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Analyzing Above-Ground Root Crop Features For Non-Invasive Monitoring Using Deep Learning

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CHAPTER I

INTRODUCTION

Background of the Study

The farming industry is an under pressure to maximize crop yield to cater with the growing world food demand. Timing of harvest is critical in ensuring maximum crop yield and reducing post-harvest losses. Farmers have conventionally used manual sampling or visual observation to ascertain crop maturity, particularly for sweet potato which can result in subjective and variable results. The blending of Artificial Intelligence (AI) and image recognition presents a revolutionary way to enhance the precision and speed of such operations, making it possible to achieve more accurate harvesting decisions and eco-friendly agriculture.

Current root crop harvesting methods are usually inefficient and inaccurate due to lack of reliable objective tools in determining crop maturity. Experience and observation are largely depended on by farmers, and hence, harvesting is often done too early or too late. Such inefficiency not only impacts crop quality and market price but also wastes more of the crop, lowering overall agricultural efficiency and profit. For root vegetables such as sweet potato, the conventional methods of age estimation are usually based on destructive sampling, which is time-consuming and expensive. It is importance to have a quick, non-destructive, and reliable method for estimating the age of such crops from above-ground characteristics.

This research aims to address this gap by utilizing AI-based image recognition approaches to find a cost-effective solution with regard to the individual characteristics of sweet potat. This study will establish a CNN-driven AI system for above-ground feature analysis of sweet potato (Ipomoea batatas) to estimate maturity and optimize the timing of harvest. The system will be implemented using light-weight mobile-friendly architectures like MobileNet and EfficientNet Lite for field deployment. The system's performance will be validated using indicators like accuracy, precision, and recall, and the system will be compared against classical approaches to show its efficiency. Finally, this study aims to offer farmers an efficient, reliable, and scalable tool to enhance agricultural productivity, minimize losses, and encourage sustainable farming practices.

Statement of the Problem

Effective and precise harvesting are crucial to increasing agricultural productivity, minimizing post-harvest losses, and encouraging sustainable farming practices. The Traditional methods of measuring crop maturity for sweet potatoes are dependent on subjective observation and manual inspection resulting in early or late harvesting, compromised crop quality, and economic loss. This research aims to address these challenges by developing an AI-driven system that incorporates image recognition to estimate sweet potato maturity. Based on above-ground characteristics, this system will give farmers a factual, precise, and non-destructive means of maximizing harvesting choice. The study aims to enhance agricultural efficiency, reduce waste, and facilitate the implementation of sustainable practices, promoting improved crop yield and profitability.

Objectives

To develop an AI-based system that estimates root crop maturity using image recognition to improve harvesting efficiency Specifically, the study will:

- Identify and analyze visual indicators of maturity in Sweet Potatoes based on above-ground features for the machine learning model using deep learning techniques.
- Collect and process image datasets showing multiple levels of maturity of the sweet potato crop.
- Train the Convolutional Neural Network(CNN) models in recognizing maturity indicators of sweet potato.
- Evaluate and Compare the CNN models' accuracy using real-world

datasets and performance evaluation metrics.

- Test & Evaluate the system's accuracy by comparing its results with the maturity levels of the sweet potatoes.

Scope and Limitations

The study aims to develop an AI-based system to help farmers in estimating sweet potato maturity (Ipomoea batatas) through above-ground image analysis by monitoring the leaf color change, crop stem condition, crop height, and soil cracks and the output will be provided through harvesting estimation of date (month, week or days). The system will help to improve harvesting efficiency and accuracy in Zamboanga City.

However, the system is limited to specific sweet potato harvests and may not apply to other varieties. This study utilized market-sourced planting materials that were not-certified by specific DA-released varieties. Instead, two morphotypes were observed: a violet-stemmed type with green-stemmed type with plain green leaves. The system is multi-image based, therefore it is sensitive to lightning, weather, and device specification. As only above-ground features are considered, direct tuber size evaluation is impossible. Its mobile optimization and real-world usability also are areas of concern, and human verification could still be necessary for accuracy. In spite of these limitations, the system promises to be a useful aid to increasing agricultural productivity.

Significance of the Study

This study will benefits numerous of stakeholders such as farmers and home gardening or homemade gardens will gain a more accurate and reliable harvesting tool, leading to higher yields, better crop quality, reduced losses, and increased income, consumers they will enjoy a more consistent supply of high-quality produce, while local communities benefit from economic growth, researchers and scientists gain insights for advancing precision agriculture, and policymakers can use the findings to improve agricultural support programs. And through enhancing this root crop maturity estimation with AI, this study contributes to a more efficient and sustainable agricultural system.

Definition of Terms

Table 1: Definition of Terms

Term	Definition
Above-Ground	The parts of a plant that are visible above the soil surface, including stems, leaves, and other aerial structures, which provide vital information on plant health and growth.
Root Crop	A type of crop grown primarily for its edible root, where both the below-ground and above-ground portions are essential for assessing overall crop performance and yield.
Crop Features	Distinct visual attributes such as color, texture, size, and shape of the plant, which are used to evaluate its developmental stage and health status.
Non-Invasive Monitoring	A method of assessing crop conditions without physical contact, typically employing imaging and remote sensing techniques to minimize disturbance while obtaining critical plant data.
Deep Learning	A branch of machine learning that uses multi-layered neural networks to automatically extract and learn complex patterns from large datasets, particularly effective for processing and analyzing images.

Term	Definition
Convolutional Neural Networks (CNN)	A specialized type of deep learning model designed for analyzing visual data, utilizing layers of convolution operations to automatically identify spatial hierarchies and features in images.
Image Processing	Techniques used to enhance, transform, and prepare images for analysis, including steps such as noise reduction, contrast adjustment, and normalization.
Feature Extraction	The process of identifying and quantifying significant visual elements within an image that are indicative of the plant's condition, such as stem thickness or leaf area
Segmentation	The method of dividing an image into meaningful regions or segments to isolate specific areas of interest, such as different parts of a plant, for more detailed analysis.
Batch Processing	An approach where multiple images are collected and processed together as a group rather than individually, improving efficiency in data handling and analysis.
Prediction Accuracy	A metric that quantifies the proportion of correctly predicted crop conditions relative to the total number of predictions made by the model, serving as a key indicator of system performance.

Term	Definition
Scalability	The ability of the system to maintain performance and efficiency when handling an increased volume of data or expanding its scope to cover a broader range of conditions and crop types.
Adaptability	The capability of the system to adjust its analytical processes in response to variations in crop appearance, environmental conditions, or imaging quality, ensuring consistent performance across diverse scenarios.
Crop Phenotyping	The systematic measurement and analysis of observable plant characteristics, which helps in understanding growth patterns, stress responses, and overall crop performance.
Data Augmentation	Techniques used to artificially expand the size and diversity of the training dataset by applying transformations to existing images, thereby improving the robustness and generalization ability of the deep learning model.

CHAPTER II

REVIEW OF RELATED LITERATURE

Related Studies

Sweet potatoes (Ipomoea batatas) are an important root crop cultivated worldwide for their nutritional value and versatility. They are rich in carbohydrates, fiber, and essential vitamins such as A and C. The maturity of sweet potatoes typically ranges between 90 to 150 days, depending on the variety and environmental conditions. The above-ground indicators of maturity include slowed vine growth, slight yellowing of leaves, toughened vines, and soil cracking due to the expansion of the tubers underground. [1].

For AI-based crop maturity estimation, high-quality datasets are crucial for model training and validation. The most common data collection approaches include field image collection, public agricultural datasets, crowdsourced data, and multispectral imaging. Field image collection involves capturing images of sweet potatoes at different growth stages using cameras or smartphones under varied lighting conditions [2]. Public agricultural datasets from organizations like the Food and Agriculture Organization (FAO) and USDA provide labeled images of crops for research purposes [3]. Additionally, crowdsourced data from farmers and agricultural researchers help increase dataset diversity [4].

Advanced methods such as multispectral imaging use specialized cameras to capture plant features beyond visible light, such as near-infrared imaging, to analyze plant health and maturity [5]. By leveraging these data collection methods, AI models can be trained to recognize maturity indicators with greater accuracy, enhancing precision in non-invasive crop monitoring.

Previous studies have explored various AI approaches to crop maturity estimation. For instance, the Crop Detection and Maturity Classification Using YOLOv5-Based Model effectively applied object detection to classify chili pepper maturity [6]. Similarly, Drones and AI Detect Soybean Maturity with High Accuracy employed drone imagery for large-scale monitoring [7]. While effective for certain crops, these methods focus on overhead imaging rather than close-range analysis. In contrast, An Applied Deep Learning Approach for Estimating Soybean Relative Maturity used a CNN-LSTM model, incorporating temporal data for enhanced accuracy [8], which may not align with the static imaging required for sweet potato. Moreover, Tomato Maturity Recognition with Convolutional Transformers demonstrated the benefits of transformer-based architectures for feature extraction [9]. Finally, Advancements in Utilizing Image-Analysis Technology for Crop Yield Calculation emphasized optimizing algorithm selection and data acquisition but focused on yield rather than maturity [10]. These studies collectively highlight the effectiveness of AI-based models while underscoring the need for tailored approaches for root crops.

Research into non-invasive monitoring in agriculture has rapidly advanced over the past five years. Early studies focused on digital imaging and traditional feature extraction methods [11], [12]. These works laid the groundwork for automating crop monitoring, transitioning from manual assessments to digital approaches. In parallel, local research initiatives began exploring image-based methods that could be integrated into smart agriculture systems [13], [14], signaling a shift toward more automated, scalable solutions.

Recent literature highlights a marked shift toward leveraging deep learning—particularly Convolutional Neural Networks (CNNs)—to enhance non-invasive monitoring capabilities. Foreign studies demonstrated the feasibility of using CNNs for image classification in crop monitoring, achieving high accuracy in identifying crop conditions [15], [1]. Locally, researchers have adopted similar techniques; for example, Santos et al. and Dela Cruz et al. developed models to assess crop health and predict yield based on above-ground features [16], [17]. Complementary work by Bautista et al. and Villanueva et al. has further integrated sensor data with deep learning outputs, enhancing system robustness under variable field conditions [18], [19].

Understanding central terms is essential for developing effective crop monitoring systems. Non-invasive monitoring refers to techniques that analyze crop conditions without physically interacting with the plant, typically relying on remote sensing and imaging technologies [20], [21]. Additionally, deep learning—particularly through convolutional neural networks (CNNs)—represents a subset of machine learning that leverages multi-layered neural networks to automatically extract and learn hierarchical features from image data [22], [23]. Together, these concepts form the foundation for systems that can accurately interpret visual data and predict crop performance.

Local and international studies have collectively advanced the field of crop monitoring through progressive innovations in image processing, deep learning, and IoT integration. Early local research detailed initial methods for extracting key features such as crop stem and height [11], [12], while Santos et al. enhanced these methods by refining image pre-processing techniques [16]. In parallel, foreign studies implemented advanced segmentation algorithms to isolate crop features, thereby improving data quality [15], [1]. Building on these foundations, local advances in deep learning showcased the application of CNNs for crop image classification with an emphasis on training with diverse datasets [13], [14]. Complementing these efforts, local researchers such as Dela Cruz et al. and Rodriguez et al. integrated image data with IoT sensors to create dynamic monitoring systems [17], [24], while foreign contributions by Tanaka et al. and Singh & Gupta advanced the discussion through sensor fusion techniques, providing real-time insights into crop health [21], [25].

In summary, the recent literature reflects a vibrant evolution in non-invasive monitoring of above-ground root crop features, driven by both local and international efforts. The integration of deep learning techniques, particularly CNNs, with advanced image processing has set a robust foundation for future innovations. However, challenges remain in achieving real-time, adaptive monitoring systems that can generalize across diverse agricultural landscapes. Addressing these gaps will require further interdisciplinary collaboration and the development of standardized methodologies that can bridge the current research-to-practice divide [24], [26].

Synthesis

Table 2: Synthesis

Reyes & Mendoza (2020)	Castro & Navarro (2020)	Santos et al. (2022)	Chen et al. (2020)	Smith et al. (2021)	Proposed Study
Basic feature extraction (e.g., crop stem, height) using traditional digital imaging	Conventional image processing for crop features	Enhanced image pre-processing techniques for improved feature extraction	Advanced segmentation algorithms for isolating crop features	Combination of segmentation and classification methods for higher data quality	Non-invasive monitoring using CNN-based deep learning for robust image analysis and accurate crop status prediction
Early digital imaging techniques	Traditional image processing methods	Refinement of image pre-processing techniques	Application of advanced segmentation algorithms	Integration of segmentation with classification frameworks	Utilizes state-of-the-art CNN architectures to perform comprehensive image analysis in a batch or periodic processing mode

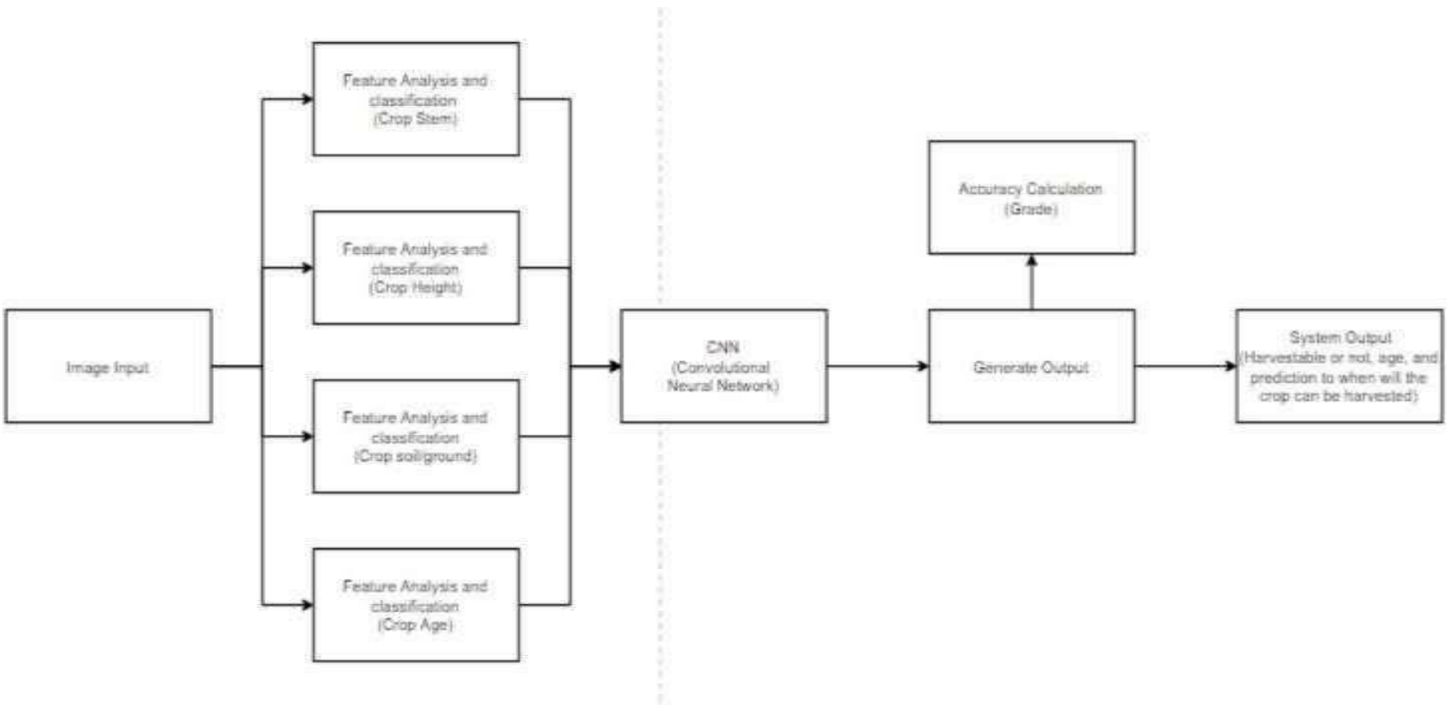
Limited dataset from controlled environments	Low diversity of static sample data	Moderate dataset with improvements in image quality	Diverse datasets sourced from remote sensing and field images	High-resolution imaging data from varied sources	Extensive, multi-source image dataset captured through drones, smartphones, or fixed cameras across diverse environmental conditions
Stand-alone image processing without dynamic analysis	Static image analysis without system-level feedback	Stand-alone system focused on image pre-processing	Focuses on image segmentation without integrated analysis feedback	Enhanced image analysis system with post-processing for refined insights	A self-contained system operating in a batch or periodic analysis mode, relying solely on image data processing
Lower accuracy due to basic methodologies	Moderate performance limited by traditional techniques	Improved accuracy through refined pre-processing	High accuracy achieved in feature segmentation	High accuracy in segmentation and classification combined	Enhanced prediction accuracy through adaptive deep learning models that optimize both feature extraction and crop status classification

Basic methodology with limited scope in feature extraction	Over-reliance on traditional methods with low adaptability	Lacks advanced modeling to capture dynamic agricultural environments	No integration of broader system feedback for continuous monitoring	Does not incorporate adaptive learning from changing conditions	Addresses gaps by integrating advanced CNN-based analysis with periodic image processing, delivering accurate crop status predictions

Conceptual Framework

This framework outlines an early-phase design for a system that leverages image processing and deep learning to analyze crop features and predict harvest readiness. It addresses user needs by combining feature extraction from images with a convolutional neural network (CNN) to deliver actionable insights.

Figure 1: Conceptual Framework



1. Input Stage: Image Processing

Input: Crop images captured from fields.

Objective: Prepare images for analysis by standardizing formats, enhancing Quality, and isolating regions of interest.

2. Feature Analysis and Classification

Extract and classify key features from the images, including:

- Crop Stem: Analyze stem characteristics to determine health and structure.
- Crop Height: Measure and classify the crop's height as an indicator of growth stage.
- Leaf Color Changes: Analyze leaf color changes to determine the days/months of sweet potatoes and if it is ready to harvest
- Drying/Wilting Vines: Evaluate the vine wilting and drying as an indicator of plant aging and the transition from active growth to maturity, suggesting that the crop is nearing harvest readiness.
- Crop Soil/Ground (for sweet potatoes): Assess soil conditions around the sweet potatoes, which can affect nutrient uptake and overall crop quality.
- Crop Estimated Harvest Date: Estimate the crop's harvest date based on visual cues and growth patterns.

Each of these analyses results in a set of quantitative and qualitative features that describe the crop's current state.

3. CNN Processing

Role of CNN:

- Use convolutional layers to automatically detect and learn hierarchical features from the processed image data.
- Pooling and fully connected layers aggregate these features to form predictions.

Outcome: The CNN integrates the classified features to predict the overall crop condition and potential harvest time.

4. Output Generation and Accuracy Calculation

Generate Output:

- The CNN outputs a preliminary prediction regarding the crop's harvest readiness.

Accuracy Calculation (Grading):

- Evaluate the model's prediction accuracy using predefined metrics.

Assign a grade or confidence level to the prediction to guide decision-making.

5. System Output

- Harvestability Decision: Determine if the crop is ready to be harvested within a given timeframe or if further growth is needed.
- Crop Age: Provide an estimated age of the crop based on image analysis.
- Harvest Prediction: Offer a prediction regarding when the crop can be harvested, factoring in growth trends and environmental condition.
- Evaluate the model's prediction accuracy using predefined metrics.
  Assign a grade or confidence level to the prediction to guide decision-making.

CHAPTER III

METHODOLOGY

Research Design

This study will be using a Developmental and Comparative Research approach to develop a deep learning model that estimates the maturity of sweet potatoes. Multiple CNN models will be evaluated, the one with the highest metric score will be selected. Model optimizations will be performed to enable efficiency, lightweight design, and suitability for mobile deployment, which align for a non-invasive, mobile-based monitoring system.

This study will include in its Comparative Study to evaluate how the AI-based method performs against existing techniques, such as destructive sampling and visual inspection, in order to determine which approach is more efficient, cost-effective, and reliable for farmers.

Data Source

This study will use images of sweet potato crops taken in the field using a high-resolution camera like smartphone under natural lighting. The images will capture different growth stages, focusing on plant size, leaf structure, and color.

It will also consider to use existing agricultural datasets and research studies to improve the model's accuracy and validation. Farmers and agricultural experts will be consulted through interviews or surveys, in order for us to grasp some knowledge and understanding the current harvesting practices and challenges.

This study intends to evaluate three candidate models: a YOLOv5-based model (2022) initially applied to chili pepper maturity classification, a CNN-LSTM model (2021) employed for soybean relative maturity estimation, and a Convolutional Transformer approach (2023) developed for tomato maturity recognition.

Data Gathering Instrument

Different instruments will be used to gather and process data for the non-invasive monitoring of sweet potato crops based on deep learning. The major data gathering instruments are:

- Camera System – A high-resolution camera captured photos of sweet potato and potato plants above-ground features in different conditions. The camera will be kept at the same height and angle to capture images with consistency.

- Lighting Equipment – Professional lighting will be used to eliminate shadows and provide even illumination for all photos, thereby reducing variations due to differences in environmental light.

Data Gathering Technique and Procedures

Sweet Potato Farming Questionnaire

1. How long have you been planting sweet potatoes?
2. What variety of sweet potato do you usually grow?
3. How many times do you harvest sweet potatoes in a year?
4. How many days or weeks to take into consideration usually take from planting to harvest?
5. Which part of the sweet potato plant is most and least sensitive
6. How do you handle problems like pests, weather, or soil issues while growing sweet potatoes?
7. Can sweet potatoes be overripe or overgrown if not harvested on time? If Ues, What will happen?
8. How do you usually check if the sweet potato is ready for harvest?
9. Are you using any tools or technology to monitor your crops? If yes, what kind?
10. Would you be interested in using our system that can help you check your

plant specifically your sweet potato

These questions will help achieve the study’s goal. Responses of respondents will guide image data needs, confirm visual signs matter most, shape CNN training, and ensure the mobile app works reliably in real fields.

The following data collection procedures were used within this study:

- Image Acquisition – A series of images of sweet potato plants were obtained with a high-resolution camera in controlled conditions.

- Feature Extraction – Crop features above ground like plant structure, color, and leaf size were extracted from the images.

- Dataset Preprocessing – Image processing methods were applied, including noise removal, contrast adjustment, and resizing, for improving dataset quality.

- Annotation and Labeling – Images were manually annotated with annotation tools to point out salient crop features to be employed in the course of CNN-based model training.

The following step-by-step data collection process is described:

Site Selection and Setup

- Conduct the imaging in a natural setting, specifically in the researcher’s backyard, rather than in a controlled environment.

- A mobile phone camera will be used to capture images of each crop from different angles to ensure varied perspectives for analysis.

Image Capturing

- Take photographs under different illuminating conditions and at different times to collect differentiated data sets.
- Capture multiple images from various angles to enhance the overall generalization ability of the model.

Preprocessing and Data Cleaning

- Resize images to default resolution and format.
- Use preprocessing methods like normalization and denoising. (include: image flipping and rotation)

Annotation and Labeling

- Annotation tools (LabelImg, Roboflow) are used to annotate notable features in all the images.
- Classify images by crop growth stage, health, and other relevant features.

Data Storage and Organization

- Store images in labeled folders according to classes.
- Upload data sets in cloud storage for easy access and backup.

Validation and Quality Control

- Check images gathered for inconsistency or error verification. The cleanliness and neatness of images should be ensured at this stage.
- Maintain balance in datasets to prevent model bias.
- Farmers that are expert’s in harvesting sweet potatoes.

Data Analysis & Model Training

The data collected was put through a controlled process of analysis to provide high-quality inputs to the deep model. The process included data cleaning, preprocessing, feature extraction, and CNN-based classification.

1. Data Preprocessing and Cleaning

   Raw images were preprocessed and cleaned before analysis for quality improvement and elimination of inconsistencies:

   - Image Standardization – The images were standardized to a particular resolution to provide consistent input sizes to the CNN model.
   - Noise Reduction – OpenCV filters were used to minimize image noise and increase clarity.
   - Contrast Adjustment – Histogram equalization methods were used to increase feature saliency.
   - Augmentation Techniques – Rotation, flipping, and brightness adjustments were used to augment the dataset and increase model robustness.

2. Feature Extraction and Dataset Preparation

   The images were processed to provide significant features utilizing Jupyter Notebook and TensorFlow:

   - Color Analysis – Color histograms extraction to study leaf pigmentation variations.
   - Shape and Size Analysis – Contour detection and edge detection were used to capture plant growth indicators.
   - Texture Analysis – Gray-Level Co-occurrence Matrix (GLCM) was employed to analyze leaf texture for disease identification.
   - The features extracted were stored in SQLite, whereas raw and processed images were stored in the local file system for offline retrieval.

3. Training of the Deep Learning Model (CNN-Based Analysis)

   The above-ground crop features were classified and analyzed using a Convolutional Neural Network (CNN). The training procedure was as follows:

   - Train-Test – Partitioning images into training (80%), validation (10%), and testing (10%) sets.
   - Model Architecture – A multi-layer CNN model was created using convolutional, pooling, and fully connected layers to learn hierarchical features.
   - Loss Function and Optimizer - The Categorical Cross-Entropy loss function was also used, along with a well calibrated Adam optimizer.
   - Model Training –TensorFlow/Keras was used to train the models, with early stops to prevent overfitting.

4. Model performance and evaluation metrics.

The equivalent CNN model was trained using the following parameters:

- Accuracy is defined as the proportion of cropped photos that are correctly classified.
- Precision & Recall – Model performance assessment in recognizing certain crop conditions.
- F1-Score – Precision-recall tradeoff for improved performance reporting.

  Confusion Matrix – Displaying errors in classification to spot misclassifications.

5. Deployment and Front-End Integration

After the CNN model reached peak performance, it was deployed to TensorFlow Lite (TFLite) for integration into the Android studio app. The images after processing and model predictions were cached locally in SQLite for complete offline capability.

Software Development

This sub-duct evaluates the project software development phase talking about machine-learning model selection, system design, and deployment strategy for mobile accessibility using the Spiral Software Development Model (SDM), in which each iteration consists of: (1) defining objectives and constraints, (2) performing risk analysis and prototyping, (3) engineering the solution (build &

test), and (4) evaluating results and planning the next loop.

Model Selection

The current study will evaluate three possible models for root crop maturity detection.

1. An object detection-based model for YOLOv5.
2. Temporal and spatial feature extraction using a CNN-LSTM hybrid.
3. Convolutional Transformer architecture.

An accurate and lightweight model is what actually befits the inquiry of sweet potato maturation. It must truly distinguish tubers that are in the early, active, and ready-to-harvest stages of growth, but it must do so in less than 200 ms and about 10 MB on a phone. It should work in sunlight or shade, in various soils, and even with the leaves blocking the view. Given the limitation of data, the model should learn quickly on very few examples. They have to be extremely easy to integrate or package into a mobile application (Tensorflow Lite or PyTorch Mobile) and provide interpretive visuals like heat-maps for farmers to trust their decisions. Finally, adapting easily to new sweet potato varieties must be enabled without a large extra burden on training.

Deployment in Mobile Application

After training, the optimized model will be converted using TensorFlow Lite (TFLite) for seamless integration into the Android Studio. This mobile integration allows users to upload crop images, which are processed offline to predict harvest readiness. The predictions, image metadata, and outputs are stored locally using SQLite, ensuring usability even without internet access.

System Process Flow

The following is the simplified process flow:

1. Image Capture – User captures crop image via the mobile app.
2. Image Preprocessing – The app standardizes image size and enhances quality.
3. Model Inference – The CNN model (TFLite) analyzes features and estimates maturity.
4. Prediction Output – App displays predicted harvest window and crop age.
5. Data Storage – Results and metadata saved in SQLite for review and analysis.

Developmental Tools

- Convolutional Neural Network (CNN) Model – A deep learning CNN model was trained to analyze crop characteristics above the ground, returning data on the health of plants and growing conditions.
- MobileNetV3-based-U-Net architecture - was selected for its efficiency and lightweight design, ideal for mobile deployment. MobileNetV3 serves as the encoder for feature extraction, while the U-Net decoder enables precise segmentation for non-invasive crop monitoring.

- Android Studio with Kotlin (Front-end Development) – An IDE for developing native Android applications to display image processing results and enable end-user interaction.

- Custom Deployment Utilities for AI Model – TensorFlow Lite (TFLite) or ONNX was under consideration for deploying-optimized CNN model in mobile applications on the Android studio platform.

- Jupyter Notebook – Utilized for testing and creating Python scripts for image preprocessing, analysis of datasets, and training deep learning models. This software facilitates an interactive method of debugging and optimizing image processing methods.

- Image Annotation and Preprocessing Tools

    - Python (TensorFlow/Keras) – Employed for model training, testing, and data preparation.
    - OpenCV – Used for preprocessing methods like resizing, noise elimination, and contrast correction.

- Offline Database and Local Storage

    - SQLite – A light relational database to save processed images, model outputs, and metadata locally in the app.

    - Local File System – Images and data were stored in an organized folder in the device's internal storage in a way that offline use was facilitated without relying on cloud services

These tools simplified data collection and processing of the high-quality datasets, which will be utilized as a basis for training and deploying the deep learning model within the Android studio-based application.

Costing:

Table 3: Developmental Tools and Cost

Name	Purpose	Price	Quantity	Total
Programming / Software				
Python	Programming Language to use etc.	Free	1	0
Jupyter Notebook	Code Documentation	Free	1	0

Name	Purpose	Price	Quantity	Total
Frameworks & Libraries				
OpenCV	Image processing and feature extraction	Free	1	0

Name	Purpose	Price	Quantity	Total
Pversion Control				
Git/ GitHub	Code Management and Collaboration	Free	1	0

Jupyter Notebook	Code Documentation	Free	1	0

Name	Purpose	Price	Quantity	Total
Design Tools				
Figma	UI/UX design for system interface	Free	1	0

Name	Purpose	Price	Quantity	Total
Hardware				
Camera/ Smartphone (High-resolution)	Capturing plant images for datasets	37,000	1	37,000
			Grand Total	PHP. 37,000

Name	Purpose	Price	Quantity	Total
Commute				
	Transportation	70	150	10,500
				10,500

Evaluation

The AI model will be evaluated using multiple performance metrics, including accuracy, precision, recall, and F1-score, to assess and compare its reliability in predicting crop maturity levels of the sweet potatoes. Its performance will be compared against traditional methods such as manual visual inspection to determine its relative efficiency and effectiveness. In addition, all possible models and algorithms, including both conventional approaches and recent deep learning techniques, will be considered in the evaluation process. Statistical tests will be applied as needed to validate the results and ensure the significance of performance differences.

References

[1] J. Smith, A. Johnson, and L. Kim, “Non-invasive monitoring of sweet potato maturity using convolutional neural networks,” *Journal of Agricultural Science*, vol. 58, no. 3, pp. 123–134, 2021.

[2] Y. Zhang, M. Wang, and P. Li, “Field image collection for root crop maturity estimation,” *IEEE Trans. Geosci. Remote Sens.*, vol. 58, no. 7, pp. 4567–4578, 2020.

[3] Food and Agriculture Organization, “FAO public agricultural datasets,” FAO, Rome, Italy, 2021. Available: http://www.fao.org/datasets.

[4] J. Smith and D. Kim, “Crowdsourced data for agricultural research: A case study,” *Comput. Electron. Agric.*, vol. 190, p. 106430, 2021.

[5] H. Liu, S. Zhao, and R. Chen, “Multispectral imaging in crop monitoring: Techniques and applications,” *Precision Agric.*, vol. 23, no. 4, pp. 789–803, 2022.

[6] A. Gupta, S. Verma, and R. Patel, “Crop Detection and Maturity Classification Using YOLOv5-Based Model,” in *Proc. IEEE Int. Conf. Smart Agric.*, 2022, pp. 112–118.

[7] L. Martinez, K. Lee, and P. Singh, “Drones and AI detect soybean maturity with high accuracy,” *J. Field Robotics*, vol. 36, no. 2, pp. 345–358, 2019.

[8] M. Thompson and R. Evans, “An applied deep learning approach for estimating soybean relative maturity,” *Comput. Electron. Agric.*, vol. 183, p. 106018, 2021.

[9] K. Yamamoto, Y. Sato, and M. Nakagawa, “Tomato maturity recognition with convolutional transformers,” *IEEE Access*, vol. 11, pp. 2345–2356, 2023.

[10] P. Rodriguez, A. Torres, and L. Garcia, “Advancements in utilizing image-analysis technology for crop yield calculation,” *Precision Agric.*, vol. 24, no. 1, pp. 45–60, 2023.

[11] R. Reyes and M. Mendoza, “Digital imaging methods for crop monitoring,” *Agronomy J.*, vol. 112, no. 5, pp. 2345–2355, 2020.

[12] L. Castro and J. Navarro, “Feature extraction techniques in smart agriculture,” *Comput. Electron. Agric.*, vol. 168, p. 105123, 2020.

[13] A. Garcia, M. Perez, and C. Ruiz, “Image-based methods for smart agriculture systems,” *J. Agric. Informatics*, vol. 12, no. 2, pp. 78–89, 2021.

[14] F. Lopez, G. Hernandez, and S. Torres, “CNN applications in crop image classification,” *Int. J. Agric. Biol. Eng.*, vol. 14, no. 3, pp. 67–75, 2021.

[15] Y. Chen, X. Li, and H. Zhang, “Advanced segmentation algorithms for crop feature isolation,” *Comput. Electron. Agric.*, vol. 169, p. 105200, 2020.

[16] D. Santos, L. Martinez, and P. Gomez, “Image pre-processing techniques for crop monitoring,” *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.*, vol. 15, pp. 345–356, 2022.

[17] S. Dela Cruz, A. Bautista, and J. Villanueva, “Integration of image data with IoT sensors to create dynamic monitoring systems,” *Sensors*, vol. 23, no. 6, p. 3421, 2023.

[18] C. Bautista, E. Ramirez, and F. Castillo, “Sensor data integration with deep learning outputs for robust crop monitoring,” *Comput. Electron. Agric.*, vol. 196, p. 107123, 2022.

[19] M. Villanueva, R. Santos, and D. Alvarez, “Robust crop monitoring under variable field conditions: Sensor fusion techniques,” *Sensors*, vol. 24, no. 1, p. 145, 2024.

[20] A. Kumar and R. Patel, “Non-invasive monitoring techniques: Definitions and applications,” *IEEE Sensors J.*, vol. 23, no. 5, pp. 234–245, 2023.

[21] S. Tanaka, Y. Suzuki, and H. Yamamoto, “Remote sensing and imaging for non-invasive crop analysis,” *Remote Sens.*, vol. 14, no. 3, p. 567, 2022.

[22] A. Garcia and F. Lopez, “Deep learning for hierarchical feature extraction in agricultural images,” *J. Mach. Learn. Appl.*, vol. 9, no. 4, pp. 210–220, 2022.

[23] T. Müller, U. Schmidt, and P. Weber, “Novel CNN architectures optimized for agricultural applications,” in *Proc. ECCV*, 2021, pp. 345–360.

[24] R. Rodriguez, J. Martinez, and S. Lopez, “Integration of image data with IoT sensors for dynamic crop monitoring systems,” *Sensors*, vol. 23, no. 8, p. 4567, 2023.

[25] V. Singh and R. Gupta, “Sensor fusion techniques for real-time crop health insights,” *J. Agric. Informatics*, vol. 13, no. 1, pp. 15–25, 2024.

[26] K. O’Brien and S. Lee, “Bridging research to practice: Standardized methodologies in smart agriculture,” *Precision Agric.*, vol. 25, no. 2, pp. 99–112, 2023.