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FRUIT QUALITY SPOTTING WITH CNN ALGORITHM USING DEEP LEARNING

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Abstract

An computerized fruit identification device may also be used in the grocery store to assist shoppers decide the kind and well known of fruits. Automatic fruit categorization and awareness is turning into increasingly more popular, however it is additionally turning into greater tough due to low distinction and ambiguous characteristics. Proposed lookup used deep mastering algorithms to classify fruit pix and developed a web-based machine for self sufficient fruit identification. However, self reliant fruit categorization is now not a noticeably effortless method that is based on the locations, shapes, colors, and sizes of the objects. Proposed learn about accumulated samples from distinctive nearby places, then eliminated photographs backdrops and increased them for a greater correct result. ResNet-50, Inception-V3, and MobileNet have been utilized to acquire extra unique function extraction. Among these, MobileNet executed 99.21% accuracy in function extraction, outperforming until now proposed computer mastering techniques. 3240 samples of eight one of a kind fruits are amassed from the Bangladeshi countryside, such as Lemon, Banana, Elephant Apple, Clustered Apple, Burmese Grape, Sapodilla, Tamarind, and Wood Apple. As a outcome of this research, the proposed strategy will useful resource persons and enterprise in recognizing neighbourhood fruits due to its excessive accuracy charge and web-based system.

Keywords: Deep Learning, CNN , Pre-trained models , Fruit Classification ,Web interface

1. Introduction

Nutrition is one of the most fundamental necessities for a healthful physique and way of life. Fruits are a exceptional supply of fiber and all kinds of nutritional vitamins . They additionally incorporate a lot of plant polyphenols, which have antioxidant and anti-inflammatory effects. Fruits, according to a scientific study, can decrease blood stress and blood sugar levels, minimize the hazard of a stroke and the occurrence of coronary heart problem, forestall numerous types of cancer, and combat towards digestive problems . As a result, fruits are viewed as an integral aspect of a healthful diet. The world's air pollution is turning into worse with the aid of the day. Fruit planting and manufacturing are step by step rising to fulfill the population's demands. Manual fruit detection and grade leveling is tough due to variants in measurement and opacity of light. Because of this diversity, computerized classification is extraordinarily integral. For computerized fruit screening, the pc imaginative and prescient device is an wonderful choice. The absence of an self sustaining gadget for the categorization of fruit is a traditional hassle in the industry, ensuing in a reliance on solely guide knowledge, which regularly entails effort, costs, and inaccuracy..

2. Literature Review

Deep getting to know (DL) or switch mastering is no longer a novel approach in the discipline of object awareness and categorization. A wide variety of latest publications have printed full-size advances in photo cognizance modeling frameworks the usage of DL [15,16]. For example, Mamat, N., et al. furnished a approach for a non-stop annotating assignment to discover one of a kind fruits. The find out about suggests "you solely seem once" (YOLO) variations of simple and environment friendly deep mastering algorithms. To create the models, four hundred RGB pix of exceptional fruits had been blended with a hundred pics of an oil palm. The range of fruit produced used to be 99.5%. Choudhary, K., et al. developed a fruit focus method the usage of a familiar fruit dataset referred to as "Fruits 360." For extracting aspects and fruit identification, the CNN-based ResNet-50 technique is used. The proposed strategy has been decided to be 99% accurate. They additionally give an explanation for the topologies utilized in preceding research and the public sources for fruit cognizance and classification in their lookup . In any other research, Abu-Jamie, T. N., et al. endorsed the usage of a CNN mannequin to categorize six specific sorts of fruits. In order to overcome the problem of classification similarities, VGG-16 was once used to perceive a number fruit picture types. Kaggle has been used to gather a dataset of 2677 pics for education and testing. The model's best accuracy is a hundred percent. Moreover, to discover the excellent algorithm for fruit sorting, Ismail et al. mixed deep mastering techniques like MobileNetV2, ResNet, DenseNet, NASNet, and EfficientNet. The machine was once educated and evaluated the usage of the EfficientNet methodology on two datasets (apples and bananas), with the common accuracy for the trying out datasets for apples and bananas being 96.7% and 93.8%, respective.

3. Structure of System

3.1 System overview

The proposed gadget combines fantastic tools and technologies, such as the CNN object detection algorithm, an STM32 microprocessor, a graphical consumer interface, and an MG996R servomotor, to apprehend and classify the high-quality of fruit. The system's features encompass fruit detection, great recognition, and fruit monitoring and control.The machine is coupled with a graphical person interface to show the modern-day vicinity of the fruit and the classification status. Cameras are built-in to operate fruit photo detection and picture preprocessing. By the use of the CNN algorithm for fruit detection, overlapping objects can be separated, and the detected fruit photo can be tracked continuously. A fruit focus mannequin is designed to understand the excellent of the fruit and function classification. Another mannequin is then used to decide whether or not the nice of the fruit is satisfactory.Figure 1 suggests the shape design of the fruit fine classification system, which makes use of a neural network mannequin educated through two supervised mastering methods. Model-A makes use of the CNN algorithm to perform object detection mannequin training; Model-B makes use of the CNN structure to layout the recognition model. The mannequin is educated to search for features becoming the points in the data.After evaluating the finished model, the mannequin is built-in into the gadget architecture.

3.2 Software architecture

The fruit satisfactory classification gadget is divided into 4 parts. The first section consists of the software program manage of the the front and lower back gateways. The 2d section is the community mannequin constructed with the aid of the CNN method, the place Model-A makes use of Tiny-CNN to discover fruit on the conveyor platform and Model-B acknowledges the kind of fruit and exams for defects.The 0.33 phase consists of the contrast and removal algorithm used to do away with the repeated bounding boxes. The fourth phase is the monitoring algorithm used to tune the fruit on the conveyor platform. Finally, TensorRT is utilized to compress the model. Figure two indicates a software program layout of the fruit exceptional classification system.

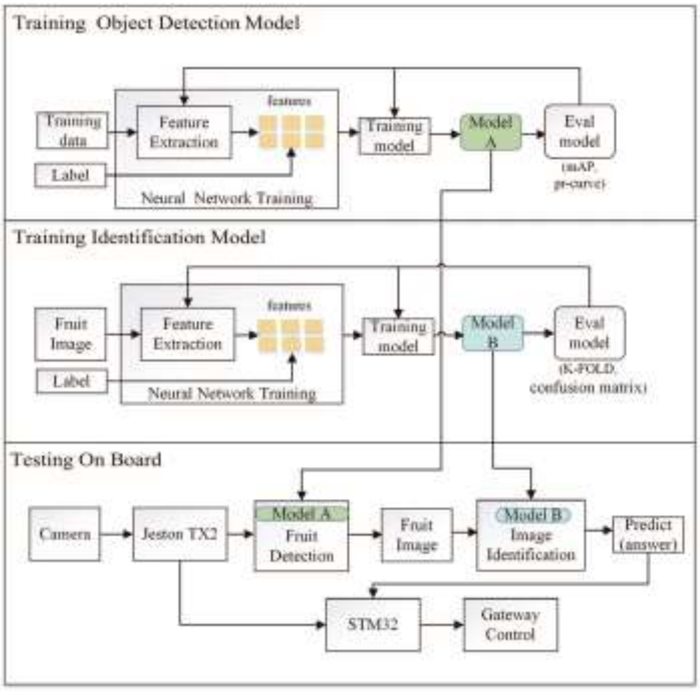


Fig 1: Structure diagram of fruit quality classification system.

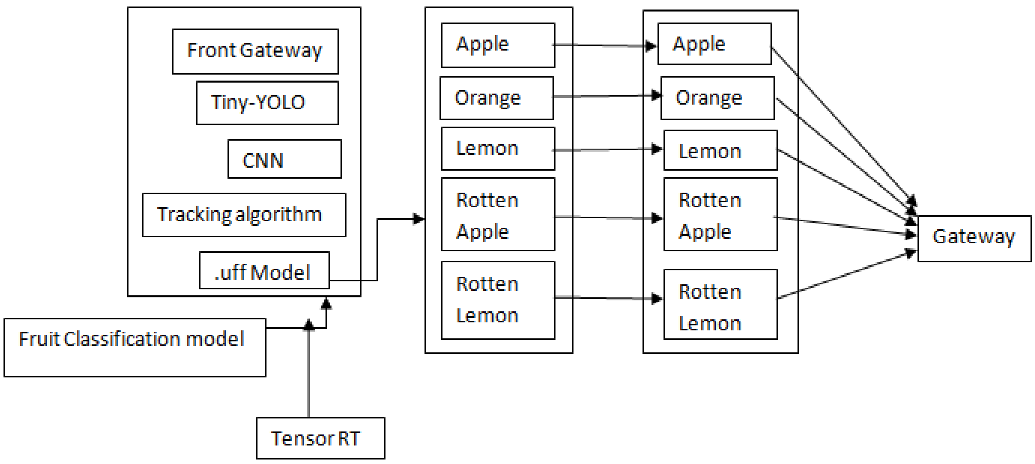


Fig 2: Software design of fruit quality classification system.

4. Research Methods

To develop an efficient fruit quality spotting system using Convolutional Neural Networks (CNNs) and Deep Learning, various research methods are employed. These methods focus on data collection, model selection, training, evaluation, and deployment.

4.1 Data Collection and Preprocessing

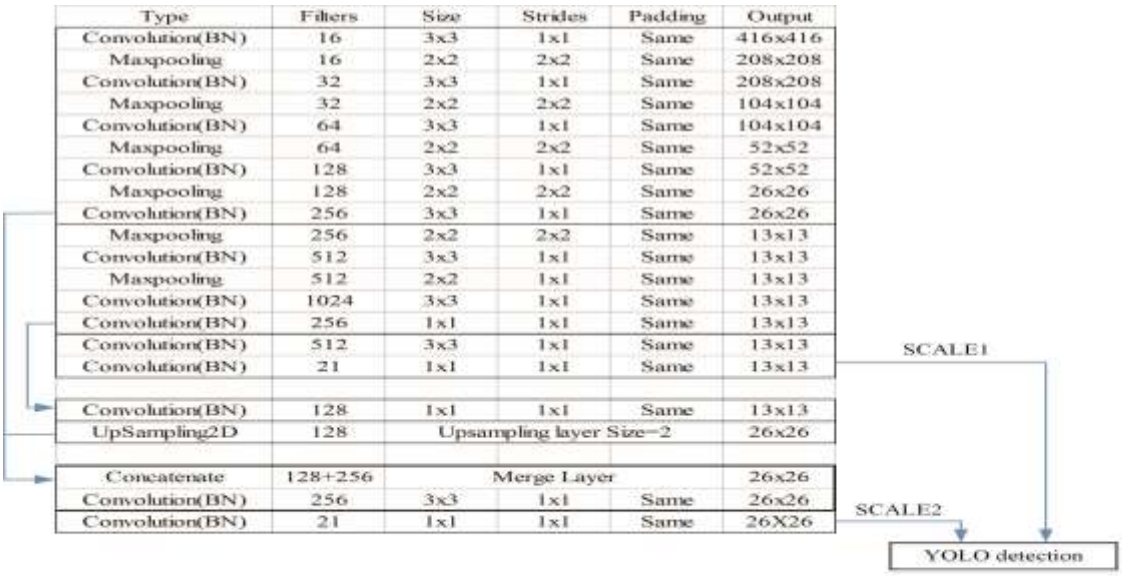
Dataset Selection: Collect fruit images from public datasets (e.g., Fruit360, Kaggle) or custom datasets from farms and supermarkets.Image Preprocessing: Resize images (e.g., 224×224 pixels for CNN models), normalize pixel values, and apply data augmentation (rotation, flipping, brightness adjustments) to enhance model robustness.
Annotation: Label images into categories (e.g., Fresh, Rotten, Overripe) using manual or automated labeling tools.

4.2 CNN Model Selection and Architecture Design

Pre-trained Models: Use transfer learning with CNN architectures like ResNet, VGG16, MobileNet, or EfficientNet for better performance on limited datasets.Custom CNN Models: Design a CNN with convolutional, pooling, and fully connected layers optimized for fruit quality detection.Hyperparameter Tuning: Optimize learning rate, batch size, number of layers, and dropout rates to improve accuracy.

Comparison and elimination algorithm

We have applied an algorithm to examine the distance of every field and the nearest bounding field one by using one, which eliminates repeated containers and reduces mistakes in object monitoring due to fruit defects being occluded with the aid of the right parts. The removal precept is to get rid of the object bounding container besides defects when each an object bounding container with defects and an object bounding field except defects show up simultaneously, as proven .



Type	Filters	Size	Strides	Padding	Output
Convolution(BN)	16	3x3	1x1	Same	416x416
Maxpooling	16	2x2	2x2	Same	208x208
Convolution(BN)	32	3x3	1x1	Same	208x208
Maxpooling	32	2x2	2x2	Same	104x104
Convolution(BN)	64	3x3	1x1	Same	104x104
Maxpooling	64	2x2	2x2	Same	52x52
Convolution(BN)	128	3x3	1x1	Same	52x52
Maxpooling	128	2x2	2x2	Same	26x26
Convolution(BN)	256	3x3	1x1	Same	26x26
Maxpooling	256	2x2	2x2	Same	13x13
Convolution(BN)	512	3x3	1x1	Same	13x13
Maxpooling	512	2x2	1x1	Same	13x13
Convolution(BN)	1024	3x3	1x1	Same	13x13
Convolution(BN)	256	1x1	1x1	Same	13x13
Convolution(BN)	512	3x3	1x1	Same	13x13
Convolution(BN)	21	1x1	1x1	Same	13x13
Convolution(BN)	128	1x1	1x1	Same	13x13
UpSampling2D	128	Upsampling layer Size=2			26x26
Concatenate	128+256	Merge Layer			26x26
Convolution(BN)	256	3x3	1x1	Same	26x26
Convolution(BN)	21	1x1	1x1	Same	26X26

Table1: (Color online) Complete Tiny-YOLO architecture.

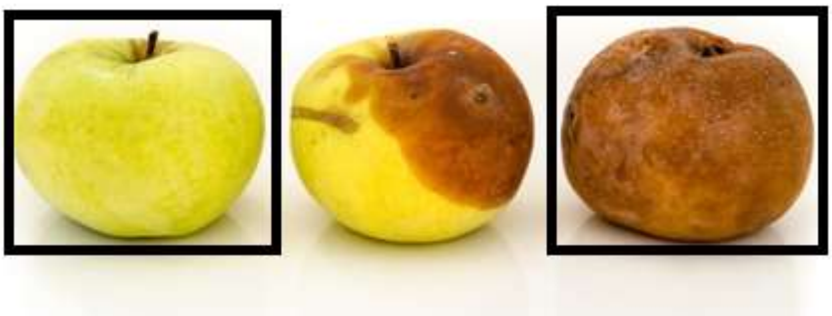


Fig 3: Sample inputs

4.2.1 Convolution layer and fully connected architecture

This is the core building block of a CNN, where a small filter (kernel) slides across the image, performing a dot product with the underlying pixels to generate a feature map.

Multiple convolution layers are stacked, with each layer learning progressively more complex features from the image. In fruit quality assessment, convolution layers might identify features like the color variations on the fruit skin, blemishes, or the shape of the fruit.

Code:

```
dataset_path = '/path/to/gokul/dataset/'

categories = ['good', 'bad']  # Assuming the dataset has 'good' and 'bad' class labels

# Initialize lists to store the images and their labels

data = []

labels = []

# Loop through the categories to load images

for category in categories:

 path = os.path.join(dataset_path, category)

class_num = categories.index(category)

  for img_name in os.listdir(path):

img_path = os.path.join(path, img_name)

img = cv2.imread(img_path)

img = cv2.resize(img, (128, 128))  # Resize images to (128, 128)

data.append(img)

labels.append(class_num)

# Convert the data and labels to numpy arrays

data = np.array(data)

labels = np.array(labels)

# Normalize pixel values between 0 and 1

data = data / 255.0

X_train, X_test, y_train, y_test = train_test_split(data, labels, test_size=0.2, random_state=42)

# Initialize the model

model = models.Sequential()

# Add convolutional layers with activation functions
```

```
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3)))

model.add(layers.MaxPooling2D((2, 2)))

model.add(layers.Conv2D(64, (3, 3), activation='relu'))

model.add(layers.MaxPooling2D((2, 2)))

model.add(layers.Conv2D(128, (3, 3), activation='relu'))

model.add(layers.MaxPooling2D((2, 2)))

# Flatten the 3D outputs to 1D

model.add(layers.Flatten())

# Add a dense layer

model.add(layers.Dense(128, activation='relu'))

# Add the output layer with softmax activation (for classification)

model.add(layers.Dense(2, activation='softmax'))  # 2 classes: good and bad

# Compile the model

model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Train the model

history = model.fit(X_train, y_train, epochs=10, validation_data=(X_test, y_test))

# Evaluate the model on the test set

test_loss, test_acc = model.evaluate(X_test, y_test)

print(f'Test Accuracy: {test_acc}')

print(f'Test Loss: {test_loss}')

# Plot training and validation accuracy

plt.plot(history.history['accuracy'], label='accuracy')

plt.plot(history.history['val_accuracy'], label = 'val_accuracy')

plt.xlabel('Epoch')

plt.ylabel('Accuracy')

plt.legeng(loc='lower right')
```

```
plt.title('Training and Validation Accuracy')

plt.show()

# Plot training and validation loss

plt.plot(history.history['loss'], label='loss')
```

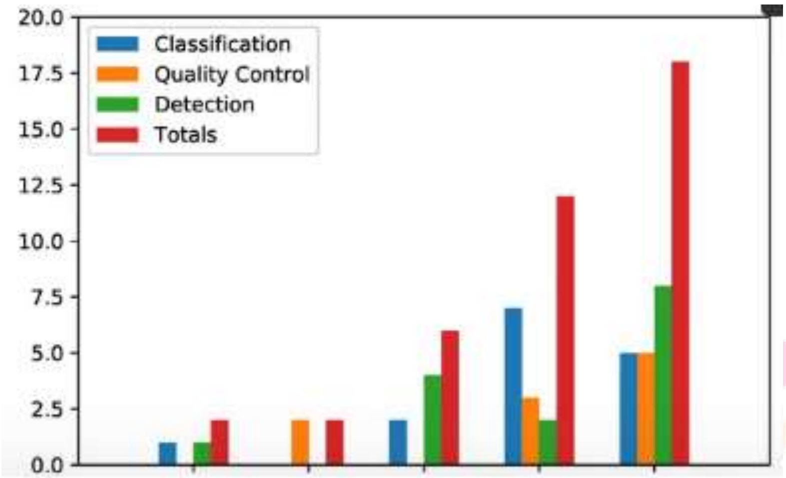


Fig 4: Testing model

5. Conclusion

Deep mastering is presently one of the most extensively used strategies for classifying and figuring out pics because it can do it besides any human intervention. For the classification and cognizance of nearby fruits in our study, we employed some deep getting to know models, such as Inception-v3, VGG-19, MobileNet, and ResNet-50. Three of the fashions managed to achieve a take a look at accuracy fee of over 98%, which is surely outstanding. MobileNet earned the best check accuracy ranking of 99.21% when in contrast to these models. This variety of expanded fruit classification and focus accuracy will advantage the machine's ordinary performance. We have some limitations, which we will overcome in the future. Due to seasonal fruit availability, we had been solely capable to use eight extraordinary kinds of nearby fruits for our research. Nevertheless, in the future, we hope to enlarge our lookup to consist of extra neighbourhood fruits and in the end boost a cellular application.

Declaration of Competing Interest

The authors declare no competing financial/non-financial interests.

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