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Machine Learning-Driven Solutions for Accurate Vegetable Classification in Online Retail

M Varaprasad Rao[1], Dr. T. Venkata Ramana[2], Dr.Banoth Samya[3], Dr. Srikanth Lakumarapu[3]

[1]Department of CSE(Data Science),CVR College of Engineering, Hyderabad, India.
varam78@gmail.com

[2]Associate Professor, Department of CSE (AIML), CVR College of Engineering, Hyderabad, India.
meetramana1204@gmail.com

[3]Associate Professor,Department of CSE,CVR College of Engineering, Hyderabad, India.
dr.srikanthcse@gmail.com&samyabanoth@gmail.com

ABSTRACT

The rapid growth of e-commerce has transformed consumer purchasing habits, including grocery shopping. While online grocery platforms offer unparalleled convenience, challenges persist in selecting fresh produce, as customers rely heavily on visual attributes such as color, size, and texture. Misclassification or inaccurate representation of vegetables often leads to dissatisfaction and diminished trust in these platforms.This research addresses these challenges by developing an AI-powered system for real-time vegetable classification. Utilizing large datasets of annotated vegetable images, advanced computer vision and machine learning techniques are employed to train models capable of accurately identifying and classifying vegetables based on their visual attributes. By incorporating state-of-the-art algorithms, the proposed system provides customers with instant and precise visual cues, ensuring an enhanced shopping experience.The integration of this system into online grocery platforms holds significant potential for improving accuracy, efficiency, and customer satisfaction. With real-time classification, customers can make informed decisions, reducing the likelihood of mismatches between their expectations and delivered items. This work not only advances online grocery shopping technology but also reinforces e-commerce platforms as reliable sources for fresh produce.

Keywords: Vegetable classification, Data analytics, E-commerce,Deep learning, Convolutional neural networks.

1. INTRODUCTION

The convenience of online grocery shopping has transformed the way consumers procure fresh produce, offering a hassle-free alternative to traditional markets. According to a recent market report, the global online grocery market is expected to reach $2 trillion by 2030, driven by increasing consumer preference for digital platforms. However, selecting fresh vegetables online remains a significant challenge due to the inability to physically inspect items. Customers often rely on visual cues such as color, size, shape, and texture to assess quality, making accurate visual representation crucial for building trust and satisfaction. Traditional methods of vegetable classification on e-commerce platforms rely heavily on manual tagging or basic image recognition systems, which are often error-prone and time-intensive. Such inaccuracies can result in customer dissatisfaction and reduced confidence in the platform. To address these issues, there is a growing need for automated solutions that can deliver real-time, precise vegetable classification to improve the online shopping experience.

This research proposes the development of an AI-based system that leverages advanced computer vision and machine learning techniques to classify vegetables with high accuracy and speed. By training models on extensive datasets containing annotated images of vegetables, this system can recognize subtle differences in visual attributes and provide instant feedback to customers.The integration of this technology into online grocery platforms has the potential to revolutionize fresh produce selection, enhancing customer satisfaction by reducing mismatches and ensuring product authenticity. Furthermore, by streamlining the classification process, e-commerce platforms can optimize their operations, catering to the growing demand for reliable and efficient online grocery shopping. This work represents a significant step towards bridging the gap between customer expectations and technological capabilities in the online grocery industry.

2. LITERATURE SURVEY

Automatic vegetable classification is an intriguing challenge in the growth of fruit and retailing industrial chain since it is helpful for the fruit producers and supermarkets to discover various fruits and their condition from the containers or stock with a view to improvising manufacturing effectiveness and revenue of the business [1]. Thus, intelligent systems making use of machine learning (ML) approaches and computer vision (CV) have been applied to fruit defect recognition, ripeness grading, and classification in the last decade [2]. In automated vegetable classification, two main methods, one conventional CV-related methodologies and the other one deep learning (DL)-related methodologies, were investigated. The conventional CV-oriented methodologies initially derive the low-level features, after which they execute image classification through the conventional ML approaches, while the DL-related techniques derive the features efficiently and execute an endwise image classification [3]. In the conventional image processing and CV approaches, imagery features, such as shape, texture, and color, were utilized as input unit for vegetable classification.

Previously, fruit processing and choosing depended on artificial techniques, leading to a huge volume of waste of labor [4]. Nonetheless, the above-mentioned techniques require costly devices (various kinds of sensors) and professional operators, and their comprehensive preciseness is typically less than 85% [5]. With the speedy advancement of 4G communication and extensive familiarity with several mobile Internet gadgets, individuals have created a large number of videos, sounds, images, and other data, and image identification technology has slowly matured [6].

Image-related fruit recognition has gained the interest of authors because of its inexpensive gadgets and extraordinary performances [7]. At the same time, it is needed to design automated tools capable of handling unplanned scenarios such as accidental mixing of fresh products, fruit placement in unusual packaging, different lighting conditions or spider webs on the lens, etc. Such situations may also cause uncertainty in the model results. The intelligent recognition of fruit might be utilized not only from the picking stages of the prior fruit but also in the processing and picking phase in the next stage [8]. Fruit identification technology depending on DL could substantially enhance the execution of fruit identification and comprises a positive impact on fostering the advancement of smart agriculture. In comparison with artificial features and conventional ML combination techniques, DL may derive features automatically, and contains superior outcomes that slowly emerged as the general methodology of smart recognition [9]. Particularly, convolutional neural network (CNN) is one of the vital DL models utilized for image processing. It is a type of artificial neural network (ANN) which utilizes convolution operation in at least one of the layers. Recently, CNNs have received significant attention on the image classification process. Specifically, in the agricultural sector, CNN-based approaches have been utilized for vegetable classification and fruit detection [10].

In [11], the authors suggest an effective structure for vegetable classification with the help of DL. Most importantly, the structure depends on two distinct DL architectures. One is a proposed light model of six CNN layers, and the other is a fine-tuned visual geometry group-16 pretrained DL method. Rojas-Aranda et al. [12] provide an image classification technique, based on lightweight

CNN, for the purpose of fastening the checking procedure in the shops. A novel images dataset has presented three types of fruits, without or with plastic bags. These input units are the RGB histogram, the RGB centroid acquired from K-means clustering, and single RGB colour.

3. PROPOSED METHODOLOGY

Begin by curating a dataset with images of vegetables corresponding to the 'vegetables' list, encompassing 'Tomato' to 'Bitter Gourd.' Ensure the dataset is comprehensive and diverse, showcasing various angles, lighting conditions, and backgrounds for each vegetable.

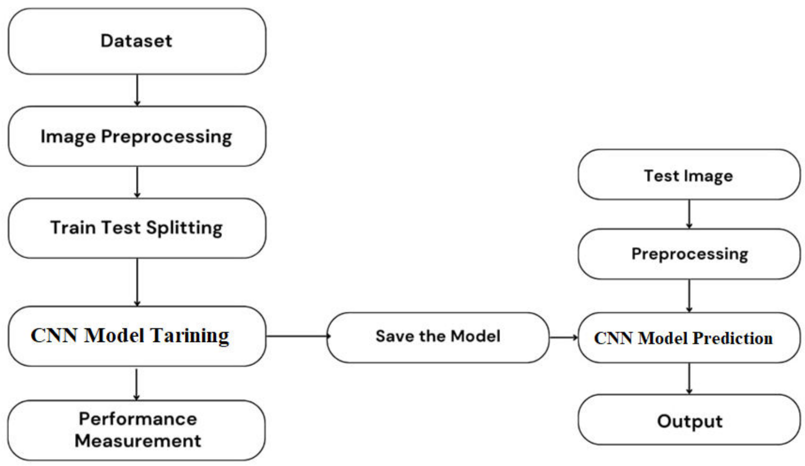


Figure 1: Proposed system model.

According to the facts, training and testing of proposed model involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1]. Convolution layer as is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$.The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.

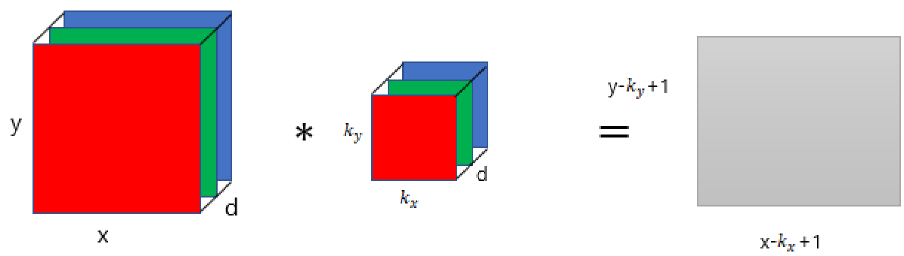
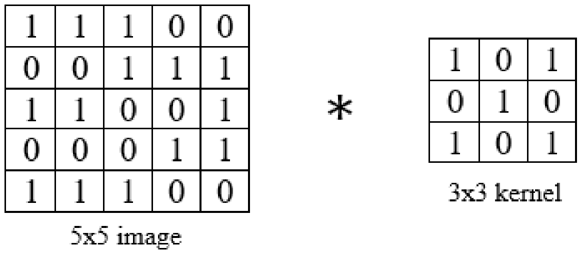
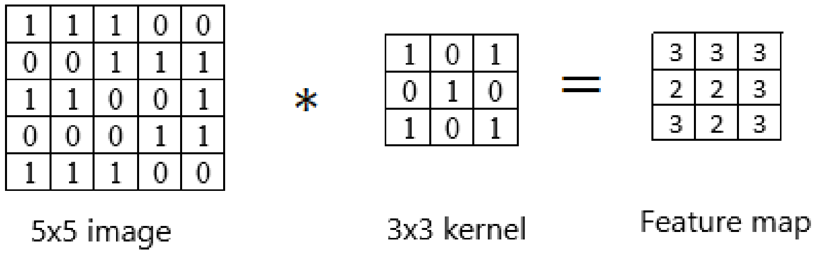


Fig.2: Representation of convolution layer process.



(a)



(b)

Fig. 3: Example of convolution layer process (a) an image with size $\mathbf{5 \times 5}$ is convolving with $\mathbf{3 \times 3}$ kernel (b) Convolved feature map

ReLU layer: Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

Max pooing layer: This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

4. RESULTS AND DISCUSSION

Figure 4presents a user-interface screen related to the research work. It showcases elements and features relevant to the research project, providing a visual representation of the user interaction or workflow.

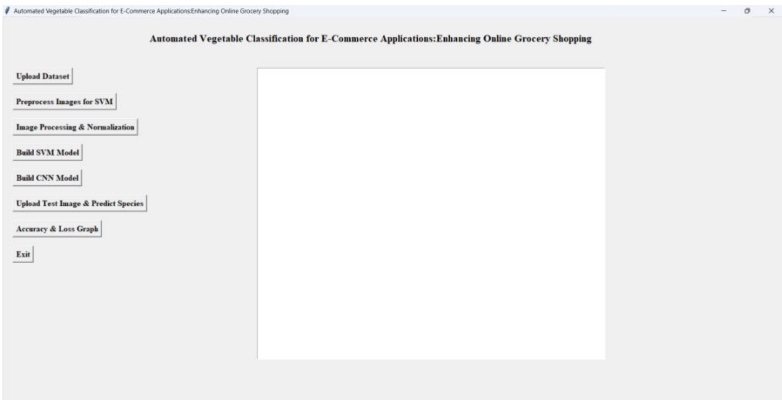


Figure 4. User-interface screen of research work.

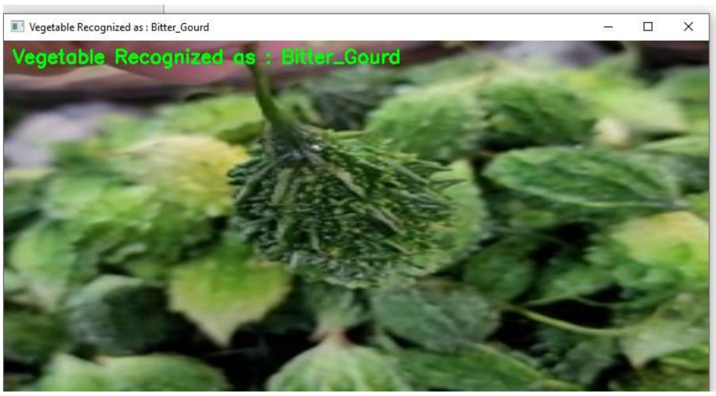


Figure 5. Sample test image predicted as bitter gourd.

Figure 5 shows a sample test image being predicted by the model as bitter gourd. It provides a visual example of the model's predictions on individual images.Figure 6 presents a graph illustrating the accuracy and loss trends of the proposed model during training. It provides insights into how well the model learns from the data over epochs, with accuracy increasing and loss decreasing over time.

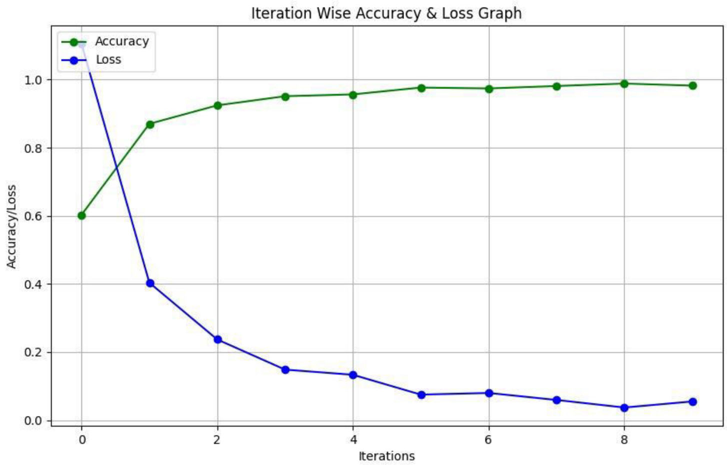


Figure 6. Accuracy and loss graph of proposed model.

5. CONCLUSION

In conclusion, the detailed operational procedure outlined above represents a comprehensive workflow for building and evaluating a Convolutional Neural Network (CNN) model for vegetable image classification. The process begins with dataset curation, emphasizing diversity and completeness in capturing various aspects of each vegetable. Subsequent preprocessing steps ensure the dataset's readiness for model training, including resizing, normalization, and augmentation. The train-test split facilitates robust evaluation, with 80% of the data dedicated to training and 20% for assessing the model's performance. The CNN model is then constructed and trained, leveraging optimization techniques to minimize classification error. Performance metrics offer a nuanced understanding of the model's effectiveness, guiding potential refinements. Testing the model with a new vegetable image validates its generalization capabilities, and the language-to-English conversion add-on enhances user interaction. So, this detailed procedure ensures a systematic and thorough approach to developing a reliable vegetable classification system, balancing model intricacies with practical considerations.

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