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Short Paper

Detection of Nutrient Deficiencies in *Coffea Arabica* Leaves Using the YOLO Object Detection Algorithm

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ABSTRACT

Purpose – Nutrient deficiencies in coffee plants can severely impact plant health and yield, making timely detection crucial for farmers. Traditional methods, such as visual examination and soil testing, are inefficient and lack scalability. This study aims to develop a model using YOLOv7 to detect multiple nutrient deficiencies in *Coffea arabica* leaves, offering a practical and real-time solution for coffee farmers to monitor plant health and optimize yield.

Method – A dataset of 462 images of coffee leaves showing nutrient deficiencies (Potassium, Magnesium, Manganese, Sulfur, Copper, Molybdenum, Iron, and Zinc) was compiled, with labels verified by experts. Two YOLOv7 models were trained for 100 epochs: a fixed resolution model and a multi-resolution model. A prototype system was also developed to detect these deficiencies in real time for end-users.

Results – The multi-resolution YOLOv7 model achieved 75% accuracy, surpassing expectations given the limited dataset size. The multi-resolution model outperformed the fixed-resolution model, demonstrating the efficacy of this approach in detecting multiple nutrient deficiencies simultaneously.

Conclusion – The study confirmed the potential of YOLOv7 in real-time detection of multiple nutrient deficiencies in coffee leaves, providing an efficient, scalable solution for farmers. This technology could enable timely interventions to improve crop health and yield.

Recommendation – Further expansion of the dataset and real-world testing are recommended to validate and improve the model's accuracy. Exploration of additional learning models and techniques could further enhance detection performance.

Practical Implications – This research highlights the potential of integrating deep learning models, like YOLOv7, in agricultural monitoring systems. The developed prototype provides farmers with a tool to optimize plant health management, showcasing the broader impact of AI technology in improving efficiency and productivity in agriculture.

Keywords – YOLOv7, *Coffea Arabica*, Nutrient Deficiencies, Object detection, Artificial Intelligence

INTRODUCTION

Coffee holds an esteemed position as one of the most widely consumed beverages worldwide, captivating the taste buds and cultures of people across the globe. Its significance extends beyond its flavor, with increasing interest in its impact on health and economics, making it a subject of great importance for both research and public health (Cornelis, 2019). Because of its biochemical properties and the positive impacts on health that outweigh any potential negative effects, coffee has the potential to be a functional food, as demonstrated by recent studies (Messina et al., 2015). Moreover, coffee serves as a vital economic commodity for many developing countries, including Tanzania and Uganda, upon which they heavily rely (Nugroho & Lakner, 2022).

A little over two hundred years ago, coffee was first brought to the Philippines (Luat, 2022). For the Filipino people, coffee has always been a part of their lives, both for the poor and the wealthy (Laurico et al., 2021). The Philippines is a member of the International Coffee Organization (ICO), which unites approximately 60 countries that produce coffee (International Coffee Organization, 2023). This production plays a significant role in the economy and the employment of people (Reinecke et al., 2012).

However, several journals mentioned how the lack of nutrients and minerals greatly affects the production quality of coffee (Sunnexdesk, 2017, Wang et al., 2022, Saha, 2018). To shed light on what macronutrients and micronutrients are, a journal describes them as essential chemical elements required in large (macronutrient) or small (micronutrient) amounts for the growth of plants, e.g., nitrogen, phosphorus, and zinc (Sosa et al., 2019).

Minerals and nutrients in coffee are important for both the health of the coffee plant and the quality of the coffee beans that are harvested. A deficiency of any essential nutrients can have a negative impact on the growth and yield of the coffee plant. Calcium, for example, is a crucial macronutrient in coffee and is involved in several physiological processes that affect crop development, production, and stress response (Nagao et al., 1986). Iron-deficiency anemia, also known as IDA, is one of the most prevalent types of anemia in the

Philippines, which is caused by a lack of iron in the diet. Pregnant women (24.6%), elderly men (23.0%), elderly women (19.1%), and breastfeeding women (16.7%) can all show symptoms of it (Kreißl, 2009).

Macronutrient and micronutrient deficiencies have been a problem in the production of quality coffee beans. Currently, there are journals that tackle what methods to use against the problems of nutrient deficiency in coffee leaves, such as the difference method (Nagao et al., 1986). However, there is a lack of research regarding how we can use these technologies for the use of farmers with limited technology.

The traditional way of identifying nutrient deficiencies in plants comprises methods such as visual examination, soil testing, and consideration of abiotic stresses (NParks Buzz, 2020). The visual examination involves looking at the plant's leaves, stems, and roots to identify what nutrients are lacking. For instance, a lack of nitrogen results in the entire plant turning light green, followed by the older leaves beginning to yellow and moving toward the younger leaves, which causes the plant to become weak, stunted, and spindly. Traditional methods for identifying nutritional deficiencies in coffee plants include a visual examination of the coffee plant and soil testing (NParks Buzz, 2020; University of Massachusetts Amherst, n.d.). However, these methods have significant limitations in terms of efficiency, accuracy, and scalability. Manual examination requires expertise and is time-consuming, especially for large-scale coffee farms, while soil testing, though more precise, requires costly specialized equipment.

A review by Hashimi et al. (2023) highlights that visual symptoms remain a widely used method for identifying nutrient deficiencies, as nutrient mobility within plants results in distinct deficiency patterns. However, the study also points out that similar symptoms can be caused by both biotic and abiotic factors, leading to potential misdiagnosis. Similarly, Chen et al. (2014) investigated nutrient deficiencies in rice plants, showing that nitrogen deficiency leads to chlorotic, light-green leaves, while phosphorus deficiency results in stunted growth and dark green, erect leaves. These studies underscore the continued reliance on visual assessment despite its inherent subjectivity and susceptibility to misinterpretation.

While visual examination provides some insights, soil testing has emerged as a more accurate method. Soil samples from the plant's growing environment are analyzed to determine their nutrient contents. However, it is important to note that this method requires specialized equipment and expertise, making it a costly approach (University of Massachusetts Amherst, n.d.).

With the rapid growth of technology, these traditional methods can be done more effectively, with less time, and with reduced costs. Deep learning Algorithms like Convolutional Neural Networks (CNNs) are now available to be able to perform traditional methods like the ones previously mentioned. In the field of image processing, CNNs have been a significant breakthrough, particularly for tasks involving images, audio outputs, and speech recognition. CNNs assign dedicated weights to different parts of an input image, enabling them to distinguish and classify various inputs (Saha, 2022). Comprising convolutional, pooling, and fully connected layers, CNNs progressively analyze images, focusing on features such as color, edges, and object shapes (Schaefer, 2021).

CNNs prove invaluable in the detection of plant diseases from leaf images. Shallow CNNs, combined with classic machine learning classification, have shown promise in this domain (University of Massachusetts Amherst, n.d.). For instance, soybean plant disease classification is an exemplary case, where a CNN model trained on 12,673 leaf images captured in an uncontrolled environment achieved an impressive classification accuracy of 99.32% (Walleign et al., 2023). This demonstrates CNN's ability to classify plant diseases from images taken in natural settings accurately.

Automated plant type identification is essential for the application of pesticides, fertilizers, and the harvesting of different species. CNN architecture can be implemented to classify different plant species based on their appearance. The implementation of CNN is said to be quite effective compared to SVM classifiers with different kernels (Luat et al., 2022).

Although research has been conducted about detecting nutrient deficiencies in *Coffea arabica* leaves, there are still gaps to be filled. For example, in the study conducted by Tenaye et al. (2022), image classification was used as the main technique to detect deficiencies. In which they made use of the CNN architectures Mobile-Net, VGG16, and InceptionV3. Furthermore, existing studies often focus on detecting only a limited range of nutritional deficiencies (Cornelis, 2019; Sosa et al., 2019). Hence, this study proposes an alternative method making use of object detection models through YOLOv7 that can detect a larger range of deficiencies while being able to detect multiple deficiencies in a single leaf.

To achieve these, object detection techniques such as You Only Look Once (YOLO) can be utilized. Object detection refers to the process of identifying objects in an image belonging to specific classes. This involves detecting all instances of objects from known classes, such as people, cars, or faces. Although the number of objects in an image is usually small, there are numerous possible locations and scales at which they can appear, requiring exploration. It is used for the identification and localization of objects within an image or video through bounding boxes (EOS Data Analytics, 2022). This is done through the use of Convolutional Neural Networks (CNN) to detect objects.

Residual Blocks, Bounding Box Regression, and Intersection Over Union are three approaches used by YOLO algorithms. In the Residual Box, an image is divided into various grids in which objects will be detected. Bounding Box Regression would then highlight the objects detected in the grid. Lastly, Intersection Over Union would ensure that the predicted bounding boxes are equal to the real boxes of the objects (Karimi, 2021). Currently, YOLOv7 is known as one of the most accurate object detectors boasting 56.8% average precision among all known real-time object detectors (Wang et al., 2022).

Identifying nutrient deficiencies in plants is crucial for maintaining their health and maximizing crop yield. Therefore, this study aims to help farmers themselves identify the lack of nutrients in the coffee plant, manifested through its leaves.

LITERATURE REVIEW

Detecting nutrient deficiencies in Coffea arabica leaves is essential for ensuring plant health and optimizing coffee production. Traditional methods, which often rely on manual inspection, can be time-consuming and subjective. Recent advancements in image processing and machine learning have introduced automated approaches to address these challenges.

A study by Tenaye et al. (2022) developed an image processing-based system for detecting nutrient deficiencies in Coffea arabica leaves. The research employed an experimental design, which included dataset preparation, classification model development, and performance evaluation. Among the (CNN) Convolutional Neural Networks architectures evaluated, MobileNet, a pre-trained deep learning model, achieved the best performance, demonstrating its effectiveness in identifying nutrient deficiencies in coffee plants.

Lewis and Espineli (2020) developed a CNN-based model to classify and detect nutritional deficiencies in coffee plants. Their study utilized image processing techniques, converting the images into grayscale and binary values for thresholding and segmentation. The results show that the CNN model has high accuracy in identifying deficiencies, including Boron, Calcium, Iron, Nitrogen, Phosphorus, Potassium, Magnesium, and Zinc across various coffee varieties, including Coffea arabica. Similarly, Santana et al. (2023) proposed an algorithm using CNNs and aerial imagery for automatic coffee plant counting. An algorithm based on machine learning was developed for the automatic counting of coffee plants from remotely piloted aircraft RGB images. It presented 96.8% accuracy with images without spectral treatment. Although their focus was on plant enumeration, the methodology highlights the versatility of CNNs in analyzing coffee plant images, which could be adapted for nutrient deficiency detection.

A comprehensive review by Alif and Hussain (2024) investigates the transformative potential of various (YOLO) You Only Look Once variants, from YOLOv1 to the state-of-the-art YOLOv10, in the context of agricultural advancements. The primary objective is to elucidate how these cutting-edge object detection models can re-energize and optimize diverse aspects of agriculture, ranging from crop monitoring to livestock management. However, challenges such as detecting small or occluded objects remain. Later variants of YOLO have been designed to tackle these challenges, aiming to improve performance across diverse datasets.

Among these variants, YOLOv7 has gained prominence for its real-time detection capabilities, enhanced accuracy, and speed. Kusuma and Soewito (2023) explored the optimization of real-time object detection on mobile devices by introducing a multi-object detection system based on a quantified YOLOv7 model. Their findings demonstrated that

YOLOv7 effectively balances detection performance and computational efficiency, making it well-suited for deployment in resource-constrained environments such as mobile platforms.

Integrating YOLOv7 into agricultural applications has shown promise in various studies. For instance, an improved YOLOv7 algorithm enhances small object detection in UAV images, which is pertinent to identifying subtle features indicative of nutrient deficiencies in plant leaves. Li et al. (2024) propose an efficient YOLOv7-UAV algorithm in which a low-level prediction head (P2) is added to detect small objects from the shallow feature map, and a deep-level prediction head (P5) is removed to reduce the effect of excessive down-sampling. YOLOv7-UAV is quantified and compiled by Vitis-AI and deployed on the FPGA (AXU3EG) platform to achieve higher energy efficiency, which is improved by 12 times compared to the GPU platform. The modified algorithm incorporated an extra low-level prediction head to better capture small object features, thereby improving detection accuracy.

Further advancements in YOLO-based models for agricultural applications are seen in the work of Zambre et al. (2024), who integrated Spatial Transformer Networks (STNs) into YOLO to enhance spatial awareness and detection accuracy. Their STN-YOLO model refines object detection by focusing on key regions within an image to address spatial invariance challenges. While Li et al. (2024) emphasized UAV-based monitoring, Zambre et al. (2024) targeted spatial transformation techniques that improved model robustness and reduced the number of false positives, as evidenced by higher precision scores in their dataset evaluations.

By leveraging the capabilities of YOLOv7, it is feasible to develop an object detection model tailored to identify nutrient deficiencies in *Coffea arabica* leaves. Such a model would analyze leaf images, detect visual symptoms of nutrient deficiencies, and facilitate timely interventions to address plant health issues. This approach not only streamlines the diagnostic process but also contributes to sustainable coffee cultivation practices.

Objectives

The project aims to create an object detection model using YOLOv7 that can detect nutrient deficiencies present in *Coffea arabica* leaves. Specifically, the objectives of the project are to:

1. Create an annotated dataset of *Coffea arabica* leaves.
2. Create an AI model using the YOLOv7 object detection algorithm.
3. Incorporate the created model into a usable prototype.

The scope of this study is to develop a YOLOv7 model that can be used to identify the nutrient deficiencies in *Coffea arabica* leaves precisely. Expanding the ability of the model to accommodate other types of coffee leaves and provide prescriptions for the deficiencies detected is reserved for future research. While the study may create an application to showcase the model's functionality, the development of a fully practical application is beyond the project's scope. Therefore, the primary output of the study will be a model that can detect nutrient deficiencies of *Coffea arabica* leaves.

MATERIALS AND METHODS

Data Collection

In this study, a diverse dataset of *Coffea arabica* leaf images was gathered for analysis. The data collection process involved capturing 462 pictures of *Coffea arabica* leaves from the coffee farm of Benguet Coffee Project, a coffee farm located in the Saint Louis University Sacred Heart Medical Center. The selection of the coffee farm was based on the recommendation of the researchers' research adviser and its reputation for producing high-quality *Coffea arabica*. To replicate the approach of a typical farmer taking pictures, cameras from different smartphones were used, allowing for variations in image quality and perspectives.

To ensure variability in the dataset, leaves were selected from different trees across the farm. This ensured a representation of various ages, health conditions, and other attributes.

There are a few limitations to consider on the dataset used in this study. First, was that the data collection was limited to a single coffee farm, which may introduce some degree of site-specific bias. Next, the dataset size of 462 images may not be enough to capture all deficiencies and their variations.

Data Annotation

Upon acquiring the *Coffea arabica* leaf dataset, researchers collaborated with coffee leaf analysis experts to identify and observe nutritional deficiencies in the leaves. Deficiencies in essential nutrients such as Potassium, Magnesium, Manganese, Sulfur, Copper, Molybdenum, Iron, and Zinc were determined through careful examination.

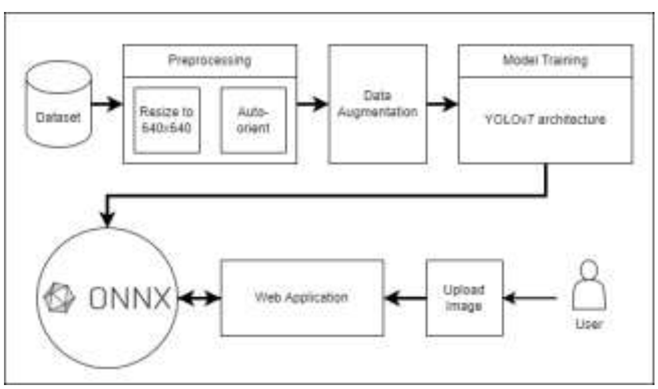

Figure 1. AI Model

To annotate the images and indicate nutrient deficiency characteristics, researchers used the VGG Image Annotator (VIA), a user-friendly web-based software. The images were divided among researchers, who followed expert-provided guidelines in PowerPoint slides outlining deficiency details, visual symptoms, and appearances. Specific leaf areas with deficiencies were highlighted using polygons for accurate object detection. In cases of multiple deficiencies within a leaf, each lacking nutrient was labeled accordingly. Otherwise, the leaf was labeled as healthy. All labeled images were verified by a coffee expert to ensure accuracy.

Data Preprocessing

To increase the accuracy and consistency of the data, image preprocessing is a crucial stage in any computer vision project. In this step, the unprocessed pictures of nutritionally deficient *Coffea arabica* leaves are transformed into data that can be used to train a YOLOv7 model.

All images were resized to a uniform resolution of 640 x 640 pixels, the default setting of YOLOv7. This resizing step ensured that the images had the same dimensions, facilitating subsequent analysis and processing. The auto-orient function was also applied to the images to ensure consistent orientation across the dataset. This process automatically adjusted the images to the correct orientation based on their embedded metadata.

Data Augmentation

To increase image diversity and robustness, data augmentation techniques were used. Each training example underwent multiple transformations, including horizontal and vertical flipping, 90-degree rotations (clockwise, counter-clockwise, and upside-down), random cropping with zooming (0% to 37%), random rotation (-14° to +14°), horizontal and vertical shearing (-22° to +22° and -12° to +12° respectively), up to 1.5 pixels of Gaussian blur, and up to 1% pixel noise. This resulted in a total of 655 augmented images from the initial set of 462.

Model Training

The training methodology involved training two versions of the model: one using multi-resolution images and the other using fixed-resolution images, allowing for a comparison of their performance. The multi-resolution model would be able to take input images of any resolution, while the fixed resolution model would resize the input images to 640x640.

The YOLOv7 architecture offers multiple models with varying parameters. For this project, the standard model was employed, which consists of 37 million parameters, and to initiate the training process, the pre-trained YOLOv7 training weights provided by the authors as the starting point for our model were used.

The dataset was split into train, test, and validation with an 80-10-10 proportion, respectively. Both models underwent training for a total of 100 epochs, with each epoch representing a complete pass through the training dataset. The fixed-resolution model was trained with 16 batches, while the multi-resolution model was initially intended to be trained with 16 batches. However, due to limited available resources, the number of batches for the multi-resolution model was reduced to 8.

Training the multi-resolution model presents additional challenges as the dataset becomes more complex due to the inclusion of varied sizes of objects. This requires more computational resources and can result in a more resource-intensive training process. Considering the limitations of available resources, the number of batches was reduced for the multi-resolution model to manage the computational requirements.

Performance Evaluation Metrics

The models were evaluated using multiple evaluation techniques. The **confusion matrices** were generated to visualize the classification performance of the two models. Then, the researchers calculated the accuracy, precision, and recall of the models. Accuracy shows how many predictions were made right. A model with high precision means the model will produce fewer false positive predictions, and a high recall indicates that the model accurately detects most of the positive occurrences. Thus, this research aims to create a model with maximum accuracy, precision, and recall.

Prototype

As one of the research objectives, the researchers created a usable prototype that allows farmers to either upload a photo of their coffee plant's leaves or use their cameras to provide real-time detection of deficiencies.

To create the prototype, the researchers first converted the YOLOv7 model to ONNX. ONNX is an ML framework that allows conversion between different machine learning frameworks. Then, the researchers used the converted ONNX file to create the prototypes. After the prototype has detected the deficiencies, the farmer can refer to the table below, which provides remedies that have been identified with the assistance of a coffee expert.

RESULTS

Model Performance Evaluation

Table 1 summarizes the P curve results for both models. The Fixed Resolution model shows non-significant p-values (all 1.00 at p=0.973), indicating no evidence to reject the null hypothesis. In contrast, the Multi-Resolution model exhibits a high confidence threshold (1.00 at threshold 0.958) and achieves a precision of 1.00, indicating no false positive predictions.

The F1 curve results show moderate performance for both models. The Fixed Resolution model has an F1 score of 0.41 (threshold 0.364), while the Multi-Resolution model has an F1 score of 0.51 (threshold 0.122). Adjusting the Multi-Resolution model's threshold may improve precision and recall.

Table 1. Performance Evaluation Table

Model	P-curve Value	F1-curve Score	R-curve Score
Fixed Resolution	1.00 at threshold 0.973	0.41 at 0.364	0.78 at 0.000
Multi-Resolution	1.00 at threshold 0.958	0.51 at 0.122	0.90 at 0.000

Table 2. PR-curve Scores Table

Deficiency	Fixed Resolution	Multi-Resolution
Healthy	0.995	0.995
Copper	0.547	0.591
Iron	0.000	0.498
Magnesium	0.586	0.828
Manganese	0.995	0.995
Molybdenum	0.612	0.605
Potassium	0.626	0.678
Sulphur	0.090	0.140
All Classes	0.556 mAP@0.5	0.666 mAP@0.5

The R curve scores reveal distinct characteristics. The Multi-Resolution model achieves an exceptional recall of 0.90 (threshold 0.000), accurately identifying 90% of positive instances. The Fixed Resolution model has an average recall of 0.78 (threshold 0.000), accurately identifying around 78% of positive instances.

The PR curve, or Precision-Recall curve, illustrates the tradeoff between precision and recall for a classification model across different threshold values. The PR curve results show that the average precision across all classes at a threshold of 0.5 is 0.556 for fixed resolution and 0.666 for multi-resolution.

Figure 2 presents the training and validation set performance of the model. The box, objectless, and classification losses exhibit a steady decline over four epochs. The precision initially improves rapidly from the first epoch but gradually decreases after 50 epochs. Similarly, the recall demonstrates a steady improvement from the first epoch but experiences a consistent decline after ten epochs. The mean Average Precision (mAP) follows a similar pattern, with a rapid improvement from the first epoch, unstable performance between ten and seventy epochs, and a subsequent decline after eighty epochs.

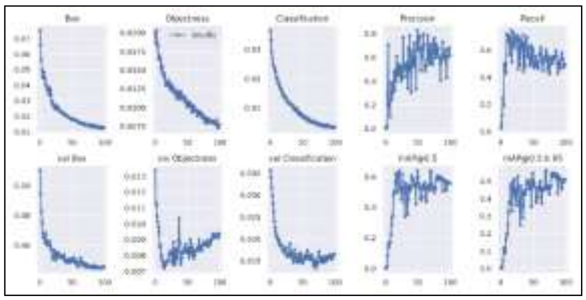

Figure 2. Training and Validation Graph of Fixed-Resolution Model

In Figure 3, the box, objectness, and classification losses are displayed, along with the precision, recall, and mAP@0.5 performance of the multi-resolution model. The box, objectness, and classification losses consistently start from the first epoch, indicating a stable training process. The precision shows improvement from the first epoch but exhibits unstable performance thereafter. On the other hand, the recall and mAP consistently improve from the first epoch, reflecting the model's ability to capture more relevant instances and achieve a higher precision-recall tradeoff throughout the training process.

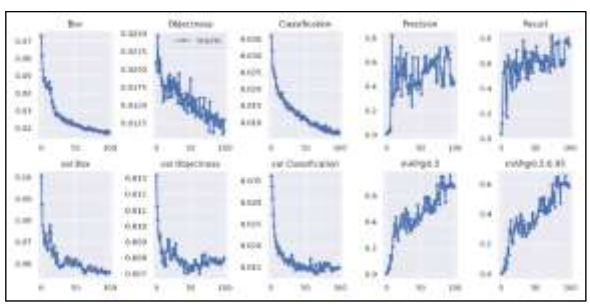

Figure 3. Training and Validation Graph of Multi-Resolution Model

The confusion matrix indicates that the model achieved 47% correct predictions in the Healthy class, 100% in Iron deficiency, 33% in Manganese, 50% for Molybdenum, 57% Potassium, 67% Sulfur, and 0.08% in Zinc. The accuracy of Iron, Molybdenum, Potassium, and Sulphur indicates that the model could detect these nutrient deficiencies well. In contrast, Healthy, Manganese, and Zinc class accuracy rates may not be satisfactory, especially Zinc, which indicates poor performance. The model's overall accuracy is 50%, meaning that the model performs moderately in general.

Based on the Confusion Matrix of the Multi-Resolution Model, the model achieved 64% for correctly predicting the Healthy class, 100% for Iron, 100% for Manganese, 100% for Molybdenum, 71% for Potassium, 87% for Sulphur, and 14% for Zinc. The model performs very well in correctly predicting the Healthy, Iron, Manganese, Molybdenum, Potassium, and Sulphur classes while poorly predicting the Zinc class. The model's overall accuracy is 75%, which implies that the model performs very well in general.

Table 3. Confusion Matrix Summary of Fixed and Multi-Resolution Model

Deficiency	Fixed Resolution Model Accuracy	Multi-Resolution Model Accuracy
Healthy	64%	47%
Iron	100%	100%
Manganese	100%	33%
Molybdenum	100%	50%
Potassium	71%	57%
Sulphur	87%	67%
Zinc	14%	0.08%
Overall Accuracy	75%	50%

Prototype

The researchers developed two prototypes to cater to different user preferences and technological capabilities. The first prototype allows farmers to upload images of their coffee plants' leaves to identify their nutrient deficiencies. The second prototype allows farmers to use their device's camera for real-time detection of their coffee plant's nutritional deficiencies.

Figure 4. Image Upload and Real-time Detection Prototype

This prototype allows users to upload their coffee leaf images or detect real-time nutrient deficiency using the device's camera. Then, as shown in the screenshot, the image will be analyzed, and the prototype will provide its predictions of the specific nutrient deficiencies present in the image.

DISCUSSION

Dataset

The images used in the study played an important role in the creation of our model. It consists of 462 pictures of *Coffea arabica* leaves captured from the coffee farm of Farm to Cup, a coffee shop located in La Trinidad. The diversity of the images allowed us to capture different deficiencies and allowed us to develop a model that can accurately predict nutrient deficiencies in *Coffea arabica* plants.

Fixed Resolution vs Multi-Resolution

The multi-resolution model exhibits better PR curve, F1 curve, and R curve scores than the fixed-resolution model. It suggests that the multi-resolution model has improved performance regarding classification accuracy, trade-offs between precision and recall, and better ranking abilities across varying resolutions. This indicates that the multi-resolution model is more capable of handling the complexities and variabilities present in the input data, resulting in overall better performance. Furthermore, the multi-resolution model demonstrates an overall accuracy rate of 75%, while the fixed-resolution model achieves an accuracy rate of 50%. With a 25% higher accuracy rate, this significant overall accuracy difference strengthens the multi-resolution model's superiority. The multi-resolution model outperforms the fixed-resolution model's capability to handle varying input resolutions and deliver superior results.

While the multi-resolution model outperforms the fixed-resolution model based on the multi-evaluation metrics, there can still be situations or scenarios where the fixed-resolution model is preferred. In terms of computational efficiency, the fixed-resolution model is computationally more efficient than multi-resolution models. If a system has limited computational resources, the fixed-resolution model is preferred. It is simpler in architecture and easier to interpret. Simplicity is advantageous when the complexity of the multi-resolution model poses challenges in model understanding and deployment, and is time-consuming.

Model Prototype

By developing a prototype that utilizes the researchers' created model to detect nutritional deficiencies in *Coffea arabica* plants, farmers can take proactive measures to improve or maintain the health of their plants.

In terms of accuracy, the created model, which has a high precision and recall, ensures that the prototype is accurate. However, factors such as lighting conditions and image quality may affect the accuracy.

Performance-wise, the prototype performs more slowly than the second prototype. This is because the prototype allows farmers to upload their images at any size. As a result, the prototype has to resize the image before it can process it, which can take some time. On the other hand, the second prototype is optimized to use a fixed input size, eliminating the need to resize the video, resulting in more efficiency.

CONCLUSION

Coffee is a widely consumed beverage and an economic commodity for many countries. Nutrient deficiencies in coffee plants can significantly impact the plant's growth, yield, and overall quality of the harvested beans. The inefficiency and lack of scalability of traditional methods for determining nutrient deficiencies, including visual inspection and soil testing, were highlighted in the paper. It is crucial to develop modern tools to make it easier for farmers to detect nutritional deficiencies.

There are limited studies conducted on detecting nutrition deficiencies in coffee leaves, and most of them use classification techniques such as CNN. But there are also instances where multiple deficiencies can be seen in one leaf. To overcome these limitations, the study proposed the use of object detection algorithms, particularly the You Only Look Once (YOLO) approach with the YOLOv7 model, to accurately identify and localize nutrient deficiencies in *Coffea arabica* leaves. Among the models trained, multi-resolution models showed a higher accuracy, recall, and precision.

RECOMMENDATION

Although the application of YOLOv7 to detecting nutrient deficiencies in *Coffea arabica* leaves has shown positive results, there are several important areas for further research and development to enhance its robustness, scalability, and applicability. One key direction is expanding the dataset to include other coffee species, such as Coffea canephora (commonly known as Robusta), which is widely grown across the world. By incorporating a broader range of coffee species and nutrient deficiencies, the model can become more versatile and applicable to a wider variety of coffee farms globally, increasing its overall utility.

In addition, further optimization and fine-tuning can be performed to enhance its accuracy and detection capabilities. This can involve experimenting with different model architectures, hyperparameter tuning, or exploring other state-of-the-art object detection models.

Furthermore, collaborating with agricultural experts is also crucial to ensure that the model outputs are meaningful and useful in the field. So, their expertise can help refine the detection criteria, interpret the results, and suggest actionable steps for correcting nutrient deficiencies in plants.

IMPLICATIONS OF THE STUDY

Practical Implication

The findings of the study have significant implications for the coffee industry as well as agricultural innovations. Farmers can do away with time-consuming, labor-intensive techniques like visual inspections and soil testing by employing the YOLOv7 object detection model to identify nutritional shortages in *Coffea arabica* leaves. The development of this model not only makes it easier to diagnose arabica leaf deficiencies but also empowers farmers to take timely and informed actions to improve plant health, leading to higher yields and better-quality beans. The significance of flexibility in identifying nutrient deficits is emphasized by the comparison of fixed-resolution and multi-resolution models. The better performance of the multi-resolution model, especially in terms of accuracy, recall, and precision (75% vs. 50%), suggests that it is robust enough to handle a variety of leaf pictures as well as complex data variability. This shows that multi-resolution models are more capable of detecting multiple deficiencies in a single leaf and can better handle real-world farming conditions.

However, the study also recognizes that resource-constrained environments may benefit from the fixed-resolution model, which is simpler and more computationally efficient. This balance between accuracy and resource efficiency makes both models valuable depending on the use case, emphasizing the need for adaptable solutions in agriculture.

Social Implication

Coffee is one of the most widely consumed beverages globally, and its farming supports millions of coffee growers, particularly in developing countries. The ability to efficiently manage crop health through AI-powered tools has profound social implications. By improving the accuracy and efficiency of nutrient deficiency detection, this research can contribute to more sustainable coffee farming practices. As a result, farmers could experience increased productivity, better quality beans, and improved livelihoods. Moreover, the integration of AI-based tools like smartphone applications into farming practices has the potential to reduce labor costs and enhance the overall efficiency of agricultural operations.

This shift could have a broader societal impact by improving food security, reducing environmental impacts, and contributing to the economic development of coffee-growing regions.

DECLARATIONS

Conflict of Interest

The researchers declare no conflict of interest in this study.

Informed Consent

The researchers have read and understood the provided guidelines included in this journal publication.

Ethics Approval

The researchers affirm their commitment to the accepted ethical standards.

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