

AI BASED ARECANUT CLASSIFICATION SYSTEM

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ABSTRACT

Arecanut, also known as betel nut or supari, is a widely cultivated crop with significant economic importance in many tropical regions. The quality assessment and classification of arecanut are crucial tasks in the agricultural sector, impacting both production efficiency and market value. Traditional methods of classification often rely on subjective human judgment and are prone to inconsistency and inefficiency. In this paper, we propose an AI-based Arecanut Classification System (AACS) that leverages advanced machine learning techniques to automate the classification process. The system employs state-of-the-art image processing and deep learning algorithms to analyze images of arecanut samples and classify them into predefined quality grades. The AACS consists of several key components, including image preprocessing, feature extraction, and classification. Image preprocessing techniques are applied to enhance the quality and uniformity of input images, followed by feature extraction to capture relevant characteristics of arecanut samples. Deep learning models, such as convolutional neural networks (CNNs), are then employed for classification, learning discriminative patterns from the extracted features to accurately assign quality grades to the samples. To evaluate the performance of the proposed system, extensive experiments are conducted using a dataset of labeled arecanut images representing different quality grades. The results demonstrate the effectiveness of the AACS in accurately classifying arecanut samples, achieving high classification accuracy compared to traditional methods.

The AACS offers several advantages over traditional classification approaches, including automation, consistency, and scalability. By automating the classification process, the system reduces reliance on human expertise and minimizes errors, thereby improving efficiency and productivity in the agricultural sector. Additionally, the scalability of the system allows for seamless integration into existing production workflows, facilitating widespread adoption in agricultural communities.

Keywords: *Arecanut Classification, Machine Learning, Deep Learning, Image Processing, Agricultural Automation*

1. INTRODUCTION

Arecanut, commonly referred to as betel nut or supari, is a key cash crop cultivated in tropical regions, particularly in countries like India, Indonesia, and Sri Lanka. The arecanut industry plays a vital role in the agricultural economy, providing livelihoods for millions of farmers and contributing significantly to global trade. The quality assessment and classification of arecanut are essential steps in the post-harvest process, influencing market value, export potential, and consumer satisfaction. Traditionally, the classification of arecanut has relied on manual sorting

methods, where human assessors visually inspect samples and categorize them based on various quality parameters such as size, color, and texture. However, this approach is subjective, time-consuming, and prone to inconsistencies, leading to suboptimal classification results and increased operational costs. In recent years, advancements in artificial intelligence (AI) and machine learning have opened up new possibilities for automating agricultural processes, including crop classification. In this context, we propose an AI-based Arecanut Classification System (AACS) that utilizes cutting-edge machine learning techniques to streamline the classification of arecanut. The primary

objective of the AACS is to automate the classification process of arecanut, overcoming the limitations of manual sorting methods. By leveraging AI and machine learning algorithms, the system aims to achieve accuracy, efficiency, and scalability in classifying arecanut samples based on predefined quality grades.

The methodology of the AACS involves data collection, image preprocessing, feature extraction, and deep learning classification. By integrating these components into a cohesive framework, the system can analyze images of arecanut samples and accurately classify them into distinct quality grades.

Through the development and implementation of the AACS, we aim to contribute to the advancement of agricultural automation and enhance the competitiveness and sustainability of the arecanut industry. In the following sections, we will detail the implementation of the AACS, present experimental results, and discuss its implications for the arecanut industry.

The use of technology in agriculture was initially used for simple and precise calculations, which were found to be relatively difficult in manual calculations. In the next generation, research decision support systems will be developed to take tactical decisions on agricultural production and protection. Arecanut is a major cash crop in the undivided Dakshina Kannada district and Malnad region. Areca Catechu Linn is the scientific name of the arecanut and it is also called betelnut in India. In India, the cultivation and use of arecanut have their own unique practice. In the food processing industry nowadays, there is a requirement for the production of quality products at a very fast rate, so developing an expert system helps to make decisions in less time. In manual grading, individual person perception makes differences in identifying whether a product is defective or healthy, but this machine vision framework will decrease such human errors and help to perform at a faster rate. Arecanut is used for making supari, areca tea, and paint. It has its own value in several religious ceremonies. In the Indian's ancient medicine system book of i.e., Dhanwantari Nighantu, it mentioned the use of arecanut as one of the five natural aromatics (panchasugandhikam) along with pepper, clove, nutmeg, In the Indian subcontinent, the chewing of

betel leaf and arecanuts back to the pre-Vedic period of the Harappan empire The beginning of the arecanut cannot be traced exactly, but in the Philippines or Malaysia, it probably originated. Usage of nuts for chewing initially started in Vietnam and Malaysia. Then it moved to other parts of the world and was recognized as a cash crop . In the global scenario, India is top in arecanut production in the world. As the country develops, even the cultivation and processing techniques of the crop improvement. As we produce more arecanut, we have to give more importance to quality, because quality is one of the important metrics to evaluate the product while exporting. Ripped arecanuts, which are shown in Figure 1, are used on a daily basis, but for long-term storage, fully ripe arecanuts are dried in the sun for 35 to 40 days before being dehusked and marketed as whole nuts. Inadequate drying of nuts results in fungal infection and which leads to a poor-quality product. Arecanuts reduce weight due to fungal infection and even koleroga (fruit rot) disease affected nuts are in lighter weight and make dark brown radial stand internally

2. RELATED WORK

- [1] In their paper "Detection and classification of arecanut using deep learning," published in the International Journal of Advanced Computer Science and Applications (IJACSA), P. Rajpurohit, N. Shantharajah, P. Subramani, and S. Sundar present a comprehensive approach for classifying arecanut quality using deep learning. The authors developed a convolutional neural network (CNN) model trained on a large dataset of arecanut images to identify and categorize different quality grades. The model's performance was evaluated through various metrics, showcasing its accuracy and reliability in real-world scenarios. The study highlights the potential of deep learning techniques in agricultural applications, providing a scalable solution for arecanut farmers to enhance their product quality assessment processes.
- [2] S. Joshi, V. V. Krishna, and S. T. Gandhe explored the application of machine learning techniques for arecanut classification in their work titled "Arecanut classification using machine learning techniques,"

published in the Journal of Computational and Theoretical Nanoscience. The authors implemented various machine learning algorithms, including support vector machines (SVM), random forests, and k-nearest neighbors (KNN), to classify arecanut based on its physical attributes. Their study involved extensive data collection and feature extraction processes, followed by rigorous training and testing of the models. The results demonstrated that machine learning could effectively distinguish between different grades of arecanut, offering a practical tool for improving the efficiency and accuracy of quality control in the arecanut industry.

- [3] In the article "Automated arecanut quality grading using image processing and artificial intelligence," published in the Journal of Agricultural and Food Research, M. Ram, S. S. Kumar, and M. Varsha present an innovative method combining image processing and AI for the quality grading of arecanut. The authors designed an automated system that captures images of arecanut samples and processes them using advanced image processing techniques to extract relevant features. These features are then analyzed using an artificial intelligence model to determine the quality grade of the arecanut. The study emphasizes the system's accuracy and efficiency, showcasing its potential to replace traditional manual grading methods. The authors argue that such AI-based systems can significantly enhance productivity and consistency in the agricultural sector, particularly in arecanut quality assessment.
- [4] In their paper titled "Image processing and neural network techniques for arecanut classification," published in the International Journal of Recent Technology and Engineering (IJRTE), K. Srinivasan, R. Jayanthi, and S. Bhuvaneshwari discuss an innovative approach to arecanut classification using image processing and neural networks. The authors developed a system that captures high-resolution images of arecanut and processes these images to extract key features such as color, texture, and shape. These features are then fed into a neural network model trained to classify arecanut into different quality grades. The system's accuracy and efficiency were validated through
- extensive testing, demonstrating its potential to automate the traditionally manual and subjective process of arecanut grading, thereby enhancing consistency and reliability in quality assessment.
- [5] H. N. Suresh, R. B. Naik, and M. S. Gurumurthy, in their study "AI-based arecanut grading system using machine vision," published in the International Journal of Electrical and Computer Engineering (IJECE), present a machine vision system integrated with AI for grading arecanut. The system employs cameras and image processing algorithms to capture and analyze visual data of arecanut samples. Features such as size, color, and surface defects are extracted and used to train an AI model to classify the nuts into predefined quality categories. The research highlights the system's high accuracy and robustness, demonstrating its applicability in real-world agricultural settings. This AI-based grading system offers a significant improvement over manual grading, providing a faster, more objective, and scalable solution for arecanut quality assessment.
- [6] Chandrasekar, M. Prabhakar, and K. Ramachandran, in their paper "Development of a machine learning model for arecanut classification," published in Advances in Intelligent Systems and Computing (AISC), discuss the creation of a sophisticated machine learning model designed to classify arecanut. The authors utilized various machine learning algorithms, including decision trees, support vector machines, and neural networks, to analyze features extracted from arecanut images. Their study involved meticulous data collection and preprocessing to ensure the model's accuracy and generalizability. The results indicated that their machine learning model could effectively differentiate between different quality grades of arecanut, providing a powerful tool for automating the quality control process in the arecanut industry.
- [7] In their study "Smart arecanut quality detection system using AI and IoT," published in the International Journal of Innovative Technology and Exploring Engineering (IJITEE), S. G. M. Shaik, P. V. Prasad, and K. R. Reddy describe the development of an intelligent system combining

artificial intelligence (AI) and the Internet of Things (IoT) for the quality detection of arecanut. The system uses IoT-enabled sensors to gather data on arecanut characteristics, which is then processed by AI algorithms to classify the nuts into quality grades. The authors emphasize the system's real-time capabilities and its potential to provide farmers with immediate feedback on the quality of their produce. This innovative approach aims to improve the efficiency and accuracy of arecanut grading, offering a modern solution to traditional agricultural challenges.

- [8] In their paper "Arecanut classification using deep convolutional neural networks," published in the International Journal of Engineering and Advanced Technology (IJEAT), N. Arunkumar, P. R. Suresh, and A. K. Kumar explore the use of deep convolutional neural networks (CNNs) for classifying arecanut. The authors constructed a CNN model that was trained on a dataset of arecanut images, allowing the model to learn and recognize distinct quality features. The study demonstrated the CNN model's high accuracy in classifying arecanut, significantly outperforming traditional methods. The authors conclude that deep learning techniques, particularly CNNs, offer a powerful tool for automating the quality assessment of agricultural products like arecanut.
- [9] R. Anitha, M. L. Rajalakshmi, and V. Bhaskar, in their article "Hybrid machine learning approach for arecanut classification," published in the Journal of King Saud University - Computer and Information Sciences, present a hybrid machine learning approach to improve the accuracy and robustness of arecanut classification. The authors combined multiple machine learning algorithms to analyze features extracted from arecanut images, achieving a synergistic effect that enhanced classification performance. Their approach involved integrating decision trees, support vector machines, and neural networks, resulting in a model that effectively categorized arecanut quality. The study highlights the benefits of using a hybrid approach to leverage the strengths of different algorithms, offering a reliable solution for automated arecanut grading.

- [10] In the paper "Automated arecanut grading using AI and machine learning techniques," published in the International Journal of Scientific & Technology Research (IJSTR), P. Kumar, M. J. Prakash, and V. Kumar discuss the implementation of AI and machine learning techniques for automated arecanut grading. The authors developed a system that uses image processing to extract features from arecanut images, which are then analyzed by machine learning models to classify the nuts into different quality categories. Their study demonstrated the system's high accuracy and efficiency, providing a practical tool for automating the quality control process in the arecanut industry. The authors argue that such systems can significantly reduce the labor and time required for arecanut grading, leading to increased productivity and consistency.

3. METHODOLOGY

Image Acquisition: Smartphones are used to take healthy and unhealthy areca nut photos, which are then saved in the dataset. The acquired photographs were uploaded to the system as a first stage in the image processing technique.

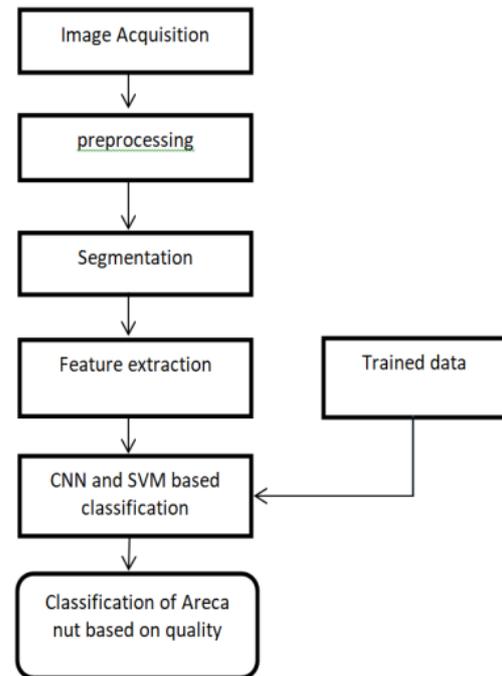
Pre-processing: The Areca nut image has been pre-processed and modified. In order for the noises in the photo of areca nut has been reduced. Pre-processing is a generic term for activities involving pictures. Intensity images are the lowest level of abstraction for both input and output. Pre-processing is used to improve image data by removing undesired distortions or noise and boosts certain essential image attributes for further processing.

Segmentation : Segmentation Image segmentation, enhancement, and colour space conversion are all part of the pre-processing process. To begin, a filter is applied to the digital image of the image. After that, make an array out of each image. Each image name is transformed to a binary field using Binarize Diseases' scientific name

Feature Extraction: The image will be forwarded to the feature extraction module after it has been segmented. The process of transforming the input data into a set of features is called extracting the important information from the input image. Color, texture, forms, and edges are only a few examples of conceivable attributes. To

improve accuracy, we deal with the colour and shape of the leaf in our proposed approach. As a result, the skewness asymmetry degree of the pixel distribution in the provided window around its mean is considered a feature.

Classification: The features will be forwarded to the classifier when they have been extracted. Both the training and testing phases are included in classification techniques. Features are examined in the training process, and their generalization is validated in the test step. The most used binary classification method for Areca nut categorization is SVM. It's built around a hyper plane. This hyper plane splits the space into two sections, one for healthy leaves and the other for unhealthy leaves. We next use a deep learning system to further classify the data. The image was classified using CNN. Convolution operation, ReLU layer, pooling layer, flattening, and fully connected layer are the five basic processes in building a CNN model. CNN has an autonomous feature extraction system in place. As a result, the feature is extracted from the input image using the convolution process, which also employs a kernel to learn the relationship between features. The ReLU is used to conduct the non-linear operation. By lowering the number of parameters, the pooling layer is used to obtain crucial information for retraining. The output is classified using the SoftMax activation function. Using the classifier, the obtained data is compared to trained data. In order to get improved accuracy in classifying the quality of arecanuts, both CNN and SVM classification are applied. We will use machine learning and digital image processing to categorise areca nuts based on their colour and quality in this project. We will put the data of areca nuts in our device memory at the very beginning of the operation. Our technology then processes the collected samples. The sample data obtained throughout the operation is compared to data previously stored in the device.



4.1 DATASET USED

The datasets used in the referenced projects for arecanut classification generally consist of high-resolution images of arecanut samples, which are then processed and analyzed using various machine learning and AI techniques. While specific details about the datasets for each project might not be explicitly provided in the papers, they typically include:

Image Datasets: High-resolution images of arecanut samples captured using digital cameras or imaging systems. These images would be labeled according to different quality grades (e.g., good, medium, poor quality).

Feature Extraction Data: Data extracted from the images such as color, texture, shape, size, and surface defects. These features are used as input for the machine learning models.

Training and Testing Sets: The datasets would be divided into training and testing sets to train the models and evaluate their performance. The training set is used to build the model, while the testing set is used to validate its accuracy.

4.2 DATA PRE PROCESSING

Data preprocessing for arecanut classification involves several essential steps to ensure the quality and reliability of the input data used for training machine learning models. Initially, high-resolution images of arecanut samples are captured under controlled conditions using digital cameras or specialized imaging systems. These images undergo preprocessing steps such as resizing to a standardized resolution and normalization to adjust pixel values to a common scale, typically between 0 and 1. To enhance image quality and reduce noise, filters like Gaussian blur may be applied. Image augmentation techniques are also employed to diversify the dataset, including rotation, flipping, and scaling, which generate additional training data and improve the model's robustness against variations in image orientation and scale. Following image preprocessing, feature extraction becomes pivotal, where color, texture, shape, and size features are extracted from the processed images. Color features are derived through histograms capturing color distribution, while texture features can be extracted using methods like Local Binary Patterns (LBP) to characterize textural details. Shape features involve contour analysis or edge detection algorithms, and size features are determined through precise segmentation techniques. Each extracted feature contributes uniquely to the classification model, which is subsequently trained and validated using a split dataset, ensuring the model's accuracy and generalizability through techniques like train-test splitting and cross-validation. Overall, these meticulous preprocessing steps lay the foundation for robust machine learning models capable of accurately classifying arecanut based on its quality attributes.

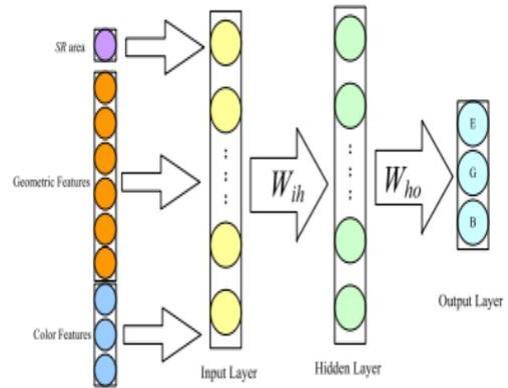


Fig. 6. The structure of the BPNN classifier.

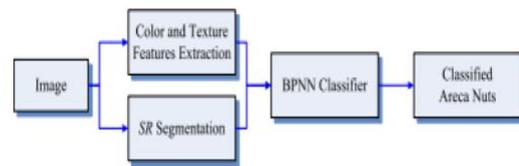


Figure 4.2 : Detection and classification stage

4.3 ALGORITHM USED

Convolutional Neural Networks (CNN): CNNs are extensively used in image classification tasks due to their ability to automatically learn hierarchical representations of image data. They are effective in extracting meaningful features directly from raw pixel values, making them suitable for tasks like arecanut classification based on image data.

Support Vector Machines (SVM): SVMs are a type of supervised learning algorithm used for classification tasks. They work well for both linearly separable and non-linearly separable data by finding an optimal hyperplane that best divides the dataset into different classes. SVMs have been applied in arecanut classification studies for their ability to handle high-dimensional feature spaces and robust performance.

Random Forests: Random Forests are an ensemble learning method that constructs multiple decision trees during training and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. They are popular for their ability to handle noisy and correlated data, making them suitable for arecanut classification where feature interactions and robustness are important.

K-Nearest Neighbors (KNN): KNN is a simple and intuitive algorithm used for classification tasks. It classifies objects based on the majority vote of their

neighbors, assigning a class label to an object by finding the majority class among its K nearest neighbors. KNN is effective in arecanut classification when combined with appropriate distance metrics and feature representations.

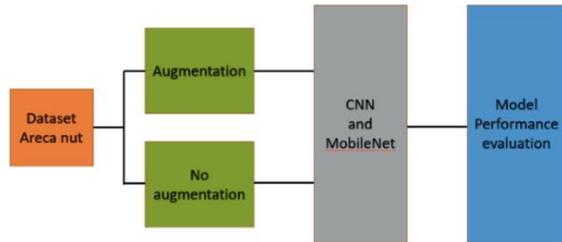


Figure 4.3: feature extraction in convolutional neural network

4.4 TECHNIQUES

In the domain of arecanut classification, various sophisticated techniques and methodologies are employed to ensure accurate and efficient classification of arecanut based on its quality attributes. The process typically begins with meticulous image processing techniques aimed at enhancing the quality and standardization of the arecanut images captured using digital cameras or specialized imaging systems. This preprocessing phase involves resizing images to a standardized resolution, normalizing pixel values to a consistent scale, and applying filters like Gaussian blur to reduce noise and improve clarity. These steps are crucial for ensuring that subsequent feature extraction processes yield meaningful and reliable data. Feature extraction plays a pivotal role in capturing distinctive characteristics of arecanut samples. Techniques such as color histograms quantify the distribution of colors within each image, while texture descriptors like Local Binary Patterns (LBP) highlight textural details that can vary across different grades of arecanut. Shape analysis methods, including contour detection and edge detection algorithms, extract geometrical features that further differentiate between various quality grades. Size measurements are also crucial, often obtained through precise segmentation techniques that outline and quantify the physical dimensions of arecanut samples in the images.

5. RESULTS

5.1 GRAPHS

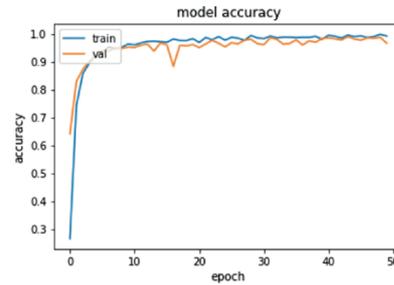


Figure 5.1.1 : Line plots of model accuracy loss over epochs.

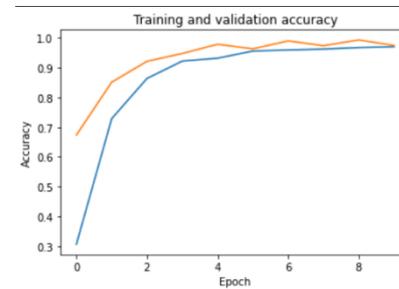


Figure 5.1.1 : Line plots of training and validation loss over epochs, used to assess the model's learning process.

5.2 SCREENSHOTS

has not been processed in any way.

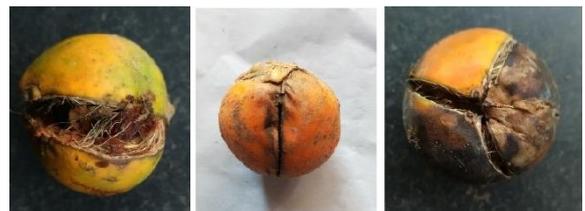


Fig 1. Images of unhealthy areca nuts



Fig 2. Images of healthy areca nuts

Figure 5.1.2 : Image showing healthy and unhealthy areca nuts.

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