Barcode-less fruits classification using deep learning

Alaa Sheta[1], Abdel Karim Baareh[2], Amal Abdel-Raouf[1], Peter Rausch[3]
[1]Department of Computer Science, Southern Connecticut State University, New Haven, USA
[2]Department Computer Science, Information Technology College, Isra University, Amman, Jordan
[3]Department Computer Science, Nuremberg Institute of Technology Georg Simon Ohm, Nuremberg, Germany

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ABSTRACT

Barcode-less fruit recognition technology has revolutionized checkout by eliminating manual barcode scanning. This technology automatically identifies and adds fruit items to the purchase list, significantly reducing waiting times at the cash register. Faster checkouts enhance customer convenience and optimize operational efficiency for retailers. Adding barcodes to fruits requires adhesives on the fruit surface that may cause health hazards. Leveraging deep learning techniques for barcode-less fruit recognition brings valuable advantages to industries, including advanced automation, enhanced accuracy, and increased efficiency. These benefits translate into improved productivity, cost reduction, and superior quality control. This research provides our initial idea of developing a convolutional neural network (CNN) designed specifically for automatic fruit recognition, even in challenging real-world scenarios. The proposed method assists fruit sellers in accurately identifying and distinguishing between different types of fruit that may exhibit similarities. A dataset with 44,406 images of different fruit types is used to train and test our technique. Employing a CNN, the developed model achieves an impressive classification accuracy of 97.4% during the training phase and 88.6% during the testing phase, respectively, showcasing its effectiveness in precise fruit recognition.

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Corresponding Author:

Amal Abdel-Raouf
Department of Computer Science, Southern Connecticut State University
New Haven, CT, USA
Email: abdelraoufa1@southernct.edu

1. INTRODUCTION

Barcode scanning streamlines the checkout process for most products in retail stores. Nowadays, barcodes are utilized everywhere. During checkout in the supermarket, customers scan barcodes to purchase various products. A barcode is a readable code with encoded numbers or patterns of lines and spaces. This sequence together is unique for a product. Barcodes are attached to products to specify essential information about an item. This information is commonly accessed from an inventory database. Scanning barcodes can speedily get data about a product, such as the value, make, or description. There are several types of barcodes, either one or two dimensions. A 1-dimensional (1D) barcode, sometimes called a linear barcode, can store text information of up to 20 characters. A 2-dimensional (2D) barcode can be presented using various shapes such as rectangles, hexagons, and other geometric patterns. They are named matrix codes. 2D barcodes can store larger datasets of up to about 2,000 characters. 2D barcodes are relatively more secure than 1D barcodes because they allow data encryption. Scanning fruits and vegetables presents a unique challenge, requiring manual identification and searching within the system.

There are two primary classification problems: i) distinguishing between various fruit types, such as apples and oranges, and ii) classifying fruits of the same type (e.g., various apples). Exact classification is difficult due to variations in the fruit's form, color, and various factors. Additionally, fruits can be enclosed in plastic bags, adding another layer of complexity.

In today's age, barcode technology remains extensively used in fruit stores and superstores to acquire fruit prices and essential information, such as tracing the source of a product. One significant advantage of barcode scanning technology is its reasonably low cost compared to other technologies. Barcode scanning is implemented using scanners, which are relatively low-cost and easy to sustain. This technology also allows stores to easily access their inventory database to check the status and availability of any item, so it helps minimize cost and effort in managing and planning reserves.

Machine learning has gained extensive attention, mainly algorithms focused on object detection and recognition [1]. Typically, fruit stores and supermarkets package fruits and vegetables in small boxes and utilize barcodes to determine their prices [2], [3]. Nevertheless, many customers still prefer the hands-on experience of selecting fruits rather than prepackaged alternatives. Huo *et al.* [1] provided a method to improve the accuracy of QR image code recognition by proposing an enhanced adaptive median filter algorithm and QR code distortion correction technique based on artificial neural networks. The proposed method compares the distorted QR images and their pattern. This method shows significance in QR code recognition. Barcode-less fruit recognition technology helps achieve threefold: i) it advances a customer's shopping experience by allowing no-bar code scanning. Therefore, the purchase process becomes much more accessible by only recognizing the fruit or vegetables by camera, ii) the purchase process becomes faster, thus helping minimize the customer's wait time and enhance customer experience, and iii) minimize the loss of items, intentional or unintentional.

Deep learning models can extract the best features that describe an object from many images and recognize or classify many objects in these images [4], [5]. Deep learning was also utilized in disease diagnosis, such as sleep apnea, with promising results [6], [7]. CNN was successfully used in image classification for fruit and vegetable recognition [8]. Aranda *et al.* [9] developed a CNN with a few layers to achieve this task so that the checkout process at the supermarket is quick and straightforward. Innovative technology in fruit recognition offers numerous advantages in various applications [10], [11]. Firstly, enables efficient fruit detection and classification, facilitating automation and streamlining processes in the agricultural industry. With smart devices equipped with advanced sensors and imaging capabilities, fruits can be accurately recognized and categorized based on features such as shape, color, size, and texture. This technology brings benefits to both farmers and consumers. Farmers can leverage fruit recognition to optimize harvesting operations, ensuring that only ripe and high-quality fruits are picked, thereby reducing waste and maximizing productivity. In earlier research, scientists proposed various methods merging computer vision and machine learning to manually extract features from fruits and classify them based on these computer vision features [2], [12]. These methods employed computer vision algorithms to analyze fruits' color, shape, size, and texture characteristics, which can be used as input for classification algorithms. Many of these approaches involved preprocessing or feature extraction using computer vision techniques and applying different classifiers. However, these classifiers often needed more robustness across all types of fruits, leading to higher misclassification rates.

Although barcode scanning technology does have many advantages, it was found that it still has several drawbacks. For example, barcode scanners are not free of charge, particularly in big stores where we need many machines that might encounter malfunctions. This technology can not avoid human error. Human workers can still make mistakes while scanning the product. Errors in providing product information might cause both inventory errors and customer disappointment. Moreover, this dependence on barcodes presents a significant challenge for shopkeepers who must remember and manage the barcodes associated with each fruit category [13], [14]. One important issue related to barcodes is that, in many cases, the adhesives used on the barcode stickers might contain harmful chemicals that could affect human health [15]. The skin of fruits and vegetables might absorb the substances in adhesives. Therefore, it is mandatory to investigate more about the adhesives utilized for barcode stickers. A wide variety of chemicals are utilized in the manufacture of adhesives. Adhesives might have harmful chemicals that affect customer's health. An important question arises: can we invest in barcode-less item recognition technology?

Our proposed work includes the development of a barcode-less fruit recognition model based on CNN. The proposed model was trained on a large data set of images containing 15 different fruits and vegetables. We designed our CNN model with limited complexity and a limited number of layers. The images in our database were resized to 64×64 pixels. Each class had a maximum of 100 images. The study reports the challenge of correctly recognizing the characteristics of fruits and vegetables with a barcode-based method. The basic idea of recognizing fruits or goods without barcodes can be presented in Figure 1.

Figure 1. Barcode less recognition system [16]

2. METHOD

Deep learning is a subdivision of artificial intelligence (AI). Deep learning is a standard extension of the well-known artificial neural network model. It can learn from various data types, including images, texts, and numerical data. It has the credit of being the reason for the success of various achievements in the AI domain, such as natural language processing, self-driving cars, and many others. Deep learning is one of the potent techniques that has been successfully used for detection, recognition, and classification in many real-life applications [17], [18]. Each layer comprises multiple neural nodes with activation functions connected to nodes in preceding and subsequent layers.

During training, the parameters of the neural network are adjusted to best fit the available data. With sufficient training, deep neural network models can achieve remarkable pattern recognition capabilities comparable to or surpassing human-level performance. Deep learning has been successfully used in significant applications such as troop camouflage detection [19], automated COVID-19 detection per x-ray chest images [20], biomedical applications [21], computer vision [22], improving computational chemistry and drug design [23], addressing safety issues in the interface between pedestrians and autonomous vehicles [24], and classifying alzheimer's disease [25]. The typical structure of CNNs comprises the following layer types:

- Convolutional layers: these layers apply a set of learnable filters (kernels) to the input image, extracting features by convolutions. Each filter detects specific patterns or features in the image, such as edges or textures. Convolutional layers help to capture spatial hierarchies and local patterns in the data.
- Pooling layers: these layers are utilized in neural networks to decrease the input's spatial dimensions (width and height) through downsampling. There are several types of pooling in CNN. They include max, min, and average pooling. The pooling technique helps reduce the features' complexity from one layer to another. It also helps reduce overfitting and the model sensitivity to changes in the input. Pooling also causes downsampling, which allows the CNN model to pay more attention to significant features of the input images. Mainly, pooling helps maintain the most relevant features while reducing the input's spatial size.
- Batch normalization layers: this layer is responsible for reducing the possible overfitting and making the model better generalized. It makes the model less sensitive to variations in the initial random weight and hybrid parameters adopted for training it.
- Activation layers: several possible activation functions have been utilized in the literature. The rectified linear unit (ReLU) is the most adopted function in CNNs. The ReLU function produces zeros for negative values while keeping positive values unchanged.
- Fully connected layers: these layers, also recognized as dense layers, show a central role in deep neural networks. These layers establish connections between every neuron in one layer and the subsequent layer. They contribute to the classification process by leveraging the extracted features to make predictions. In classification tasks, the neurons in the final fully connected layer align with the given output classes, enabling the network to assign class labels to the input data.

These layers are stacked together to form the architecture of a CNN. The input flows through the convolutional, pooling, and activation layers to extract features and progressively reduce the spatial dimensions. After flattening the developed feature maps, they are advanced through fully connected layers for some applications (i.e., classification). Designing the appropriate architecture for a CNN within a deep learning context necessitates a blend of domain expertise, experimental exploration, and adherence to established methodologies.

Our proposed approach introduces a simple and efficient CNN framework comprising 16 layers (see Figure 2). The adopted CNN architecture design for fruit detection is provided in Table 1. In our specific scenario, we focus on constructing a streamlined architecture that optimizes computational efficiency while upholding a commendable level of classification accuracy. Notably, indiscriminate augmentation of layers can often lead to overfitting the data. In our pursuit, however, we managed to strike a harmonious equilibrium, attaining a satisfactory classification performance across the training and testing stages. Furthermore, we bound the inherent characteristics of original color images with dimensions of 64×64×3. This choice of resolution affords us the advantage of constraining the complexity of the CNN architecture, consequently enhancing its efficiency. This framework permits the network to learn the best features from a large dataset of input images without preprocessing. To evaluate the performance of our proposed network, we implement experiments using an image dataset incorporating diverse real-world scenarios, described in the following section.

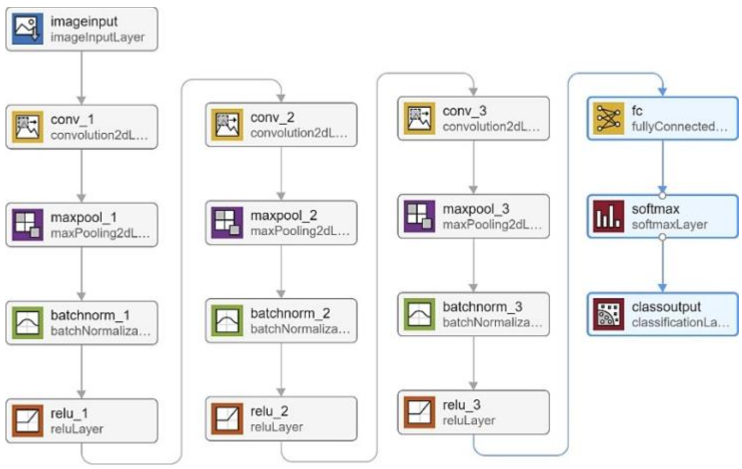


Figure 2. Proposed CNN architecture

Table 1. Proposed CNN network architecture developed using MATLAB

No.	Name	Description
1	imageinput	Image Input: 64×64×3 images with' zerocenter' normalization
2	conv 1	Convolution: 8 3×3×3 convolutions, stride [1, 1], padding' same'
3	maxpool 1_	Max Pooling: 2×2, stride [2, 2], padding [0, 0, 0, 0]
4	batchnorm 1_	Batch Normalization: 8 channels
5	relu 1_	ReLU: Rectified Linear Unit activation
6	conv 2	Convolution: 16 3×3×8 convolutions, stride [1, 1], padding' same'
7	maxpool 2_	Max Pooling: 2×2, stride [2, 2], padding [0, 0, 0, 0]
8	batchnorm 2_	Batch Normalization: 16 channels
9	relu 2_	ReLU: Rectified Linear Unit activation
10	conv 3	Convolution: 32 3×3×16 convolutions, stride [1, 1], padding' same'
11	maxpool 3_	Max Pooling: 2×2, stride [2, 2], padding [0, 0, 0, 0]
12	batchnorm 3_	Batch Normalization: 32 channels
13	relu 3_	ReLU: Rectified Linear Unit activation
14	fc	Fully Connected: 15 fully connected layer
15	softmax	Softmax: Softmax activation
16	classoutput	Classification Output: Crossentropy with' Apple' and 14 other classes

3. DATASET

In this research, we employed a database compiled by Hussain *et al.* [26]. The database comprises a total of 44,406 fruit images that were gathered over a span of 6 months. These images were captured in a controlled laboratory environment. They encompassed various scenarios and diverse lighting conditions, including fluorescent lighting, natural light shadows, sunshine, pose variations, illumination variations, camera-capturing artifacts, specular reflection shading, and shades. The images were captured on a transparent background using an HD Logitech web camera with a 320×258 pixels resolution. The dataset, as presented in [26] consists of multiple fruit classes, such as apple, banana, carambola, guava, kiwi, mango, muskmelon, orange, peach, pear, persimmon, pitaya, plum, pomegranate, and tomato. A sample of the adopted dataset is shown in Figure 3. To determine calibration, all images were resized to a resolution of 64×64 pixels. Each class had a maximum of 100 images.

Figure 3. Sample of the fruits [25]

4. RESULTS AND DISCUSSION

To assess the performance of our model, we employ the accuracy metric, which gauges the ratio of correct predictions to the total predictions made during each phase. In our experiments, we achieved a training accuracy of 97.4% and a testing accuracy of 88.6%. These accuracy metrics provide insights into the model's performance on the training and testing datasets. The high training accuracy of 97.4% indicates that the model has effectively learned to make accurate predictions on the training data. This suggests that the model has successfully captured the underlying patterns and features within the training dataset. On the contrary, the testing accuracy of 88.6% demonstrates the model's ability to generalize its predictions to previously unseen data. Although the testing accuracy is slightly lower than the training accuracy, it still showcases the model's competence in handling new data effectively. For a visual representation of the model's learning process, please refer to Figure 4 which illustrates the convergence curves for both loss and accuracy. Figures 5(a) and (b) provides a confusion chart for training and testing cases. These visualizations affirm that the model has learned to generalize effectively and can accurately predict new, unseen examples.

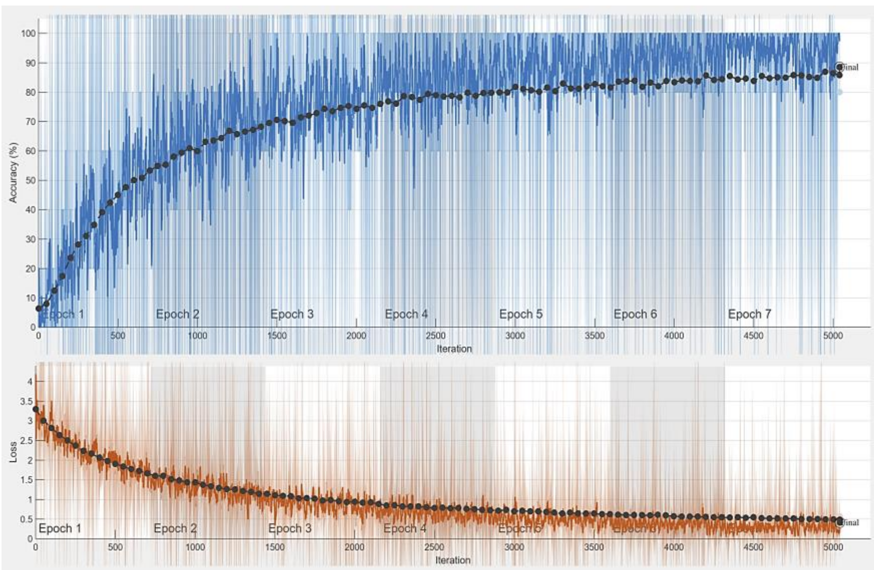
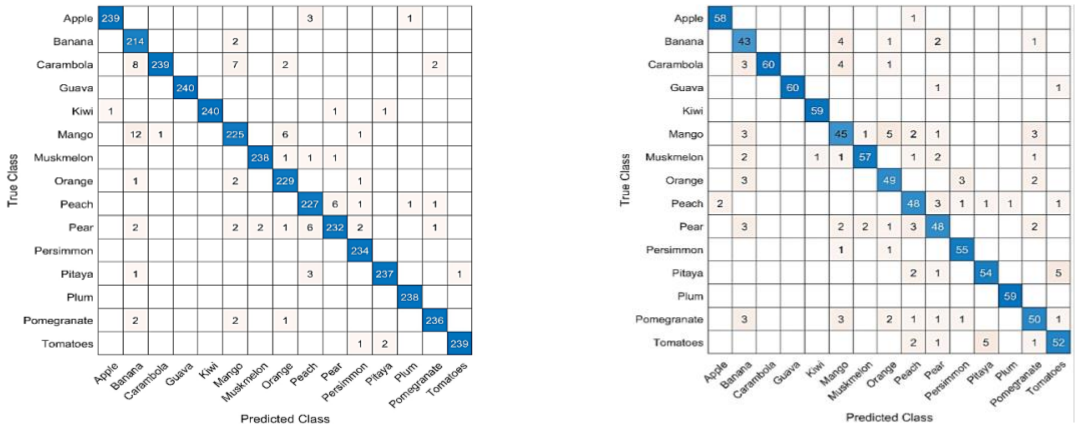


Figure 4. Accuracy and loss curves after training the proposed CNN



(a) (b)

Figure 5. The confusion chart of (a) training and (b) testing cases

5. CONCLUSION

This research designed a CNN model with 16 hidden layers to recognize 15 fruits and vegetables. Scanning fruits and vegetables presents a challenge, demanding manual work by employees to pick up the correct item in a database. The proposed model can distinguish between similar fruits in sizes and shapes. Our data set had 44,406 images of various fruit types utilized for model development. The performance of the developed CNN model was 97.4% and 88.6% at both the training and testing phases, respectively. This application of deep Learning can help enhance market productivity, reduce the need for workers with unique skills, and allow better quality control. This model could be deployed on mobile phones for possible use at supermarkets.

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BIOGRAPHIES OF AUTHORS

Alaa Sheta obtained his Ph.D. of Information Technology from George Mason University, Virginia, U.S.A. in 1997. Prior to that, he earned his B.E. and M.Sc. degrees in Electronics and Communication Engineering from Cairo University, Egypt in 1988 and 1994, respectively. Currently, he holds a tenured professorship at the Department of Computer Science in Southern Connecticut State University in New Haven, Connecticut, USA. His research interests span various areas including deep Learning, meta-heuristics, machine learning, data mining, image processing, and robotics. He has made significant contributions to these fields, publishing more than 170 papers in esteemed international journals and conferences. In addition to his scholarly achievements, he has actively participated in various capacities such as serving as a chair, guest editor, and program committee member for numerous international events. He can be contacted at email: shetaa1@southernct.edu.

Abdel Karim Baareh holds a Doctor of Informatics/Artificial Intelligence degree from Damascus University, Syria, which he earned in 2009. He also completed his B.Sc. and M.C.A (Computer Application) degrees from Mysore and Bangalore University, India, in 1992 and 1999, respectively. Currently, he is on sabbatical leave and affiliated with the Department of Data Science and Artificial Intelligence at the Information Technology College, Isra University in Jordan. He holds a permanent professorial position within the Department of Computer Science at Al-Balqa Applied University, Jordan. His extensive research portfolio spans various domains, including metaheuristics, global optimization, machine learning, data mining, bioinformatics, graph theory, and parallel programming. Over the years, he has contributed significantly to his field, with a publication record that boasts over 35 papers in international journals and conferences. He can be contacted at email: baareh@bau.edu.jo or baareh@gmail.com.

Amal Abdel-Raouf received her M.Sc. in Computer Engineering from Cairo University in 1994 and her Ph.D. in Computer Science and Engineering in June 2005 from the University of Connecticut, United States. She is currently a professor at the Department of Computer Science, Southern Connecticut State University, CT, United States. She is the author of many papers in journals and international conferences in the field of software engineering. She has worked as a technical commit- tee member and a reviewer of many journals, international conferences, and workshops. Her research interests include big data, software engineering, software quality, real time systems, parallel and distributed computing, object-oriented systems, and artificial intelligence. She can be contacted at email: abdelraoufa1@southernct.edu.

Peter Rausch is a professor of Information Systems at the Nuremberg Institute of Technology-George Simon Ohm, with an extensive publication record comprising numerous papers, articles, and book chapters. Notably, he recently authored a book on performance management and business intelligence. His ongoing research endeavors are centered on fuzzy technologies, business planning, and process automation. His academic journey includes earning a Ph.D. in business administration from Frankfurt University and several years of professional experience in software development, business process optimization, and consulting. In a previous role as a program manager, he led process and tool management within the Department of Sales Support at Sun Microsystems, Germany. Subsequently, he took charge of an integration environment as part of an industry solution at a software company. His academic career continued as a professor of Information Systems at Coburg University of Applied Sciences before he accepted an offer in 2008 to become a professor of Information Systems at the Technische Hochschule Nürnberg-Georg Simon Ohm. He can be contacted at email: perausch@prof-rausch.de.