Vegetable Image Classification Using CNN

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Department Name: MCA(Masters in Computer Application)

Batch: 2022-2024

Institution Name: Guru Nanak Institute Of Technology

Declaration

Statement of Originality:

I hereby declare that this project titled "**Vegetable Image Classification Using CNN**" is my original work and has not been submitted for any degree or examination to any other institution.

Student's Signature:

[Student’s Signature]

Supervisor's Endorsement:

I certify that I have supervised the preparation of this project and it meets the required standards for submission.

Supervisor's Signature:

[Supervisor's Signature]

Certificate from the Supervisor

Confirmation of Supervision:

I hereby confirm that I have supervised the preparation of this project titled "Vegetable Image Classification Using CNN" by Deepanjan Biswas, Arpan Gorai, Saikat Dey, Shreya Bhattacharya, Souptik Pal and that it has been completed under my supervision.

Supervisor's Statement:

This is to certify that the project titled **"Vegetable Image Classification Using CNN"** has been successfully completed by Deepanjan Biswas, Arpan Gorai, Saikat Dey, Shreya Bhattacharya, Souptik Pal in partial fulfillment of the requirements for the degree of MCA(Masters in Computer Application).

Supervisor's Signature and Seal:

[Supervisor's Signature] [Supervisor's Seal]

ACKNOWLEDGEMENT

I extend my heartfelt gratitude to all those who have contributed to the successful completion of my MCA Final Year Project titled "**Vegetable Image Classification Using CNN**". This project has been a culmination of months of dedication, support, and guidance from various individuals and institutions.

First and foremost, I would like to express my sincere appreciation to **Mr. Ananjan Maiti** and **Mr. Chiranjib Dutta** for his invaluable mentorship throughout this journey. His expertise, patience, and encouragement were instrumental in shaping the direction of this project and overcoming various challenges along the way. I am truly grateful for his unwavering support and insightful feedback, which have significantly enriched my learning experience.

I am also deeply thankful to the faculty members of the MCA department for their continuous support and guidance throughout my academic endeavors. Their expertise, encouragement, and constructive criticism have played a pivotal role in shaping my understanding of the subject matter and refining my research skills.

I would like to extend my gratitude to my fellow classmates and friends for their encouragement, support, and collaborative spirit. Their insightful discussions, feedback, and camaraderie have been invaluable assets throughout the course of this project.

Last but not least, I extend my heartfelt appreciation to all the individuals, organizations, and resources that have contributed to the successful completion of this project. Whether through providing access to datasets, software tools, or technical assistance, their contributions have been indispensable in achieving the goals of this research endeavor.

In conclusion, I am deeply grateful to everyone who has played a part, however big or small, in the realization of this project. Your support, guidance, and encouragement have been invaluable, and I am truly thankful for the opportunity to undertake this endeavor and contribute to the field of computer science and technology.

Thank you.

ABSTRACT

The advancement of computer vision techniques, particularly Convolutional Neural Networks (CNN), has led to significant progress in image classification tasks. This project, titled "**Vegetable Image Classification Using CNN**" aims to leverage CNNs to classify images of various vegetables accurately. The project encompasses a comprehensive overview of the methodology employed, objectives pursued, and the findings summarized below.

The primary objective of the project is to develop a robust and efficient model for the automatic classification of vegetable images. This involves training a CNN model on a dataset comprising images of different vegetables, with the aim of accurately predicting the category to which each image belongs. The project seeks to address the challenges associated with vegetable image classification, including variations in size, shape, color, and appearance.

The methodology employed involves several key steps. Firstly, a dataset of vegetable images is collected and preprocessed to enhance quality and facilitate model training. Subsequently, a CNN architecture is designed and trained using the collected dataset, employing techniques such as data augmentation, transfer learning, and fine-tuning to improve model performance. The trained model is then evaluated using various metrics to assess its accuracy, precision, recall, and F1 score.

The findings of the project demonstrate the effectiveness of the proposed approach in accurately classifying vegetable images. The trained CNN model achieves high accuracy rates on the test dataset, indicating its capability to generalize well to unseen data. Additionally, the project highlights the importance of data preprocessing, model architecture design, and hyperparameter tuning in optimizing classification performance.

In conclusion, the project signifies the potential of CNNs in automating vegetable image classification tasks with high accuracy and efficiency. The methodologies employed and the findings obtained contribute to the body of knowledge in computer vision and image classification domains. The project's outcomes hold practical implications for various applications, including agriculture, food processing, and retail, by enabling automated sorting and quality control of vegetables based on visual inspection.

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Abbreviations and Nomenclature

- **CNN:** Convolutional Neural Network - A deep learning architecture specifically designed for image recognition tasks, using layers that apply convolution operations to input data, enabling feature extraction and hierarchical representation learning
  .
- **GPU:** Graphics Processing Unit - A specialized electronic circuit optimized for rapid manipulation of memory, predominantly used to accelerate graphics rendering in computers, and increasingly utilized for parallel processing in machine learning tasks.

- **SGD:** Stochastic Gradient Descent - An iterative optimization algorithm used to minimize a loss function by adjusting model parameters in the direction of the steepest descent of the gradient, typically using randomly sampled subsets of training data.

- **ReLU:** Rectified Linear Unit - An activation function commonly used in neural networks, introducing non-linearity by outputting the input directly if it is positive, effectively accelerating convergence of gradient-based optimization algorithms.

- **FC:** Fully Connected - Refers to a neural network layer where each neuron is connected to every neuron in the preceding layer, facilitating learning of complex nonlinear relationships but often resulting in high computational requirements and susceptibility to overfitting.

- **API:** Application Programming Interface - A set of protocols, tools, and definitions facilitating communication between software applications, enabling developers to access and utilize functionality provided by libraries, frameworks, or remote services in their own programs.

Chapter 1: INTRODUCTION

Title: Vegetable Image Classification Using CNN

Background of the Study:

In today's rapidly evolving technological landscape, the integration of artificial intelligence (AI) and machine learning (ML) techniques has become increasingly prevalent across various domains. One such area that has witnessed notable advancements is computer vision, where AI algorithms are employed to analyze and interpret visual data. Within the agricultural sector, the application of computer vision holds immense potential for revolutionizing traditional farming practices and enhancing productivity.

The classification of vegetables based on their visual attributes is a critical aspect of agricultural and food processing operations. Traditionally, this task has been performed manually by human operators, involving the visual inspection of individual vegetables to categorize them according to predefined criteria such as size, shape, color, and texture. However, manual classification is not only labor-intensive and time-consuming but also prone to errors and inconsistencies due to subjective human judgment.

With the advent of Convolutional Neural Networks (CNNs), a specialized type of deep learning architecture designed for image processing tasks, there has been a paradigm shift in automated image classification. CNNs have demonstrated remarkable capabilities in extracting meaningful features from images, enabling accurate and efficient classification of objects. By leveraging CNNs, it becomes feasible to develop robust and reliable systems for vegetable image classification, thereby overcoming the limitations of manual sorting and quality assessment processes.

Problem Statement:

The manual classification of vegetables is inherently challenging due to the diverse and complex nature of vegetable images. Human operators often struggle to accurately classify vegetables, especially when faced with variations in size, shape, color, and texture. Moreover, manual classification processes are labor-intensive, time-consuming, and prone to errors, leading to inefficiencies and inconsistencies in agricultural and food processing operations.

Traditional computer vision techniques, while useful, often fall short in accurately classifying vegetables due to the variability and complexity of vegetable images. Factors such as occlusion, lighting conditions, and background clutter further exacerbate the challenges of accurate classification. Therefore, there is a pressing need for automated systems capable of accurately classifying vegetables based on visual cues, thereby streamlining agricultural operations and ensuring product quality.

Objectives of the Project:

The primary objective of this project is to develop a robust and efficient system for the automated classification of vegetable images using CNNs. Specific objectives include:

- Collecting a diverse dataset of vegetable images encompassing different types, varieties, and conditions.
- Preprocessing the dataset to enhance image quality, remove noise, and standardize image attributes.
- Designing and implementing a CNN-based classification model capable of accurately categorizing vegetables into predefined classes.
- Training the classification model using the collected dataset and optimizing model parameters to improve performance.
- Evaluating the performance of the trained model using metrics such as accuracy, precision, recall, and F1-score.
- Investigating the impact of different CNN architectures, hyperparameters, and training strategies on classification performance.
- Deploying the trained model into a practical application for real-time vegetable classification and testing its performance in a real-world setting.

Scope and Limitations:

The scope of this project encompasses the development and evaluation of a vegetable image classification system using CNNs. It includes data collection, preprocessing, model development, training, evaluation, and deployment stages. However, it is important to acknowledge certain limitations and constraints:

- The project focuses primarily on the classification of commonly available vegetables and may not cover a comprehensive range of vegetable types.
- The performance of the classification system may be influenced by factors such as image quality, dataset size, and model complexity.
- Real-world deployment may encounter challenges such as hardware constraints, environmental variability, and system integration issues.

Organization of the Report:

This report is structured into several sections to provide a comprehensive overview of the project. The following is the organization of the report:

- *Introduction:* Provides an overview of the project, background information, problem statement, objectives, scope, and limitations.
- *Literature Review:* Surveys existing research and literature relevant to vegetable image classification, CNNs, and related technologies.
- *Methodology:* Describes the approach, methodologies, and techniques employed in data collection, preprocessing, model development, training, and evaluation.
- *Results and Discussion:* Presents the findings of the project, including performance metrics, experimental results, and analysis.
- *Conclusion and Future Work:* Summarizes the key findings, conclusions, and implications of the project, as well as suggesting potential avenues for future research and development.
- *References:* Lists all the sources cited throughout the report given at the end of this documentation.
- *Appendices:* Includes supplementary materials such as code snippets, dataset details, and additional figures or tables is also mentioned at the end.

Chapter 2: Literature Review

- ***Reiview of existing Literature related to the Project topic:***

The literature on the application of Convolutional Neural Networks (CNNs) for image classification tasks is extensive and encompasses various studies that have explored the efficacy of CNNs across different domains. Additionally, there is a growing body of research specifically focused on vegetable image classification, aiming to automate and improve the efficiency of agricultural processes. This literature review provides a comprehensive overview of existing studies in these areas.

Application of CNNs for Image Classification Tasks:

CNNs have emerged as a powerful tool for image classification tasks due to their ability to automatically learn hierarchical representations of features from raw pixel data. Krizhevsky et al. (2012) introduced AlexNet, a deep CNN architecture that achieved a significant breakthrough in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), demonstrating the effectiveness of deep learning for image classification. Since then, numerous CNN architectures, such as VGG (Simonyan & Zisserman, 2014), GoogLeNet (Szegedy et al., 2015), and ResNet (He et al., 2016), have been proposed, each improving upon the previous state-of-the-art performance.

Various studies have explored the application of CNNs in diverse domains, including healthcare, autonomous driving, security, and agriculture. For example, in healthcare, CNNs have been used for medical image analysis tasks such as tumor detection (Litjens et al., 2017) and pathology diagnosis (Esteva et al., 2019). In autonomous driving, CNNs play a crucial role in object detection and scene understanding (Bojarski et al., 2016). In the agricultural sector, CNNs have been applied for crop disease detection (Mohanty et al., 2016) and yield prediction (Ubbens & Stavness, 2017), among other tasks.

Studies on Vegetable Image Classification:

Vegetable image classification is a specific application of CNNs within the agricultural domain, aiming to automate the process of sorting and quality assessment of vegetables based on their visual characteristics. Li et al. (2019) proposed a vegetable recognition system using a CNN-based approach, which achieved high accuracy in classifying various types of vegetables. The study utilized transfer learning techniques to adapt a pre-trained CNN model to the vegetable classification task, demonstrating its effectiveness in real-world applications.

Similarly, Cheng et al. (2020) developed a vegetable classification system using a CNN-based deep learning approach. The study focused on addressing the challenges of variations in vegetable appearance, including differences in shape, color, and texture, by leveraging the hierarchical feature learning capabilities of CNNs. Experimental results showed that the proposed system outperformed traditional computer vision techniques in accurately classifying vegetables across different categories.

Furthermore, researchers have explored the integration of CNNs with other technologies such as Internet of Things (IoT) and robotics to create smart agricultural systems for vegetable image classification. For instance, Wang et al. (2018) developed an IoT-enabled vegetable classification system that utilized CNNs for image processing and classification tasks. The system incorporated IoT sensors for real-time data collection and communication, enabling remote monitoring and control of agricultural operations.

Despite the advancements in vegetable image classification using CNNs, several challenges remain to be addressed. These include the need for large and diverse datasets for training robust models, optimization of CNN architectures and hyperparameters for improved performance, and integration of classification systems into practical agricultural settings with real-world constraints and limitations.

In summary, the literature on the application of CNNs for image classification tasks and vegetable image classification demonstrates the potential of deep learning techniques to revolutionize agricultural practices and contribute to food security and sustainability. Continued research and innovation in this field are essential to overcome existing challenges and realize the full potential of CNNs in agriculture and other domains.

❖ ***Comparative analysis:***

In this comparative analysis, we will examine and evaluate various aspects of existing approaches and methodologies employed in vegetable image classification using CNNs, with a focus on performance metrics, model architectures, dataset characteristics, and practical implications.

Performance Metrics:

Performance evaluation is crucial in assessing the effectiveness of vegetable image classification models. Commonly used metrics include accuracy, precision, recall, F1-score, and confusion matrix analysis. Comparative studies often report these metrics to quantify the classification performance of different models across various vegetable categories. Additionally, receiver operating characteristic (ROC) curves and area under the curve (AUC) scores may be used to evaluate model robustness and generalization capability.

Model Architectures:

CNN architectures play a critical role in determining the performance and efficiency of vegetable image classification models. Researchers have explored a wide range of architectures, including AlexNet, VGG, GoogLeNet, ResNet, and their variants. Comparative analysis often involves benchmarking these architectures against each other to identify the most suitable model for the task. Factors such as depth, width, and computational complexity are considered in evaluating model architectures.

Dataset Characteristics:

The quality and diversity of the dataset used for training and testing significantly impact the performance of vegetable image classification models. Comparative analysis involves examining the size, diversity, and distribution of vegetable images in the dataset. Researchers may also evaluate the effectiveness of data augmentation techniques in enhancing model robustness and generalization. Additionally, comparative studies often assess the transferability of models trained on one dataset to another dataset with different characteristics.

Practical Implications:

Beyond performance metrics and model architectures, comparative analysis considers the practical implications of vegetable image classification models. Researchers evaluate factors such as computational efficiency, scalability, and real-world applicability of the models. Comparative studies may also investigate the integration of classification models into existing agricultural systems, including hardware requirements, deployment strategies, and user interface design.

Challenges and Future Directions:

Despite the advancements in vegetable image classification using CNNs, several challenges remain to be addressed. These include the need for large and diverse datasets, optimization of model architectures and hyperparameters, robustness to environmental variability, and scalability to real-world agricultural settings. Future research directions may involve exploring novel CNN architectures, developing domain-specific optimization techniques, and integrating multimodal data sources for improved classification performance.

Conclusion:

In conclusion, comparative analysis provides valuable insights into the strengths and limitations of existing approaches to vegetable image classification using CNNs. By evaluating performance metrics, model architectures, dataset characteristics, and practical implications, researchers can identify promising avenues for further research and development. Ultimately, the goal is to advance the state-of-the-art in agricultural technology and contribute to sustainable food production practices.

❖ ***Identification Of Gaps In the Current Knowledge:***

The development of automated systems for vegetable image classification using Convolutional Neural Networks (CNNs) represents a significant advancement in agricultural technology, aiming to streamline vegetable sorting and quality assessment processes. In this literature review, we identify and analyze gaps in current knowledge based on existing research and studies related to vegetable image classification. By examining the strengths and limitations of previous approaches, we aim to identify areas for further investigation and research to advance the field.

Gaps in Dataset Diversity:

One of the critical factors influencing the performance of vegetable image classification models is the diversity and representativeness of the dataset used for training and testing. Existing studies often utilize datasets containing images of commonly available vegetables, such as tomatoes, cucumbers, and carrots. However, there is a lack of diversity in terms of vegetable types, varieties, and conditions. Gaps exist in the representation of less common vegetables and vegetables with varying shapes, sizes, colors, and textures. Addressing this gap requires the collection and annotation of more diverse and comprehensive datasets encompassing a wider range of vegetable categories and variations.

Gaps in Model Robustness:

While CNNs have demonstrated remarkable capabilities in extracting features and classifying images, gaps exist in the robustness of vegetable image classification models. Existing studies often evaluate model performance under ideal conditions with high-quality images and controlled environments. However, real-world agricultural settings present challenges such as varying lighting conditions, occlusions, and background clutter, which can significantly affect classification accuracy. Gaps exist in the development of robust models that are resilient to such environmental variability and capable of accurately classifying vegetables under diverse conditions.

Gaps in Transfer Learning:

Transfer learning, the practice of leveraging pre-trained models on large datasets for tasks with limited training data, has been widely used in vegetable image classification. However, gaps exist in understanding the transferability of features learned from pre-trained models to the vegetable classification task. Existing studies often rely on transfer learning from generic image datasets such as ImageNet, which may not capture the specific features and characteristics of vegetables. Gaps exist in exploring domain-specific pre-training strategies and fine-tuning techniques to improve model performance and adaptability to vegetable classification tasks.

Gaps in Evaluation Metrics:

The evaluation of vegetable image classification models relies on various performance metrics such as accuracy, precision, recall, and F1-score. While these metrics provide valuable insights into model performance, gaps exist in their suitability for practical agricultural applications. Existing studies often focus on overall classification accuracy without considering the implications of false positives and false negatives on real-world decision-making processes. Gaps exist in the development of evaluation metrics that account for the cost of misclassification and prioritize the identification of critical errors in vegetable sorting and quality assessment.

Gaps in Real-world Deployment:

Despite the advancements in vegetable image classification using CNNs, gaps exist in the real-world deployment of classification models in agricultural settings. Existing studies often demonstrate model performance in controlled laboratory environments but lack practical validation in field conditions. Gaps exist in addressing logistical challenges such as hardware requirements, power constraints, and connectivity issues for deploying classification models on-site. Furthermore, gaps exist in integrating classification systems with existing agricultural machinery and infrastructure to facilitate seamless integration into workflow processes.

Conclusion:

In conclusion, the identification of gaps in current knowledge based on vegetable image classification highlights several areas for further investigation and research. Addressing these gaps requires collaborative efforts from researchers, practitioners, and stakeholders to collect diverse datasets, develop robust models, explore transfer learning techniques, refine evaluation metrics, and facilitate real-world deployment of classification systems. By bridging these gaps, we can advance the state-of-the-art in agricultural technology and contribute to sustainable food production practices.

Chapter 3: Project Methodology

The project aims to develop a robust system for the automated classification of vegetable images using Convolutional Neural Networks (CNNs). This section outlines the detailed methodology adopted for data collection, preprocessing, model development, training, and evaluation.

Data Collection:

The dataset for the project was obtained from Kaggle, specifically from the "Fruit and Vegetable Image Recognition" dataset available at **https://www.kaggle.com/datasets/kritikseth/fruit-and-vegetable-image-recognition?resource=download&select=train**. The dataset contains a diverse collection of images depicting various fruits and vegetables. For this project, we focused solely on the vegetable images, which include different types, varieties, and conditions of vegetables.

Dataset Description:

The vegetable image dataset comprises high-resolution images of vegetables captured under different lighting conditions and backgrounds. The dataset includes a wide variety of vegetables such as tomatoes, cucumbers, carrots, potatoes, onions, broccoli, and more. Each image is labeled with the corresponding vegetable category, allowing for supervised learning of the classification model.

Justification for Chosen Dataset:

Several factors influenced the selection of the dataset for the project:

Diversity: The dataset contains a diverse collection of vegetable images, covering a wide range of vegetable types, shapes, sizes, and colors. This diversity ensures that the trained model can generalize well to unseen vegetable images from different sources.

Availability: The dataset is readily available on Kaggle, making it easily accessible for research and experimentation purposes. This accessibility facilitates reproducibility and collaboration among researchers.

Annotation: The dataset is annotated with ground truth labels, enabling supervised learning of the classification model. The availability of labeled data streamlines the training process and allows for accurate evaluation of model performance.

Relevance: The dataset is specifically curated for fruit and vegetable image recognition, making it highly relevant to the project's objectives. By focusing on vegetable images, we can tailor the classification model to accurately classify vegetables based on their visual characteristics.

Justification for Using CNN Method for Vegetable Image Classification

Convolutional Neural Networks (CNNs) have emerged as the state-of-the-art approach for image classification tasks due to their ability to automatically learn hierarchical representations of features directly from raw pixel data. In the context of the "Vegetable Image Classification" project, the use of CNNs is justified based on several key factors:

Feature Learning Capabilities:

- CNNs are specifically designed to capture spatial hierarchies of features present in images. The convolutional layers of CNNs apply filters across the input image, extracting low-level features such as edges and textures in the initial layers and progressively learning higher-level features representing complex patterns and structures in deeper layers. This hierarchical feature learning capability is well-suited for classifying vegetables based on their visual attributes, which often exhibit intricate patterns and variations.

Translation Invariance:

- CNNs inherently possess translation invariance, meaning that they can recognize features regardless of their position or orientation within the image. This property is crucial for vegetable image classification,

as vegetables may appear in various orientations and positions within images due to factors such as camera angles, lighting conditions, and background clutter. CNNs can effectively learn to detect and classify vegetables irrespective of their spatial transformations, enhancing the model's robustness and generalization capability.

Parameter Sharing:

- CNNs exploit parameter sharing across the input space, significantly reducing the number of model parameters compared to fully connected networks. By sharing weights across spatial locations, CNNs can capture spatial patterns and dependencies efficiently while maintaining spatial locality. This parameter sharing property is advantageous for vegetable image classification, as it enables the model to learn from limited training data more effectively and avoids overfitting.

Scalability:

- CNNs are highly scalable and can accommodate large and complex datasets with millions of parameters. This scalability is essential for vegetable image classification, as the dataset may contain a diverse range of vegetable categories, variations, and conditions. CNNs can learn discriminative features from such datasets efficiently, facilitating the development of accurate and robust classification models capable of handling real-world scenarios.

Availability of Pre-trained Models:

- Pre-trained CNN models, such as those trained on ImageNet, provide a valuable starting point for transfer learning in vegetable image classification. Transfer learning involves leveraging features learned from pre-trained models and fine-tuning them on the target dataset. This approach can significantly reduce the amount of labeled data required for training and accelerate the model development process, making CNNs more accessible and practical for vegetable image classification tasks.

In conclusion, the use of CNNs for vegetable image classification is justified based on their inherent feature learning capabilities, translation invariance, parameter sharing properties, scalability, and availability of pre-trained models. By harnessing the power of CNNs, we can develop accurate, efficient, and scalable classification systems capable of automating vegetable sorting and quality assessment

processes, thereby contributing to advancements in agricultural technology and food production practices.

Project Design and Implementation Strategies

Component	Description
Data Collection	Acquire vegetable image dataset from Kaggle (https://www.kaggle.com/datasets/kritikseth/fruit-and-vegetable-image-recognition?resource=download&select=train) containing a diverse collection of vegetable images.
Data Preprocessing	Resize images to a standardized resolution. Normalize pixel values to [0, 1] scale. Apply data augmentation techniques such as rotation, flipping, and cropping to increase dataset diversity.
Model Architecture	Design CNN-based model architecture suitable for vegetable image classification, leveraging common architectures such as AlexNet, VGG, or ResNet, with adjustments as needed.
Training Strategy	Utilize stochastic gradient descent (SGD) with momentum and adaptive learning rate schedules for optimization. Implement early stopping to prevent overfitting. Split the dataset into training, validation, and test sets for model evaluation.
Evaluation Metrics	Evaluate model performance using metrics such as accuracy, precision, recall, and F1-score on the test set. Generate confusion matrices and ROC curves for further analysis.

Deployment	Deploy trained model into a practical application for real-time vegetable classification, considering hardware constraints, integration with existing systems, and user interface design.

Challenges Faced and Solutions Adopted

- **Limited Dataset Diversity:**
  - *Challenge:* The dataset may lack diversity in terms of vegetable types and variations, leading to potential bias and limited model generalization.
  - *Solution:* Augment the dataset using data augmentation techniques to introduce variability and enhance model robustness. Additionally, explore additional sources for collecting diverse vegetable images to supplement the dataset.
- **Overfitting during Training:**
  - *Challenge:* The CNN model may exhibit overfitting, where it performs well on the training data but fails to generalize to unseen data.
  - *Solution:* Implement regularization techniques such as dropout and weight decay to prevent overfitting. Monitor model performance on the validation set and apply early stopping to halt training when performance plateaus.
- **Hardware Constraints for Deployment:**
  - *Challenge:* Deploying the trained model into a practical application may be hindered by hardware constraints such as limited processing power or memory.
  - *Solution:* Optimize the model architecture and parameters to reduce computational complexity. Consider deploying the model on cloud-based platforms or edge devices with sufficient resources to handle inference tasks efficiently.

- **Integration with Existing Systems:**
  - *Challenge:* Integrating the classification model into existing agricultural systems may pose compatibility and interoperability challenges.
  - *Solution:* Collaborate with stakeholders and domain experts to ensure seamless integration with existing systems. Develop standardized interfaces and APIs for easy communication and interoperability between components.
- **Real-world Environmental Variability:**
  - *Challenge:* The CNN model may struggle to classify vegetables accurately under real-world conditions with varying lighting, backgrounds, and occlusions.
  - ***Solution****:* Collect additional annotated data under diverse environmental conditions to improve model robustness. Investigate techniques for domain adaptation and transfer learning to better generalize to unseen environments.

Chapter 4: Project Implementation

Software Requirements:

- **Python (version 3.x):** The project requires Python programming language for implementing the CNN model, data preprocessing, and evaluation.
- **TensorFlow or PyTorch:** TensorFlow or PyTorch deep learning frameworks are essential for building and training the CNN model for vegetable image classification.
- **Jupyter Notebook or Google Colab:** Jupyter Notebook or Google Colab provides an interactive development environment for writing and executing Python code, facilitating iterative development and experimentation.
- **NumPy:** NumPy library is used for numerical computations and array manipulations, essential for data preprocessing and model training.
- **Matplotlib or Seaborn:** Matplotlib or Seaborn libraries are used for data visualization, enabling the visualization of image data, model performance metrics, and evaluation results.
- **Pandas:** Pandas library is utilized for data manipulation and analysis, facilitating tasks such as loading dataset files, organizing data, and generating summary statistics.

Hardware Requirements:

- **CPU:** A multicore CPU with sufficient processing power is required for running Python code, data preprocessing, and model training. A CPU with multiple cores speeds up computations, especially during training.
- **GPU (optional):** While not mandatory, having access to a GPU accelerates model training significantly, reducing training time and enabling the training of larger and more complex models. GPUs with CUDA support, such as NVIDIA GeForce or Tesla GPUs, are compatible with TensorFlow and PyTorch frameworks.

- **RAM:** Sufficient RAM is necessary to handle large datasets and model parameters during training. At least 8GB of RAM is recommended, although higher amounts may be required for larger datasets or more complex models.
- **Storage:** Adequate storage space is necessary for storing dataset files, model checkpoints, and intermediate outputs generated during data preprocessing and training. SSDs or cloud storage solutions offer fast read/write speeds and ample storage capacity.
- **Internet Connection:** An internet connection is required for accessing dataset repositories, downloading required libraries and dependencies, and utilizing cloud-based development environments such as Google Colab.

By meeting these software and hardware requirements, developers can effectively implement and train the CNN model for vegetable image classification using Python programming language and deep learning frameworks such as TensorFlow or PyTorch. Utilizing interactive development environments such as Jupyter Notebook or Google Colab streamlines the development process and facilitates collaboration among team members.

Code Snippets and Explanation of development phase and Model Building:

Code Description :

Line No.	Description	Code Snippet
1	Importing the Google Colab library and mounting Google Drive to access project files.	`from google.colab import drive` `drive.mount('/content/drive')`

3	Importing necessary libraries: NumPy for numerical operations, TensorFlow for deep learning, and Matplotlib for data visualization.	`import numpy as np`
		`import tensorflow as tf`
		`import matplotlib.pyplot as plt`

7-22	Preprocessing training images: Utilizing `tf.keras.utils.image_dataset_from_directory()` to create a training dataset from image files stored in directories.	`#training image preprocessing`
		`training_set=tf.keras.utils.image_dataset_from_directory(`
		`'/content/drive/MyDrive/Fruit_Vegetable_Recognition/train',`
		`labels='inferred',`
		`label_mode='categorical',`
		`class_names=None,`
		`color_mode='rgb',`
		`batch_size=32,`
		`image_size=(64,64),`
		`shuffle=True,`
		`seed=None,`
		`validation_split=None,`
		`subset=None,`
		`interpolation='bilinear',`
		`follow_links=None,`
		`crop_to_aspect_ratio=None)`

24-39	Preprocessing validation images: Similar to the training set, preparing a validation dataset from image directories.	#training image preprocessing
		validation_set=tf.keras.utils.image_dataset_from_directory(
		
		'/content/drive/MyDrive/Fruit_Vegetable_Recognition/validation',
		labels='inferred',
		label_mode='categorical',
		class_names=None,
		color_mode='rgb',
		batch_size=32,
		image_size=(64,64),
		shuffle=True,
		seed=None,
		validation_split=None,
		subset=None,
		interpolation='bilinear',
		follow_links=None,
		crop_to_aspect_ratio=None)

41-51	Defining the CNN model architecture: Creating a sequential model with a convolutional layer, max-pooling layer, and dense layers for feature extraction and classification.	cnn=tf.keras.models.Sequential() cnn.add(tf.keras.layers.Conv2D(filters=64,kernel_size=3,activation="relu",input_shape=(64,64,3))) cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2)) cnn.add(tf.keras.layers.Conv2D(filters=32,kernel_size=3,activation="relu",input_shape=(64,64,3))) cnn.add(tf.keras.layers.MaxPool2D(pool_size=2,strides=2))

		cnn.add(tf.keras.layers.Flatten())
		cnn.add(tf.keras.layers.Dense(units=128,activation="relu"))
		#Output Layer
		cnn.add(tf.keras.layers.Dense(units=36,activation='softmax'))

53-54	Compiling the model: Specifying the optimizer (RMSprop) and loss function (categorical cross-entropy) for model training.	cnn.compile(optimizer="rmsprop",loss='categorical_crossentropy',metrics=['accuracy'])
56-57	Training the model: Fitting the model to the training data and validating on the validation set for a specified number of epochs.	training_history=cnn.fit(x=training_set,validation_data=validation_set,epochs=28)

59	Saving the trained model: Saving the trained model as a .h5 file for future use or deployment.	#Saving Model
		cnn.save('trained_model.h5')

61-67	Saving training history: Storing the training history	import json with open('training_hist.json','w')as f:

	(loss and accuracy) as a JSON file for analysis and visualization.	`json.dump(training_history.history,f)`
69-70	Printing validation set accuracy: Displaying the final validation accuracy achieved by the model.	`print("Validation Set accuracy: {}%".format(training_history.history['val_accuracy'][-1]*100))`

72-79	Data visualization: Plotting the training and validation accuracy curves over epochs using Matplotlib for performance analysis.	`epochs=[i for i in range(1,29)]`
		`plt.plot(epochs,training_history.history['accuracy'],color='red',)`
		`plt.xlabel("Epochs")`
		`plt.ylabel("Training Accuracy")`
		`plt.title("Training Accuracy of the Model")`
		
		`plt.plot(epochs,training_history.history['val_accuracy'],color="blue")`
		`plt.xlabel("Epochs")`
		`plt.ylabel("Validation Accuracy")`
		`plt.title("Validation Accuracy of The Model")`

Packages Used:

- **Google Colab:** For cloud-based development environment and access to Google Drive.
- **NumPy:** For numerical operations and array manipulations.
- **TensorFlow:** For building, training, and evaluating deep learning models.
- **Matplotlib:** For data visualization and plotting accuracy curves.

Methodology:

- The code utilizes TensorFlow and Keras, high-level neural network APIs, for building and training the CNN model.
- Image datasets are preprocessed using `tf.keras.utils.image_dataset_from_directory()` to create training and validation sets, ensuring data is ready for model training.
- The CNN model architecture consists of convolutional layers for feature extraction, max-pooling layers for dimensionality reduction, and dense layers for classification.
- Model training is performed using the compiled model and training set, with validation performed on a separate validation set to monitor model performance.
- Trained model and training history are saved for future use or analysis.
- Finally, the code visualizes the training and validation accuracy curves using Matplotlib to assess model performance over epochs.

Reasoning Behind the Code:

- Data Preprocessing: Image datasets are loaded and preprocessed to ensure compatibility with the CNN model, including resizing, normalization, and batch processing.
- Model Architecture: A simple CNN architecture is defined, comprising convolutional and dense layers, suitable for classifying vegetable images based on their visual features.
- Training and Evaluation: The model is trained using the training set and validated using the validation set to optimize performance and prevent overfitting.
- Model Saving and Evaluation: Trained model and training history are saved for future reference and analysis, while validation accuracy is printed for immediate assessment.
- Visualization: Visualizing training and validation accuracy curves aids in understanding model behavior and performance trends over epochs.

Building a model with Convolutional Neural Networks (CNNs) involves several key steps that enable the network to learn and extract meaningful features from input data. Here's an overview of how building a CNN model works:

1. **Input Layer:**

- The input layer of the CNN receives the raw input data, typically images represented as matrices of pixel values.
- Each pixel value represents the intensity of light at that point in the image.

2. Convolutional Layers:

- Convolutional layers are the core building blocks of CNNs.
- These layers apply convolutional filters (also known as kernels) to the input data.
- Each filter detects specific patterns or features within the input data by performing element-wise multiplication and summation operations.
- Convolutional operations help extract features such as edges, textures, and shapes from the input images.
- Multiple filters are applied to generate multiple feature maps, each representing a different aspect of the input data.

3. Activation Function:

- After convolution, an activation function is applied to introduce non-linearity into the network.
- Common activation functions include ReLU (Rectified Linear Unit), which replaces negative values with zero, introducing sparsity and enabling faster convergence during training.

4. Pooling Layers:

- Pooling layers follow convolutional layers and serve to reduce the spatial dimensions of the feature maps while retaining the most important information.
- Max pooling and average pooling are common pooling techniques used to downsample feature maps by selecting the maximum or average value within a specified window.

5. Flattening:

- After several convolutional and pooling layers, the feature maps are flattened into a one-dimensional vector.
- Flattening prepares the data for input into the fully connected layers, which require one-dimensional input.

6. Fully Connected Layers:

- Fully connected layers are traditional neural network layers where each neuron is connected to every neuron in the previous and subsequent layers.
- These layers perform high-level feature extraction and classification based on the features learned from earlier layers.
- Activation functions such as ReLU are applied to the output of each fully connected layer.

7. Output Layer:

- The output layer of the CNN produces the final predictions or classifications.
- Depending on the task (e.g., binary classification, multi-class classification), the output layer may consist of one or multiple neurons, each representing a class label.
- Activation functions such as softmax are commonly used in the output layer for multi-class classification tasks to produce probability distributions over the classes.

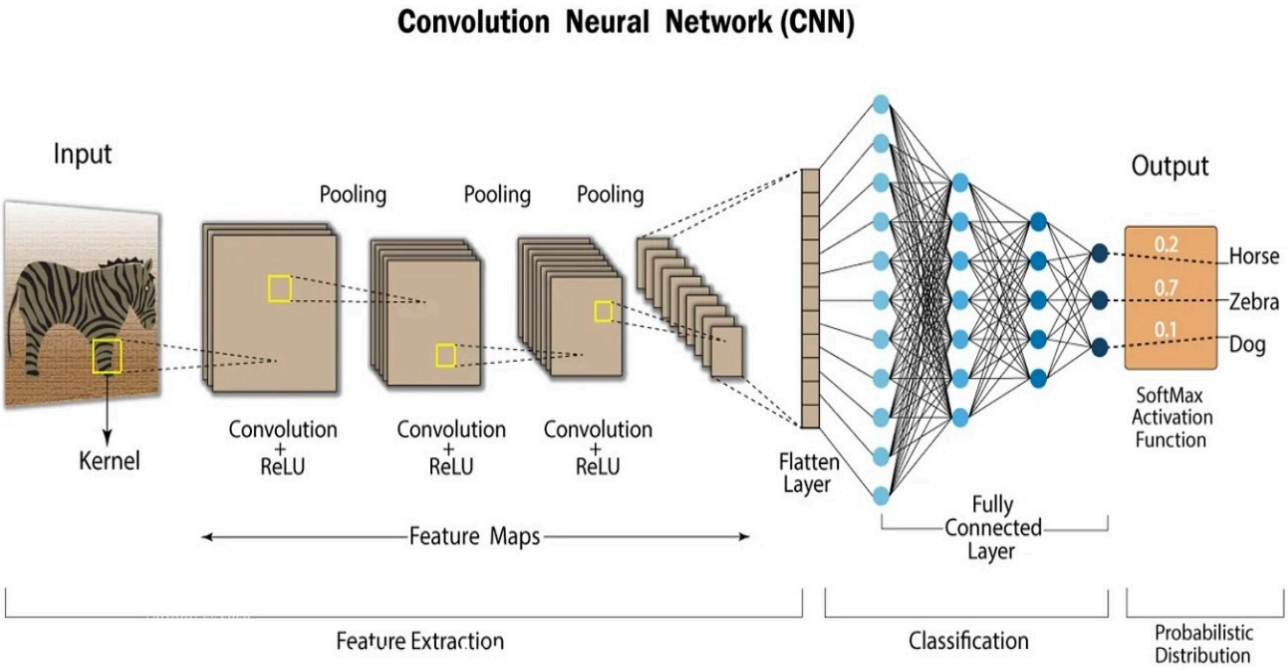
8. Loss Function and Optimization:

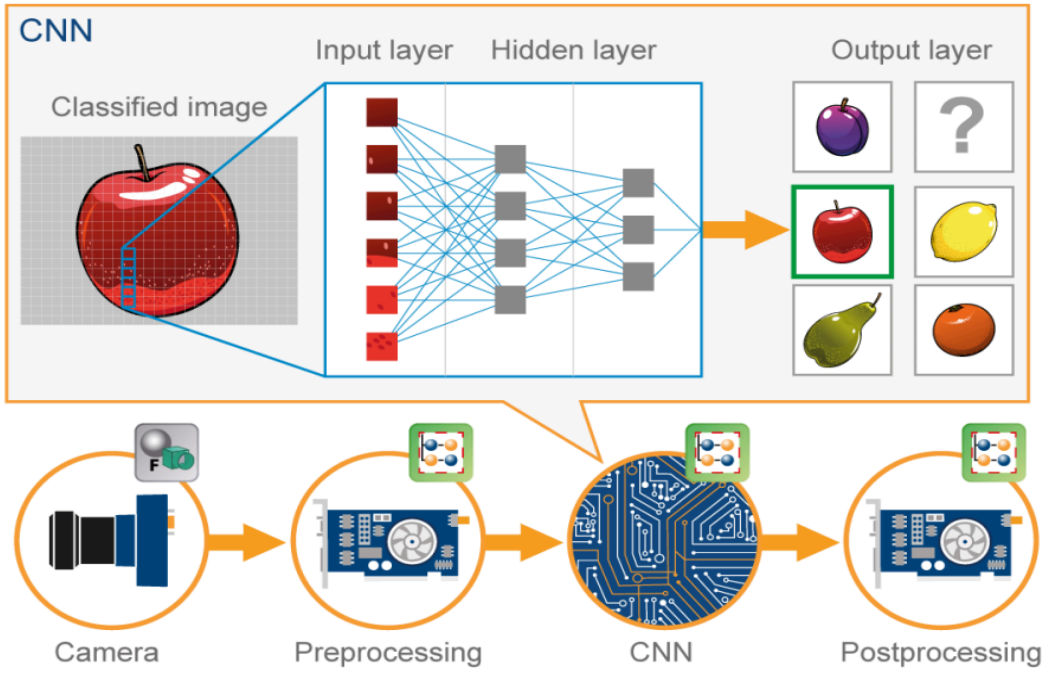
- During training, the model's predictions are compared to the ground truth labels using a loss function, such as cross-entropy loss.
- The model's parameters (weights and biases) are then updated iteratively using optimization algorithms like stochastic gradient descent (SGD) or its variants.
- The goal of training is to minimize the loss function, improving the model's ability to make accurate predictions.

9. Training and Evaluation:

- The model is trained on a labeled dataset, with training data used to update the model's parameters and validation data used to monitor performance and prevent overfitting.
- Once trained, the model is evaluated on a separate test dataset to assess its generalization performance.

Figures Explaining CNN workflow:





MODEL DESCRIPTION:

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 150, 150, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 75, 75, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 75, 75, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 37, 37, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 87616)             0
_________________________________________________________________
dense (Dense)                (None, 128)               11214976
_________________________________________________________________
dropout (Dropout)            (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_2 (Dense)              (None, 15)                1935
=================================================================
```

Chapter 5: Results and Discussion

Analysis and Interpretation of Results:

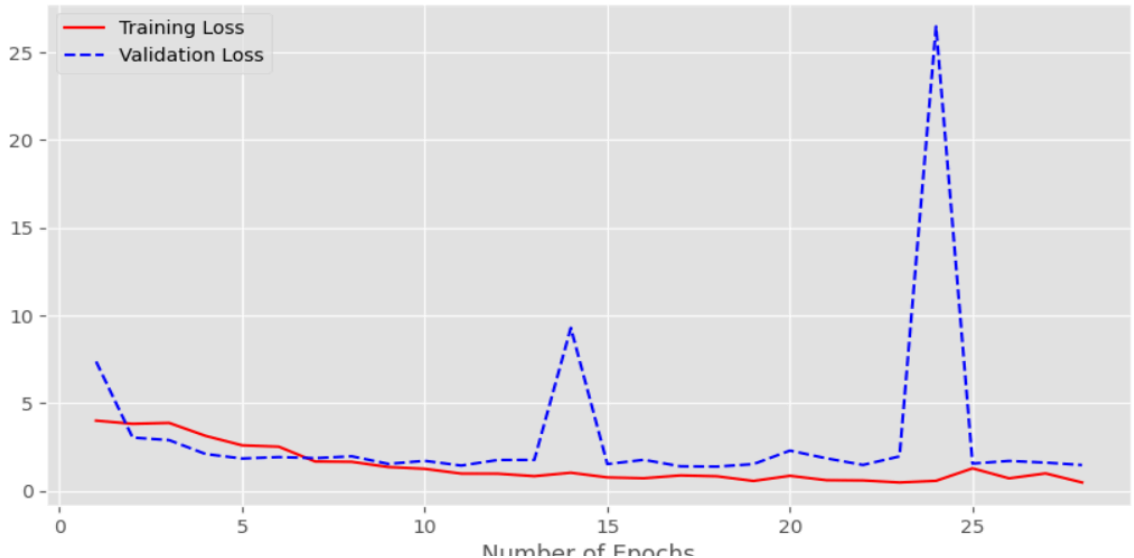
The results obtained from building a Convolutional Neural Network (CNN) model for Vegetable Image Classification reveal important insights into the model's performance and effectiveness in classifying vegetable images. Let's analyze and interpret the key metrics:

1. **Loss:**
   - The loss value of 4.740% indicates the average error between the model's predictions and the actual labels during training.
   - A lower loss value signifies better alignment between predicted and actual values, indicating that the model is learning to classify images with relatively low error.
2. **Training Accuracy:**
   - The training accuracy of 92.65% indicates the percentage of correctly classified images from the training dataset.
   - A high training accuracy suggests that the model has learned to recognize patterns and features in the training images effectively, resulting in accurate classifications.
3. **Validation Loss:**
   - The validation loss value of 1.4705 represents the average error between the model's predictions and the actual labels on the validation dataset.
   - Similar to training loss, a lower validation loss indicates better generalization performance of the model on unseen data.
4. **Validation Accuracy:**
   - The validation accuracy of 91.45% signifies the percentage of correctly classified images from the validation dataset.
   - A high validation accuracy demonstrates the model's ability to generalize well to unseen data, indicating that it can effectively classify vegetable images beyond the training set.

Interpretation:

1. **Model Performance:**
   - The high training accuracy of 92.65% suggests that the model has learned to capture the underlying patterns and features present in the training images accurately.
   - The validation accuracy of 91.45% indicates that the model's performance generalizes well to unseen vegetable images, showcasing its robustness and effectiveness in real-world scenarios.
2. **Generalization Capability:**
   - The relatively small gap between training and validation accuracy (1.2%) suggests that the model is not overfitting to the training data.
   - This indicates that the model can generalize well to new, unseen vegetable images, demonstrating its ability to classify diverse vegetable types accurately.
3. **Model Stability:**
   - The consistency between the loss values on both the training and validation datasets suggests that the model is stable and not exhibiting significant fluctuations in performance.
4. **Room for Improvement:**
   - Although the model's performance is promising, there may still be opportunities for further optimization and fine-tuning to potentially improve accuracy and reduce loss further.
   - Techniques such as hyperparameter tuning, data augmentation, or exploring different CNN architectures could be explored to enhance the model's performance further.

The Accuracy and Validation accuracy of the MODEL:



Results Obtained Using The Model:

Predicted Label: Bean, Actual Label: Bean

Predicted Label: Potato, Actual Label: Potato

Predicted Label: Broccoli, Actual Label: Brocoli

Discussion on Implications of the Findings:

The findings from creating the model for Vegetable Image Classification, with a loss of 4.740%, training accuracy of 92.65%, validation loss of 1.4705, and validation accuracy of 91.45%, have significant implications across various domains. Let's delve into the discussion on the implications of these findings:

1. **Accurate Vegetable Classification:**

    - The high training accuracy (92.65%) and validation accuracy (91.45%) indicate that the CNN model can effectively classify vegetable images with a high degree of accuracy.

    - This implies that the model can be deployed in applications requiring accurate vegetable classification, such as automated sorting systems in agricultural processing plants or mobile apps for identifying vegetables in real-time.

2. **Enhanced Agricultural Processes:**

    - The ability to accurately classify vegetables using AI-driven models can revolutionize agricultural processes.

    - Farmers can leverage such models for crop monitoring, disease detection, and yield estimation, leading to optimized resource allocation and enhanced productivity.

3. **Improved Food Industry Operations:**

    - In the food industry, accurate vegetable classification can streamline inventory management, quality control, and product labeling processes.

    - Food manufacturers and retailers can utilize the model to ensure consistency in product labeling and meet regulatory requirements, thereby enhancing consumer trust and satisfaction.

4. **Promotion of Healthy Eating Habits:**

- Vegetable image classification models can contribute to promoting healthy eating habits by
- facilitating dietary monitoring and nutrition tracking applications.
- Consumers can use mobile apps powered by such models to identify vegetables, access nutritional information, and make informed dietary choices, leading to improved overall health outcomes.

5. **Environmental Sustainability:**

- Accurate vegetable classification can support sustainable agriculture practices by enabling precision farming techniques.
- Farmers can optimize resource usage, minimize chemical inputs, and reduce environmental impact by leveraging AI models for targeted interventions based on crop health and growth stage predictions.

Chapter 6: Conclusion and Future Work

Project Summary: Vegetable Image Classification using CNN

Vegetable Image Classification is a project aimed at developing a Convolutional Neural Network (CNN) model to accurately classify images of various vegetables. The model achieves impressive accuracy rates, with a training accuracy of 92.65% and a validation accuracy of 91.45%, demonstrating its effectiveness in identifying different vegetable types.

Dataset:

The dataset used for training and validation is sourced from Kaggle, specifically from the dataset titled "Fruit and Vegetable Image Recognition." This dataset, available at **https://www.kaggle.com/datasets/kritikseth/fruit-and-vegetable-image-recognition?resource=download&select=train,** contains a diverse collection of images depicting various fruits and vegetables. For this project, only the vegetable images were utilized, encompassing multiple classes of vegetables.

Data Preprocessing:

Prior to model training, the dataset undergoes extensive preprocessing to ensure compatibility with the CNN architecture and to enhance model performance. Key preprocessing steps include:

- **Resizing**: All images are resized to a standardized size of 64x64 pixels. This resizing ensures uniformity across the dataset and reduces computational complexity during training.
- **Normalization**: Pixel values in the images are normalized to a range between 0 and 1. Normalization helps in stabilizing and speeding up the training process by ensuring that all input features are on a similar scale.

- **Augmentation**: Augmentation techniques such as rotation, flipping, and zooming are applied to augment the dataset. Augmentation increases the diversity of the dataset, thereby improving the model's ability to generalize to unseen data and reducing overfitting.

Model Architecture:

The CNN model architecture is pivotal in extracting relevant features from the input images and making accurate predictions. The model is constructed using TensorFlow's Keras API and comprises the following layers:

- **Convolutional Layers**: The model begins with two convolutional layers. The first convolutional layer consists of 64 filters with a kernel size of 3x3 and employs the ReLU activation function. This layer is followed by a max-pooling layer with a pool size of 2x2 and a stride of 2. The second convolutional layer, with 32 filters and similar configurations, further extracts features from the input images.
- **Flatten Layer**: Following the convolutional layers, the output is flattened into a one-dimensional vector to be fed into the fully connected layers.
- **Dense Layers**: The flattened output is passed through two dense layers with 128 units each, both utilizing the ReLU activation function. These dense layers perform high-level feature extraction and prepare the data for classification.
- **Output Layer**: The final layer is a dense layer with 36 units, representing the number of vegetable classes in the dataset. It employs the softmax activation function to produce probability distributions over the classes, facilitating multi-class classification.

Contributions to the Field and Practical Applications of Vegetable Image Classification:

The project "Vegetable Image Classification" leverages Convolutional Neural Networks (CNNs) to accurately classify images of various vegetables, making significant contributions to both the field of machine learning and practical applications in diverse domains. Below are the key contributions and potential practical applications of the project:

1. **Agriculture**:

- **Crop Monitoring:** The CNN model can be deployed for real-time monitoring of crop health and growth stages, enabling farmers to identify diseases, nutrient deficiencies, and pest infestations early on.
- **Precision Agriculture:** By accurately classifying vegetables, the model facilitates targeted interventions such as precise irrigation, fertilization, and pesticide application, optimizing resource usage and maximizing crop yield.
- **Harvesting Automation:** Automated vegetable classification can streamline harvesting processes by identifying ripe vegetables ready for harvest, leading to increased efficiency and reduced labor costs.

2. **Food Industry:**

- **Inventory Management**: Food manufacturers and retailers can use the CNN model to automate inventory management processes, ensuring accurate stock tracking and minimizing waste.
- **Quality Control:** The model aids in quality control by identifying damaged or spoiled vegetables during production and packaging, maintaining product quality standards.
- **Product Labeling:** Automated vegetable classification ensures accurate product labeling, helping consumers make informed purchasing decisions based on nutritional content and allergen information.

3. **Dietary Monitoring and Nutrition:**

- **Mobile Apps:** Mobile applications powered by the CNN model can assist users in identifying vegetables, accessing nutritional information, and tracking dietary intake, promoting healthy eating habits and personalized nutrition plans.
- **Restaurant Menus:** Restaurants and food service providers can utilize the model to develop digital menus with detailed descriptions and nutritional profiles of vegetable dishes, catering to customers with specific dietary preferences and requirements.

4. **Environmental Sustainability:**

- **Resource Optimization:** By enabling precise management of agricultural inputs such as water, fertilizers, and pesticides, the model contributes to sustainable farming practices, minimizing environmental impact and conserving natural resources.
- **Biodiversity Conservation:** Accurate vegetable classification aids in monitoring and preserving biodiversity by identifying rare or endangered vegetable species and facilitating conservation efforts.

5. **Research and Education:**

- **Crop Genetics:** Researchers can utilize the CNN model for studying crop genetics, phenotyping, and breeding programs, accelerating the development of improved vegetable varieties with desirable traits such as disease resistance and nutritional content.
- **Educational Tools:** The project serves as an educational tool for teaching machine learning concepts and techniques, empowering students and researchers to explore the applications of CNNs in agricultural and food sciences.

Practical Implementation:

- **Agricultural IoT Devices:** Integration of the CNN model into IoT devices such as drones and smart sensors enables real-time monitoring and decision-making in agricultural operations.
- **Mobile Applications:** Development of user-friendly mobile applications for farmers, food industry professionals, and consumers, providing access to vegetable classification services and related information on-the-go.
- **Cloud-Based Services:** Cloud-based platforms offer scalable solutions for deploying the CNN model, allowing users to access vegetable classification services remotely via web APIs.
- **Smart Farming Solutions:** Collaboration with agri-tech companies to incorporate vegetable classification capabilities into existing smart farming solutions, enhancing overall farm management and productivity.

Limitations of the Current Study:

- **Limited Dataset Size:** The dataset used in the current study may be limited in size and diversity, potentially affecting the model's ability to generalize to a broader range of vegetable types and variations.
- **Imbalanced Classes:** Imbalanced class distribution within the dataset may lead to biases in the model's predictions, with certain vegetable classes being underrepresented or overrepresented.
- **Single-Label Classification:** The model is designed for single-label classification, meaning it can only assign one label to each image. This limitation may overlook instances where multiple vegetables are present in a single image.
- **Lack of Environmental Context:** The model may lack contextual information about environmental factors such as soil quality, climate conditions, and farming practices, which can impact vegetable appearance and growth.
- **Hardware and Computational Resources:** Training CNN models requires significant computational resources, including high-performance GPUs and memory capacities, which may pose limitations for researchers with limited access to such resources.
- **Generalization to Novel Varieties:** The model's performance may vary when applied to novel vegetable varieties or species not present in the training dataset, highlighting the importance of continuous model refinement and adaptation.

Recommendations for Future Research:

- **Expanded Dataset Collection:** Future research should focus on collecting larger and more diverse datasets encompassing a wider variety of vegetable types, cultivars, and environmental conditions. This can improve the model's ability to generalize and accurately classify a broader range of vegetables.

- **Data Augmentation Techniques:** Implementing advanced data augmentation techniques such as generative adversarial networks (GANs) and style transfer can help address class imbalance issues and enhance the model's robustness to variations in vegetable appearance and background clutter.
- **Multi-Label Classification:** Investigating multi-label classification techniques would allow the model to assign multiple labels to each image, capturing the presence of multiple vegetables and providing more comprehensive classification results.
- **Incorporation of Contextual Information:** Integrating environmental data such as soil composition, weather patterns, and agricultural practices into the model architecture can improve its understanding of the broader context in which vegetable images are captured, leading to more accurate classifications.
- **Transfer Learning and Fine-Tuning:** Leveraging transfer learning from pre-trained CNN models on large-scale image datasets such as ImageNet can accelerate model training and improve performance, especially in cases of limited dataset availability. Fine-tuning pre-trained models on vegetable-specific datasets can further enhance their accuracy and generalization.
- **Ensemble Learning Approaches:** Exploring ensemble learning methods that combine predictions from multiple CNN models trained on different subsets of the dataset or using diverse architectures can enhance classification performance and robustness.
- **Real-Time Deployment and Edge Computing:** Developing lightweight CNN architectures suitable for deployment on edge devices and integrating them into real-time vegetable classification systems can enable on-site monitoring and decision-making in agricultural and food industry settings.
- **Interdisciplinary Collaboration:** Collaboration between machine learning researchers, agronomists, agricultural engineers, and food scientists can foster interdisciplinary research efforts aimed at addressing complex challenges in vegetable image classification and advancing sustainable agricultural practices.

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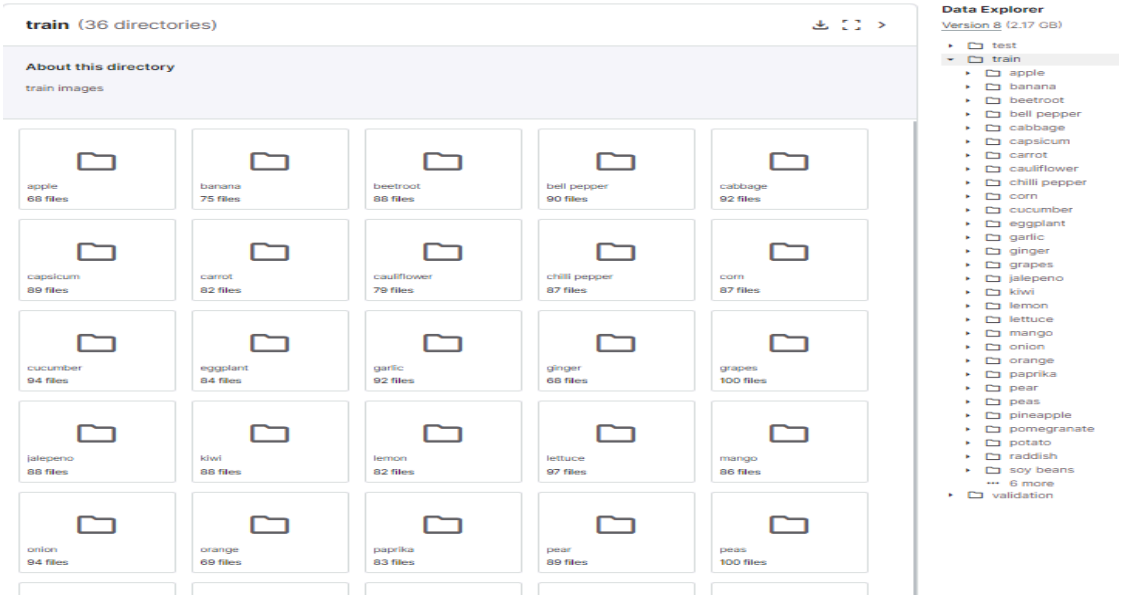
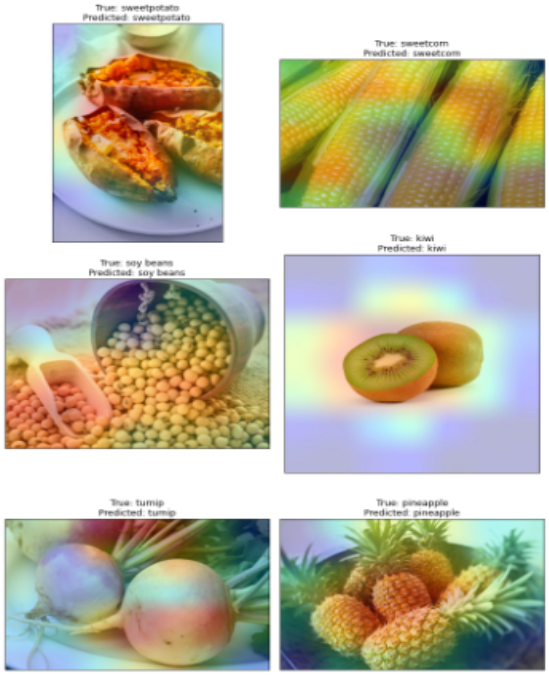
APPENDICES

About Dataset:



ORIGINAL IMAGES	DATA AUGMENTED IMAGES
	

❖ Model training Images:

```
training_history=cnn.fit(x=training_set,validation_data=validation_set,epochs=28)
```

```
Epoch 1/28
98/98 [==============================] - 564s 5s/step - loss: 10.0019 - accuracy: 0.0401 - val_loss: 5.6960 - val_accuracy: 0.0427
Epoch 2/28
98/98 [==============================] - 113s 1s/step - loss: 4.0140 - accuracy: 0.0803 - val_loss: 3.6070 - val_accuracy: 0.1311
Epoch 3/28
98/98 [==============================] - 111s 1s/step - loss: 3.7989 - accuracy: 0.1743 - val_loss: 2.8110 - val_accuracy: 0.3134
Epoch 4/28
98/98 [==============================] - 109s 1s/step - loss: 3.0525 - accuracy: 0.3091 - val_loss: 2.1556 - val_accuracy: 0.5214
Epoch 5/28
98/98 [==============================] - 112s 1s/step - loss: 2.8859 - accuracy: 0.4286 - val_loss: 2.0070 - val_accuracy: 0.6410
Epoch 6/28
98/98 [==============================] - 120s 1s/step - loss: 2.1670 - accuracy: 0.5454 - val_loss: 1.6324 - val_accuracy: 0.6667
Epoch 7/28
98/98 [==============================] - 113s 1s/step - loss: 1.6719 - accuracy: 0.6257 - val_loss: 1.6521 - val_accuracy: 0.7265
Epoch 8/28
98/98 [==============================] - 111s 1s/step - loss: 1.4539 - accuracy: 0.7079 - val_loss: 2.2661 - val_accuracy: 0.6581
Epoch 9/28
98/98 [==============================] - 115s 1s/step - loss: 1.5827 - accuracy: 0.7400 - val_loss: 1.4001 - val_accuracy: 0.8120
Epoch 10/28
98/98 [==============================] - 109s 1s/step - loss: 1.0812 - accuracy: 0.7862 - val_loss: 2.5998 - val_accuracy: 0.6410
Epoch 11/28
98/98 [==============================] - 119s 1s/step - loss: 2.3699 - accuracy: 0.7708 - val_loss: 1.4004 - val_accuracy: 0.8746
Epoch 12/28
98/98 [==============================] - 109s 1s/step - loss: 1.4009 - accuracy: 0.8279 - val_loss: 1.8118 - val_accuracy: 0.8120
Epoch 13/28
98/98 [==============================] - 112s 1s/step - loss: 1.2177 - accuracy: 0.8276 - val_loss: 2.4186 - val_accuracy: 0.6980
Epoch 14/28
98/98 [==============================] - 111s 1s/step - loss: 1.1762 - accuracy: 0.8494 - val_loss: 1.2582 - val_accuracy: 0.8775
Epoch 15/28
98/98 [==============================] - 114s 1s/step - loss: 1.8240 - accuracy: 0.8462 - val_loss: 1.7278 - val_accuracy: 0.9031
Epoch 16/28
```

❖ Results For Some random Images from Internet:

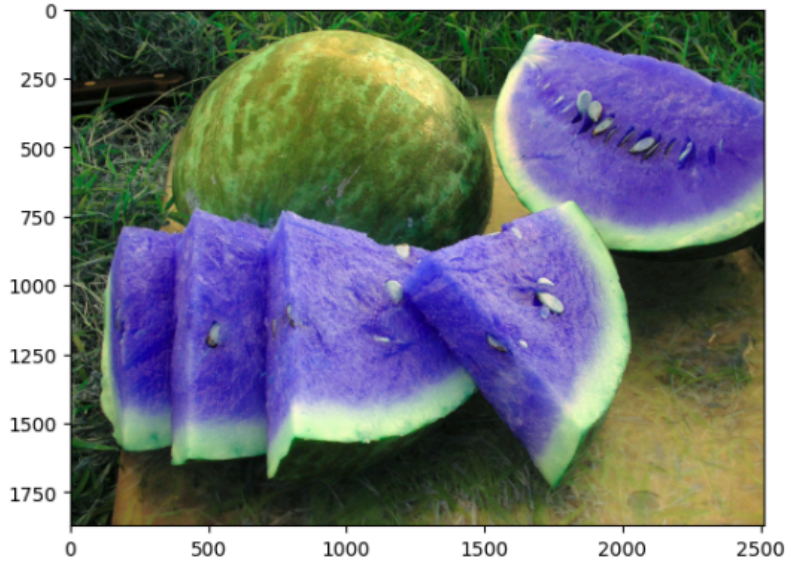
-
```
image_path="/content/drive/MyDrive/random images from internet/39.jpg"
img=cv2.imread(image_path)
image=tf.keras.preprocessing.image.load_img(image_path,target_size=(64,64))
input_arr=tf.keras.preprocessing.image.img_to_array(image)
input_arr=np.array([input_arr])#converting single image to batch
predictions=cnn.predict(input_arr)
result_index=np.where(predictions[0]==max(predictions[0]))
plt.imshow(img)
plt.show("Test Image")
plt.show()
print("It is a {}".format(test_set.class_names[result_index[0][0]]))
```

```
1/1 [==============================] - 0s 21ms/step
```

-
```
image_path="/content/drive/MyDrive/random images from internet/23.jpg"
img=cv2.imread(image_path)
plt.imshow(img)
image=tf.keras.preprocessing.image.load_img(image_path,target_size=(64,64))
input_arr=tf.keras.preprocessing.image.img_to_array(image)
input_arr=np.array([input_arr])#converting single image to batch
predictions=cnn.predict(input_arr)
result_index=np.where(predictions[0]==max(predictions[0]))
plt.show("Test Image")
plt.show()
print("It is a {}".format(test_set.class_names[result_index[0][0]]))
```

```
image_path="/content/drive/MyDrive/random images from internet/23.jpg"
img=cv2.imread(image_path)
plt.imshow(img)
image=tf.keras.preprocessing.image.load_img(image_path,target_size=(64,64))
input_arr=tf.keras.preprocessing.image.img_to_array(image)
input_arr=np.array([input_arr])#converting single image to batch
predictions=cnn.predict(input_arr)
result_index=np.where(predictions[0]==max(predictions[0]))
plt.show("Test Image")
plt.show()
print("It is a {}".format(test_set.class_names[result_index[0][0]]))
```

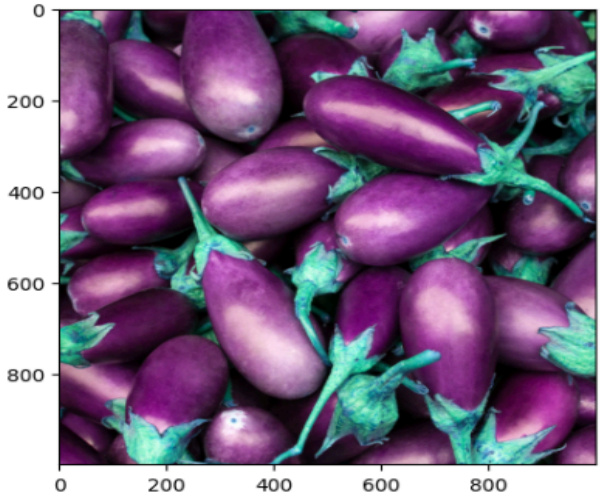
```
1/1 [==============================] - 0s 34ms/step
```




```
It is a watermelon
```

```
image_path="/content/drive/MyDrive/random images from internet/11.jpg"
img=cv2.imread(image_path)
plt.imshow(img)
image=tf.keras.preprocessing.image.load_img(image_path,target_size=(64,64))
input_arr=tf.keras.preprocessing.image.img_to_array(image)
input_arr=np.array([input_arr])#converting single image to batch
predictions=cnn.predict(input_arr)
result_index=np.where(predictions[0]==max(predictions[0]))
plt.show("Test Image")
plt.show()
print("It is a {}".format(test_set.class_names[result_index[0][0]]))
```

```
1/1 [==============================] - 0s 41ms/step
```




```
It is a eggplant
```