Artificial Intelligence Applications Coursework

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Abstract

This activity handles image classification by using Deep Learning by using framework TensorFlow. Python, which is nowadays considered as the lingua franca of machine learning tasks is used. TensorFlow framework which comes packaged with libraries to handle deep learning is used. The Dataset consist of flowers category which there are five (5) types of flowers. Deep neural network (DNN) has been choosing as the best option for the training process because it produced a high percentage of accuracy. Results are discussed in terms of the accuracy of the image classification in percentage. Roses get 90.585 % and same goes to another type of flowers where the average of the result is up to 90 % and above.

1. Introduction

Image classification is growing and becoming a trend among technology developers especially with the growth of data in different parts of industry such as e-commerce, automotive, healthcare, and gaming. The most obvious example of this technology is applied to Facebook. Facebook now can detect up to 98

One of the dominant approaches for this technology is deep learning. Deep learning falls under the category of Artificial Intelligence where it can act or think like a human. Normally, the system itself will be set with hundreds or maybe thousands of input data in order to make the 'training' session to be more efficient and fast. It starts by giving some sort of 'training' with all the input data (Faux Luthon, 2012). Image classification has become a major challenge in machine vision and has a long history with it. The challenge includes a broad intra-class range of images caused by color, size, environmental conditions and shape. It is required big data of labelled training images and to prepare this big data, it consumes a lot of time and cost as for the training purpose only (X. Li Guo, 2013).

In this Project, deep neural network, based on TensorFlow is used with Python as the programming language for image classification. Thousands of images are used as the input data in this project. The accuracy of each percentage of 'train' session will be studied and compared.

2. Methods

Humans are needed to manually annotate a vast number of datasets in a supervised learning context. Models then use the data to understand complicated underlying correlations between the data and the label, allowing them to predict the title based on the data. Deep learning models are notoriously data-hungry, requiring massive quantities of data to obtain decent results. Deep learning's recent triumphs may be attributed to ever-improving technology and the availability of enormous human-labeled datasets (Smith, 2020).

One of the critical disadvantages of supervised deep learning is that it requires many human-labeled datasets to train. This luxury is not accessible in many disciplines since getting massive datasets annotated by specialists may be logistically challenging and expensive. While obtaining labeled data might be difficult and costly, we usually have access to many unlabeled datasets, particularly picture and text data. As a result, we need to figure out how to leverage these underutilized datasets for learning.

Image Classification consists of four (4) phases throughout this process and each of the phases will be discussed. Each of the phases are included on TensorFlow as the open source software and Python as its programming language. Then, the process is continued to collect some of the images (inputs), by applying DNN and lastly all images will be classified into their groups.

3. Experiments of research papers

The characteristics from the bottleneck layer (which have the form 161616) are extracted during the testing phase and used as a feature vector for the Machine Learning-based prediction during the testing phase to optimize memory and processing time. Figures 1 and 2 show the convolution layers added to our AE-CNN model's bottleneck layer to decrease the number of features to 786 (= 16 16 3) and 192 (= 8 by 8 by 3) from the 4096 parts recovered from the bottleneck layer.

Experimental settings and criteria

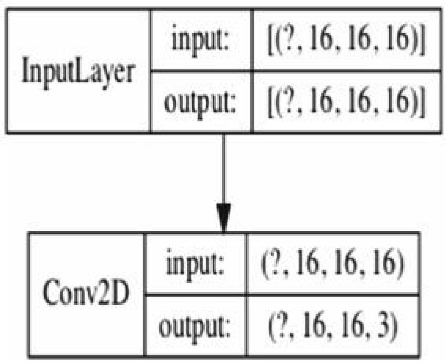


Figure 1. Summary of the convolution layers added to the latent space of the AE-CNN model to reduce the number of features to 76

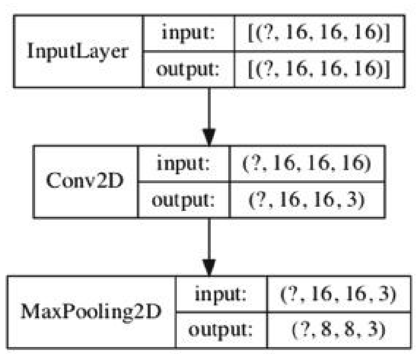


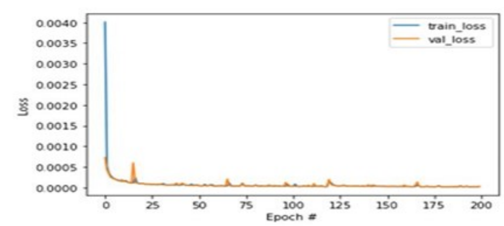
Figure 2. Summary of the convolution layer added to the latent space of the AE-CNN model to further reduce the number of features to 192

3.1. Experimental Results of Research Papers

We present a novel Auto-Encoder, a model that learns compressed versions of the input data based on the stated requirement. While training the network, it may also employ supervised learning approaches. As a consequence, we may call our auto-encoder a ”self-supervised learning approach.” On the latent space level, most extant Auto-Encoder models have a few layers that are ”fully linked.” Instead of using FC layers, convolutional layers are used in this experiment. It is possible to reduce the training time of a model by just using convolutional layers and without including any FC layers in the network (Patil, Abhinav, 2021).

Furthermore, fully linked layers of a network cannot learn visual patterns or convolutional layers, among other things. This is the most significant benefit that our technique has over different approaches. The following are the contributions made by the work: A top goal is developing an effective Auto-Encoder model from which we can extract global features that we may utilize to classify Lung Ultrasound Image data. To improve the accuracy of the labeled data obtained from our proposed model’s Latent space, we use a machine learning classifier (ML classifier) (specifically, the XG-Boost algorithm). Our objective is to get the original pictures from the output of our model with the smallest amount of loss possible while maintaining the highest level of quality (Van, 2020).

3.2. Discussion



First, as seen above, we created a CNN-based Autoencoder model that produces the same output as the input with the least amount of loss. We examined two separate data sets, including 800 and 1900 photos from open source in the public domain1,2, respectively. We split the photographs into five categories, with each class including at least 150 images. After that, we used the 1900-image data set to train our AE-CNN model (Srinivas, 2015).

We utilized 1000 of them for training and the remaining pictures for validation. Figure 6 depicts the performance of our model. A few examples of the photographs that correlate to the data set we looked at. The first, second, third, and fourth rows correspond to the first, second, third, and fourth classes. In addition, we tested the second dataset, which has roughly 800 photos (Van, 2020).

With the help of our recommended AE-CNN technique, we extracted the properties of each image from these 800 photographs and used them to train the ML models for accurate prediction. Other classifiers' performance has been evaluated against these qualities, which have also been used as benchmarks. n-CoVID-19 was detected in ultrasound images, and the classification results are shown in the table below, which compares the performance of multiple machine learning models in detecting n-CoVID-19 (Patil, Abhinav, 2021).

Table 1. Accuracy table

Name of Classifier	4096 Features	768 Features	192 Features
XG-Boost	93.3%	96.6%	91.1%
MLP	92.5%	86.76%	76.15%
KNN	88.8%	88.8%	91.1%

The accuracy of various classifiers is shown in the table above when varying amounts of input attributes are used to compare them. As shown in Table 1, the XGBoost classifier has the highest accuracy value of 96 %, while MLP has the second-highest accuracy value of 92 %.

4. Experiments and Training of personal code

The Dataset consists images for five flowers species. The distribution of these flowers is as below

Flower Type	Number of instances
Dandelion	898
Tulips	799
Sunflower	699
Daisy	633
Roses	641
TOTAL	**3670**

The data inputs (five type of different flowers) undergoes training with multiple hidden layers. The inputs are also set with fixed-size of the 224x224 RGB image. The convolution process is configured with MobileNet as it produces an efficient convolution neural networks. During the training process we start by collecting images of the flowers after which we train the model on this data using Deep Neural Network (DNN). We then run for validation and testing and if the output is not as desired we start all over again using Deep Neural Network (DNN). The process only ends upon a successful classification. The process starts with inserting sets of flower images as an input, and then all the inputs undergo training using Deep Neural Network. The images are trained until the model can classify all the images.

4.1. Results

Following is the description of the model's classification on the images. The model obtained 100 % accuracy on classifying Tulips flowers images The Sunflower images are classified at an accuracy of 99.45 % Dandelion obtained an accuracy of 99.21 % Daisy on the other hand scored 99.13 %. Notably, Roses had the least accuracy scoring 90.8 %.

5. Conclusion

To accomplish the goal of identification, one must perform image processing and recognition on the fundamental picture transformation and transformation and the transformed picture. To accommodate the nature of the image information, it is stored in a two-dimensional space, enabling it to maintain a significant quantity of information. Ultrasound is equivalent to radiography and computed tomography in detecting abnormalities in the pleura line. Lung ultrasonography is helpful in the early diagnosis and follow-up of suspected viral infections, which may occur even before respiratory symptoms appear in some instances. Traditional methodologies such as PCA-based feature extraction have depended on various applications for many years, including face recognition and object identification.

Compared to older designs like ResNet, DensNet, Inception, and VGG-16, any approach with a simple network architecture seems to offer several benefits in classification problem execution speed. A CNN-based Auto-Encoder model, which was used to extract features for lung image classification, is presented in this research, and it is shown to be successful. In addition, our suggested model (AE-CNN) has demonstrated its ability to recreate the original picture. Using the XG-Boost Classifier, we attained the most fantastic accuracy of 96.6 percent by applying machine learning to features recovered from latent space.

6. References

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