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DETECTION OF UNHEALTHY FRUITS USING IMAGE CLASSIFICATION BASED ON A DEEP TRANSFER LEARNING FRAMEWORK

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Abstract

This paper presents a methodology for detecting unhealthy lemons in a lemon dataset based on a deep Convo-lutional Neural Network (CNN) and transfer learning. Initially, a CNN model was developed and trained, after which a new model was framed on the existing CNN model using transfer learning. The base model was trained to a satisfying level of accuracy (of 98.55%). Afterwards, we incorporated this pre-trained model into a customized transfer learning framework. The final model was tested using a different augmented lemon dataset. In this case, no additional training was performed on the transfer learning model and the resultant model achieved an accuracy of 95.91 %.

Keywords: CNN, Feature detection, Transfer learning.

INTRODUCTION

Quality control in the agricultural sector is a critical issue that needs to be dealt with because it is related to the assessing the end products of farming. Since the end products of farming are to be consumed by the customers for better marketing facilities, they must be edible and in good shape and form. So, machine learning techniques can be used to check the quality of farming. Applying machine learning techniques in agriculture using automatic detection systems and environmental sensors is an emerging topic of interest. Earlier, there were manual methods of farming, where the farmers had to physically visit yards of land and check healthy/unhealthy fruits/crops. The approach was costly and very time-consuming. However, nowadays, with the advent of machine learning techniques, automatic detection of healthy/unhealthy crops/fruits and pest control is easy, user-friendly, and viable because it is not only less costly but equally time-saving. In this paper, we deal with a significant issue: how to detect unhealthy fruits (Fig. 1) that pests have attacked. The unhealthy lemons in the figure show rotten skin, which could be viewed easily in local supermarkets. This automatic detection enables us to provide a list of healthy fruits. Nowadays, nutrition is a prominent area directly and indirectly related to the agricultural sector. In this respect, it is more important to make correct choices of food because unhealthy items can damage the organs in the body, thereby leading to many diseases like obesity, increased body weight, stress issues, and heart-related problems. In this paper, have modeled a deep-learning framework which initially consists of a trained CNN network. Then, we added few layers as a part of transfer learning and tested it on an entirely new version of augmented healthy and unhealthy lemons. Some samples of lemons used are shown in Fig. 1.

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Fig. 1. *Good and bad quality lemons*

RELATED WORK

In this section, we shall discuss a few notable works in farming technology using deep learning and machine learning techniques to detect unhealthy crops and fruits. Lekha et al. [1] classified sour lemons using the convolutional neural network (CNN) along with other methods such as SVM and RF (Random Forest) and obtained an accuracy of 98.75%. In order to classify lemon disorders, Gupta et al. [2] suggested a hybrid model which incorporated the SVM and CNN using 4821 orange pictures and attained 89.6% accuracy. Dhiman et. al. [3] trained the exact areas of the disease with varying level of severity. The VGGNet was trained on this disease, and 96% accuracy was achieved in detecting the healthy conditions and 97% accuracy in detecting the medium severe conditions. Dhiman et. al. [4] proposed an efficient system for smart disease prediction using CNN-LSTM model. The model was trained on nearly 2950 fruit images and attained 98.25 % accuracy. Dang-Ngoc et al. [5] performed an image analysis of citrus leaf disease based on texture, color and shape features through region segmentation, where the leaf features are fed to SVM to classify the diseases. Here, the authors proposed a hierarchical SVM which gives the infected leaf detection rate of 92.5%, and the highest accuracy rate of 91.76%. Nagpal et al. [6] used a deep CNN model and tested it on a dataset of seven citrus fruits. The highest accuracy achieved is 98.40 %. Singh et al. [7] used the deep transfer learning coupled with CNN on 1363 images from the maize plant disease dataset and attained a 99.16 % detection rate.

Our main contributions are summarized as follows:

- We have initially trained a single "generic" CNN on a large set of lemon images (healthy and unhealthy), which would be then made available to farmers and fine-tuned on-site to allow for the local lighting conditions, camera characteristics, the particular variety of lemon and so on.
- In the next part we have introduced a novel model with additional layers intended for training and thus designed a transfer learning framework.
- Our initial generic model obtained an accuracy of as high as 98.55%. Next, we tested the smaller 2^{nd} group of augmented lemons (healthy and unhealthy) without additional training. So, here the transfer learning concept was perfectly applied.
- An additional significant contribution of our work is that our model demonstrates robustness against overtraining. This is achieved through a partitioning strategy and optimized batch processing. The entire dataset was subdivided into three distinct splits: 50% for training, 30% for validation, and 20% for testing. By allocating a substantial portion (30%) to the validation set, we have improvised the model performance by reducing the likelihood of overfitting to the training data.
- Furthermore, a batch size of 56 was chosen based on empirical experimentation, which has really helped maintain model stability and further mitigates the risk of overfitting.

PROPOSED METHODOLOGY

This section (including Fig. 2) describes the proposed model. The model parameters are clearly portrayed in Table I. Our proposed workflow is as follows:

Image Dataset

Initially, the input to the system consisted of the dataset in which both healthy and unhealthy lemons were present. The dataset is freely available from Kaggle at https://www.kaggle.com/datasets/yusufemir/lemon-quality-dataset. We considered 1125 healthy and 951 unhealthy lemons. Now, after adding the transfer part, we trained and tested our model on a different dataset of lemons (https://www.kaggle.com/datasets/edbertkhovey/augmented-lemon-dataset).

Proposed Architecture

Nowadays, many deep learning models are prevalent like DenseNet[8], VGG-16[9], VGG-19[10] etc. Most related works [11] on transfer learning have actually relied on deep-learned networks which was experimented on a particular kind of dataset. In our case, we have two different kinds of lemon datasets, the first one is non-augmented and the 2nd one is augmented. Our network structure is also very simple, yet achieved a high accuracy on varied datasets. There are examples of works [12] who have used deep learning models, then implemented transfer learning by replacing the final classifier layer, and then retraining the model to obtain final prediction results. In our case even after adding the two layers, our network was not overtrained. This is the main contribution and uniqueness of the present work. However, these networks are built on a sequentially branching set of modules and often fail to capture the edge information. In the present case, since we are trying to capture detailed information on whether a lemon is unhealthy/healthy solely by relying on the structure of the outer skin of the lemon fruit, a detailed architecture is needed that could robustly detect any 'unhealthy' category of lemons. In the deep CNN model, the first layer is the convolutional layer. We have implemented 64 filters, each [3x3] in size, utilizing the ReLU activation function and applying same padding for optimal performance. If there are too many layers in a network, the product of the derivative decreases until the partial derivative approaches zero and ultimately vanishes. If there are too many layers in a network, the product of the derivative decreases until the partial derivative approaches zero and ultimately vanishes. This is called the vanishing gradient problem. This problem

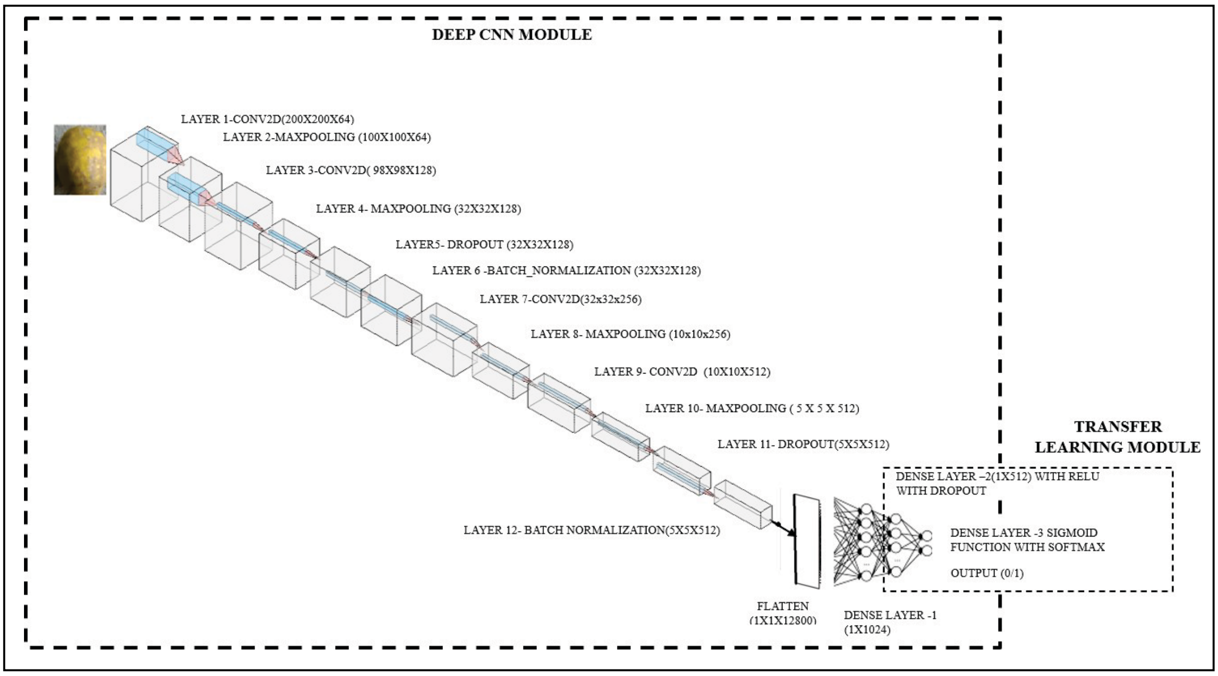

Fig 2. Proposed Architecture

has a significant impact on the performance of the network. So, in order to tackle this, we have used the ReLU activation function in convolutional layer. The padding technique makes the output feature map similar to the input data. Layer 2 comprises max-pooling with a pool size of [2x2]. Layers 3 and 4 also comprise an alternation of convolution (with the ReLU activation function) and max-pooling. The advantage of using a large-sized convolutional layer with filters is that it preserves the minutest details, which can extract deep-level features automatically. It might be essential to discard some neurons that are being used during classification. This is done further to speed up the training performance of the network. Keeping that in mind, Layer 5 denotes a dropout layer. The output sizes of Layers 5 and 6 are the same because discarding a few neurons will not affect the overall size of the feature map being fed into Layer 6. Finally, the convolved feature maps of Layer 5 are now fed to Layer 6 and batch normalized. Batch normalization is a technique used between layers of a neural network to speed up the training process and increase learning accuracy. Layers 7, 8, 9, and 10 are constructed as another set of alternative convolutional layers with ReLU and max-pooled layers. The final

Table I. Table of parameters

Layer	Type	Network Parameters	Model
Layer1	Convolution	Filter size: 3x3 Filter number:64 padding: same Activation function = ReLU	Deep CNN
Layer2	Pooling	Pool size:2x2 Pooling Type: Max-pooling	
Layer3	Convolution	Filter size:3 x3 Filter number:128 Activation function = ReLU	
Layer4	Pooling	Pool size:2x2 Pooling Type: Max-pooling	
Layer5	Dropout	0.2	
Layer6	Batch Normalization	---------------------	
Layer7	Convolution	Filter size:3 x3 Filter number: 256 padding: same Activation function=ReLU	
Layer8	Pooling	Pool size:3x3 Pooling Type: Max-pooling	
Layer9	Convolution	Filter size:3 x3 Filter number: 512 padding: same Activation function = ReLU	
Layer10	Pooling	Pool size:2x2 Pooling Type: Max-pooling	
Layer11	Dropout	0.3	
Layer12	Batch Normalization	---------------------	
F	Flatten	--------------------	
D	Dense Layer 1	No of neurons=1024	
D	Dense Layer 2	No of neurons=512 Activation function=ReLU	Transfer Learning
	Dropout	0.3	
D	Dense Layer 3	Total number of neurons=2 Activation function=Sigmoid	

feature map of size [5x5x12] is finally fed to Layer 11 and then Layer 12 for dropout and, yet again, batch normalization. Now, we have added two additional layers named Flatten and Dense Layer 1. The purpose of the Flatten layer is to convert the input feature map into a single-dimensional vector, which would be fed into the following neural network for further classification. Dense Layer 1 is a part of Deep CNN, and it is a convention to set this layer as 4 or 5 times more than the last max-pooled layer. However, in our present case, we kept this layer simple and used double the size of the last max-pooled layer, so the size of Dense Layer 1 became 1x1024. So, the design of the first part of the proposed network (Deep CNN Model) is complete. The next part of our network is the Transfer Learning Model. Transfer learning is beneficial for improving the Deep CNN performance. It adds a few layers to the existing network to enhance performance. In order to do so, we have categorically experimented with two new layers, namely Dense Layer 2 and Dense Layer 3. Dense Layer 2 is constructed with a half the size of Dense Layer 1. Here, the ReLU activation function is used. The final output layer of this hybrid framework is Dense Layer 3 with a sigmoid function whose output is either 0 or 1 (Healthy or Unhealthy). Adding the last two layers simultaneously has increased our testing performance.

EXPERIMENTAL RESULTS

In pursuit of practical applications, we utilized a diverse dataset consisting of a dataset of healthy and unhealthy lemons for our testing purposes. Initially, after training our CNN model without the transfer learning part, we obtained the results enlisted in Table II.

Table II. *Performance Evaluation*

ACCURACY	PRECISION	RECALL
0.98	0.98	0.98

Table II enlists the accuracy, precision and recall after the initial training process.

After adding our transfer learning part, we performed a test on a smaller set of augmented lemon images from a different dataset. Here, we did not perform any additional training. After testing this model, the performance obtained is enlisted in Table III. This illustrates the robustness of our transfer learning model.

Table III. *Performance Evaluation after transfer learning*

ACCURACY	PRECISION	RECALL
0.95	0.93	0.97

COMPARATIVE ANALYSIS OVER SOTA

To emphasize the robustness of our method over the related works on unhealthy fruit detection, we have enlisted a brief comparison over the related works in Table IV. Applying our transfer learning model, we show how our method excels over the previous ones. As we see, none of the works mentioned in Table IV has used the concept of transfer learning as we have done in the present work.

CONCLUSION AND FUTURE SCOPE

This paper is based on detection of healthy and unhealthy lemons and can be used in the agricultural domain. Now, deep learning methods are being used for detection of unhealthy fruits in the agricultural domain. As a part of the future work, we are aiming at pest-control of fruits. Another interesting domain would be pest control of the various categories of crops like potatoes and tomatoes which can cause massive damage to the farmers. This would be an interesting domain because, we are aiming at pest-control based techniques to avoid the damage of crops. There are many diseases which affects vast areas of crops.

Also, as a part of our future work, we will use a proper hardware setup of the greenhouse which can help to breed healthy lemons. By integrating real time pest control, such as IoT-based cameras and sensors in greenhouses, our approach for real-time detection of unhealthy fruits could allow for continuous monitoring and an adaptive response to environmental conditions which can improve the overall crop health. Also, the fusion of deep learning and IOT will create a technology which will not only enable us to improve crop-health but also help in crop monitoring techniques.

Table IV. *Comparative Analysis*

<table>
<tr><th>Reference</th><th>Year</th><th>Details of Dataset</th><th colspan="2">Accuracy</th><th>Model Used</th></tr>
<tr><td>Lekha et. al. [1]</td><td>2023</td><td>Diseased Healthy Lemons</td><td colspan="2">98.75%</td><td>CNN+SVM+Random Forest</td></tr>
<tr><td>Gupta et al. [2]</td><td>2023</td><td>Unhealthy Oranges</td><td colspan="2">89.6%</td><td>Hybrid model SVM+CNN</td></tr>
<tr><td>Dhiman et al. [4]</td><td>2023</td><td>Citrus fruits</td><td colspan="2">97.18% with Magnitude-Based Pruning and 98.25% with Magnitude-Based Pruning with Post Quantization</td><td>CNN-LSTM model</td></tr>
<tr><td>Dang-Ngoc et al. [5]</td><td>2021</td><td>Citrus leaf diseases</td><td colspan="2">infected leaf detection rate was 92.5%, and the highest accuracy rate was 91.76%.</td><td>Hierarchical SVM</td></tr>
<tr><td>Nagpal et al. [6]</td><td>2022</td><td>Seven citrus fruits</td><td colspan="2">98.40%</td><td>Deep CNN Model</td></tr>
<tr><td>Singh et al. [7]</td><td>2022</td><td>maize plant disease dataset</td><td colspan="2">99.16%</td><td>AlexNet model with CNN for feature extraction</td></tr>
<tr><td>Saini et. al. [13]</td><td>2023</td><td>Citrus fruits</td><td colspan="2">98.26 %</td><td>DCNN with AlexNet for feature extraction</td></tr>
<tr><td rowspan="2">Proposed Work</td><td rowspan="2">2024</td><td rowspan="2">Two different varieties of the healthy and four different varieties of the diseased fruits</td><td>Diseased +Healthy Lemons</td><td>98.55 %</td><td rowspan="2">Transfer Learning Used</td></tr>
<tr><td>Diseased+Healthy Lemons (different version)</td><td>95.91 %</td></tr>
</table>

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