

CAR DEFECT DETECTION USING MACHINE LEARNING FOR INSURANCE

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Abstract — In this system convolutional neural systems are used to distinguish whether a sleeper on a given image is denoted or not. Using transfer learning to take improvement of available models that are trained on a more all-purpose object acknowledgment task, very reasonable performances have been accomplished, which expression the great openings of this slant. In the end, correspondingly a promising attempt fashionable classifying coach damages into a few different modules is presented. Lengthwise the way, the main focus be located taking place the influence of certain hyper-parameters and on seeking tentatively founded ways to get a feel for them, all with the unprejudiced of progressing to adequate results as fast as possible. System undeveloped doors for future collaborations on spitting image recognition projects in wide-ranging and for the car coverage field in particular.

INTRODUCTION

Equipment are changing rapidly. Long-standing technologies are continuously being exchanged by new and sophisticated ones. These new-fangled technologies are empowering people to have their labor done efficiently. The playing field of supercomputer vision has greatly established during the last span, mainly because of the gain in multiplying power and available doppelgänger datasets. We do this exploration in cooperation with the Retirement fund, Actuarial & Insurance Services (PAIS) subdivision of PwC Nederland, which is concerned with recommended and conciliation happenings in the fields of pensions and insurances (PwC, 2015). PAIS also contains a small, but strong and ambitious team devoted to data knowledge consulting, which requirements to gain more involvement in deep learning submissions (such as mainframe vision).

KEYWORDS

Computer vision, image recognition, convolutional neural networks, transfer learning, ImageNet.

PROPOSED SYSTEM

Be familiar with car damage is a bit more difficult, comparatively because pre-trained models be located usually not accomplished on doing this task, but generally because our image dataset for scratched cars be located very limited in size. A larger and better spitting spitting image dataset be present projected to enable the keeping fit of much restored models. If possible, such a dataset should contain images that are in point of fact used for car damage prerogatives, with labels representing more exact cataloging of the damage.

SYSTEM ARCHITECTURE

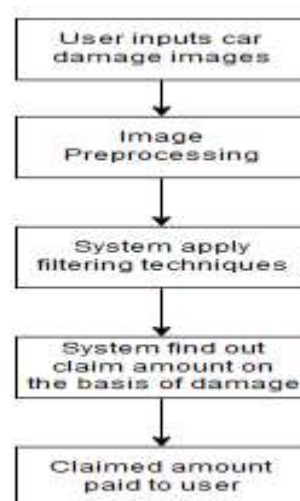


Fig -1: System Architecture

- **Processing Techniques:**

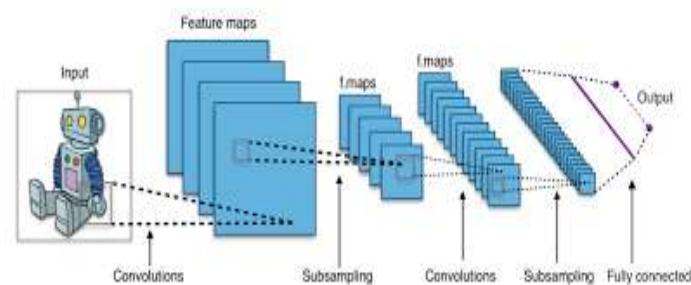
The color conversion model is very important to extract the required features. In this work, two conversion such as RGB to Gray and RGB to HSI are done and RGB, Gray and HSI color model are used as an input images for feature extraction module.

- **Feature Extraction:**

Feature Extraction is the most important step in the analysis of images. It is a process of gathering distinguishable information from the image itself from an object or group of objects. At last step use CNN model and detect diabetic disease.

CNN (Convolutional Neural Networks) Algorithm:

In AI, Convolutional Neural Networks (CNN or ConvNet) are unpredictable feed forward neural systems. CNNs are utilized for picture arrangement and acknowledgment in light of its high exactness. It was proposed by PC researcher Yann LeCun in the late 90s, when he was roused from the human visual impression of perceiving things. The CNN pursues a various leveled model which takes a shot at structure a system, similar to a pipe, lastly gives out a completely associated layer where every one of the neurons are associated with one another and the yield is handled.



CONCLUSION

We ought to taken some good first steps for the context of car damage recognition. Although make out cars has been done before, we exposed that it is relatively easy to achieve identical good results here (99.0% accuracy) consuming transference learning.

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