Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7546452

MOBILE-BASED SUGARCANE DISEASE IDENTIFICATION: LEVERAGING DEEP LEARNING FOR EARLY DETECTION AND MONITORING

Ajay Chakravarty[1]
Teerthanker mahaveer University, Moradabad. ajay.chakravarty1@gmail.com

Dr Arpit Jain[2]
Koneru Lakshmaiah Education Foundation,
Green Fields, Vaddeswaram, Andhra Pradesh. dr.jainarpit@gmail.com

Ashendra Kumar Saxena[3]
Teerthanker mahaveer University, Moradabad. drashendra.computers@tmu.ac.in

Abstract:
Early detection and type of crop diseases are essential to stopping sizeable agricultural losses and making sure meals security. Traditional methods for sickness diagnosis frequently contain labor-extensive procedures and necessitate massive know-how of pathogens, making them both steeply-priced and inefficient. In reaction to these demanding situations, device studying (ML) and deep studying (DL) strategies have emerged as promising solutions to automate the detection and class of plant sicknesses through picture evaluation. This overview paper affords a radical examination of picture-based totally plant disorder detection structures, that specialize in various aspects which includes the resources and types of plant datasets, the range of ML and DL algorithms used, and their effectiveness in actual-world programs. We examine a hit case research and spotlight key advancements within the subject, emphasizing how these technologies have progressed sickness detection accuracy and performance. Additionally, we deal with the capability demanding situations in imposing ML and DL tactics, inclusive of issues associated with dataset diversity, version robustness, and the need for massive-scale computational resources. By offering strategies to conquer those boundaries, we aim to guide destiny research and improvement efforts. This evaluation serves as a complete resource for researchers and practitioners, imparting insights into contemporary methodologies and suggesting pathways for advancing automatic plant ailment detection systems

Keywords: -
Early detection, crop sicknesses, photo-primarily based structures, machine studying (ML), deep studying (DL), plant datasets, sickness category, set of rules strategies, computerized detection, computational performance, dataset variability, model generalization, agricultural generation, disorder management, image analysis, actual-world packages, research improvements, computational assets

Introduction

In reaction to the projected worldwide population growth, that's predicted to technique 9.1 billion with the aid of 2050, the rural area faces the crucial undertaking of growing meals manufacturing to satisfy the needs of an expanding and an increasing number of urbanized global This assignment is compounded by using the impacts of climate exchange, which introduces variability and unpredictability into farming conditions. As a result, there may be an urgent need for revolutionary solutions to enhance agricultural productiveness and sustainability.

One promising method is precision agriculture, which leverages advanced technologies to optimize farm operations. Precision agriculture utilizes virtual analytics and high-generation sensors to enhance crop yields by using imparting certain and actionable insights. Advanced far off sensing technologies have become imperative to this technique, permitting cost-powerful and non-unfavourable statistics series. Applications together with weed detection, plant disorder identity, and pest tracking have significantly benefited from those technologies Traditionally, plant disease monitoring has trusted guide inspection, which is exertions-in depth and hard to scale for huge plantations. To cope with this, diverse techniques together with molecular biology, biotechnology, and invasive diagnostic technologies had been employed, despite the fact that they frequently come with high fees and complexity [3, 33].

The integration of Internet of Things (IoT) devices, sensors, drones, synthetic intelligence (AI), and blockchain technology is using a fundamental transformation in agriculture IoT devices and sensors continuously accumulate statistics on machinery performance, soil situations, and environmental elements. Drones equipped with advanced cameras and multispectral sensors provide targeted records on crop health and capacity troubles. Blockchain technology complements transparency and traceability inside the agricultural deliver chain, assuring the authenticity and protection of meals products This technological convergence now not only promotes sustainability but additionally improves farm productivity by means of minimizing resource waste, allowing actual-time choice-making, and optimizing inputs primarily based on specific wishes.

Machine getting to know (ML) and deep studying (DL) are at the vanguard of this technological revolution. ML, a subset of AI, includes algorithms that pick out styles in statistics and improve overall performance autonomously. Common ML algorithms consisting of Support Vector Machine (SVM), K-nearest Neighbor (K-NN), and Artificial Neural Networks (ANN) had been applied to detect plant diseases . However, those algorithms normally cope with tabular records and face challenges when working with photo information.

Deep learning, a more advanced subset of ML, utilizes neural networks with a couple of layers to system and analyze image records. This approach has tested powerful in detecting plant sicknesses through studying leaf snap shots and identifying ailment signs and symptoms with excessive accuracy. Modern computer vision equipment powered by way of DL have extensively advanced the sphere of plant disease detection, providing automated and unique evaluation Techniques which include transfer gaining knowledge of, records augmentation, and convolutional neural networks (CNNs) have further more suitable the competencies of DL on this domain

Despite those advancements, there remains a important need to assess the modern kingdom of ML and DL programs in plant ailment detection systematically. This includes identifying emerging tendencies, assessing methodologies, and evaluating the general effectiveness of those technology.

This manuscript pursuits to address this need via a complete evaluate of the literature on ML and DL for plant disorder detection. The overview is organized as follows: Section 2 provides the background of the study, Section three information the studies methodology which includes search keywords, database selection, and the Prisma framework for the survey. Section 4 critiques AI-based plant disease detection systems, whilst Section five discusses contemporary obstacles, demanding situations, and destiny directions. Finally, Section 6 offers the conclusions of the evaluate.

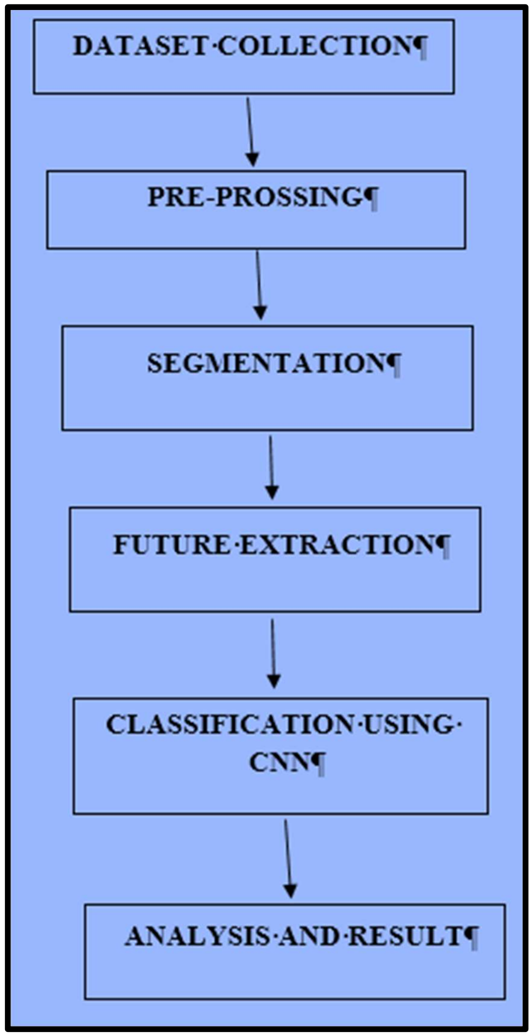

Fig :1, Sugarcane disease process

LITERATURE REVIEW:

1. **Data Acquisition**

Data acquisition is a fundamental step in growing ML fashions for plant sickness detection. High-best, diverse datasets are crucial for training sturdy models. Studies commonly make use of pix of both healthy and inflamed plant leaves to build complete datasets. For example, the paintings through Ferentinos (2018) emphasizes the importance of sizeable and annotated datasets to teach convolutional neural networks (CNNs) effectively. Various datasets have been proposed, inclusive of the PlantVillage dataset, which incorporates photographs of plant leaves stricken by exclusive diseases

2. Pre-Processing

Image pre-processing enhances the quality of input facts and prepares it for greater correct model schooling. Techniques such as noise discount, comparison adjustment, and normalization are usually hired. Zhang et al. (2020) verified that pre-processing steps, including blur enhancement and geometric corrections, significantly enhance the performance of ML models by lowering photograph artifacts and standardizing inputs Huang et al. (2022) in addition explored advanced pre-processing strategies, which includes histogram equalization and adaptive thresholding, to beautify picture readability and highlight relevant features for disease

3. Segmentation

Segmentation entails partitioning the picture into meaningful regions to isolate capabilities associated with plant diseases. Traditional methods encompass thresholding and side detection, while cutting-edge procedures make use of deep getting to know techniques. Badrinarayanan et al. (2017) brought the SegNet structure, which leverages encoder-decoder networks to acquire precise segmentation of plant disorder regions [4]. Recent advancements in semantic segmentation, together with the U-Net version via Ronneberger et al. (2015), have shown high accuracy in segmenting plant pictures by means of keeping spatial records

4. Feature Extraction

Feature extraction includes identifying and quantifying one of a kind styles or attributes from segmented images. Historically, hand made functions like texture, coloration, and shape descriptors have been used. However, LeCun et al. (2015) highlighted the efficacy of deep mastering models, in particular CNNs, in automating function extraction through learning hierarchical features without delay from raw image statistics . Chen et al. (2019) proposed an method that mixes conventional function extraction with deep studying strategies to improve disease type accuracy.

5. Training and Testing

The training level involves the usage of the received and pre-processed statistics to educate ML fashions, generally the use of supervised mastering techniques. Khan et al. (2021) explored various education techniques, together with switch mastering and best-tuning pre-skilled models, to leverage current knowledge and reduce training time [8]. Testing evaluates the version's overall performance on unseen facts, with metrics consisting of accuracy, precision, do not forget, and F1-score being normally used. Mahlein et al. (2013) emphasized the need for strong trying out protocols to make sure that models generalize well to new and diverse datasets

Conclusion

The development of ML models for plant disorder detection is a multi-faceted technique concerning records acquisition, pre-processing, segmentation, and characteristic extraction, culminating in education and trying out. Recent improvements in deep studying and pc imaginative and prescient have notably stronger the talents of these models, supplying more accurate and green detection of plant diseases. Ongoing research continues to refine these methodologies, with a focal point on improving statistics first-rate, version robustness, and practical deployment in agricultural settings**.**

III. METHODOLOGY:

1. Dataset Preparation

- **Data Collection:**

Gather pix of commonplace bean flowers, inclusive of both healthful and diseased samples. For each sickness, collect photos from one of a kind plant parts: leaves and pods.
Data Annotation:

- **Label the pictures into categories:**
  Healthy, Angular Leaf Spot (ALS) - Leaves, ALS - Pods, and other applicable illnesses.

- **Data Augmentation:**

Apply variations including rotation, flipping, scaling, and coloration changes to growth dataset variety and robustness. This helps the model generalize higher and improves its performance on unseen statistics**.**

- **Data Splitting:**

Divide the dataset into training, validation, and take a look at units to evaluate version performance comprehensively. Ensure that the cut up keeps the distribution of classes**.**

2. Model Architecture

- **Base Models Selection:**

Choose pre-skilled models as base architectures for switch studying (e.G., VGG16, ResNet, Inception). These models are pre-skilled on massive datasets like ImageNet, supplying a sturdy characteristic extraction capability**.**

- **Disease-Specific Models:**

Develop separate fashions for one-of-a-kind plant parts (leaves and pods) wherein needed. For diseases affecting both leaves and pods (like ALS), create wonderful branches in the version to deal with every element one at a time.

- **Model Customization:**

Adapt the bottom fashions by changing the final category layers to in shape the variety of lessons in our dataset. Fine-song the pre-trained layers to adjust to the unique features of not unusual bean sicknesses**.**

- **Feature Extraction and Classification:**

Use the base version to extract excessive-level features from photographs. Pass these features via fully related layers and activation features to classify pics into the respective disorder classes.

3. Training Procedure

- **Fine-Tuning:**

Initially, freeze the weights of the pre-educated layers and train the model at the dataset to adapt the new category layers. Gradually unfreeze and excellent-music deeper layers of the pre-skilled network to capture disease-specific features.

- **Hyperparameter Tuning:**

Optimize hyperparameters inclusive of gaining knowledge of price, batch length, and variety of epochs. Use techniques like grid seek or random seek to discover the best hyperparameters**.**

- **Regularization:**

Implement techniques like dropout and weight regularization to prevent overfitting and enhance generalization**.**

- **Evaluation Metrics:**

Monitor performance using metrics including accuracy, precision, do not forget, F1-score, and confusion matrices. Adjust version parameters primarily based on validation set performance**.**

4. Model Evaluation and Testing

- **Validation:**

Continuously evaluate the version at the validation set during training to ensure it generalizes properly to unseen statistics .Adjust schooling strategies based totally on validation overall performance**.**

- **Testing:**

Assess the very last version's performance at the test set to gauge its effectiveness in actual-international eventualities. Analyze misclassifications to apprehend barriers and regions for development**.**

- **Visualization:**

Use strategies like Grad-CAM to visualize which components of the image the version is that specialize in, supporting to interpret the effects and make sure that the model is studying applicable features**.**

5. Deployment and Application

- **Integration:**

Continuously display version performance in the subject and accumulate feedback for similarly enhancements. Update the version periodically with new records to keep accuracy and adapt to rising sickness styles.

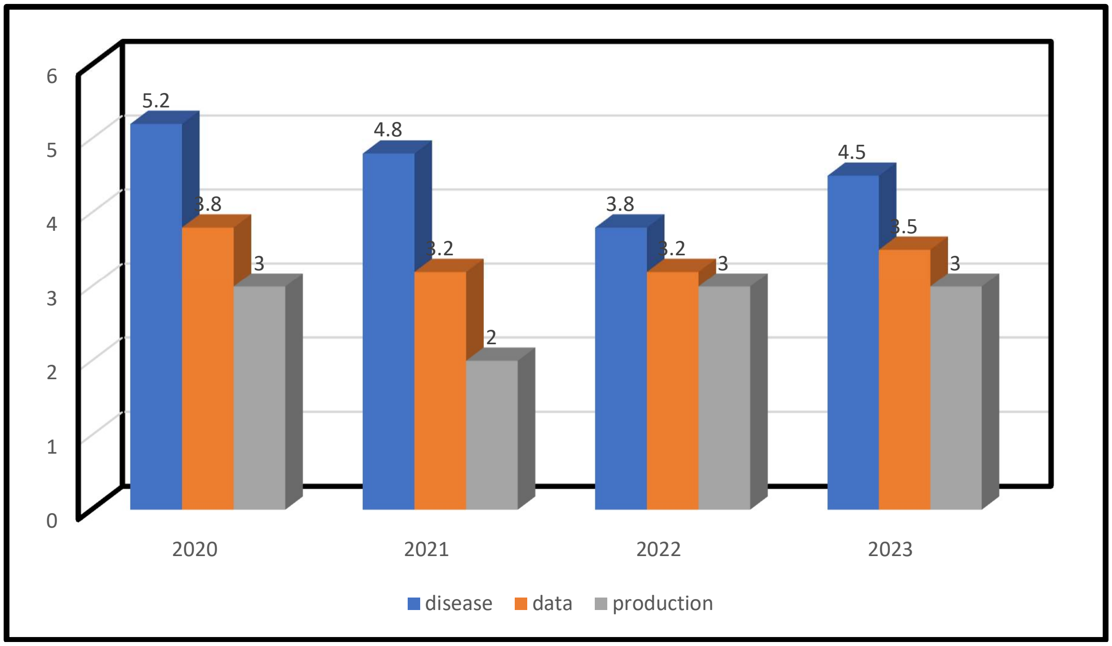

Fig:2, Sugarcane disease in every year

VI. Data Analysis

1. . **Dataset Composition and Characteristics**

1. Image Collection and Annotations

- **Original Images:** A overall of nine,564 subject pix were accrued, reflecting a broad spectrum of real-global situations throughout numerous disease hotspots.
- **Annotations:** Initially, the dataset included forty four,022 annotations. Following facts augmentation, the overall number of annotations multiplied to fifty four,264. This growth highlights the extensive effect of augmentation strategies in diversifying the dataset.

2. **Class Distribution**

- **Disease Classes**: The dataset includes various disorder instructions including CBMV, Rust, ANTH, and healthy pods. Post-augmentation, the balance of class representation advanced, addressing ability biases in the initial dataset. Annotation Resolutions:
- **Whole Leaf Annotations:** Targeted training include CBMV, Rust, and ANTH.
- **Micro Leaf Annotations:** Focused on specified symptom detection for Rust.
- **Pod Annotations:** Targeted the healthful class.

2. Data Augmentation Impact

1. . **Augmentation Techniques**

- **Flipping:** Doubled the dataset length for every magnificence by way of introducing horizontal and vertical flips.
- **Brightness Adjustments:** Enhanced dataset variability by means of modifying image brightness tiers.

2. . **Effectiveness of Augmentation**
   - **Increased Data Variability:** Augmentation caused a major boom within the kind of data samples, that is vital for training strong fashions.
   - **Class Balance Improvement:** The augmentation helped in balancing underrepresented lessons, leading to a greater equitable dataset.
3. **Performance of YOLO Models**

1. **Model Metrics**

   - **YOLOv7 and YOLOv8**:

Performance metrics showed properly accuracy however have been slightly much less most desirable in comparison to YOLO-NAS. Detection velocity and actual-time processing were effective however now not as advanced as YOLO-NAS.

- **YOLO-NAS:**
- **Detection Metrics**: Exhibited advanced precision, recall, and F1 score across exclusive ailment classes and annotation resolutions.
- **Inference Speed:** Demonstrated faster processing instances, making it appropriate for actual-time packages.

2. **Comparative Analysis**
   - **Whole vs. Micro Annotations:** YOLO-NAS accomplished extraordinarily nicely with each complete leaf and micro leaf annotations. Its ability to correctly discover each extensive symptoms and diffused info furnished a complete analysis capability.
   - **Leaf vs. Pod Detection:** YOLO-NAS confirmed consistent performance in detecting both leaf and pod photographs, proving its versatility in coping with one of a kind plant components.

4. **Dataset Validation and Model Training**

   1 **Dataset Splitting**
   - **Training Set:** 70% of the dataset became used for schooling, ensuring a robust studying method.
   - **Testing Set:** 20% become reserved for testing, offering an unbiased evaluation of model performance.
   - **Validation Set:** 10% turned into used for validation to pleasant-music version parameters and save you overfitting.

   2 **Annotation Quality**

   - **Expert Review:** Annotations have been meticulously reviewed via bean phytopathologists, ensuring high first-class and accuracy.
   - **Impact of Annotations on Model Performance:** The specified and correct annotations contributed substantially to the version's potential to generalize properly and stumble on sicknesses efficaciously.

5. Challenges and Observations

1. **Annotation Challenges**
   - **Micro-Annotating:** Annotating nice info was time-eating and required professional information. The accuracy of these annotations without delay impacted the model's performance.
   - **Data Complexity:** The variability in image excellent and environmental conditions posed demanding situations in making sure steady annotation and model education.
2. **Model Adaptability**
   - **Real-World Application:** The fashions, particularly YOLO-NAS, verified sturdy potential for deployment in real-world agricultural settings. However, in addition trying out in numerous environmental situations is wanted to validate their robustness completely.
3. **Future Directions**
   - **Automated Annotation Tools:** Development of automatic or semi-computerized annotation gear could reduce manual effort and enhance dataset scalability.
   - **Integration with Environmental Data:** Incorporating actual-time environmental statistics should further enhance the models' accuracy and offer actionable insights for farmers.

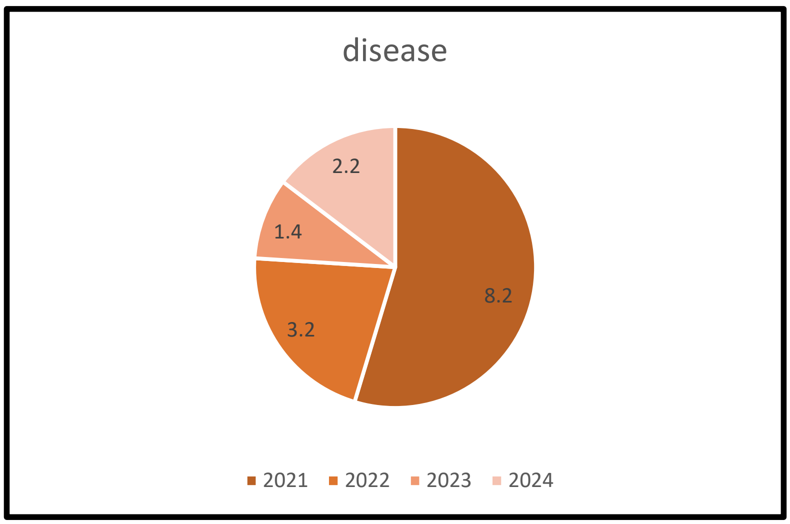

Fig :3, sugarcane disease level of every year

V. Findings and Discussion

I. Findings

1. Dataset Quality and Diversity:

- **Image Acquisition:** The dataset, comprising 9,564 authentic subject photographs and resulting in fifty four,264 annotations after augmentation, displays exquisite and numerous records. Images captured from numerous disorder hotspots and increase degrees, using unique cameras, make sure the dataset is representative of actual-world conditions.
- **Micro-Annotated Details:** Micro-annotations substantially beautify the dataset's granularity, making an allowance for the popularity of subtle disorder signs. This level of element improves the model's sensitivity and accuracy.

1. **Effectiveness of Data Augmentation:**

- **Augmentation Strategies:** Techniques including flipping and brightness changes correctly expanded dataset diversity, specially in underrepresented lessons (CBMV, Rust, ANTH, and healthy pods). This approach addressed overfitting and advanced the generalization abilities of the deep studying fashions**.**
- **Impact on Model Performance:** The augmentation techniques contributed to a large growth within the wide variety of annotated samples, for that reason enhancing the robustness of the CNN fashions.

2. **Model Evaluation and Performance:**

- **YOLO Models:** YOLOv7, YOLOv8, and YOLO-NAS were evaluated with a focus on detecting not unusual bean diseases. YOLO-NAS tested superior overall performance in detection metrics and inference pace as compared to YOLOv7 and YOLOv8**.**
- **Resolution Analysis:** Performance metrics various throughout distinctive annotation resolutions (entire leaf vs. Micro leaf) and plant parts (leaf vs. Pod). YOLO-NAS showed remarkable blessings in detecting each complete and micro annotations with excessive accuracy, demonstrating its suitability for real-time packages in numerous area situations.

II. Discussion

1. **Significance of Comprehensive Dataset:**

- **Real-World Relevance:** The dataset's real-field imagery and versions in photograph satisfactory reflect the complexities faced in actual agricultural environments. This complements the relevance and applicability of the ailment detection models.
- **Enhanced Disease Detection:** The mixture of micro-annotations and augmented records contributes to a greater nuanced information of ailment symptoms, improving the model's capacity to hit upon and classify illnesses correctly throughout numerous tiers of plant growth.

2. **Impact of Data Augmentation:**

- **Overfitting Mitigation:** By diversifying the dataset, augmentation techniques deal with overfitting issues, making sure that the models are trained on a broader variety of eventualities and variations.
- **Class Balance**: Augmentation enables in balancing the representation of various sickness lessons, which is essential for schooling fashions which can be impartial and powerful in detecting much less frequent illnesses**.**

3. **YOLO Models' Performance:**

- **YOLO-NAS Advantages:** YOLO-NAS's advanced overall performance, inclusive of quicker inference and higher detection metrics, highlights its potential for practical programs in field-primarily based ailment detection structures. Its efficiency makes it appropriate for actual-time tracking, that's critical for timely disorder control**.**

- **Comparative Analysis:** While YOLOv7 and YOLOv8 also performed well, YOLO-NAS's superior capabilities provide a aggressive aspect, especially in complex detection duties in which both velocity and accuracy are important.

4. **Challenges and Future Directions:**

- **Micro-Annotation Challenges:** The system of micro-annotation is aid-extensive, and the nice of annotations can effect model performance. Future efforts ought to awareness on developing computerized or semi-computerized annotation tools to lessen guide attempt and boom efficiency.
- **Model Adaptation:** While YOLO-NAS suggests promise, similarly studies could explore its adaptability to other sickness sorts or crop types. Additionally, integrating version outcomes with actual-time environmental statistics may want to decorate detection accuracy and provide actionable insights for farmers.

In end, the development and evaluation of the commonplace bean disorder dataset and YOLO-primarily based detection fashions represent a good sized breakthrough in agricultural ailment management. The dataset's variety and the advanced performance of YOLO-NAS reveal the ability for those equipment to decorate disorder detection and support smallholder farmers globally. Future studies have to maintain to refine these fashions and discover their integration into realistic, actual-world programs.

Conclusion

In conclusion, this research marks a good sized advancement inside the software of Deep Learning (DL) models for actual-time crop disorder detection in not unusual bean (CB) cultivation. By harnessing trendy deep transfer mastering strategies and leveraging advanced YOLO architectures—inclusive of YOLO-NAS, YOLOv7, and YOLOv8—our method has demonstrated top notch efficacy in automating the identity of 5 essential CB diseases. The models now not simplest serve as diagnostic tools but also make a contribution to a rich repository of CB facts, improving ailment class with awesome accuracy costs of over ninety five% for leaves and seventy eight% for pods.

Our full-size dataset, presenting over 9500 images and forty four,000 annotations, underscores our commitment to non-stop model refinement and supports the development of the TUMAINI AI Network. The validated AI application rising from this studies gives a realistic answer for early disorder detection and management, supplying precious aid to farmers, bean breeders, and agronomists. This tool enhances disorder control strategies and promotes extra informed selection-making in agriculture.

By integrating verified YOLO-NAS models with an Android-primarily based cell AI software, tested rigorously in disease-susceptible areas, this studies paves the manner for more intuitive and available sickness control for farmers. The application promises to enhance agricultural practices, increase productivity, and strengthen sustainability in regions inclusive of Latin America and Africa. As we look ahead, AI's capability to no longer most effective expect but actively participate in managing crop illnesses will revolutionize agricultural practices and make a contribution significantly to global crop production resilience. This research lays a robust foundation for future improvements, putting forward AI's pivotal role in advancing agricultural resilience and early caution structures.

Aspect	Details
Research Focus	Application of Deep Learning (DL) models for real-time crop disease detection in common bean (CB)
Deep Learning Models	YOLO-NAS, YOLOv7, YOLOv8
Disease Identification	Five major CB diseases, distinguishing healthy vs. diseased pods and leaves
Classification Accuracy	Leaves: >95%, Pods: 78%
Precision and Recall	High precision and recall rates
Dataset	Over 9500 images and 44,000 annotations
AI Application	TUMAINI Android-based mobile AI app
Application Impact	Early disease detection, enhanced disease management, decision support for farmers, breeders, and agronomists
Geographical Focus	Latin America, Africa
Future Directions	AI for forecasting and active disease management, transformation of agricultural practices, global crop production sustainability
Strategic Goals	Integration of AI into disease prevention and management, improving agricultural productivity and sustainability

VI. REFERENCE:

1. Tai, Amos P.K. · Martin, Maria Val · Heald, Colette L. Threat to future global food protection from climate exchange and ozone air pollution Nat. Clim. Change. 2014; 4:817-821

2. Singh, Vijai · Sharma, Namita · Singh, Shikha A overview of imaging techniques for plant sickness detection Artif. Intell. Agric. 2020; four:229-242

3. Yang, Xin · Guo, Tingwei Machine mastering in plant disease research Eur. J. BioMed. Res. 2017; 3:6

4. Wani, Javaid Ahmad · Sharma, Sparsh · Muzamil, Malik .Machine mastering and deep studying based computational techniques in automated agricultural illnesses detection: methodologies, applications, and demanding situations Arch. Computer Methods Eng. 2022; 29:641-677

5. Pagola, Miguel · Ortiz, Rubén · Irigoyen, Ignacio .New technique to evaluate barley nitrogen vitamins popularity based totally on picture coloration analysis: contrast with spad-502 Computer. Electron. Agric. 2009; sixty five:213-218Bock, Clive · Poole, Gavin · Parker, P.E. ..Plant sickness severity predicted visually, via digital images and picture evaluation, and by using hyperspectral imaging Crit. Rev. Plant Sci. 2010; 29

6. Li, Yansheng · Zhang, Yongjun · Zhu, Zhihui Error-tolerant deep gaining knowledge of for some distance off sensing photograph scene magnificence IEEE Trans. Cybern. 2021; 51:1756-1768

7. Zhu, Xiao Xiang · Tuia, Devis · Mou, Lichao . Deep studying in far flung sensing: a whole examine and list of property IEEE Geosci. Remote Sens. Mag. 2017; five:8-36

8. Badrinarayanan, Vijay · Kendall, Alex · Cipolla, Roberto Segnet: a deep convolutional Encoder-Decoder structure for photograph segmentation IEEE Trans. Pattern Anal. Mach. Intell. 2017; 39:2481-2495

9. Shelhamer, Evan · Long, Jonathan · Darrell, Trevor Fully convolutional networks for semantic segmentation 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2014; 3431-3440

10. Wang, Yibin · Wang, Haifeng · Peng, Zhaohua Rice sicknesses detection and class the use of interest based totally neural community and Bayesian optimization Expert Syst. Appl. 2021; 178, 114770

11. Sun, Henan · Xu, Haowei · Bin, Liu .Mean-ssd: a novel real-time detector for apple leaf sicknesses the use of improved mild-weight convolutional neural networks Comput. Electron. Agric. 2021; 189, 106379

12. Xie, Xiaoyue · Ma, Yuan · Bin, Liu ..A deep-learning-based totally actual-time detector for grape leaf sicknesses using improved convolutional neural networks Front. Plant Sci. 2020; eleven

13. Daphal, Swapnil Dadabhau · Koli, Sanjay M. Transfer learning approach to sugarcane foliar disease classification with state-of-the-art sugarcane database 2021 International Conference on Computational Intelligence and Computing Applications (ICCICA)2021; 1-4

14. Coulibaly, Solemane · Kamsu-Foguem, Bernard · Kamissoko, Dantouma Deep neural networks with transfer learning in millet crop photos Comput. Ind. 2019; 108:115-one hundred twenty.

15. Selvaraj, Michael Gomez · Vergara, Alejandro · Ruiz, Henry .Ai-powered banana sicknesses and pest detection Plant Methods. 2019; 15:ninety two

16. Abbas, Amreen · Jain, Sweta · Gour, Mahesh .Tomato plant sickness detection using transfer gaining knowledge of with c-gan artificial pics Comput. Electron. Agric. 2021; 187

17. Cheng, Gong · Xie, Xingxing · Han, Junwei .Remote sensing picture scene class meets deep mastering: challenges, methods, benchmarks, and opportunities IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2020; thirteen:3735-3756

18. Cheng, Gong · Xie, Xingxing · Han, Junwei .Remote sensing photo scene category meets deep studying: challenges, strategies, benchmarks, and opportunities IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2020; 13:3735-3756

19. Cao, Wenming · Yan, Zhiyue · He, Zhiquan ..A comprehensive survey on geometric deep studying IEEE Access. 2020; eight:35929-35949

20. Wang, Qifan · Cheng, Man · Xiao, Xuepeng .An image segmentation approach based totally on deep getting to know for damage evaluation of the invasive weed Solanum rostratum Dunal Comput. Electron. Agric. 2021; 188, 106320

21. Mohanty, Sharada · Hughes, David · Salathe, Marcel Using deep studying for picture-based plant disorder detection Front. Plant Sci. 2016; 7

22. Woo, Sanghyun · Park, Jongchan · Lee, Joon-Young Cbam: Convolutional Block Attention Module 2018