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Smart Weighing Machine Integrated With Object Recognition

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ABSTRACT: Consumers are the reason businesses exist, ensuring their satisfaction is critical to a company's success. As time goes on, people's lives are getting increasingly hectic; therefore, every minute saved can be really valuable. Customers may opt for a different grocery shop if the billing process is time-consuming. Therefore, it is important to remodel the fruit and vegetable identification process of self-service systems in the retail industry, concentrating mainly on speeding up the process and making the system user-friendly. Computer vision in self-service systems can detect items easier by transferring the task from a human to a machine. The goal of the research is to study the scope of a system that recognizes fruits and vegetables in the grocery store using photos collected by a camera. Customers can use the system to label the items and assign a price based on their weight. To classify photos of products captured by the camera, an image classifier was developed and assessed.

KEYWORDS: Smart Weighing Machine, Image Recognition, Convolutional Neural Network, Deep Learning**.**

I.INTRODUCTION

In recent years, product automation has attracted a wide range of support. The need for systems that reduce processing time emerges as a result of consumer's expectations of ongoing effort to save time. In supermarkets, identifying products are typically done manually by a cashier or via self-service technology. The checkout process at a grocery shop is made easier by a Grocery Store Cashier. They run the register, receive payments, deliver invoices, bag products, and may help customers on occasion.

A self-checkout system allows customers to process their purchases from a merchant on their own. They're an alternative to the standard checkout with a cashier. The customer takes on the role of a cashier by scanning barcoded items, weighing things without barcodes and selecting the correct variety from a display panel, and then paying for the things by inserting cash or putting payment card information into the machine. In developed nations, self-service systems are common. The retailer benefits from self-checkout equipment since labor costs are decreased. However, there are significant drawbacks for billing loosely packed products that do not have barcodes. Customers weigh it themselves and choose the product name from a drop-down menu on the User Interface. Because the identification is done manually, the human factor may alter the conclusion. This process is time-intensive, repetitious, and mistake pronely. There's a danger that the user will press the incorrect button or misunderstand the application.

Amazon is a firm that has made significant technological advancements in artificial intelligence, image recognition, and the automation of physical labor. Amazon launched a product called Amazon Go that allows customers to shop without having to deal with cashiers or self-service checkouts. The store is outfitted with several cameras and sensors. Amazon has succeeded in establishing a store where technology identifies the things that customers select. Customers do not need to check out; after they leave the store with their chosen items, the price will be automatically deducted from the customer's Amazon Pay account. Except for Amazon Go, the other two methods are time-consuming and difficult. Amazon is attempting to establish a monopoly in the field of in-store automation. So it is time to invest in next-generation retail technology. What we propose is a semi-automated process that enables computer vision to automate the identification of fruits and vegetables in retail self-service systems.

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II.PROPOSED SYSTEM

The working of the system is quite simple and the data flow of the same is illustrated in Figure 1.

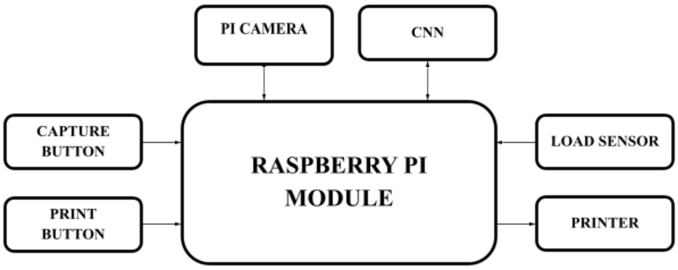

Fig. 1 Block diagram showing data flow of the proposed system.

To classify an object, a convolutional neural network has been tested and retrained to suit our application. The user can interact with the system using two pushbuttons. After collecting the required fruit or vegetable on a weighing case, the user can place it on the weighing machine set-up using a load cell, analog to digital converter (ADC), and a display unit. Once that process is done, he/she can press the capture button. When the capture button is pressed, the processor detects it and instructs the camera to take a picture. This image is fed to the Convolutional Neural Network (CNN), which makes a prediction about the class of the fruit or vegetable. Prediction from CNN is stored on the processor along with the weight retrieved from the weighing machine. Price according to the weight is calculated and all these information are stored as a list. These processes happen in a matter of seconds. The user can continue weighing as many items as he/she wants. When he/she is done, he/she can get the bill by pressing the print button. When the print button is pressed, the list containing all the items weighed is sent to the receipt printer and it prints the bill. After this, the list is cleared automatically, and the system is ready for the next customer.

III.HARDWARE

The components and the specifications are chosen specifically for making a prototype of the proposed system. Affordability and availability have indeed influenced in selecting the components. Therefore, some of the component specifications are beyond the range of actual specifications which is needed for making a commercial product that meets industrial standards. The hardware of the system is constituted by a processor (Raspberry Pi 3+ Model), 5 MegaPixel camera module, 10 kg load cell and its display unit, activation mechanism, and a thermal receipt printer with USB/Bluetooth connection. A micro SD card is required for Raspberry Pi to act like a hard disk. The camera module communicates with the processor using the MIPI camera serial interface protocol. Using the camera module of Raspberry Pi will make the configuration easier.

IV. CLASSIFICATION ALGORITHM

Convolutional Neural Networks (CNN) have excelled at large-scale image recognition challenges in recent years. But obtaining sufficient training data and developing the models from the ground is expensive or impracticable in many applications. Transfer learning is a useful tactic in deep learning in which a model created for one job is employed as the framework for a model on a specific challenge. We leverage transfer learning in this research by selecting a pre-trained architecture called MobileNet version 2 and fine-tuning it to the kinds of photos we use. MobileNet is an architecture developed by the Google AI team to function on mobile and embedded vision applications. To reduce processing time and model size, MobileNet uses depth-wise separated convolutions, which make it perfect for our hardware.

V. TRAINING METHODOLOGY

In our research, we use six different classes. Apple, Beetroot, Carrot, Okra, Orange, and Pineapple are the product classes chosen. These classes were chosen because they are regularly purchased at supermarkets. The dataset has been constrained in order to keep the study to become too large. These restrictions are based on the fact that all categories of fruit or vegetable fall into the same group. Using the Raspberry Pi camera module, a fresh dataset with 42 training and 8 validation photos per class was manually constructed. Items were photographed without being placed in plastic bags for the sake of simplicity. Figure 2 shows few examples of the newly acquired datasets.

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Fig. 2 Sample images of fruits and vegetables taken using Raspberry Pi camera module

The training data are saved in a specific format such that there is the main data folder, and within that data folder, each type of data must have its own folder holding the associated photographs. The folder names must correspond to the names of the classes they represent. The model is constructed in three steps:

1. Reconfiguration of the base model: After loading the dependencies such as Keras (with Tensorflow backend), Numpy, Matplotlib, Pandas, and others, import the pre-trained MobileNet v2 model. Remove the last layer, which contains 1000 neurons, and replace it with a few dense layers that will allow the model to learn more complicated features. Finally, add our own final layer of 6 neurons.
2. Loading training data into ImageDataGenerators: Specify the path to our training data so that images are loaded in batches and trained by ImageDataGenerators.
3. Model training and evaluation: A stochastic gradient descent (SGD) optimizer is utilized to compile. After that, the generator is used to train the model, which is saved and later used to forecast which class a fresh unseen image belongs to.

VI. RESULT AND DISCUSSION

The result of training and validation are shown in Figure 3. We can see that both the training and validation accuracy increasing after each epoch and finally reaching 100%, while training and validation loss is decreasing. All validation images were predicted accurately.

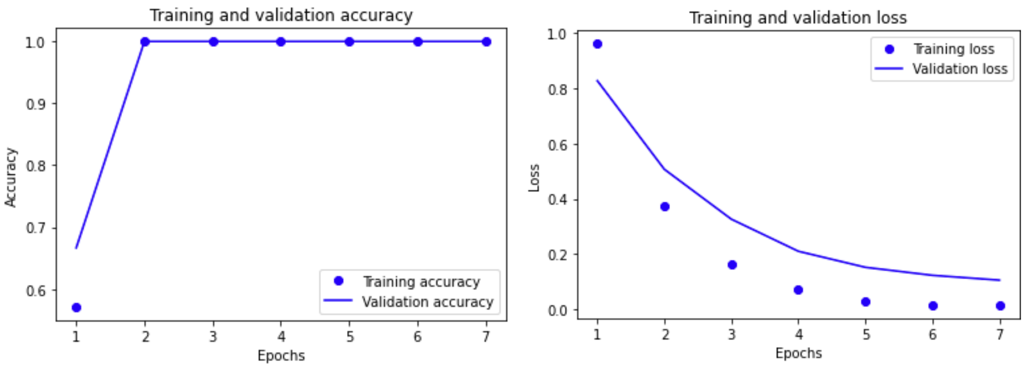

Fig. 3 Training and validation result plotted as a graph.

The model was trained and validated with images of a fruit or a vegetable sitting alone in a white background. To further test the model's efficiency, it was fed with images of fruit or vegetable sitting as a group and the model successfully predicted the result. Prediction accuracy value was 0.97964454 for Apple, 0.73974514 for Beetroot, 0.94280165 for Carrot, 0.91575164 for Okra, 0.77586365 for Orange and 0.7683236 for Pineapple. These values are great considering the complexity of the testing image and the lower amount of training data.

VII.CONCLUSION

In this paper, we propose a system that uses image recognition to automate the identification of fruits and vegetables in the grocery store. As a classifier, Mobilenet v2 was employed. MobileNet gave accurate forecasts as well as quick identification results. Retraining the network on datasets from its real-world surroundings could improve its accuracy. When photos captured with the Raspberry Pi camera module were utilized as training data, more accurate predictions were achieved. Additionally, if more photographs are collected, classes can be divided into subclasses including several forms of fruit or vegetable. The apple class, for example, could be divided into subclasses such as Granny Smith, Pink Lady, and Royal Gala, which are all different sorts of apples. However, there's a chance that breaking a class down into

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subclasses for each variety of fruit or vegetable will be too difficult for the network to classify. Implementing a series of networks can help us obtain more precise behavior. The first network is solely responsible for determining the type of fruit. One of many subsequent networks focusing on a single type of fruit is tasked with classifying the subset of fruit.

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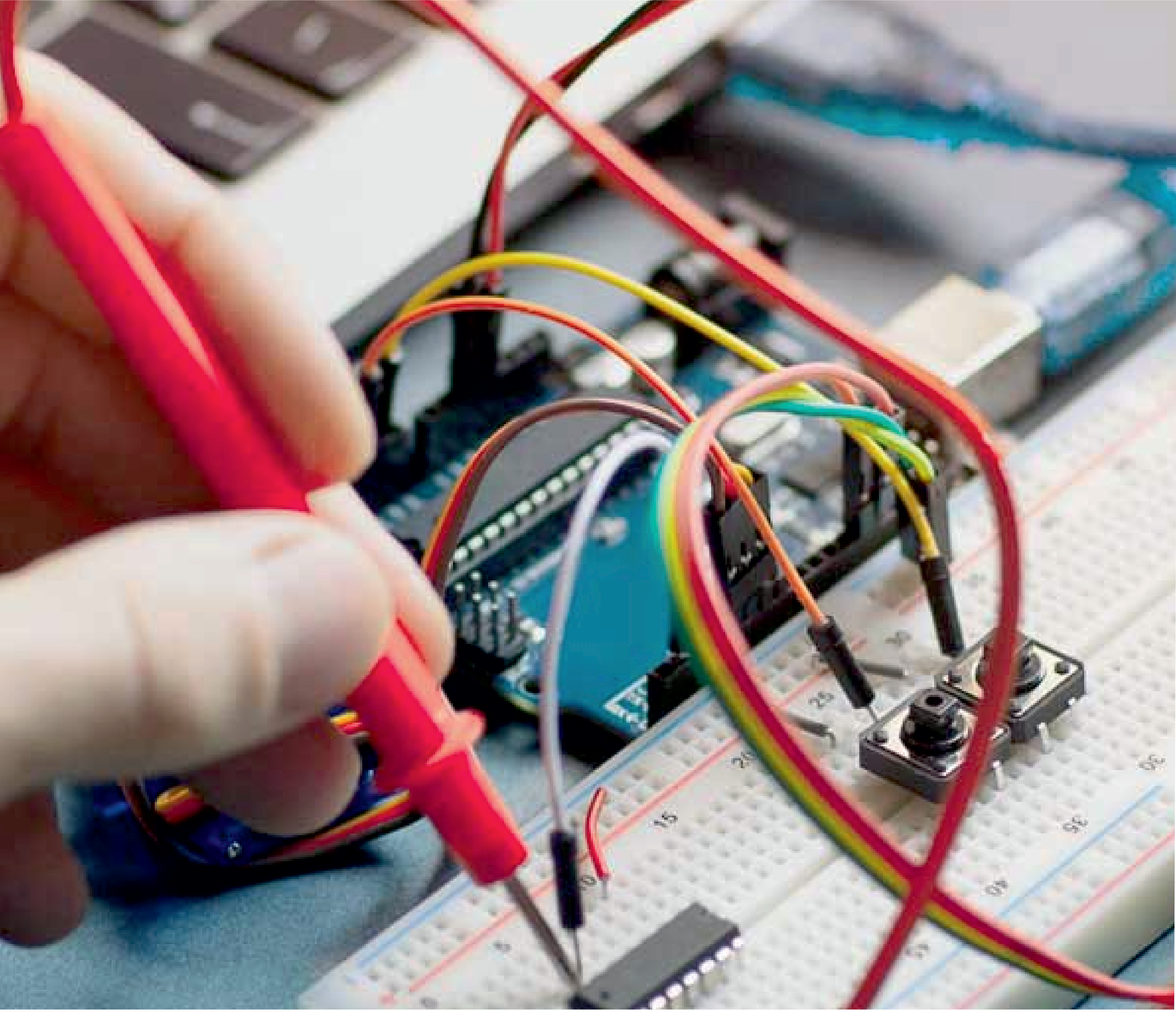

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