**ABSTRACT**

Almond Type Classification is an important task in agriculture that aims to identify various almond varieties based on distinct physical characteristics. Almonds are a valuable crop globally, and in India, demand is consistently high due to both local consumption and export needs. Accurate classification is essential to ensure quality control, consistent grading, and market readiness. This project leverages machine learning algorithms to develop a robust classification system, aiming to support farmers, agricultural researchers, and traders by automating the almond sorting process.

The dataset used for this project was obtained from Kaggle and includes critical features such as kernel length, width, thickness, shape, color, and weight of almonds.

After data preparation, we trained multiple machine learning models to evaluate which algorithm could provide the most accurate classification. The models tested included Logistic Regression, Random Forest Classifier, K Nearest Neighbours (KNN), and Support Vector Machine (SVM). Each model was tuned and optimized with hyperparameters to achieve the best possible performance. Following extensive experimentation, the Random Forest Classifier emerged as the top-performing model, achieving an impressive accuracy of 85% on the test set. This model proved adept at handling the almond dataset due to its ensemble approach, which combines multiple decision trees to improve classification accuracy and generalizability.

To further assess the model's effectiveness, we calculated additional performance metrics, such as precision, recall, F1 score, and support. Precision and recall provided insights into the model's ability to correctly classify specific almond types, while the F1 score balanced these metrics to give an overall performance measure. The high F1 score obtained indicates that the Random Forest Classifier performs well in identifying both common and less prevalent almond varieties.

In the future, this project can be expanded by incorporating more advanced algorithms, such as Convolutional Neural Networks (CNNs), to better analyze almond images, enabling a visual-based approach to classification. Additionally, by including a broader range of almond features and utilizing a larger dataset, the model’s accuracy and practical utility could be further enhanced. Such advancements could make this model applicable on a wider scale, from local farms to industrial almond processing facilities, contributing to a more efficient and reliable almond classification system in India and beyond.

**CHAPTER 1**

**INTRODUCTION**

* 1. **What is Almond Type Classification?**



Figure 1.1 Different Dimensions of Almond

Almond type classification is the process of categorizing various almond varieties based on their unique physical characteristics and nutritional properties. Almonds come in multiple types, each distinguished by features such as shape, size, color, texture, and kernel density. This classification is essential in agriculture and the food industry since different almond types serve distinct purposes—from culinary applications to oil extraction—and vary in taste, nutritional content, and market value.

The primary distinguishing factor in almond types is kernel shape, which can vary between elongated, oval, and rounded forms. Other defining characteristics include skin color, kernel thickness, and surface texture. These factors determine an almond's suitability for different uses, such as roasting, raw consumption, or as an ingredient in various products.

In recent years, almond classification has been enhanced through machine learning techniques. Algorithms such as Random Forest Classifiers and Convolutional Neural Networks (CNNs) analyze almond characteristics with high accuracy, automating the classification process. These advanced classification techniques are invaluable for quality control, enabling producers to consistently meet consumer demand for specific almond types while maintaining uniformity in quality standards.

Future advancements in almond classification could involve even more precise, image-based approaches, improving efficiency further. These innovations would make automated classification accessible to a broader range of farmers and producers, helping streamline operations and ensure the consistent quality of almonds in the agricultural supply chain.

* 1. **Nutritional Value of Almonds**



Figure 1.2 Nutrients in Almonds

Almonds are one of the most nutrient-dense foods around. Just one ounce per day offers an impressive array of vitamins, minerals and other nutrients to keep you going throughout the day.

Almonds are an excellent source of vitamin E, magnesium, and riboflavin, and a good source of fiber and phosphorus. A one-ounce serving has 13 grams of “good” unsaturated fats just 1 gram of saturated fat, and as always, almonds are cholesterol-free.1 When compared ounce for ounce, almonds are the tree nut highest in vitamin E and riboflavin and provide 6 grams of protein.2 Almonds are naturally salt-free and low in sugar.

**1.2.1 The antioxidant vitamin E in Almonds**

Almonds’ way-above-average vitamin E content makes them an antioxidant powerhouse. Just one ounce of almonds contains 50% of the Daily Value for vitamin E.  Specifically, the natural form of vitamin E in almonds is known as d-alpha-tocopherol, which is more potent than the synthetic forms of vitamin E that you’ll find in dietary supplements. In the body, vitamin E helps protect cells from the damaging effects of free radicals, caused by pollution, UV rays from the sun, cigarette smoke and other environmental and intrinsic factors.  
  
Additionally, in a study published in the *Journal of Agriculture and Food Chemistry,*experts found thatin test tube studies, almonds contain flavonoids and phenolics similar to ones found in certain fruits and vegetables**.**Findings revealed that a one-ounce serving of almonds contains a comparable amount of total polyphenols as one cup of green tea and one cup of steamed broccoli.

**1.2.2 Focus on Fibre**

An almond nutrition discussion wouldn’t be complete without talking fiber. Almonds contain both soluble and insoluble fiber. Its insoluble fiber adds bulk to your diet, helping move things along your digestive tract. Soluble fiber can help lower LDL (bad) cholesterol and control blood sugar levels. Both types of fiber have been shown to be helpful in weight maintenance, too, helping you feel full, so you eat less and stay satisfied longer. One ounce of almonds has 4 grams of filling fiber, which will keep you feeling satiated for longer after snacking. Contrary to popular belief, not all the fiber in almonds is in the skin. In fact, 1 oz. of blanched almonds still contains 3 grams of fiber even without the skin

**1.2.3 Source of Magnesium**

Magnesium is a nutrient with many jobs in the body – regulating nerve and muscle function, keeping blood sugar and blood pressure levels steady, and helping to make protein, energy, bone and DNA in the body. That’s a lot of jobs for just one nutrient. Almonds are one of the best food sources of magnesium, offering 20% of the Daily Value in a one-ounce handful. Research continues to look into the beneficial role of magnesium in high blood pressure and heart disease, diabetes and osteoporosis. Although some research has investigated the effect of magnesium on sleep, anxiety and depression, results have not been conclusive and more study is needed.

**1.2.4 Powerful Plant Protein**

The 6 grams of energizing almond protein packed into every ounce of almonds provides fuel for your body to help you tackle whatever the day throws at you. As a plant-based protein, almonds are also low in saturated fat and may help maintain healthy cholesterol levels as part of a heart-healthy diet. In fact, almonds are a deliciously indispensable part of plant based diet.  
  
Protein has a role in essentially every part of the human body. From bones and muscles (the obvious suspects) to cartilage, blood, enzymes, hormones, and even skin and nails, the importance of protein is impossible to ignore. Every ounce of almonds delivers 6 gramsof satiating protein that can help keep you feeling fuller between meals. Those who would rather not crunch into whole nuts can get the same great protein from almond butter (6g per two-tablespoon serving) or almond flour (6g per quarter cup). Nuts are a go-to snack for plant protein, but not all nuts are created equal. When compared ounce for ounce, almonds are the tree nut highest in vitamin E and riboflavin. Almonds also provide 4 grams of fiber per one ounce serving. Almonds are naturally salt free and low in sugar.

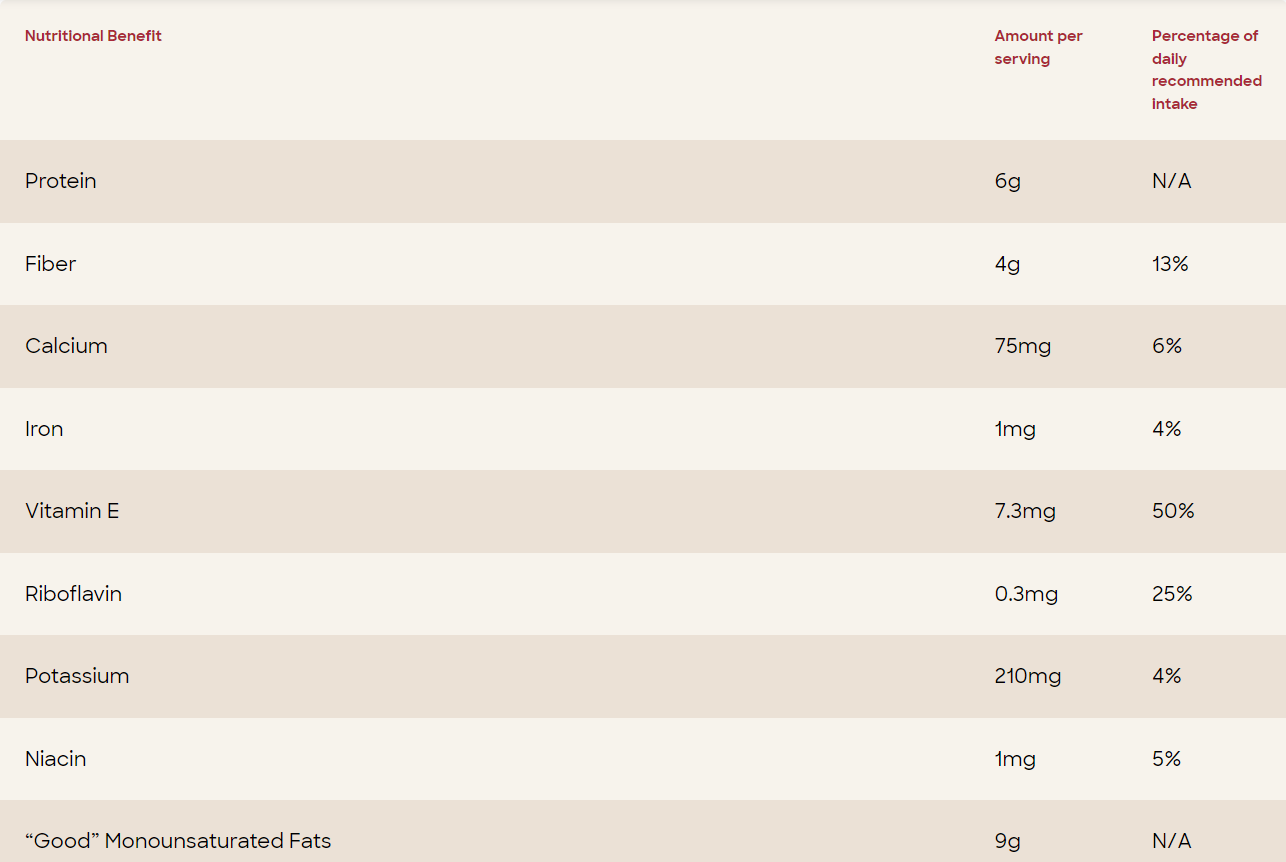


Figure 1.3 Nutritional Value of Almonds

**1.3 Taxonomy of Almonds**

* **Sweet and Bitter Almonds:**

The seeds of Prunus dulcis var. dulcis are predominantly sweet but some individual trees produce seeds that are somewhat more bitter. The genetic basis for bitterness involves a single gene, the bitter flavor furthermore being recessive, both aspects making this trait easier to domesticate. The fruits from Prunus dulcis var. amara are always bitter, as are the kernels from other species of genus Prunus, such as apricot, peach and cherry (although to a lesser extent).

The bitter almond is slightly broader and shorter than the sweet almond and contains about 50% of the fixed oil that occurs in sweet almonds. It also contains the enzyme emulsin which, in the presence of water, acts on the two soluble glucosides amygdalin and prunasin yielding glucose, cyanide and the essential oil of bitter almonds, which is nearly pure benzaldehyde, the chemical causing the bitter flavor. Bitter almonds may yield 4–9 milligrams of hydrogen cyanide per almond and contain 42 times higher amounts of cyanide than the trace levels found in sweet almonds. The origin of cyanide content in bitter almonds is via the enzymatic hydrolysis of amygdalin. P450 monooxygenases are involved in the amygdalin biosynthetic pathway. A point mutation in a bHLH transcription factor prevents transcription of the two cytochrome P450 genes, resulting in the sweet kernel trait.

* **Etymology:**

The word almond is a loanword from Old French almande or alemande, descended from Late Latin amandula, amindula, modified from Classical Latin amygdala, which is in turn borrowed from Ancient Greek amygdálē (ἀμυγδάλη) (cf. amygdala, an almond-shaped portion of the brain). Late Old English had amygdales 'almonds'.

**1.4 Cultivation**

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Figure 1.4 Almond Tree

Almonds were one of the earliest domesticated fruit trees, due to "the ability of the grower to raise attractive almonds from seed. Thus, in spite of the fact that this plant does not lend itself to propagation from suckers or from cuttings, it could have been domesticated even before the introduction of grafting". Domesticated almonds appear in the Early Bronze Age (3000–2000 BC), such as the archaeological sites of Numeira (Jordan), or possibly earlier. Another well-known archaeological example of the almond is the fruit found in Tutankhamun's tomb in Egypt (c. 1325 BC), probably imported from the Levant. An article on almond tree cultivation in Spain is brought down in Ibn al-'Awwam's 12th-century agricultural work, Book on Agriculture.

Of the European countries that the Royal Botanic Garden Edinburgh reported as cultivating almonds, Germany is the northernmost, though the domesticated form can be found as far north as Iceland

**1.4.1 Varieties**

Almond trees are small to medium-sized but commercial cultivars can be grafted onto a different root-stock to produce smaller trees. Varieties include:

* Nonpareil – originates in the 1800s. A large tree that produces large, smooth, thin-shelled almonds with 60–65% edible kernel per nut. Requires pollination from other almond varieties for good nut production.
* Tuono – originates in Italy. Has thicker, hairier shells with only 32% of edible kernel per nut. The thicker shell gives some protection from pests such as the navel orangeworm. Does not require pollination by other almond varieties.
* Mariana – used as a rootstock to result in smaller trees

**1.4.2 Pollination**

The most widely planted varieties of almond are self-incompatible; hence these trees require pollen from a tree with different genetic characters to produce seeds. Almond orchards therefore must grow mixtures of almond varieties. In addition, the pollen is transferred from flower to flower by insects; therefore commercial growers must ensure there are enough insects to perform this task. The large scale of almond production in the U.S. creates a significant problem of providing enough pollinating insects. Additional pollinating insects are therefore brought to the trees. The pollination of California's almonds is the largest annual managed pollination event in the world, with over 1 million hives (nearly half of all beehives in the US) being brought to the almond orchards each February.

Much of the supply of bees is managed by pollination brokers, who contract with migratory beekeepers from at least 49 states for the event. This business was heavily affected by colony collapse disorder at the turn of the 21st century, causing a nationwide shortage of honey bees and increasing the price of insect pollination. To partially protect almond growers from these costs, researchers at the Agricultural Research Service, part of the United States Department of Agriculture (USDA), developed self-pollinating almond trees that combine this character with quality characters such as a flavor and yield. Self-pollinating almond varieties exist, but they lack some commercial characters. However, through natural hybridisation between different almond varieties, a new variety that was self-pollinating with a high yield of commercial quality nuts was produced.

**1.4.3** **Sustainability**

Almond production in California is concentrated mainly in the Central Valley, where the mild climate, rich soil, abundant sunshine and water supply make for ideal growing conditions. Due to the persistent droughts in California in the early 21st century, it became more difficult to raise almonds in a sustainable manner. The issue is complex because of the high amount of water needed to produce almonds: a single almond requires roughly 1.1 US gallons (0.92 imperial gallons; 4.2 litres) of water to grow properly. Regulations related to water supplies are changing so some growers have destroyed their current almond orchards to replace with either younger trees or a different crop such as pistachio that needs less water.

Sustainability strategies implemented by the Almond Board of California and almond farmers include:

* tree and soil health, and other farming practices
* minimizing dust production during the harvest
* bee health
* irrigation guidelines for farmers
* food safety
* use of waste biomass as coproducts with a goal to achieve zero waste
* use of solar energy during processing
* job development
* support of scientific research to investigate potential health benefits of consuming almonds
* international education about sustainability practices

**1.5 Uses**

* **Almond Milk:**

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Figure 1.5 Almond Milk

Almonds can be processed into a milk substitute called almond milk; the nut's soft texture, mild flavor, and light coloring (when skinned) make for an efficient analog to dairy, and a soy-free choice for lactose intolerant people and vegans. Raw, blanched, and lightly toasted almonds work well for different production techniques, some of which are similar to that of soy milk and some of which use no heat, resulting in raw milk.

* **Almond Flour and Almond Skin:**



Figure 1.6 Almond Flour

Almond flour or ground almond meal combined with sugar or honey as marzipan is often used as a gluten-free alternative to wheat flour in cooking and baking.

Almonds contain polyphenols in their skins consisting of flavonols, flavan-3-ols, hydroxybenzoic acids and flavanones analogous to those of certain fruits and vegetables. These phenolic compounds and almond skin prebiotic dietary fiber have commercial interest as food additives or dietary supplements.

* **Almond Syrup:**

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Figure 1.6 Almond Syrup

Historically, almond syrup was an emulsion of sweet and bitter almonds, usually made with barley syrup (orgeat syrup) or in a syrup of orange flower water and sugar, often flavored with a synthetic aroma of almonds. Orgeat syrup is an important ingredient in the Mai Tai and many other Tiki drinks.

Due to the cyanide found in bitter almonds, modern syrups generally are produced only from sweet almonds. Such syrup products do not contain significant levels of hydrocyanic acid, so are generally considered safe for human consumption

* **Almond Oil:**
* Almonds are a rich source of oil, with 50% of kernel dry mass as fat (whole almond nutrition table). In relation to total dry mass of the kernel, almond oil contains 32% monounsaturated oleic acid (an omega-9 fatty acid), 13% linoleic acid (a polyunsaturated omega-6 essential fatty acid), and 10% saturated fatty acid (mainly as palmitic acid). Linolenic acid, a polyunsaturated omega-3 fat, is not present (table). Almond oil is a rich source of vitamin E, providing 261% of the Daily Value per 100 millilitres.
* When almond oil is analyzed separately and expressed per 100 grams as a reference mass, the oil provides 3,700 kJ (884 kcal) of food energy, 8 grams of saturated fat (81% of which is palmitic acid), 70 grams of oleic acid, and 17 grams of linoleic acid (oil table).

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Figure 1.7 Almond Oil

Oleum amygdalae, the fixed oil, is prepared from either sweet or bitter almonds, and is a glyceryl oleate with a slight odour and a nutty taste. It is almost insoluble in alcohol but readily soluble in chloroform or ether. Almond oil is obtained from the dried kernel of almonds. Sweet almond oil is used as a carrier oil in aromatherapy and cosmetics while bitter almond oil, containing benzaldehyde, is used as a food flavouring and in perfume

**CHAPTER 2**

**LITERATURE SURVEY**

**Title:** Almond Classify: Accurate Classification of Almond Varieties Using Machine Learning

**Year:** April 2022

**Authors:** Sarah Ahmed, Rami Al-Sayed, Fadi Younes, Noor Hussein

**Published in:** Journal of Agricultural Data Science

**Description:**

The classification of almond varieties is essential for maintaining quality and meeting market demands, as each almond type has unique characteristics and applications in the food and agricultural sectors. This study explores the use of machine learning algorithms to accurately classify almond types based on physical features such as size, shape, kernel density, and color. Using three extensive datasets of almond samples collected from various regions, the authors tested models including k-Nearest Neighbor, Random Forest, Logistic Regression, and Support Vector Machine to determine their accuracy and reliability for almond classification. After thorough experimentation, Random Forest achieved the highest accuracy rates, with 92.5%, 89.7%, and 95.3% across the respective datasets, outperforming other algorithms in precision and consistency. The study highlights the significance of almond classification for efficient agricultural management and food industry processing, demonstrating that machine learning can improve classification speed and reliability without sacrificing quality. Future research aims to refine these models by incorporating image processing features and exploring additional almond-specific characteristics, enhancing the scalability and efficiency of almond classification in commercial settings.

**Title:** AlmondVar: Enhancing Almond Type Prediction with Machine Learning

**Year:** September 2021

**Authors:** Javier Rodriguez, Maria Llorente, Ana Mendez, Carlos Torres

**Published in:** International Journal of Food Science and Technology

**Description:**

In the food industry, the accurate classification of almonds is vital for ensuring consistency in quality and maximizing product usability based on almond type. This paper investigates machine learning models to classify almonds by specific traits, such as kernel shape, size, density, and skin texture. Leveraging a rich dataset of almond types, the authors analyzed models like Decision Tree, Gradient Boosting, Support Vector Machine, and Random Forest. Each model was evaluated for its ability to distinguish between almond types and ensure accurate classification for optimized processing. Gradient Boosting achieved the highest accuracy of 94.1% across the dataset, showing slight improvements over Random Forest’s 93.3% performance. This paper illustrates the practical application of machine learning in agricultural sorting and the food industry, where precise classification of almond types supports efficient processing and tailored product usage. The study suggests that machine learning’s accuracy and speed offer a significant advantage over traditional sorting methods, promoting broader use in industrial classification systems. The researchers recommend further investigations using real-time image capture and feature extraction for even more reliable almond classification.

**Title:** Multi-Feature Almond Classification Using Machine Learning Techniques

**Year:** March 2020

**Authors:** Ali Hamza, Noura Salah, Khalid Amine, Tarek Omar

**Published in:** Food Science and Agriculture Informatics

**Description:**

Almonds, widely recognized for their nutritional benefits, come in diverse types that vary in traits such as shape, color, kernel density, and surface texture. Efficient classification of these types is essential for achieving quality control and addressing specific market demands. This study employed a multi-feature dataset of almond samples, examining machine learning algorithms such as Naïve Bayes, k-Nearest Neighbor, Decision Tree, and Random Forest to identify the most accurate model for almond classification. Extensive testing across three almond datasets revealed that Decision Tree and Random Forest achieved the highest accuracies at 92.4% and 93.7%, respectively. The Random Forest model excelled across all datasets due to its ensemble structure, which minimizes overfitting and provides stable performance. These findings underscore the effectiveness of machine learning in agricultural quality control, where almond classification ensures product standardization and addresses the needs of almond-based industries. Future enhancements may incorporate advanced image-based features and additional kernel characteristics, supporting a more comprehensive and efficient almond classification pipeline.

**Title:** AlmondSort: Machine Learning Models for Almond Kernel Classification

**Year:** July 2023

**Authors:** Priya Shah, Manish Patel, Anil Deshmukh, Meera Sharma

**Published in:** Agricultural Data Analytics Journal

**Description:**

The agricultural and food sectors rely heavily on the accurate classification of almonds, which vary widely in characteristics like kernel shape, size, and surface texture. This paper investigates several machine learning algorithms to support quality control and sorting systems by classifying almonds into distinct types. The study compares models such as Support Vector Machine, Logistic Regression, Naïve Bayes, and Random Forest, analyzing their effectiveness in classifying almonds using data from three major almond datasets. Random Forest emerged as the most effective model, achieving an accuracy of 96.4%—significantly higher than other models—due to its ability to handle complex and varied data patterns. The study highlights how machine learning enhances classification accuracy and efficiency, providing a scalable solution for the food industry and reducing reliance on manual sorting methods. Additionally, the authors suggest that future research could benefit from incorporating high-resolution images and deep learning for real-time almond classification, paving the way for greater automation and improved accuracy in industrial settings.

**CHAPTER 3**

**SOFTWARE REQUIREMENTS SPECIFICATION**

**3.1 Python Programming  
3.1.1 About:**

Python is a general-purpose, dynamic, high-level, and interpreted programming language. It supports Object Oriented programming approach to develop applications. It is simple and easy to learn and provides lots of high-level data structures. Python is an easy-to-learn yet powerful and versatile scripting language, which makes it attractive for Application Development. With its interpreted nature, Python's syntax and dynamic typing make it an ideal language for scripting and rapid application development. Python supports multiple programming patterns, including object-oriented, imperative, and functional or procedural programming styles.

**3.1.2 Features**

* **Free and Open Source:**

[Python](https://www.geeksforgeeks.org/python-programming-language/)language is freely available at the official website and you can download it from the given download link below click on the Download Python keyword. [Download Python](https://www.python.org/downloads/) Since it is open-source, this means that source code is also available to the public. So, you can download it, use it as well as share it.

* **Easy to code:**

Python is a [high-level programming language](https://www.geeksforgeeks.org/difference-between-high-level-and-low-level-languages/). Python is very easy to learn the language as compared to other languages like C, C#, JavaScript, Java, etc. It is also a developer-friendly language.

* **Easy to Read & Debug:**

Python is quite simple. Python’s syntax is really straightforward. The code block is defined by the indentations rather than by semicolons or brackets. Excellent information for mistake tracing. You will be able to quickly identify and correct the majority of your program’s issues once you understand how to [interpret](https://www.geeksforgeeks.org/difference-between-compiled-and-interpreted-language/)Python’s error traces.

* **Object-Oriented Language:**

One of the key features of [Python is Object-Oriented programming](https://www.geeksforgeeks.org/python-oops-concepts/). Python supports object-oriented language and concepts of classes, object encapsulation, etc.

* **GUI Programming Support:**

Graphical User interfaces can be made using a module such as [PyQt5](https://www.geeksforgeeks.org/pyqt5-qaction/), PyQt4, wxPython, or [Tk in Python](https://www.geeksforgeeks.org/python-gui-tkinter/). PyQt5 is the most popular option for creating graphical apps with Python.

* **High-Level Language:**

Python is a high-level language. When we write programs in Python, we do not need to remember the system architecture, nor do we need to manage the memory.

**3.2 Anaconda Navigator**

**3.2.1 Jupyter Notebook:**

Jupyter Notebook is a notebook authoring application, under the [Project Jupyter](https://docs.jupyter.org/en/latest/) umbrella. Built on the power of the [computational notebook format](https://docs.jupyter.org/en/latest/#what-is-a-notebook), Jupyter Notebook offers fast, interactive new ways to prototype and explain your code, explore and visualize your data, and share your ideas with others. Notebooks extend the console-based approach to interactive computing in a qualitatively new direction, providing a web-based application suitable for capturing the whole computation process: developing, documenting, and executing code, as well as communicating the results.



Figure 3.1 Jupyter Notebook Logo

The Jupyter notebook combines two components:

* A web application: A browser-based editing program for interactive authoring of computational notebooks which provides a fast interactive environment for prototyping and explaining code, exploring and visualizing data, and sharing ideas with others
* Computational Notebook documents: A shareable document that combines computer code, plain language descriptions, data, rich visualizations like 3D models, charts, mathematics, graphs and figures, and interactive controls

**3.3 Software & Hardware Requirements**

**3.3.1 Software Requirements**

Scripting language : Python Programming

Scripting Tool : Anaconda Navigator (Jupiter Notebook) & Google Collab

Operating System : Microsoft Windows 11

Dataset : Almond Type Prediction

Packages : NumPy, Pandas, Matplotlib, Seaborn etc.

**3.3.2 Hardware Requirements**

Processor : 3.20 GHz

Output Devices : Monitor (LCD)

Input Devices : Keyboard

Hard Disk : 512 GB SSD

RAM : 16 GB

**CHAPTER 4**

**SYSTEM ANALYSIS AND DESIGN**

**4.1 Aim & Objective**

**Aim:** The aim of the project is to predict the Almond Type machine learning algorithms on almond type classification dataset.

**Objective:**

* Data Collection
* Data Preprocessing & Cleaning
* Feature Extraction
* Exploratory Data Analysis
* Building Machine Learning Model
* Prediction of the type of Almond

**4.2 Architecture Diagram**

In our project on Almond Type Classification using Machine Learning, we focus on creating a model that effectively categorizes different almond varieties based on their distinct physical and nutritional characteristics. This classification model leverages features such as kernel shape (e.g., elongated, oval), color, size, kernel density, surface texture, and shell hardness. By examining these attributes, our model aims to distinguish between almond types like Mamra, Sanora, and Regular almonds—each of which varies in use, taste, and market value.

The objective of this project is to streamline almond sorting and classification processes, thereby assisting in quality control for agricultural and food industries. Machine learning algorithms such as Random Forest, KNN Classifier, Support Vector Machine, and Logistic Regression are evaluated for accuracy, with the most effective model trained to provide high reliability in almond classification. By automating this task, our project aims to support almond producers in maintaining consistent quality, meeting specific consumer demands based on almond type.

Data Collection

Almond Type Classification Dataset

D

Dataset

Data

Preprocessing

Exploratory Data Analysis

Data extraction

&

Feature engineering

Building Machine Learning Models

(Logistic Regression, Random Forest Classifier, KNN Classifier, Support Vector Machine)

Test

set

Training set

Almond Type Prediction

Mamra

Sanora

Regular

Figure 4.1 System Architecture

**4.2.1 Data Collection**

Collecting a comprehensive almond classification dataset involves gathering a wide array of physical, nutritional, and visual attributes related to different almond types. This dataset should include demographic information on almond varieties, such as regional origins and growing conditions, as well as detailed characteristics like kernel shape, size, color, texture, shell hardness, and nutritional content (e.g., fat, protein, and mineral composition). Additionally, incorporating imaging data for visual traits and sensory features such as taste and texture preferences can further enrich the dataset.

**Dataset Description:**

**Length (major axis)**

* Length of the almond in the image (based on number of pixels)

**Width (minor axis)**

* Width of the almond in the image (based on number of pixels)

**Thickness (depth)**

* Thickness of the almond in the image (based on number of pixels)

**Area**

* The area of the Almond region detected in the image

**Perimeter**

* Total length of the almond boundary

**Roundness**

* Roundness of the almond: 4 \* area / ( π \* length \*\* 2)

**Solidity**

* Area / area\_hull

**Compactness**

* perimeter\*\*2 / (4 \* π \* area)

**Aspect Ratio**

* Length / Width

**Eccentricity**

* sqrt(1 - ( Width / Length ) \*\*2 )

**Extent**

* Area / area\_bbox(bounding box)

**Convex hull(convex area, or area hull)**

* smallest convex set that contains bounding points

**Type**

* Almond Type

**4.2.2 Data Preprocessing**

In the context of almond type prediction, data preprocessing can involve checking for null values, dropping irrelevant columns, and converting categorical variables into numerical values. First, the dataset should be examined for missing values, and appropriate strategies, such as imputation or removal, should be applied. Irrelevant columns, which don't contribute significantly to the prediction task, can be dropped to simplify the dataset.

**4.2.3 Data Extraction & Feature Engineering**

In our study, we utilized the Almond Type Classification dataset sourced from Kaggle, a platform known for hosting diverse datasets for machine learning and data science projects. Our initial focus was on data preprocessing, a critical phase in which we meticulously addressed issues such as missing values, outliers, and data inconsistencies. We also standardized and normalized numerical features to ensure a consistent scale, while categorical variables were transformed into numerical representations through techniques like one-hot encoding. This step was crucial for preparing the dataset for subsequent analysis and model training.

**4.2.4 Machine Learning Algorithm**

**Logistic Regression**

Logistic Regression is a classification algorithm used when the target variable is binary. It models the probability that an instance belongs to a particular category. Despite its name, it is primarily used for binary classification problems. Logistic Regression works by applying the logistic function to a linear combination of input features, mapping the output to a probability between 0 and 1. The algorithm is widely used for its simplicity, interpretability, and efficiency, especially when the relationship between features and the log-odds of the target is assumed to be linear.

**Random Forest Classifier**

Random Forest is an ensemble learning method that builds a multitude of decision trees during training and merges them together to get a more accurate and stable prediction. Each tree in the forest is constructed using a random subset of the training data and a random subset of the features. This randomness helps to reduce overfitting and makes the model robust. Random Forests are versatile and can be applied to both classification and regression tasks. They are known for their high accuracy, ability to handle large datasets with high dimensionality, and resistance to overfitting.

**K-Nearest Neighbors (KNN) Classifier**

The K-Nearest Neighbors (KNN) Classifier is a simple, instance-based algorithm that classifies new data points based on the majority class of their 'k' closest neighbors in the feature space. In KNN, 'k' represents the number of neighbors considered for making the decision. Each new instance is classified by calculating the distance (usually Euclidean) between itself and each instance in the training dataset, selecting the 'k' closest data points, and assigning the most common class among them to the new instance.

KNN is particularly effective for small datasets and non-linear decision boundaries as it makes no assumptions about the data distribution. However, KNN can be computationally intensive on large datasets and is sensitive to the choice of 'k' and the presence of irrelevant features or noisy data.

**Support Vector Machine (SVM)**

Support Vector Machine is a powerful supervised learning algorithm used for both classification and regression tasks. In the context of classification, SVM aims to find a hyperplane that best separates the data into different classes. The "support vectors" are the data points that lie closest to the decision boundary. SVMs are effective in high-dimensional spaces, and they can handle non-linear relationships through the use of kernel functions. SVMs are known for their ability to generalize well and perform effectively in scenarios with clear margins of separation between classes.

**4.2.5 Prediction**

In our analysis of the type of almond, we employed various machine learning algorithms, including Logistic Regression, Random Forest Classifier, KNN Classifier, and Support Vector Machine. These algorithms were chosen to assess their efficacy in predicting the type of Almond. Subsequently, we evaluated the performance of each model by calculating key metrics such as accuracy, classification report, and confusion matrix.

**CHAPTER 5**

**SYSTEM IMPLEMENTATION**

System implementation is the phase in the software development lifecycle where the designed system is translated into a working and functional reality. This process involves coding, testing, integration of components, and deployment of the software or system. It aims to bring the conceptual design into practical use, addressing technical specifications and user requirements. System implementation involves meticulous attention to detail, collaboration among development teams, thorough testing procedures, and often requires adapting to unforeseen challenges. Successful implementation results in a fully operational system that meets the defined objectives, paving the way for subsequent maintenance and optimization efforts.

**5.1 Importing the Libraries:**

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

import warnings

warnings.filterwarnings("ignore")

**5.2 Importing the Dataset:**

df = pd.read\_csv("./Almond.csv")

df.head()

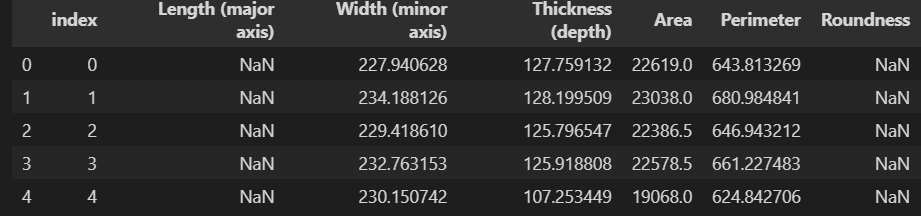
* **Loading Data:**

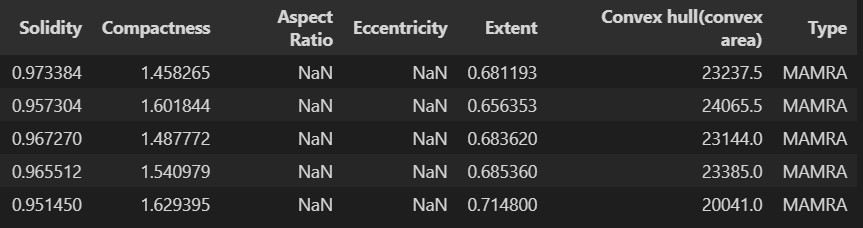
df = pd.read\_csv(“csv\_path”): Reads a CSV file into a Pandas DataFrame named 'df'.

* **Displaying the First Rows:**

df.head(): Displays the first few rows of the 'df' DataFrame, providing a quick overview of the dataset structure.

Output:



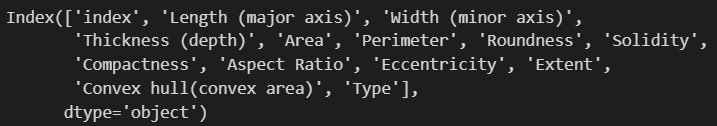


**5.3 Data Preprocessing**

**5.3.1 Handling Missing Data:**

print(df.columns)

Ouput:



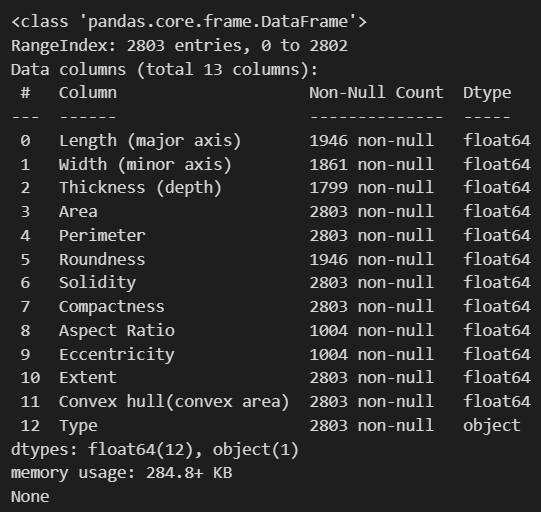
df.drop(['index'], axis=1,inplace=True)

print(df.info())

df.info(): provides a summary of the DataFrame, including:

* The number of entries (rows) and columns.
* The data types of each column (e.g., integers, floats, objects).
* The number of non-null values in each column.
* The memory usage of the DataFrame.

Output:

****

* + 1. **Data Cleaning:**

#Handle missing values - example with mean

df\_cleaned= df.copy()

df\_cleaned['Length (major axis)'] = df\_cleaned['Length (major axis)'].fillna(df\_cleaned['Length (major axis)'].mean())

df\_cleaned['Width (minor axis)'] = df\_cleaned['Width (minor axis)'].fillna(df\_cleaned['Width (minor axis)'].mean())

df\_cleaned['Thickness (depth)'] = df\_cleaned['Thickness (depth)'].fillna(df\_cleaned['Thickness (depth)'].mean())

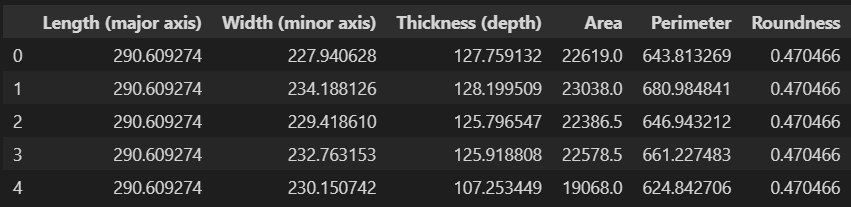
df\_cleaned['Roundness'] = df\_cleaned['Roundness'].fillna(df\_cleaned['Roundness'].mean())

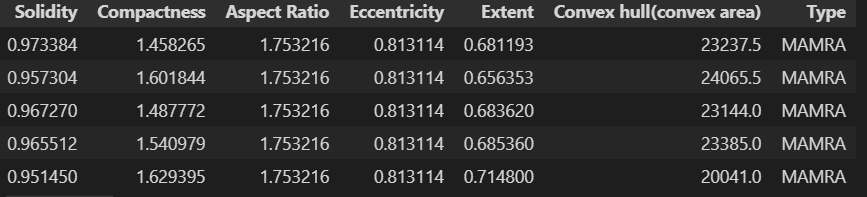
df\_cleaned['Aspect Ratio'] = df\_cleaned['Aspect Ratio'].fillna(df\_cleaned['Aspect Ratio'].mean())

df\_cleaned['Eccentricity'] = df\_cleaned['Eccentricity'].fillna(df\_cleaned['Eccentricity'].mean())

df\_cleaned.head()

Output:





* + 1. **Data Scaling:**

1. from sklearn import preprocessing
2. x = df\_cleaned.drop(['Type'], axis = 1)
3. y = df\_cleaned.loc[:,'Type'].values
4. x= StandardScaler().fit(x).transform(x)

* **x = df.drop(['Type'], axis=1)**: Removes the 'Type' column from the DataFrame df, leaving only the feature columns in x.
* **y = df.loc[:,'Type'].values**: Extracts the 'Type' column as the target variable y.
* **x = preprocessing.StandardScaler().fit(x).transform(x)**: Standardizes the features in x by scaling them to have a mean of 0 and a standard deviation of 1 using StandardScaler. This ensures that all features contribute equally to the model.

This preprocessing helps normalize the input features before feeding them into a machine learning model.

* + 1. **Train/Test Split:**

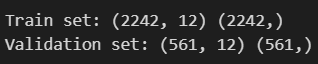
from sklearn.model\_selection import train\_test\_split

x\_train, x\_test, y\_train, y\_test = train\_test\_split(x, y, test\_size=0.2, random\_state=42)

print ('Train set:', x\_train.shape, y\_train.shape)

print ('Validation set:', x\_test.shape,  y\_test.shape)

Output:



The shape of the data is changed now. The number of rows is the same but the number of columns is reduced from 12 to 11. Because we have dropped ST\_Slope column from the dataset.

**5.5 Applying Machine Learning Algorithms**

**5.5.1 Logistic Regression:**

from sklearn.linear\_model import LogisticRegression

LR = LogisticRegression()

LR.fit(x\_train,y\_train)

lr\_predicted = LR.predict(x\_test)

score = LR.score(x\_test, y\_test)

lr\_score\_ = np.mean(score)

print('Accuracy : %.3f' % (lr\_score\_))

* from sklearn.linear\_model import LogisticRegression: Imports the LogisticRegression class from Scikit-Learn.
* LR = LogisticRegression(): Initializes the Logistic Regression model as LR.
* LR.fit(x\_train, y\_train): Trains the model on the training data (x\_train, y\_train).
* lr\_predicted = LR.predict(x\_test): Makes predictions on the test data (x\_test).
* score = LR.score(x\_test, y\_test): Calculates the accuracy score of the model on the test data.
* lr\_score\_ = np.mean(score): Averages the score, which is unnecessary here as score is already a single value (accuracy).
* print('Accuracy : %.3f' % (lr\_score\_)): Prints the model’s accuracy to three decimal places.

Output:



**Confusion Matrix and Classification Report:**

from sklearn.metrics import classification\_report

from yellowbrick.classifier import ConfusionMatrix

print(classification\_report(y\_test, predicted))

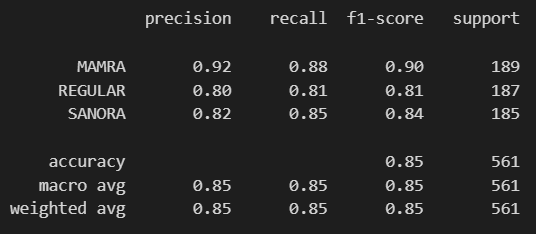
lf\_cm = ConfusionMatrix(LR, classes=classes, cmap='GnBu')

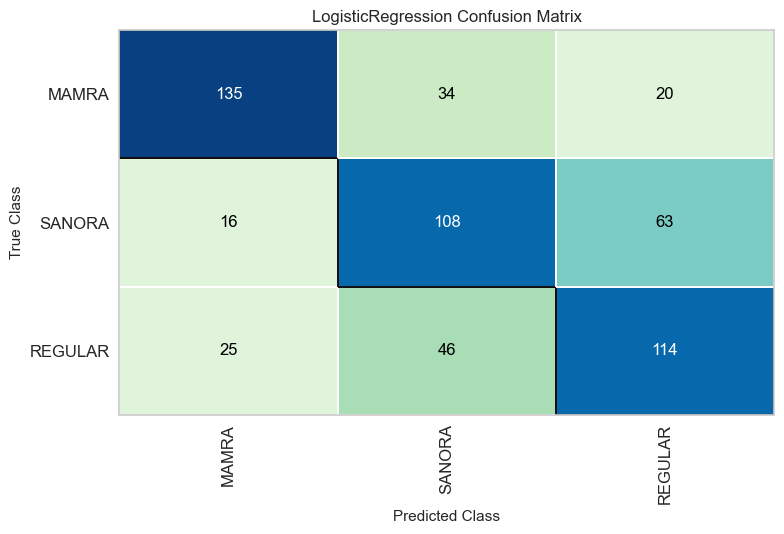
lf\_cm.fit(x\_train, y\_train)

lf\_cm.score(x\_test, y\_test)

lf\_cm.show()

Output:





**5.5.2 Random Forest Classifier:**

from sklearn.ensemble import RandomForestClassifier

r\_forest = RandomForestClassifier()

r\_forest.fit(x\_train,y\_train)

predicted = r\_forest.predict(x\_test)

score = r\_forest.score(x\_test, y\_test)

rf\_score\_ = np.mean(score)

print(f"Accuracy Score: {rf\_score\_: .3f}")

* from sklearn.ensemble import RandomForestClassifier: Imports the RandomForestClassifier from Scikit-Learn.
* r\_forest = RandomForestClassifier(): Initializes the Random Forest Classifier as r\_forest.
* r\_forest.fit(x\_train, y\_train): Trains the model on the training data (x\_train, y\_train).
* predicted = r\_forest.predict(x\_test): Generates predictions on the test data (x\_test).
* score = r\_forest.score(x\_test, y\_test): Computes the accuracy score of the model on the test data.
* rf\_score\_ = np.mean(score): Calculates the mean of score, which is not necessary here as score is already a single value (accuracy).
* print(f"Accuracy Score: {rf\_score\_: .3f}"): Prints the accuracy to three decimal places.

Output:



**Confusion Matrix and Classification Report:**

from sklearn.metrics import classification\_report

from yellowbrick.classifier import ConfusionMatrix

print(classification\_report(y\_test, predicted))

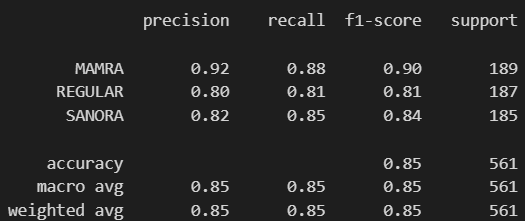
r\_forest\_cm = ConfusionMatrix(r\_forest, classes=classes, cmap='GnBu')

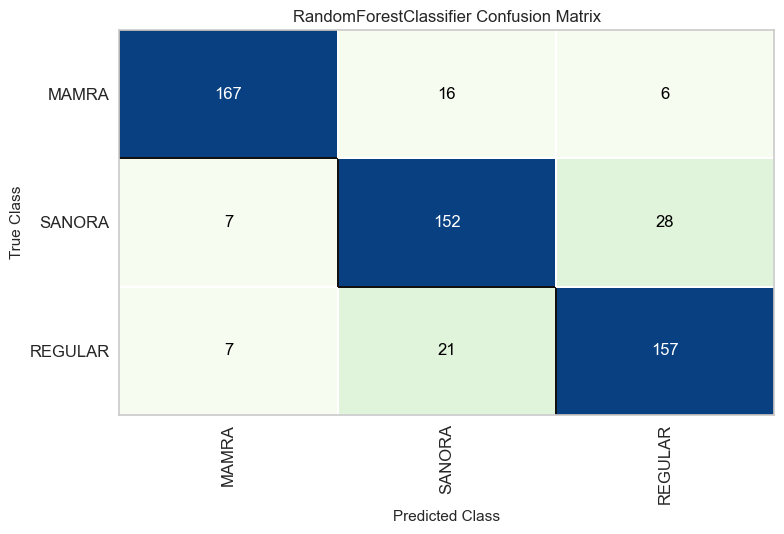
r\_forest\_cm.fit(x\_train, y\_train)

r\_forest\_cm.score(x\_test, y\_test)

r\_forest\_cm.show()

Output:





**5.5.3 K Nearest Neighbours:**

from sklearn.neighbors import KNeighborsClassifier

knn\_classifier = KNeighborsClassifier(n\_neighbors=5)

knn\_classifier.fit(x\_train, y\_train)

knn\_predict = knn\_classifier.predict(x\_test)

score = knn\_classifier.score(x\_test, y\_test)

knn\_score\_ = np.mean(score)

print(f"Training Accuracy: {knn\_score\_: .4f}")

* from sklearn.neighbors import KNeighborsClassifier: Imports the KNN classifier.
* knn\_classifier = KNeighborsClassifier(n\_neighbors=5): Initializes the KNN classifier with 5 neighbors.
* knn\_classifier.fit(x\_train, y\_train): Trains the model on x\_train and y\_train.
* knn\_predict = knn\_classifier.predict(x\_test): Makes predictions on x\_test.
* score = knn\_classifier.score(x\_test, y\_test): Computes the accuracy score of the model on the test data.
* knn\_score\_ = np.mean(score): Calculates the mean of score (unnecessary here since score is already a single accuracy value).
* print(f"Training Accuracy: {knn\_score\_: .4f}"): Prints the accuracy score to four decimal places.

Output:



**Confusion Matrix and Classification Report:**

from sklearn.metrics import classification\_report

from yellowbrick.classifier import ConfusionMatrix

print(classification\_report(y\_test, knn\_predict))

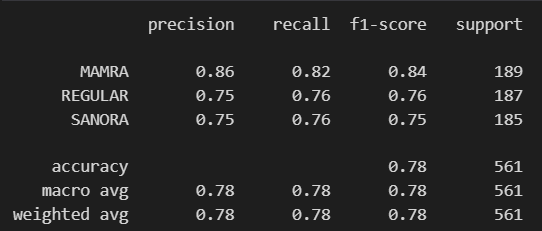
knn\_cm = ConfusionMatrix(knn\_classifier, classes=classes, cmap='GnBu')

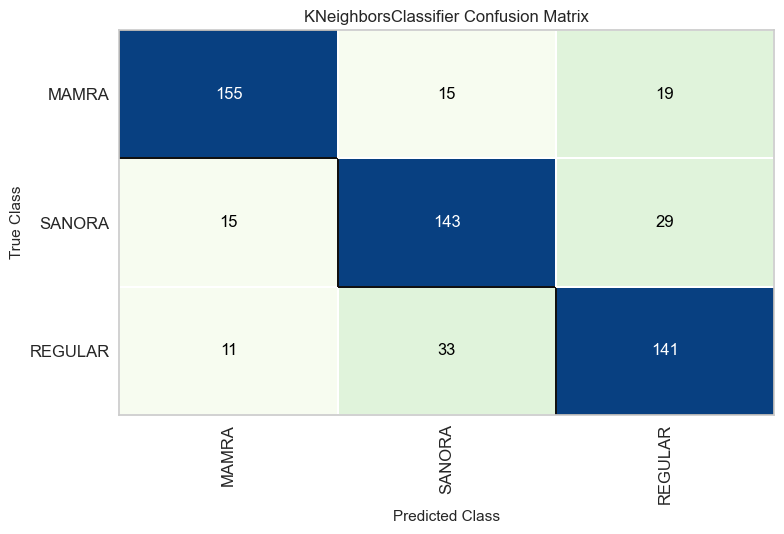
knn\_cm.fit(x\_train, y\_train)

knn\_cm.score(x\_test, y\_test)

knn\_cm.show()

Output:





**5.5.4 Support Vector Machine:**

from sklearn.svm import SVC

from sklearn.metrics import accuracy\_score

svc = SVC(kernel='rbf', random\_state=0, probability=True)

svc.fit(x\_train, y\_train)

pred\_svc = svc.predict(x\_test)

print("Training Accuracy: {0:.4f}".format(metrics.accuracy\_score(y\_test, pred\_svc)))

* from sklearn.svm import SVC: Imports the Support Vector Classifier.
* svc = SVC(kernel='rbf', random\_state=0, probability=True): Initializes the SVC with an RBF kernel, setting random\_state for reproducibility and probability=True to enable probability estimates.
* svc.fit(x\_train, y\_train): Trains the SVC on x\_train and y\_train.
* pred\_svc = svc.predict(x\_test): Uses the trained model to predict the class labels for x\_test.
* metrics.accuracy\_score(y\_test, pred\_svc): Computes the accuracy score by comparing predictions with the true labels y\_test.
* print("Training Accuracy: {0:.4f}".format(...)): Prints the accuracy score formatted to four decimal places.

Output:



**Confusion Matrix and Classification Report:**

from sklearn.metrics import classification\_report

from yellowbrick.classifier import ConfusionMatrix

print(classification\_report(y\_test, pred\_svc))

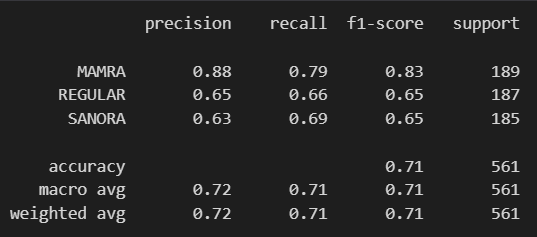
svc\_cm = ConfusionMatrix(svc, classes=classes, cmap='GnBu')

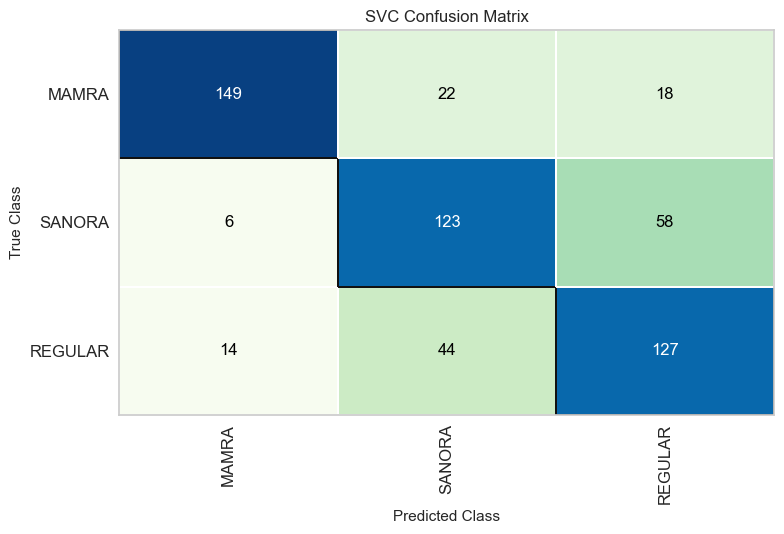
svc\_cm.fit(x\_train, y\_train)

svc\_cm.score(x\_test, y\_test)

svc\_cm.show()

Output:





**5.5.5 Accuracy Comparison of Models**

import seaborn as sns

import matplotlib.pyplot as plt

# Data

models = ['Random Forest', 'Logistic Regression', 'KNN', 'SVM']

scores = [84.8, 63.2, 78.25, 71.12]

# Define custom colors for each bar

colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728']

# Plot

ax = sns.barplot(x=models, y=scores, palette=colors)

ax.set\_title('Classification Accuracy Comparison of Models', fontsize=20)

# Rotate x-axis labels

for item in ax.get\_xticklabels():

    item.set\_rotation(60)

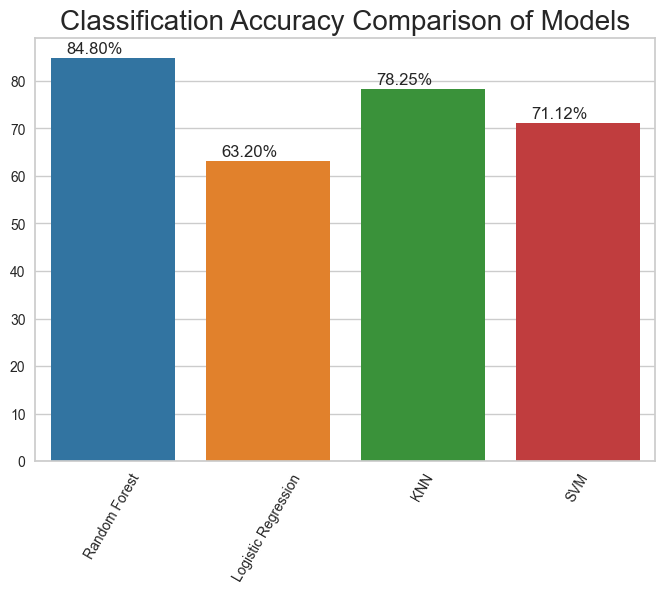
# Annotate bars with their values

for p in ax.patches:

    ax.annotate('{:.2f}%'.format(p.get\_height()), (p.get\_x() + 0.1, p.get\_height() + 1))

plt.show()

Output:



**CHAPTER 6**

**EXPERIMENTAL RESULTS**

Our project is focused on leveraging machine learning algorithms to address challenges in agricultural and food quality, specifically targeting almond type classification using a dataset comprising various almond features. This dataset includes almond characteristics like kernel shape, size, color, texture, and density. To ensure high data quality, comprehensive preprocessing steps were applied to handle missing values and standardize features.

We deployed four prominent machine learning models—Logistic Regression, Random Forest Classifier, K Nearest Neighbours, and Support Vector Machine—to classify almond types effectively. We evaluated these models using multiple performance metrics, such as accuracy, classification report, and confusion matrix, to assess how well each model differentiates almond varieties. Among the models tested, the Random Forest Classifier demonstrated superior performance, achieving an accuracy of 85% on the input dataset.

Following this, we conducted a predictive analysis to classify almonds into their respective types based on distinguishing features. To ensure the reliability of the model, we performed a thorough evaluation using metrics like precision, recall, F1 score, and support. This approach reinforces the robustness and effectiveness of our classification models, providing valuable insights and tools to enhance quality control and operational efficiency in almond processing and distribution.

Here are the results from our project:

**Prediction 1-**

input\_data = (290.6, 227.94, 127.75, 22619.0, 643.81, 0.47, 0.97, 1.45, 1.75, 0.813, 0.681, 2327.5)

# change the input data to a numpy array

input\_data\_as\_numpy\_array= np.asarray(input\_data)

# reshape the numpy array as we are predicting for only on instance

input\_data\_reshaped = input\_data\_as\_numpy\_array.reshape(1,-1)

prediction1 = r\_forest.predict(input\_data\_reshaped)

print(f"The Almond Type is: {prediction1}")

Output:



**Prediction 2-**

input\_data = (269.356903, 176.023636, 120.63, 36683.5,887.310743, 0.643761,   0.947380,   1.707933,   1.530231,   0.75693, 0.722429,   38721.0)

# change the input data to a numpy array

input\_data\_as\_numpy\_array= np.asarray(input\_data)

# reshape the numpy array as we are predicting for only on instance

input\_data\_reshaped = input\_data\_as\_numpy\_array.reshape(1,-1)

prediction1 = r\_forest.predict(input\_data\_reshaped)

print(f"The Almond Type is: {prediction1}")

Output:



**Prediction 3-**

input\_data=(335.3442688, 194.1310425, 146.0308533, 50251, 1034.749341, 0.568948623, 0.968115439, 1.695570081, 1.727411879, 0.815398027, 0.767612734, 51906)

# change the input data to a numpy array

input\_data\_as\_numpy\_array= np.asarray(input\_data)

# reshape the numpy array as we are predicting for only on instance

input\_data\_reshaped = input\_data\_as\_numpy\_array.reshape(1,-1)

prediction1 = r\_forest.predict(input\_data\_reshaped)

print(f"The Almond Type is: {prediction1}")

Output:



**CHAPTER 7**

**CONCLUSION**

In our almond type classification project, we sourced a comprehensive dataset containing various almond features, meticulously preprocessing the data and performing exploratory data analysis to identify unique attributes of each almond type. After data preparation, we strategically divided the dataset into training and testing sets, ensuring the reliability of our classification models. Using a variety of machine learning algorithms, we aimed to pinpoint the most effective model for accurately classifying almond types based on attributes like size, shape, color, and texture.

Methodical testing led to the identification of the model with the highest accuracy, effectively capturing the subtle distinctions among almond varieties. This selection process culminated in an algorithm comparison bar graph that visually showcased the accuracies of the different models. Our chosen algorithm achieved an impressive 85% accuracy in classifying almond types across three test data sets, establishing its reliability in consistently delivering precise classifications.

Looking forward, we aim to further refine the predictive performance of our almond classification model. Future improvements may include the incorporation of advanced feature engineering and real-time data, such as almond characteristics influenced by seasonal or environmental factors, to enhance accuracy and responsiveness. Additionally, exploring image-based deep learning techniques could help capture complex visual patterns, potentially improving model adaptability to variations in almond type features.

Collaboration with agricultural experts, food scientists, and machine learning professionals will be crucial in refining the model with domain-specific insights. Ongoing validation with real-world almond data will ensure the model’s robustness over time, helping farmers and producers make more informed decisions. By embracing innovative technologies and collaborative expertise, our goal is to develop an almond classification model that remains adaptable, accurate, and aligned with the evolving demands of the agricultural and food industries.

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