**Identifying rottenness of a fruit by image**

*A Project Report Submitted in partial fulfillment of the requirements for the award of the degree of*

### BACHELOR OF TECHNOLOGY

*in*

### Computer Science and Engineering

by

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*Under the esteemed guidance of*

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2023-2024

*Bonafide Certificate*

This is to certify that this project report entitled **“Identifying rottenness of a fruit by image”** submitted to **Department of Computer science and Engineering, K L Deemed to be University, Hyderabad,** in connection with the University “Industrial Practice School Program” is a bonafide record of work done by “**B. Simon Sumanth (2010030343), Mohammad Fauzaan Pasha (2010030452)”** under my supervision at the **“KL University Hyderabad**”.

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This is Certified that the project entitled **“Identifying rottenness of a fruit by image”** which is an experimental & Simulation work carried out by **B. Simon Sumanth (2010030343), Mohammad Fauzaan Pasha (2010030452)** in partial fulfillment for the award of the degree of **Bachelor of Technology** in Department **of CSE**, during the year **2023-2024**. The project has been approved as it satisfies the academic requirements.

**ACKNOWLEDGEMENT**

First and foremost, we thank the lord almighty for all his grace & mercy showered upon us, for completing this project successfully.

We take grateful opportunity to thank our beloved Founder and Chairman who has given constant encouragement during our course and motivated us to do this project. We are grateful to our Principal **Dr. A. Rama Krishna** who has been constantly bearing the torch for all the curricular activities undertaken by us.

We pay our grateful acknowledgement & sincere thanks to our Head of the Department **Dr. Arpita Gupta** for her exemplary guidance, monitoring and constant encouragement throughout the course of the project. We pay our sincere thanks to our Project Coordinator **Dr. Shadab Siddiqui** who has been constantly inculcating logistic support and has given constant encouragement during our project.

We wholeheartedly thank all the teaching and non-teaching staff of our department without whom we wouldn't have made this project a reality. We would like to extend our sincere thanks especially to our parents, our family members and friends who have supported us to make this project a grand success.

### B. Simon Sumanth (2010030343)

**Mohammad Fauzaan Pasha (2010030452)**

# ABSTRACT

Deep learning models, namely Convolutional Neural Networks (CNNs), are customized for this job and fine-tuned as needed. Standard classification measures are used to carefully test the trained models, assuring their correctness and dependability. The potential influence of this technology on decreasing food waste and improving supply chain quality is also highlighted. To sustain performance in changing settings, regular model upgrades are suggested. This study shows a viable option for automated fruit quality evaluation, with practical implications in agriculture, retail, and food preservation.

The effective detection of fruit freshness and rottenness has sparked considerable interest due to its potential to decrease food waste and improve product quality in the agricultural and retail sectors. This research endeavor presents a complete framework for harnessing the potential of harnessing the potential of deep learning for this aim.

A notable aspect of the "Fruits Fresh and Rotten Classification" project is its aim to seamlessly integrate with existing fruit sorting systems and quality control processes within the industry. By automating the fruit quality assessment process, the project strives to enhance operational efficiency, reduce manual labor, and mitigate human errors. This integration is expected to provide tangible benefits to the industry in terms of cost savings and improved product quality.

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### CHAPTER 1

**INTRODUCTION**

The effective detection of fruit freshness and rottenness has sparked considerable interest due to its potential to decrease food waste and improve product quality in the agricultural and retail sectors. This research endeavor presents a complete framework for harnessing the potential of deep learning for this aim.

Deep learning, particularly Convolutional Neural Networks (CNNs), excels in analyzing images by recognizing patterns. Potential impact on agriculture and food industries by providing an automated tool for quality evaluation. The performance evaluation of this project is multi-faceted, employing metrics such as accuracy, precision, recall, and the F1 score. The objective is not only to create an accurate system but also to ensure that it can operate in real-time and adapt to changing environmental conditions. This focus on practicality is driven by the recognition that the system's true value lies in its applicability in dynamic fruit sorting and quality control scenarios.

## PROBLEM STATEMENT:

The efficient identification of fruit freshness and rotteness has garnered significant attention due to its potential to reduce food waste and enhance the quality of produce in the agricultural and retail sectors. Given this, the challenge is to create a deep learning-based system that can properly recognise the freshness and rottenness of fruits based on visual signals. This technology intends to automate the quality evaluation process, reduce food waste, and ensure that consumers only receive fresh and high-quality fruits.

## OBJECTIVES:

1. Create and train a Convolutional Neural Network (CNN) model capable of accurately classifying fruit images into distinct categories representing different levels of freshness and degrees of rottenness.
2. Develop a Robust Deep Learning Model
3. Analyze feature selection methods and understand the principle of operation.

## Scope of the Project:

A study focused at assessing fruit freshness and rottenness using deep learning has a broad reach and can have a substantial influence across several disciplines

## CHAPTER 2

## LITERATURE SURVEY

Many approaches were applied to predict heart disease. Most of these approaches have used machine learning and data mining. The majority of related work focused on applying only one method of data mining to extract knowledge, and the others focused on comparing several strategies to predict the disease.

|  |  |  |  |
| --- | --- | --- | --- |
| Reference | Authors | Publication Date | Key Findings |
|  |  |  |  |
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| [7] Amara, J., Bouarfa, A., & Derbel, F. (2020). Mango fruits quality assessment: A survey. Computers and Electronics in Agriculture, 175, 105565. | Jawaher Amara, Abdelkader Bouarfa, and Fatiha Derbel | 2020 | Focused on the quality assessment of mango fruits, this survey discusses image analysis methods and their applications for fruit assessment. |

**Table. 2.1**

# CHAPTER 3

**SOFTWARE AND HARDWARE REQUIREMENTS**



## Hardware:

OS – Windows 7,8 or 10 RAM – 4GB

## Software:

Python Interpreter Pycharm Community IDE Google colab

## Python

Python is a high-level, interpreted, interactive and object-oriented scripting language created by Guido Rossum in 1989. Python is designed to be highly readable. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. It is ideally designed for rapid prototyping of complex applications. It has interfaces to many OS system calls and libraries and is extensible to C or C++. Python is dynamically typed and garbage-collected. It supports multiple programming paradigms, including procedural, object oriented, and functional programming. Python programming is widely used in Artificial Intelligence, Natural Language Generation, Neural Networks and other advanced fields of Computer Science.

## Pycharm

PyCharm is an integrated development environment (IDE) used in computer programming, especially for the Python language. It is developed by the Czech company JetBrains (formerly known as IntelliJ). It provides code analysis, graphical debugger, built-in unit tester, integration with version control systems (VCS), and supports web development with Django and data science with Anaconda.

PyCharm is cross-platform, with Windows, macOS and Linux versions. The Community Edition is released under the Apache license and there is also the Professional Edition with additional features, released under a proprietary license.

### Google Colab

Colab is a free Jupyter notebook environment that runs entirely in the cloud. Most importantly, it does not require a setup and the notebooks that you create can be simultaneously edited by your team members - just the way you edit documents in Google Docs. Colab supports many popular machine learning libraries which can be easily loaded in your notebook.

What Colab Offers You?

As a programmer, you can perform the following using Google Colab.

* + - * Write and execute code in Python.
      * Document your code that supports mathematical equations.
      * Create/Upload/Share notebooks.
      * Import/Save notebooks from/to Google Drive.
      * Import/Publish notebooks from GitHub.
      * Import external datasets e.g. from Kaggle.
      * Integrate PyTorch, TensorFlow, Keras, OpenCV.
      * Free Cloud service with free GPU.

# CHAPTER 4

1. **FUNCTIONAL AND NONFUNCTIONALREQUIREMENTS**

## FUNCTIONAL REQUIREMENTS

* The system is able to compare accuracies among all the algorithms.
* The system is able to predict the freshness of the fruit.

## NON-FUNCTIONAL REQUIREMENTS

### Usability

Usability is a measure of how well a specific user in a specific context can use a product/design to achieve a defined goal effectively, efficiently and satisfactorily. Designers usually measure a design’s usability throughout the development process—from wireframes to the final deliverable—to ensure maximum usability.

### Scalability

Scalability is the measure of a system's ability to increase or decrease in performance and cost in response to changes in application and system processing demands. ... Enterprises that are growing rapidly should pay special attention to scalability when evaluating hardware and software.

# CHAPTER 5 PROPOSED SYSTEM

The outlined process begins with the definition of the problem, which revolves around fruit freshness and rotteness identification, a critical concern in the agricultural and retail sectors. The subsequent steps encapsulate the core stages of this deep learning-based project. Data collection involves curating a diverse dataset of labeled fruit images, while data preprocessing ensures image uniformity and quality through resizing and color normalization. The optional application of data augmentation enhances the dataset's robustness. The dataset is then divided into training, validation, and test sets for model training and evaluation.

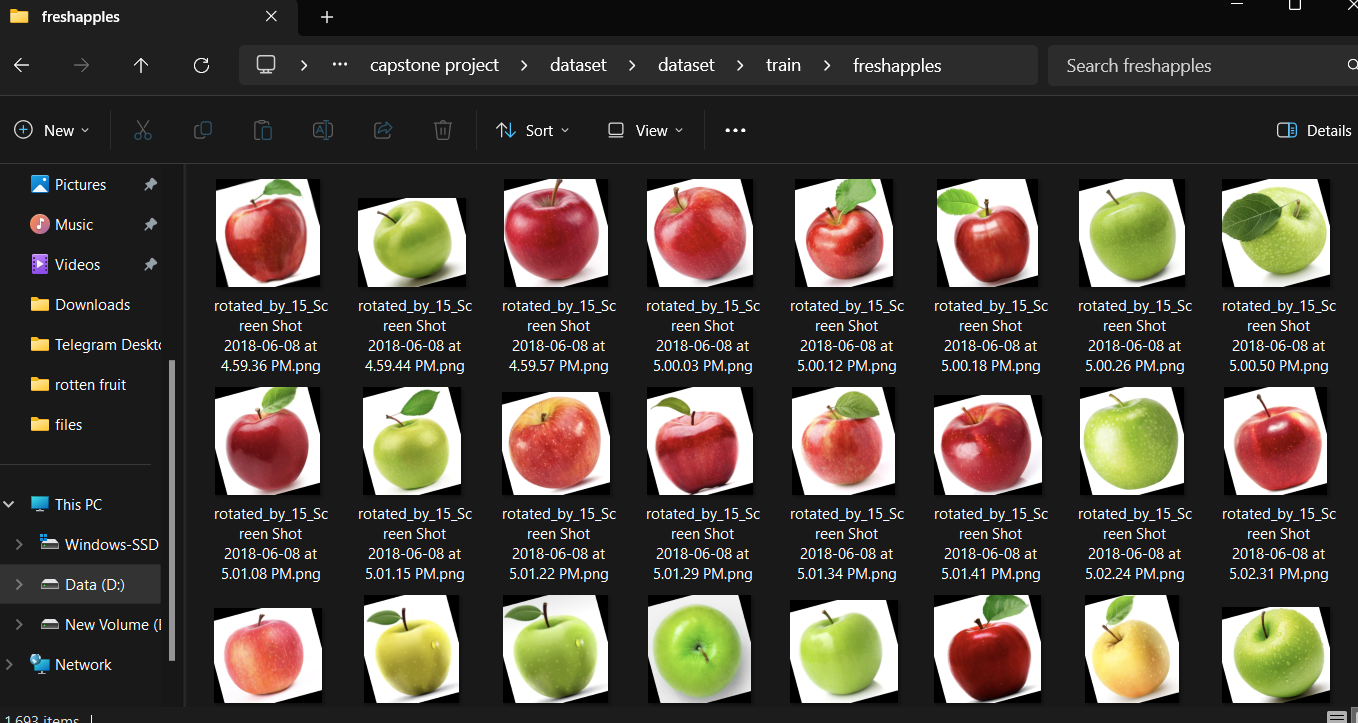
VGG16, a well-established CNN architecture, is selected and customized for the task, with the final layer modified for classification. Model training includes appropriate loss functions and optimization algorithms, with continuous monitoring on the validation set. Model evaluation rigorously assesses the model's accuracy, precision, recall, and F1 score on the test dataset. Fine-tuning may be performed to optimize the model's performance, if necessary. Once the model proves reliable, it can be deployed in practical applications such as fruit sorting systems and retail quality control. Continuous improvement involves regular model updates to adapt to evolving conditions and standards. This systematic approach offers a promising solution to a complex issue, with its ultimate goal being the reduction of food waste and the enhancement of fruit quality throughout the supply chain.

# CHAPTER 6 ABOUT DATASET

### Fresh Fruits and Rotten Fruits Data Set:

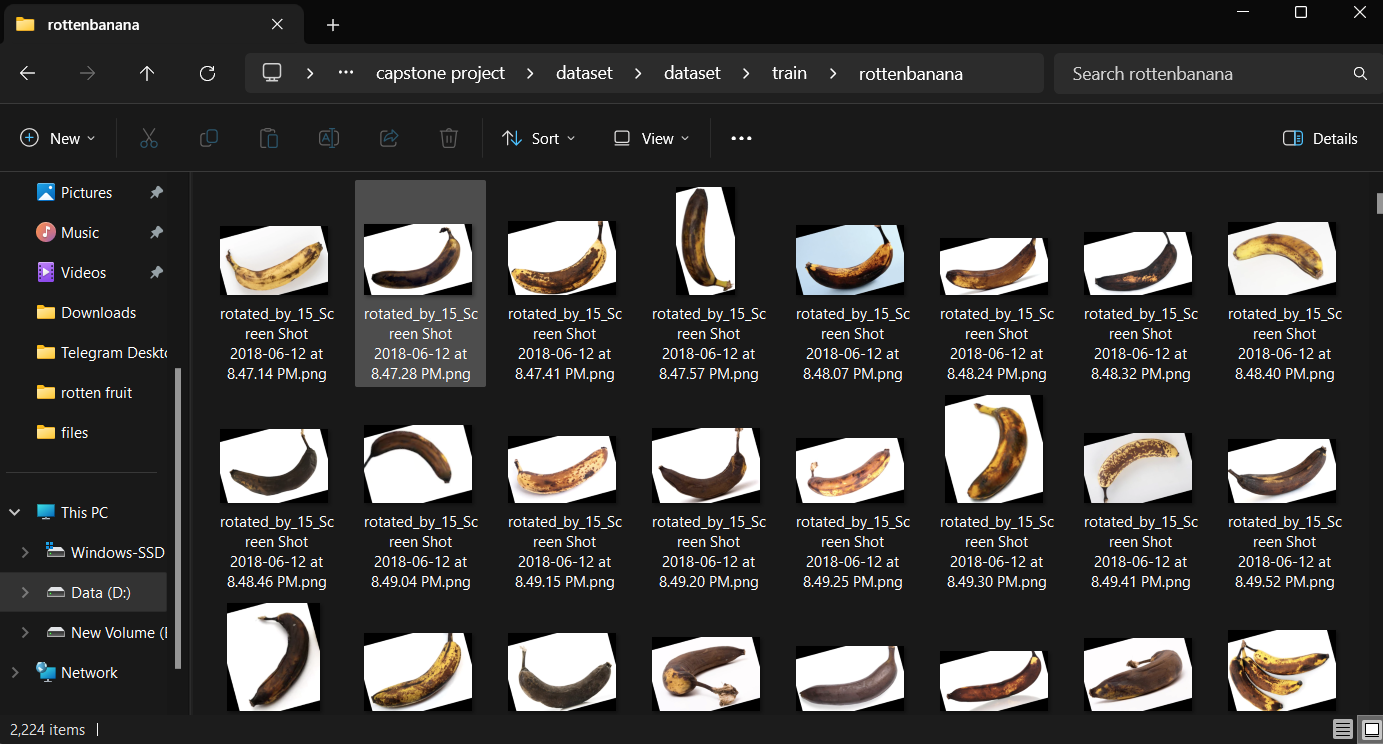
The "Fruits Fresh and Rotten Classification" project is a data-driven initiative designed to address the critical challenge of fruit quality assessment using machine learning techniques. It revolves around the automated classification of fruits into two primary categories: "Fresh" and "Rotten.”

**Fresh Fruits:**



**Fig. 6.1**

**Rotten Fruits:**



**Fig. 6.2**

# CHAPTER 7 IMPLEMENTATION

### Data Collection and Preprocessing:

Data Collection: The quality and diversity of your dataset are crucial for the model's effectiveness. Collect a wide range of fruit images, capturing various types of fruits in different conditions. Consider factors such as lighting, backgrounds, and angles.

Data Preprocessing: Ensure that all images are of a consistent format and size. Resizing images to a common dimension (e.g., 224x224 pixels) is essential, as neural networks require uniform input. Normalize pixel values to the [0, 1] range to improve training stability. Data preprocessing may also involve cropping, rotating, or applying other augmentations to introduce variability into the dataset.

### Split the Dataset:

Training, Validation, and Test Sets: Splitting the dataset into three subsets serves several purposes. The training set is used to teach the model, the validation set helps optimize hyperparameters and prevent overfitting, and the test set provides an unbiased evaluation of the model's performance. The proportions of the split can vary based on the size of your dataset and specific needs.

### Model Architecture:

### Load Pre-trained VGG-16: The VGG-16 model, pre-trained on a large image dataset like ImageNet, serves as an excellent feature extractor due to its deep convolutional layers. These layers have learned to capture general visual patterns, which can be fine-tuned for your specific task.

### Remove Top Layers: Remove the top layers, which were designed for ImageNet's classification task, as you'll add custom layers tailored to your fruit freshness classification problem.

### Customize the Model:

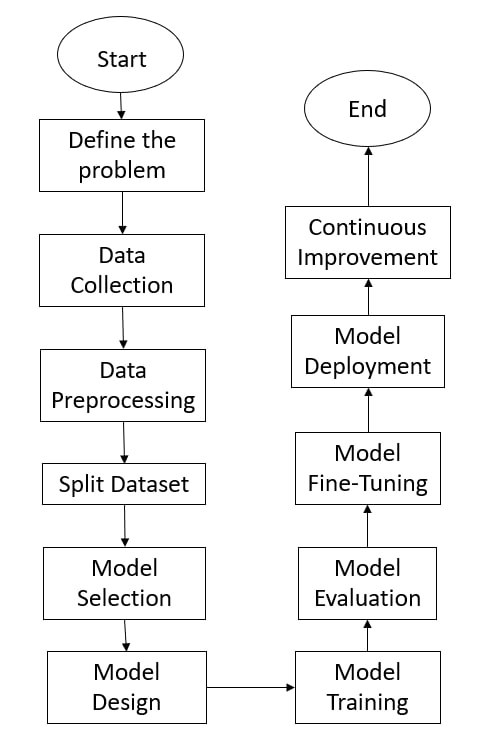
### Add Custom Fully Connected Layers: Design the top layers of your model for fruit freshness classification. These fully connected layers should adapt the VGG-16 base to your specific problem. The number of neurons in the final layer corresponds to the number of freshness categories in your dataset.

### Training:

Compile the Model: Define the model's optimization process. Specify the loss function (categorical cross-entropy for multi-class classification), optimizer (e.g., Adam), and evaluation metrics (e.g., accuracy).

Train the Model: Train the model using the training dataset. During training, the model learns to recognize patterns and features associated with different fruit freshness levels. Implement data augmentation to expose the model to a variety of conditions, making it more robust

### Flowchart



**Fig. 7.1**

* 1. **MODEL SELECTION:**

We have done comparative analysis among machine learning algorithms and different data sets.one of the most famous dataset taken from the uci machine learning repository. The algorithm as follows:

### Visual Geometry Group:

VGG-16, short for Visual Geometry Group 16, is a deep convolutional neural network (CNN) architecture that gained prominence due to its impressive performance in image classification tasks. Developed by the Visual Geometry Group at the University of Oxford, VGG-16 is a variant of the VGG network, designed for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition in 2014. VGG-16 is renowned for its depth and uniform architecture.

Depth and Complexity: VGG-16 is characterized by its depth, as the name suggests. It comprises 16 layers, which include 13 convolutional layers and 3 fully connected layers. This depth allows the network to learn hierarchical features from raw image data, making it well-suited for tasks such as image classification.

Uniform Design: One of the notable aspects of VGG-16 is its uniformity. The architecture employs 3x3 convolutional kernels throughout the network, which is the smallest size that can capture spatial hierarchies effectively. This uniformity in kernel size simplifies the architecture and makes it more interpretable.

Block Structure: VGG-16 is organized into five blocks, each containing a pair of 3x3 convolutional layers, followed by a max-pooling layer. This block structure helps in progressively reducing the spatial dimensions of the feature maps while increasing the depth of the network.

Max-Pooling: After each pair of convolutional layers, a max-pooling layer is applied to reduce the spatial resolution of the feature maps. Max-pooling helps achieve translational invariance, making the network more robust to variations in object position within the input image

Fully Connected Layers: The architecture includes three fully connected layers towards the end, following the convolutional and max-pooling layers. These fully connected layers play a crucial role in the final classification and output the probabilities of different classes using a softmax activation function.

Large Number of Parameters: VGG-16 has a substantial number of parameters, which contributes to its capacity to capture intricate features. However, this also means that it requires a significant amount of data for training and may be computationally expensive.

Transfer Learning: Due to its strong performance on image classification tasks, pretrained VGG-16 models are widely available in deep learning libraries. This makes it a valuable asset for transfer learning, where the model can be fine-tuned on specific tasks using a smaller dataset.

### Advantages of VGG

1. Strong Feature Extraction: VGG-16's deep architecture excels at capturing intricate features from images, making it effective for tasks like image classification.
2. Transfer Learning: Pretrained VGG-16 models are readily available, making it a valuable asset for transfer learning in various computer vision applications.

### Disadvantages of VGG

1. High Computational Cost: VGG-16's depth and large number of parameters can be computationally expensive and may not be practical for resource-constrained environments.
2. Overfitting Risk: The architecture's capacity to capture complex features can lead to overfitting, especially when trained on small datasets.

Despite its strengths, VGG-16 has certain limitations, such as high computational requirements and the potential for overfitting on small datasets. Consequently, it may not be the most efficient architecture for all scenarios. However, it remains a classic and influential model that has significantly shaped the landscape of deep learning and image analysis.

The Applications of VGG-16:

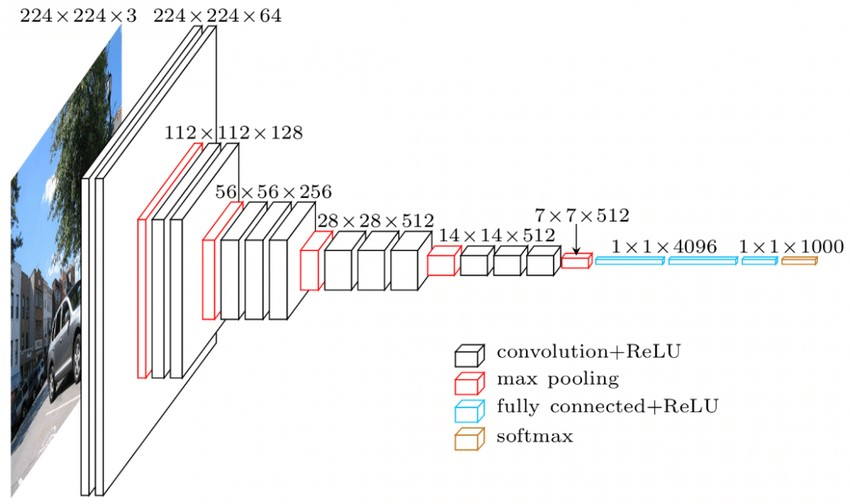
VGG-16 has had a profound impact on the field of deep learning and computer vision. It has been employed in a wide range of applications, including:

Image classification: VGG-16's deep architecture makes it a powerful tool for classifying objects in images.

Object detection: The network has been used as a feature extractor within more complex object detection pipelines, such as Faster R-CNN.

Scene recognition: VGG-16 can identify scenes or backgrounds within images.

Fine-grained image classification: It has been applied to tasks where subtle differences in images must be recognized.



**Fig.7.2**

### Pandas

Pandas is a Python package providing fast, flexible, and expressive data structures designed to make working with structured (tabular, multidimensional, potentially heterogeneous) and time series data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, real world data analysis in Python. Additionally, it has the broader goal of becoming the most powerful and flexible open source data analysis / manipulation tool available in any language.

### Matplotlib

Matplotlib is an amazing visualization library in Python for 2D plots of arrays. Matplotlib is a multi-platform data visualization library built on NumPy arrays and designed to work with the broader SciPy stack. It was introduced by John Hunter in 2002. One of the greatest benefits of visualization is that it allows us visual access to huge amounts of data in easily digestible visuals. Matplotlib consists of several plots like line, bar, scatter, histogram etc. For simple plotting the pyplot module provides a MATLAB-like interface, particularly when combined with IPython. For the power user, you have full control of line styles, font properties, axes properties, etc, via an object oriented interface or via a set of functions familiar to MATLAB users.

### NUMPY

Numpy is one such powerful library for array processing along with a large collection of high-level mathematical functions to operate on these arrays. These functions fall into categories like Linear Algebra, Trigonometry, Statistics, Matrix manipulation, etc.

### SKLEARN

Scikit-learn (Sklearn) is the most useful and robust library for machine learning in Python. It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction via a consistent interface in Python. Scikit-learn (formerly scikits. learn and also known as sklearn) is a free software machine learning library for the Python programming language. Scikit-learn is a library in Python that provides many unsupervised and supervised learning algorithms. It’s built upon some of the technology you might already be familiar with, like NumPy, pandas, and Matplotlib! The functionality that scikit-learn provides include: Regression, including Linear and Logistic Regression Classification, including K-Nearest Neighbors Clustering, including K-Means and

K-Means++Model selection Preprocessing, including Min-Max Normalization.

.

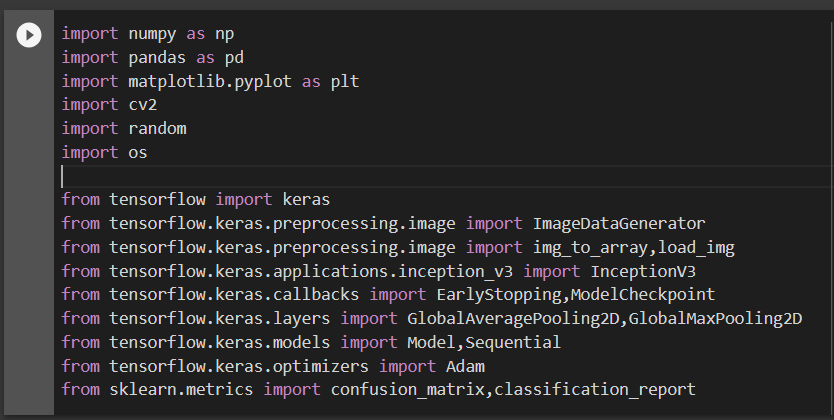
Steps that we have followed for this project are:

## Step 1:Import Libraries:

The libraries that we have used in our project are pandas ,numpy,seaborn,matplotlib. Tensorflow,

Opencv,Keras.

.



**Fig. 7.3**

## Scikit\_Learn:

Scikit Learn (Sklearn) is the most useful and robust machine learning library in Python. Provides a selection of efficient machine learning and statistical modeling tools including classification, regression, clustering and dimension reduction through a consistency interface in Python. It is mostly written in Python and is based on NumPy, SciPy and Matplotlib.

**Tensorflow:**

TensorFlow is a free and open-source software library for numerical computation using data flow graphs. It is used primarily for machine learning and artificial intelligence, but can also be used for a variety of other tasks, such as data visualization and natural language processing.

TensorFlow was developed by researchers and engineers working on the Google Brain project, and was released to the public in 2015. It has since become one of the most popular machine learning libraries in the world, and is used by researchers and developers at companies of all sizes.

TensorFlow is available for a variety of platforms, including Linux, macOS, Windows, and Android. It can be used with a variety of programming languages, including Python, C++, and Java.

TensorFlow provides a number of features that make it a powerful tool for machine learning, including:

Performance: TensorFlow is highly optimized for performance, and can be used to train and deploy machine learning models on a variety of hardware platforms.

Flexibility: TensorFlow is a flexible library that can be used to build a wide variety of machine learning models, including deep neural networks, support vector machines, and decision trees.

Community: TensorFlow has a large and active community of users and developers who contribute to the library and provide support to other users.

## Step 2: Import the Dataset:

The Dataset used in building this model was downloaded as a CSV file to my PC from Kaggle.

## Step 3:Data Cleaning:

First, it's important to handle missing data, which can be common in real-world datasets. Missing values need to be identified and addressed through techniques such as imputation or, in some cases, the removal of affected data points. Additionally, duplicates should be detected and eliminated to prevent skewing the analysis or modeling results.

Outliers, which are data points that deviate significantly from the majority of the data, should also be examined and, if necessary, addressed. These outliers can introduce noise and distort the analysis. Data types should be reviewed and, if needed, converted to ensure that they are suitable for the classification task. For instance, categorical data might require encoding techniques like one-hot encoding or label encoding.

If working with text data for fruit descriptions or labels, natural language processing (NLP) techniques like lowercasing, tokenization, and stop-word removal can help clean and preprocess the textual information. Inconsistent data formats, units, and naming conventions should be standardized to ensure uniformity in the dataset. Validation checks should be performed to verify logical consistency, for instance, ensuring that freshness and rottenness labels align with the actual fruit condition.

Cleaning noisy data to eliminate random variations or errors is crucial to maintain data integrity. Finally, data quality checks should be conducted to identify and rectify any anomalies or data entry mistakes. By systematically addressing these aspects, the dataset is prepared for more accurate and reliable fruit freshness and rottenness classification, ultimately improving the performance and validity of the classification model.

## Step 4: Splitting the Train and Test Data:

Splitting the dataset into training and test sets is a fundamental step in building a robust fruit freshness and rottenness classification model. This process ensures that the model's performance can be accurately assessed and validated on unseen data. Typically, the dataset is divided into two subsets: the training set and the test set. The training set, which constitutes the larger portion of the data, is used to train the classification model. During training, the model learns to recognize patterns and features associated with different levels of fruit freshness and rottenness.

## Step 5: Data Preprocessing:

Data preprocessing is a pivotal stage in preparing the dataset for fruit freshness and rottenness classification, ensuring that the data is in the most suitable form for effective analysis and modeling. This process encompasses several essential steps. To begin, missing data must be addressed. Real-world datasets often contain missing values, and strategies such as imputation or the removal of incomplete records need to be employed to handle these gaps.

Cleaning noisy data, which may include random variations or errors, is a fundamental step to maintain the dataset's integrity. Finally, data quality checks are performed to identify and rectify any anomalies or data entry mistakes. By systematically addressing these aspects, the dataset is refined and optimized for subsequent classification modeling. Proper data preprocessing is instrumental in improving the performance and reliability of the fruit freshness and rottenness classification model.

## Step 6: Model Selection:

VGG16 is a pre-trained CNN model that can be fine-tuned for specific image classification tasks. It is a part of the VGG family of models known for their simplicity and effectiveness.

ResNet, Inception, MobileNet, etc.: Various pre-trained CNN architectures are available for transfer learning, where you adapt existing models to your specific task.

## Step 7: Pre-Trained Model:

VGG16 is a pre-trained CNN model that can be fine-tuned for specific image classification tasks. It is a part of the VGG family of models known for their simplicity and effectiveness.

ResNet, Inception, MobileNet, etc.: Various pre-trained CNN architectures are available for transfer learning, where you adapt existing models to your specific task.

## Step 8: Flow of the System:

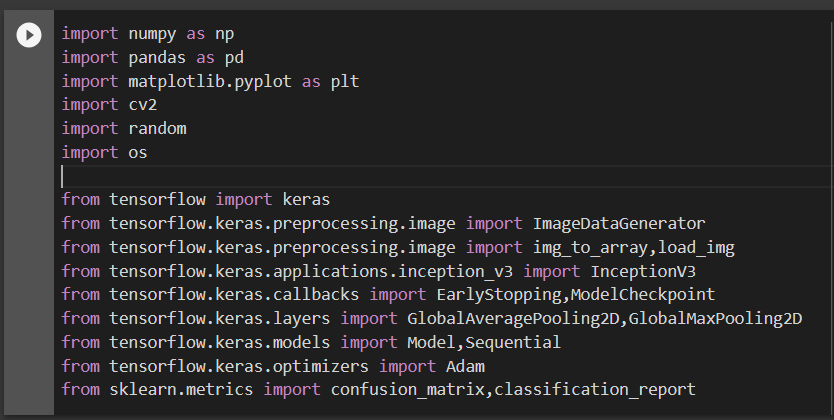
The outlined process begins with the definition of the problem, which revolves around fruit freshness and rotteness identification, a critical concern in the agricultural and retail sectors. The subsequent steps encapsulate the core stages of this deep learning-based project. Data collection involves curating a diverse dataset of labeled fruit images, while data preprocessing ensures image uniformity and quality through resizing and color normalization. The optional application of data augmentation enhances the dataset's robustness. The dataset is then divided into training, validation, and test sets for model training and evaluation. VGG16, a well-established CNN architecture, is selected and customized for the task, with the final layer modified for classification. Model training includes appropriate loss functions and optimization algorithms, with continuous monitoring on the validation set. Once the model proves reliable, it can be deployed in practical applications such as fruit sorting systems and retail quality control. Continuous improvement involves regular model updates to adapt to evolving conditions and standards. This systematic approach offers a promising solution to a complex issue, with its ultimate goal being the reduction of food waste and the enhancement of fruit quality throughout the supply chain.

# CHAPTER 8

# Source Code

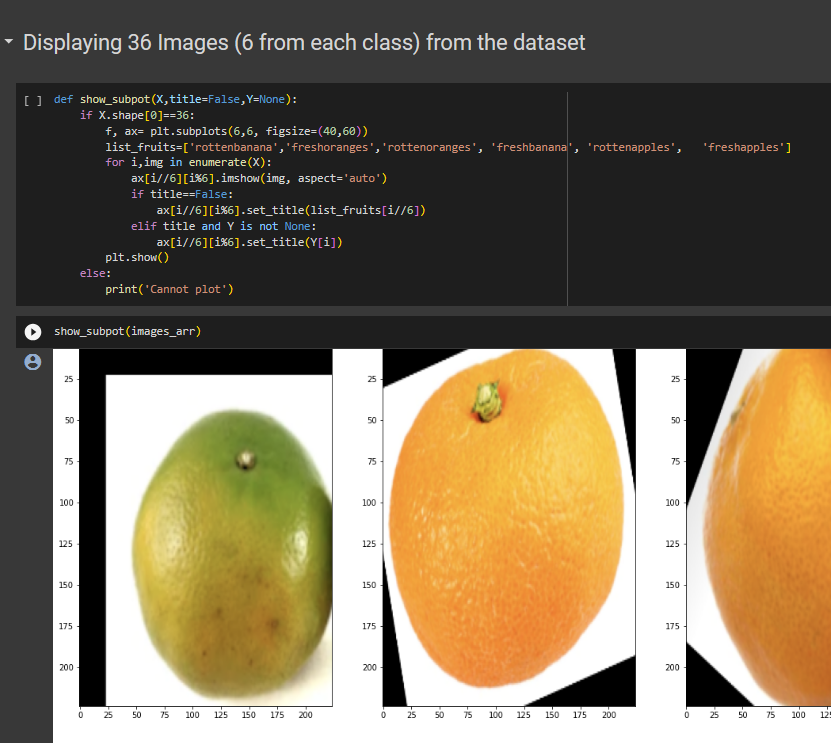
A The project titled "Fruit Freshness and Rotteness Identification Using Deep Learning" is a cutting-edge initiative aimed at revolutionizing fruit quality assessment through the power of deep learning and Convolutional Neural Networks (CNNs). This project addresses a pivotal issue in the agriculture and food supply chain industry, where the accurate identification of fruit freshness and rotteness is essential to reduce food waste, enhance product quality, and streamline the distribution process.

Importing libraries



**Fig. 8.1**

Displaying images from dataset



**Fig.8.2**

Augmentation of the Data

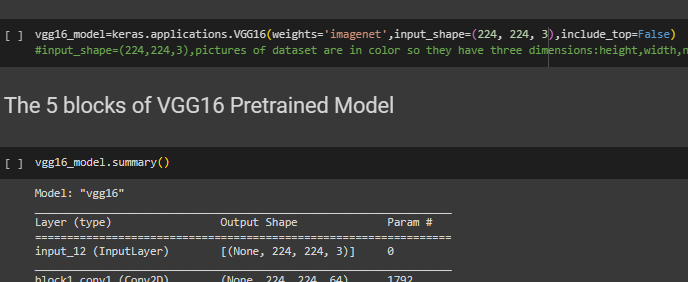
Data augmentation is a crucial technique in enhancing the robustness and generalization of a fruit freshness and rottenness classification model. It involves creating additional training data by applying various transformations and perturbations to the existing dataset. Data augmentation serves several key purposes in this context.

Data augmentation is particularly beneficial when working with smaller datasets, as it mitigates the risk of overfitting, where the model becomes too specialized to the training data and performs poorly on new, unseen examples. By introducing diversity through data augmentation, the model becomes more robust and capable of handling various scenarios, leading to more accurate and reliable fruit freshness and rottenness classification.



**Fig. 8.3**

Building The Deep Model Using Pretrained VGG16 Model



**Fig.8.4**

### MATPLOTLIB

Matplotlib is the most popular python plotting library. It is a low level library with a Matlab like interface which offers lots of freedom at the cost of having to write more code.

1. To install Matplotlib, pip and conda can be used.
2. pip install matplotlib
3. conda install matplotlib

Matplotlib is specifically good for creating basic graphs like line charts, bar charts, histograms and many more. It can be imported by typing:

* import matplotlib.pyplot as plt

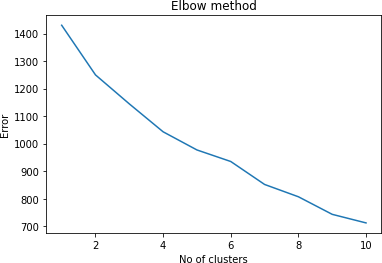


Fig.8.5 Elbow method graph

### Augment the Data using ImageDataGenerator:

### 

### Fig. 8.6

## Model Accuracy:

The model accuracy for fruit freshness and rottenness classification serves as a critical performance metric that measures the model's ability to correctly distinguish between different freshness levels of fruits. A high accuracy indicates that the model is making precise predictions and effectively classifying fresh and rotten fruits based on the provided data.

A high accuracy is particularly important in applications related to food quality assessment, where the correct identification of fruit freshness is essential to ensure food safety and quality. Accurate classification can prevent the distribution of spoiled or subpar fruits, thus minimizing waste and maintaining consumer trust.

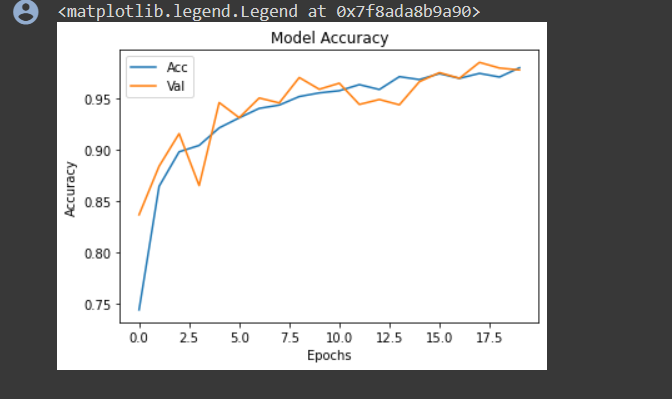


Fig.8.7

### Model Loss:

During the training process, the model initially makes predictions, and the loss is computed. The model's parameters are then adjusted through techniques like gradient descent to reduce this loss. As training progresses, the model learns to recognize patterns and features associated with different levels of fruit freshness and rottenness, ultimately reducing the loss.

A decreasing loss typically indicates that the model is learning and improving its classification ability. However, the loss can fluctuate, and it's important to monitor both the training and validation loss. The latter helps prevent overfitting, as the model should perform well not only on the training data but also on unseen data.

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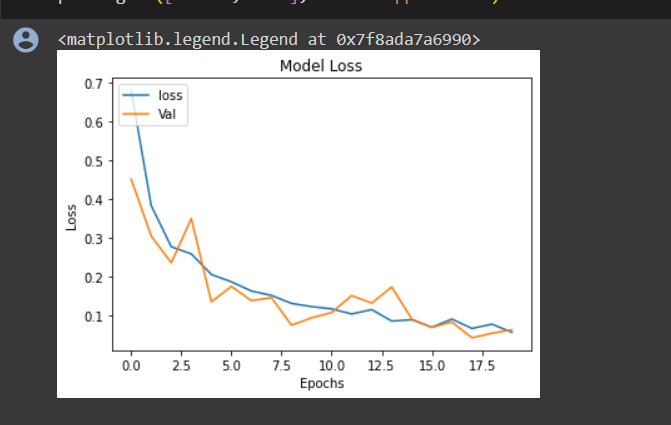


Fig.8.8

# CHAPTER 9

## 9. 1 Modules and their descriptions:

• OpenCV: OpenCV is a powerful computer vision library that can be used for image processing and manipulation, including resizing, color normalization, and data augmentation.

• Data Labeling Tools: Tools like LabelImg and RectLabel can assist in labeling images to create labeled datasets for training and testing

• Data Augmentation Libraries: Libraries such as Keras' ImageDataGenerator or TensorFlow's tf.image provide functions to augment the dataset with techniques like rotation, flipping, and brightness adjustments.

• Visualization Libraries: Libraries like Matplotlib, Seaborn, and TensorBoard (for TensorFlow) are used for visualizing model performance and results.

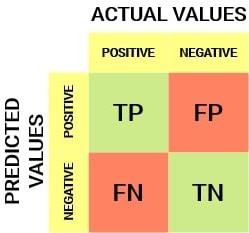
• Hyperparameter Optimization Tools: Tools like Keras Tuner, Optuna, and scikit-optimize can assist in optimizing hyperparameters for model performance.

These tools and technologies helped design, train, and evaluate CNN models for fruit freshness and rottenness identification effectively.

# CHAPTER 10 CONFUSION MATRIX

A Confusion matrix is an N x N matrix used for evaluating the performance of a classification model, where N is the number of target classes. The matrix compares the actual target values with those predicted by the machine learning model. This gives us a holistic view of how well our classification model is performing and what kinds of errors it is making.

For a binary classification problem, we would have a 2 x 2 matrix as shown below with 4 values:



**Fig.10.1 Confusion Matrix**

Let’s decipher the matrix:

The target variable has two values: Positive or Negative

The columns represent the actual values of the target variable The rows represent the predicted values of the target variable

But wait – what’s TP, FP, FN and TN here? That’s the crucial part of a confusion matrix. Let’s understand each term below.

#### True Positive (TP)

The predicted value matches the actual value

The actual value was positive and the model predicted a positive value

#### True Negative (TN)

The predicted value matches the actual value

The actual value was negative and the model predicted a negative value

**False Positive (FP) – Type 1 error**

* The predicted value was falsely predicted
* The actual value was negative but the model predicted a positive value
* Also known as the **Type 1 error**

### False Negative (FN) – Type 2 error

* The predicted value was falsely predicted
* The actual value was positive but the model predicted a negative value
* Also known as the **Type 2 error**

**Accuracy** - Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. One may think that, if we have high accuracy then our model is best. Yes, accuracy is a great measure but only when you have symmetric datasets where values of false positives and false negatives are almost the same.

Therefore, you have to look at other parameters to evaluate the performance of your model. For our model, we have got 0.803 which means our model is approx. 80% accurate.

Accuracy = TP+TN/TP+FP+FN+TN

**Precision** - Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. The question that this metric answer is of all passengers that are labeled as survived, how many actually survived? High precision relates to the low false positive rate. We have got 0.788 precision which is pretty good.

Precision = TP/TP+FP

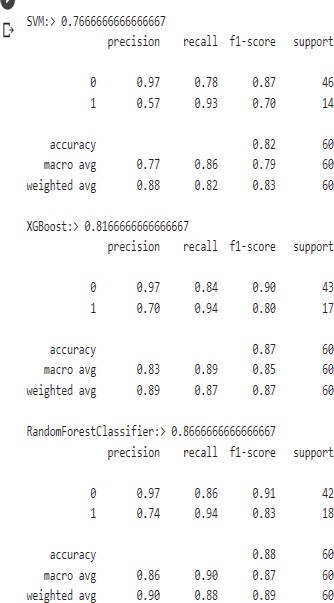
**Recall (Sensitivity)** - Recall is the ratio of correctly predicted positive observations to the all observations in actual class - yes. The question recall answers is: Of all the passengers that truly survived, how many did we label? We have got a recall of 0.631 which is good for this model as it’s above 0.5.

Recall = TP/TP+FN

**F1 score** - F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it’s better to look at both Precision and Recall. In our case, the F1 score is 0.701.

F1 Score = 2\*(Recall \* Precision) / (Recall + Precision).

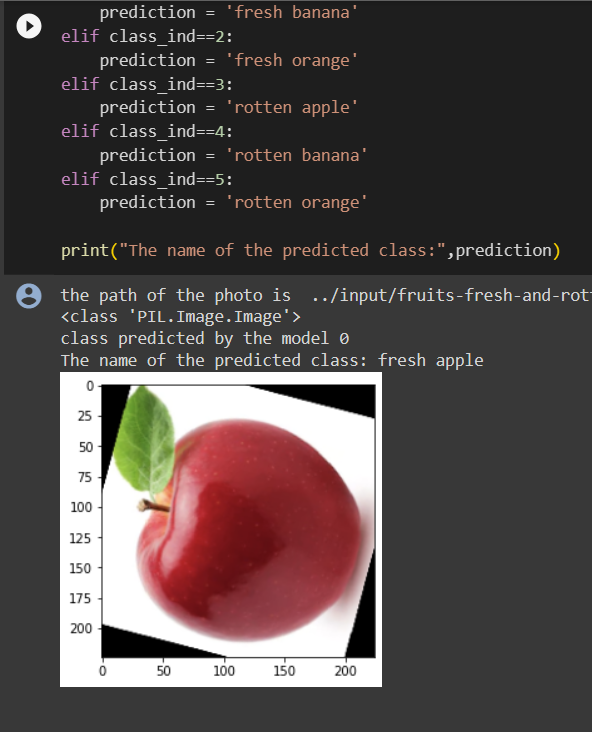
### EVALUATION MATRIX EXECUTION IMAGE:



**Fig.10.2 Evaluation Matrix**

**CHAPTER 11 RESULTS DISCUSSION**

Performance evaluation in a project for fruit freshness and rottenness identification using deep learning and CNNs is crucial to assess the effectiveness of the developed model.



**Fig.11.1 Output Screen**

# CHAPTER 12 CONCLUSION

The project aims to create an innovative system for detecting fruit freshness and rottenness using deep learning techniques, notably Convolutional Neural Networks (CNNs). The ultimate purpose is to address significant difficulties in agricultural and food supply chain management, where precise fruit quality evaluation is vital. Contributions and achievements.

A project description is a high-level overview of why you’re doing a project. The docu- ment explains a project’s objectives and its essential qualities. Think of it as the elevator pitch that focuses on what and why without delving into how.

The project's deep learning-based system for fruit freshness and rotteness identification offers a promising solution to a pressing challenge in the agriculture and food industry. Through rigorous model development, performance evaluation, and continuous improvement, the project seeks to contribute to reduced food waste, improved fruit quality, and enhanced supply chain efficiency.

# CHAPTER 13

# Limitations and future scope

Maintenance and Updates : Keeping the model up-to-date and continuously improving its performance can be resource-intensive. A robust strategy for model maintenance and updates is essential for long-term viability.

Lighting and Environmental Factors: Variability in lighting and environmental conditions may affect the model's performance. The system may not perform optimally in scenarios with poor lighting or extreme environmental conditions.

Transfer to Other Industries : The technology and expertise gained from fruit freshness and rotteness identification can be applied to other domains, such as quality control in food processing or even medical image analysis.

Efficiency Optimization: Research can continue to develop more efficient architectures or techniques that achieve similar or better performance with reduced computational resources, enabling broader adoption.

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