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AUTOMATED VEGETABLE CLASSIFICATION FOR E-COMMERCE APPLICATIONS: ENHANCING ONLINE GROCERY SHOPPING

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ABSTRACT

The convenience of online shopping has revolutionized the way consumers procure goods, including groceries. However, in the domain of fresh produce, customers often face challenges in accurately visualizing and selecting items, as they rely heavily on visual cues such as color, size, and shape. Automated vegetable classification aims to address this issue by utilizing technology to assist customers in making informed choices. The primary challenge in this context is to develop a system that can accurately and swiftly classify vegetables based on visual attributes. This involves training a model to recognize and differentiate between various types of vegetables, taking into account factors like color, size, shape, and texture. Therefore, the online grocery shopping continues to grow in popularity, providing an efficient and user-friendly experience is crucial for e-commerce platforms. Automating the process of vegetable classification can enhance the accuracy and speed at which customers can select their produce, reducing the likelihood of mismatches between expectations and delivered items. This, in turn, boosts customer satisfaction and confidence in online grocery shopping. This work aims to revolutionize the online grocery shopping experience by employing advanced computer vision and machine learning techniques. By leveraging large datasets of annotated vegetable images, this research endeavors to train a model capable of accurately classifying vegetables in real-time. Through the integration of state-of-the-art algorithms, the system will provide customers with instant and precise visual cues, empowering them to confidently select their produce online. This advancement holds the potential to significantly enhance the efficiency and satisfaction of online grocery shopping, further establishing e-commerce platforms as a reliable source for fresh produce.

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

1. INTRODUCTION

Over the past decade, the landscape of retail has undergone a radical transformation, primarily propelled by the burgeoning trend of online shopping. This paradigm shift in consumer behavior has not spared the domain of grocery shopping, an essential aspect of daily life. The convenience and accessibility offered by e-commerce platforms have redefined the way consumers acquire goods, presenting an unprecedented opportunity for innovation. One critical aspect of this transition, however, has remained a challenge—the selection of fresh produce. In the realm of online grocery shopping, customers frequently encounter hurdles when attempting to accurately visualize and select fresh vegetables. Unlike non-perishable items that can be precisely described through standardized attributes, the selection of produce relies heavily on nuanced visual cues. These cues, encompassing factors such as color, size, shape, and texture, are crucial in ensuring that customers receive the quality and variety of vegetables they desire. Recognizing the limitations of conventional e-commerce platforms in this regard, there is a pressing need for innovative solutions to enhance the user experience and bridge the

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gap between the virtual and physical realms of grocery shopping. One prevailing issue in the current landscape is the reliance on manual image tagging and categorization for vegetable listings. This labor-intensive process not only consumes valuable time but is also susceptible to inconsistencies arising from human subjectivity. As the diversity of available vegetables expands and customer demand continues to surge, the manual approach becomes increasingly untenable. To overcome these challenges, the key imperative is to develop a system that can swiftly and accurately classify vegetables based on their visual attributes.

This initiative sets out to revolutionize the online grocery shopping experience by seamlessly integrating advanced computer vision and machine learning techniques. At its core, the project seeks to address the fundamental challenge of training a model capable of recognizing and differentiating between various types of vegetables in real-time.

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

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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

3.1 Overview

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.

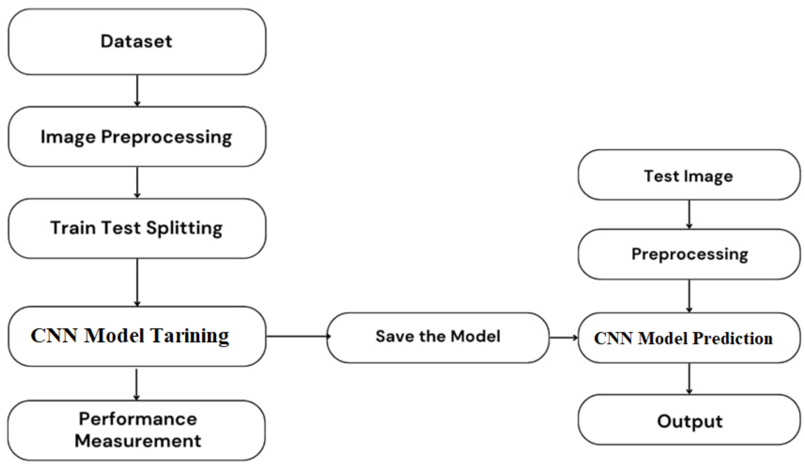

Figure 1: Proposed system model.

3.2 Basic CNN 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 $F\left(k_x, k_y, d\right)$. 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

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size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.

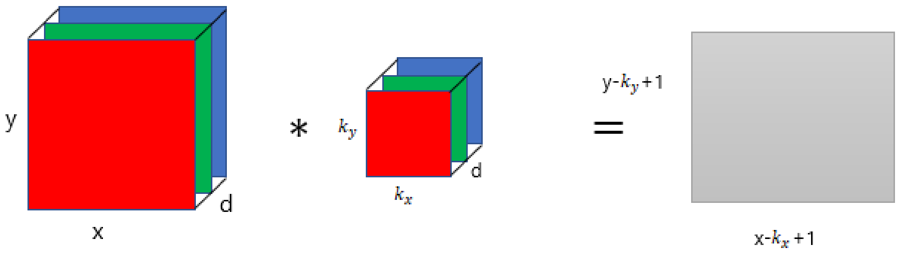
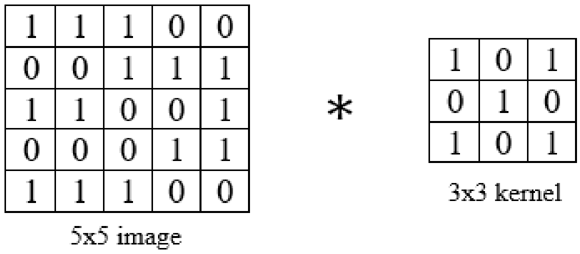
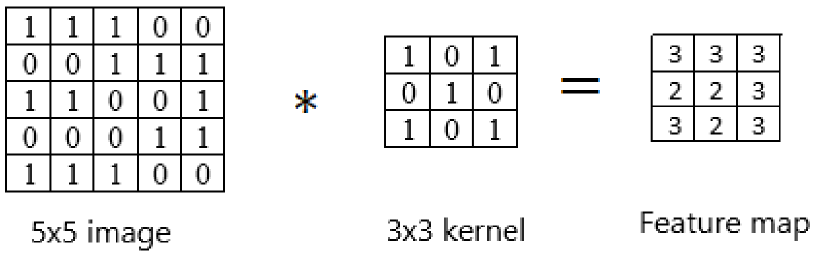


Fig. 2: Representation of convolution layer process.



(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

3.2.1 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:

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

3.2.2 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

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Figure 8 presents 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.

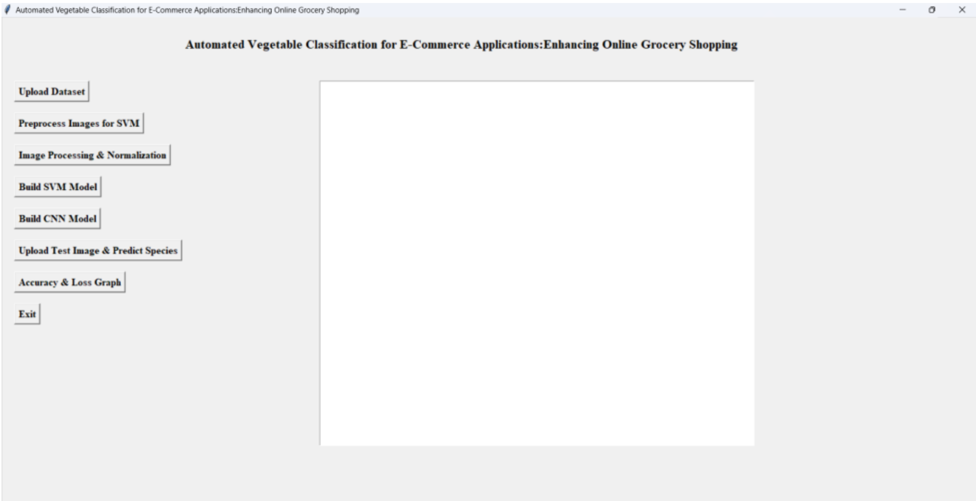

Figure 4. User-interface screen of research work.

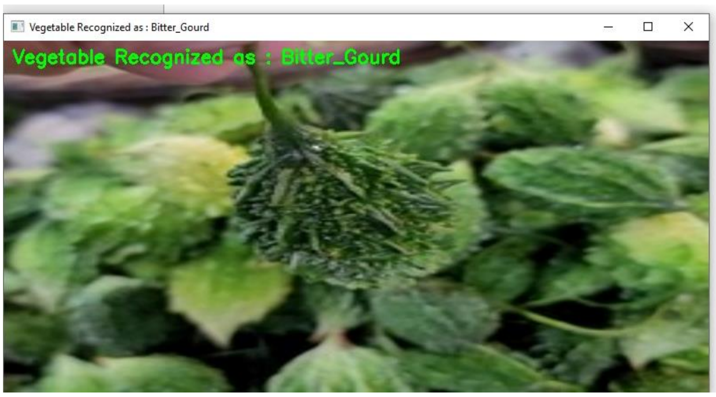

Figure 5. Sample test image predicted as bitter gourd.

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.

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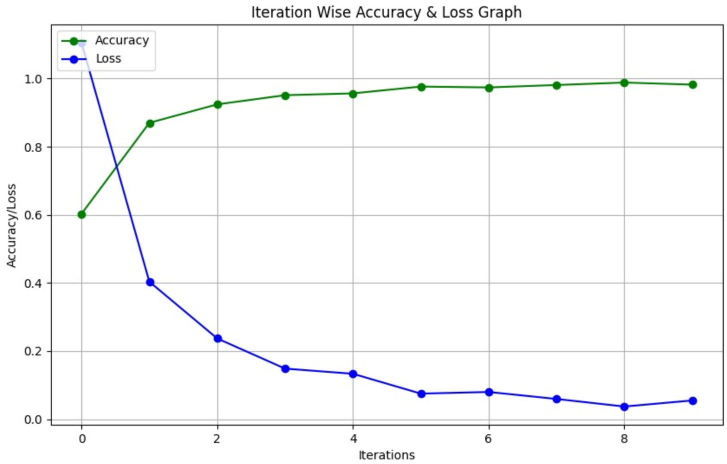

Figure 6. Accuracy and loss graph of proposed model.

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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