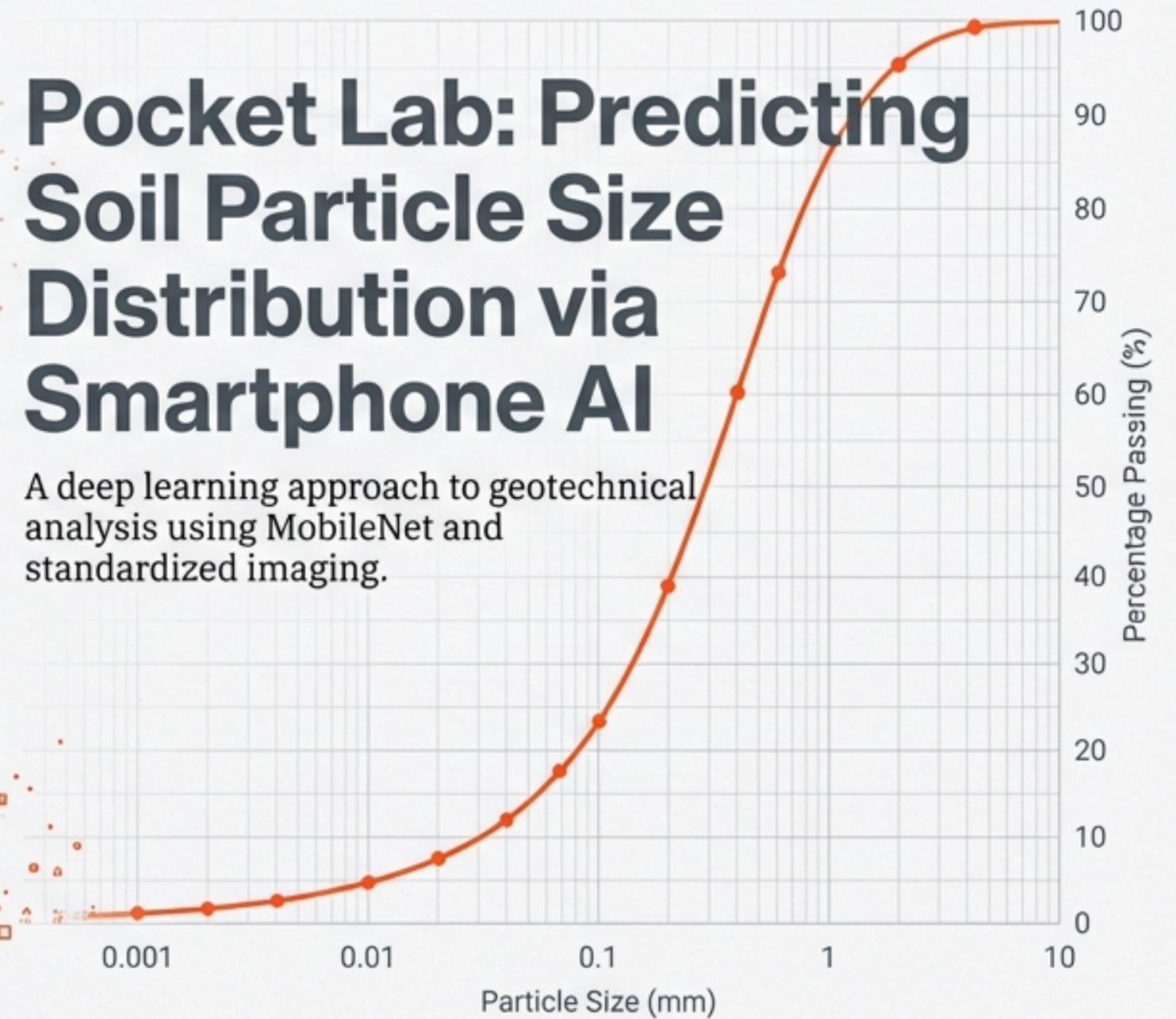# Pocket Lab: Predicting Soil Particle Size Distribution via Smartphone AI

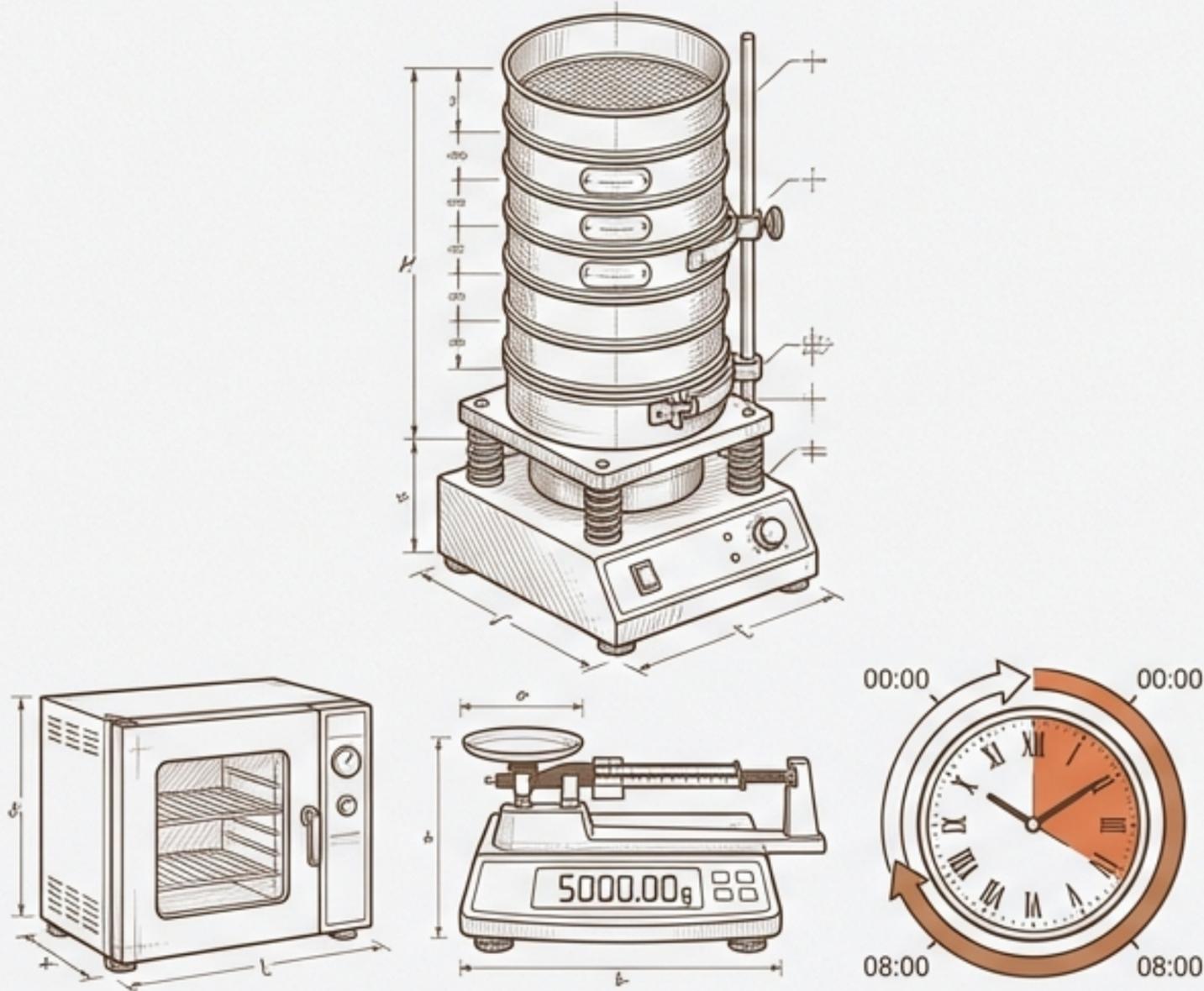A deep learning approach to geotechnical analysis using MobileNet and standardized imaging.

Based on research by Enrico Soranzo, BOKU University

Proc. of the 3rd Workshop on the Future of Machine Learning in Geotechnics (3FOMLIG), Florence, Oct 2025.

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The Physical Bottleneck in Geotechnical Speed

The Old Way

Labor Intensive: ISO-standard sieving and sedimentation require heavy equipment and hours of manual processing.
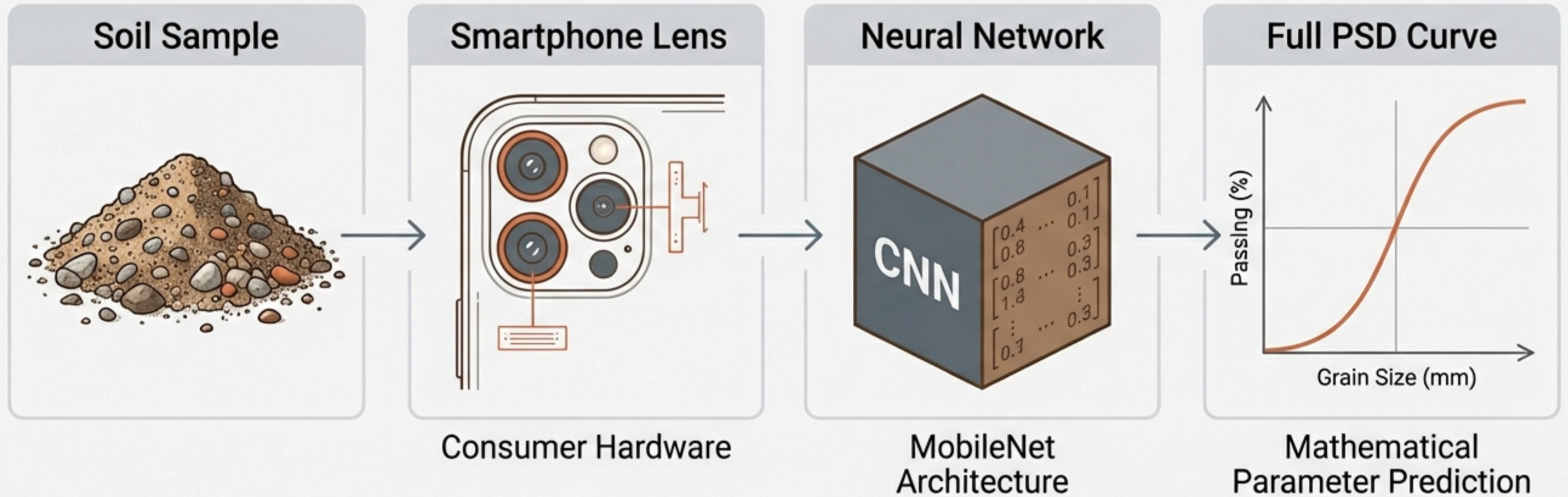
The Gap

The Gap: Industry needs a method as accessible as a consumer device, but as rigorous as a lab test.

- Existing digital methods only output "texture classes" (e.g., sandy loam).
- Critical engineering data (hydraulic conductivity, residual water content) requires the full PSD curve.

From Granular to Digital

Replacing mechanical separation with Computer Vision.

Soil Sample	Smartphone Lens	Neural Network	Full PSD Curve
	Consumer Hardware	MobileNet Architecture	Mathematical Parameter Prediction

The Innovation: Unlike previous studies that merely classify soil types, this model extracts physical properties from pixel data to predict the mathematical parameters of the distribution curve itself.

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Standardizing the Input: The Dark Chamber

To treat an image as scientific data, lighting and perspective must be constant variables.

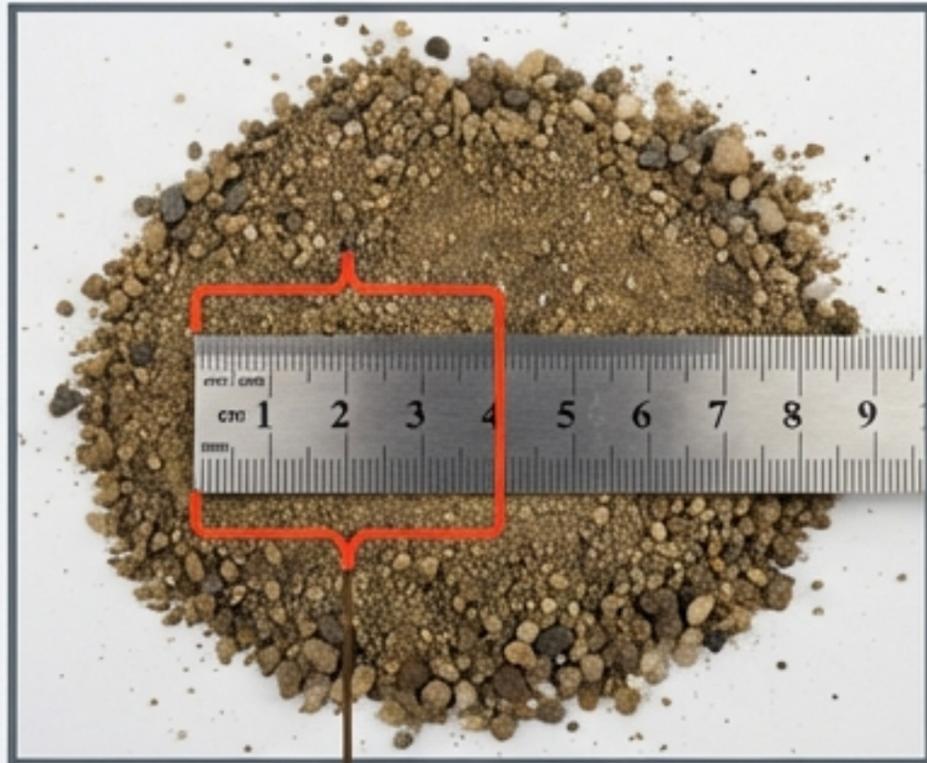Aperture: 45 × 45 mm

Fixed Distance: 210 mm

Soil Sample
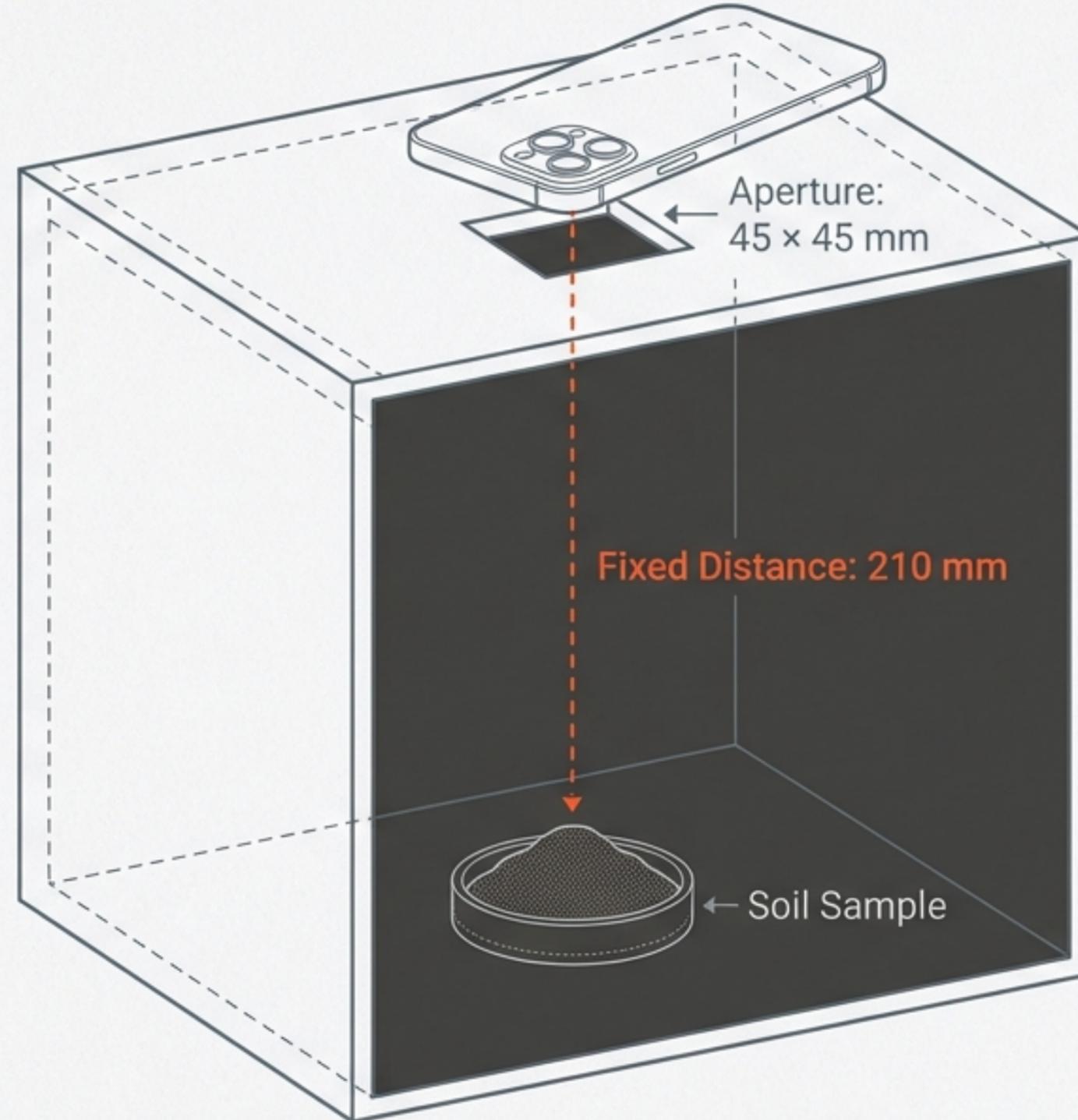
Validated Devices:
- Motorola Edge (4000×1800)
- Samsung A52 (6936×9248)
- iPhone 14 (4032×3024)

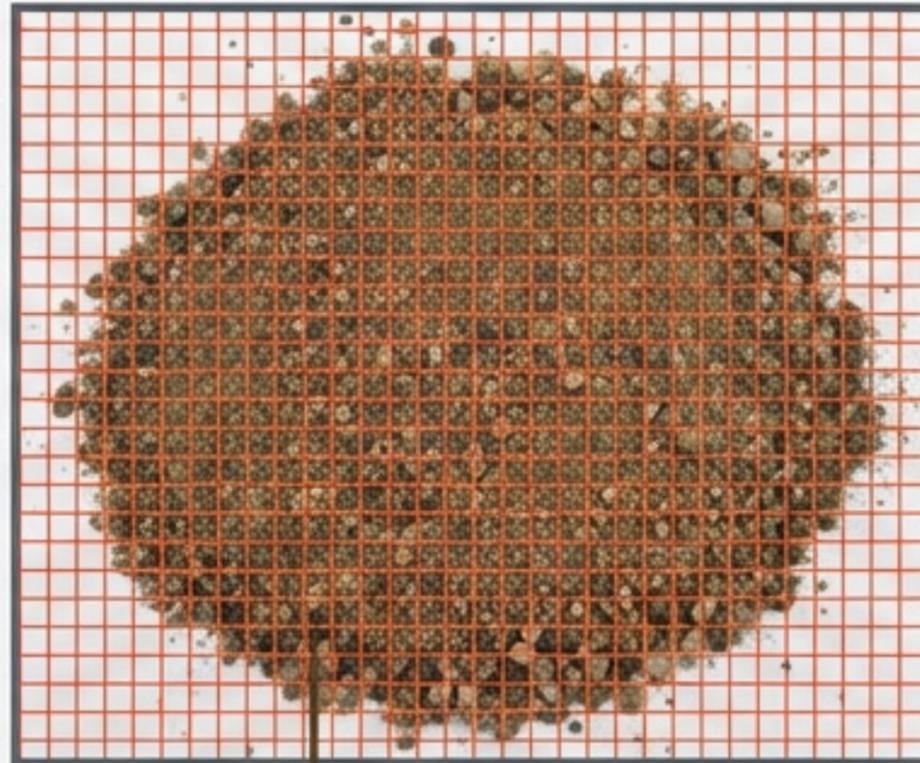NotebookLM

Data Pre-processing: From Photo to Tensor

The pipeline normalizes hardware differences (resolution, angle of view) before the AI analysis.

Calibration

Scaling

Cropping

Calculate Pixels
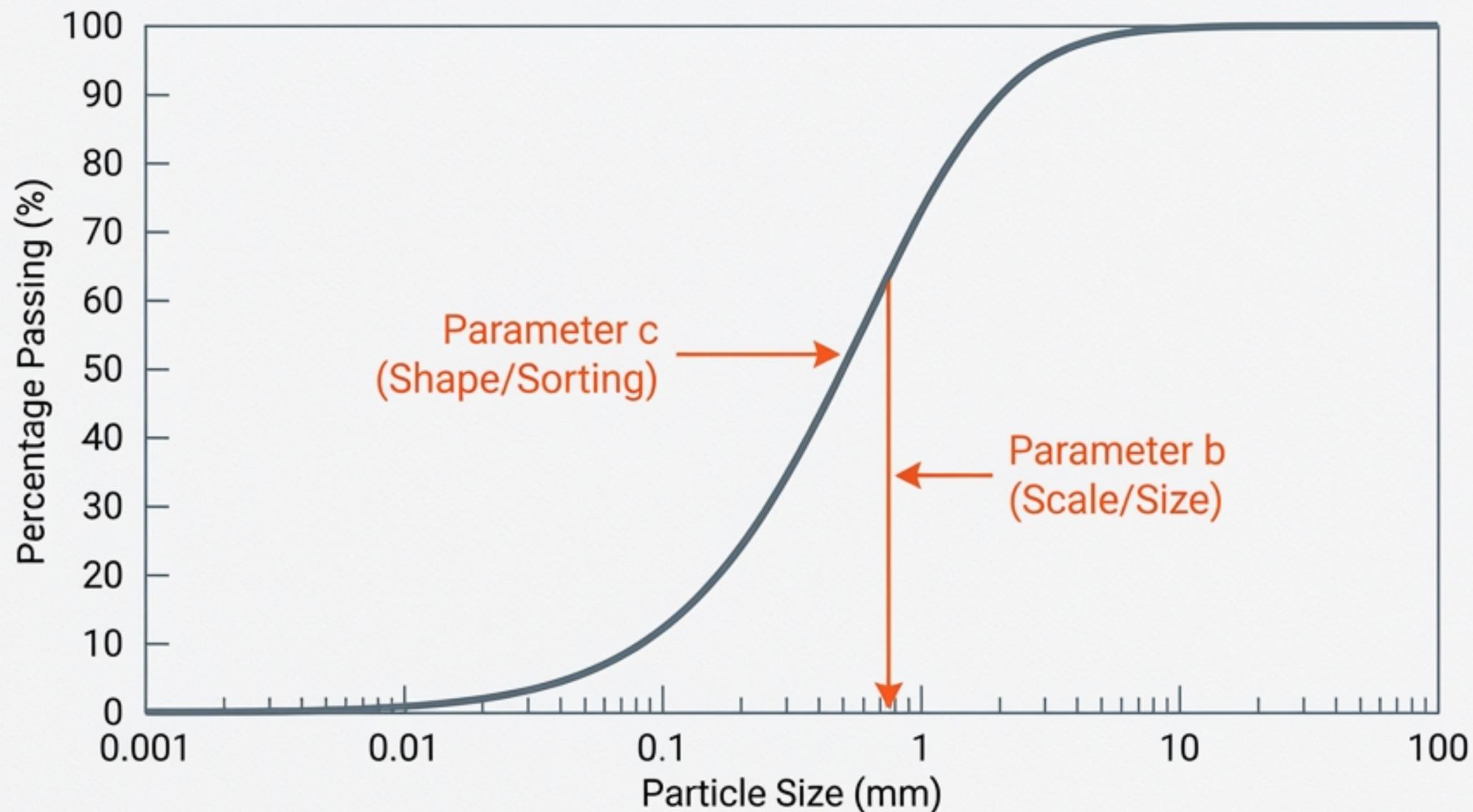Per MM (PPM)

Resized to
Standard 4.6 PPM

Final Input:
400 × 400 pixel tensor

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Ground Truth & The Weibull Distribution

The Dataset: 56 soil samples from Austria and Germany (Silt, Sand, Gravel).

The Goal: The model does not count every grain. It predicts the shape parameters of the Weibull distribution curve.
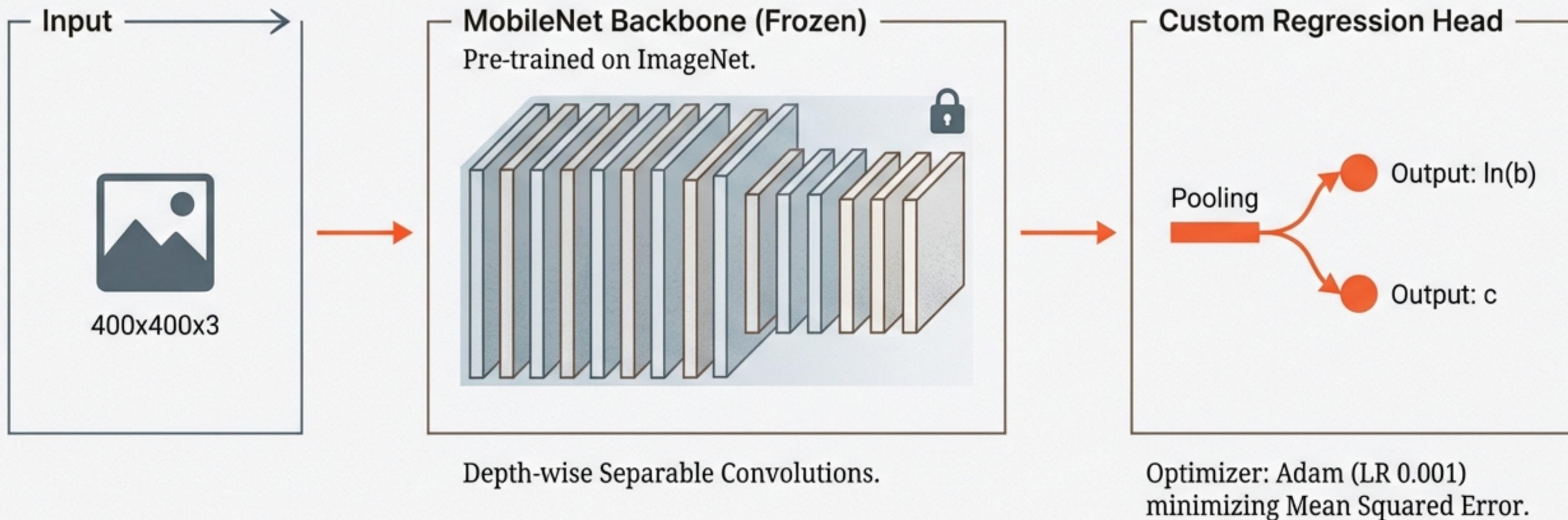

Formula: $F(d \leq d_i) = 1 - \exp\left[-\left(\frac{d_i}{b}\right)^c\right]$
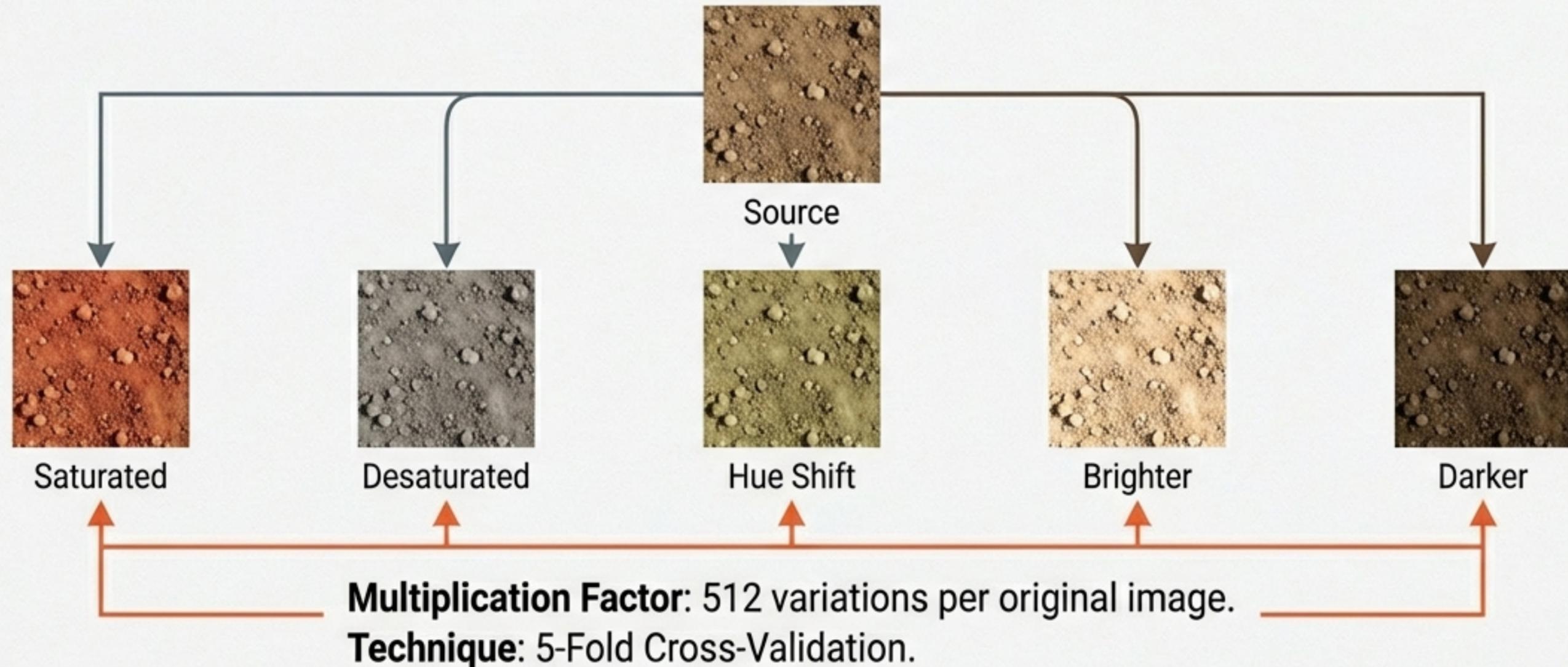
Network Output Targets: $\ln(b)$ and c

The Engine: MobileNet Architecture

Leveraging Transfer Learning on a lightweight architecture designed for mobile vision.

Input

400x400x3

MobileNet Backbone (Frozen)
Pre-trained on ImageNet.

Depth-wise Separable Convolutions.

Custom Regression Head

Pooling

Output: ln(b)

Output: c

Optimizer: Adam (LR 0.001) minimizing Mean Squared Error.

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Training for Robustness

Data augmentation teaches the model to ignore irrelevant lighting variations and focus on grain structure.

Source

Saturated

Desaturated

Hue Shift

Brighter

Darker

Multiplication Factor: 512 variations per original image.
Technique: 5-Fold Cross-Validation.

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Performance Metrics

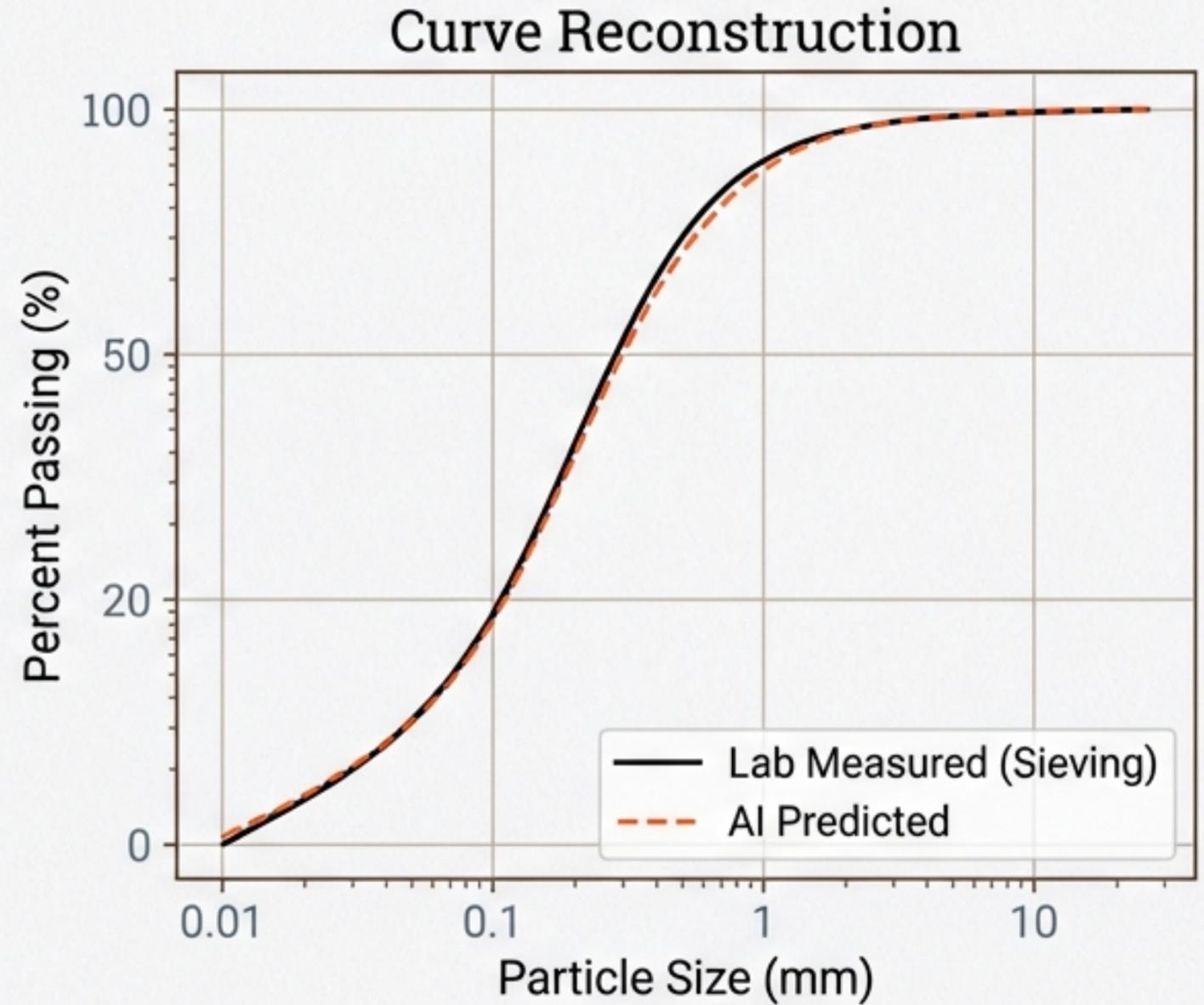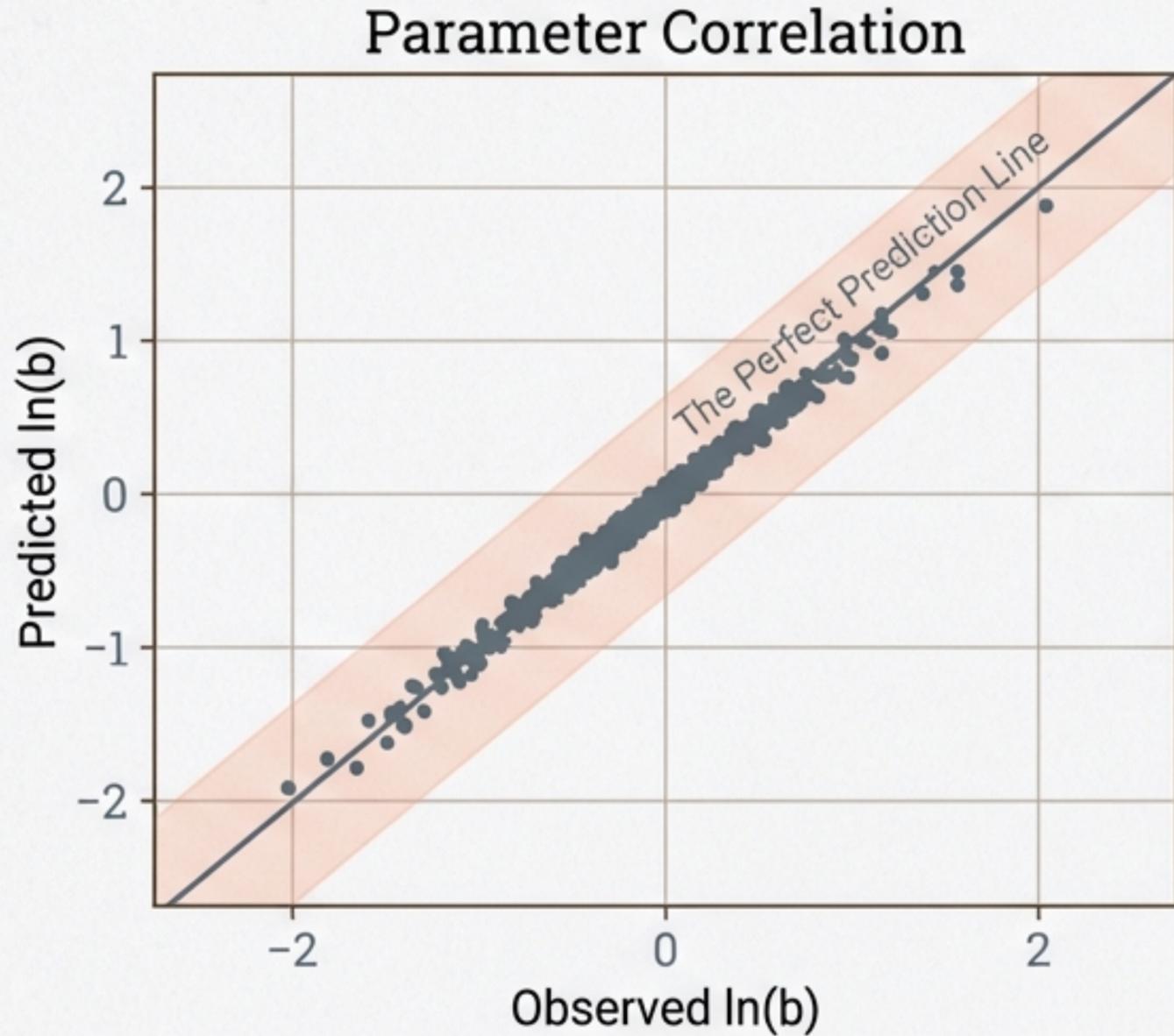| Training Accuracy	Testing Accuracy
1.000	**> 0.95**
R² Score	R² Score
MAPE (Mean Absolute Percentage Error): 2.3%	MAPE: 6.1% - 12.9%

High correlation confirms smartphone imagery captures sufficient data to reconstruct complex geotechnical parameters.
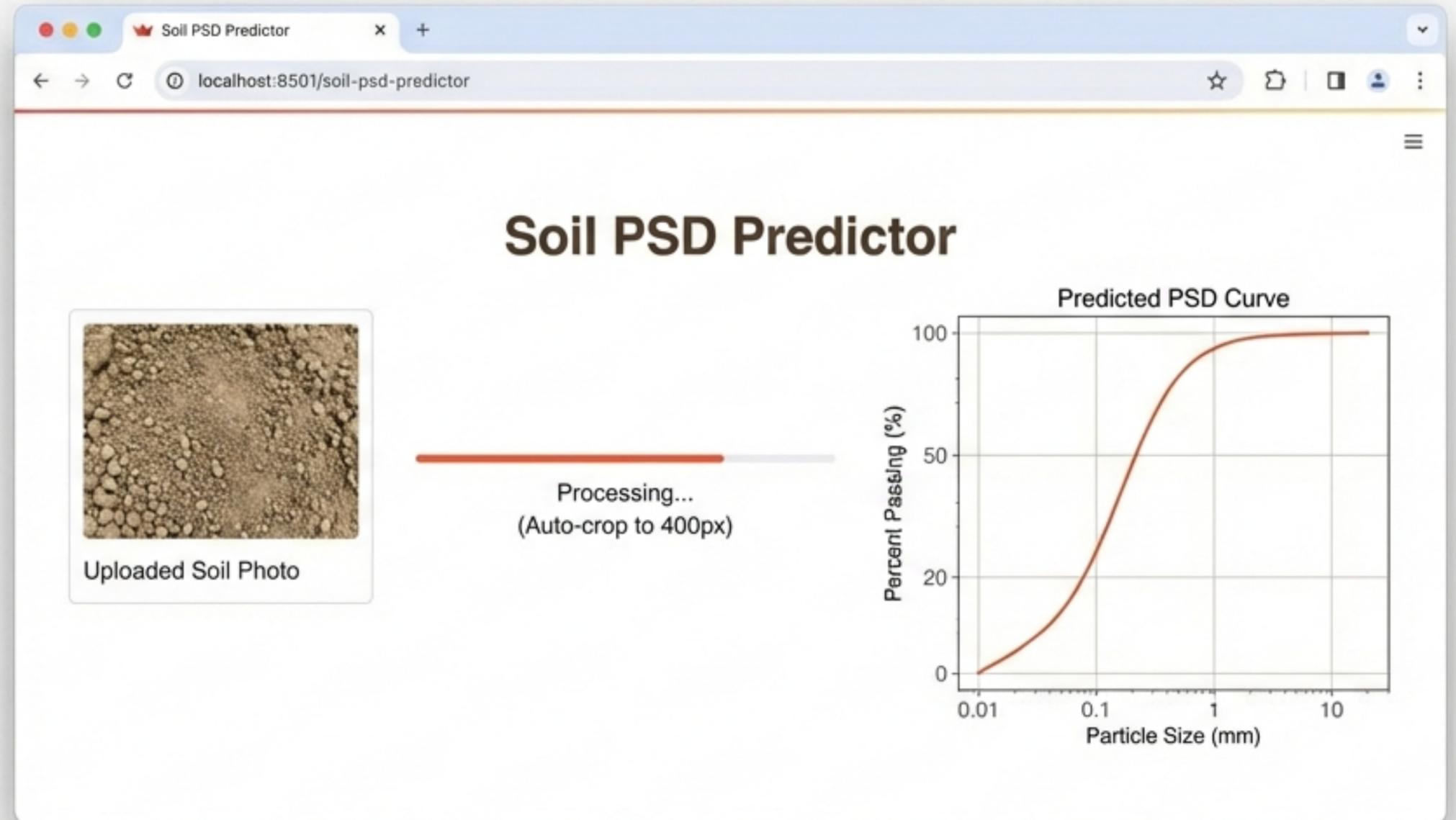
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Visual Verification: Prediction vs. Reality

The tight correlation and precise curve overlap demonstrate the AI's high fidelity in reconstructing complex geotechnical parameters.

From Theory to Practice: The Web App

Real-time deployment
via Streamlit allows instant
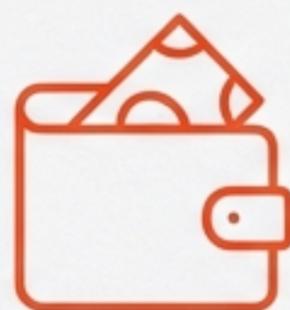analysis in the field.

Supported Sensors: Helevated, Motorola Edge, Samsung A52, iPhone 14.
Ready for iPhone 16 (48MP).

The Advantages of Digital Sieving

Rapid & Efficient

Drastically reduces time-to-result compared to 24-hour oven drying and mechanical shaking cycles.

Cost-Effective

Replaces expensive industrial lab equipment with standard consumer smartphones and a simple light box.

Full Interpolation

Unlike simple classifiers, this calculates the entire curve, providing data on fine particle content often missed by visual inspection.

Limitations & Future Horizons

Current Constraints
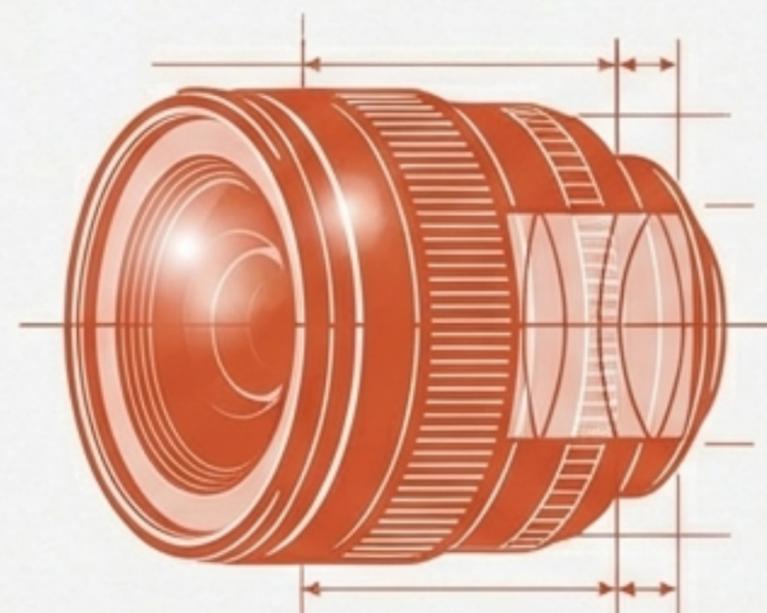
Resolution Limit: 4.6 Pixels Per MM.

Geography: Training data centered on Austrian/German geologies.

Future Work

Clay Accuracy: Expanding dataset for very fine fractions.

Global Sensors: Integration with iPhone 16 and diverse camera sensors.

Democratizing High-Quality Soil Analysis

- Scientific-grade data via consumer hardware.

- The "Pocket Lab" is a realized tool, not just a concept.

- Accessible, rigorous, and scalable.

Acknowledgments & References

Funding

Key Contributors

Enrico Soranzo, Anand D'Souza, Stefan Resch, Dennis Tegen.

Key References

- Soranzo et al. (2025): Machine Learning Prediction of Soil Particle Size Distribution...

- Howard et al. (2017): MobileNets: Efficient Convolutional Neural Networks...

- Buscombe (2020): SediNet...

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GRID Project

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