Title: Deep Learning-Based Classification of Fruit Diseases: An Application for

Precision Agriculture

Link: https://cdn.techscience.cn/ueditor/files/TSP_CMC_66-2/TSP_CMC_12945/TSP_CMC_12945.pdf

Year: 2021

Summary:

1. Introduction

Early plant disease detection is economically vital. Artificial intelligence can be used to extract fruit color, shape, or texture data, thus aiding the detection of infections at a very early stage, thus reducing disease spread and increasing cure rates. Automated strategies based on digital image processing are used to check fruit type and quality. Computer vision techniques can be used to detect shapes. Mobile devices place unprecedented demand on computing, edge computing, and the Internet of Things (IoT). Mobile edge caching avoids possible bottlenecks and improves user experience by reducing the time taken to transfer data from a server to an end-user.
Automated fruit classification is less well-established, and its efficacy is hotly debated. Machine-learning algorithms have attracted much interest for automated fruit packing and grading.
A plant disease classification technique was proposed using pretrained GoogleNet and AlexNet models to extract deep features. A robust DCNN model with a metaheuristic architecture was used to detect and classify tomato diseases with an accuracy of 85.9%. Machine-learning approaches are replacing manual methods in many industries, and image-based fruit classification avoids the drawbacks of gas sensors, infrared imaging, and liquid chromatography devices. A custom dataset of 1,653 images of 18 fruit types was used to validate a method that extracted and classified FRFE features using a single-layer feedforward NN.

2 Objectives and Contributions: To improve image-based fruit classification, we used CNNs, which extract more detailed features and work efficiently with large datasets. We used 5G technology and cloud computing to classify mobile images using MEC. The method was based on hand-crafted features and utilized a minimum redundancy maximum relevance (mRMR)-based feature selection technique to ensure the inclusion of relevant features only.

3 The Fruit Classification Framework: Our CNNs have an infrastructure layer, a resource engine layer, and a data engine layer. The infrastructure layer contains a device sublayer, a local edge cache unit, MEC orchestrators, and RANs. Mobile phones with cameras capture images or video frames that are saved locally and then transferred via 5G to the local edge cache unit. The 5G network contains multiple SCs connected to separate cache memory units, which are reserved by CPs for MNOs.

3.1 Hybrid DL Model: The data engine uses the pretrained VGG19 model and pyramid histogram of oriented gradient (PHOG)feature extraction technique to detect and classify fruits. PHOG represents edges in vector form, using pyramid representation and histogram of oriented gradients. It extracts features from different sub-regions at various resolutions, and then concatenates all HOG feature vectors into a single feature vector. A hybrid deep learning model for fruit classification uses edge directions and local intensity gradients to describe object shape and structure.

3.1.2 The CNN: CNNs were initially developed to recognize handwriting. They differ from other ML methods in that they accept preprocessed images rather than feature vectors. Supervised CNN training uses comprehensive datasets such as ImageNet, and the VGG19 model has 16 convolutional layers, 5 pooling layers, 3 FCLs, and 2 dropout layers. It also features an extractor and a classifier. Transfer learning is vital for smaller datasets with limited numbers of samples or classes. CNN fine-tuning yielded better results than generic feature extraction, and the VGG19 model was trained using a mini-batch size of 64, learning rate of 0.0001, weight decay of 0.005, and a momentum of 0.8.

4.1 Datasets and Experimental Setup: The Fruit-360 dataset contains 65,429 images of 95 different classes. Ten-fold cross-validation and seven classification methods were used to test the performance of our method. The publicly available Plant Village dataset was used to test the model in terms of disease classification performance. The accuracy, FNR rate, and training time was recorded for all seven classifiers using 10-fold cross-validation. We evaluated the classification method via three experiments, and the highest classification accuracy was obtained by activating the fully connected fc7 layer in the VGG19 DCNN model. The FNR rate was 9.6%, the sensitivity was 90.4%, the precision was 90.6%, and the training time was 89.5 s.

4.2.2 Discussion: A classification technique based on shape, color, and textural features was used to classify 24 fruit classes in the Fruit-360 dataset. The accuracy rates were higher than 97.5%.

4.3.1 Classification Results: We evaluated our model using three experiments, and the highest classification accuracy was 94:24% for the VGG19 model. The FNR rate was 5:76% and the training time was 84:2 s for the Cubic SVM.

4.3.2 Discussion: To determine the validity of the model, it was compared with existing techniques. A DCNN-based approach provided an overall classification accuracy of 97.80% when used with multi-level fusion followed by entropy selection. The VGG19 training loss decreased rapidly to less than 20% after 5,000 iterations, and the overall network accuracy increased gradually, reaching 99% after 5,000 iterations. Fine-tuning increased the overall accuracy from 87.3% to 99.97%.

5. Conclusion: We combined a DCNN model with PHOG features to classify fruits using 5G and cloud technology. The method was associated with good classification accuracy and should aid fully automated robotic harvesting.

Title: An Effective Pomegranate Fruit Classification Based On CNN-LSTM Deep

Learning Models

Link: https://sciresol.s3.us-east-2.amazonaws.com/IJST/Articles/2021/Issue-16/IJST-2021-432.pdf

Year: 2021

Summary:

1 Introduction

Pomegranate is one of the major fruits produced in India. Convolutional Neural Network was used to detect diseases in pomegranate fruits post-yield given marketing and export.

Tomato leaf disease detection using CNN (2) employed 3 convolutional layers, and produced a testing accuracy of 91.2%. A VGGNet CNN Model developed to detect diseases in sugarcane (3) gave a training accuracy of 95.40%, and a classification accuracy of 99.17%.

A CNN LSTM model was able to detect good and bad apples with an accuracy of 99.2%, and a tensor flow model was able to detect diseases such as bacterial blight, Cercospora, anthracnose with an accuracy of 90%.

Using CNN, we can classify mango leaves infected by anthracnose disease, identify 14 crop species and 26 diseases, and recognize different types of fruits with an accuracy of 98%. Various works have been done to detect diseases in pomegranate fruit and leaves using deep neural networks and CNN. CNN has been shown to produce effective accuracy results in detecting plant or fruit diseases. The present study uses LSTM and CNN to classify pomegranate fruits into normal and abnormal. The accuracy of the classification is improved by using several parameters such as learning rate, input bias, output bias.

2.1 Convolutional Neural Network (CNN)

CNN (20) is a type of deep neural network that mimics a biological neural network. It is suitable for pattern recognition and voice recognition and is popular in classification dataset.

Dropout Layer: This layer helps prevent the model from over fitting by randomly setting the outgoing edges of hidden units to 0 at each update of the training phase.

LSTM is used to solve the problem of short term memory using gates and it uses three gates namely input gate, forget gate and output gate.

2.3 CNN-LSTM Model

The CNN model described above can handle a single image, but we need to repeat this process for multiple images and allow the LSTM to build up an internal state by updating weights.

3 Proposed Methodology

In the current study, a deep model is proposed that is based on deep features extracted using CNN and LSTM network. The model sorts images into normal and abnormal using class labels 0 and 1 respectively.

4.1 Dataset Acquisition

Due to the non-availability of benchmark dataset on pomegranate fruits, we have obtained the data by visiting pomegranate farms in and around Bangalore. The dataset includes 6519 images belonging to two different classes namely healthy and diseased.

4.2 Experimental Setup

The proposed model was implemented using the Python toolbox and used 62% of the dataset for training and 38% for testing.

4.2.1 Significance of hyperparameters

The most important hyperparameters for a CNN Model are the number of epochs, learning rate and drop out.

Number of Epochs

A machine learning algorithm uses 23 epochs to complete the entire training dataset. The number of epochs is decided based on several parameters and a deep understanding of the data is indispensable.

Learning Rate

Learning-rate is a hyperparameter used in the training of neural networks.

Activation Function

ReLU is a kind of activation function used in neural networks, especially in CNNs. It enables models to learn quickly and perform better by overcoming the problem of vanishing gradient.

4.2.2 Performance Evaluation

The confusion matrix is a table with two rows and columns that shows the performance of a binary classifier.

In Table 4, we have shown that CNN LSTM produces higher accuracy in the classification process than previous research carried out using machine learning algorithms.

5 Conclusion and Future Work

The current study implements a CNN LSTM model using Python to detect diseased pomegranate and classify them into normal and abnormal. The proposed model has a classification accuracy of 98.17%.

Title: A fruits recognition system based on a modern deep learning technique

Link: https://iopscience.iop.org/article/10.1088/1742-6596/1327/1/012050/pdf

Year: 2021

Summary:

1. Introduction

DNNs have been used to identify, classify, and differentiate between different kinds of fruits using Computer vision technology, and have shown to outperform other algorithms.

A CNN is used to classify 2-D input images and recognize the objects based on pooling and convolution layers. An optimal scheme is introduced for differentiating between a variety of fruits using a dataset, which is accessible and simulates real-time prediction using EfficientNet.

2. Deep learning algorithms

Deep Learning is a sub-field of Machine Learning that models high-level abstractions in data by using a large set of labeled data and neural network architectures.

The concept of deep learning was first put forward back in the 1980s, and has been experiencing research growth in the last decade, including natural language processing, image classification, and information retrieval, etc.

Artificial Neural Network gets its inspiration from the human brain system and consists of integrated processing units named as neurons. It has an input, hidden, and output layer.

2.1. Convolutional neural networks

CNNs are neural networks that can quickly identify, classify, and recognize any features in an image. The first CNN, commonly known as LeNet, was created by Yann LeCun in 1988.

In a CNN classifier, the convolution operation is performed over pixels in an image, and the ReLU and Pooling layers are used to transform the image into the required dimension without blurring it. The fully connected layer is used to identify the images and classify them as per the accuracy achieved.

2.2. EfficientNet

EfficientNet use pre-trained convolution neural networks for conducting image related functions as a base network, which allows for more precise and efficient models to be created.

EfficientNet-B0 conducts a grid search of the base network to determine the relationships between the different scaling dimensions of the network while considering both model size and available computational resources.

3. Dataset

For training and testing, we used 77917 different fruits pictures of 103 categories from the fruits 360 dataset. We used 13218 images (75%) to create the training set and the rest 4406 images (25%) for testing the model.

4. Experimental results

We applied EfficientNet-b0 on Fruit Dataset to discover the better classification performance of the network. The accuracy of the proposed model was 95.67 %, which is exceptionally good and promising to use in real-world applications.

5. Conclusion

This paper explores a fruits recognition classifier based on EfficientNet algorithm, which achieved the best test accuracy of 98% in case 4 from 11 to 15 epochs and best training accuracy of 96.79% at epoch 13.