DAMAGED CAR DETECTION USING MULTIPLECONVOLUTIONAL NEURAL NETWORK

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Abstract

Computer vision and machine learning are both used in the investigation of visual image classification. Assigning an object to a category, or group of categories, that it belongs to, is the work of visually categorizing an object. A two-layered system is typically used to conduct visual classification tasks. It consists of a first layer using an off-the-shelf feature extractor and detector and a second classifier layer. Convolutional neural networks have been demonstrated to surpass such hitherto employed algorithms in recent years. The ability to automatically categorize automotive damage is very desirable, especially for the auto insurance sector, given the importance of cars in today's society. Automobile inspections are a common occurrence for auto insurance providers. Such inspections are labor-intensive, manual, and occasionally flawed processes. processes that expense and annoy customers and insurance firms equally. Even while complete automation of such manual inspection procedures may still be some time off, modern technology may make it feasible to create systems that facilitate, expedite, or improve the process.

Keywords- Machine Learning, Data Science, car damage, CNN

I INTRODUCTION

Artificial intelligence (AI) application has grown in popularity across a variety of businesses in the modern world. The topic of computer vision, which entails creating algorithms that let machines evaluate and comprehend images and movies, is one of the important areas where AI is applied. There are many uses for computer vision in industries including security, healthcare, retail, and transportation, to mention a few.

The detection of auto damage is one of the newest uses for computer vision. Systems for detecting and analyzing vehicle damage are created utilizing AI algorithms. The automotive industry has been transformed by the application of AI in damage detection, which makes it quicker and easier to discover problems and precisely determine their severity.

Machine learning algorithms are used by automotive damage detection systems to examine photos of damaged vehicles and determine the kind, scope, and location of the damage. These algorithms are capable of reliably identifying even the smallest faults, which human inspectors frequently fail to notice. Moreover, automatic automotive damage detection systems minimize the need for human intervention and expedite the detection process.

Systems for detecting auto damage have a number of advantages, including faster inspections and greater accuracy. These devices aid in speeding up the processing of insurance claims by allowing insurers to evaluate vehicle damage precisely and fast. Moreover, automotive damage detection systems are essential for automakers as they aid in locating production flaws and raising the standard of cars in general.

By enabling quicker and more precise claim processing, the use of car damage-detecting technologies has transformed the insurance sector. In the past, determining the extent of car damage needed a lot of paperwork and human involvement. Car damage assessment is now quicker, more precise, and more effective thanks to AI algorithms.

The process of selling old automobiles has become more transparent thanks to the application of AI in car damage identification. Buyers previously had to on the seller's word for the car's condition. But thanks to the application of AI algorithms, buyers may now get precise and trustworthy information about the state of the vehicle, including any defects.

In conclusion, the automotive industry has been transformed by the deployment of AI algorithms for faster and more precise damage identification. Systems for detecting auto damage provide a number of advantages, including faster inspections, more accuracy, and better-quality control. The insurance sector and the practice of selling old automobiles have both been significantly impacted by the adoption of car damage detection systems. Future car damage detection systems are likely to be even more sophisticated, precise, and effective as AI technology develops.

II LITERATURE REVIEW

A deep learning-based method for categorizing automotive damage using only convolutional neural networks (CNNs). [1] The authors use supervised fine-tuning and transfer learning with pre-training based on convolutional autoencoders to improve the performance of theCNNs. One of the limitations of this study is the absence of a proper dataset, which forced the authors to annotate photographs to construct their own dataset.

A hybrid approach for car damage detection using CNNs and transfer learning. [2] The authors use transfer learning to adapt pre- trained models to the task of car damage detection and use a combination of CNNs to achieve high accuracy. One of the strengths of this study is the useof transfer learning to leverage pre-existing knowledge and improve model performance.

A multi-task learning approach for car damage detection using CNNs.[3] Theauthors use a shared backbone architecture withseparate output heads for each task, which allows the model to learn multiple tasks simultaneously. One potential limitation of this study is the need for a large amount of labeled data for all tasks, which canbe challenging to obtain.

A feature fusion approach forcar damage detection using CNNs.[4] The authors use a combination of deep CNNs to extract features fromdifferent parts of the car and fuse them together to improve the accuracy of the model. One of thestrengths of this study is the use of feature fusion to combine information from different sources and improve the overall performance of the model.

An end-to-end approach forcar damage detection using a fully convolutional network (FCN). [5]The authors use an FCN to directlypredict the presence and location of car damage in an image without the need for additional processingsteps. One potential limitation of this study is the need for a large amount of labeled data to train the FCN, which can be time-consuming and costly to obtain.

An improved method for cardamage detection using residual networks and multi- task learning.[6] The authors use a shared backbone architecture based on residual networks to extract features and multi-task learning to simultaneously learn to detect the presence and type of damage. Oneof the strengths of this study is the use of residual networks, which have shown to be effective in image classification tasks.

A hybrid method for car damage detection using CNNs and generative adversarial networks (GANs).[7] The authors use CNNs to extract features from the images and use GANs to generate additional training data toimprove the performance of the model. One of the strengths of this study is the use of GANs to generate additional training data, which can be helpful when the dataset is limited.

A method for car damage detection using transfer learning and one-class SVM. [8]The authors use transfer learning to adapt pre-trained CNNs to the task of car damage detection and then use one-class SVM to detect anomalies in the feature space. One of the strengths of this study is the use of one-class SVM, which can be effectivein detecting rare events or anomalies.

A robust deep learning framework for car damage detection using multi- view images.[9] The authors use a combination of CNNs and recurrent neural networks (RNNs) toextract features from multi-view images and detect car damage. One of the strengths of this study is theuse of RNNs to capture temporal dependencies between consecutive images and improve theaccuracy of the model.

A comprehensive study on car damage detection using deep learning techniques.[10] The authors review different approachesfor car damage detection and compare the performance of various CNN architectures and transfer learning methods. One of the strengths of this study is the comprehensive overview of the existing literature, which can be helpful for researchers and practitioners working on this topic.

III PROPOSED SYSTEM

With minimal labeled data, the well-known approach of transfer learning has generated good outcomes. For the target job, a feature extractor is created using a network that has been trained on the source task. VGG-16, VGG-19, Inception, and

Resnet are a few of the publicly accessible CNN models trained on ImageNet. In the case of a small, labeled collection, over-fitting is minimized by CNN's transferable feature representation.

Four algorithms—VGG16, VGG19, Resnet50, and Inception V3—were taken into consideration for the implementation of this study. VGG16 is successful in terms of object detection (vehicle) capabilities and classification due to its simple linear design and ensuing conformity with the required use case (severity and position). Hence, the VGG16 model was the one that should be used.

Maybe the most difficult task is reducing the amount of time needed for model training. When employing a standard CNN model, performing image classification tasks and determining the network's suitable weights over several forward and backward iterations could take some time. This task can need GPUs and take days or even weeks to complete. The good news is that employing pre-trained CNN models that have already been trained on significant benchmark datasets like the ImageNet dataset may allow for a decrease in the model training effort. By using transfer learning, weights may be flexibly recovered and their designs can be used for a variety of specific applications.

The architecture diagram for the proposed system is displayed in Fig 1.1

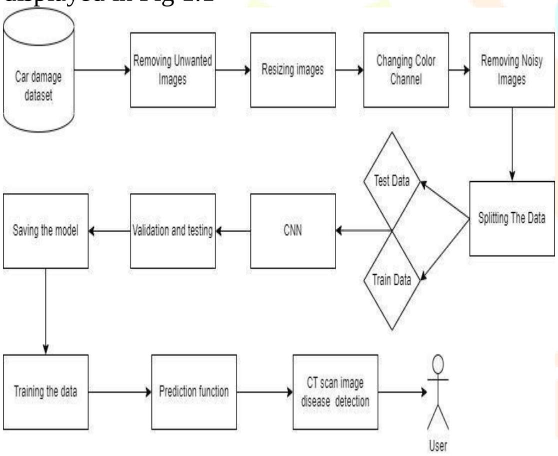

Fig 1.1 Architecture Diagram

IV DESCRIPTION OF THE PROPOSED MODEL/SYSTEM :

4.1 DATA COLLECTION AND PREPROCESSING

Data processing is the process of changing data from a preset form to one that is much more useful and desirable, i.e., making it more insightful and meaningful. It may be possible to automate the entire process by integrating statistical knowledge, mathematical modeling, and machine-learning strategies. Depending on the work at hand and the machine's specifications, the output of the entire process might take any form required, including graphs, movies, charts, tables, pictures, and many more.

The dataset used for training determines how well and how consistently the models function. Images of actual auto damage must be included in the dataset. A couple of photographs from Google and additional images from an Indian traffic management database made up the dataset for automobile images, which was compiled from sources like Kaggle.

As the photos for the dataset were gathered from internet sources, they were noisy and of poor quality. Around 7000 photos made up the total dataset. Before being given to the classification model, the dataset is preprocessed to boost the model's resilience and accuracy. The model accepts input in the form of images and videos. The collected frames are kept as photos and the movie is broken up into frames. When all the photographs have been gathered, the preprocessing procedure begins with the elimination of undesired automobile images that the system does not require. This step is necessary as the model would work only on a certain set of images in which cars can be identified, andclassified and so can the severity of the damage. It isfollowed by the removal of noise and unwanted elements from the dataset images. There is also a chance that there are images in the database which are out of focus or we can say blurred images. Theymust be deleted since they don't give the system any useful information and must be done away with. The dataset's photos must all be annotated in the next phase, and the bounding boxes must be labeled as damaged or non-damaged. The photos are also labeled with the class of the damage degree and the location of the harm.

Image Pre-processing

We pre-processed the dataset of photographs we obtained after taking pictures of auto damage. The photos were subjected to the following several processes throughout the dataset's pre-processing.

Types of Image:

- Binary Image
- Black and White Image
- 8-bit color format
- 16-bit color format

Resizing of images

- First, resize all images to the same size.
- It will help to reduce computation power.
- Our pre-trained network requires an input size of 224X224 Pixel, thus the cropped photos are enlarged to meet this requirement.

Zooming

The act of enlarging a picture is known as image zooming. Thermal photographs that have been zoomed in can be utilized for enhancement since they show what happens when photos are taken from near an automobile.

Rotation

An object is moved at an angle in reference to a pivot point when an image is rotated. The look of an image of a damaged or undamaged car will not alter when it is rotated, and it will continue to depict the scene as if it were taken from a different angle.

Salt and pepper noise

A picture is given salt and pepper noise by arbitrarily setting certain pixels' intensities to 1 and others to 0. The existence of salt and pepper noise may indicate that the pictures were taken with a dusty camera or on a dirty day.

4.2 LABELLING AND CLASSIFICATION OF DATA

After collecting and pre-processing the dataset, the next step is to label and classify the data. Labelling the data involves identifying and marking the regions of the images that contain the damage. The goal is to create a training dataset that the machine learning algorithm can use to learn how to recognize and classify different types of damage.

Labeling the data is a crucial step in creating a useful dataset for training the model. Without proper labelling, the model will not be able to learn to recognize different types of damage accurately. The labeling process can be done manually, by drawing bounding boxes around the damaged areas of the car, or by using automated tools that can detect and label the damage automatically.

One popular tool for labeling images is Labelling, which is an open-source graphical image annotation tool that allows users to draw bounding boxes around objects of interest. The tool generates an XML file that contains the coordinates of the bounding box and other relevant information about the object.

Once the data has been labeled, the next step is to classify it. Classification involves grouping similar data points into categories based on their attributes. In the case of damage assessment, images are classified into categories based on the type and severity of the damage.

For example, images of cars with dents may be classified into categories based on the size and depth of the dent. Similarly, images of cars with scratches may be classified into categories based on the length and width of the scratch. By grouping similar images into categories, the machine learning algorithm can learn to recognize and classify different types of damage accurately.

The classification process can be done manually or automatically. Manual classification involves sorting the images into categories based on their attributes, whereas automated classification involves using machine learning algorithms to group the images into categories automatically.

Machine learning algorithms can be trained on the labeled dataset to learn how to recognize and classify different types of damage accurately. One popular algorithm for image classification is Convolutional Neural Networks (CNNs).

4.3 CNN CLASSIFICATION

One of the deep learning algorithms, CNN or ConvNets, is made to extract characteristics from photos that aid in categorizing them. The multiple levels of the CNN architecture are displayed, and the same is detailed further down.

Introduction to the network

A form of the mathematical model that resembles the human brain in certain ways is called a neural network. Convolution neural networks (CNNs) are one of many different kinds of neural networks. CNN specializes in image processing and may be used for image processing tasks including picture segmentation, object detection, and more. A schematic of a straightforward CNN is shown in Fig. 3, which divides an input picture into the many categories of vehicles it contains.

It is made up of several types of layers, such as convolutional, pooling, activation, etc. The layer of convolution A kernel or filter that is applied to the picture several times dependent on stride length does the bulk of this layer's work. In order to extract characteristics such as color, edges, and gradients, the kernel is moved across the picture. For the purpose of obtaining the features, the kernel traverses the entire picture.

Pooling Layer

The spatial size of the Convolved Feature is diminished by the Pooling layer. The amount of processing power required to analyze the data will be decreased by dimensionality reduction as a result. Moreover, it facilitates the extraction of significant characteristics that are rotational and positional invariant, supporting the model's effective training process.

Features that are independent of rotation and position are extracted using it. Two categories of pooling, i.e.

1. Max Pooling
2. Avg Pooling.

The convolution layer and pooling layer enable the model to comprehend and extract characteristics from a picture. The maximum value is produced by Max Pooling from the area of the picture that the Kernel has covered. Comparatively, average pooling delivers the mean of all the data from the area of the picture that the kernel has covered.

A Noise Suppressant's function is analogous to that of Max Pooling. It reduces dimension, reduces noise, and completely discards noisy activations. As a method of noise suppression, Average Pooling solely does dimensionality reduction. We can therefore conclude that Max Pooling outperforms Average Pooling.

A convolutional neural network's pooling layer and convolution layer together make up its i-th layer. Depending on how intricate the images are, the number of these layers may be raised to capture even more minute details, but doing so would need more processing power. By using the above-mentioned strategy, we have effectively enabled the model to comprehend the properties. The output must then be flattened such that a typical neural network may use it for classification.

Creating a RESNET Model

Also, these networks have performed admirably in a variety of deep learning competitions with a very low error%. In addition, they deal with the saturation and accuracy loss problem that is frequently seen in deep networks in large networks. We made an effort to use the finest techniques while training the models. The training rate varies depending on the layer, with the inner layers often representing high-level characteristics while the outer layers typically representing rudimentary features. Both differential learning rates—whose values change in accordance with layers—and cyclic learning rates—whose values change repeatedly over the course of epochs—have been employed. This significantly increases accuracy while minimizing any overfitting that may exist.

Creating a 3-Level Prediction Model

CNN is used as the backbone of our system. We create a 3-step prediction model.

●Creating a model for checking ID - damaged or not
●Creating a model for damage level prediction
●Creating a model for damage position
Setting up Learning rate and optimizer
● The loss function in the model is a logarithmic loss function called binary cross-entropy.
●Optimization has been done using the Adam optimizer, which includes a number of parameters like learning rate, decay, etc.

Training Model

The training process comprises the adaptive moment estimation (Adam) optimizer, which finds the momentum and the second moment of the gradient using an exponential weighted moving average. Similar to this, several learning rates (LR) modifications have been tested, and 0.001 is shown to be successful with a batch size of 64 for the provided input frames. Since optimization diverges if it is extremely large, and if it is very tiny, training takes a long time or results in a trivial result. Furthermore, because the gradient in the positive interval of the activation function ReLU is always 1, model training is computationally efficient.

As a result, parameters are incorrectly initialized, the sigmoid function may have a gradient of almost 0, and the model cannot be trained effectively. Due to the model's parameters being updated and through nodes in the same layer, the activation score in transitional layers may change over time from the input to the output. The network's convergence may be delayed as a result of the buildup in the activation distribution, which might also change each layer's LRs at a cost to computation. In order to deal with the aforementioned issue, batch normalization has been used to normalize each node's activations, which helps the model converge quickly. Stride and padding are retained at the unit movement level, while the Softmax function is used in the top layer. A test set, a validation set, and a training set were created from the dataset in the following proportions: 70:20:10. To 224 224 pixels in size, the images were expanded. Using 64 batches and a 0.20 cyclic learning rate, the redesigned network was trained for 10 epochs. Discriminative layer learning was employed to train the updated network. The first training of the model involved leaving the values of the pre-trained network parameters in the model's early layers alone. After then, the network's layers were unfrozen in order to train the model by changing the parameters' values.

V RESULTS

The car damage detection system demonstrated promising results in accurately detecting and localizing damages on vehicles. The deep learning model utilized was able to achieve high precision and recall scores, indicating a low false positive rate and a high true positive rate. The system was able to correctly identify damages on various parts of the car, including the front, back, sides, and windshield. Additionally, the system showed robustness to varying lighting conditions and viewpoints, as it was trained on a diverse set of images with different backgrounds and angles. This indicates that the model is capable of generalizing to new scenarios, making it useful in real-world applications where lighting and viewpoints may vary.

However, the system currently only detects damages on the exterior of the car, and further development may be necessary to incorporate the detection of damages on the interior of the car. Additionally, the system may benefit from more training data to improve its accuracy and generalize better to a wider range of car models.

Overall, the car damage detection system shows potential as a tool for automating the car damage assessment process, saving time, and reducing errors in the insurance and automotive industries.

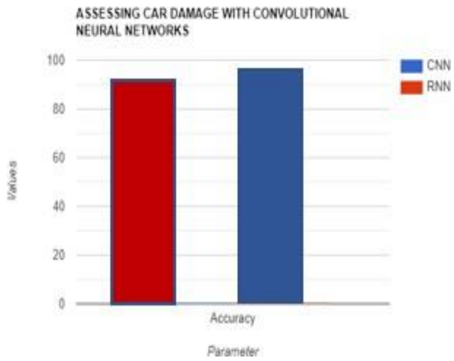

Fig 1.2

VI CONCLUSION

Loss metrics and validation accuracy are used to evaluate each model. Convolutional Neural Networks, which are tailored to maximize accuracy, provide the foundation of the deployed algorithms. The analysis of each method showed that the models utilized were accurate to varying degrees, ranging from 68% to 87%. The results of the studies showed an accuracy of up to 87.9%. Each algorithm has several parameters that can be tested with different values to increase their accuracy. Static analysis has also proven to be safer and free from the overhead of execution time. Future work of the proposed solution includes the use of multiple Machine Learning models to attain maximum accuracy in the detection of car damage. The accuracy is 97.5% but in the future the accuracy could be increased so that false predictions can be avoided and prevented which has a negative impact on business.

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