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Damage Detection of An Automobile

[1] R Melvin Raj, [2] R Jyosthna, [3] N Ramya Madhuri, [4] R Akshay Sunny, [5] A Pratima

[1] [2] [3] [4] [5] School of ECE, REVA University Bangalore, India.
Corresponding Author Email: [1] melvinraj1771@gmail.com, [2] jyosthna2203@gmail.com, [3] ramyamadhuri198@gmail.com, [4] akshayrsunny@gmail.com, [5] pratima.a@reva.edu.in

Abstract*— As a result of the proliferation of automobile in- dustries today. There have been an increasing number of car accidents, not all of which are serious, but the automobile is damaged. Detecting automobile damage at the site of an accident using images is exceptionally beneficial as it may significantly lower the cost of processing the insurance reimbursement process while also providing more convenience to automobile users. In most cases, this damage is detected and assessed manually from the car's images during the car evaluation process. In this paper, we worked on the problem of automation of vehicle damage detection which can be used by insurance companies to automate the process of vehicle insurance claims in a rapid fashion. The recent advances in computer vision largely due to the adoption of fast, scalable, and end-to-end trainable Convolutional Neural Networks make it technically feasible to recognize vehicle damages using semantic segmentation. We manually collected and annotated images from various online sources containing different types of vehicle damages and we used U-NET architec- ture to detect the damage of an automobile.

Index Terms*—Image classification, Semantic segmentation, UNET, IoU Score.

I. INTRODUCTION

In today's world, we can observe that the number of vehicles we use is quickly expanding, let's agree that there isn't a single street without a car. As a result, an increase in the number of automobiles on the road may lead to an increase in the percentage of accidents occurring nearby; additionally, the number of accidents occurring nearby would be significant; the accidents would not be particularly serious, but the automobile would be damaged, prompting people to file insurance claims. Our whole idea focuses on this question about how can we identify a damage of a vehicle without having to assess it manually? To keep the procedure quiet, we developed a deep learning model that utilizes image processing to classify the photographs and calculate whether or not the vehicle is damaged. The model would replace the human assessment to check the damage and it would analyze the damage in a fraction of the time and with minimal human interaction. Thus, dam- age assessment at the site of accident is potentially crucial challenging. Furthermore, completing this challenge brings up a diverse range of computer vision difficulties such as identification and classification of images and objects.

This paper discusses about utilizing U-NET architecture to identify car damage after manually collecting and annotating photographs from multiple web sources containing various forms of vehicle damages with recent advances in computer vi- sion which are largely adapted of being quick, expandable, and complete trainable CNN (Convolutional Neural Networks), have made deep convolutional networks technically feasible for recognizing vehicle damages.

II. METHODOLOGY

To commence with, we gather photographs of one's dam- aged automotive through various sources, which then is anno- tated using an online annotating and training tool, we produce the ground truth of the image(as shown in fig 2). By doing this we create a mask over the image of different pixel's for different regions. The masked images are next used by our model to identify the elements of our image and analyze the detection of damage.

A. DATA PRE-PROCESSING

Our dataset collected through various sources includes resiz- ing them first to the dimension of 224 X 224. The data is in 8 bit unsigned integer range (0 to 255), which are preprocessed and added into an empty list and converted into an numpy array of two dimension (2D) with dimension as (number of images, 224, 224, 3) for RGB image and (number of masked images,224, 224, 1) reading for grayscale image. '1' in the dimension is to read a grayscale image.

After converting into a numpy array, now we've 2 sets of i.e., train images with shape and mask images with shape.

On the masked images label encoding is performed which involves translating the labels into a numeric format so that they can be read by machines and make's the pixel range from 0-N (re-arranging order), as the next step, dataset was divided into training set and validation set with random state and shuffle as ON. Later, One hot encoding for multi-class segmentation was performed which is described as the process of translating categorical data variables, into numerical values.

The classes for One hot are encoded as (100, 010, 001) for our specific dataset classes (background, damaged,

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undamaged) [1] - [3].

The output of all the above steps results as the input of the model.

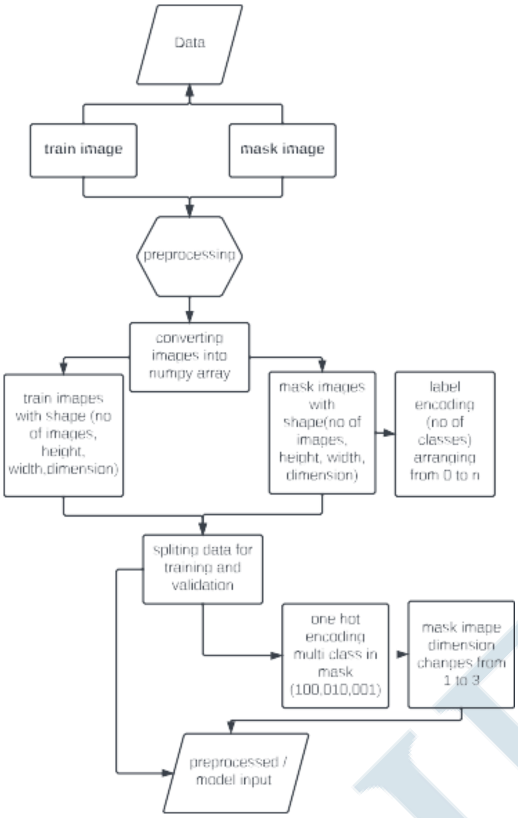

Fig. 1. Flowchart representing the raw image data to preprocessed image data for model input

Fig. 2. Original image and masked image

B. MODEL ARCHITECTURE

We use an U-net Architecture for sematic segmentation with Residual neural network with skip connections network as backbone.

The different types of Residual neural network backbone are Resnet: resnet34, resnet50, resnet101

ResNext: resnext50, resnext101.

We have tried with other backbone's like EfficientNet and Inception, but it fails when we predict on validation set. The input for this U-net Architecture is a image shape of (224 x 224 x3) with pre-trained imagenet weights.

The working of U-net architecture with our image shape (224 x 224 x 3) the downsampling(encoder) to extract the feature and upsmapling(decoder) to get it back to the original shape with the backbone [4] - [5].

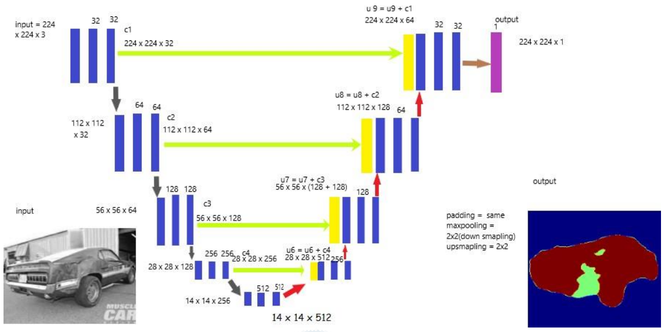

Fig. 3. U-net model architecture with input size (224,224,3) with encoder and decoder

Downsmapling(encoder) - The C1, C2 are the convolution layers as shown in fig 3. The P1, P2 are the Maxpooling layers as shown in fig 3.

A. Upsmapling(decoder) -

The U6 takes parallel encoder output and concatenate with the pervious output The C6,C7 are the convolution 2D transpose as shown in fig 3.

B. Output layer -

Uses softmax activation function with number class as output.

C. Regulization -

1. BatchNormalization
2. Dropout(final layer)

Input = 224 x 224 x 3 **#Contracting path** or downsampling C1 = tf.kears.layers.Conv2D(32(3,3), activation='relu', padding='same)(input)

C1 = tf.kears.layers.Conv2D(32(3,3), activation='relu', padding='same')(c1)

P1 = tf.kears.layers.Maxpooling2D((2,2))(c1)

C2 = tf.kears.layers.Conv2D(64(3,3), activation='relu', padding='same')(p1)

C2 = tf.kears.layers.Conv2D(64(3,3), activation='relu', padding='same')(c2)

P2= tf.kears.layers.Maxpooling2D((2,2))(c1)

D. #Expansive path

U6= tf.keras.layers.Conv2DTranspose(256,(2,2),strides=(2,2), padding='same')(u6)

U6=tf.kears.layers.concatenate([u6,c4])

C6 = tf.kears.layers.Conv2D(256(3,3), activation='relu', padding='same')(u6)

C6 = tf.kears.layers.Conv2D(256(3,3), activation='relu', padding='same')(C6)

E. #Output

F1= tf.keras.layers.Flatten(C6)

Output= tf.kears.layers.Conv2D(224(3,3),activation='Softmax',

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padding='same')(C1)

This way we use resnet50 for convolution layers.

III. PERFORMANCE EVALUATION(IOU MATRIX) AND LOSS FUNCTION

IOU is an evaluation matrix which is utilized to measure accuracy over segmentation mask (class area).

The formula of which is given by –

$J(A, B) = A \cap B / A \cup B$(1)

Where, J is jaccard distance A = set 1 and B = set 2

Whilst, considering our model as an example –

Fig. 4. Intersection over union of damaged area.

The above image depicts damage data of a car and intersection over union of damage area. Where the yellow highlight shows the ground truth or the mask and the red is for the predicted range of damage. [6]

With addition we also calculate F1 score.

A. Loss functions:

We combine focal loss and dice loss which is good for multiclass segmentation. Focal loss is important when it comes to data imbalance.

In dataset we have background as majority class and damaged area as a minority and thus there is a lot of imbalances in the dataset.

B. Formula for focal loss:

$L(gt, pr) = -gt * \alpha * (1-pr)^{\gamma} * log(pr)$..(2)

C. Formula for dice loss:

$L(precission, recall) = 1-(1+\beta^2)\frac{precission * recall}{\beta^2 * precision + recall}$(3)

IV. ADVANTAGES

1) Advancement in the project can help us detect the level of damage and aid user in insurance reimbursement process.
2) It aids the user in expediting the process of filing an insurance claim for his vehicle.
3) Aids in the process of pricing used cars based on the severity of damage.

V. DISADVANTAGE(S)

The major drawback of the proposed model only identifies the physical visible damage and not of the internal or the interior damage.

The lack of higher accuracy is due to the lower resolution of the images which affects pixel wise(accurate) ground truth of the damaged area of an automobile.

VI. RESULTS

Our goal is to segment the damage area from a car. We utilized U-net model with ResNet50, ResNet101 and ResNext101 and achieved 71% mean IoU score approximately with Resnext101. An Iou score greater than 0.5 (50%) is a good score in semantic segmentation.

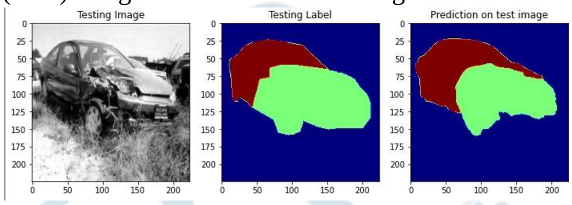

Fig. 5. ResNet Model

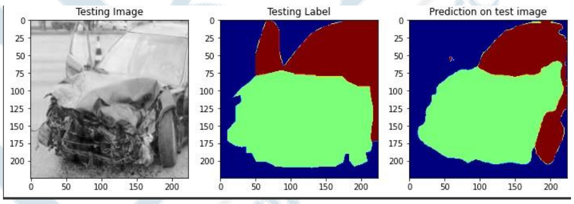

Fig. 6. ResNext Model

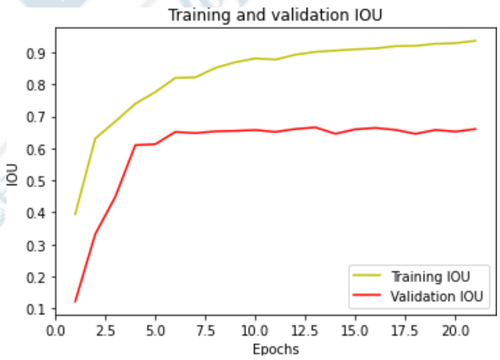

Fig. 7. ResNet50's training vs validation's mean IoU score

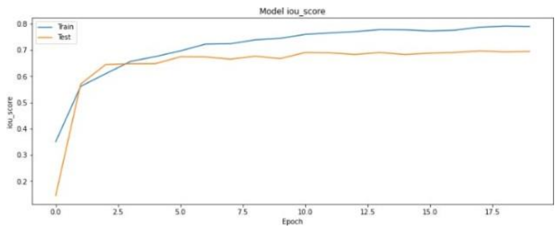

Fig. 8. Resnext101 training vs validation's mean IoU score with 20 epoch's

Backbone	Mean IOU
ResNet50	64%
ResNet101	67%
ResNext101	71%

VII. CONCLUSION

In this work, a U-NET architecture which is efficient, adaptable, and trainable from beginning to finish Convolutional Neural Networks has been used to detect damage of a vehicle. The trained model when tested gives the maximum accuracy of 71% with ResNext101 and can be used for various applications which majorly includes identifying the severity of the damage of the vehicle and classify it into minor, moderate and majorly damaged for helping a user decide if the part has to be repaired or renewed. Secondly, it assists the filing and insurance reimbursement, which aids in speeding the insurance process by mostly eliminating the human need. It also supports in the process of deciding the value of a renewed automobile based on the extent of damage. The IoU score is expected to be less due to the model predicting pixel to pixel, while the ground truth images were partially annotated.

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