A Comprehensive Study of AI-Driven Multi-Modal Imaging Techniques for Legume Classification, Quality Assessment, and Shelf-Life Prediction

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Abstract

Legumes like chickpeas, pigeon pea, dry beans, and green gram are very useful in terms of nutritional value and sustainability across the globe. Yet the process involved in the classification and grading of legumes as well as the life expectancy of the same crops is mainly manual, thus inconsistent and inefficient. This study therefore introduces a methodology that uses Artificial Intelligence (AI) together with multi-modal sensing technologies for the classification and shelf-life assessment of legumes. The approach uses the latest developments in deep learning for feature extraction, multi-modal data fusion and intelligent prediction in order to get precise varietal classification, quality evaluation and shelf-life prediction. Furthermore, temporal analysis is used to model the dynamics of spoilage for various storage conditions. This system would ensure increased robustness, scalability, and usability, while promoting the use of evidence-based decision making in post-harvest handling and agriculture supply chains. It would promote improvements in quality assurance, reductions in post-harvest losses, and precision agriculture.

Keywords: Legume Crops, Multi-Modal Imaging, Computer Vision, Deep Learning, Varietal Classification, Quality Grading, Shelf-Life Prediction, Precision Agriculture

1. Introduction

Leguminous crops like chickpea (Cicer arietinum), pigeon pea (Cajanus cajan), dry bean (Phaseolus vulgaris), and green gram (Vigna radiata) are economically important crops because of their nutritional value in terms of protein and other nutrients as well as their role in improving soil fertility through biological nitrogen fixation. These crops are crucial from the perspective of world food security, particularly in those regions where protein from plants forms the bulk of the diet. Moreover, leguminous crops are essential in sustainable agriculture because of their role in improving soil quality and reduction in fertilizer usage [1]. The rising need for good quality pulses in both domestic and international markets has created a need for accurate techniques of varietal identification, quality grading and post-harvest management. Good varietal identification is required for seed purity, breeding purposes and certification. In the same manner, quality grading plays a critical role in determining the value of the pulse in the market since the consumer's acceptance is greatly influenced by the quality grading according to size, shape, color, texture and moisture level. Shelf-life prediction is just as important as poor post-harvest management results in loss of quality, spoilage by fungi and poor germination ability [2]. These processes have been traditionally done by expert individuals visually. However, such methods are not only labour-intensive and time-consuming but also subjectively done with inconsistencies that result from differences in human judgment. In addition, visual inspection alone cannot be used to detect any slight internal changes linked to age, moisture content, and spoilage. With the growing agricultural sector, there is a need for automation in the quality control of legumes [3]. Current developments in AI, machine learning, computer vision, and imaging techniques have made it possible to create automated systems for quality evaluation in agriculture. RGB imaging technology is extensively applied for capturing external features like color, size, shape, and texture, whereas hyperspectral imaging (HSI) technology offers detailed spectral information that reflects internal features like composition, moisture, and structure. Furthermore, thermal imaging technology is an important complement to RGB and HSI, as it is used for measuring temperature distribution, storage degradation, and insect and moisture damage [4]. Despite considerable achievements made in image-based inspection in agriculture, most of the current studies are either dedicated to one problem or use one sensor type. There are few investigations dealing with the combination of varietal identification, quality assessment, and shelf-life prediction within one algorithm. In addition to this, the use of RGB, hyperspectral, and thermal imaging for legume assessment has been less explored. The current research endeavors to address these challenges through proposing an innovative multi-sensor-based AI solution for assessing the quality of legumes.

2. Literature Review

Table 1 below provides a comparative analysis of some recent artificial intelligence and deep learning approaches used for chickpea and legume analysis such as variety identification, disease detection and quality inspection. It illustrates the approaches used, accuracy rates obtained and contributions made by the studies in question in the use of deep learning and artificial intelligence for precision agriculture. These studies prove that deep learning, transfer learning and multi-modal sensing technology can be used effectively to enhance chickpea and legume identification, disease detection, and quality inspection processes. Even though VGG16, ResNet-18 and ConvNeXt architectures based on CNN have shown above 90% accuracies, optimization techniques, spectroscopy and data fusion from different sources have been emphasized recently for improved performance and reliability.

Table 1: Comparative Analysis of AI-Based Approaches for Chickpea and Legume Classification, Disease Detection, and Quality Assessment

Paper	Method	Dataset	Accuracy	Description
Taheri-Garavand et al. [5]	CNN (Modified VGG16)	Chickpea Seeds	94%	Deep learning-based seed variety classification. Robust to lighting variations and suitable for mobile deployment.

Ulu et al. [6]	ResNet-18, ConvNeXt	Chickpea Dataset (13 varieties)	95–97 %	Uses advanced CNN architectures for multi-variety chickpea classification. High performance but dependent on dataset quality and preprocessing.
Orchi et al. [7]	CNN, SVM	Legume Disease Dataset	88–92 %	Integrates image and environmental data for disease detection. Improves diagnosis accuracy but sensitive to noise and environmental variations.
Kılıç et al. [8]	Transfer Learning + Machine Learning Hybrid	Chickpea Dataset	93–96 %	Combines deep feature extraction with classical ML classifiers. Enhances generalization, especially for limited datasets.
Haile et al. [9]	VGG16 + Pelican Optimization Algorithm (POA)	Chickpea Disease Images	96%	Classifies disease severity levels with optimized feature selection. High accuracy but computationally intensive.
Zia et al. [10]	CNN + Near-Infrared (NIR) Spectroscopy	Chickpea Flour Dataset	94–97 %	Predicts quality parameters such as protein and moisture content. Non-destructive, accurate, and suitable for quality monitoring.

3. **Research Gaps**

➢ **Absence of Consolidated Multi-Task Solutions:** Research efforts have largely been focused on the solution to particular tasks like variety classification, quality rating, or disease identification, with no much concern for a consolidated approach involving all these tasks.

➢ **Incomplete Integration of Multi-Modality:**Most of the methods have depended on a single source of data like either RGB images or spectra.

➢ **Inadequate Performance in Real-World Situations:** Models that have been trained under controlled conditions perform inadequately when placed in a real-world environment due to varying illumination, background and different types of crops.

➢ **Inadequate Estimation Techniques for Shelf-Life:** There is a dearth of research in relation to shelf-life estimation and only a few AI-based models have been developed for such purposes.

➢ **Ignoring the Timing of Deterioration:** The current methods only focus on one-time observation and ignore the process of aging, moisture loss, and spoilage of fruits and vegetables.

➢ **Scarcity of Standardized Big Data Datasets:** The shortage of different legume datasets hampers the development, testing, and comparison of various models.

➢ **Scarcity of Tests for Defects inside Seeds:** Traditional imaging methods are designed to test the external parameters and ignore internal defects that affect the quality and longevity of seeds.

➢ **Lack of Scalability and Practical Implementation:** Most of the approaches proposed by scientists cannot be applied in the agricultural sector because they have been developed only for academic purposes.

4. Problem Statement

Leguminous crops such as chickpea, pigeon pea, dry beans, and green gram are essential for food security and sustainable agriculture. Nevertheless, varietal differentiation, quality assessment, and shelf-life estimation processes in these crops are done through subjective and manual means that consume more time and may not be consistent. Current approaches are based on the use of single modalities and have been developed to solve only one particular problem at a time. In order to address all these issues, the proposed research proposes an AI-based multi-modal imaging and computer vision framework that incorporates RGB, hyperspectral, thermal, and environment data to analyze the crop in totality.

5. System Architecture

The proposed architecture in Figure 5.1 is an AI-based multi-modal imaging and computer vision framework to analyze legume crops automatically. The process starts by collecting legume samples and obtaining the data through RGB, hyperspectral, thermal imaging, and environmental sensors. The data obtained is pre-processed in order to improve the quality and extract essential features from the data including color, texture, shape, spectrum, and temperature. These extracted features will be processed through representation learning using deep learning algorithms in order to capture complex relationships among the data. The AI-based prediction engine analyzes the data by classifying varieties, performing quality grading and predicting the shelf life of the legumes.

6. Expected Outcomes

The suggested multi-modal imaging and computer vision approach powered by AI technology is expected to offer an effective and accurate automated solution for legumes' crops analysis. Utilizing RGB, hyperspectral, thermal, and environmental data with the help of deep learning technologies, the solution is expected to provide accurate varietal classification, quality grading, and shelf-life prediction of legumes. It is expected that the framework will help optimize the process of post-harvest management and improve it with the help of minimized losses and quality reduction due to manual inspections and decisions.

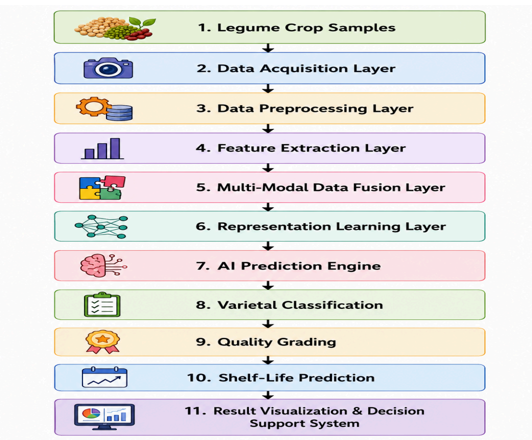

Figure 5.1. System Architecture of the Proposed Multi-Modal Legume Analysis Framework.

7. Conclusion

The presented study is centered around thorough analysis of already existing legume datasets in order to establish their compatibility with artificial intelligence and machine learning based agricultural applications. A special attention will be paid to the analysis of key characteristics of a dataset, which include multivariate data presence, feature variety, data quality and applicability in actual agricultural settings. Besides that, the research will explore currently existing problems, such as class imbalance problem, lack of standardization of the dataset, insufficient scalability of the dataset and poor representation of real-world variance. All the results obtained during the process will become a solid basis for the literature review and help define research gaps.

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