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Vision Based Automatic Motor Vehicle Insurance Claim Assessment. Team Memebers: Hari Prasath M (2002041)

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ABSTARCT
The number of individuals driving a car increases every day, increasing the number of car insurance claims filed. The registration and processing life cycle of insurance and deciding for every claim and manual examination by the engineer who caused the problem report, followed by a surveyor's actual examination, takes a long time. Vehicle insurance processing using images is a critical sector with room for automation. An end-to-end system is proposed to automate this procedure, which would be advantageous to both the corporation and the environment customer. A Convolutional Neural Network (CNN) is used to classify the types of car damage being present. However, it does not operate well due to a small labeled data set. The effect of domain-specific pre-training followed by fine-tuning is then investigated. There is no publicly available dataset for car damage classification.

CHAPTER-1: INTRODUCTION

1.1 INTRODUCTION

Today's car insurance sector wastes much money owing to claims leakage. Claims leakage, also known as underwriting leakage, is the gap between the amount puid on a claim and the amount the insurance company would have paid. Visual inspection and validation have been used to decrease these impacts. They do, however, cause delays in the processing of claims. A few start-ups have made attempts to reduce claim processing time. The need for an automated method to process car insurance claims is urgent.

CNN-related methodologies have been applied to classify the damages in the car. In specific, general damage types like door, bonnet, trunk, lights, windshield, dent, and bumper are considered. There is no publicly available dataset for car damage classification to our knowledge. As a result. developed our own dataset by manually annotating photographs found on the internet. Due to characteristics such as high inter- class similarity and scarcely evident defects, the classification task is difficult. I tried a variety of strategies, including immediately training a CNN, pre-training a CNN with a YOLOx5 and then fine-tuning it, and so on. I also design a way to locate a specific type of damage. Experimental data support the effectiveness of my proposed method.

1.2 AUTOMATIC DAMAGE DETECTION IN CAR:

Auto insurance has become a flourishing sector in India, which has an estimated 230 million automobiles and is still reliant on traditional manual methods of filing repair claims. It requires a survey inspector to examine each car that has been reported as damaged and make an estimate of the damages as well as the claim

CHAPTER-3: PROBLEM DESCRIPTION

3.1 PROBLEM STATEMENT

Predicting the intensity and position of the damages in cars and based on these, to aid the insurance company to provide a reasonable compensation for that damage instantly without the involvement of garage/workshop. In Car Insurance industry, a lot of money is being wasted on Claims leakage. Claims leakage is the gap between the optimal and actual settlement of a claim. Visual inspection and validation are being used to reduce claims leakage. But doing inspection might take a long time and result in delaying of claims processing. An automated system for doing inspection and validation will be of great help in speeding up the process.

The process is to automate the Visual inspection and validation of vehicle damage. The input data we have are car damaged images. For

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Validation of Vehicle damage we will divide the problem into three stages.

1. First we check whether the given input image of car has been damaged or not.
2. Second we check on which side (Front, Rear, Side) the Car in image has been damaged.
3. Third we check for the Severity of damage (Minor, Moderate, Severe). The datasets available for the car damage are minimal and besides no dataset is available based on the classification of specific part damaged. There is a need to develop a dataset based on the above category to increase the efficiency of the detection in the object detection algorithms. The process is to create a dataset on the basis of the damaged part in the car with 12 classes, which is as follows bonnet, front windshield, head light. front bumper, roof, door, door glass,

CHAPTER 4: COMPARISON OF EXISTING ALGORITHMS

4.1 CRACK DAMAGE DETECTION USING CNN: 4.1.1 ARCHITECTURE:

Multiple layers, including as input, convolution, pooling, activation, and output, can be used to build a general CNN architecture; convolution and pooling operations are performed in the convolution and pooling layers. When the architecture of a CNN is made up of multiple layers, it is called a deep CNN. Other auxiliary layers, such as dropout and batch normalisation (BN) layers, can be used in conjunction with the aforementioned layers depending on the intended function. This research was carried out using MatConvNet (Vedaldi and Lenc, 2015).

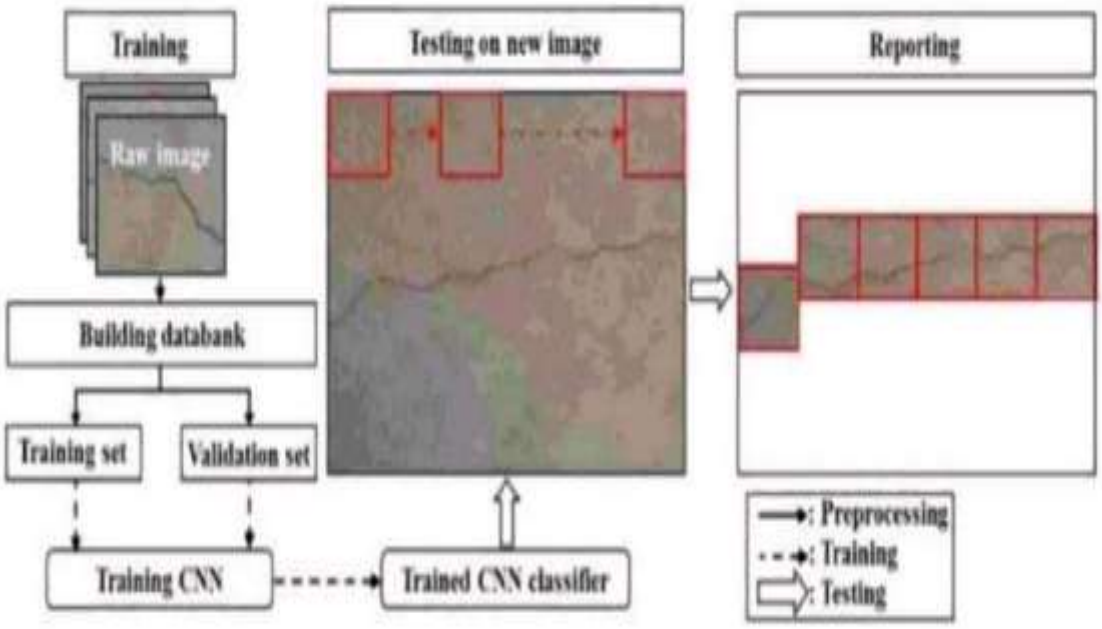

Fig. 4.1 Flow Chart for Detecting Cracks.

The first layer is the input layer, which has a resolution of 256 256* 3 pixels, with cach dimension indicating height, width, and channel. Input data is passed through the architecture and is generalised to 11 96 spatial sizes. The vector is sent into the rectified linear unit (ReLU) layer, which includes the 96 elements. After convolution, the softmax layer predicts whether each input data the sense that it produces predictions after only one forward propagation through the neural network, the approach "looks once" at the image. After non-max suppression, it provides discovered.

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4.2 YOLO v5 ARCHITECTURE

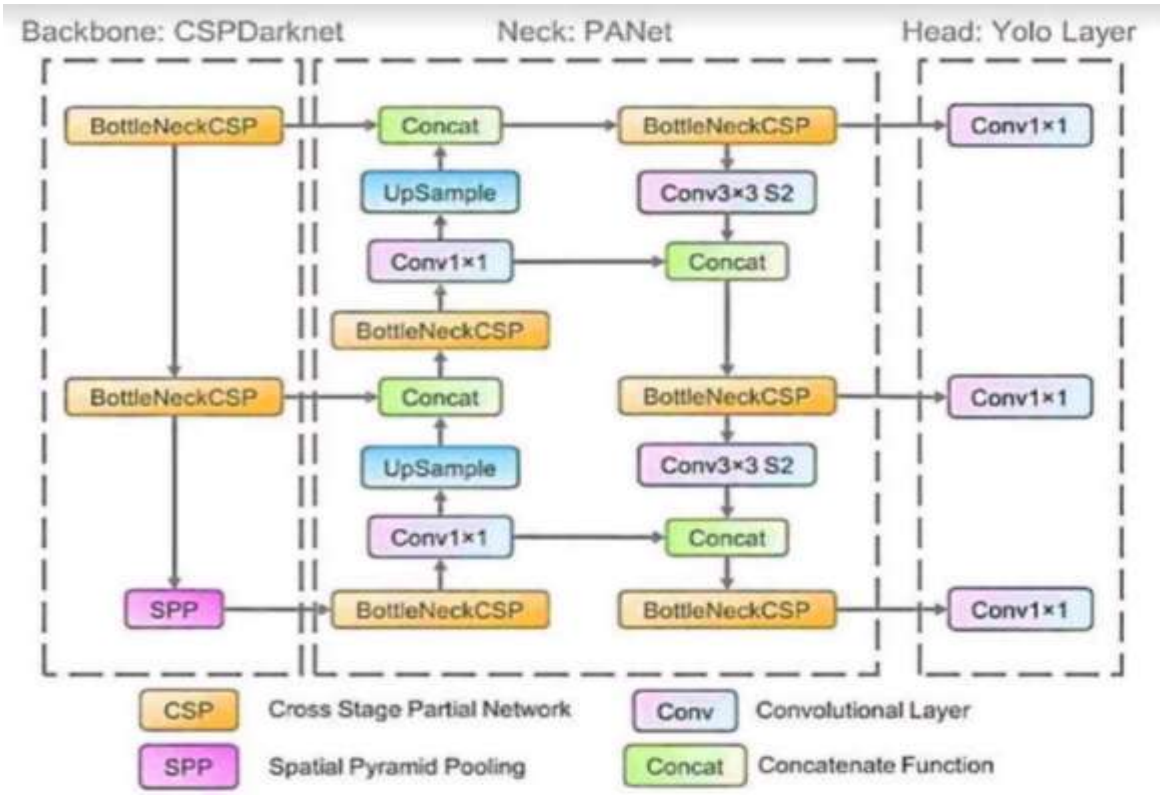

Fig 5.5 ARCHITECTURE OF Yolov5.

BACKBONE:

The most common usage of Model Backbone is to extract essential features from an input image. In YOLO v5, the CSP (Cross Stage Partial Networks) backbone is utilised to extract rich in valuable attributes from an input image.

NECK:

CHAPTER-6: DATASET

The dataset consists of various images of the damaged cars based on the intensity and the portion of damage on the cars. There are more than 1000 images being collected as dataset in both the divisions i.e., portion and intensity of the damage. These datasets are being trained using YOLO v5 algorithms to detect the damage in the car.

DATASET OF CAR DAMAGE BASED ON SEVERITY:

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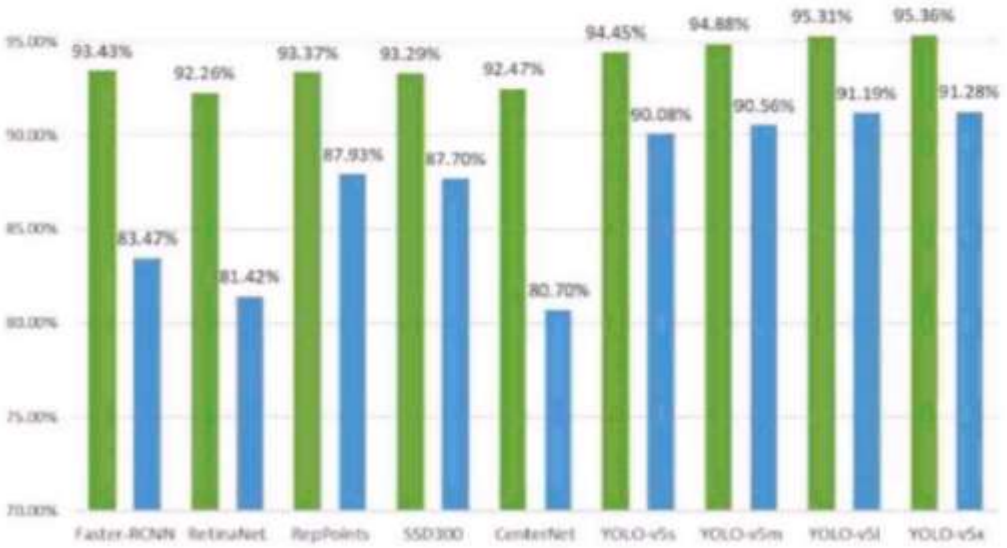
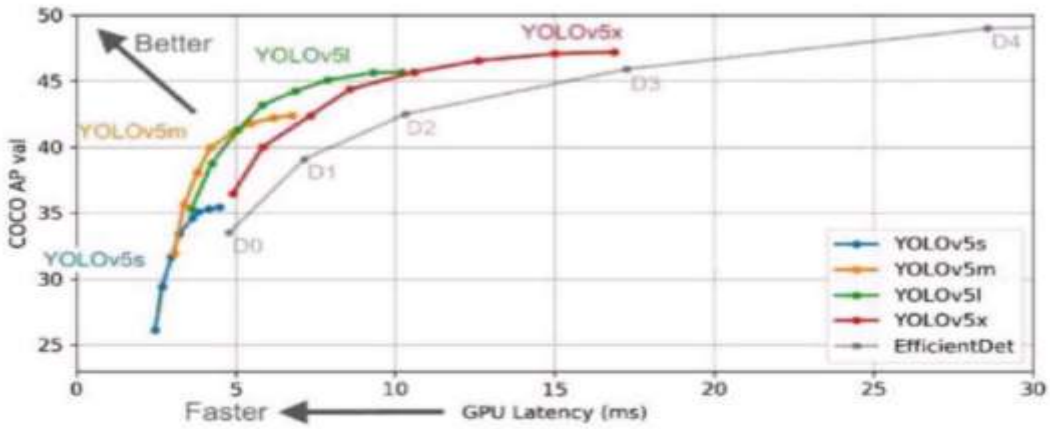
MEDIUM	

CHAPTER-7: RESULTS AND CONCLUSION

7.1RESULTS:





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7.2 CONCLUSION

Deep neural network model which recognizes the damage in a car is simulated in YOLO v5 algorithm. Results show that the implementation is capable of achieving high accuracy and clockperformance with low resource utilization. In future, this model can be integrated with other image processing algorithms to build a real-time damage detection system. In this project, the YOLO v5 deep learning approaches-based framework is proposed for damage detection in the car for insurance claiming system. The damaged car image is given as the input. The proposed system detects the damaged region using a YOLO v5 algorithm. After the damaged region is localized, the CNN model is used to classify the damage based on the severity and portion of the damage. The model is trained with the collected image dataset from the service centre consisting of more than 3000 images of damaged cars. This system makes it easy for the detection of damage in the car and insurance claiming process of the insurer. The results show that the framework helps achieve good accuracy with a correct rate of 87.36%.

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