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CAR DAMAGE DETECTION USING DEEP LEARNING

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Abstract - *Image-based vehicle insurance processing is a key industry with a lot of possibilities for automation. We look at the subject of car damage categorization in this paper, where certain damages are classed as minor and others as serious. In several of the categories, fine-granularity is feasible. We go into the bowels of knowledge. We'll use based ways for this. We attempted to train a CNN straight at first. However, it does not work well with data due to the small number of tagged samples. The impact of pre-training in the domain is next examined, followed by fine-tuning. Finally, we put ensemble and transfer learning to the test. According to research, transfer learning outperforms domain-specific fine-tuning. We have a high level of commitment.*

1. INTRODUCTION

A lot of money is lost today in the car insurance market owing to claims leakage. The discrepancy between the actual claim and the underwriting claim is referred to as claims leakage or underwriting leakage. The amount that was paid and the amount that should have been paid if all of the industry's best practices were used. Visual examination, Validation and other techniques have been employed to reduce such impacts. They do, however, cause delays in the processing of claims. There have been initiatives by a small number of start-ups to reduce claim processing times. For automotive insurance claims, an automated method is available. An hour of processing is required. We use Convolutional Neural Networks in this paper. (CNN)-based systems for classifying various types of vehicle damage. Damage types include bumper dent, door dent, glass shatter, headlight shattered, tail lamp damaged, scratch, and smash. To our knowledge, there is no publicly available dataset on car damage classification on the other hand. As a result, we created our own set of data. The categorization task is challenging when using images from the internet and manually tagging them based on these qualities. There is a great deal of inter-class similarity, but the consequences are minor. We used to experiment with a variety of methodologies, such as direct training a CNN, pre-training a CNN with an auto-encoder, and then fine-tuning with transfer learning from large CNNs that had been taught, establishing an ensemble classifier on top of ImageNet the collection of trained classifiers. The most effective method appears to be transfer learning combined with ensemble learning. Experiments have shown that our strategy is a viable alternative to the one that has been proposed.

2. LITERATURE SURVEY

Several models have been implemented for car damage detection. So, when it comes to object detection the Deep Learning [DL] has always been effective and shown promising results. One of the most accepted detection algorithms is the CNN (Convolutional Neural Network), as it executes well for computer vision tasks such as visual objects detection and recognition.

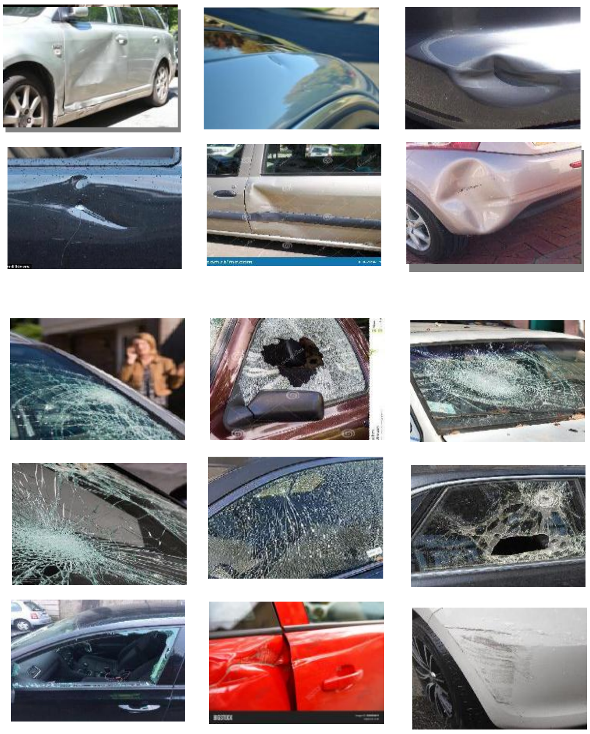
Deep learning has been exceptional in image classification, with computing resources based on transfer learning solutions and extensive use of data. Pre-trained CNN models are very complex to understand. Large amounts of labelled data and computer resources are needed for supervised methods. Whereas, unsupervised pre-training techniques such as Autoencoders, proved to enhance the generalization performance of the classifier in case of a small quantity of labelled sample. For images, Convolutional Autoencoders (CAE) have been effective.

One of the well-known techniques which has shown results for small labelled data is Transfer Learning. There are a bunch of CNN models trained on ImageNet. These models are available publicly such as VGG-19, VGG-16, Alex net, Inception, Resnet. Transferable feature representation learned by CNN minimizes the effect of over-fitting in case of small labelled sets.

To the best of our knowledge, deep learning-based techniques have not been employed for automated car damage classification, especially for the fine granular classification.

3. DATASET DESCRIPTION

Because there was no standard dataset for this topic, we decided to create our own by gathering photographs of damaged cars from the internet. After gathering a large number of them, we discovered that the dataset had numerous photographs of entirely scrambled and damaged automobiles, which had to be avoided for better model training. The second thing we saw was that the number of photographs was insufficient, thus data augmentation was a viable option. The number of photos has risen to 970 from 600. When there was no publicly available dataset for automobile damage classification, we generated our dataset with 970 car damaged photos that included various types of car damage. The dataset was then divided into two folders, Specifically, train and Val (training and validation). There are 777 photographs in the train folder and 194 images in the validation folder. We spent a long time preparing the dataset because everything was done by hand, including labelling each image according to the damage classification.



4. TRANSFER LEARNING

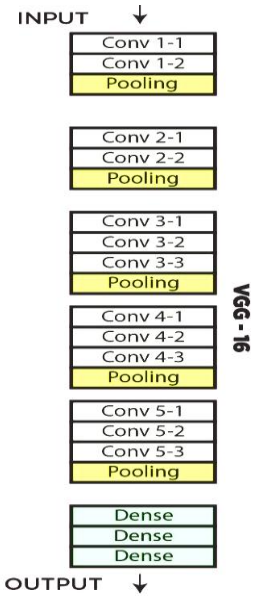
Several assumptions must usually be included in training, validation, and test data with the underlying distribution for a certain task when training a deep learning model. If it does not work, the mapping and features must be rebuilt from the ground up, which is a difficult task. Transfer learning is the answer to this arduous task. This approach focuses mostly on feature extraction and suitable data from sources, which is then applied to the task at hand.

Transfer learning is beneficial for a variety of reasons, one of which is to minimize training time and improve model efficiency. It solves classification and clustering problems as well as overfitting issues. There's no need to start from scratch; pre-trained weights can be used to continue training our model, saving time and GPU resources. We got a coco file (in.h5 format) from the official website for the initial phase because it provides us with pre-trained weights that would generate numids for each picture classification. The main aspect is that there should be clarity as to what knowledge is useful for the model and between the source and target task. A common concept used in the field of deep learning which reduces time and the model can adapt to new changes and update from time to time. Algorithms, for instance, Mask R-CNN, has the ability to create an efficient model

5. PROPOSED METHODOLOGY

1.Collecting Images/data: More above 1000 images were collected which were further segregated into 3 categories that are Scratch, Dent and Glass Broken in the damage class. So, each category will have certain number of images to be trained over the Mask RCNN.

2.VGG annotator: VGG Image Annotator is a simple and standalone manual annotation software for image, audio and video. VGG runs in a web browser and does not require any installation or setup. The complete VGG software fits in a single self-contained HTML page of size less than 400 Kilobyte that runs as an offline application in most modern web browsers.



The input to the network is image of dimensions (224,224,3). The first two layers have 64 channels of 3*3 filter size and similar padding. Then after a max pool layer of stride (2,2), two layers which have convolution layers of 256 filter size and filter size (3, 3). After that a max pooling layer of stride (2, 2) which is same as previous layer. After which there are 2 convolution layers of filter size (3,3) and 256 filter. After that there are 2 sets of 3 convolution layer and a max pool layer. Each have 512 filters of (3, 3) size with same padding. This image is then passed to the stack of two convolution layers. In these convolution and max pooling layers, the filters we use is of the size 3*3 instead of 11*11 in AlexNet and 7*7 in ZF-Net. In many of the layers, it also uses 1*1 pixel which is used to manipulate the number of input channels. There is a padding of 1-pixel (same padding) done after each convolution layer to prevent the spatial feature of the image. This is the second step related to Project.**3.Json file:** After the second step of annotating the image using VGG annotator the desired file is saved in the json file on which the conventional neural networks are applied. This is the third step in the Project.

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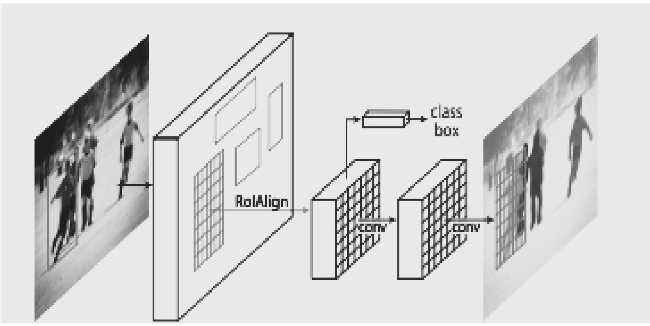
4.Apply Mask RCNN: Mask R-CNN is best at detecting the objects in the input image. It has a very low detection time which can also be used in real-time systems. It is very similar to Faster R-CNN. The stage of region proposal generation is same in both the architecture the second stage which works in parallel predict class, generate bounding box as well as outputs a binary mask for each RoI (Region of Interest).



It comprises of –

- Backbone Network
- Region Proposal Network
- Mask Representation
- RoI Align

5.Neural Network Extracting Features: Feature extraction is generally used on convolution base as convolution base are more generic than densely connected layers. The advantage of Convolution base is they are reusable. The feature maps of the convnet are the presence maps of generic concepts over a picture which is useful regardless of the computer-vision problem or any other problem.

In densely connected layers, feature extraction is not visible as it no longer contains any information about the objects that are located in input image as these layers get rid of where notion of space is whereas object location is still described by the convolutional feature maps exists. Densely connected features are useless where object location matters in problem.

Convolution bases of VGG16 network which is trained on ImageNet is popularly used for feature extraction. Among others are Xception, ResNet50, InceptionV3, VGG19, MobileNet model etc.

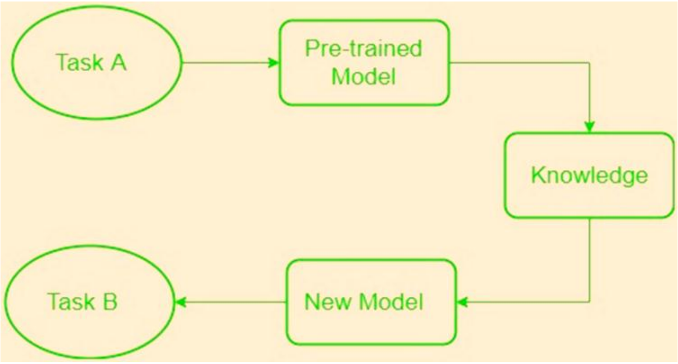
6.Deployment of Transfer Learning: We humans are very much kin and experienced in applying transfer learning in our day-to-day life. For e.g., when we do a project or assignment on particular topic in which there is an involvement of mathematics, here we don't bring new formulas or rules to solve that particular activity. We apply various techniques, formulas and rules which are already defined into our activity. This is known as transfer learning.

This makes our work easy and fast to finish. For instance, if you know how to ride a bicycle and if you want are to ride a motorbike which you have never done before. In such a case, our experience with a bicycle will come into play and handle tasks which are involved during biking. This will make things easier compared to a complete beginner. Such learnings are very useful in real life as it makes us more perfect and allows us to earn more experience.

Following the same approach, a term was introduced Transfer Learning in the field of machine learning. This approach involves the use of knowledge that was learned in earlier tasks, and apply it to solve the problem in the related target task. While most machine learning is designed to address a single task, the development of algorithms that facilitate transfer learning is a topic of ongoing interest in the machine-learning community.

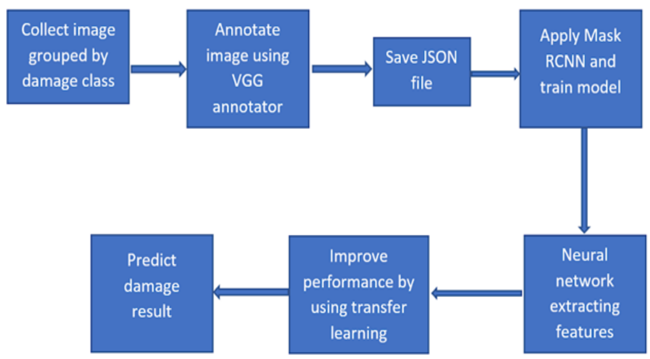
Why Transfer Learning?

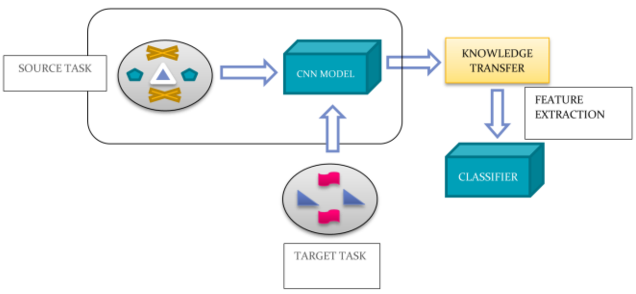
Many deep neural networks trained on images have a curious phenomenon in common: in early layers of the network, a deep learning model tries to learn a low level of features, like detecting edges, colours, variations of intensities, etc. Such kind of features appears not to be specific to a particular dataset or a task because of no matter what type of image we are processing either for detecting an animal or vehicle. In both cases, we have to detect these low-level features. All these features occur regardless of the exact cost function or image dataset. Thus, learning these features in one task of detecting animal can be used in other tasks like detecting humans. This is what transfer learning is. Nowadays, it is very hard to see people training whole convolutional neural network from scratch, and it is common to use a pre-trained model trained on a variety of images in a similar task, e.g., models trained on ImageNet (1.3 million images with 1500 categories), and use features from them to solve a new task.



7.Predict Damage Result: Using the flavors of above 6 points the result is predicted and the resultant is stored or shown over the screen.

6. BLOCK DIAGRAM





7. CONCLUSION

In this paper, we proposed a deep learning-based solution for car damage classification. Since there was no publicly available dataset, we created a new dataset by collecting images from the web and manually annotating them. We experimented with various algorithms such as Yolo v5 and Faster CNN. We observed that the transfer learning combined with Mask RCNN performed the best. We also note that only car specific features may not be effective for damage classification. It thus underlines the superiority of feature representation learned from the large training set.

8. REFERENCES

[1] www.geeksforgeeks.org/mask-r-cnn-ml/

[2] Bengio Y. Lecun Y., Bottou L. and Haffner P., "Gradient-based learning applied to document recognition," Proceedings of IEEE, vol. 86, no. 11, 1998.

[3] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton, "Imagenet classification with deep convolutional neural networks," in Advances in Neural Information Processing Systems 25, F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, Eds., pp. 1097–1105. Curran Associates, Inc., 2012.

[4] Michael Giering Mark R. Gurvich Soumalya Sarkar, Kishore K. Reddy, "Deep learning for structural health monitoring: A damage characterization application," in Annual Conference of the Prognostics and Health Management Society, 2016

[5] www.projectpro.io/recipes/what-is-feature-extraction-neural-networks#:~:text=Feature%20extraction%20in%20neural%20networks%20contains%20the%20representations,new%20classifier%20which%20is%20already%20trained%20from%20scratch.

[6] https://www.geeksforgeeks.org/ml-introduction-to-transfer-learning/

[7] Müller M. Detektion und Klassifikation von Krafteinwirkungen auf die Fahrzeugaußenhaut auf Grundlage piezoelektrischer Signale. Phd thesis. University of Rostock; 2013.

[8] Baumgärtel H, Kneifel A, Gontscharov S, Skwarek V, Krieger K-L. Drei-kanaliger piezoelektrischer Sensor zur Detektion von Bagatellschäden und deren Ursprungsort an Fahrzeugkarosserieteilen. Sensoren im Automobil, München, 2014.

[9] Kammeyer KD, Kroschel K. Digitale Signalverarbeitung. 7th Edition. Wiesbaden: Vieweg Teuber Verlag; 2009.

[10] The MathWorks Inc. Envelope Detection.http://www.mathworks.de/de/help/dsp/examples/envelope detection.html,Application note, accessed Jan. 2014.

[11] H. Baumgärtel, V. Skwarek, A. Kneifel, S. Gontscharov, K.-L. Krieger Intelligent monitoring of vehicle bodydamages for CarSharing applications Electronics in Vehicles, Baden-Baden (2013) Bd. 16