ruin. Further, we additionally collected pics which belong to a no damage magnificence. The pictures had been gathered from net and have been manually annotated. Desk I shows the description of the dataset. A. Information augmentation it's far acknowledged that an augmentation of the dataset with affine transformed photographs improves the generalization performance of the classifier. For this reason, we synthetically enlarged the dataset classes teach length Aug. Teach length

TABLE I Description of our dataset.

Classes	Train size	Aug. train size	Test size
Bumper Dent	186	1116	49
Door dent	155	930	39
Glass shatter	215	1290	54
Head-lamp broken	197	1182	49
Tail-lamp broken	79	474	21
Scratch	186	1116	46
Smash	182	1092	45

Approx. Five instances via appending it with random rotations (among -20 to twenty tiers) and horizontal flip transformations. For the category experiments, the dataset was randomly split into eighty%-20% where eighty% turned into used for schooling and 20% turned into used for trying out. Table I describes the dimensions of our educate and take a look at units.

Fig. 1 indicates pattern photos for each elegance. Notice that the category mission is non-trivial due to excessive inter-elegance similarity. In particular, because the damage does not cover the complete picture (however a small section of it), it renders type mission even greater tough.

IV. TRAINING A CNN

In the first set of experiments, we skilled a CNN beginning with the random initialization. Our CNN structure consists of 10 layers: Conv1-Pool1-Conv2-Pool2-Conv3-Pool3-Conv4- Pool4-FC-Softmax in which Conv, Pool, FC and SoftMax denotes convolution layer, pooling layer, completely related layer andA SoftMax layer respectively. Each convolutional layer has 16 filters of length five _ five. A RELU non-linearity is used for every convolutional layer. The entire number of weights in the network are around 423K. Dropout became added to every layer which is understood to improve generalization overall performance. We trained a CNN at the authentic as well as on the augmented dataset.

Table II indicates the result of the CNN training from random initialization. It can be visible that the information augmentation certainly enables to improve the generalization and offers higher overall performance that simply training at the unique dataset. We're aware that the statistics used for training the CNN (even after augmentation) is quite much less as compared to the number of parameters and it may bring about overfitting. But we accomplished this experiment to set a benchmark for rest of the experiments. Method without Augmentation with Augmentation

TABLE II Test accuracy with CNN training and (CAE + fine-tuning).

Method	Without Augmentation			With Augmentation		
	ACC	PREC	Recall	ACC	PREC	Recall
CNN	71.33	63.27	52.5	72 46	64 03	61 01
AE-CNN	73.43	67.21	55.32	72 30	63 69	59 48

A. Convolutional Autoencoder Unsupervised pre-education is a famous approach, recognised to be useful in instances wherein training statistics is scarce. Fig. 1. Pattern images for automobile damage types. Rows from pinnacle to backside indicates harm kinds Bumper dent, Door dent, Glass shatter, Head-lamp damaged, Tail-lamp damaged, Scratch, smash and No damage

The number one goal of an unmonitored getting to know technique is to extract beneficial features from the unlabelled dataset by way of mastering the input facts distribution. They locate and do away with input redundancies, and typically best hold vital components of the information which generally tend to assist the category venture. A fully related auto-encoders, in particular in case of photographs, results in massive range of trainable parameters. Convolutional Autoencoders (CAE) provide a higher alternative due to much less number of parameters because of sparse connections and weight sharing. CAEs are skilled in a layer sensible manner where unsupervised layers may be stacked on top of every other to construct the hierarchy. Each layer is skilled independently of others in which output of a previous layer acts as an enter for the subsequent layer. Eventually, the entire set of layers are stacked and excellent-tuned by using back-propagation the usage of the pass entropy objective function. Unsupervised initialization has a tendency to keep away from local minima and boom the networks overall performance stability. For training a CAE, we used unlabelled pix from Stan

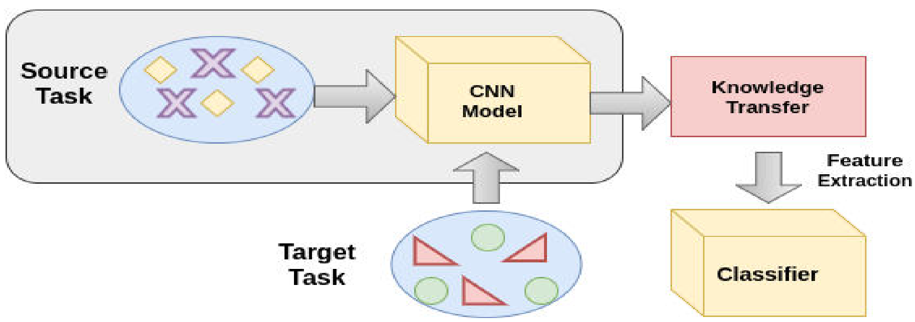


Fig. 2. Transfer learning setup used in our experiments. Source task is ImageNet classification while the target task is car damage classification.

Ford vehicle dataset. The dimensions of the dataset turned into synthetically extended by using including rotation and flip alterations. Due to the fact thatThe target photos belong to car damage type, we assume that gaining knowledge of the automobile specific features have to help the type mission. The layers are then high-quality-tuned using a smaller mastering price in comparison to the training. The row, AE-CNN, in table II indicates the result with autoencoder pre-training. It is able to be seen that an autoencoder pre-training does help the type mission. A similar test turned into accomplished using augmented car harm photographs and there as nicely we see development in the check accuracy as compared to no pre-training.

V. TRANSFER LEARNING

Transfer gaining knowledge of has shown promising results in case of small categorized statistics. Within the transfer gaining knowledge of setting, information from the supply mission is transferred to the target challenge. The intuition is that some know-how is specific to character domain names, even as a few know-hows may be commonplace among distinctive domains which may also assist to improve performance for the target domain / challenge. But, within the cases wherein the source area and target domain aren't associated with each different, brute-pressure transfer can be unsuccessful and may result in the degraded overall performance. In our case, we use the CNN fashions which might be educated at the ImageNet dataset. Because the ImageNet dataset includes car as a class, we expect the switch to be useful which we considerably validate by using experimenting with multiple pre-trained models. Fig. 2 suggests the switch gaining knowledge of test setup we use. Due to the fact that we use pre-trained fashions which are educated for ImageNet, the source mission is the ImageNet classification. The pre-educated model is used as a characteristic extractor for goal undertaking i.E. Automobile harm snap shots. Desk III shows the information of pre-skilled networks used, their parameters and characteristic measurement. We enter vehicle harm snap shots to each community and extract feature vectors. We then teach a linear classifier on these capabilities. We experimented with two linear classifiers, a linear SVM and a SoftMax. In case of linear SVM, the penalty parameter C turned into set to one for all experiments. In case of the SoftMax classifier, we used ad delta optimization scheme and go entropy loss. We skilled the classifier for one hundred epochs and selected the model with satisfactory class overall performance. Also, for the reason that statistics augmentation helps the classifier in generalization, we teach linear classifiers on augmented characteristic set as well.

Fig. 3. Examples of test images mis-classified as 'no damage' class with Resnet. Note that the damaged portion is barely visible.

Table III indicates the accuracy, precision and keep in mind whilst the usage of these pre-educated models. It can be seen that the Resnet performs the great amongst all of the pre-educated models. The facts augmentation boosts the performance in most of the instances. During the experimentation, it was found that the Softmax classifier works better than linear SVM and it's far faster to educate. Quite, the Google internet pre-trained version satisfactory-tuned using car dataset, achieved the worst. It suggests that best automobile object-based totally capabilities might not be effective for classifying harm kinds. The negative overall performance of autoencoder based totally technique may additionally as properly be because of this effect. It underlines the effectiveness of characteristic representation found out from huge and various input records distributions.

We observe that the fundamental aspect in the mis-classifications is the ambiguity between harm experiment with ensemble of the pre-trained classifiers. For each schooling picture, magnificence probability predictions are obtained from a couple of pre-educated networks. The weighted average of class posteriors is then used to reap the very last choice class. The weights to be used for the linear aggregate are discovered via fixing following least squares optimization. The optimization is solved the use of gradient descent wherein getting to know fee is adjusted to yield the exceptional take a look at overall performance. Due to the fact Softmax finished the first-rate, we use it for obtaining magnificence posteriors. Table IV indicates the end result of the experiment. It can be visible that the ensemble and 'no damage' magnificence. This isn't sudden because, the harm of a component typically occupies a completely small part of the photograph and renders identification tough even for the human observer. Fig. 3 indicates few examples of take a look at pics of harm which are mis-categorised as no harm.

A. Ensemble method

To in addition enhance the accuracy, we carried out an an test with ensemble of the pre-trained classifiers. For every education image, category chance predictions are got from a couple of pre-trained networks. The weighted common of category posteriors is then used to acquire the remaining selection class. Theweights to be used for the linear mixture are realized by means of fixing following least squares optimization The optimization is solved the usage of gradient descent the place studying fee is adjusted to yield the nice take a look at performance. Since SoftMax carried out the best, we use it for acquiring classification posteriors. Table IV indicates the end result of the experiment. It can be viewed that the ensemble(Top-3 and All) works better than the individual classifiers, as expected.

Model	Params	Dim	Without Augmentation						With Augmentation					
			Linear SVM			Softmax			Linear SVM			Softmax		
			Acc	Prec	Recall	Acc	Prec	Recall	Acc	Prec	Recall	Acc	Prec	Recall
Cars [14]	6.8M	1024	57.33	47 24	56 46	60 38	47 23	32 39	58 45	48.58	56 97	64 25	52 73	39 16
Inception [13]	5M.	2048	68.12	57 46	55 53	71 82	61 75	56 71	68 60	58.50	54 44	71 50	69 47	52 81
Alexnet	60 M.	4096	70.85	61 68	64 60	70 85	61 42	58 09	73 26	62.83	61 72	73 91	66 83	63 36
VGG-19 [12]	144M.	4096	82.77	78 62	73 16	84 22	80 76	73 60	82 29	76.30	70 60	83 90	80 74	73 41
VGG-16 [12]	138M.	4096	83.74	77 79	75 41	84 86	81 91	73 56	82 93	78.62	71 96	82 72	78 99	70 30
Resnet [15]	25.6M.	2048	86.31	80 87	78 30	**88.24**	84 38	81 10	87 92	84.40	78 94	87 92	83 68	79 47

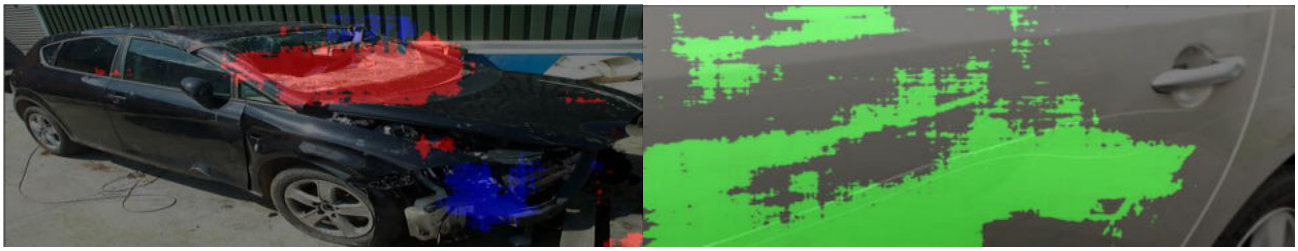
TABLE III
Classification performance for transfer learning. Comparison of test accuracies with different pre-trained CNN models. Note that Resnet performs the best.

Ensemble	Without Augmentation			With Augmentation		
	Acc	Prec	Recall	Acc	Prec	Recall
Top-3	89.37	88.05	80.91	88 40	85 88	78 91
All	**89.53**	88.16	80.92	88 24	86 45	78 41

TABLE IV
Classification performance for Ensemble technique using Top-3 and All models

B. Damage localization

With the identical approach, we can even localize the broken portion. For every pixel in the take a look at image, we crop a place of measurement one hundred a hundred round it, resize it to 224 224 and predict the type posteriors. A injury is viewed to be detected if the chance fee is above positive threshold.Fig. four suggests the localization overall performance for harm kinds such as glass shatter, smash and scratch with Resnet classifier and chance threshold of 0.9.



(a) (b)

VI. CONCLUSION

In this paper, we proposed a deep studying primarily based answer for vehicle harm classification. Since there used to be no publicly on hand dataset, we created a new dataset via accumulating pics from internet and manually annotating them. We experimented with a couple of deep mastering based totally strategies such as education CNNs from random initialization, Convolution Autoencoder based totally pre-training accompanied via supervised pleasant tuning and switch learning. We determined that the switch mastering carried out the best. We additionally be aware that solely vehicle precise aspects may additionally no longer be advantageous for harm classification. It as a consequence underlines the superiority of function illustration realized from the massive coaching set.

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