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"Black Pepper Grading System using Feature Extraction and Machine Learning Approaches"

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Abstract : One of the most often used spices, black pepper has a distinct flavor that works well in both food and medicinal. In the agricultural industry, pepper grading is an essential procedure for guaranteeing uniform product quality and cost. Processed pepper berries are currently sorted by size, shape, and color by hand. This approach is labor-intensive, subjective, time-consuming, and error-prone because it mostly depends on the grader's experience. Using image processing and machine learning approaches, an automated pepper grading system can be created to get around these problems. Since the color of the peppers is a crucial indicator of their ripeness and quality, color feature extraction is a crucial step in the suggested procedure.
Furthermore, the incorporation of CNN (Convolutional Neural Network) feature extraction enables the automatic learning and analysis of intricate properties, including texture, form, and other visual patterns. Through the integration of CNN's sophisticated capabilities with color feature extraction, the method improves pepper grading's precision, reliability, and effectiveness. This automated method decreases labor expenses, minimizes human mistake, and gives farmers and food processors insightful data to help them make better decisions.

Keywords: Black pepper, Feature Extraction, Image Processing, Machine learning

I. Introduction

One of the main concerns for pepper traders and consumers is pepper berry grading. Any individual or even a private company cannot complete this task since the certification needs to meet a specified criterion that is confidently accepted by the global pepper market. Pepper berries that have been processed are sorted according to size, color, moisture content, and other factors. By undermining customer confidence and market openness in the pepper sector, manual grading can lead to irregular quality assessments and deceptive labeling, which can have an effect on food security. Peppers' distinct color qualities are important markers of their overall grade, maturity, and freshness. Automated color attribute analysis reduces human subjectivity by enabling objective and consistent evaluation.
It is less expensive and time-consuming to test the quality of peppers using image processing and machine learning techniques. By employing a clever, automated, and affordable approach, this research study aims to contribute to the development of a system that could help to enhance the socioeconomic status and country incomes of local farmers.
Although other studies have investigated grading schemes that include color, texture, size, and moisture content according to literary categories [2, 5, 6, 7, 9, and 10], Numerous studies have examined the relationship between color and moisture content; their findings indicated that as the moisture level decreased during the drying process, the dried pepper's color darkened. This experiment involved measuring the color and moisture content of the dried black peppers.
Although there are color-based grading systems for white pepper, there is not much research on their use with black pepper, especially when using sophisticated methods. By creating the first black pepper grading system that makes use of CNN (Convolutional Neural Network) feature extraction in addition to color feature extraction, this research fills the gap. Through the combination of these techniques, the system provides a more reliable solution than conventional methods by improving evaluation and classification accuracy and consistency for black pepper grades.

2. Literature Review

A Grain Quality Classification System[1] uses neural networks and image processing to present a cutting-edge technique for classifying rice quality. The work focuses on using texture and color information extracted from photographs to accurately classify rice samples according to their quality standards. By using a two-layered backpropagation neural network, the system successfully classifies inputs. The study uses three crucial quality metrics and emphasizes the extraction of 31 relevant elements. The method shows promise for greatly improving the evaluation of rice quality in the food and agriculture sectors.

Authentication of geographical growth origin of black pepper based on volatile organic compounds profile[2] Verification of the provenance of black pepper's geographical growth using the profile of volatile organic compounds: By utilizing a high-resolution gas chromatography mass spectrometry equipment to analyze the volatile organic compounds (VOCs) profile, the study seeks to determine the geographic origin of black pepper. Verification of the origin of black pepper's geographic growth Considering the profile of volatile organic compounds: By utilizing a high-resolution gas chromatography mass spectrometry equipment to analyze the volatile organic compounds (VOCs) profile, the study seeks to determine the geographic origin of black pepper. The researchers' main goal is to distinguish black peppercorns from Malaysia and India. This study aims to identify unique chemical fingerprints linked to the growth hotspots through VOC analysis.

Deep Learning-Based Classification of Chili Quality[3]. talk about grading and classifying chili after harvest. The "You Only Look Once" (YOLO) approach is implemented, utilizing convolutional neural networks (CNN) to recognize objects in real-time. They improve the accuracy of distinguishing good and bad conditions of harvested chilies by utilizing this widely known image recognition approach.

Grain Quality Detection by using Image Processing for public distribution[4] draw attention to the negative effects of contaminants on the composition and quality of food, focusing on wheat and rice grains. Based on training, their system divides grains into three classes: good, bad, and middling. Notably, the research provides a novel technique for measuring the quality of pulse grains by pixel area measurement, thereby greatly improving the precision of evaluating food grain quality. Both research essentially use cutting edge approaches, such as deep learning and image processing, to improve and fine-tune quality evaluation methodologies in various food situations, which may have favorable effects on food distribution and consumption.

Pepper Berries Grading using Artificial Neural[5] study tackles the difficult task of evaluating pepper berries, which is important to both consumers and pepper traders. The study offers a cutting-edge IT method for evaluating pepper berries that could take the place of some physical testing while also enhancing quality control. This system is based on combining an Artificial Neural Network (ANN) with image processing techniques. The suggested solution offers a cutting-edge method to improve the precision and effectiveness of pepper berry grading, benefiting the trade sector as well as customers, by utilizing image analysis and the power of ANNs.

The goal of the study Automated Machine for Sorting Sarawak Pepper Berries[6] paper is to improve the sorting of Sarawak White Pepper, a major export for Malaysia. The research presents an innovative approach that uses robotics and image processing techniques to automatically grade pepper berries based on their quality levels. The sorting process in the suggested system is controlled by an Arduino Mega and a color sensor. Through the integration of these technologies, the research presents a novel strategy to optimize and enhance the sorting process of Sarawak White Pepper berries, hence augmenting the export quality and trade procedures associated with this precious commodity.

The goal of the project is to enhance processed pepper berry grading and quality control using iPepper: Intelligent Pepper Grading and Quality Assurance System[7]. When grading, the researchers take into account the important variables of size, color, moisture content, and extraneous matter content. As part of their approach, they provide the "iPepper" system, which combines machine learning and image processing methods. The system makes use of a number of data sources, such as colorometer readings, picture attributes, and information on the pepper berries' moisture content. Through the integration of these methods, the study offers a sophisticated and all-inclusive system that provides a more precise and efficient way to grade and guarantee the quality of processed pepper berries.

The study focuses on using image processing methods to analyze rice grain quality in an economical and effective manner using Machine Vision based Quality Analysis of Rice Grains[8]. It takes less time to use this procedure than more conventional ones. The size and form characteristics of rice grains are used in the research methods to evaluate the rice grain quality. The procedure comprises locating each grain's end points and identifying the grain's boundary region. This is accomplished by taking measurements of the grains' length, width, and diagonal size. The study offers a machine vision-based method that uses the advantages of image processing to improve analysis speed and accuracy while offering an alternate way to assess rice grain quality.

Automated Mobile-based Grader for Piper Nigrum[9] this research study is to create a thorough system for rating pepper berries. The research includes the design, development, testing, and evaluation of a mobile application prototype that is completely automated. The program is meant to make the process of grading pepper berries easier. The research introduces "lada," an automated mobile-based grading tool, to show that such a method is feasible. This system offers a technology solution that expedites the grading process and adds to increased efficiency and accuracy in pepper berry classification. It successfully classes pepper berries into their appropriate grades.

A cool comparison of black and white pepper[10] is comparison of the aroma and taste characteristics of white pepper (WP) and black pepper (BP) is the main objective of this study. Thanks to its unique flavor and aroma, black pepper is a popular spice that is used all over the world. The possibility of unintentional or deliberate grade mixing or switching is included in the study. The volatile organic compound (VOC) compositions of reference quality black pepper (BP), white pepper (WP), and lower-grade (LG) products from the spice sector were examined by the researchers using Proton Transfer Reaction – Mass Spectrometry (PTR-MS). The study also included a comparison between the reference materials and retail samples of white and black pepper from different European Union nations. The study sheds light on the distinctions and parallels between these two varieties of pepper.

3. METHODOLOGY

In this context, we introduce a black pepper grading approach based on two distinct categories. Black peppercorns displaying a uniform black color are designated as Grade A. Conversely, pepper lots featuring a mix of brown and black grains fall under Grade B. This simplified yet effective grading system streamlines the assessment process, allowing for quick differentiation between two major pepper quality classifications. In other words, the scope of the work is limited to classify whether a given Black peppercorns Grade A or Grade B. In order to extract such changes in peppercorns we go with some pre-processing steps, feature extraction and then finally we go with classification to identify whether the peppercorns are Grade A or Grade B.

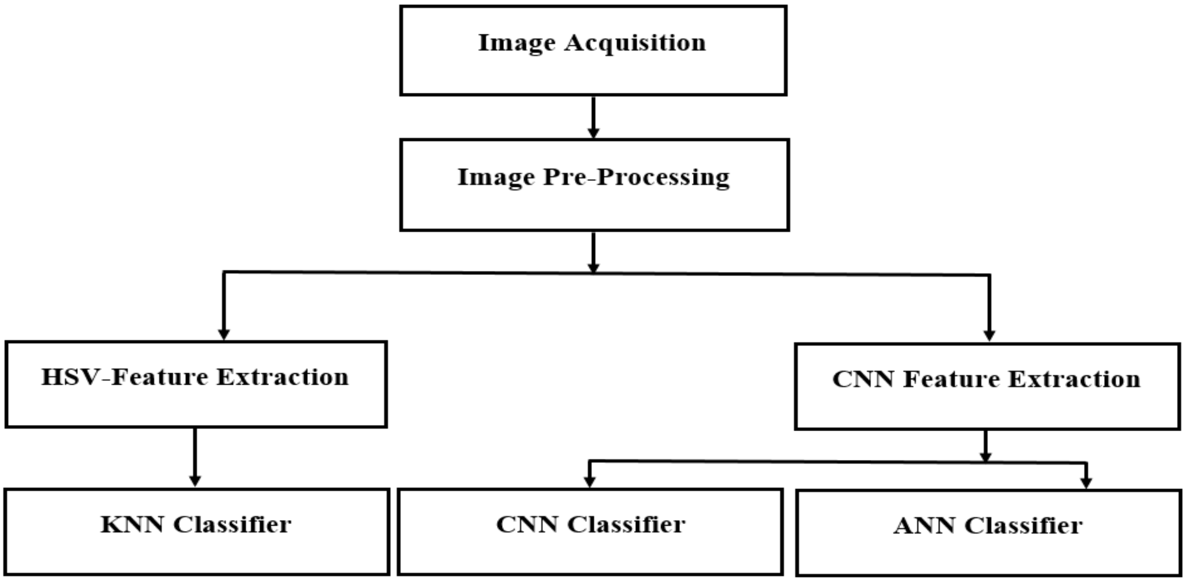

Figure 3.1: Flow chart of Proposed Approach

3.1 Image Acquisition

To ensure consistency and minimize pre-processing procedures, we used a plain white sheet as the background for the peppercorns when creating our dataset. To capture fine details, we used a high-resolution 50-megapixel camera and focused at a distance of 11 cm from the peppercorns. We were able to obtain rich photos during the 15 days of ideal lighting in mid-May for data collecting. We gathered peppercorns of various colors, identifying black peppercorns as Grade A and a combination of the other colors as Grade B. In the end, we collected 600 samples total—300 of which were Grade A peppercorns and 300 of which were Grade B peppercorns.

(a) Grade-A Peppercorn Images

(b) Grade-B Peppercorn Images

Figure 3.2: Sample Peppercorn Dataset

3.2 Preprocessing

In this Process our approach leverages established image processing techniques. We conducted experiments on a dataset consisting of total 600 images, in that we segregated as 300 Grade A images and 300 Grade B images, all captured under daylight conditions using Smart phone. These images were collected against a homogeneous background, negating the necessity for extensive preprocessing. Later on resizing the images to 256x256 dimensions based on the project requirement.

3.3 Feature Extraction

In this method, We extract the color Feature to the provided resized images. This technique was selected because it can precisely measure minute color differences between Grade A and Grade B peppers, which can vary over time and improve classification accuracy. Furthermore, our approach incorporates CNN feature extraction to identify intricate visual patterns and HSV color feature extraction to capture subtle color information. Together, these methods create a thorough framework for accurately classifying peppers according to their changing visual characteristics.

3.3.1 HSV Model:

When it comes to human perception of color, an HSV color model is the most accurate. The way RGB or CMYK create colors is not the same as how humans see color. The spectrum is simply made up of these primary colors merged together. Value is represented by the V, saturation by the S, and hue by the H. Below is a succinct explanation of every element along with the formulas that define them:

Hue: Hue is an image's "color" component. It defines the predominant color-perceiving wavelength of light. The hue value is a number between 0 and 360 degrees, where 240 degrees is blue, 120 degrees is green, and 0 and 360 degrees is red. Because the hue value is spherical, a value that is marginally above 360 degrees is also marginally above 0 degrees.

$$H = \theta * (360° / 2\pi) \quad (1)$$

Saturation: A color's "vividness" or "purity" are represented by its saturation. A color with a high saturation value is vibrant, whereas a color with a low saturation value is more grayscale or neutral. A color's saturation falls between 0 and 1, where 0 represents total unsaturation (gray) and 1 represents full saturation (pure color).

$$S = (Cmax - Cmin) / Cmax \quad (2)$$

Value: Value is a measure of a color's brightness. It has a range of 0 to 1, where 1 is the brightest color that may exist and 0 is total darkness.

$$V = Cmax \quad (3)$$

Algorithm to convert RGB image to HSV:

- **Calculate Maximum and Minimum:**

$$V = max = \max(R, G, B)\ ,\ min = \min(R, G, B) \quad (1)$$

- **Saturation (S):**

$$S = \frac{max - min}{max} \quad \text{if } V \neq 0\text{; otherwise, } S=0. \quad (2)$$

- **Hue (H):**

If R is dominant: H = 60 * ((G - B) / (V - min))
If G is dominant: H = 60 * (2 + (B - R) / (V - min))
If B is dominant: H = 60 * (4 + (R - G) / (V - min)) **(3)**

- **Adjust Hue if Negative:**

$$H = H + 360, if\ H < 0 \quad (4)$$

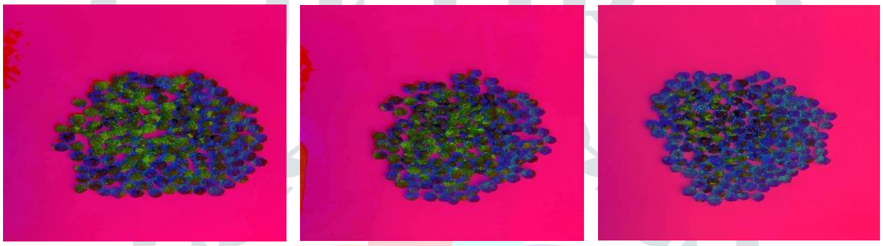

Figure 3.3: RGB to HSV Converted Images

Using this method, RGB photos are resized, converted to HSV, and the mean values of hue, saturation, and value are extracted to create an HSV feature matrix. The HSV features of each image are then represented by storing these extracted values in a matrix format.

3.3.2 CNN features:

CNN feature extraction improves classification by capturing complex visual patterns in images by using learning hierarchical features. Convolutional layers in this process identify features such as edges and textures, while pooling layers down-sample and save important data. Features are retrieved from black peppercorn photos using a pre-trained VGG16 model. Each image is loaded, resized, and pre-processed by the script especially for VGG16. After extracting features, the model flattens them into a 1D array so that they can be used for additional analysis or categorization.

3.4 Classifiers:

In this project we used K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNN), and Artificial Neural Networks (ANN) classifiers to differentiate black peppercorns into Grade A and Grade B. CNN is great at collecting spatial patterns in image data, KNN classifies based on closeness in the feature space, and ANN can adapt to complicated relationships in both image and non-image data. This method makes use of the advantages of each classifier to provide reliable and accurate categorization.

3.4.1 K-Nearest Neighbour (KNN):

KNN is a classification technique that delays computation until evaluation by locally approximating functions. Since it uses distance calculations—specifically, Euclidean distance—to categorize data points, data normalization becomes essential when features have different scales. This study shows that KNN is flexible enough to handle a wide range of data formats by classifying peppercorns based on segmented picture features.

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

To find the nearest neighbors, the procedure entails computing Euclidean distances between data points. In order to classify fresh data points according to the majority class, the formula determines similarity by choosing the k nearest neighbors. This straightforward but efficient method groups together comparable data points to enable precise forecasts in situations where data structure is important.

3.4.2 Convolutional Neural Network (CNN):

A Convolutional Neural Network (CNN) classifier was used in this study to categorize various Black peppercorn qualities. Because they automatically identify and extract pertinent characteristics from picture data without the need for manual feature extraction, CNNs are strong deep learning models created especially for image analysis applications. Convolutional layers, which identify spatial patterns, pooling layers, which lower dimensionality, and fully linked layers, which carry out the final classification, are components of the network design. The CNN successfully catches minute differences and complex patterns that differentiate peppercorn quality by processing input pictures through this hierarchical structure, allowing for precise and dependable sample categorization.

3.4.3 Artificial Neural Network (ANN):

In this study, The Multilayer Perceptron (MLP) model, when applied to an Artificial Neural Network (ANN), provides a flexible and fundamental architecture for supervised learning tasks like regression and classification. The MLP is made up of several interconnected layers: an output layer that produces the final predictions, one or more hidden layers that use connections between neurons to learn intricate patterns, and an input layer that takes in the data. Activation functions are used by each neuron in the network to process inputs, enabling the ANN to effectively model complicated data and capture non-linear relationships.

4. Result and Discussion

We calculate the classification rate for a binary classification problem, specifically differentiating between Grade A and Grade B classes in each experiment, to evaluate the effectiveness of our suggested approach. We evaluate our method against two cutting-edge techniques to show its efficacy: one created by L.A.I. abamalie[1], which uses color features to analyze In order to obtain more important peppercorn features, we also experimented with CNN feature extraction, another feature extraction technique. Given that the suggested method views this issue as a two-class problem, we provide two classes for every trial across the two datasets. We use two classes at a time using the same process to calculate the classification rates for the two approaches. Below mentioned tables represents the classifications results of KNN and CNN:

For K-Nearest Neighboring

Table 4.1: confusion matrix of KNN classifier

	Grade A	Grade B
Grade A	85	5
Grade B	1	89

For Convolutional Neural Network

Table 4.2 confusion matrix of CNN classifier

	Grade A	Grade B
Grade A	398	2
Grade B	3	397

The findings of our suggested method, which we provide in this chapter, show that our Convolutional Neural Network (CNN) feature extraction strategy performs better than previous approaches. This improvement results from the fact that, although Pabamali et al. [1], only examined color information, we also took other important feature parameters into account when examining peppercorn properties. Ultimately, the CNN feature extraction method yields the best results for our classification assignment because our work is the first to suggest a solution for the black peppercorns dataset.

5. Conclusion

In this study, we suggest a novel method for determining whether a image of black peppercorn is Grade A or Grade B. Applications for this categorization include guaranteeing food security and grading pepper in the marketplace. In our research, only peppers with a black hue are rated as Grade A, or of good quality, whereas peppers with a mix of brown, black, and orange colors are rated as Grade B, or of poor quality. In order to accomplish our goal, we have taken color characteristics and other significant factors out of the peppercorn photos in order to compare the Grade A and Grade B peppercorn quality.

A new rule is presented in the suggested method for utilizing feature values to categorize an image as either Grade A or Grade B. Our next goal is to increase the black peppercorn dataset in order to solve multiclass problems, as the scope of current work is restricted to a two-class problem.

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