CLASSIFICATION OF VEGETABLE IMAGES USING DCNNADAPTIVE LEARNING

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Abstract : In this paper, an effort is made to accurately classify vegetable images. For this classification, a dataset of 3000 photos from 5 classifications is used. The best machine learning tool for categorization issues is the convolutional neural network, a deep learning technique. However, for CNN to be effective in naturally occurring picture classification issues, vast datasets are necessary. Here, we test the effectiveness of CNN for classifying images of vegetables by building a CNN model from scratch. In order to evaluate the accuracy with the usual CNN, multiple pre-trained CNN architectures utilizing transfer learning are used. This paper suggests comparing common CNNs with their designs in order to determine which method would be most accurate and efficient when used with fresh image datasets. All of the CNN architectures that have been proposed have experimental results. Additionally, a comparison between created CNN models and pre-trained CNN architectures is conducted. And the study demonstrates that the transfer learning technique can outperform classic CNN with a small dataset by making use of prior knowledge obtained from relevant large-scale work.

Keywords: Classification, CNN, Vegetables

1. INTRODUCTION

One of the most often consumed foods in everyday meals is produced. Vegetables of various varieties are produced by people worldwide. According to a census, there are about a hundred thousand different vegetable species on Earth [1]. In addition, vegetables are crucial for human health due to their high nutritional, mineral, phytochemical, and dietary fibre content. In terms of colour, texture, and shape, many vegetable types are comparable. The same vegetable has multiple names depending on the country. Several typical procedures, from vegetable cultivation through distribution, are carried out a hand. similar to picking and organizing vegetables. Additionally, it can be challenging for a customer to identify a vegetable in the market due to the similarities between various crops. The fact that many processes from vegetable cultivation to consumption still need manual work and are therefore labor-intensive seriously hinders the development of the commercialization of vegetable products. A vegetable image classifier must be introduced in order to automate the picking, sorting, and labeling of vegetables in order to address this problem and save time and money. Nowadays, classification and detection are the two main types of agricultural research activity. Vegetables come in a variety of varieties, yet many people are unaware of them. Therefore, the design of a vegetable classifier will also bring simplicity to people's life. Additionally, distribution centres and superstores manually sort veggies. Therefore, this research is carried out to find solutions to these issues. This study aims to improve the classification accuracy of vegetable images using pre-trained DCNN with transfer learning and CNN. Convolutional neural networks are frequently used nowadays for classification, segmentation, image recognition, and other processes. The greatest strength of CNN is its deep network architecture, which allows it to automatically learn mid- to high-level concepts from fresh data [2], [3].

II. RELATED WORK

The goal of this study is to classify vegetable photos more accurately and effectively. Finding an efficient model and a method that works well in terms of accuracy, speed, and the cost is also important. Om Patil et al. [4] used InceptionV3 (also known as GoogLeNet) for vegetable classification tasks almost three years ago. The suggested model can categorize four different types of vegetables—carrots, onions, cucumbers, and tomatoes—by fine-tuning the inception network and utilizing the transfer learning technique. Their improved inception-V3 has 99% accuracy for a relatively smaller sample of about 1200 photos. Deep neural networks were proposed by Yuki Sakai et al. [5] to classify vegetables by learning the object and extracting information. Their DNN model had a 97.58% recognition rate. With only 200 total photos and 8 different varieties of veggies, the dataset they used was incredibly limited. They employed 3 million iterations, which is a time-consuming and expensive process, to learn how to recognize vegetables. A transfer learning model built on a deep convolutional neural network has been employed by Frida Femling et al. [6]. They made use of Raspberry Pi for image collecting. They only used inception-V3 and MobileNet for their work, and both provided 96% and 97% accuracy, respectively. Their model is valued by two characteristics. The time it takes to categorize an image of a fruit or vegetable is one factor, as does the propagation time. Be that as it may, the dataset size is little as it contains 4,000 pictures from ImageNet and a sum of 4,300 pictures of 10 classes. Zhu L et al. [7], proposed AlexNet network for vegetable picture grouping. And furthermore, a relative report is finished by tending to the Help Vector Machine classifier and the customary back proliferation brain organization. They worked with 5 sorts of vegetables-pumpkin, mushrooms, broccoli, cauliflowers, and cucumber. What's more, pictures were gotten from the ImageNet dataset and were extended by taking on the information extension technique to a sum of 24,000 pictures so that overfitting is diminished. The most noteworthy exactness they acquired from their trial is 92.1% with the AlexNet net¬work. Guoxiang Zeng [8], proposed a picture saliency strategy and VGG design for the order assignment of leafy foods. To decrease the pointless clamor from the picture, they retransferred thick elements from each picture and sifted the muddled foundations of it. Furthermore, for deciding the huge region in an info picture, they pick a base up chart based visual saliency (GBVS) model [9]. They utilized a sum of 12,173 pictures spreading over 26 classifications, among them 13 classes were vegetables (3678 pictures)- broccoli, celery, cowpea, green onion, garlic, cucumber, mushroom, carrot, onion, pumpkin, Chinese cabbage, tomato, and pepper. Furthermore, the characterization precision of their model is 95.6%. Li et al. [10] proposed a better VGG model (VGG-M-BN) and got 96.5% precision. They worked with 10 classes of vegetables. Pictures were for the most part gathered from the ImageNet dataset and were extended by embracing the information development strategy.

Although this multitude of works is great, every one of them have limitations with regard to precision, proficiency, and adequacy. The normal issue we found in those works is the size of the dataset and dataset source. Also, the preparation season for the vast majority of the work is so lengthy. Also, as far as cost and time, long preparation time is wasteful. What's more, not very many specialists work with just vegetable order [4], [5], [7], [10] yet all of that work have restrictions. The base sort of vegetable they worked with was four [4], and the most extreme was ten [10] .

III. METHODOLOGY

This investigation of vegetable picture grouping proposed a created CNN model and cutting edge CNN model with a transfer learning method. In 2012, a cutting edge happened in the picture acknowledgment region through the ILSVRC(ImageNet Enormous Scope Visual Acknowledgment Challenge) contest on the ImageNet dataset [11]. At this point, various kinds of profound convolutional brain network structures are presented that fluctuate in quantities of layers as well as intricacy and are accessible for use by anybody. In the beyond a couple of years, utilizing transfer learning ideas like adjusting and layer freezing in CNN designs beat the conventional AI models with regards to execution and effectiveness for picture order issues. Here, we utilized a CNN model and four cutting-edge CNN structures - VGG16, InceptionV3, ResNet, and MobileNet. These four models are pre-prepared on the

ImageNet dataset, a huge scope dataset that contains 1 million preparation information generally creatures and day-to-day protests. By applying transfer learning strategies, learned elements of these DCNN models might assist with making exceptionally profound organization design compelling for our dataset.

A. CNN

In the field of PC vision, convolutional brain network fundamentally a standardized multi-facet perceptron (MLP) has been the most powerful development. Lately, CNN has ruled the PC vision and picture handling field for enormous scope picture acknowledgment, order, and division task. An ordinary CNN begins with an information layer, closes with a result layer, in the middle between them there exist different secret layers. Convolutional, pooling, standardization (ReLU), completely associated layers are essential for the secret layer [12]. information as info. The picture is then reshaped to an ideal size and sent to the following layer which is a convolutional layer. There exists various piece or channel that really slides over the info and performs component wise augmentations to separate elements. Here, through an actuation capability, the negative weighted information will be supplanted with zero otherwise it will go to straightforwardly yield. The most broadly utilized actuation capability is ReLU (Corrected Direct Unit) and for some sorts of brain organizations, it is the default initiation capability. It's a non-direct capability and quicker than the other initiation capability like-Sigmoid, Scaled Dramatic StraightUnit (SELU), Outstanding Straight Unit (ELU), Gaussian Blunder Direct Unit (GELU) and so forth. Highlights that are retransferd from the convolutional layer then, at that point, shipped off the pooling layer. This layer protects just significant elements from a huge picture by decreasing boundaries. Then, at that point, the completely associated layer deciphers these profoundly sifted pictures into classifications. What's more, another non-straight capability named softmax at last gives the decimal probabilities went from 0 to 1 to each class. In this examination, a 6-layer convolutional brain network is suggested that is totally worked without any preparation. The information picture size is chosen to 32x32 for diminishing by and large computational time so a decent model can be made concerning proficiency. Information increase procedures like revolution, rescale, shear, zoom, and even flip are additionally applied to the 32x32 size 3-channel preparing picture information. ReLU was utilized as the actuation capability with each convolutional layer. What's more, for further developing speculation blunder a dropout pace of 0.25 is utilized with the goal that it can defeat overfitting issues. At last, softmax is utilized to track down the probabilities of each class in decimal numbers.

B. Transfer learning

Building and preparing a profound convolutional brain network without any preparation is tedious, exorbitant, and hard. A profound organization implies it contains various layers, where it can likewise be numerous convolutional layers in careful request or grouping to characterize the specific picture. To learn highlight planning, when this sort of enormous and profound engineering is being prepared from the beginning, needs a huge scope dataset. Transfer learning is a method of re-utilizing a formerly evolved model on a second related task. The usage of information that is gained from a past space for the improvement and streamlining of another space is the center thought of it [12]. The idea of transfer learning in the field of ML was first introduced in quite a while 95 studio named "Figuring out how to Learn", plan of which was a long lasting ML procedure that can hold and reuse currently educated data [14]. It can rapidly transfer gained highlights from one(source) space to the another(target) space utilizing a more modest dataset in the quickest way utilizing the most straightforward way [15]. Thus, the idea of transfer learning is embraced in this examination and for this situation target space is vegetable picture characterization. Two methodologies are accessible for executing transfer learning-one is "Pre-prepared Model" approach and another is "Foster Model Methodology". In profound learning, the most generally utilized approach is the "Pre-prepared Model Methodology" and it was chosen for this exploration. In this methodology, a pre-prepared source model that is prepared for enormous scope information is chosen, and afterward the entire model or portions of the model are utilized as the beginning stage for a model of another undertaking. Where tweaking of the model might be expected on the information yield sets of the objective space. Tweaking alludes that, keeping the loads and inclinations of certain layers thawed and involving them for preparing so the pre-prepared model can perform well on the preparation information..

C. Tuning CNN Models for Transfer Learning

Tweaking alludes to the strategy of utilizing gained highlights or loads and inclinations from a pre-prepared profound CNN as the instatement of an objective CNN model with the goal that the objective CNN can be prepared on track information in a regulated way [2]. As the interrelation between our objective dataset and the source area dataset is remarkable, for every engineering we utilized layer-wise calibrating. We fined-tuned our four cutting edge CNN models by freezing the convolutional base so that recently educated loads and predispositions can be reused in our undertaking. We involved the full design for all intents and purposes, aside from the result layer which is fundamentally the last completely associated layer. Here, convolutional base is the proper element extractor, and the extricated component will be utilized for arranging the info picture. For retraining these transferd organizations we set the quantity of classes in the result layer to 15 alluding to our multi-class grouping task. At long last, the last layer was retrained.

IV. RESULTS AND DISCUSSION

The generated 6-layer CNN model has approximately 1 million parameters and a 3-channel input image size of 32x32. Four conv2D layers and two fully connected layers make up the 6-layer CNN model. Training is carried out with a batch size of 64 and 50 epochs using the Adam optimizer with a learning rate of 0.001. We were able to get the best accuracy out of the constructed CNN model using this training combination. Our constructed CNN model has a validation accuracy of 97.6% and a testing accuracy of 96.5%.

B. Comparative Results

Finding the best accuracy from a created CNN model with a short dataset is more difficult. Building a CNN model from start is not a simple task. Changing the CNN models' parameters, such as their learning rate, dropout, activation function, and activation layer count, is crucial for achieving the highest level of accuracy. The accuracy of the proposed 6-layer CNN, which has been adjusted and optimized for the working vegetable dataset, is 96.5%, which is the highest accuracy compared to all previous work that has been done by developing a model from scratch.

V. CONCLUSION

The most significant sector is agriculture, but it places less emphasis on digitization than other sectors do. There has been some prior research on classifying vegetables, but they are of limited scope, have a very tiny dataset, and are of lower accuracy. This research is carried out to address such challenges by taking into account those factors. In this work, two methods for classifying vegetable images are used, a standard CNN model and CNN-based pre-trained models. The proposed, entirely new, six-layer typical CNN model. On the other hand, modern CNN architectures that have already been trained are improved and put to use. Only 10 different vegetable types are chosen from a variety of vegetable species for the primary research on the vegetable image classification challenge. . A locally constructed dataset with 3000 photos divided into 10 classes is utilized for both training and testing. The effectiveness of conventional CNN and pre-trained CNN is also compared in order to determine which is more effective, time-saving, and superior. Additionally, experimental findings for various models and methodologies are reviewed, and a total accuracy of 96.5% is reported. It is abundantly obvious from the experimental findings that pre-trained CNN architectures are the wave of the future for machine vision. Additionally, it now has the highest accuracy for the task of classifying vegetables, which is highly encouraging.

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