# PROJECT PROPOSAL

## SeedGuard AI: Empowering African Farmers Through Smart Crop Detection


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## Problem Statement - The Challenge We Are Tackling

Picture this: A smallholder farmer in rural Nigeria receives seeds from a supplier, but has no way of knowing whether these seeds are genetically modified. This scenario plays out across Africa daily, where millions of farmers, the true guardians of our continent's food security, face an increasingly complex agricultural landscape.

The reality is that GMOs are entering African agriculture at an unprecedented pace. While the GMO debate involves many nuances around corporate control, environmental impact, and food sovereignty, one thing is clear: farmers deserve the right to know what they're planting. Currently, they have no affordable, accessible way to make this determination.

This isn't just about technology,it's about preserving the autonomy and traditional knowledge that has sustained African agriculture for millennia.

## Existing Solutions - What is Already Out There (And Why It's Not Enough)

We've looked at existing solutions, and frankly, they fall short:

**DNA Lab Testing** is the gold standard for GMO detection, but it's completely out of reach for most African farmers. At $500+ per test, requiring sophisticated laboratories, it might as well be on another planet for rural communities.

**Certification Programs** like the Non-GMO Project work well for processed foods in supermarkets, but they're irrelevant for the unprocessed crops, seeds, and local markets that define African agriculture.

**Plant Identification Apps** like PlantNet and iNaturalist are fantastic for identifying species, but they can't tell the difference between GMO and traditional varieties of the same crop. A maize plant is a maize plant to these apps, whether it's genetically modified or an heirloom variety passed down through generations.

**The bottom line?** There's a massive gap between what farmers need and what technology currently offers them.

# Objectives - Our Vision

We want to build something different: a proof-of-concept machine learning model that looks at images of crop fields and classifies them as either "Industrial Agriculture" (high probability of GMO presence) or "Traditional Agriculture" (likely non-GMO, traditional practices).

Think of it as giving farmers a smart pair of eyes that can spot the telltale signs of industrial farming systems where GMOs are most commonly used.

## Our Specific Goals

1. **Create a Smart Detection System:** Develop an AI model that can distinguish between industrial and traditional farming practices through field images
2. **Build Our Own Dataset:** Since no suitable dataset exists, we'll create one by intelligently gathering images that represent different farming approaches
3. **Keep It Mobile-Ready:** Compare lightweight models like MobileNetV3 and EfficientNet-Lite that can eventually run on smartphones
4. **Make It Deployable:** Convert the best model to TensorFlow Lite for easy integration into mobile apps
5. **Demonstrate Practical Use:** Build a simple web API to show how this could work in the real world

# Dataset Information - The Dataset We Are Building: CropSystem-2K

Since we can't get direct "GMO vs. non-GMO" images (for obvious reasons), we're taking a clever proxy approach. We'll create a dataset of about 2,000 images across two categories:

**Industrial Agriculture Indicators (GMO-Likely):**

- Vast monoculture fields stretching to the horizon
- Perfect rows of identical plants with suspiciously uniform growth
- Dead, brown weeds between crop rows (signs of herbicide use)
- Marketing images from major seed companies
- Crops known for heavy GMO adoption like Bt cotton

**Traditional Agriculture Indicators (Non-GMO Likely):**

- Diverse, intercropped fields with multiple species growing together
- Crops showing natural variation in size and growth
- Healthy, living weeds mixed with crops

- Traditional farming practices like mixed cropping
- Heirloom varieties with their characteristic diversity

We'll gather these images using smart web scraping, searching for terms like "Roundup Ready fields," "organic intercropping," "agroecology," and similar keywords.

## Why This Approach Makes Sense

Here's the thing: you can't tell if a plant is genetically modified just by looking at it. The modifications are at the genetic level, invisible to the naked eye. But what you *can* see are the farming systems that typically accompany GMO adoption.

Industrial agriculture and GMO crops go hand in hand. When farmers adopt GMO seeds, they typically also adopt the entire industrial package: herbicides, monocultures, intensive inputs, and standardized practices. These create visible patterns that our AI can learn to recognize.

This approach is:

- **Practical:** We can actually gather this type of data
- **Meaningful:** It answers the farmer's real question: "Is this likely GMO?"
- **Unbiased:** We don't need proprietary data from agribusiness companies
- **Scalable:** It provides a foundation for larger applications

## Modeling & Deployment Plan - Our Game Plan

**Step 1: Smart Data Collection** We'll build a web scraper using Python's Beautiful Soup library to gather images from agricultural research sites, farming forums, and open databases. We're targeting quality over quantity.

**Step 2: Data Preparation** Clean up the dataset, remove duplicates, standardize image sizes, and apply data augmentation techniques to make our model more robust to real-world variations.

**Step 3: Model Training and Testing** We will use transfer learning, starting with models pre-trained on ImageNet and fine-tuning them for our specific task. Our candidates are:

- MobileNetV3-Small (ultra-fast, works on basic phones)
- EfficientNet-Lite (better accuracy while staying mobile-friendly)

**Step 4: Rigorous Evaluation** We will test our models on accuracy, precision, recall, and F1-score, while keeping an eye on model size for mobile deployment.

**Step 5: Mobile Optimization** Convert the winner to TensorFlow Lite format, ready for smartphone deployment.

## Looking Ahead: The Bigger Picture

This project is just the beginning. We envision SeedGuard eventually becoming:

**Phase 1 (Now):** A solid ML model that can classify farming systems

**Phase 2 (Next):** A mobile app that farmers can actually use in their fields

**Phase 3 (Future):** A comprehensive platform with offline seed bank maps, SMS integration for basic phones, and community reporting features

## What Success Looks Like

By the end of this project, we'll have:

- A working web scraper for agricultural image datasets
- Our novel CropSystem-2K dataset, freely available to researchers
- Performance benchmarks for lightweight CNN models on this task
- A TensorFlow Lite model achieving over 80% accuracy
- Complete documentation and code repository for reproducibility

## Community Impact - The Impact We Are After

This isn't just a tech project,it's about empowerment. We want to help African farmers:

- Make informed decisions about their seeds and crops
- Protect and preserve indigenous seed varieties
- Bring transparency to agricultural supply chains
- Contribute data that can inform better agricultural policies

## Standing on the Shoulders of Giants

We are inspired by organizations like the Alliance for Food Sovereignty in Africa (AFSA) and Biovision Africa Trust, whose research highlights exactly the challenges we're trying to address. Our approach builds on their advocacy with practical technology solutions.

# References


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