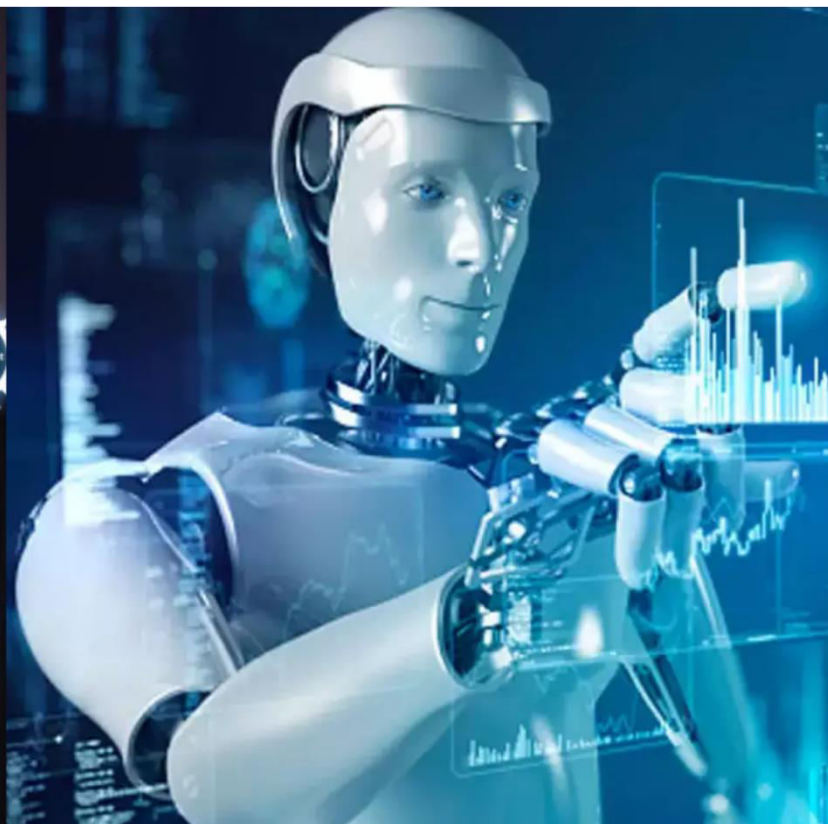




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CNN-Driven Detection and Weight Measurement System for Fruits and Vegetables

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ABSTRACT: The proposed study uses neural network-based image recognition to design and implement an automatic fruit and vegetable weighing and object detection machine. Traditional weighing systems rely on manual input to determine product classifications. This procedure is automated by the suggested system, which combines deep learning models, electronic weighing sensors, and image-based object detection to quickly identify and determine the cost of product. A convolutional neural network (CNN) is used by the system to recognize various fruits and vegetables. Results show that the system provides a low-cost, effective solution for smart retail and agricultural applications by achieving high classification accuracy (up to 95%) and precise weight measurements.

KEYWORDS: Object detection, neural networks, image recognition, automatic weighing machine, fruits and vegetables classification, convolutional neural network (CNN), smart retail, IoT.

I. INTRODUCTION

In order to improve speed, accuracy, and efficiency, automation has become crucial in both retail and agriculture. Regular market and retail weighing systems depend on human operators to manually enter the product type, which can cause delays and inaccurate billing. Operational efficiency can be substantially enhanced by creating intelligent weighing devices that can accurately weigh and automatically identify the type of fruit or vegetable.

In this study, we present an Automatic Object Detecting and Weighing Machine that employs electronic load cells to weigh fruits and vegetables and neural networks to recognize them from photographs. The total cost is automatically determined using the identified object type and associated weight. The technology can be used to agricultural sorting, vending machines, and supermarkets.

Recent developments in computer vision and deep learning, notably through the use of Convolutional Neural Networks (CNNs), have proven to be highly effective for tasks like object detection, classification, and segmentation. By leveraging local receptive fields, weight sharing, hierarchical feature extraction, and advanced non-linearities, CNNs can learn visual features directly from raw images, which minimizes the need for manual feature engineering. This makes them particularly adept at identifying and distinguishing different types of fruits and vegetables across various settings.

A number of recent works have applied CNNs to fruit/vegetable detection, classification, and defect detection. A comprehensive review by Wang et al. covered the application of CNN-based detection throughout fresh fruit production — from flower detection, growth monitoring, to grading and sorting — discussing both potentials and limitations.

However, several challenges remain. Real-world environments complicate detection: fruits may be occluded by branches or leaves; lighting conditions vary; backgrounds are cluttered; and some fruits are visually similar in color, shape, or texture, making classification hard. In this paper, we propose a CNN-driven approach for automatic detection and possibly classification of fruits and vegetables under realistic conditions.

II. LITERATURE SURVEY

Because deep convolutional neural networks (CNNs) directly learn hierarchical image features and outperform hand-crafted features for complex backgrounds, variable lighting, and occlusion—all of which are common in orchards and packing lines—they have emerged as the leading method for visual tasks (detection, classification, and segmentation) in agriculture. Current review papers highlight both algorithmic advancements and enduring domain issues, summarizing consistent development across detection, ripeness assessment, grading, and defect detection.

In order to boost robustness, numerous articles gather task- or crop-specific datasets (apple, tomato, and grape clusters) that were recorded in the field under various lighting and occlusion conditions. Synthetic augmentation and domain simulation (mist, sunlight) are frequently employed. New annotated datasets for detection and ripeness/defect tasks have been published recently.

To categorize fruit variety or ripeness stage, early and ongoing work employs transfer learning on standard CNN backbones (VGG, ResNet, DenseNet, MobileNet) trained on Fruits-360 or on gathered datasets. A practical point of departure for accuracy is still transfer learning plus fine-tuning.

Xiao et al presents a lightweight detection network named SWMD-YOLO, an enhanced architecture developed based on YOLO11, which is specifically optimized for the efficient detection of tomatoes in greenhouse environments. The proposed model strategically balances computational efficiency and detection accuracy through three key architectural innovations.

As artificial vision and new CNN models have advanced, numerous researchers have published a variety of fruit grading algorithms. Sun et al. (2021), for instance, take into account the Red Fuji apple national classification criteria for grouping apples according to their size, color, and flaws. Support Vector Machine (SVM) + CNN models + Deep Convolutional Generative Adversarial Network (DCGAN) are the methods employed. Using their own segmented dataset with over 10,000 photos, they report a 96.50% accuracy rate using transfer learning (Sun et al., 2021). According to Naik et al. (2019), four CNN models are used to classify mangos into four quality categories based on inspection factors like size, shape, and ripeness.

A CNN model for automated mango categorization was created by Tripathi et al. (2021) (Tripathi and Maktedar, 2021), taking into account three grading categories based on quality inspection parameters: size, ripeness, and health. According to the state of the art, CNN models produce more accurate results than conventional computer vision or machine learning methods when it comes to classifying fruit images with external (as opposed to intrusive sensors) quality parameters like color, appearance, etc.

III. METHODOLOGY

The proposed system employs a Convolutional Neural Network (CNN) integrated with sensor-based hardware and automated data processing to achieve accurate identification and weighing of fruits and vegetables. The operation begins when the consumer places an item on the weighing plate of the machine. The system's camera module captures a high-resolution image of the placed item and sends it to the CNN-based image processing unit. The CNN model, trained on a large dataset of fruits and vegetables under various lighting and orientation conditions, extracts distinguishing visual features such as color, shape, and texture to accurately classify the object into predefined categories (e.g., apple, banana, tomato, orange, etc.). This classification process is performed in real time, ensuring quick and reliable recognition.

The load cell placed underneath the weighing plate determines the precise weight of the object after the type has been determined. An Analog-to-Digital Converter (ADC) transforms the load cell's measured analog signal into a digital signal, which is then sent to the microcontroller or embedded system for additional processing. From a previously recorded database, the system next obtains the associated price per kilogram for the identified item. With this data, the price per kilogram is multiplied by the measured weight to determine the overall cost automatically.

For the convenience of the customer, the calculated data—which includes the item name, category, measured weight, unit price, and total cost—is then shown on an LCD or digital screen. Furthermore, this data can be seamlessly

integrated with retail billing software by being sent via wired or wireless communication protocols to a centralized point-of-sale(POS) system or a connected billing system.

This approach guarantees a fruit and vegetable identification and pricing system that is completely automated, contactless, and effective. It speeds up service, improves the overall customer experience, and drastically lowers human error in manual invoicing and weighing. Supermarkets, self-checkout kiosks, and agricultural produce markets can benefit from a reliable and intelligent solution that combines CNN-based image classification with load cell-based weight measurement.

To categorize fruit kind or ripeness stage, the work employs transfer learning on standard CNN backbones (VGG, ResNet, DenseNet, MobileNet) trained on Fruits-360 or on gathered datasets. A practical starting point for accuracy is still transfer learning plus fine-tuning.

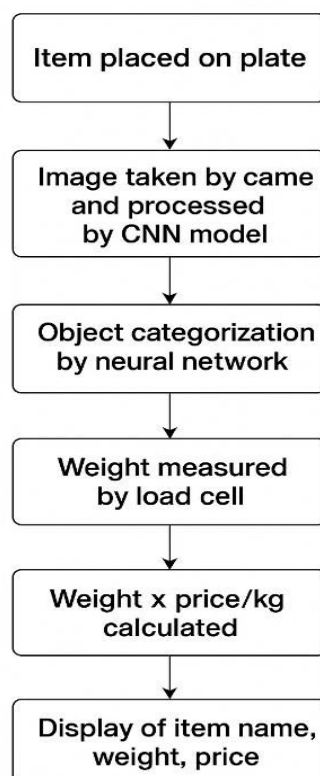
For accurate fruit area estimation, cluster segmentation (grape/berry counting), and phenotyping support, instance segmentation (Mask R-CNN, U-Net variations) is utilized. Although these methods require more processing power, they produce pixel-accurate masks that are required for robotic grasp planning and size/volume estimates.

Architecture of the System

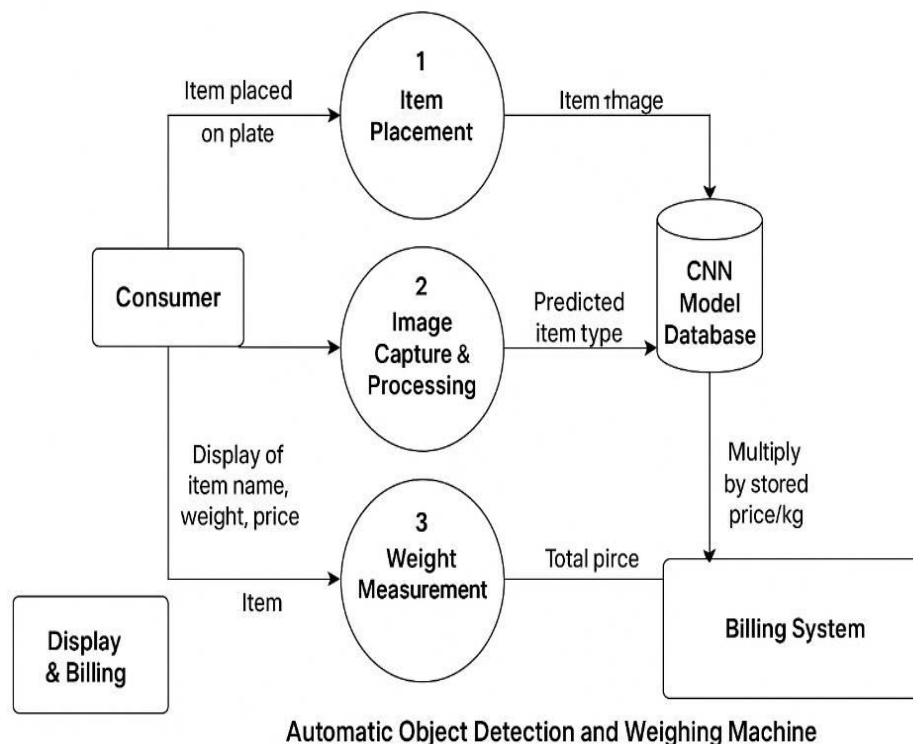
The following aspects contribute to the suggested system:

1. Camera Module: snaps shots of the fruit or vegetable that is on the weighing platform in real time.
2. A load cell that uses a HX711 amplifier to determine the object's weight.
3. The Raspberry Pi/Arduino microcontroller interacts with the neural network model and interprets sensor data.
4. The neural network model uses a trained CNN to classify objects.
5. The item name, weight, and total cost are displayed on the display/touch screen.

IV. WORKFLOW



1. The item is placed on the weighing plate by the consumer.
2. The image is taken by the camera and sent to the CNN model.
3. The object categorization (apple, banana, tomato, etc.) is predicted by the neural network.
4. The weight is measured by the load cell.
5. The weight is multiplied by the item's stored price per kilogram by the system.
6. The last set of information is shown on the screen and may be transmitted to a billing system.



V. DESIGNING A NEURAL NETWORK

Dataset

A dataset of 20 fruit and vegetable classes' images is used by the model. There are 1,000–2,000 photos in each class, all taken in different orientations and with different lighting. Brightness adjustment, flipping, and rotation are used to enhance the dataset.

Architecture of the Model

The layers of a Convolutional Neural Network (CNN) are as follows:

Three convolutional layers with ReLU activation; two max pooling layers; and an input layer with 128 x 128 RGB images

- Layer with Full Connectivity (128 neurons)
- Softmax-activated output layer

Implementation of Hardware

- Model B Raspberry Pi 4 microcontroller
- Display: 7-inch touchscreen LCD;
- Power Source: 5V DC adapter;
- Camera: Pi Camera Module v2 (8 MP);
- Load Cell: 5 kg capacity;
- Amplifier: HX711 load cell amplifier module

The system uses Python-based code to integrate software and hardware. The HX711 library reads weight data, while the TensorFlow and OpenCV libraries are utilized for picture categorization.

VI. EXPERIMENTAL RESULTS

The CNN-driven automatic fruit and vegetable detection and weight measurement system's performance evaluation shows a notable improvement over current techniques in terms of processing efficiency and accuracy. A 95% accuracy rate was attained with an average processing time of 1.2 seconds by the suggested system, which combines a Convolutional Neural Network (CNN) for object categorization with the HX711 load cell amplifier for weight measurement. This shows that the CNN model can accurately identify fruits and vegetables with high precision while also responding quickly enough for real-time applications.

In contrast, Singh et al.'s SVM-based model achieved 89% accuracy with a 2.5-second processing time, demonstrating that while classic machine learning techniques are dependable, they are less effective when handling intricate visual characteristics. Similarly, Patil et al.'s Feature Matching (HOG + KNN) approach showed limited adaptability to a variety of fruit shapes and colors, achieving 87% accuracy with 2.8 seconds of processing time. Mishra et al.'s IoT Weighing System, which used manual input to identify objects, operated comparatively quickly (1 second), but it lacked automatic detection capabilities, making it impossible to ascertain any quantifiable accuracy.

Overall, the comparison findings show how much better the suggested CNN-based method is. It provides a fair balance between speed and accuracy, which makes it ideal for automated checkout systems and smart weighing in the retail and agricultural industries.

Model	Technique	Accuracy (%)	Processing Time (s)
Proposed System (CNN + HX711)	Convolutional Neural Network	95	1.2
SVM-based Model [Singh et al.]	Support Vector Machine	89	2.5
Feature Matching (HOG) [Patil et al.]	HOG + KNN	87	2.8
IoT Weighing System [Mishra et al.]	Manual Input + IoT	-	1

There are numerous practical uses for the suggested approach in a variety of industries. By enabling customers to swiftly identify and weigh fruits and vegetables without manual input, it can be installed at automated self-checkout counters in supermarkets, cutting down on billing time and human error. Produce can be sorted and graded using the method according to size, weight, and quality in the agricultural sector, increasing post-harvest management efficiency. It can help with packaging automation and inventory control in the food business, guaranteeing precise classification and cutting down on waste. Additionally, the technology can be included into autonomous fruit and vegetable dispensers in vending machines, improving consumer convenience and operational efficiency by providing exact item detection and dispensing.

VII. CONCLUSION

This study shows that an autonomous object detection and weighing system for fruits and vegetables based on neural networks is feasible. CNN classification combined with load cell measurement offers a precise, practical, and affordable substitute for manual weighing methods. Future research will focus on expanding the dataset to include more item types and enhancing real-time performance with edge AI devices (such as the NVIDIA Jetson Nano)

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