

Detection of Rotten Fruits at Pomona Fruit House Using the Convolutional Neural Network Method

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Abstract

The growing public awareness of healthy lifestyles has led to an increasing demand for fresh and high-quality fruits. However, during storage and distribution, fruits are prone to spoilage due to environmental and biological factors. The manual identification process of spoiled fruits remains limited in terms of accuracy and efficiency. To address this issue, this study proposes the application of digital image processing technology based on Convolutional Neural Network (CNN) to automatically detect the condition of fruits. This system is designed to assist in quality monitoring at locations such as Rumah Buah Pomona by classifying fresh and spoiled fruits based on their visual features. This solution is expected to improve the effectiveness of fruit distribution and reduce potential losses caused by unfit products.

Keywords: spoiled fruit, digital image processing, Convolutional Neural Network (CNN), fruit classification, automatic detection, fruit quality.

1. Introduction

The development of the agricultural industry and fruit distribution in Indonesia has shown significant growth along with the increasing public awareness of healthy lifestyles and the demand for high-quality fruit consumption [1]. In places such as Rumah Buah Pomona, maintaining fruit quality during storage and distribution is a crucial aspect to ensure that fruits reach consumers in a fresh and consumable condition [2]. Consumer demand for fresh fruit drives businesses to improve distribution systems and fruit quality monitoring to prevent damage before being sold.

Fruit spoilage is generally caused by various factors, such as high humidity, improper storage temperature, physical damage, microorganism infection, and uncontrolled ripening processes [3]. If not properly managed, rotten fruits can reduce market value and pose health risks to consumers [4]. Unfortunately, the process of identifying rotten fruits is still largely conducted manually by warehouse workers or vendors, which not only consumes time and energy but also has a relatively high error rate.

A more modern and accurate technological approach is needed to detect fruit conditions, especially on a large scale such as warehouses and fruit distribution centers. One potential approach is the application of digital image processing technology based on deep learning, particularly the Convolutional Neural Network (CNN) method, which has been proven capable of recognizing objects based on visual features such as color, texture, and shape [5]. CNN can classify fruit conditions with high accuracy and can be implemented automatically in web-based systems [6].

Considering the urgency and necessity of a more efficient and accurate fruit quality monitoring system, the author has chosen this topic for the final project entitled "Detection of Rotten Fruits at Pomona Fruit House Using the Convolutional Neural Network Method." This research is expected to contribute to improving the effectiveness of digital and automated fruit quality monitoring, thereby assisting fruit businesses such as Rumah Buah Pomona in maintaining product quality and reducing losses caused by spoiled fruits.

2. Theoretical Review

A website, in general, is a collection of digital pages that provide information in various formats, such as text, images, animations, and other media, which can be accessed via the internet worldwide. Initially, websites were developed as an information medium using the concept of hyperlinks to make it easier for users to explore diverse sources of online information. Thanks to the concept of multimedia, websites are able to deliver information in various forms, including text, images, audio, and video [7].

A website is a platform that functions as a medium to convey information and promote products so that they can be more widely recognized by the public. It is an internet-based application containing multimedia documents, such as text, images, audio, animations, and videos, which are accessed via the HTTP (Hypertext Transfer Protocol) using software called a browser. Websites serve various purposes, including as a medium for promotion, marketing, information sources, educational media, and communication tools [8].

A website is also a medium for presenting information on the internet in various formats, such as images, videos, text, audio, and interactive content. Websites enable interconnections between documents (hypertext) through links, which can be accessed using a browser [9].

The Convolutional Neural Network (CNN) method is very popular in the field of deep learning because of its ability to extract features from image inputs and reduce their dimensionality without altering the essential characteristics. CNN consists of neurons that have weights and biases. Each neuron receives input and performs a dot product operation with the input to calculate the output, which is then passed on to the next layer [15].

CNN is specifically designed to handle image processing problems and is a highly effective method for classifying, identifying, and recognizing patterns in images. Its architecture is inspired by the way the human brain processes visual information, which enables CNNs to better understand image details. In CNNs, the data used is usually two-dimensional, such as images or audio spectrograms. The core operation in CNN is convolution, which is performed using a set of convolutional kernels (filters). These kernels have weights and biases that are used to identify important features in an image. During the convolution process, the input matrix (image) is processed through filters that produce feature maps representing the main characteristics of the image. With this mechanism, CNNs are highly efficient in handling problems involving two-dimensional structured data, such as images or audio spectrums, and allow CNNs to recognize complex patterns with a very high level of accuracy [16].

3. Method

This study employs the Convolutional Neural Network (CNN) method to detect rotten fruits at Rumah Buah Pomona. In this stage, several important steps are involved in designing an object detection system to analyze fruit conditions. The following is the system flow diagram used:



Figure 1. System Diagram

This diagram illustrates the process flow of the fruit condition inspection system using video-based object detection technology. The explanation of each stage is as follows:

1. **Camera/Video Input**
The initial stage begins with capturing images or videos using a camera directed at the fruits in the sorting line or storage area. The camera serves as a visual data collection tool, providing input for the system to detect rotten fruits.
2. **Object Detection System**
At this stage, the system analyzes visual data from the camera using computer vision algorithms, specifically CNN, to recognize and detect fruit conditions. The system automatically identifies fruits in the video and evaluates whether they show signs of spoilage, such as changes in color, texture, or shape.
3. **Fruit Feasibility Assessment System**
Once objects are detected, the system performs a real-time assessment of fruit feasibility. Each analyzed fruit is classified into “edible” or “inedible” categories based on the visual analysis results. This ensures the sorting process is more accurate and consistent.
4. **Database**
All analysis results are stored in a centralized database. This database records information such as detection time, the number of rotten fruits, and the total number of fruits analyzed. Such information is useful for reporting, analyzing fruit quality trends, and supporting rapid, data-driven operational decision-making.

Overall, this system provides an efficient and real-time automation solution for detecting rotten fruits compared to manual methods, which are slower and less consistent.

The detection system utilizes the Single Shot Detector (SSD) algorithm, one of the popular methods in computer vision due to its efficiency in detecting objects in a single process (one-shot detection). SSD enables the system to simultaneously predict object locations and classifications in one processing step, eliminating the need for separate stages.

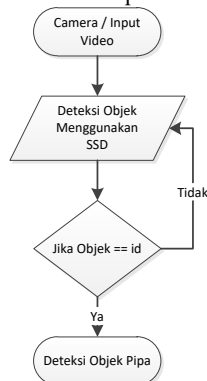


Figure 2: Object Detection Flowchart

The following are the stages of training the SSD model in the context of rotten fruit detection:

1. **Dataset Collection**
The dataset consists of fruit images under various conditions, both fresh and rotten. Each image is manually annotated to mark the fruit areas and their spoilage levels.
2. **Data Preprocessing**
 - a. **Image Augmentation:** Techniques such as rotation, flipping, or adding noise are applied to increase data variability.
 - b. **Normalization:** All image data is normalized to have uniform pixel values, usually within the range [0, 1].
 - c. **Resizing:** Images are resized to match the input size required by the SSD model, i.e., 300x300 pixels.
3. **SSD Model Architecture**
SSD is built on a base architecture such as VGG16 as its backbone. The model combines multiple CNN layers to predict bounding boxes at different scales, which is useful for detecting fruits of various sizes and positions.
4. **Model Training**
 - a. **Parameter Initialization:** Initial weights are set using pretrained weights to accelerate and stabilize training.
 - b. **Loss Function:** SSD uses a combination of bounding box regression and object label classification.
 - c. **Batch Training:** Data is trained in batches of a certain size. In this study, 16 images per batch were used to speed up training.

With this approach, the SSD model can serve as the core of an automated, web-based, real-time fruit quality monitoring system. The system is capable of detecting rotten fruits with adequate accuracy and high efficiency.

In the software application development process, system requirement analysis is crucial to ensure that the application is completed on time and meets its objectives. This analysis helps make the development process more structured, efficient, and well-directed.

The functional analysis of this detection system outlines the key features of the rotten fruit inspection and detection application:

1. **Home Menu**
The Home menu is the initial screen when the application runs. It contains a “Start” button, which activates the detection process. When clicked, the system activates the camera and begins monitoring the recorded fruits.
2. **Object Detection System for Fruit Inspection**
In this menu, the fruit detection process automatically begins when fruits pass through the camera monitoring area. The system analyzes the visual condition of the fruits to determine whether they are rotten or edible. If the fruit is classified as edible, it will be labeled “Fresh”; otherwise, if rotten, it will be labeled “Rotten.” This process runs in real-time and without manual intervention.
3. **Fruit Detection Data Menu**
This menu displays the detection results of processed fruits. The displayed information includes the number of fresh and rotten fruits, as well as the date and time of each inspection. The data can also be stored in the database as an archive and used for further analysis by the fruit house management.

4. Result

The results of this study are presented in the following explanation:

1. **Initial Menu Display**

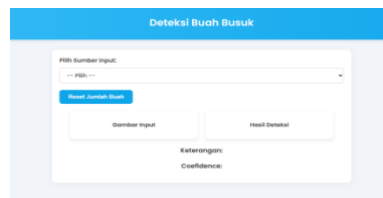


Figure 3: Website Interface

This website is designed to detect fruit conditions (fresh or rotten) using three main input methods: via webcam, IP camera, and image upload. Detection is performed using a pre-trained artificial intelligence model (model.h5) to classify fruit conditions.

The website provides a dropdown menu with three main options as input sources:

- a. **IP Camera**

Allows users to perform real-time fruit detection using an IP camera (CCTV or remote streaming camera). The application accesses video streams from the IP camera through RTSP or HTTP streaming protocols. This is suitable for industrial or remote agricultural use.

- b. **Webcam**

Activates the camera directly connected to the user's computer or laptop. Images are captured in real time from the webcam and sent to the server for fruit condition detection (fresh or rotten). This method is used for quick, local detection.

- c. **Choose File**

Users can manually select an image from their device (PC/laptop) to upload to the system. The system then classifies the uploaded image using the deep learning model.

After choosing one of the input methods above, users can access the following features:

- i. **Start Webcam/IPCam**

Captures images from the video source (webcam or IP camera). Images are automatically sent to the Flask backend for detection.

- ii. **Choose File**

Opens a file explorer window to select an image from the device. The chosen image will be displayed on the screen and prepared for detection.

- iii. **Upload and Detect**

The selected image (via webcam, IP camera, or manual file upload) is sent to the server. The backend processes the image using the model.h5. The classification results are returned and displayed, including:

Label: “Fresh” or “Rotten”

Confidence score

iv. Clear Screen

Clears all previously displayed classification results. Resets the page view so the user can start a new detection session from scratch.

2. Process Display

This display shows the experimental results of detecting apple conditions (fresh or rotten) using the designed system. Tests were conducted on 7 apple images, as shown in Figures 4.2 to 4.8.

Each apple image had different conditions, ranging from fresh apples to those showing spoilage. These images were input one by one into the system through the Choose File feature, then detected using the pre-trained deep learning model (model.h5).

The purpose of this experiment was to test:

- Whether the system can distinguish between fresh and rotten apples.
- The accuracy of classification under varying lighting and fruit texture conditions.

From the tests, the system successfully classified the fruit conditions in all images with good accuracy and consistency. Each prediction displayed the detection label (e.g., “Rotten”) along with a confidence score, representing the system’s certainty in its classification.

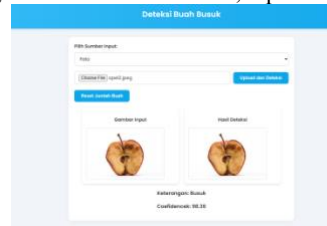


Figure 4: Experiment 1

In the first test, an apple image was input into the system for classification. The image showed physical signs of spoilage, such as discoloration and texture changes.

The system successfully identified the apple as rotten, with a confidence score of 98.36%. This indicates very high certainty, as the image features strongly matched rotten apple characteristics learned during training.

The detection was based on visual features such as discoloration, dark spots, and uneven texture, which the model recognized as spoilage indicators. This result demonstrates the system’s ability to detect rotten apples under clear visual conditions.

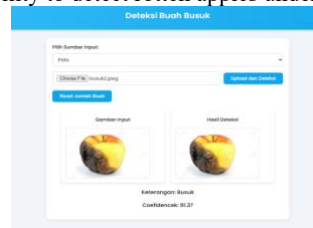


Figure 5: Experiment 2

In the second test, another apple image with spoilage signs was used. Unlike the first image, this apple had different characteristics, such as blackened areas and spots caused by natural fermentation or environmental factors like humidity and temperature.

The system classified the apple as rotten with 91.37% confidence. Though slightly lower than the first test, this is still considered very high, showing the model’s robustness against variations in shape, lighting, and angle.

This experiment confirmed that the deep learning-based system generalizes well and can reliably detect rotten apples under varied conditions.

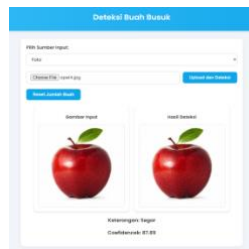


Figure 6: Experiment 3

The third test used an image of a fresh apple with smooth skin, consistent bright red color, and no visible spoilage.

The system classified it as fresh with 87.89% confidence. This demonstrates the model’s ability to distinguish fresh apples by recognizing features such as:

- Bright, uniform skin color.
- Absence of black spots, wounds, or decay marks.
- Smooth surface texture.

Although lighting and angle can affect classification, the system still achieved accurate results, confirming its capability to generalize fresh apple conditions.

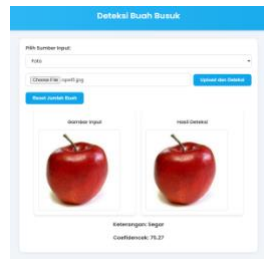


Figure 7: Experiment 4

In the fourth test, another fresh apple image was used. The apple appeared good overall, though slight variations in lighting and color were observed due to less-than-ideal capture conditions.

The system classified it as fresh with 75.27% confidence. Although lower than the previous test, the classification was still correct.

This result highlights the effect of lighting, angle, and image quality on confidence scores but confirms that the model can still classify correctly under suboptimal conditions.

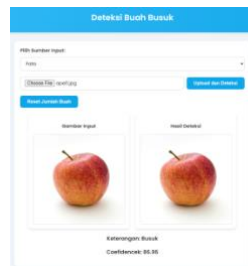


Figure 8: Experiment 5

The fifth test used an image of a visually fresh apple. However, the system misclassified it as rotten with 86.96% confidence—a false positive error.

Possible causes included:

- Shadows misinterpreted as spoilage spots.
- Angle of capture causing dark or blurry areas.
- Natural color variations mistaken for spoilage.
- Model overfitting to certain visual features.

This indicates the need for:

More diverse training data.

Improved preprocessing (e.g., lighting normalization).

Better generalization techniques.

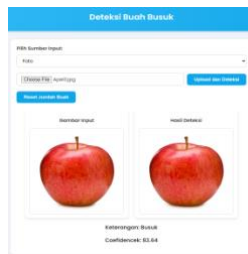


Figure 9: Experiment 6

The sixth test also misclassified a fresh apple as rotten with 83.64% confidence, another false positive.

Potential causes:

- Natural skin textures mistaken as spoilage.
- Insufficient training data for fresh apple variations.
- Uneven or overly bright lighting.
- Over-sensitivity to minor features.

This reinforced the need to enhance the dataset, preprocessing, and augmentation methods. It also suggested integrating contextual information (e.g., storage time, temperature) for real-world applications.

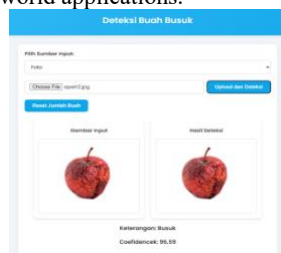


Figure 10: Experiment 7

In the seventh test, the system correctly identified a clearly rotten apple with 96.59% confidence.

The model effectively recognized spoilage indicators such as black spots, wrinkled skin, and discoloration, showing strong performance under obvious visual conditions.

This confirmed the model's reliability in detecting truly rotten fruits with high certainty.

3. Dataset Display

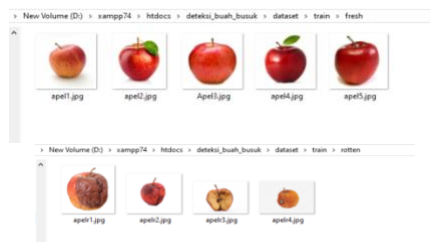


Figure 11: Dataset Display

In this experiment, a dataset of 9 apples was used:

a. 5 fresh apples

b. 4 rotten apples

The images were organized into dedicated folders for training and testing:

a. dataset/train/fresh – contains images of fresh apples.

b. dataset/train/rotten – contains images of rotten apples.

During testing, images from both folders were alternately fed into the system to evaluate classification accuracy.

This dataset structure ensured realistic evaluation and helped the model distinguish between fresh and rotten apples based on visual features rather than memorizing patterns.

5. Conclusion

The conclusions from this research are as follows: The rotten fruit detection system based on image processing and machine learning has been successfully designed and implemented, capable of detecting fruit conditions in real-time with adequate accuracy. This system facilitates the automatic identification of fresh and rotten fruit through inputs from a webcam, IP camera, or static images. The accuracy level of detection is highly influenced by the quality of the dataset and the lighting conditions during image capture. Testing shows that the system is able to detect rotten fruit with high confidence, although there are still cases of failure caused by environmental conditions and variations of fruit that are not fully represented in the model. This system has the potential to be applied in various scenarios of automatic fruit quality monitoring, helping reduce human errors and speeding up the fruit selection process both at industrial and small-scale levels.

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