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ORIGINAL

Fruit and vegetable self-billing system based on image recognition

Sistema de auto-facturación de frutas y verduras basado en el reconocimiento de imágenes

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ABSTRACT

Introduction: shopping centers have become a necessary aspect of living, especially for city dwellers. To realize the identification and settlement of fruits and vegetables lacking bar codes is a major problem in supermarket self-service settlement.
Method: in this study, we proposed a novel Garra Rufa fish-optimized multi-objective convolutional neural network (GRFO-MCNN) for fruit and vegetable detection and freshness recognition. To improve feature identification performance, the GRFO-MCNN integrates the CBAM, which consists of the CAM and the SAM. Freshness recognition and fruit and vegetable detection are greatly enhanced by the CBAM by focusing on pertinent regions of images.
Results: the proposed model integrate with the automated settlement system which transform the fruits and vegetable purchases by streamline identification and payment process. The Raspberry Pi, a microcontroller with a camera unit, makes up the suggested model to automate the billing system. For this study, we used a Raspberry Pi module to automatically acquire image data of fruits and vegetables.
Conclusions: the suggested approach is contrasted with the other traditional approaches. The result shows the suggested approaches outperformed in accuracy (0,93), MAE (0,11), and RMSE (0,53). The fruits and vegetables that are arranged for automatic weighing are captured by the camera module. The microprocessor receives as an input the cost of various products per kilogram automatically. Consequently, the Raspberry Pi automatically calculates and shows the overall lprice of the products on the monitor.

Keywords: Fruit and Vegetables; Freshness Recognition; Automatic Billing System; Raspberry Pi; Automatic Monitor; Cost; Garra Rufa Fish Optimized Multi-Objective Convolutional Neural Network (GRFO-MCNN).

RESUMEN

Introducción: los centros comerciales se han convertido en un aspecto necesario de la vida, especialmente para los habitantes de la ciudad. Para darse cuenta de la identificación y el establecimiento de frutas y verduras que carecen de códigos de barras es un problema importante en el autoservicio de supermercados de liquidación.
Método: en este estudio se propuso una nueva red neuronal convolucional multiobjetivo (GRFO-MCNN) para la detección y reconocimiento de frescura de frutas y verduras. Para mejorar el rendimiento de identificación de características, el GRFO-MCNN integra el CBAM, que consiste en la CAM y el SAM. El reconocimiento de frescura y la detección de frutas y verduras se ven mejorados por el CBAM, centrándose en las regiones pertinentes de las imágenes.
Resultados: el modelo propuesto se integra con el sistema de liquidación automatique transforma las compras de frutas y verduras mediante la agilidel proceso de identificación y pago. El Raspberry Pi, un microcontrolador con unidad de cámara, constituye el modelo propuesto para automatizar el sistema de

facturación. Para este estudio, se utilizó un módulo Raspberry Pi para adquirir automáticamente datos de imágenes de frutas y verduras.
Conclusiones: el enfoque sugerido se contrasta con los otros enfoques tradicionales. El resultado muestra que los enfoques sugerisuperaron en precisión (0,93), MAE (0,11), y RMSE (0,53). Las frutas y verduras que están dispuestas para un pesaje automático son capturadas por el módulo de cámara. El microprocesador recibe como una entrada el costo de varios productos por kilogramo automáticamente. En consecuencia, Raspberry Pi automáticamente calcula y muestra el precio total de los productos en el monitor.

Palabras clave: Frutas y Hortalizas; Reconocimiento de Frescura; Sistema de Facturación Automática; Raspberry Pi; Monitor Automático; Costo; Red Neuronal Convolucional Multiobjetivo (GRFO-MCNN).

INTRODUCTION

The fruit and vegetable self-billing system is an example of the modern trend that has been designed to solve the current need for effective management of procurement in the sphere of agriculture. This new system revolutionizes the procurement, invoicing, and management of fruits and vegetables in several ways for the suppliers and buyers.(1) In its simplest form, the automatic billing system empowers the farmers and producers help to develop direct self-billing for the products they are automatically selling, which excludes the intervention of third-party companies or the paper-based billing process.(2) Through the utilization of what may be regarded as modern resources like the Internet and digital invoicing tools, growers can record their produce, make stock checkups, and issue bills directly.(3) The self-billing aspect regarding fruits and vegetables is one of the best because it creates a strong buyer and supplier relationship that assures all the transactions being performed on the system.(4)

As every transaction gets recorded, both the buying as well as the selling side can look for the exact spot and ascertain the quantity, quality, and price of the product that has been sold. Such transparency must pay off not only in ending most conflicts but also in terms of making the right decisions for procurement and other future agreements.(5) Furthermore, the automatic billing system ensures fairness in product pricing and guarantees timely payments for farmers and producers. It simplifies the process, making it easier to ensure that payments are made promptly.(6)

Moreover, the self-billing system helps to improve accountability and quality in every link of thesupply chain. Computerized records that contain information that includes harvest date, batch number, and handling procedures are essential in pinpointing products that are behind complaints or recalls.(7) The research aims to design a self-billing system using fruit and vegetable detection, classification and freshness recognition, utilizing the Garra Rufa fish-optimized multi-objective convolutional neural network (GRFO-MCNN) along with Raspberry Pi technology.

The following categories apply to the remaining research: Related works are discussed in section 2. In section 3, we outline our proposed methodology. The results of our methods will be assessed in section 4. Section 5 presents a conclusion on the study's information.

By employing a DLNN technique, the study presented a novel, quicker, more accurate fruit retail invoicing system.(8) The system utilized strain meters load cells and clusters to classify fruits, and a Raspberry Pi chip was used for picture processing and weight calculation. That computes weight, total cost, and fruit type recognition automatically. An intelligent food recognition and payment system was presented in the article using computer vision technologies and the Cascade R-CNN algorithm.(9) Next, a handheld device was used to take images of food, and the food was identified using a depth neural network. An automated billing system that recognizes vegetables and fruits as well as subsequently shows the total bill was suggested in the study.(10) The main objectives of the project were to identify fruits, show those fruits, and then bill for these goods.Reducing the amount of time needed for the accounting system at bill counters was the primary goal of the study.(11) The product must be rescanned for those who want to remove an added item.

A lightweight CNN-based image classification technique was presented in the paper to improve the checkout procedure in shopping centers.(12) Various input characteristics were included in the CNN structure to improve classification accuracy. Research established a DL framework for classifying and identifying fruits.(13) The described system developed autonomous fruit identification using the supermarket's self-service system. A smart trolley constructed using IoT and including a modern billing system was presented in a research that not only makes shopping safer and easy but also helps shoppers avoid waiting in line.(14) The suggested system comprised a Raspberry Pi, an LCD, and a barcode scanner coupled to a smart trolley. A smart trolley concept was suggested in the study to address the COVID-19 billing counter time-wasting problem.(15) Customers and mall workers alike save time with RFID-enabled item scanning and purchase amount displays on an LCD. During the pandemic, social distance was ensured by creative methods. A novel strategy utilizing computer vision in conjunction with webcam connectivity and digital scales was proposed in the study.[16] The goal was to reduce the amount of human labor required to complete the billing procedure. Computer vision was utilized in checkout systems to scan fruits.

METHOD

The main processes included in the system are automatic weighing through load cell, detection, and classification of fruits and vegetables, along with freshness recognition. The microprocessor already has the cost per kg of every item entered to automatically calculate the total cost of the purchases. After that, the information per item will be sent to raspberry pi where it will perform the overall calculation of all the item. The total amount will be display on the screen and will also facilitate the automatic settlement.

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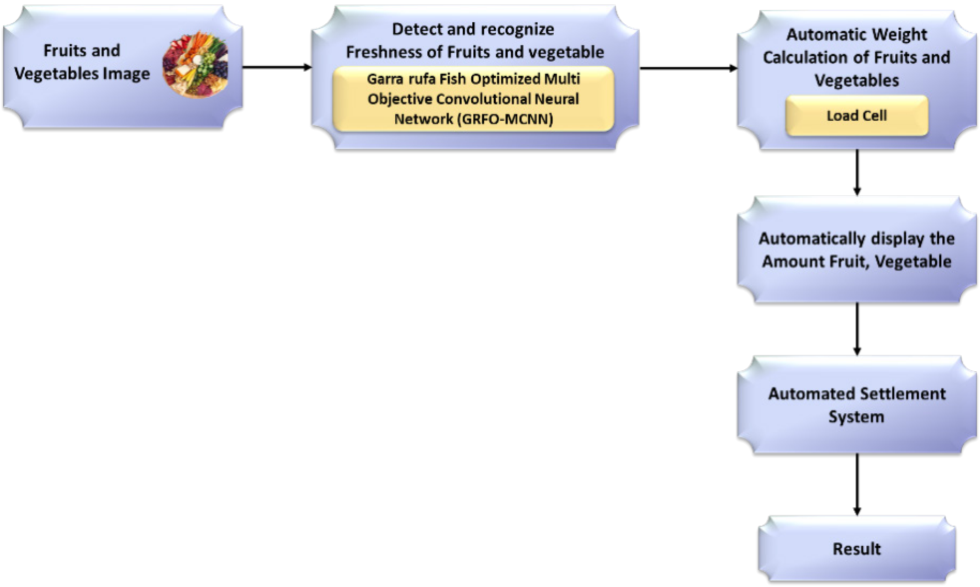

Figure 1. Automatic billing system process

The camera module records the freshness of fruits/vegetables that are placed on the tray beneath the load cell. The vegetable and fruit identification and freshness are also done by our proposedmethod with CBAM. The automatic weight of the items on the tray is determined using the load cell.

Fruit and Vegetable Image Collection

Various fruit and vegetable images,such as 200 images,were chosen for testing (20 %) and training (80 %). Some of the selected categories are apple, bell pepper, cauliflower, broccoli, carrot, orange, strawberry, and mango.Sample of fresh and rotten fruits and vegetables are shown in figure 2.

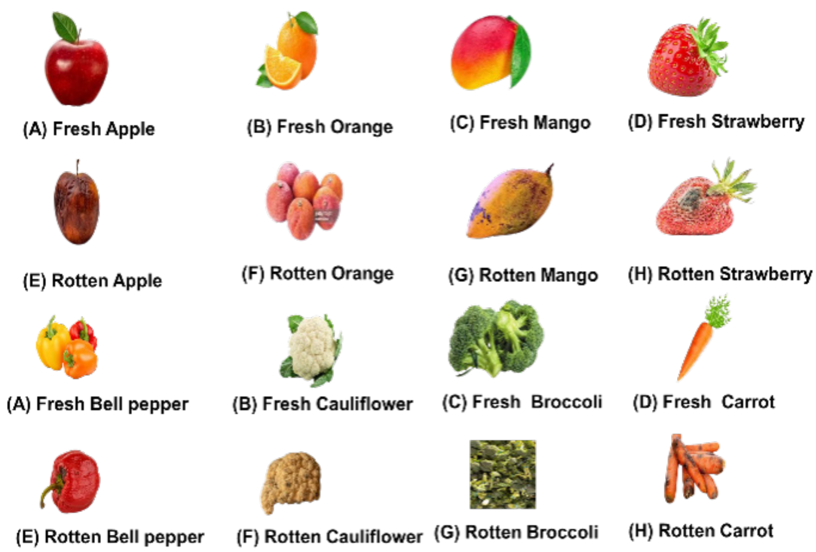

Figure 2. Sample of fresh and rotten fruits and vegetables

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Fruit and vegetable recognition

GRFO-MCNN: the proposed technique of utilizing Garrarufa fish's movement to optimize multiple objectives in Convolutional Neural Networks. It relies on the fish's swarming behavior to optimize CNN in multiple goals at once, providing great potential for future improvements of artificial intelligence.

Garrarufa fish optimization algorithm (GRF algorithm)

The optimization method finds the best approach to solve problems by applying mathematical concepts and algorithms. To begin, an objective function that is usually tied to many technical difficulties is defined. Next, a set of requirements and constraints that must be satisfied to attain the intended outcome are identified. The software can start the procedure of optimization, which entails using mathematical methods to determine the most efficient and effective value of the parameter to solve the problem once these have been determined. Because the method of optimization is iterative, resources will be allocated differently each time until the ideal solution is discovered. The three steps of the GRF process are follower'scrossover, leader'scrossover, and GRF initialization.

Initialization: each particle is divided into multiple groups, all of which have their own set of guidelines for both local and global ideal group placements. This is the basic idea of GRF. Starting hypotheses are also necessary for the GRF technique, such as the idea that every fish may behave as a guide or a follower based on the globally optimal location for each group. When the strong leader reaches the higher ideal score before the next iteration, some followers will migrate from the really weak leader to the stronger one. It is required to initially assume this maximum percentage of followers. The inertia weight ω and the velocity coefficients and must be assumed as additional beginning parameters.

$$number\ of\ followers = \frac{total\ particles - overall\ groups}{overall\ groups} \quad (1)$$

Crossover of leaders: there are two leader crossover procedures involved in the GRF technique that must be taken into account. In the first step, new leaders are chosen for each group, and in the second, the best leader who can guide the greatest number of followers is selected. These stages give this technique versatility by acting as principles of guidance that determine its essential components.

Crossover of followers: the flexible migration between the groups increases the probability of discovering the optimal solution in the issue space. The incredibly complex problems may mislead any optimization algorithms that are rigid when switching between different search areas. The high proportional equation order and multiple parameters in complex problems lead to this problem. Using the follower crossovers between the groups, GRF used a technique to keep looking into the issue's broader field space. Fish from each group will be randomly assigned to move toward the dominant leader first. Secondly, a single stride needs to be made toward every leader by determining the position W_{jand} velocity u_j using the conventional equations (2) and (3), respectively.

$$u_j(s+1) = \omega u_j(s) + d_1 q_1 \left(o_j(s) - W_j(s)\right) + d_2 q_2 \left(H_j(s) - W_j(s)\right) \quad (2)$$

$$W_j(s+1) = W_j(s) + u_j(s+1) \quad (3)$$

All followers and leaders will be included in the recalculated fitness function based on the group figures. The GRF method's new steps are represented by equations (4 and 5).

$$moving\ followers_j = integer\ (£ * random) \quad (4)$$

$$followers_{ji} = Max(\left(followers_{ji-1} - moving\ followers_j\right), 0) \quad (5)$$

The chance of a migrating fish is greatest at £.

Multi-objective Convolutional neural network (MCNN)

The deep learning technique utilized to solve intricate pattern identification and categorization issues with a large number of databases is a Multi-objective convolutional neural network. The four main layers of the model are convolution, max-pooling, fully connected, and output layer, which are stacked on top of each other. The adaptability of the architecture to change its configuration based on tasks related to outcomes makes it novel. Many tenable parameters are available, such as the learning rate and dropout rate, which are employed in complicated processing to address issues with pattern recognition and classification.

The proposed MCNN architecture, which we utilized to classify,is depicted in figure 3. The AlexNet architecture, which has six convolutional layers each, three max-pooling layers, ReLU, two dense or fully connected layers, and a final layer that serves as an output layer with a soft-max activation function, is the model's inspiration. In addition, CBAM is included in MCNN to improve its feature recognition performance. By concerning on relevant areas of images, which are essential for tasks like identifying the freshness of fruits and vegetables, CBAM is an attention machismo created to enhance CNNs.

The image is converted into an ID array using flatten that functions as a hidden layer, improving efficiency and simplifying data handling. While each max-pooling and convolutional layer has a 3x3 dimension, each input image and feature map has a different size. CNN is trained using either the BPA or SGD

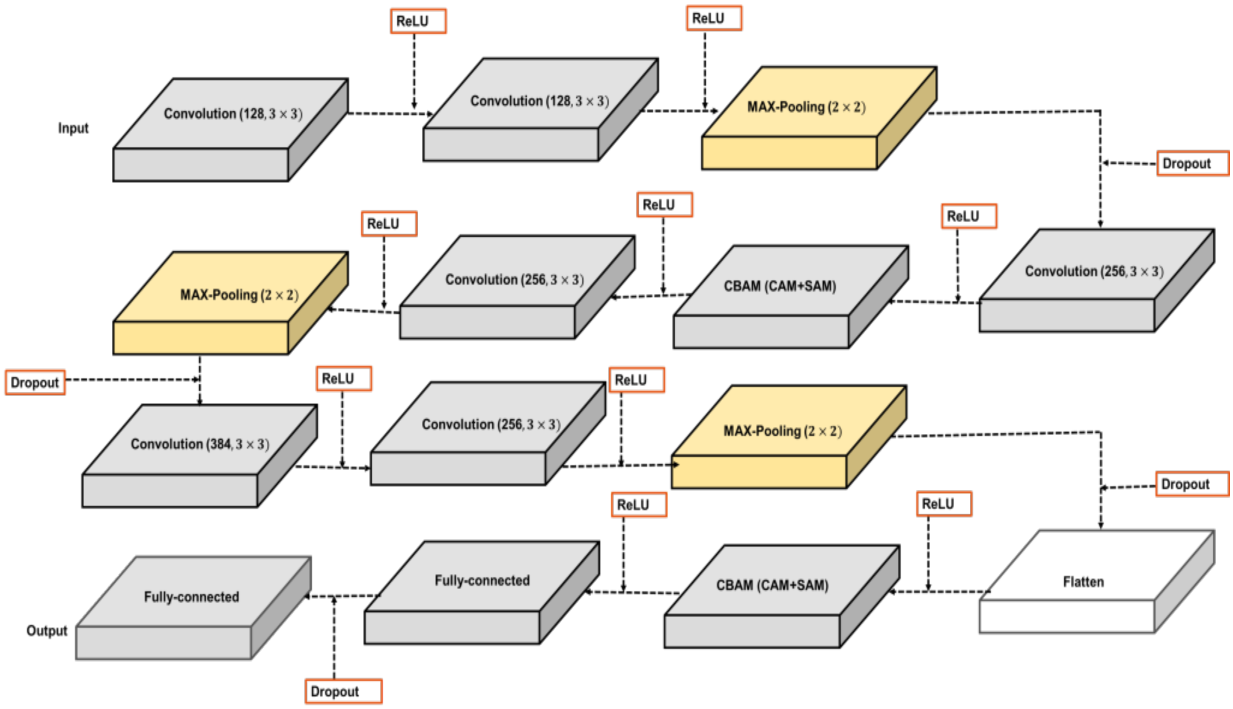

Figure 3. The architecture of the proposed MCNN

The weighted volume and the input volume are convolved. The input layer expands or contracts based on the spacing and outstripping. While the depth increases during the convolution process, the spatial height and width decrease. To model a more complicated target function that varies nonlinearly with the input, a function of nonlinear activation has been included for each layer. ReLU lessens the likelihood that a gradient may vanish. Additionally, this adds simplicity to the model. Pooling aids in lowering the activation function's spatial size and computational requirements. Because max pooling performs better and has a greater convergence rate, it is utilized more frequently.The max-pooling layer is used to down-sample the photos. It lessens the possibility of over-fitting as well. The last layer, known as the dense or completely linked layer, is in charge of classifying an image. The following are additional specifications for the suggested multilayer convolutional neural network:

The MCNN has undergone a major architectural improvement with the addition of the CBAM. The MCNN can highlight certain areas and features in images by using CBAM's dual attention mechanism, which consists of CAM and SAM.

CBAM integration with MCNN

Two consecutive modules, channel attention and spatial attention are used by CBAM to apply attention.

- Squeeze Operation: using global average pooling, aggregates feature data across spatial dimensions to provide a channel descriptor.

$$y_d = \frac{1}{G \times X} \sum_{j=1}^{G} \sum_{i=1}^{X} E(j, i, d) \qquad (6)$$

- Excitation Operation: by using a neural network and sigmoid activation, this method computes attention weights per channel based on the channel attribute.

$$b_d = \sigma\left(X_1\left(\delta(X_o y)\right)\right) \qquad (7)$$

- Recalibration: applying these attention weights to the initial feature map.

$$E_d = b_d \odot E \qquad (8)$$

MCNN continuously refines the features it represents by using CBAM before activation functions, batch normalization, and convolutional layers. By doing this, the network is better able to concentrate on pertinent features of the input images, which improves its capacity to handle complex pattern recognition and classification tasks with large datasets. All things considered, CBAM's incorporation into MCNN highlights how versatile and successful it is in enhancing the network's performance in a range of challenging image identification applications.

The method converts regular-sized images into a set of aspects for additional analysis. It makes use of max pooling, the ReLU activation function, and convolutional layers with 128 to 256 features to minimize the size of the images, the layers includefeature extraction and dropout which are flattened supplementary convolutional layers. These Two thick layers with ReLU activation are used for feature extraction. The accuracy of the model is then assessed using a final output that has softMax activation.

Usage of fruit and vegetables recognition and freshness detection

The MCNN model is specially made for achieving two goals

Vegetables and fruits detection: The model was determined if an image consist of fruits or vegetables by applying a classification algorithm. This involves both the pooling layer and convolutional layer to identify the unique features of vegetables and fruits.

Freshness recognition: the model assesses the fruits and vegetables' freshness one more time. The use of CBAM enhances the MNCC's ability to accurately determine the freshness level by enabling it to concentrate on significant aspects of the images that indicate freshness, as well as color, and texture.

The MCNN model successfully handles the challenging tasks of identifying and categorization fruits and vegetables as well as their freshness by utilizing the sophisticated architecture and the CBAM attention mechanisms.

Garrarufa fish optimized multi-objective Convolutional neural network (GRFO-MCNN)

The proposed method to enhance the Fruit and Vegetable Self-Billing System is the GRFO-MCNN this new approach combines the deep learning model of the Convolutional Neural Network (CNN) with the biologically inspired optimization technique that was originally inspired by the movements of GarraRufa fish to handle many problems simultaneously. The GRFO-MCNN technique, which makes use of the grazing mechanism of Garrarufa fish, is essentially an improvement on the CNN network's architecture.

The model imitates the random and adversarial movement of these fish, and through its movement, it carries out exploitation and diversification in the solution space while retaining the best solutions for numerous objectives. This was accomplished by CNN's ability to process images efficiently, a feature that would come in handy for identifying different kinds of vegetables and fruits in the context of this system's billing. These layers allow the network to extract details from input images in a way that facilitates accurate classification and identification of the type of produce.

The GRFO-MCNN further incorporates the CBAM, which is made up of the Spatial Attention Module (SAM) and the CAM. Through the use of relevant areas inside images, the CBAM greatly improves fruit and vegetable detection as well as freshness recognition. By merging biological and artificial notions, this integration enhances the system's accuracy and speed of reaction, making it an effective solution. The GRFO-MCNN advances fruit and vegetable self-billing closer to complete automation and smooth integration into current processes by combining these adaptive features. This establishes a fresh standard for a more accurate and automated retail experience.

The Load cell

In this study, the load cell was used to automatically calculate the weights of the fruits and vegetables. An applied force, such as strain, pressure, shrinkage, or power, is converted into a measured electrical signal by the load cell, also known as a transducer. Different types of load cells exist. Receptive load cells are devices that rely on the concept of piezo-electricity, whereas capacitive load cells operate based on variations in capacitance.

Several strain gauges are fastened to resistive load cells via an elastic member. The load cell used in this work has four strain gauges attached to it, one on top of the other. When a force is applied, the elastic component deforms, which causes strain to occur when the force is applied to the load cell. Consequently, this causes two of the gauges that measure strain to be in compression and the other two to be in tension. The load cell's change in resistance is translated into the equivalent voltage using a Wheatstone bridge.

Automatic Calculation of total amount

Following the prediction of the fruit class, our model automatically reads the weight procedures receives its weight as inputs, and automatically computes the weight per kilogram. After classifying, recognizing freshness, and automatically weighing all fruits, and vegetables, add collectively all the costs to calculate the total cost automatically.

Automatic settlement system

The entire procedureof buyingvegetables and fruits is automated by the GRFO-MCNN model's automatic settlement mechanism. The first step involves using a Raspberry Pi module that has a camera attached to it to take pictures of vegetables placed on a scale. The GRFO-MCNN algorithm processes these photos and uses sophisticated computer vision to determine the type of produce and rate its freshness.

The product is simultaneously weighed using an electronic weighing scale, and the weight reading is processed by a computer to compute the overall cost by utilizing previously saved pricing data. For client confirmation, this pricing information is shown in real-time on a monitor. The system makes it easy for users to complete purchases by supporting a variety of payment methods, including credit cards and digital wallets.

Faster transactions and fewer price mistakes lead to higher efficiency. Several payment methods and a streamlined shopping process without the requirement for manual item labeling further improve client convenience. Overall, the automated settlement system is a cutting-edge strategy for raising customer satisfaction and operational effectiveness in retail environments.

RESULTS

To evaluate our proposed method performance, utilize some evaluation metrics, such as accuracy, MAE, and RMSE. Compared with some existing approaches such as MobileNetV2 (SSDLite), EfficientDet D0, EfficientDet D1, EfficientDet D2, Hybrid EfficientNet B0, Hybrid EfficientNet B1, and Hybrid EfficientNet B2.[17]

Experimental setup

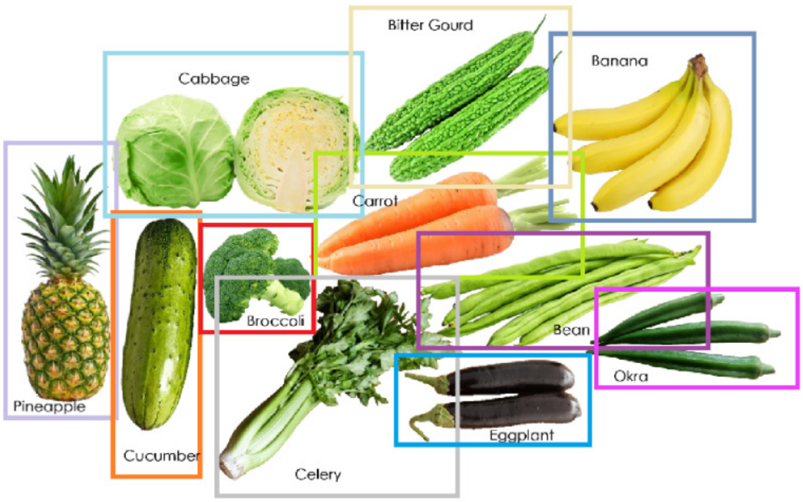

Figure 4. Detection of Fruits/vegetables recognition

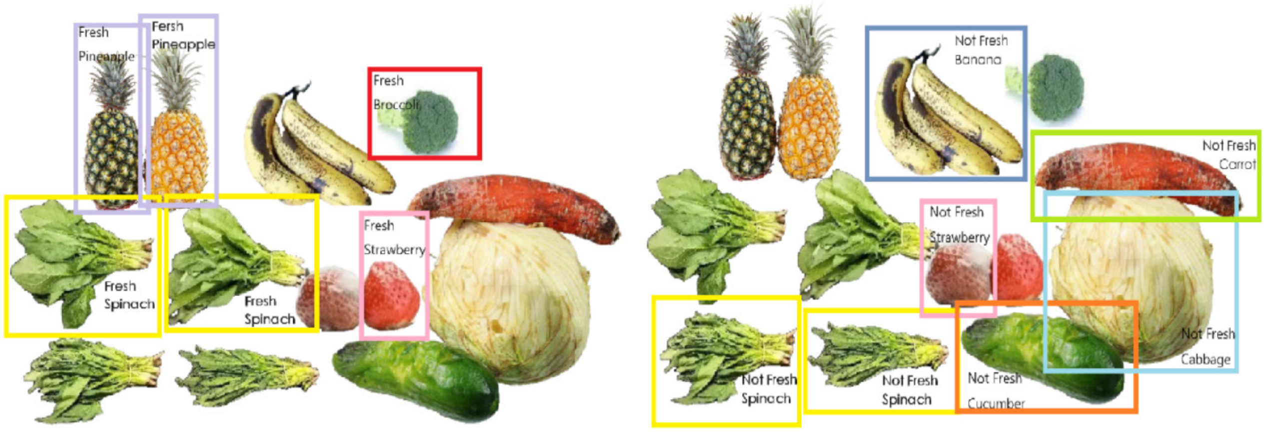

Figure 5. Recognition of Fruits/vegetables freshness(rotten/fresh)

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The Raspberry Pi is programmed using the Raspbian programming language. GRFO-MCNN is created with common Python libraries. The load cell that is connected to the board is used to automatically weigh the fruit. Once the inputs are acquired, the overall amount is computed automatically.Fruits/vegetablefreshness recognition and detection are presented in figure 4.Our proposed methodis effective in detection andrecognition of fruit and vegetable freshness which is shown in figure 4-5.

Every time the market rate changes, the price of the fruits and vegetables is updated automatically regularly. Table 1 displays the outcomes of theautomatic price detection of Fruits/vegetables recognition.

Table 1. The outcome of automatic price detection offruit and vegetable recognition

Product	Price P/kg	Weight (kg/g)	Price of the Product
Apple	120	2kg	240
Mango	90	2kg	180
Orange	80	3kg	240
Strawberry	160	500g	80
Broccoli	110	1kg	110
Carrot	70	500g	35
Bell Pepper	80	500g	40
Cauliflower	60	1kg	60
Total price			985

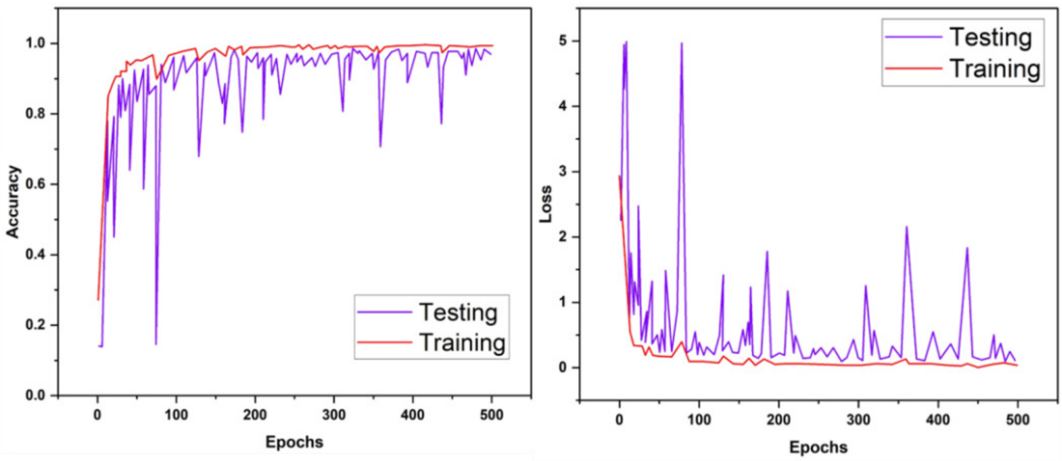

Figure 6. Result of accuracy and loss

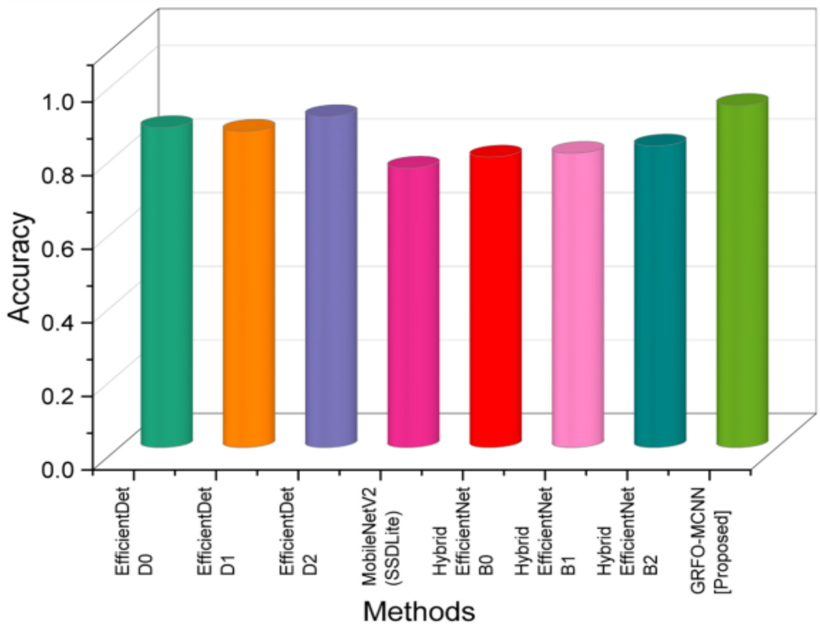

Figure 7. Result of Accuracy

The degree of precision between the estimated and actual values in the model is known as prediction accuracy. An accurate and safe forecast is indicated by a highly accurate prediction rate of the model. The difference between the expected and actual outcomes is measured as a loss. It calculates the inaccurateness of the model. The model can produce more precise forecasts by minimizing loss by employing a predefined metric. Figure 6 shows the accuracy and loss results.

Accuracy calculates the percentage of accurate fruit andvegetable detection and freshness recognition. It is computed as the fraction of accurate forecasts to all forecasts. Figure 7 illustrates the result of accuracy. Existing methods such as MobileNetV2 (SSDLite), EfficientDet D0, EfficientDet D1, EfficientDet D2, Hybrid EfficientNet B0, Hybrid EfficientNet B1, and Hybrid EfficientNet B2 obtained accuracy rates of 0,76, 0,87, 0,86, 0,90, 0,79, 0,80, and 0,82, correspondingly. The proposed GRFO-MCNN method obtained an accuracy value of (0,93). It demonstrates that the performance of our suggested method is superior to that of existing methods.

The average number of errors in fruit andvegetable detection and freshness recognitionis represented by MAE. It is calculated by taking the mean of the absolute deviations between the values that were expected and those that occurred. Figure 8 illustrates the result of MAE. Existing methods such as MobileNetV2 (SSDLite), EfficientDet D0, EfficientDet D1, EfficientDet D2, Hybrid EfficientNet B0, Hybrid EfficientNet B1, and Hybrid EfficientNet B2 obtained MAE rates of 0,39, 0,20, 0,20, 0,16, 0,32, 0,30, and 0,288, correspondingly. The proposed GRFO-MCNNmethod obtains an MAEscore of (0,11). It demonstrates how our suggested approach outperforms the existing methods.

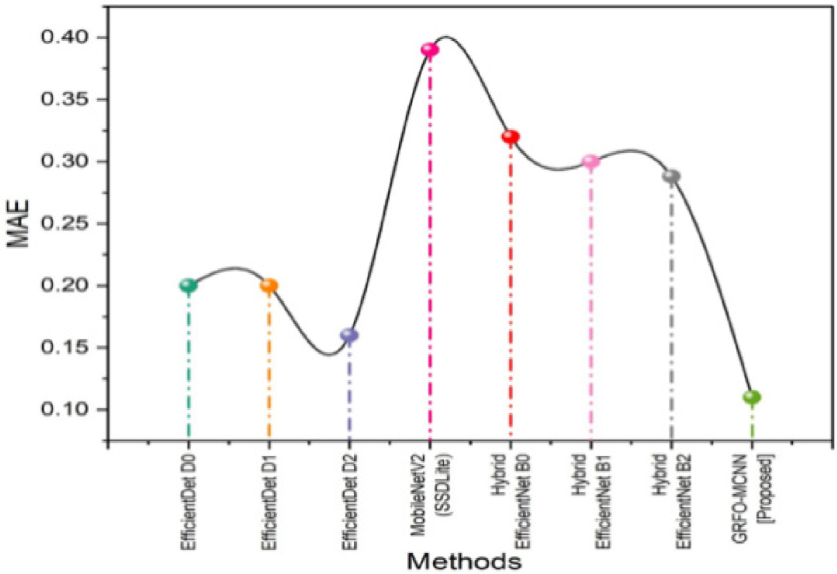

Figure 8. Result of MAE

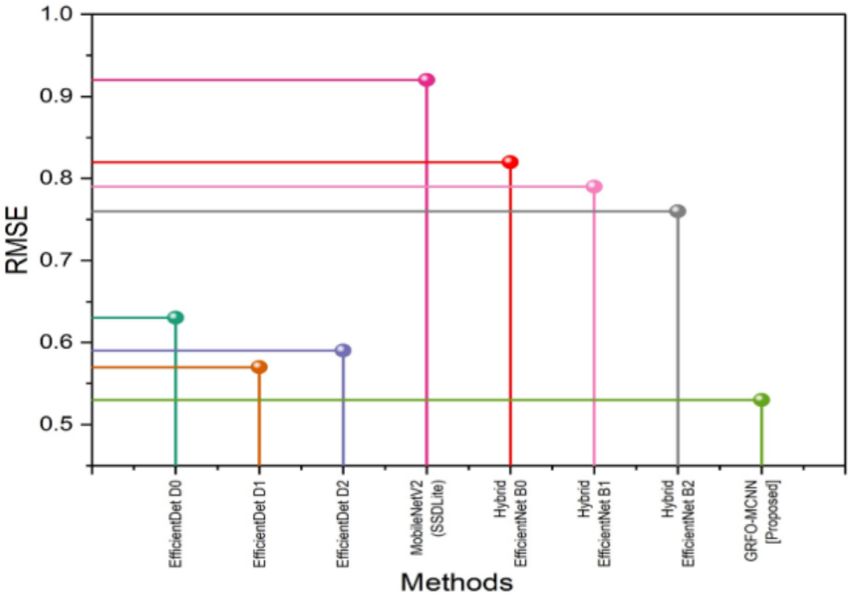

Figure 9. Result of RMSE

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When predictingfruit andvegetable detection and freshness recognition, RMSE is utilized to highlight accuracy, especially for greater errors. It is computed by taking the average of the squared differences and square rooting it. Figure 9 presents the result of RMSE. Existing methods such as MobileNetV2 (SSDLite), EfficientDet D0, EfficientDet D1, EfficientDet D2, Hybrid EfficientNet B0, Hybrid EfficientNet B1, and Hybrid EfficientNet B2 obtained RMSE rates of 0,92, 0,63, 0,57, 0,59, 0,82, 0,79, and 0,76, in that order. The proposedGRFO-MCNN method obtains an RMSEvalue of (0,53). It demonstrates how our suggested approach outperforms the existing methods. Table 2 presents the results of all measures.

Table 2. Result of all measures

Efficient Det			MobileNetV2 (SSDLite)	Hybrid EfficientNet			GRFO-MCNN [Proposed]
D0	D1	D2		B0	B1	B2	
Accuracy							
0,87	0,86	0,90	0,76	0,79	0,80	0,82	0,93
MAE							
0,20	0,20	0,16	0,39	0,32	0,30	0,288	0,11
RMSE							
0,63	0,57	0,59	0,92	0,82	0,79	0,76	0,53

CONCLUSIONS

Self-billing on fruit andvegetables makes them take charge of their automaticweighing thus improving the overall checkout procedures in supermarkets. Therefore, our study proposes a new solution, the GarraRufaFish-Optimized Multi-objective Convolutional Neural Network (GRFO-MCNN) designed specifically for the self-billing process of fruits and vegetables in shopping centers.Especially, Multi-objective Convolutional Neural Network (MCNN) to detect fruits and vegetables and also integration of CBAM into the MCNN to recognize the freshness of the fruits and vegetables.The suggested model incorporate with the computerized settlement systemwhich transform the fruits and vegetable purchases by update identification and payment process.Our technique of capturing the images produced with the help of Raspberry Pi technology outperforms the existing algorithms in terms of efficiency parameters. It is recommended that cost data per kilogram be integrated to allow for easy computation and presentation of total prices thus making the shopping experience very appealing to the consumers and also more favorable to the retailers. Experimental result shows our proposed method attained accuracy (0,93), MAE (0,11), and RMSE (0,53), rates compared with existing methods. The self-billing system of GRFO-MCNN for Fruit and Vegetables faces challenges on scalability due to complexity in computation. Future research could involve improving the real-time processing system and incorporating environmental variables into the system for improved functioning in automated billing systems.

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