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

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ABSTRACT
Online shopping's ease has revolutionized the way people buy products, especially groceries. However, because fresh food is mostly chosen online based on visual signals like color, size, and form, shoppers frequently find it difficult to choose. The goal of automated vegetable classification is to help consumers by improving their selection process using technology. Due of human subjectivity, manual image tagging and classification are time-consuming and inconsistent on traditional e-commerce platforms, and they don't scale well with rising vegetable demand. Creating a system that swiftly and reliably classifies vegetables according to their visual characteristics—that is, their color, size, shape, and texture—is the primary problem. Offering a quick and easy food shopping experience is essential as the trend of online grocery buying continues. Vegetable classification done automatically can increase customer confidence and satisfaction by decreasing mismatches between delivered items and expectations and by speeding up and improving consumer selection accuracy. With the use of cutting-edge computer vision and machine learning techniques, the project seeks to revolutionize the online grocery shopping experience. This work aims to provide accurate, real-time vegetable classification by training models on large datasets of annotated photos. Modern algorithms will be integrated into the system to deliver prompt, accurate visual signals, enabling customers to confidently choose produce online and increasing the effectiveness and happiness of online grocery shopping.
Keywords: Automated Vegetable Classification, Online Grocery Shopping, Computer Vision, Machine Learning, Visual Cues, E-Commerce Applications.

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 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 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

The research begins 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.

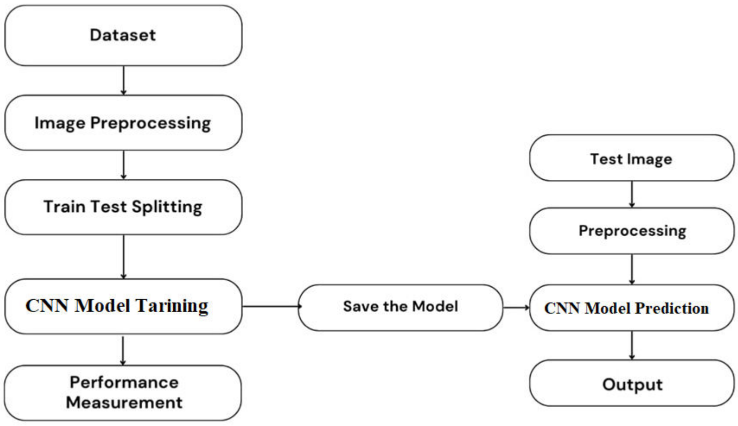

Figure 1: Proposed system model.

Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a type of deep neural network designed for processing structured grids of data, such as images or spatial data. Unlike traditional neural networks, CNNs leverage spatial hierarchies of features and local receptive fields to capture patterns efficiently. They are widely used in computer vision tasks, including image classification, object detection, and segmentation.

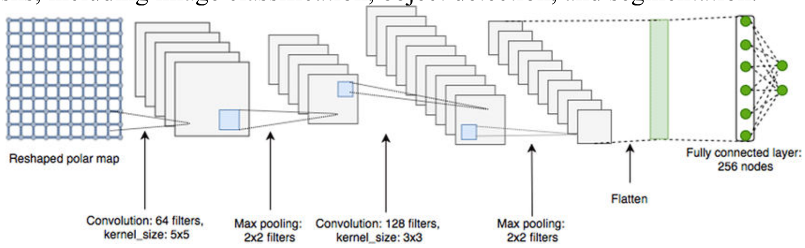

Fig. 2: Architectural of CNN model.

Convolutional Layers: At the core of a CNN are convolutional layers. Each layer consists of a set of learnable filters (or kernels) that slide over the input data, performing element-wise multiplication with local regions and producing feature maps. This process allows the network to learn hierarchical representations of patterns in the data. Mathematically, for an input I and a filter K, the output feature map O is computed as:

$$O(i,j)=\sum m\sum n I(i+m,j+n)\cdot K(m,n)$$

where i,jrepresents the spatial location in the output feature map.

Pooling Layers: Pooling layers follow convolutional layers and serve to downsample the spatial dimensions of the feature maps while retaining important features. Max pooling, for instance, selects the maximum value from each region of the feature map defined by a pooling window, thus reducing the spatial size and providing translation invariance.

Activation Functions: Activation functions like ReLU (Rectified Linear Unit) are applied after each convolutional and pooling layer to introduce non-linearity, allowing the network to learn complex relationships in the data.

Architectural Components

Fully Connected Layers: Following multiple convolutional and pooling layers, fully connected layers aggregate features learned by previous layers to make final predictions. These layers connect every neuron from one layer to every neuron in the next layer, enabling high-level reasoning.

Dropout: To prevent overfitting, dropout layers randomly deactivate a fraction of neurons during training, forcing the network to learn redundant representations and improving generalization.

Loss Functions: CNNs are typically trained using gradient-based optimization methods such as stochastic gradient descent (SGD). Common loss functions include softmax cross-entropy for classification tasks and mean squared error for regression.

Backpropagation: The backpropagation algorithm computes gradients of the loss function with respect to the network parameters, enabling efficient updates of weights through gradient descent.

4. RESULTS AND DISCUSSIONS

Figure 3presents 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.

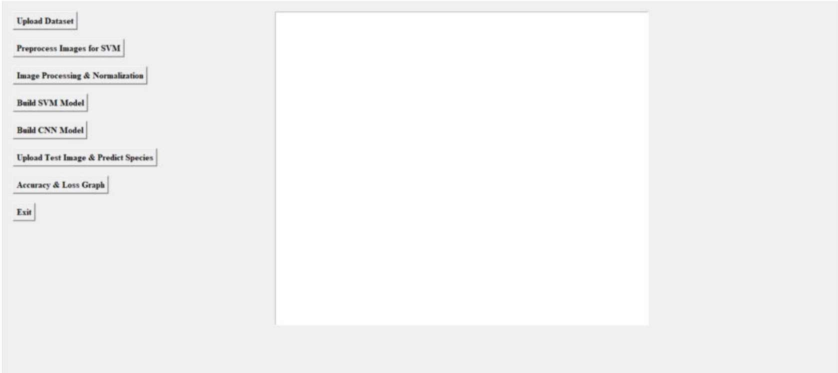

Figure 3. user-interface screen of research work.

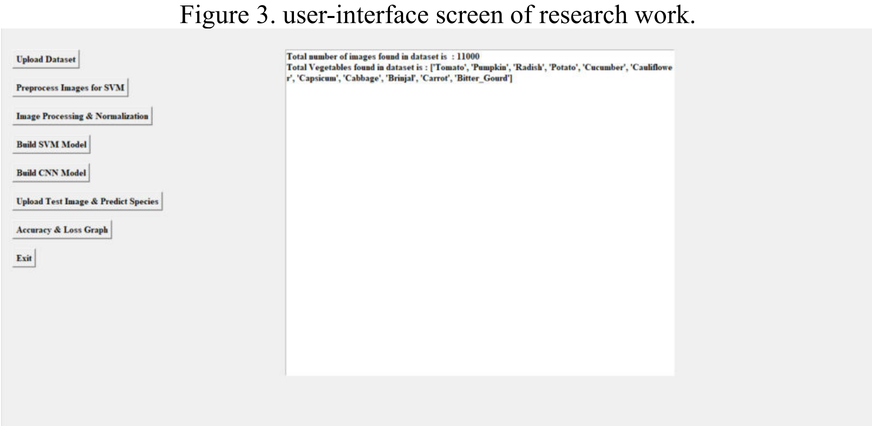

Figure4. Dataset after preprocess as per Proposed model.

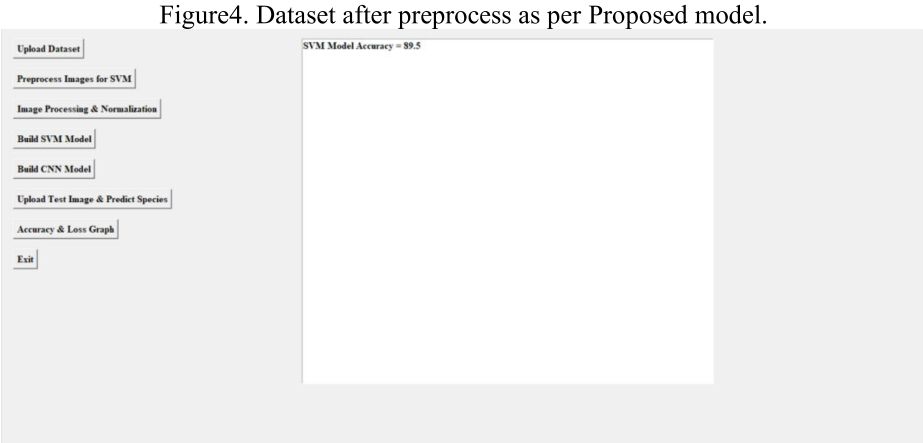

Figure 5. Existing SVM model accuracy (89.5%).

Figure 4 Showcases the dataset after undergoing preprocessing steps according to the proposed model. Preprocessing include tasks such as cleaning, normalization, or feature extraction to prepare the data for model training.

Figure 6. CNN model building with accuracy.

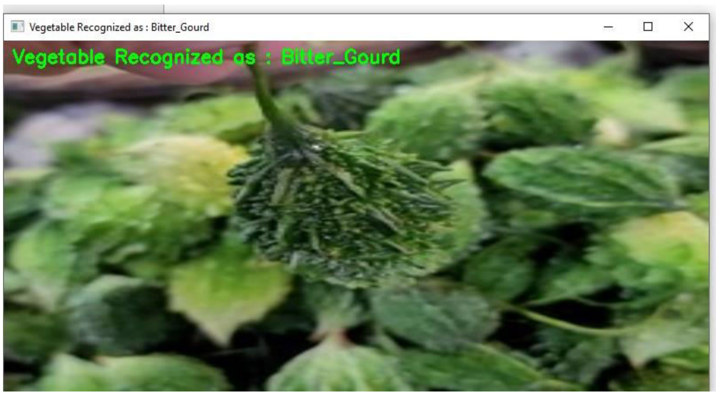

Figure 7. Sample test image predicted as bitter gourd.

Figure 5 displays the accuracy of an existing Support Vector Machine (SVM) model, which is reported as 89.5%. The accuracy represents the model's performance in correctly classifying instances.Figure 6 illustrates the process of building a Convolutional Neural Network (CNN) model, along with the reported accuracy of 98.21%. This figure represents the training phase of the CNN model.Figure 7 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 8 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.

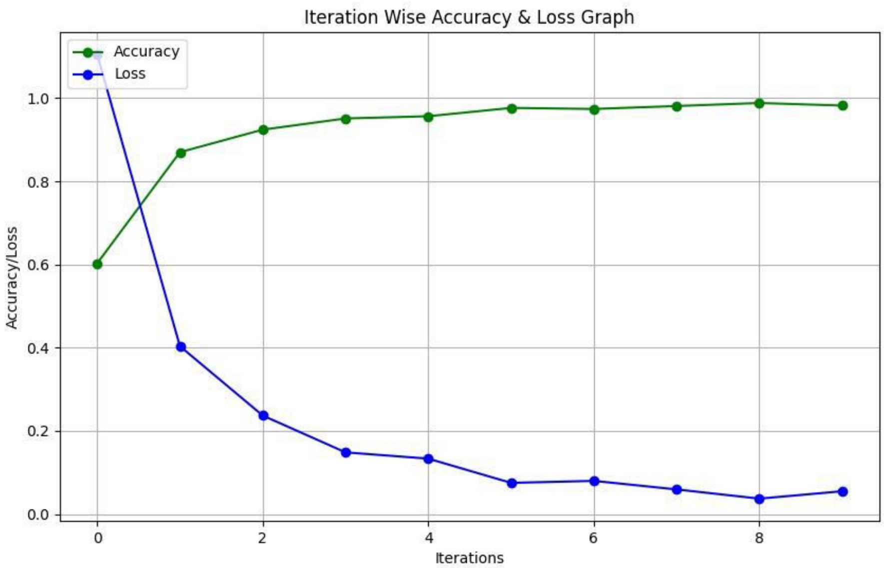

Figure 8. Accuracy and loss graph of proposed model.

5. CONCLUSION AND FUTURE SCOPE

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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