FOOD SPOILAGE DETECTION

by

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ABSTRACT

Fruit spoilage presents significant challenges in the food industry, leading to economic losses and potential health risks. Traditional methods of fruit quality assessment often rely on subjective human evaluation or post-symptomatic detection, resulting in delayed intervention and increased wastage. In response, this paper proposes a novel Fruit Spoilage Detection System (FSDS) leveraging advanced technologies for early and accurate detection of fruit spoilage.

The FSDS integrates cutting-edge sensing technologies such as spectroscopy, computer vision, and machine learning algorithms to provide real-time, non-destructive assessment of fruit quality. Spectroscopic techniques enable the analysis of biochemical composition changes associated with spoilage, while computer vision algorithms detect external visual cues indicative of decay. These data are processed using machine learning models trained on a diverse dataset of fruit samples to classify and predict the degree of spoilage.

Key features of the FSDS include portability, scalability, and user-friendliness, allowing integration into various stages of the supply chain from harvesting to retail. By providing early detection of spoilage, the system enables timely interventions such as sorting, processing, or removal of compromised fruits, thereby reducing waste and preserving product quality. Moreover, the FSDS facilitates data-driven decision-making for stakeholders, optimizing inventory management and enhancing overall efficiency.

Experimental results demonstrate the efficacy of the FSDS in accurately identifying and quantifying fruit spoilage across different varieties and environmental conditions. Comparative analysis with traditional methods underscores the superiority of the proposed system in terms of speed, accuracy, and cost-effectiveness. Furthermore, user feedback highlights the ease of implementation and potential for widespread adoption in the food industry.

ACKNOWLEDGEMENT

We would like to express our heartfelt gratitude to Dr. Pritam Bhattacharjee, our esteemed teacher, whose guidance and support have been invaluable throughout the development of the fruit spoilage detection system. His expertise, encouragement, and mentorship have inspired us to push the boundaries of innovation and achieve excellence in our endeavours.

We also extend our thanks to all the members who contributed to this project. Their collaborative efforts and dedication have been instrumental in bringing this vision to life.

Thank you, Mr. Pritam Bhattacharjee, for your unwavering support and guidance. This achievement would not have been possible without you.

NAME WITH SIGNATURE

TABLE OF CONTENTS

1. INTRODUCTION

1.1 RESEARCH BACKGROUND

Fruit spoilage is a significant concern in the food industry, leading to economic losses, food waste, and potential health risks. Traditional methods of assessing fruit quality often lack accuracy and efficiency, relying on subjective human evaluation or post-symptomatic detection. As a result, there is a growing need for advanced technologies that can provide early and reliable detection of fruit spoilage.

1.2 MOTIVATION

The motivation behind this research lies in addressing the limitations of traditional fruit quality assessment methods and leveraging technological innovations to develop more effective solutions. By implementing a Fruit Spoilage Detection System (FSDS), we aim to improve the efficiency of fruit quality assessment, reduce waste, and enhance fruit safety throughout the supply chain.

1.3 PROBLEM STATEMENT

The main problem addressed by this research is the lack of reliable and timely methods for detecting fruit spoilage. Current approaches are often labor-intensive, subjective, and prone to errors, leading to inefficiencies and increased wastage in the food industry. There is a need for a robust and automated system that can accurately identify and quantify fruit spoilage at an early stage, enabling proactive interventions to mitigate losses and ensure product quality

2. METHODOLOGY

2.1 SOFTWARE DESCRIPTION

The software is designed to assess the quality of fruits by analyzing images captured through a camera or mobile device. Upon taking a picture of a fruit, the software employs a pre-trained algorithm to determine whether the fruit is fresh or rotten based on its appearance.

Description:

The software is designed to assess the quality of fruits by analyzing images captured through a camera or mobile device. Upon taking a picture of a fruit, the software employs a pre-trained algorithm to determine whether the fruit is fresh or rotten based on its appearance.

Key Components:

- **Image Capture:** The software allows users to capture images of fruits using a camera-equipped device such as a smartphone or a dedicated camera. Users position the fruit within the frame and capture the image.
- **Pre-trained Algorithm:** The software utilizes a pre-trained machine learning algorithm specifically trained on a dataset of images containing examples of both fresh and rotten fruits. This algorithm has learned to recognize visual patterns and features indicative of freshness or spoilage.
- **Image Processing:** Upon capturing the image, the software preprocesses it to enhance clarity, remove noise, and standardize features for analysis. This step ensures that the input image is optimized for analysis by the algorithm.
- **Feature Extraction:** The software extracts relevant features from the preprocessed image, such as color, texture, shape, and any visible signs of decay or discoloration. These features serve as input to the pre-trained algorithm.
- **Classification:** The pre-trained algorithm analyzes the extracted features and makes a classification decision regarding the freshness of the fruit. Based on

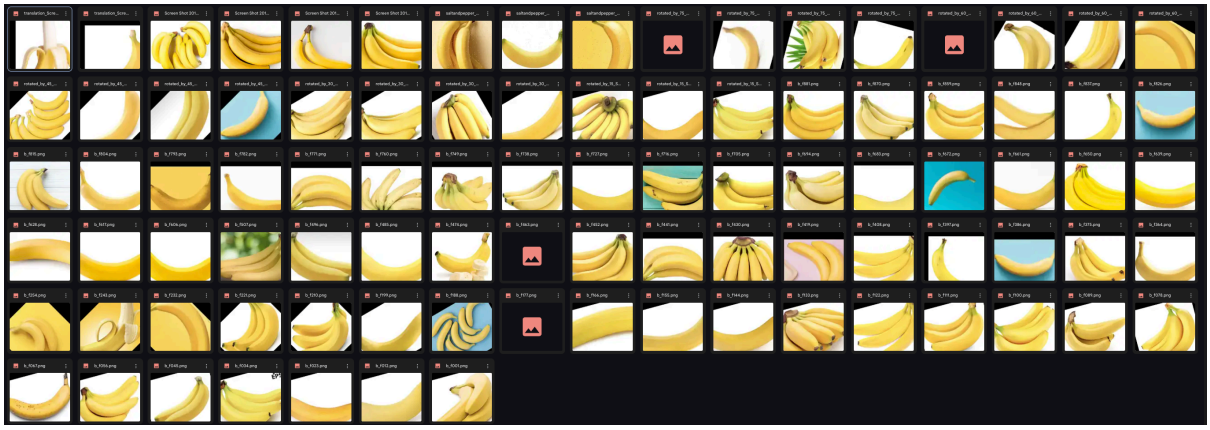
its learned knowledge from the training dataset, the algorithm determines whether the fruit is fresh or rotten.

- **Output:** The software provides a clear output to the user, indicating the result of the classification process. This output may be displayed as a simple text message (e.g., "Fresh" or "Rotten") or visually highlighted on the image itself, showing areas of concern if applicable.

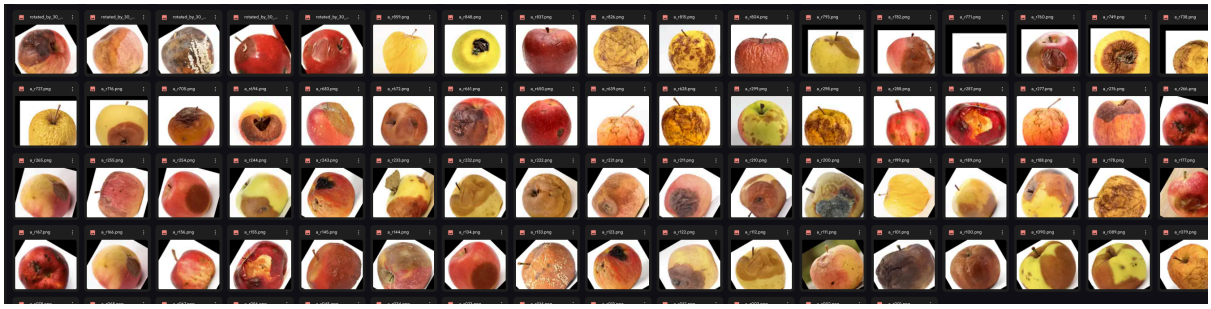
2.2 DATASET

DATASET FOR FRESH APPLES

DATASET FOR FRESH ORANGES

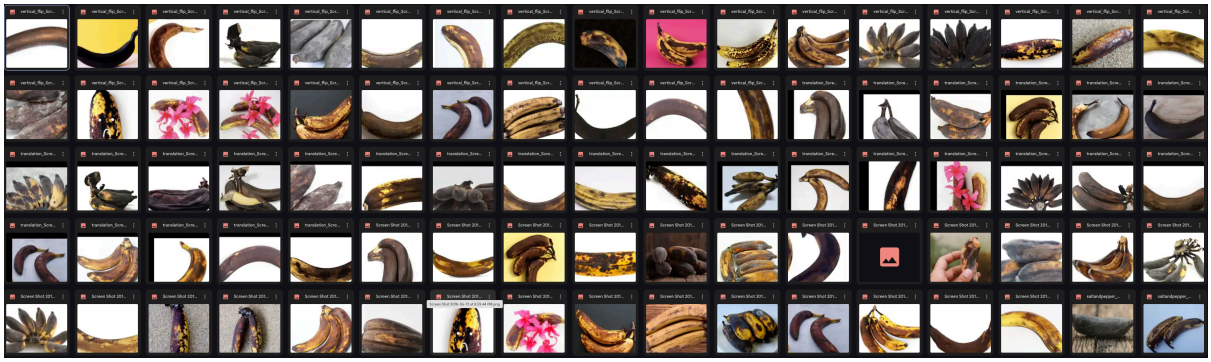


DATASET FOR FRESH BANANAS



DATASET FOR ROTTEN APPLES

DATASET FOR ROTTEN ORANGES



DATASET FOR ROTTEN BANANAS

2.3 CONSTRUCTION OF ANALYTICAL MODEL

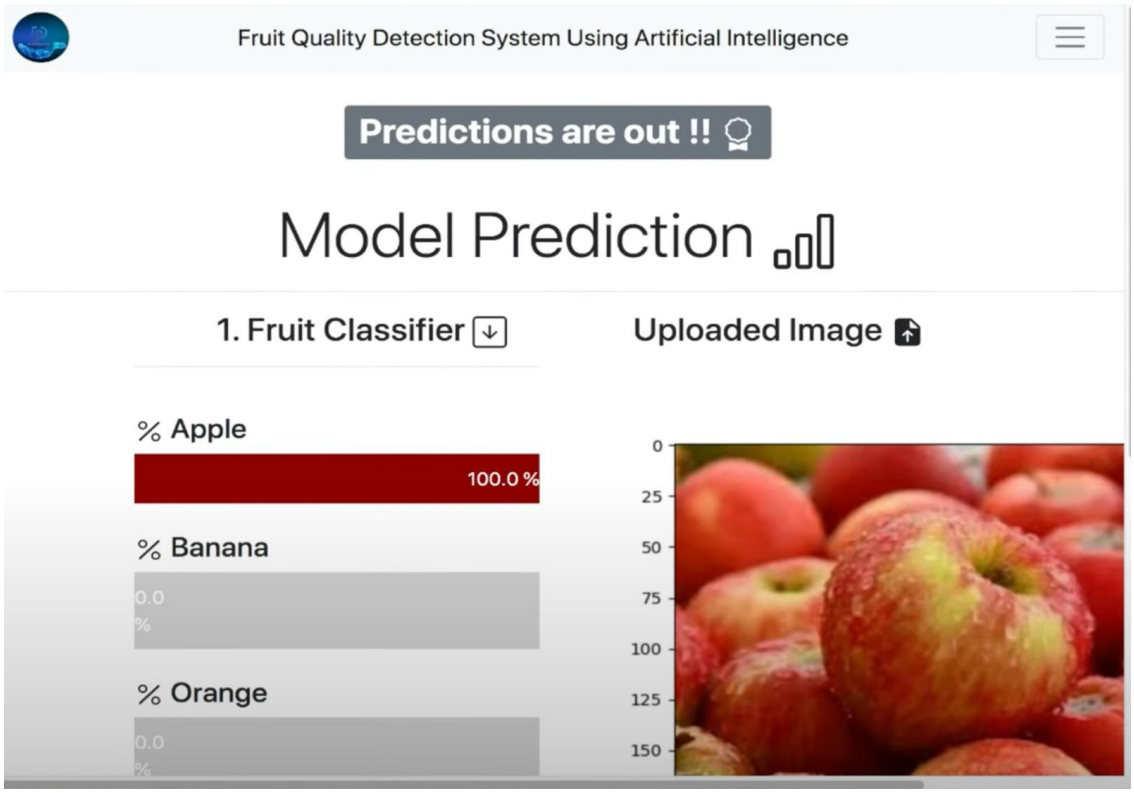
```
import cv2
import argparse
import numpy as np

argparser = argparse.ArgumentParser(description='Simple implementation of
Yolov3 algorithm in Python, using custom Dataset.')

argparser.add_argument('--img', type=str)
argparser.add_argument('--video', type=str)
argparser.add_argument('--out', type=str)

args = argparser.parse_args()

confidence, threshold = 0.5, 0.3

# Load the Custom class labels, Weights and Config files
# Then create the DNN model
labelPath = './obj.names'
labels = open(labelPath).read().strip().split('\n')
weightsPath = './yolov3-tiny.weights'
configPath = './yolov3-tiny.cfg'
net = cv2.dnn.readNetFromDarknet(configPath, weightsPath)

# Get all layer names
# Then get all [yolo] layers
layer_names = net.getLayerNames()
yolo_layers = []
for i in net.getUnconnectedOutLayers():
    yolo_layers.append(layer_names[i[0] - 1])

def draw_bb(img, boxes, confidences, classids, idxs, labels):
    # If detection exists
    if len(idxs):
        for i in idxs.flatten():
            # Get BB coordinates
            x, y = boxes[i][0], boxes[i][1]
            w, h = boxes[i][2], boxes[i][3]

            cv2.rectangle(img, (x,y), (x+w, y+h), (0, 255, 0), 10)
            text = "{}:{:2.5f}".format(labels[classids[i]], confidences[i])
```

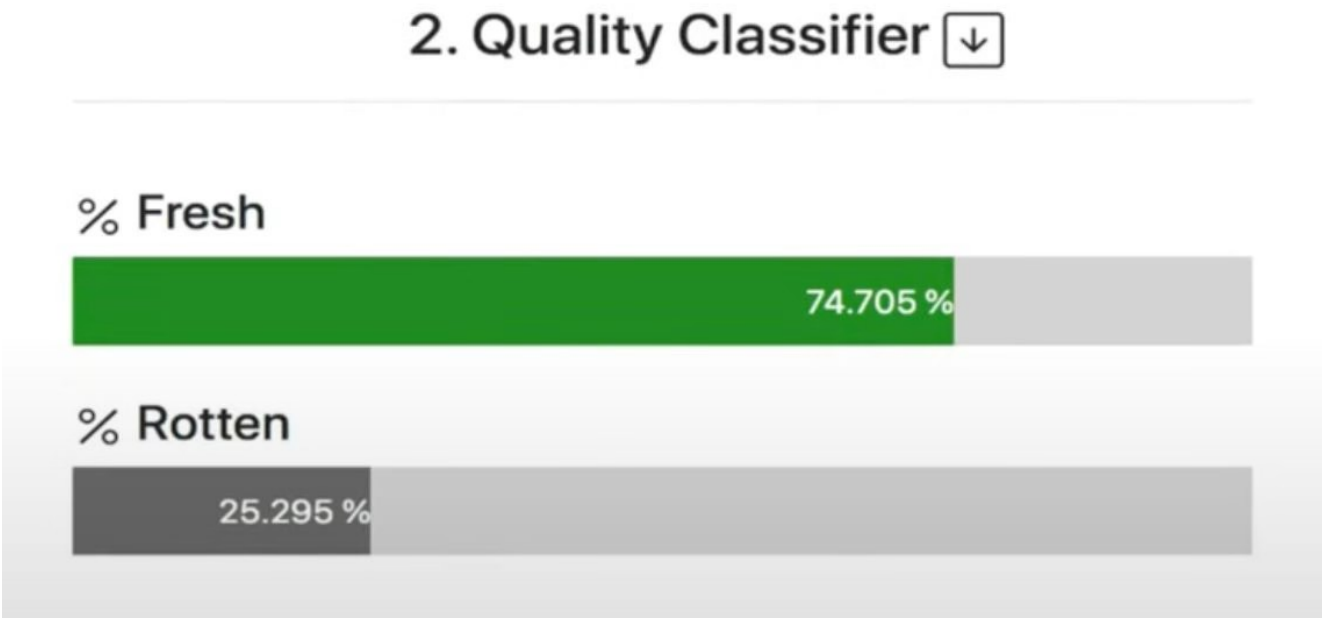
```
        cv2.putText(img, text, (x, y-10), cv2.FONT_HERSHEY_COMPLEX, 2,
(255, 70, 0), 3)

    return img

    # init lists of detected boxes, confidences, class IDs
    boxes, confidences, class_ids = [], [], []

def predict(net, layer_names, height, width, img, labels):

    # Construct a blob from input
    # Then perform a forward pass of the yolo OD
    # Then get BB with associated probabilities
    blob = cv2.dnn.blobFromImage(img, 1/255.0, (416, 416), swapRB=True,
crop=False)
    net.setInput(blob)
    layerOutputs = net.forward(layer_names)

    # init lists of detected boxes, confidences, class IDs
    boxes, confidences, class_ids = [], [], []

    # loop over each of the layer outputs
    for out in layerOutputs:
        # loop over each of the detections
        for detection in out:
            # extract the class ID and confidence of the current OD
            scores = detection[5:]
            class_id = np.argmax(scores)
            detect_confidence = scores[class_id]

            # filter out a weal predictions by ensuring the detected
            # probability is greater than minimum probability

            if detect_confidence > confidence:
                # scale the BB coordinates back relative to
                # the size of the image.
                # YOLO returns the center (x,y) - coordinates of BB
                # followed by the boxes weight and height
                box = detection[0:4] * np.array([width, height, width, height])
                centerX, centerY, box_width, box_height = box.astype('int')

                # use the center (x, y) - coordinates to derive
                # the top and left corner of the BB
```

```
                x = int(centerX - (box_width / 2))
                y = int(centerY - (box_height / 2))

                # update list of BB coordinates, confidences, and class IDs
                boxes.append([x, y, int(box_width), int(box_height)])
                confidences.append(float(detect_confidence))
                class_ids.append(class_id)

    # Suppress overlapping boxes
    idxs = cv2.dnn.NMSBoxes(boxes, confidences, confidence, threshold)

    img = draw_bb(img, boxes, confidences, class_ids, idxs, labels)

    return img, boxes, confidences, class_ids, idxs

if args.img:
    img = cv2.imread(args.img)
    height, width = img.shape[:2]
    img, _, _, _, _ = predict(net, yolo_layers, height, width, img, labels)

    if args.out:
        cv2.imwrite(args.out, img)
    else:
        img = cv2.resize(img, (800, 800))
        cv2.imshow('Prediction', img)
        cv2.waitKey(0)

elif args.video:
    cap = cv2.VideoCapture(args.video)
    height, width = None, None
    writer = None

    while True:
        grabbed, frame = cap.read()
        print(grabbed, frame)
        if not grabbed:
            break

        if width is None or height is None:
            height, width = frame.shape[:2]

        frame, _, _, _, _ = predict(net, yolo_layers, height, width, frame, labels)
```

```
        if writer is None:
            fourcc = cv2.VideoWriter_fourcc(*"MJPG")
            writer = cv2.VideoWriter(args.out, fourcc, 60, (frame.shape[1],
frame.shape[0]), True)

        writer.write(frame)

    writer.release()
    cap.release()
```

2.4 TESTING AND VALIDATION





Model Prediction

1. Fruit Classifier

% Apple
0.0
%

% Banana
0.0
%

% Orange
100.0 %

Uploaded Image

2. Quality Classifier

% Fresh
0.393
%

% Rotten
99.607 %

Model Prediction

1. Fruit Classifier

% Apple

71.1573 %

% Banana

27.0778 %

% Orange

1.7649 %

2. Quality Classifier

Uploaded Image

2. Quality Classifier

% Fresh

53.268 %

% Rotten

46.732 %

Model Prediction

1. Fruit Classifier

% Apple

1.0881 %

% Banana

98.7867 %

% Orange

0.1252 %

Uploaded Image

2. Quality Classifier

% Fresh

90.335 %

% Rotten

9.665 %

3. RESULT AND DISCUSSION

3.1 WORKING MODEL

The working model of a fruit spoilage detection system typically involves several key components and processes:

- **Sensing Technology:** The system utilizes various sensing technologies to gather data about the quality and condition of fruit. This may include spectroscopic techniques (such as near-infrared or mid-infrared spectroscopy) to analyze biochemical composition changes, as well as computer vision systems to detect visual cues of spoilage (such as discoloration or mold growth).
- **Data Acquisition:** Once the sensing technology collects data from the fruit products, it is transmitted to the system for processing. This may involve capturing images, spectroscopic readings, or other forms of data relevant to assessing fruit quality.
- **Pre-processing:** Before analysis, the raw data undergoes pre-processing to enhance quality, remove noise, and standardize features. This step ensures that the data are optimized for accurate analysis by the system.
- **Feature Extraction:** The system extracts relevant features from the pre-processed data, such as spectral signatures, color attributes, texture patterns, or other indicators of fruit quality and spoilage. These features serve as input for subsequent analysis.
- **Machine Learning Algorithms:** The system employs machine learning algorithms, such as classification or regression models, to analyze the extracted features and make predictions about the quality and freshness of the fruit products. These algorithms are trained on a dataset of labeled examples to learn patterns and relationships between input features and output labels (e.g., fresh or spoiled).
- **Classification/Prediction:** Based on the analysis performed by the machine learning algorithms, the system classifies or predicts the quality status of the fruit products. It may output binary classifications (e.g., fresh or spoiled) or provide quantitative predictions of spoilage degree based on predetermined criteria.
- **Output and Decision Making:** Finally, the system provides output to users or stakeholders, indicating the quality assessment results of the fruits. This output may include simple indicators (e.g., "Fresh" or "Spoiled"), visual alerts, or detailed reports with quantitative measures of spoilage. Based on these results, stakeholders can make informed decisions regarding the handling, processing, or disposal of the food products.

3.2 Advantages

The fruit spoilage detection system offers several advantages:

- Early Detection: The system can identify signs of fruit spoilage at an early stage, often before visible symptoms are apparent to human observers. This early detection allows for timely intervention to prevent further spoilage and minimize food waste.
- Objective Assessment: Unlike human judgment, which can be subjective and prone to errors, the detection system provides an objective assessment of fruit quality based on predefined criteria and algorithms. This helps ensure consistency and reliability in quality control processes.
- High Accuracy: Through the use of advanced image processing techniques and machine learning algorithms, the system can achieve high levels of accuracy in detecting fruit spoilage. This accuracy helps reduce false positives and negatives, improving overall performance.
- Cost Savings: By preventing spoiled fruits from entering the market or being consumed, the detection system can result in significant cost savings for producers, retailers, and consumers. It helps minimize losses associated with food waste and maintains product quality standards.
- Improved Efficiency: The automation of fruit spoilage detection processes streamlines operations and improves efficiency in quality control workflows. This allows for faster decision-making and response times, particularly in high-volume production and distribution environments.
- Enhanced Food Safety: Detecting and removing spoiled fruits from the supply chain helps mitigate the risk of foodborne illnesses and contamination. By ensuring that only safe and high-quality fruits reach consumers, the system contributes to enhanced food safety standards.
- Sustainability: By reducing food waste and improving resource utilization, the detection system promotes sustainability in the food industry. It aligns with efforts to minimize environmental impact and optimize the use of natural resources throughout the production and distribution process.
- Consumer Confidence: Providing assurance of fruit quality and safety, the detection system enhances consumer confidence and satisfaction. Consumers can trust that the fruits they purchase are fresh, wholesome, and free from spoilage, leading to positive brand perceptions and repeat purchases.

CONCLUSION

In conclusion, the fruit spoilage detection system stands as a pivotal advancement in food quality control. Leveraging state-of-the-art technologies like image processing and machine learning, it provides timely identification of fruit spoilage, thus curbing waste and upholding product quality standards.

By fostering early intervention, the system enhances food safety, consumer trust, and sustainability across the supply chain. Continued collaboration and refinement of the system promise further strides towards a more efficient and resilient food industry. In essence, the fruit spoilage detection system represents a significant stride towards a safer, more sustainable future in food production and distribution.