Cassava Root-Volume Estimation

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PROBLEM STATEMENT

Cassava is Africa's most important tuber crop, crucial for food security. However, low yield per hectare remains a challenge. Traditional root volume estimation methods are labor-intensive and invasive, limiting large-scale analysis. A non-invasive, automated solution is needed to optimize yield, improve crop selection, and enhance stress resilience.

WHY IS CASSAVA IMPORTANT TO AFRICA?

Africa produces over 50% of the world's cassava; Nigeria alone contributes nearly 20% of global output

Cassava contributes to the livelihood of more than 300 million Africans and is the number one crop in Africa by total output

It provides over 50% of local food intake in many regions of africa

Cassava production is especially significant in countries like Nigeria, Ghana, and the DRC, which account for over 50% of the global production increase between 2000 and 2019

Grows well in poor soils and drought conditions. Acts as both a subsistence and cash crop for smallholder farmers.

Source: The paper by Waidi Gbenro Adebayo on" Cassava Production in Africa" (2020)

Limitations of Traditional Methods

They are destructive

- Roots must be uprooted and cleaned to measure volume manually (via water displacement, 3D scanning, or weighing).
- This destroys the plant, making it impossible to monitor root growth over time or track development across stages.

Not scalable

- On a field with thousands of cassava plants, it's impractical to uproot and measure each one.
- Limits usage to small samples, reducing statistical robustness and generalizability.

Labor-intensive and slow

- Requires manual digging, washing, and measuring, often taking hours per plant.
- Not feasible for large-scale phenotyping, breeding trials, or field surveys.

Inconsistent and error-prone

- Human error in cutting, cleaning, or measuring leads to inconsistent data.
- Soil clumps or damage during uprooting can skew volume measurements.

Atanbori, J., Montoya-P, M. E., Selvaraj, M. G., French, A. P., & Pridmore, T. P. (2019). Convolutional neural net-based cassava storage root counting using real and synthetic images. Frontiers in Plant Science, 10, 1516.
Source: The paper by Waidi Gbenro Adebayo on" Cassava Production in Africa"

POTENTIAL IMPACT OF THE SOLUTION

Boosts Cassava Yield and Productivity

Enables farmers and breeders to estimate root volume without uprooting, allowing for Early yield prediction, Selection of high-performing varieties and Real-time growth tracking

Empowers Breeding and Research Programs

Speeds up genotype selection by providing accurate, scalable root volume data and Helps researchers test drought-tolerant, disease-resistant, or high-yield varieties

Improves Decision-Making for Farmers

Farmers can monitor growth non-destructively and optimize harvest time

Supports precision agriculture with data-driven decisions

Reduces Environmental Impact

Eliminates the need for destructive root sampling, reducing:

- Soil disturbance
- Labor waste
- Land overuse

Scalable for National and Global Applications

Governments and NGOs can use it in cassava improvement programs

Can be adapted to other root crops (e.g., yam, sweet potato) in the future

Lays Foundation for Smart Farming Tools

Opens the door for integration with:

- Drones, GPR, smartphone apps
- Remote monitoring systems
- AI-based yield forecasting dashboards

Gap

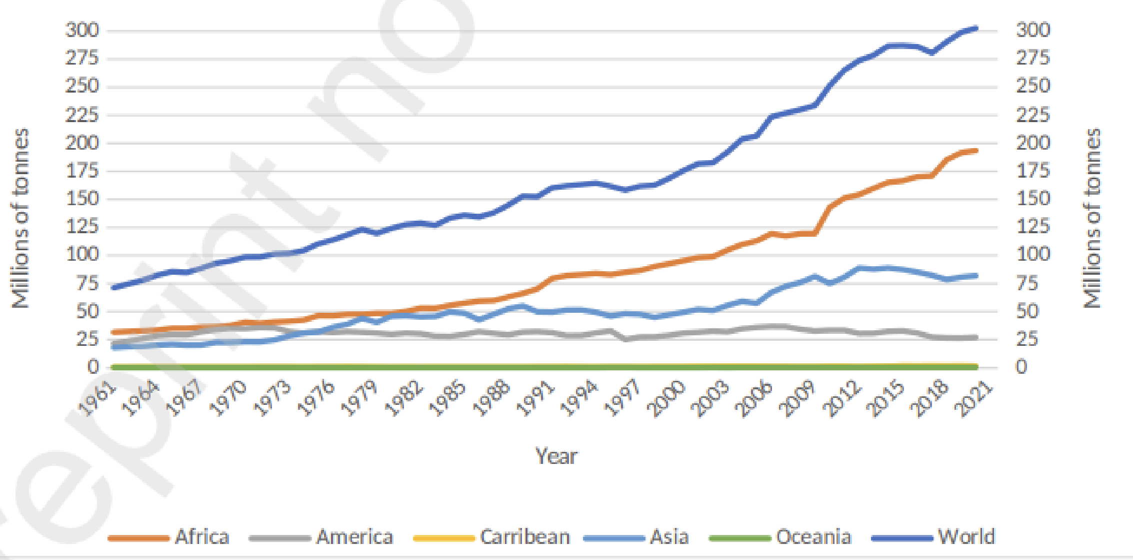
Despite high total output, Africa's cassava yield per hectare (avg. 8.9 tons/ha) is well below the global average (11.3 tons/ha) and far below the potential yield (up to 80 tons/ha)

Current cassava studies using machine learning primarily focus on classification tasks like disease detection or crop segmentation. However, no existing solution accurately estimates cassava root volume non-invasively. Traditional methods remain manual and destructive.

LITERATURE REVIEW

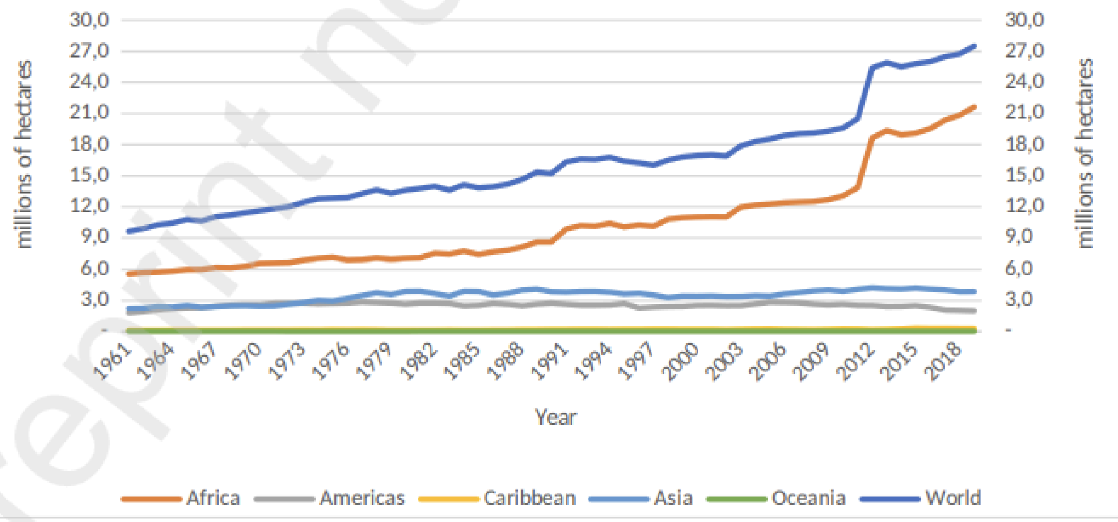
Cassava Production in Africa: A Panel Analysis of the Drivers and Trends by Waidi Gbenro Adebayo (2023)

Figure 1: World and Regional Cassava Production in Tonnes 1961-2020



Source: Computed by the author using FAOSTAT Data

Figure 2: World and Regional Cassava Harvested Area in Millions of Hectares (1961-2019)



Source: Computed by the author using FAOSTAT Data

- Analyzed cassava production data from 37 African countries (1961–2020) using panel regression.
- Found that 95.6% of output growth was due to land expansion, while only 2% came from yield improvements.
- Despite new high-yield, pest-resistant varieties, average yield per hectare remains low (8.9 t/ha vs. potential of 80 t/ha).
- Highlights an urgent need for sustainable intensification and non-invasive, tech-based solutions to boost yield without expanding farmland.

LITERATURE REVIEW

Emerging Technologies for Root Phenotyping

- Ground Penetrating Radar (GPR): Non-destructive imaging technique that detects subsurface root structures by measuring electromagnetic wave reflections (Lantini et al., 2020; Liu et al., 2017).
- GPR correlates well with root biomass but requires sophisticated processing and ML interpretation (Adebayo, 2023).
- Other sensing methods include ultrasonic resonance and multispectral imaging, mostly effective for above-ground water content but limited for buried roots (Fariñas et al., 2019).

Papers Referred :
1) Ground Penetrating Radar (GPR) Detects Fine Roots of Agricultural Crops in the Field (2017)

2) Application of Ground Penetrating Radar for Mapping Tree Root System Architecture and Mass Density of Street Trees (2020)

3) Instantaneous and Non-Destructive Relative Water Content Estimation from Deep Learning Applied to Resonant Ultrasonic Spectra of Plant Leaves (2019)

Machine Learning in Plant Biomass and Water Content Estimation

- ML models (Random Forest, SVM, CNNs) have been successfully applied to predict above-ground biomass and leaf water content from remote sensing data (Wang et al., 2025; Nyalala et al., 2021).
- Atanbori et al. (2019) applied CNNs to count cassava storage roots using real and synthetic images, improving phenotyping automation but focusing on root count, not volume.
- These ML applications highlight the potential but also the gap in direct root volume estimation using subsurface sensing.

Papers Referred :
1) Estimating Maize Leaf Water Content Using Machine Learning with Diverse Multispectral Image Features (2025)

2) Convolutional Neural Net-Based Cassava Storage Root Counting Using Real and Synthetic Images (2019)

3) Instantaneous and Non-Destructive Relative Water Content Estimation from Deep Learning Applied to Resonant Ultrasonic Spectra of Plant Leaves (2019)

LITERATURE REVIEW

Model 1: Pinus Biomass Estimation Using Ensemble Learning (Antúnez et al., 2025)

- Combines allometric variables (height, diameter, age) with Random Forest and Gradient Boosting to predict biomass.
- Effective for forest trees with vertical root structure, but unsuitable for cassava's lateral, tuberous root morphology.
- No integration of imaging or subsurface data; limited applicability to cassava root volume estimation.
- Demonstrates potential of multivariate ML but highlights need for subsurface imaging fusion.

Predictive Modeling of Volume and Biomass in Pinus pseudostrobus Using Machine Learning and Allometric Approaches (2024)

Model 2: Maize Leaf Water Content Estimation Using Multispectral Data (Wang et al., 2025)

- Uses UAV and ground-based multispectral imaging with ML regression (SVM, RF) to estimate leaf water content.
- Achieves high accuracy but limited to above-ground foliage, unable to penetrate soil to roots.
- High equipment cost and soil signal attenuation limit adoption for root water content monitoring in cassava

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- Illustrates how spectral imaging benefits crop water estimation, but roots require different sensing methods.

Estimating Maize Leaf Water Content Using Machine Learning with Diverse Multispectral Image Features (2025)

LITERATURE REVIEW

Additional Existing Models & Techniques

- Minirhizotron imaging: Uses transparent tubes and cameras to observe root growth but it is labor-intensive (Adebayo, 2023).
- 3D Scanning (Laser, Photogrammetry): Effective for biomass estimation of uprooted roots but destructive and unsuitable for field-scale, longitudinal studies.
- MRI and X-ray CT: Provide high-resolution root water content and volume data but are expensive and impractical for field use.
- None of these techniques combine non-invasive field applicability with automated, high-throughput analysis.

Summary of Literature Gaps

- Most models focus on above-ground traits or require destructive sampling.
- No existing ML model fully integrates GPR-based subsurface sensing with image processing and metadata fusion for cassava root volume estimation.
- Soil heterogeneity, root morphology complexity, and cost limit current methods.
- Opportunity exists for a multimodal AI system combining GPR radar, handcrafted and learned features, and environmental data — tailored for cassava.

OUR SOLUTION

CNN-based LSTM
model for root volume
prediction

Our Inspiration?

1) Use of ML for Root Traits (Atanbori et al., 2019)

- **Idea Taken:** CNNs are effective at processing plant root imagery (real + synthetic).
- **How We Used It**: Adopted a CNN backbone to extract features from GPR slices — inspired by their success in root detection.

2)Subsurface Sensing Gap (All literature + Adebayo, 2023)

- **Idea Taken:** No existing models used GPR for cassava root volume.
- **How We Used It**: Our model is GPR-based, directly addressing the non-invasive, subsurface estimation gap highlighted across all papers.

3) Fariñas et al. (2019) – Non-destructive Sensing

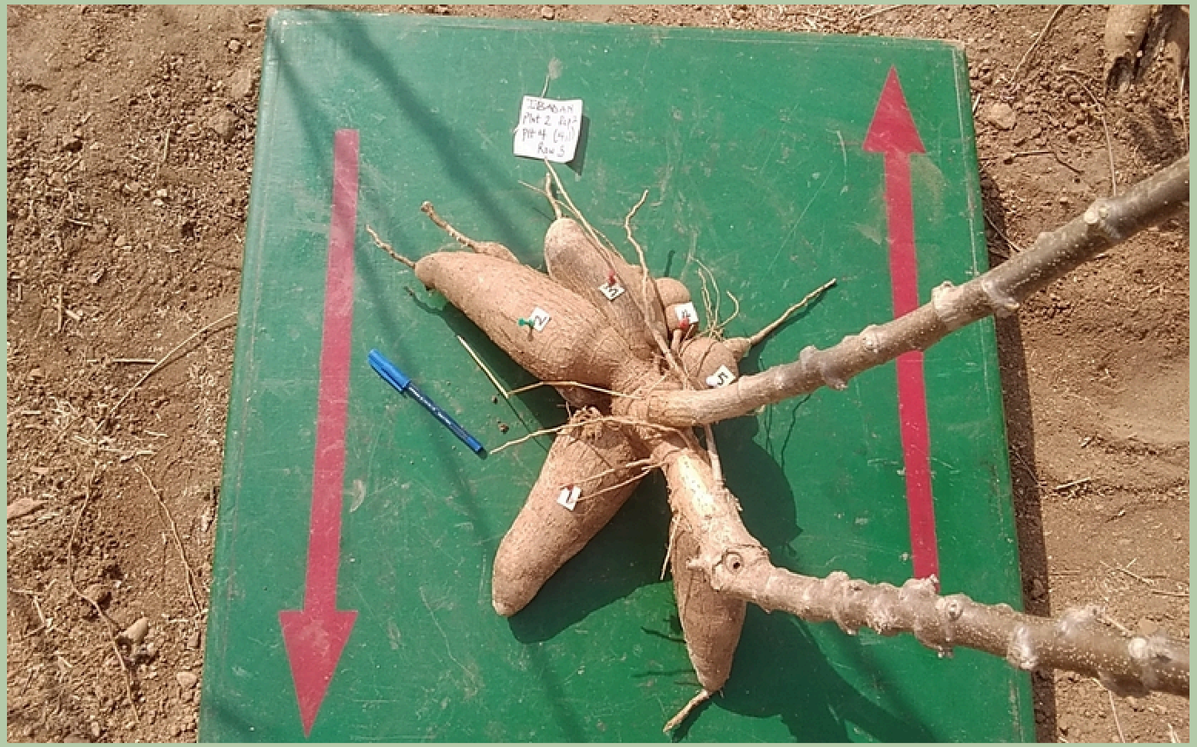
- **Idea Taken:** Ultrasonic and spectral signals can estimate internal traits like water content non-destructively.
- **How We Used It**: Reinforced the importance of preserving the plant and using indirect signals (GPR) interpreted by ML — a core value of our approach.

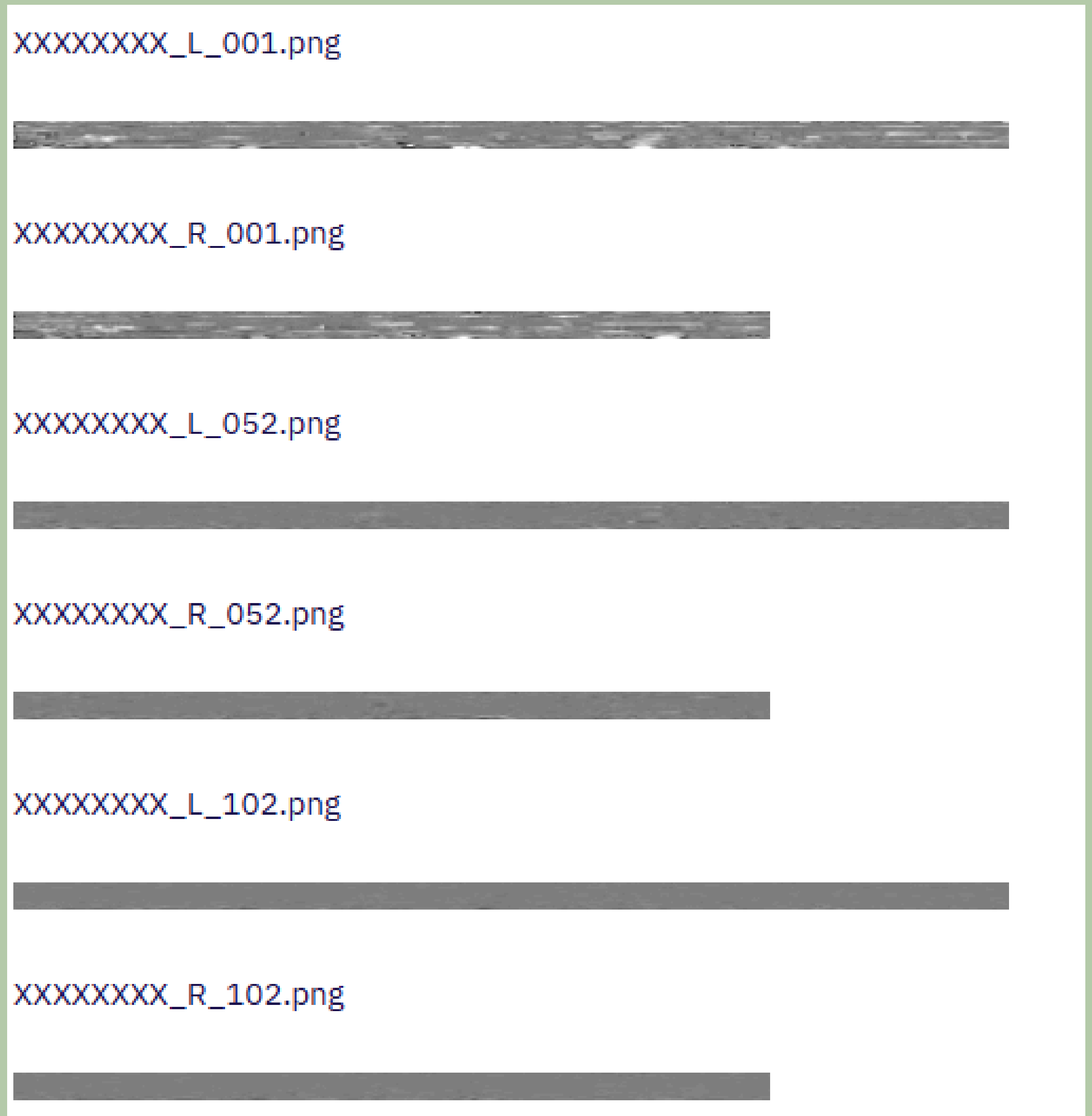
4) sequential patterns- Wang et al., (2025)

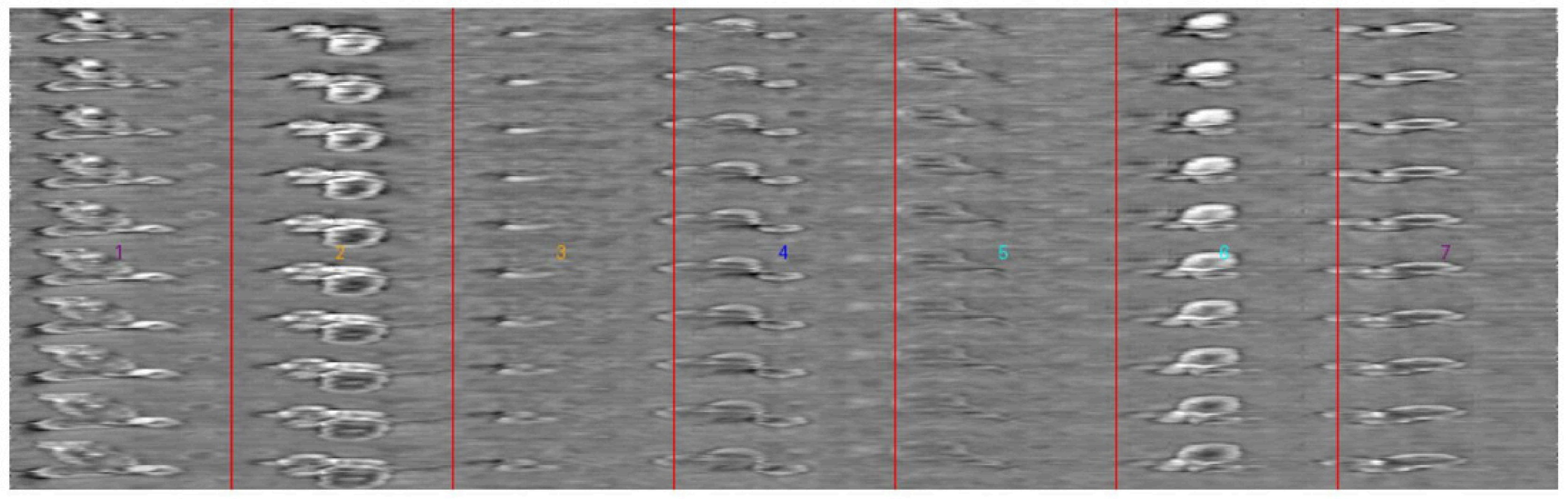
- **Idea Taken:** It Validated the use of sequential patterns (spectral or spatial).
- **How We Used It**: Inspired our use of LSTM to model root depth-wise structure in GPR slices.

OUR DATA

- GPR scan images of cassava roots.
- corresponding labels
- Corresponding volume measurements.







Data Preprocessing

Load Image Slices

For each sample, 21 grayscale slices per side (L and R) are loaded.

Images are named like: folder_L_001.png, ..., folder_R_021.png.

Handle Missing or Corrupted Files

If a file is missing or unreadable, it's replaced with a black image (all zeros)

Transformations

Convert to PIL image.

Resize to fixed size (default: 128×128)

Convert to PyTorch tensor.

Stacking Slices

Stack 21 image slices per side to form shape (21, H, W).

Combine both sides into final shape (2, 21, H, W).

How does our model work?

1) Input:

- 2 views per root sample: Left and Right
- Each view has 21 grayscale image slices

2) Image Preprocessing:

- Resize all slices to 128×128
- Stack slices to shape: (2, 21, 128, 128)

3) CNN Feature Extraction:

- CNN processes each 2D slice
- Outputs 32-dimensional feature vector per slice

4) LSTM Sequence Modeling:

- LSTM processes sequence of slice features
- Captures depth-wise/root structure patterns
- Outputs final hidden state (64-D) per view

5) Feature Fusion:

- Concatenate final LSTM outputs from L and R
- Combined feature vector: (batch, 128)

6) Fully Connected Layers:

- Dense layers process fused features
- Predict root volume (scalar output)

7) Output:

- Single predicted volume value per sample

Challenges Faced

Data Inference

The Data was challenging to deal with in the sense of visualization

Each image was split into Left and Right of the root and could have upto 7 roots in it

Lack of Clarity at the Start

We weren't sure how to approach the problem initially.

Most discussed implementations were using YOLO, which was pre-trained so ruled out.

Lack of Sequence Awareness

CNN process each image independently, but the volume depends on the sequence of slices.

The model wasn't learning the depth progression of the root.

Using CNN + LSTM (based on suggestion)

Added an LSTM on top of CNN features to model the slice sequence.

This significantly improved predictions and made better use of the image stack.

Performance Metrics

Root Mean Squared Error (RMSE)

- Validation RMSE: 1.374
- Public Leaderboard RMSE: 1.075
- Private Leaderboard RMSE: 1.385

What does this tell us?

Private RMSE ≈ Validation RMSE → performs well on unseen data

Model can predict root volumes within ±1.3 units of the true value

Future work

Can This Be Deployed at Plaksha?

For SugarCane

Plaksha Context: Sugarcane is being grown – possible use of GPR for non-destructive root monitoring

Why It Could Work:
GPR has been used to detect fibrous root systems (e.g., maize)
Could aid in non-invasive crop health tracking or root growth analysis

Challenges

- Need labeled GPR scans of sugarcane with true root volume
- Sugarcane root structures differ from cassava; more diffused
- *Requires GPR hardware, data collection, and fine-tuning the model