

Apple Quality Classification using Deep Learning

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Abstract: *Classifying apple quality is essential for refining the apple sales market and boosting sales. Currently, most methods based on convolutional neural networks (CNNs) rely heavily on large amounts of training data to achieve good performance. However, because there is no large public dataset available for apple appearance, it's challenging to reach high accuracy with only a small number of samples. To address this, we propose an enhanced CNN-based method for classifying apple appearance quality using limited data. First, we use a Support Vector Machine (SVM) for image segmentation to eliminate noise from the environment, which can reduce recognition accuracy. Next, we feed the segmented images into a Deep Convolutional Generative Adversarial Network (DCGAN) to generate more training data..*

Keywords: Feature extraction, machine learning algorithms, apple, image preprocessing, Image Processing, Convolutional Neural Network (CNN), Machine Learning, etc

I. INTRODUCTION

The production of fruits and crops across the globe is highly influenced by various diseases. A decrease in production leads to an economic degradation of the agricultural industry worldwide. Apple trees are cultivated worldwide, and apple is one of the most widely eaten fruits in the world. The world produced an estimated 86 million tons of apples in 2018, and production and consumption have increased ever since. However, the average national yield of apples is low in comparison to the potential yield of apples. The major factors for the low production of apples are ecological factors, poor post-harvest technologies, less thrust on basic research, inadequate supply of quality planting materials to farmers and socio-economic constraints, etc. Despite their high consumption and medicinal benefits, apple trees are prone to a variety of diseases caused due to insects and micro-organisms such as bacteria. There are several diseases which attack apple, the major one being anthracnose (*Neofabraea* spp.) cedar apple rust (*Gymnosporangiumjuniperivirginianae*), fireblight (*Erwiniaamylovora*), scab (*Venturiainaequalis*) and powdery mildew (*Podosphaeraleucotricha*). The proper care of trees using fertilizers is thus an important step. A timely determination of such conditions in the leaves can help the farmers and prevent further losses by taking proper actions. The primary advantage of using deep learning techniques is to eliminate the need for feature extraction.

II. PURPOSE

Ensuring the quality of apple is crucial for both producers and consumers. However, traditional methods of assessing apple quality, which often rely on manual inspection, are time-consuming, inconsistent, and prone to human error. The challenge lies in developing an automated system that can accurately and efficiently detect the quality of apples based on various parameters such as color, size, shape, texture, and the presence of defects or diseases

Key objectives :

- To develop an accurate and efficient system for apple appearance quality classification using deep learning techniques.
- To address the challenge of limited training data by applying image augmentation through Deep Convolutional Generative Adversarial Networks (DCGAN).
- To improve the robustness of the classification system by using Support Vector Machine (SVM) for image segmentation and noise reduction.



III. OBJECTIVE OF SYSTEM

- To automate the process of apple quality classification using machine learning.
- To minimize dependency on large-scale public datasets.
- To enhance classification accuracy with small training samples.
- To reduce the impact of environmental noise through effective image segmentation.
- To generate synthetic training data using DCGAN for data augmentation.

IV. PROPOSED SYSTEM

Skin diseases are a widespread health concern affecting millions of people worldwide. These conditions can range from mild irritations to severe, potentially life-threatening illnesses. Early detection and accurate diagnosis of skin diseases are crucial for effective treatment and prevention of complications

SYSTEM ARCHITECTURE

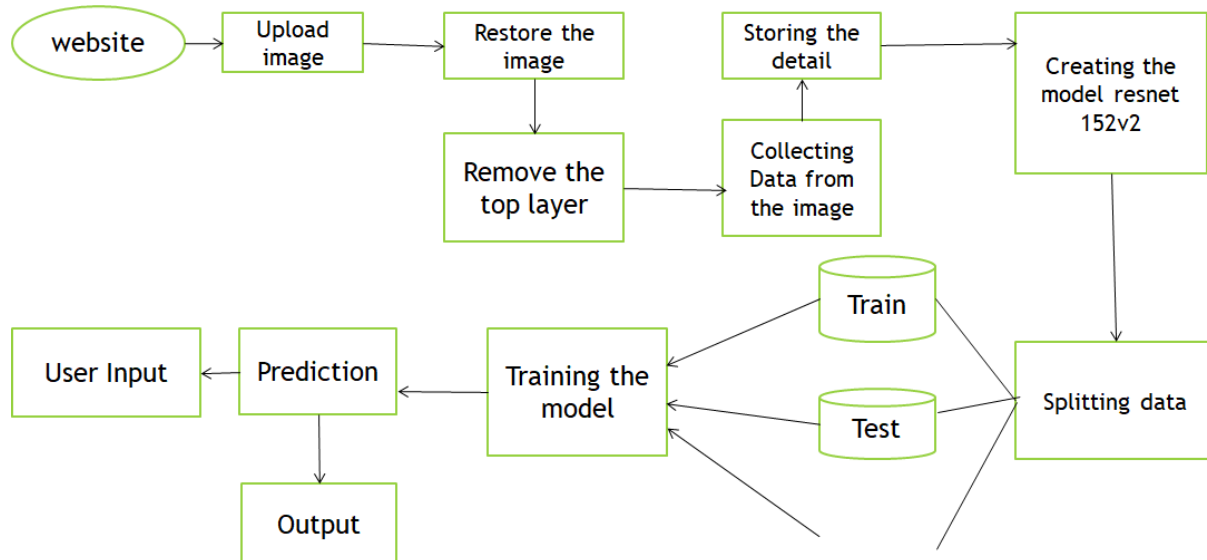


Fig 1. Architecture

1. **GLCM (Gray Level Co-occurrence Matrix)**: Extracts texture features from the image (e.g., smoothness, roughness).
2. **HOG (Histogram of Oriented Gradients)**: Captures shape and edge details from the image.
3. Together, these two extract meaningful features that help in distinguishing image classes.
4. **SVM (Support Vector Machine)**: A supervised learning algorithm used for classification.
5. It takes the feature vectors and learns to separate them into classes (e.g., high-quality, medium-quality, low-quality apples).
6. The final result where each image is classified based on the learned model.
7. For example: "Grade A Apple", "Grade B Apple", etc.
8. These are the raw images (e.g., apples) that are to be classified based on their appearance.

V. IMPLEMENTATION

1. Input Dataset

This image shows the apple dataset used for training and testing:
The first two rows are training samples labeled as "bad" or "good".
The bottom two rows are testing samples, also labeled.



Bad apples have spots, rot, or discoloration.

Good apples are fresh, clean, and ripe

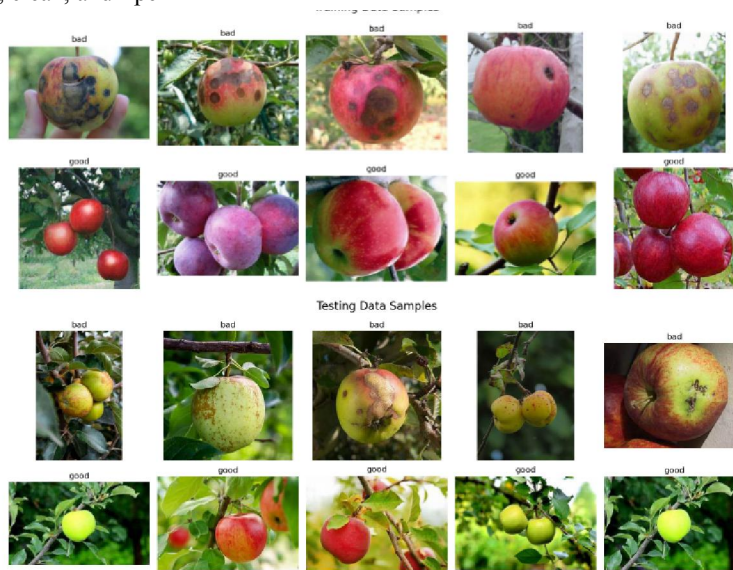


Fig 2. Input Dataset

2. Train Model

This is the structure of your Convolutional Neural Network (CNN):

conv2d: Applies 32 filters to detect features from the image.

max_pooling2d: Reduces image size and retains important features.

conv2d_1: Another conv layer with 64 filters for deeper features.

max_pooling2d_1: Again, downsamples the data.

flatten: Converts image features to a flat vector.

dense: Fully connected layer with 64 neurons.

dense_1: Final output layer with 2 neurons (for "good" and "bad").

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
flatten (Flatten)	(None, 57600)	0
dense (Dense)	(None, 64)	3,686,464
dense_1 (Dense)	(None, 2)	130

Total params: 3,705,986 (14.14 MB)

Trainable params: 3,705,986 (14.14 MB)

Non-trainable params: 0 (0.00 B)

FIG 3. Train Model

Loss and Accuracy

Accuracy starts low and improves slightly.



Loss decreases but not steadily.

Validation Accuracy is unstable and mostly low (around 46%).

Indicates overfitting — model does well on training but poorly on unseen data.

```

setit_warn(it_super_not_called)
2/2 12s 4s/step - accuracy: 0.4125 - loss: 3.1603 - val_accuracy: 0.5333 - val_loss: 1.2815
Epoch 2/10
2/2 2s 1s/step - accuracy: 0.5742 - loss: 0.9654 - val_accuracy: 0.4667 - val_loss: 1.2300
Epoch 3/10
2/2 2s 1s/step - accuracy: 0.5000 - loss: 1.2161 - val_accuracy: 0.4667 - val_loss: 0.9321
Epoch 4/10
2/2 2s 1s/step - accuracy: 0.5000 - loss: 0.9097 - val_accuracy: 0.4667 - val_loss: 0.7354
Epoch 5/10
2/2 2s 1s/step - accuracy: 0.5000 - loss: 0.7158 - val_accuracy: 0.4667 - val_loss: 0.6837
Epoch 6/10
2/2 2s 882ms/step - accuracy: 0.5904 - loss: 0.6628 - val_accuracy: 0.6000 - val_loss: 0.6934
Epoch 7/10
2/2 2s 1s/step - accuracy: 0.6262 - loss: 0.6756 - val_accuracy: 0.6000 - val_loss: 0.6971
Epoch 8/10
2/2 2s 1s/step - accuracy: 0.8511 - loss: 0.6548 - val_accuracy: 0.4667 - val_loss: 0.7032
Epoch 9/10
2/2 2s 1s/step - accuracy: 0.5342 - loss: 0.6389 - val_accuracy: 0.4667 - val_loss: 0.7036
Epoch 10/10
2/2 2s 1s/step - accuracy: 0.5771 - loss: 0.5987 - val_accuracy: 0.4889 - val_loss: 0.6999

```

Fig 4. Loss and accuracy

Confusion Matrix

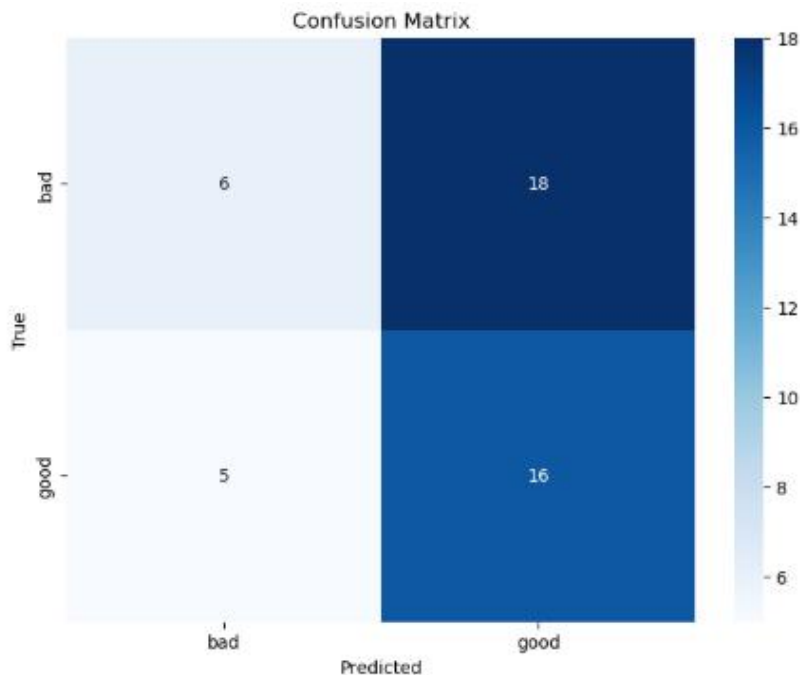


Fig 5. Confusion Matrix

VI. CONCLUSION

Deep Learning (DL) techniques have emerged as a more practical and effective method for diagnosing depression, offering improved accuracy and adaptability compared to traditional approaches. Depression remains one of the most prevalent mental health disorders and is considered among the leading causes of disability and mortality worldwide. In response to this growing public health concern, researchers and healthcare professionals increasingly rely on Machine



Learning (ML) and DL methodologies to enhance early detection, accurate prediction, and data-driven decision-making processes.

In a recent systematic literature review, research trends were explored with a focus on the application of ML and DL techniques in the context of mental health diagnosis. The review specifically highlighted the utilization of social media datasets—such as posts from platforms like Twitter, Reddit, and Facebook—which provide rich, real-time behavioral data that can be analyzed for signs of depression. These studies indicate a growing interest in leveraging linguistic cues, sentiment analysis, and user engagement patterns as predictive features in automated mental health screening tools. The integration of these techniques opens up promising avenues for scalable, non-invasive, and accessible mental health support system

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