CLASSIFICATION OF KALE (BRASSICA OLERACEA VAR. ACEPHALA) USING CONVOLUTIONAL NEURAL NETWORK MODELS

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ABSTRACT

Kale, or Brassica oleracea, is regarded as a "superfood" because of its nutritional content and culinary adaptability. This study investigates the automatic classification of Brassica oleracea leaves using deep learning methods, namely InceptionV3, DenseNet201, ResNet50, MobileNetV2, DenseNet169, Xception, and VGG19. The models are trained and assessed for their ability to classify the unique features of kale leaves using a dataset of annotated photos. In addition to contributing to the advancement of scientific knowledge about this plant species, the analysis has applications in the fields of agriculture, cooking, and health. An efficient system for classifying leaves can aid in determining potential culinary uses, improving growing methods, and finding differences in food qualities. This study highlights the societal significance of classifying Brassica oleracea leaves using deep learning techniques, branching out with the goal of utilizing artificial intelligence to enhance healthcare, culinary arts, and agriculture.

Keywords: brassica oleracea var. oleracea, inceptionV3, denseNet201, ResNet50, mobileNetV2, denseNet169, xception, and VGG19.

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1. INTRODUCTION

The Brassicaceae family includes Brassica oleracea, also referred to as Kale (Acephala Group). Rich in vital minerals like calcium, iron, and vitamins A, C, and K, kale is a leafy green vegetable that has become popular as a healthy ingredient to a variety of recipes, from salads to smoothies. It is distinguished by its loose growth habit and severely serrated leaves. It enhances the visual appeal of foods with its vivid range of leaf hues, which include dark green, purple, and blue-green. It is renowned for having a flavor characteristic that is slightly bitter. It is frequently chosen for fall and winter harvests because of its resilience to cold, making it a staple in many regions [1].

Kale (Brassica oleracea var. Acephala), a leafy vegetable, has gained popularity as a "superfood" in recent years because of its potential anticancerogenic and antioxidant properties, which help to explain the presence of various compounds from the polyphenol, glucosinolate, terpenoid, or carotenoid group. In addition, kale is farmed for its leaves and blossom buds and is a significant vegetable crop in ancient agricultural practices on the Iberian Peninsula [2].

All forms of cabbage have succulent leaves that are free of hairs and covered with a waxy coating, which often gives the leaf surface a gray-green or blue-green colour. The plants grow best in mild to cool climates and tolerate frost; some forms tolerate hard freezing at certain periods of growth. Hot weather impairs growth and quality. The common forms of cabbage may be classified according to the plant parts used for food and the structure or arrangement of those parts [3].

This strong crop can withstand cold conditions and grows continuously. It will yield more because it can remain in the field for an extended period of time. It features large, glossy, dark green leaves that are smooth and visually appealing on a strong stem. It takes 90 to 100 days to mature. It can also be fed to animals as feed. It is simple to cook and readily digested. Grown all over Africa, this is a very popular kind of seed. It is advantageous for farmers because it has been created to provide high yields up to six months before flowering. The leaves cook up easily and have a nice flavor. In the community market, it is well-liked. It is meant for hot climates. It is resilient and does not decay from the black [4].

The nutritional value and visual appeal of kale have gained a lot of attention. It is considered one of the healthiest vegetables due to its high vitamin and mineral content, low calorie content, and high vitamin C concentration (200% of the daily recommended intake per serving). This hardy vegetable grows well in pots, rows in backyard gardens, and even as a focal point in landscape designs. A minimum of 12 to 18 inches, or as little as 6 inches, separation between rows is necessary for development to be at its best. When kept at least 8 inches deep, kale grows well in pots as small as 6 gallons. Full sun and well-draining, nutrient-rich soil are ideal growing conditions for kale, although occasional afternoon shade may be beneficial during intense summer heat [5].

Researchers are still investigating the importance of Brassica oleracea var. There is growing interest in examining the leaf characteristics of these adaptable plants and their wide range of uses due to their horticultural and nutritional uses. Understanding the complex properties of kale leaves helps people make well-informed decisions about including kale in their diets and cooking techniques. The technique of dividing a digital image into several significant areas or segments is known as image segmentation. The goal is to simplify or transform an image's representation into more digestible and relevant components. In order to analyze, interpret, and work with the visual data, these segments usually smooth the image by adding objects or areas of focus [6].

The purpose of this study is to learn more about the characteristics of Brassica oleracea, or kale, with an emphasis on its leaves. This also entails learning the parameters needed for different algorithms. Convolutional Neural Networks (CNNs) have broad applications ranging from image and video recognition, image categorization, recommender systems, natural language processing, to medical image analysis. The properties of leaves may be categorized by using a Convolutional Neural Network (CNN). CNNs function by importing qualities from the images, disregarding the need for manual feature extraction. These characteristics are not predetermined; rather, they are acquired during the training process on a set of images. CNNs construct comprehensive patterns of learning, specifically suited for computer vision tasks, by learning feature detection through multiple hidden layers. Accurately recognizing and categorizing leaf traits is essential to grasping the advantages and applications of a specific variant. This program is developed to distinguish Brassica oleracea leaves and quickly provide various categories based on their characteristics. Machine-based methods for identifying and categorizing leaves in agricultural products have become essential for progress. Convolutional Neural Networks (CNNs) are coordinated counterparts to "multilayer perceptrons" [7].

"Multilayer perceptrons" typically refer to fully connected networks, where each neuron in one layer is connected to all neurons in the subsequent layer. This high level of connectivity makes them prone to overfitting data. Common regularization techniques involve adding some form of regularization term to the loss function. CNNs, however, offer an alternative approach to regularization by using progressive downsampling of data and aggregating more complex patterns using smaller and more selective filters. As a result, CNNs exhibit lower levels of connectivity and complexity compared to fully connected networks [8]

2. REVIEW OF RELATED LITERATURE

A vegetable called Brassica oleracea var. Acephala, commonly known as Kale, originated in Western Europe and, along with its other varieties from the Crucifer family, is classified as one of the healthiest vegetables. It is rich in antioxidants and fiber, which help reduce the risk of chronic diseases, lower cholesterol levels, and contribute to a healthy digestive system.

According to Rachel Link, MS, RD (2023, September 15), there are two main varieties of kale: one with green leaves and the other with purple leaves. Kale central leaves do not form ahead, which is why it is most likely more closely related to wild cabbage than other related vegetables like bok choy, broccoli, Brussels sprouts, cabbage, cauliflower, and more. A wide range of nutrients, including vitamin K, vitamin A, and vitamin C, are abundant in it. Selenium, zinc, pantothenic acid, and niacin are also present in trace amounts. It includes vital compounds known as antioxidants that help reduce inflammation, prevent damage from free radicals, and lessen oxidative stress [9].

In recent decades, there has been a notable increase in organic farming, including the cultivation of kale in the USA. However, compared to conventional methods, organic kale production faces difficulties due to organic rules that limit synthetic inputs. These constraints impact postharvest handling, yield, nutrition, and disease management. Organic kale has problems, including short shelf life and food waste, even though it is a nutritional powerhouse with high levels of vitamins, minerals, and prebiotic carbs. Convolutional Neural Network (CNN). It's crucial to develop a new kale type with a longer shelf life. In addition to analyzing efforts to extend the shelf life of kale through breeding programs specifically designed for organic farming, this review will look at the vegetable's traits, consumer preferences, production processes, and nutritional value. Future studies ought to concentrate on choosing kale germplasm that is suitable for organic farming and has improved nutritional quality and shelf life [10].

Human health is significantly impacted by Brassicaceae's profusion of advantageous phytochemicals. This study looks at the phenolic components, antioxidants, and anticancer qualities of extracts from two traditional Croatian vegetables: wild cabbage (Brassica incana Ten.) and kale (Brassica oleracea L. var. acephala DC.).The phenolic groups and antioxidant activity were evaluated using spectrophotometry, and particular components such as ferulic acid, sinapic acid, salicylic acid, kaempferol, and quercetin were analyzed using LC-MS/MS. Additionally, in vitro testing on HeLa cells was used to assess the extracts' likelihood of preventing cancer. Both plant species exhibited strong antioxidant activity and substantial concentrations of phenolic compounds; LC-MS/MS revealed the presence of sinapic acid [11].

3. METHODOLOGY

3.1 Datasets

In this study, convolutional neural networks, or CNNs, were employed. Therefore, it uses a Convolutional Neural Network (CNN) as an architecture to categorize Brassica oleracea var. Acephala. data set of 501 entries.

A.) Siberian

B.) Curly

C.) Lacinato

D.) Red Russian

E.) Alboglabra

3.2 Data Partition

We separated the dataset into training and validation sets in order to maximize the performance of our model. The majority of the dataset was used for training, with a separate portion set aside for evaluation, in order to preserve an 80-20 ratio. This produced 89 validation photos and 411 training images, giving our training procedure a strong base.

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Kale var. Acephala Category	No. of Images used as Datasets	No. of Dataset for testing	No. of Dataset for validation
Siberian	100	80	20
Curly	102	80	20
Lacinato	100	81	19
Red Russian	100	89	11
Alboglabra	99	81	19
Total:	501	411	89

3.3 Data Augmentation

This snippet of code uses Tensor Flow to define a function, preprocess picture, for image normalization, which is a crucial step in preparing images for input into neural networks. The function first converts the input images to TF. float32 to guarantee accuracy in later processes. Then, it normalizes pixel values with a division of 127.5, quantizing the data in [-1, 1], and further subtracts 1 to center values around zero. Such normalization is essential for models, particularly in image-oriented tasks, since it eliminates sensitivity to pixel intensity variations. This contributes to the more efficient model effectiveness during pre-processing. The training, imagine the function contributes to the robustness of the model, because pixel value standardization is a common procedure in machine learning data augmentation. This process included image resizing to a common size resolution, normalizing pixel values between 0 and 1, and enlarging the dataset by methods such as rotation, flipping, and zooming to improve the performance of the model.

3.4 CNN Layers

The first step is to create a link to the knowledge encoded in pre-trained model layers, including InceptionV3, DenseNet201, ResNet50, DenseNet169, VGG16, Xception, and VGG19. This model is therefore considered to be a feature extractor, and the tensor ‘x’ includes advanced high-level features that are learned in the pre-trained model.

Following feature extraction, a Global Average Pooling 2D layer is applied to the tensor x. This spatial pooling method calculates the average value of every feature map, dimension, and lower spatial formation of a one-dimensional model. This is crucial for simplifying subsequent dense layers and enhancing model generalization.

On the second layer, it is densely connected, consisting of 512 units, and is enabled by ReLU. feature transformer. It extracts complex patterns and relationships from the condensed representation generated from the global mean pooling. A dropout layer is then added to avoid overfitting by randomly deactivating during training, neurons are 50 % encouraging dependence on a wide range of characteristics.

Another layer added follows, made of 256 units that use ReLU activation to fine-tune the characteristic representations. The stratified structure of these dense layers enables the model to progressively learn complex input data representations.

To strengthen the resilience against overfitting, the second dropout layer precedes the second dense layer. This adds an extra regularization step that helps the model to generalize well to new though dependence of features during training.

The last layer is fully tied to 6 units, which stands for the number of classes in the target classification task. Utilizing the SoftMax activation function converts the raw output into a class probability distribution function, the model for classification of input data into one of the It specified six classes based on learned features and patterns.

A thorough analysis of the findings constituted the study's final phase. Through the use of pre-trained models DenseNet201, (InceptionV3, ResNet50, VGG16, DenseNet169, Xception, and VGG19) architecture and potential transfer learning strategies, this methodology aimed to create a classifier that would be both precise and effective, designed to meet the unique threats of a constrained dataset and classification uses of Kale var. This included visualizing the model's predictions, comprehending any misclassifications, and interpreting the role of certain features learned by the model. Acephala.

4. EXPERIMENTATION AND RESULTS

4.1 Using Pre-Trained Models

We used the seven various convolutional neural architectures of networks (CNNs) in our extensive study, each of which was carefully selected due to its unique characteristics and benefits in image classification tasks. Our approach was based on the Inception: Volume Three model. It was renowned for offering initiation modules that made it possible to illustrate intricate spatial hierarchies. We loaded the InceptionV3 pre-trained model without its top layers in order to adapt it to our objectives, which caused the trained layers to freeze and retain crucial information. Layers were subsequently added to a base model, which included tightly connected layers to improve learning capabilities and the global average for spatial grouping. The dropout layers were thoughtfully chosen and incorporated to

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prevent overfitting while also enhancing the model's resilience. In tandem with Inception V3, our group incorporated six additional major models, each featuring its own unique architectural innovation. Strong feature sharing and efficient parameter consumption are made possible by DenseNet201's integration of densely connected layers. With 50 deep layers, ResNet50 is a powerful convolutional neural network that is excellent at picture recognition and classification. First introduced in a landmark 2015 research paper titled "Deep Residual Learning for Image Recognition," ResNet50 has become a widely used model for diverse image-related applications. With 48 convolutional layers, a Max Pooling layer, and an average pooling layer, this potent model was trained on the ImageNet dataset. ResNet50, which is available in well-known deep-learning frameworks like Keras and PyTorch, successfully trains very deep neural networks by utilizing residual connections to get around the vanishing gradients issue.

Each model in our team makes a distinct contribution to the study, and together, they create a cooperative architecture that makes the most of their individual strengths.

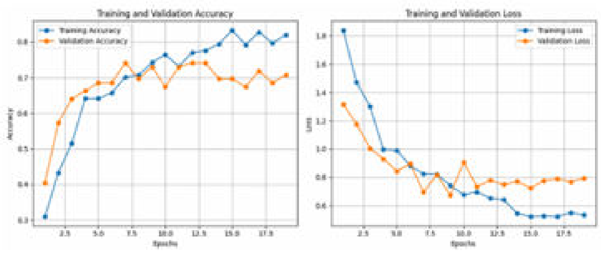
4.2 Results

An attractive association between the trained and validation datasets is evident in the suggested training history chart, which successfully depicts the convolutional neural network's training procedure.

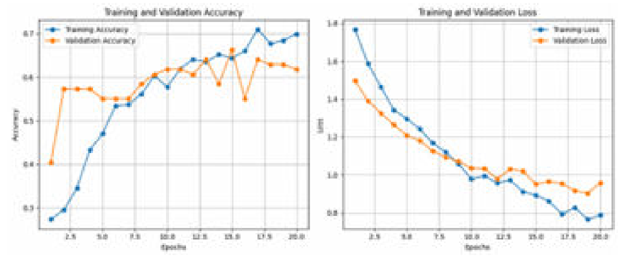
The plot on the chart's left-hand side shows how training and validation accuracy have changed throughout a number of epochs. Both curves exhibit a consistent increasing trend, suggesting that the model's ability to classify images has been steadily improving. In order to demonstrate effective learning from the given data, the training accuracy, which represents the model's performance on the training dataset, is demonstrated to increase gradually across epochs. Crucially, this improvement is closely followed by the validation accuracy, which attains a high degree of accuracy on data that has never been seen before. When curves combine to showcase a distinct advantage, it demonstrates a substantial advantage. The variety of architectural styles enables our system to effectively detect and identify a broad range of characteristics, resulting in a robust and accurate image classification system. Our objective was to leverage the unique characteristics of each model to enhance the overall efficacy of our prediction structure for a range of picture classification tasks by combining them into a single, coherent ensemble. An advanced and thorough method for resolving image recognition issues. Generalization of the model for new cases is one of the essential aspects of practical applicability.

At the same time, the right side of the figure shows the dynamics of training loss and validation loss. The two curves characteristic of a monotonic decline, showing a decrease in prediction errors as the model improves over its internal representations. The training loss, which indicates the errors in the training dataset, decreases gradually, and the validation loss follows it. The close correlation between the two curves implies that the model is not overfitting the training data but generalizing well to unseen data, producing a highly reliable and accurate classifier.

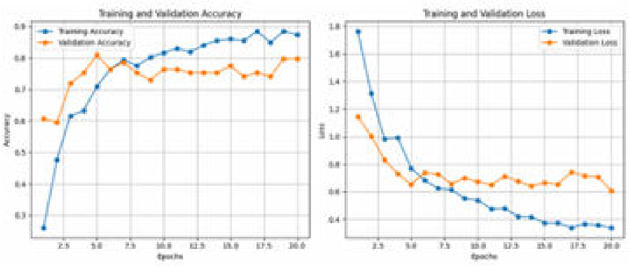
In conclusion, the training history chart clearly shows an excellent outcome with an accurate and low loss on both training and validation datasets. This means that the model architecture is effective, which has convolutional and dense layers with dropout for regularization. The high performance observed in the figure gives confidence in the model's classification accuracy beyond the training dataset, demonstrating that it can be applied to real-life situations, leading to success.



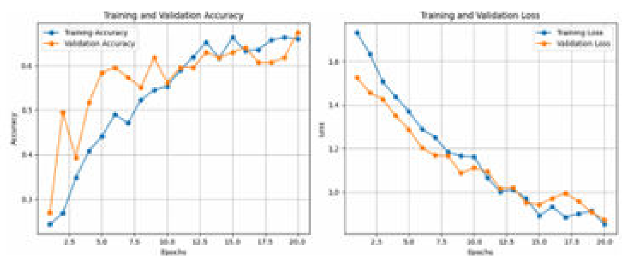
A.) InceptionV3



B.) VGG16



C.) DenseNet201



D.) VGG19

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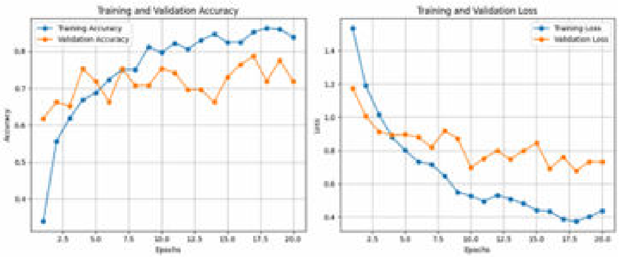
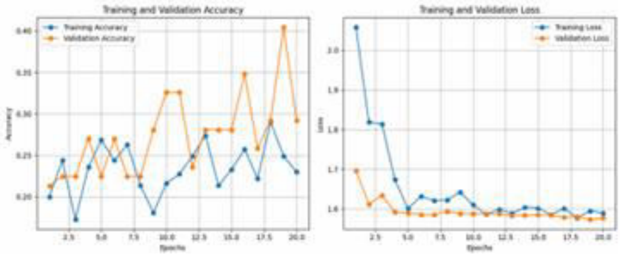
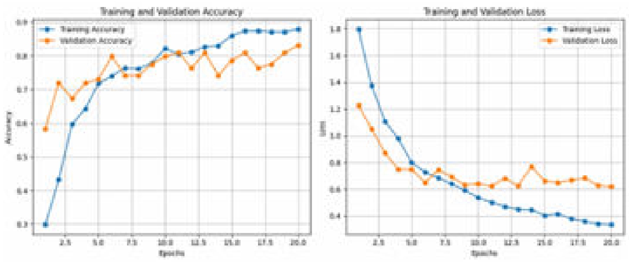


E.) Xception



F.) ResNet50



G.) DenseNet169

The epochs show the following results: a compelling representation of the program's effectiveness in determining the characteristics and classification of the processed kale. As the training progresses through successive epochs, the model continues to enhance its capacity to correctly categorize kale under characteristics and uses of categories.

Prediction visualization and confidence levels across all 7 models, including InceptionV3, DenseNet201, DenseNet169, VGG16, Xception, and VGG19, plot images with a prediction function. The function displayed a 3×5 grid for each model, displaying pictures from the training set with their real labels, predicted labels, and associated confidence scores. Notably, the reverse normalization process was used to depict the images properly. The predicted label displayed the model's classification for each image, whereas the true label represented the data set's truth. With the exception of the visualizations that were looked at in relation to the performance of ResNet50s, the confidence score is the percentage that provides insight into the model's certainty with regard to its predictions. Finding accurate predictions with low confidence levels was a key focus in order to assess each model's performance on the training set. This thorough visual examination could be utilized to compare the model's predictability and spot any possible performance variations among the various designs.

Figure-1. InceptionV3 Output.

Figure-2. VGG16 Output.

Figure-3. DenseNet201 Output.

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Figure-4. VGG19 Output.

Figure-5. Xception Output.

Figure-6. ResNet50 Output.

Figure-7. DenseNet169 Output.

With its ruffled or curled edges, curly kale adds visual appeal and texture to salads, soups, and stir-fries while also retaining sauces and dressings well. The long, narrow, somewhat wrinkled leaves of lacinato kale are ideal for making crispy kale chips and can be added to a variety of recipes or sautéed or braised. Flaunting flat, frilly leaves with purple stems and veins, red Russian kale has a mild, sweet flavor that makes it perfect for light cooking or eating raw.

Large, frilly, flat, and deep green in color, Siberian kale leaves can be steamed, sautéed, or used to casseroles and pasta dishes, among other cooking techniques. Last but not least, Alboglabra, sometimes referred to as Chinese kale or kailan, is a leafy vegetable that reaches a harvest height of roughly 30 cm. Its waxy, blue-green leaves contrast with its broad, silky, pale green stalks. Both Chinese broccoli and Chinese kale, both belong to the Alboglabra Group, are frequently used in Thai, Vietnamese, and Chinese cooking. They can be fried with other meats and vegetables, cooked and eaten like broccoli, or used to stir-fries. These various leaf forms further increase the adaptability of kale in numerous recipes by accommodating a range of culinary tastes, cooking methods, and dish presentation styles.

Types of Kale var. Acephala	Uses	Characteristics
(Siberian)	Versatile for steaming, sautéing, casseroles, and pasta dishes.	Large, frilly, flat leaves.
(Curly)	Adds texture to salads, holds dressings well, suitable for soups and stir-fries.	Ruffled or curly edges, crinkled texture.
(Lacinato)	deal for kale chips, sautéing, braising, soups, and stews.	Long, narrow, slightly wrinkled leaves.
(Red Russian)	Adds color and sweetness to salads, suitable for raw consumption or light cooking.	Flat, frilly leaves with purple stems and veins.
(Alboglabra)	Staples in Chinese, Vietnamese, and Thai cooking, used in stir-fries, boiled like broccoli, or fried with other ingredients.	Leafy vegetable, 30 cm tall, with thick pale green stems and waxy blue-green leaves.Deeply lobed, curly leaves with purple-red veins.

5. CONCLUSIONS

The method of building a comprehensive database for Brassica oleracea var. is explored in depth in this paper, but it is also made easier to understand. acephala with the latest models of convolutional neural networks (CNNs). The emphasis is on improving and honing methods for picture recognition and classification. Through a thorough analysis of several Brassica oleracea var. acephala varieties, including Siberian, Alboglabra, Curly, Red Russian, and Lacinato, this study seeks to reveal minute differences that will ultimately lead to a more accurate classification. The wide range of possible uses in the domains of agriculture, nutrition, and culinary sciences makes this research challenging. Its findings have far-reaching implications for the accurate and versatile utilization of different Brassica oleracea var. acephala varieties. Generation of a dataset based on Brassica oleracea var. acephala. By using the different CNN models, including the addition of no-head with the acosphala together with the implementation of VGG16, VGG19, ResNet50, DenseNet169, Xception, InceptionV3, and DenseNet201, many valuable insights can be attained from the classification and recognition of the different types of kale. The fact that it is rich in vitamins, minerals, and antioxidants is what makes acephala an excellent source of nutrition. Analyzing the traits and purposes of dissimilar types of Brassica oleracea var. acephala makes this great knowledge in our society, for information that everybody needs to know. The different varieties of Brassica oleracea var. acephala include Siberian, alboglabra, curly, red Russian, and lacinato. acephala, every hemisphere has its own special traits. Such types of ruffles include kale from Siberia, various cavalo locallions, ornamental collards, red railroad, blue, and red Scotch, and lacinato, also called dinosaur kale, because of its dark blue-green leaves with a bumpy texture. Basically, the purpose of conducting this research is to use sophisticated CNN models to recognize and distinguish various solid Brassica oleracea var. acephala varieties, which may lead to significant outcomes in agriculture, nutrition, and food science. In addition, this research approach can pave the way for building machine vision systems to help in the classification of plants in agro industries, as well as developing specialized instruments used in environmental monitoring.

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