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A review on image classification using deep learning

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Abstract

Classifying images helps computers identify more things that humans can see. to identify the picture in the same way a person would. Despite widespread use, issues with the current conventional system's categorization accuracy, adaptability, and impact remain unsatisfactory. Therefore, deep learning has been suggested for image categorization as a means to both address these issues and boost accuracy. In this article, we introduce the fundamental ideas behind picture classification using deep learning, review the several algorithms that may be used for this task, and then examine the benefits of utilizing deep learning for this task, as well as the numerous applications that make use of this technique.

Keywords: Images Classification; Deep learning; DNN; Computer Vision

1. Introduction

Image recognition, also known as picture classification, is the process of recognising an image and assigning it to one of a set of categories. Therefore, image recognition applications and software can determine the subject matter of an image and identify its many components. Classifying images is useful in many domains, including the study of plant diseases and the analysis of human expressions. Image categorization employing the idea of a "deep neural network" helps to compact otherwise cumbersome photos. Self-driving cars, medical diagnosis, automatic translation, etc., all make use of Deep Neural Networks. Recently, excellent results have been achieved via the use of deep neural networks to aid with picture classification. "Deep neural networks" (DNNs) are particularly useful for image recognition. A neural network is a kind of pattern-recognition computer system. The structure of the human brain served as inspiration for its design, thus the name. Input, hidden, as well as output layers make up these layers. A signal is received by the input layer, processed by the hidden layer, and then predicted by the output layer. Nodes (artificial neurons) which are linked in a network do the computation at each layer of the network. By use of feature engineering, researchers might potentially teach a deep learning model to distinguish between canines and felines. Now, picture yourself compiling data on all of the world's billions of cats as well as dogs. Because of factors including viewpoint-dependent object variability, background clutter, lighting conditions, and picture distortion, it's impossible to build precise features that will work for every image. Thanks to the functionality of the neural networks, a different strategy is possible.

To eliminate the need for manual feature extraction, neural networks are trained with the data they will eventually use. Computer vision (CV) is the academic discipline devoted to giving computers this capability. As one of several CV jobs, picture categorization lays the groundwork for addressing a wide range of CV issues, including as:

1.1. Image classification with localization

Putting a picture in a certain category and drawing a box around anything to indicate its precise location in an image.

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1.2. Object detection

Classifying various picture features and highlighting their respective locations using bounding boxes. In other words, it's a spin on object localization problems from the realm of picture categorization.

1.3. Object (semantic) segmentation

Distinguishing individual objects in a picture by their corresponding pixels as opposed to just drawing bounding boxes around them, as is done in object detection.

1.4. Instance segmentation

Identifying differences between instances of the same class (each person in a group).

The suggested work used the Inception V3 model to categories a picture as either alive or non-living, and then further into classifications such as animal, person, selfie, group shot, location, wallpaper, vehicle, etc. This work provides an alternative to picture feature extraction and image segmentation for more precise image categorization.

2. Literature Review

- In this paper [1], based on the Inception-v3 model of TensorFlow platform, author use the transfer learning technology to train a flower classification model on flower category datasets. The classification accuracy of the model are 95% on Oxford-I7 flower dataset and 94% on Oxford- 102 flower dataset, which is higher than other method.
- This paper [2] proposed a method of lung image classification based on inception-v3 transfer learning in CT images, and the method was compared with other methods. In particular, the method of lung image classification based on migration learning can achieve higher accuracy. Moreover, the neural network model based on transfer learning performs better in pulmonary image classification on JSRT database than the model based on original DCNN. he experiment proved that the experiment based on transfer learning was meaningful for pulmonary image classification. The highest sensitivity and specificity are 95.41% and 80.09% respectively in the experiment
- In article [3], the authors fine-tuned the weight parameters of three different networks (AlexNet, VGG16, & VGG19) using two different, state-of-the-art image classification datasets (GHIM10K & CalTech256). Using recall, accuracy, and F-score, the authors evaluate the effectiveness of different network designs. In addition, the authors used a "support vector machine" for the image classification to assess the stability of CNN features. They looked at how SVM stacked up against the much-talked-about CNN networks. The examination of performance showed that the VGG19 CNN design increased the average recall, accuracy, and F-score by % on both datasets. To optimise the parameters of the "pre-trained network" (VGG19) for the picture classification task, the authors use transfer learning. We also evaluate VGG19's performance in relation to those of AlexNet & VGG16. Researchers have evaluated the hybrid learning strategy, which combines the powerful feature extraction of CNN architecture with the classification accuracy of a "support vector machine" (SVM), to the various CNN designs. Analysis of performance demonstrates that the VGG19 architecture with its fine-tuned settings performs better than both the competition in the form of CNNs and hybrid learning approaches when used to the picture classification job.
- The authors offer a system for recognising bacteria that is programmed in Python and uses the Keras API on top of the "TensorFlow Machine Learning framework". This is made possible by the authors' use of machine learning for automated prediction via the use of picture categorization and the deep learning approach. In this work, researchers explore the potential of using image classification with a deep learning approach to categorise bacterial taxa. This study follows a similar line of inquiry, seeking to refine the LeNET technique by keeping an eye on the prevalent practise of conducting ever-more-extensive training across an ever-increasing number of Epochs. The findings show that further improvements in the accuracy of standard resolution bacterium image databases are possible. The results of one CNN approach may be compared with those of another, and so on. Nevertheless, only two bacterial species with significantly varied cell shapes were included in this first investigation [4].
- This research proposes [5] a "convolutional neural network" (CNN) classifier based on the image bit-plane slicing feature to enhance the identification accuracy of breast cancer images. Each texture picture is divided into the eight bit-plane images, and the suggested CNN classifier makes the most of this. Each bit plane may provide a unique set of visual details. Similarly, the authors have thoroughly investigated the fusion features on several bit planes. Recognition & classification tasks are performed using the CNN classifier. Results from

simulations run on medical picture datasets demonstrate that, on certain bit-planes, the suggested technique significantly boosts recognition rate as well as classification performance.

- In order to identify the FMRI, Xiaolong Sun et al. [6] presented a unique hybrid model (fMRI). Here, SVM serves as a recognizer while CNN acts as a trained feature extractor. Planned fusion scored 99.5 percent greater than the Haxby approach utilising the identical dataset used in the evaluation. This study investigated several learning strategies, including neural networks, random forests, adaboosts, decision trees, and K-nearest neighbours. It was at the deliberation phase that the hybrid technique's intricacy became apparent

3. Conclusion

In this study, new work is proposed to classify the images with more accuracy. The Inception V3 model is used in the proposed work. The data is collected from kaggle then after preprocess the image to make it compatible for the model. Image augmentation is performed to the training dataset. The feature extractor consists of inception layers and the classifier consists of FC and output layer. This strategy incorporates feature extraction into the design architecture and employs a new classifier layer. Researchers kept the convolutional layer weights fixed throughout training and instead taught the newly learned FC layers to infer the previously retrieved features. The prerequisite of the design architecture was the specified input's shape and size which is (224, 224, and 3).The model ran for 10 epochs. Using Inception V3 Model we made our own Fully Connected Classifier with one flatten layer and three dense layers. To test the model we fitted the test data into the model for prediction. We used accuracy score as evaluation metrics to evaluate the performance. After all the necessary steps, the model gets 99.52% of accuracy with 0.11% loss. The proposed work was able to bring more accurate and robust model than existing work.

In future work several things can be improved. The quantity of the data can be increased, the amount of data can easily increase the accuracy and robustness of the model. Further the Fully connected layers can be increase with dropouts in order to reduce over-fitting. Regularization can also be implemented to protect the model from over fitting.

Compliance with ethical standards

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Disclosure of conflict of interest

Authors have declared that no conflict of interests exists.

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