CROPSHIELD.AI

Crop Disease Detecting AI

Presented by:

Team Member	Tasks Accomplished
Jay Soni	Business Report
Sumit Tabhane	Product Report
Kajal Gaikwad	Product Report
Adi Antulay	Business Report

PROBLEM STATEMENT:

The agricultural sector, a cornerstone of global food security and economic stability, faces a critical challenge in combating crop diseases. These diseases, exacerbated by factors such as climate change, mono-cropping practices, and insufficient disease management systems, significantly reduce crop yields, inflict substantial economic losses, and threaten global food supply chains. Traditional methods for detecting crop diseases rely heavily on visual inspections and expertise, which are often inconsistent, time-consuming, and prone to error. This lack of precision leads to delayed interventions, inefficient resource utilization, and heightened vulnerability for smallholder farmers who form the backbone of global agriculture.

Current solutions are either prohibitively expensive, overly complex, or poorly adapted to the needs of farmers in resource-constrained settings. As a result, small-scale farmers, in particular, are unable to access timely, accurate disease diagnostics or actionable insights, further amplifying their risk of crop failure and economic instability.

To address this pressing issue, there is a need for an innovative, scalable, and cost-effective solution that integrates artificial intelligence (AI) and computer vision to enable early and accurate detection of crop diseases. Such a system would empower farmers with actionable recommendations, reduce crop losses, optimize resource use, and contribute to a more sustainable and resilient agricultural ecosystem, ultimately enhancing global food security.

PRESENT MARKET OVERVIEW:

The agricultural supply chain is plagued by inefficiencies that hinder profitability, sustainability, and customer satisfaction. Traditional supply chains involve multiple intermediaries, inflating costs, delaying deliveries, and reducing produce quality. Farmers lack visibility into consumer demand, leading to overproduction or underproduction, food waste, and lower profits.

Many farmers also lack access to advanced technologies for inventory management, demand forecasting, and order tracking. This limits their ability to optimize operations and compete in demand-driven markets.

Transparency is another challenge, as consumers often lack information about the source, quality, and sustainability of their food. This undermines trust, especially as demand grows for ethically sourced and fresh produce.

Food waste and sustainability concerns are significant, driven by poor demand forecasting, logistical delays, and inefficient inventory management. These issues not only hurt profitability but also increase environmental impact, including higher carbon emissions.

Finally, existing solutions often fail to offer diverse, fresh, and locally sourced options, leaving consumers underserved. A comprehensive solution addressing these inefficiencies, enhancing transparency, reducing waste, and expanding consumer choices is crucial to modernize the agricultural supply chain.

PRODUCT INTRODUCTION

Our product is a cutting-edge AI-powered platform designed to address one of agriculture's most pressing challenges: managing crop diseases effectively and sustainably. Leveraging advanced computer vision and an inbuilt machine learning model, the system can analyze images of crops to accurately identify diseases with remarkable precision. Once a disease is detected, the platform provides tailored, actionable recommendations for treatment, ensuring farmers can intervene promptly and effectively to minimize crop losses and safeguard their yields.

But our solution doesn’t stop at disease detection. It is designed to serve as a comprehensive agricultural companion, offering farmers detailed insights into sustainable farming practices and advanced agricultural methods. These insights include best practices for soil health management, crop rotation strategies, pest control techniques, and water-efficient irrigation systems. By integrating disease diagnosis with broader agricultural knowledge, the platform empowers farmers to make informed decisions that enhance productivity while reducing environmental impact.

The product is user-friendly, scalable, and cost-effective, making it accessible to farmers across varying scales of operation. By combining state-of-the-art technology with practical agricultural solutions, it bridges the gap between traditional farming methods and modern innovation, fostering a smarter, more resilient agricultural ecosystem. This tool is not just about managing challenges—it's about enabling farmers to thrive in an increasingly complex agricultural landscape.

BUSINESS NEED ASSESSMENT

The agricultural industry faces multifaceted challenges that significantly impact productivity, food security, and economic stability. Crop diseases remain one of the most critical threats, causing substantial crop losses and financial hardships, particularly for smallholder farmers who form the backbone of global agriculture. With increasing climate variability, monocropping practices, and the lack of robust disease management systems, there is an urgent need for innovative, scalable, and cost-effective solutions.

1. Market Dynamics

- **Growing Threat of Crop Diseases:** Crop diseases account for significant annual losses worldwide, with limited access to timely and accurate detection tools exacerbating the issue.
- **Demand for Precision Agriculture**: As global food demand grows, farmers seek advanced tools for efficient disease management, resource optimization, and yield improvement.
- **Technology Integration Gap**: Many regions, especially in developing economies, lack access to affordable, user-friendly agricultural technologies, leaving farmers dependent on traditional methods prone to delays and errors.

2. Key Customer Pain Points

1. Delayed and Inaccurate Disease Diagnosis

- Farmers rely on manual inspection and experience-based judgment, which often results in misdiagnosis or delayed interventions.
- Consequences include crop losses, increased disease spread, and reduced income.

2. Lack of Actionable Insights

- Diagnosis alone is insufficient; farmers need clear, practical steps to address crop diseases, including information on treatments, dosages, and preventative measures.

3. High Costs and Accessibility Barriers

- Many existing solutions are expensive or require high technical expertise, rendering them inaccessible to smallholder farmers.
- Limited connectivity in rural areas further complicates access to advanced tools.

4. Regional and Environmental Variability

- Disease prevalence and management strategies vary by region, crop type, and climatic conditions, necessitating highly localized solutions.

3. Business Requirements

- Early and Accurate Detection

- A tool capable of diagnosing crop diseases swiftly and precisely to enable timely interventions.

- Actionable Recommendations

- Providing farmers with step-by-step guidance on effective treatment methods tailored to crop type, disease severity, and local conditions.

- Affordability and Accessibility

- Ensuring cost-effective solutions with features like offline functionality and multi-language support for farmers in underserved regions.

- Scalability

- Adapting to a wide range of crops, diseases, and regional needs, ensuring the tool remains relevant in diverse agricultural contexts.

- Sustainability

- Promoting environmentally friendly practices, reducing waste, and optimizing the use of resources like water and fertilizers.

4. Market Opportunity

The precision agriculture market is projected to grow significantly, driven by rising demand for sustainable farming solutions and technology integration in agriculture. By addressing critical pain points with AI-driven crop disease detection and actionable insights, the product has the potential to tap into a market poised for disruption.

5. Competitive Advantages

- Localized Expertise: Tailored recommendations based on regional climates, crop varieties, and disease patterns.

- Actionable Insights: Practical steps for disease management, including organic and chemical treatments, pest control, and irrigation adjustments.

- Data-Driven Predictions: Leveraging AI to identify emerging disease trends and provide predictive analytics for proactive management.

- User-Centric Design: A simple, intuitive interface accessible to non-technical users, with support for low-connectivity environments.

By addressing the urgent needs of farmers, agricultural cooperatives, and policymakers, this solution bridges the gap between traditional methods and modern agricultural practices. Its focus on early detection, actionable recommendations, and affordability ensures it stands out as a transformative tool in global agriculture.

Target Audience

Audience Characteristics

1. **Farmers:** Smallholder & Subsistence Farmers: Need cost-effective, easy-to-use disease management tools to safeguard their crops.
2. **Large-Scale Farmers:** Require scalable solutions for disease monitoring and analytics across multiple regions.
3. **Agricultural Cooperatives:** Represent groups of farmers, seeking centralized tools for disease detection, best practice dissemination, and resource optimization.
4. **Agribusinesses & Enterprises:** Focused on advanced analytics, integration with existing systems, and monitoring disease trends at scale.
5. **Rural & Urban Farmers:** Limited access to expert advice or digital literacy; require localized, offline-enabled, and language-friendly interfaces.

User Needs

1. **Accessibility:** Offline functionality, multi-device compatibility, and support for diverse languages.
2. **Customization:** Tailored alerts and insights based on crops, regional conditions, and farming practices.
3. **Cost-Effectiveness:** Affordable pricing models for small and large-scale operations.

Pain Points

1. Lack of expert advice for timely action.
2. High cost and complexity of current solutions.
3. Limited adaptability to local conditions and diverse crop types.

Community Features

1. **F**orums and collaborative tools for knowledge sharing.
2. Real-time disease alerts and updates to foster proactive engagement.
3. aims to deliver a user-centric, accessible, and scalable solution, empowering its diverse audience to adopt sustainable and efficient agricultural practices.

EXTERNAL RESEARCH

1. **Early Crop Disease Detection with AI: Strategies for Prevention**

   https://www.xenonstack.com/use-cases/crop-disease-detection-with-ai

2. **Image-Based Crop Disease Detection Using Machine Learning**

   https://bsppjournals.onlinelibrary.wiley.com/doi/10.1111/ppa.14006

3. **The Era of Precision Agriculture Takes Shape**

   https://www.aem.org/news/the-era-of-precision-agriculture-has-arrived

4. **Pathogen or Plant Disease Detection and Monitoring Market Analysis**

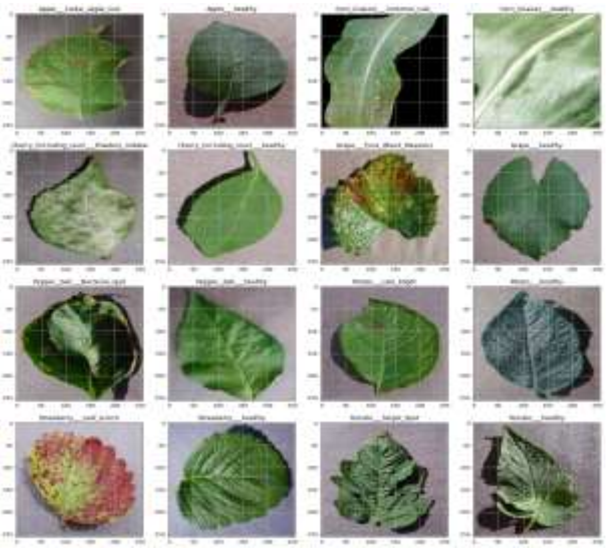
   https://bisresearch.com/industry-report/plant-disease-detection-monitoring-market.html

5. **Agtech: Breaking Down the Farmer Adoption Dilemma**

   https://www.mckinsey.com/industries/agriculture/our-insights/agtech-breaking-down-the-farmer-adoption-dilemma

6. **Plant Disease Image Dataset**

   https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset



These resources offer comprehensive information on the current landscape and advancements in AI-driven crop disease detection and precision agriculture, providing a solid foundation for external research in this field.

ML MODEL DEVELOPMENT

The CNN architecture is designed to perform multiclass classification with 38 output classes, making it suitable for applications like image-based crop disease detection. The architecture balances complexity and computational efficiency by utilizing multiple convolutional, pooling, and fully connected layers. Below is a detailed explanation of each component:

1. Input Layer
Input Shape: Images of size 224x224 pixels with 3 color channels (RGB).
This defines the input dimensions for the model.

2. Convolutional Layers
Convolutional layers are the core of the CNN, responsible for feature extraction from the input images. Each layer uses filters (kernels) to detect specific patterns such as edges, textures, or more complex structures.

Conv1:

- Filters: 32
- Kernel Size: 7x7
- Activation Function: ReLU
- Strides: 1
- Padding: Same
- Captures initial features such as edges and corners.

Conv2:

- Filters: 64
- Kernel Size: 5x5
- Activation Function: ReLU
- Strides: 1
- Padding: Same
- Extracts intermediate-level features like textures.

Conv3:

- Filters: 128
- Kernel Size: 3x3
- Activation Function: ReLU
- Strides: 1
- Padding: Same

- Captures more abstract and detailed features without reducing spatial dimensions since no pooling layer follows.

Conv4:

- Filters: 256
- Kernel Size: 3x3
- Activation Function: ReLU
- Strides: 1
- Padding: Same
- Extracts deeper, high-level features and prepares the data for classification.
- Pooling Layers
- Pooling layers reduce spatial dimensions to decrease computation and retain significant features.

3. **Pool1, Pool2, Pool3:**

- Pooling Type: MaxPooling
- Window Size: 2x2
- Reduces the size of feature maps by half after each corresponding convolutional layer, retaining the most significant features.

4. Flatten Layer

- Converts the 2D feature maps into a 1D feature vector.
- This vector is used as input for the fully connected layers.

5. Fully Connected Layers

These layers perform the classification task based on the extracted features.

Dense1:

- Neurons: 128
- Activation Function: ReLU
- Processes high-level abstract features.

Dense2:

- Neurons: 64
- Activation Function: ReLU
- Refines the extracted features further.

Dropout:
Prevents overfitting by randomly deactivating 50% of neurons during training.

Output Layer:

- Neurons: 38 (equal to the number of classes)
- Activation Function: Softmax
- Provides the probabilities for each class, making it suitable for multiclass classification.

The architecture combines convolutional and pooling layers to extract hierarchical features from input images. Fully connected layers with dropout ensure effective classification and reduced overfitting. The final layer uses softmax for multiclass probability distribution.

CNN ARCHITECTURE

Layer (type)	Output Shape	Param #
Conv1 (Conv2D)	(None, 224, 224, 32)	4,736
Pool1 (MaxPooling2D)	(None, 112, 112, 32)	0
Conv2 (Conv2D)	(None, 112, 112, 64)	51,264
Pool2 (MaxPooling2D)	(None, 56, 56, 64)	0
Conv3 (Conv2D)	(None, 56, 56, 128)	73,856
Conv4 (Conv2D)	(None, 56, 56, 256)	295,168
Pool3 (MaxPooling2D)	(None, 28, 28, 256)	0
Flatten (Flatten)	(None, 200704)	0
Dense1 (Dense)	(None, 128)	25,690,240
Dense2 (Dense)	(None, 64)	8,256
output (Dense)	(None, 38)	2,470

CODE:

In [8]:

```
# Define the CNN architecture
model = keras.models.Sequential()

# Convolutional Layer 1
# 32 filters, each with a 7x7 kernel, ReLU activation function adding 'strides' and 'padding' as sa
me
# Input shape: (224, 224, 3) - input images of size 224x224 pixels with 3 channel (RGB)
model.add(keras.layers.Conv2D(32,(7,7), activation = 'relu', strides = 1, padding="same", input_s
hape=(224,224,3), name="Conv1"))

# Max pooling with a 2x2 window size, reducing spatial dimensions by half
model.add(keras.layers.MaxPooling2D(2,2, name='Pool1'))


# Convolutional Layer 2
# 64 filters, each with a 5x5 kernel, ReLU activation function adding 'strides' and 'padding' as sa
me
model.add(keras.layers.Conv2D(64,(5,5), activation = 'relu',strides = 1, padding="same", name="Co
nv2"))
model.add(keras.layers.MaxPooling2D(2,2, name='Pool2'))

# Convolutional Layer 3
# 128 filters, each with a 3x3 kernel, ReLU activation function adding 'strides' and 'padding' as s
ame
# we are not adding Maxpooling layer, fordeeper feature extraction before reducing the spatial dime
nsions.
model.add(keras.layers.Conv2D(128,(3,3), activation = 'relu',strides = 1, padding="same",name="Co
nv3"))
```

```
# Convolutional Layer 4
# 256 filters, each with a 3x3 kernel, ReLU activation function adding 'strides' and 'padding' as s
ame
model.add(keras.layers.Conv2D(256,(3,3), activation = 'relu',strides = 1,padding="same", name="Co
nv4"))
model.add(keras.layers.MaxPooling2D(2,2, name='Pool3'))


# Flatten layer to convert 2D feature maps to 1D feature vectors
model.add(keras.layers.Flatten(name="Flatten"))

# Fully Connected Layer 1
# 128 neurons with ReLU activation.
model.add(keras.layers.Dense(128, activation='relu', name='Dense1'))
# Prevents overfitting by randomly dropping 50% of neurons.
tf.keras.layers.Dropout(0.5)

# Fully Connected Layer 2
# 64 neurons with ReLU activation.
model.add(keras.layers.Dense(64, activation='relu', name='Dense2'))
tf.keras.layers.Dropout(0.5)

# Output layer
# 38 neurons for classification (38 classes), softmax activation for multiclass classification
model.add(keras.layers.Dense(38, activation='softmax', name='output'))

# Prints model architecture.
model.summary()
```

Product Prototype

This system leverages mobile-cloud architecture and AI-driven crop disease classification to provide an end-to-end solution for early and accurate crop disease detection. The process integrates the ease of a mobile application with the robustness of cloud-based AI models and actionable insights for farmers.

1. Photo Capture (Farmer Interaction)

Farmers use a mobile device to take a clear photo of a crop leaf or plant affected by potential diseases. This step enables an easy and accessible way for farmers to initiate the disease detection process without requiring expensive equipment or specialized knowledge.

2. Image Transmission to the Cloud

The captured image is uploaded to the cloud using the mobile app. This ensures that the analysis is not constrained by the computational power of the farmer's device, making it accessible for even low-end smartphones.

3. Cloud-Server Processing

A web server receives the image and manages the backend processes. This includes cleaning the image, preparing it for analysis, and ensuring data security during the transmission.

4. Database Storage

The image is stored in a centralized database for future reference and model improvement. This step ensures scalability, allowing the system to maintain a growing repository of crop disease data, which can be used for training and improving AI models.

5. AI-Driven Classification

Pre-trained machine learning models analyze the image to identify crop diseases. These models are trained on large datasets of crop images and can accurately detect diseases based on visual patterns like discoloration, lesions, or texture changes. The system also considers environmental factors (e.g., location, climate conditions) to improve accuracy.

6. Result Generation

The system generates disease identification results, including the name of the disease, severity level, and affected plant parts. The system also provides actionable recommendations for disease management, such as pesticide suggestions, organic remedies, or cultural practices to mitigate the issue.

7. Results Sent to Farmers

The results, along with actionable insights, are sent back to the farmer's mobile device in a simple and comprehensible format (e.g., local language support, visual guides). Farmers receive targeted advice for timely intervention, reducing delays and inefficiencies.

BUSINESS MODEL

Monetization Strategy

CropShield employs a diversified revenue approach to ensure scalability and value for its user base, including farmers, cooperatives, and agribusinesses:

1. **Freemium Model**: Offers free access to basic disease detection capabilities, encouraging adoption.
2. **Premium Services**: Advanced analytics, IoT integration, real-time expert support, customizable alerts, and comprehensive historical data, available via subscription.

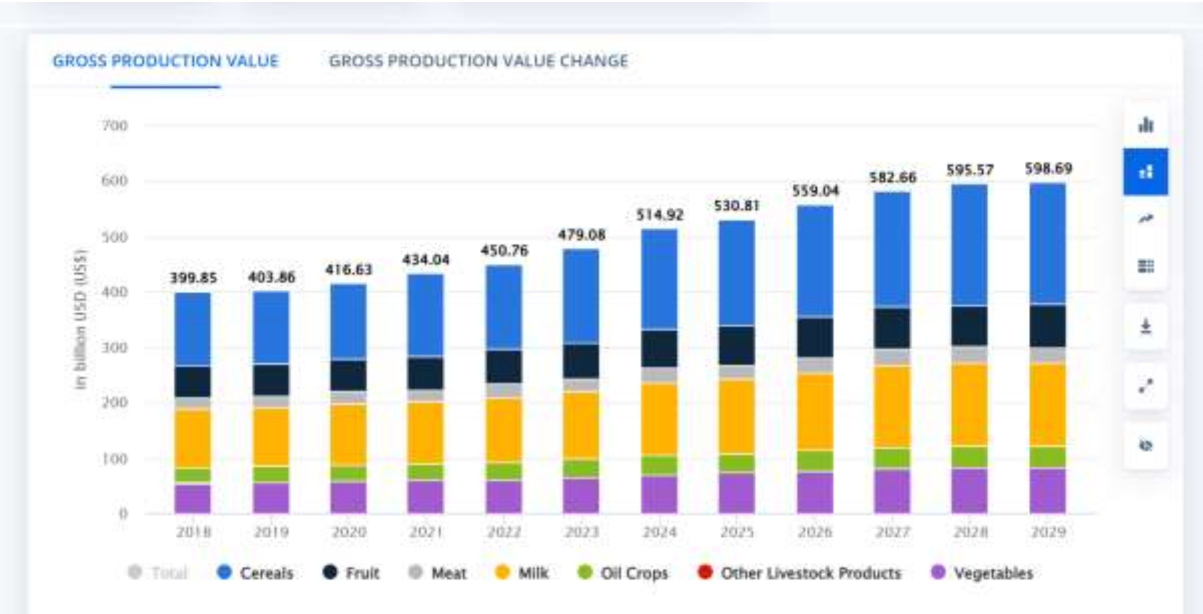
Subscription Plans

1. **Individual Plans**: Affordable options for small farmers, focusing on productivity and disease management.
2. **Cooperative Plans**: Group discounts, dashboards, and bulk licenses for farming collectives.
3. **Enterprise Plans**: Tailored features for large agribusinesses, including software integration and dedicated support.

Advertising & Sponsorship

Revenue through targeted ads and sponsored educational content related to agriculture.

The market forecast values for the gross production value of the AgTech sector are:



YEAR	Gross Production Value (Billion USD)
2025	530.81
2026	559.10
2027	582.66
2028	595.97
2029	598.69

Observations:

The market grows steadily but tapers off, indicating a potential saturation effect by 2029.

CAGR (Compound Annual Growth Rate) over this period:

CAGR = $\left(\frac{598.69}{530.81}\right)^{1/4} - 1 = 3.04\%$

The market grows at approximately 3.04% annually.

Adjusting Financial Assumptions

1. Product Pricing and Cost Assumptions:
   - Product Price: ₹500/unit
   - Cost of Operation: ₹20,000/month
2. Market Penetration:
   - Market size: Gross Production Value × Penetration Percentage
   - For each year, we estimate penetration starting from 0.005% (small-scale entry) and scaling up.

Revised Financial Equation

The monthly revenue equation becomes:

$$y = 500\,x - 20000$$

Where, x is the total number of units sold per month. The value of x depends on market penetration.

Revenue Projection: Year-wise Estimates

Year	**Market Value(Billion USD)**	**Penetration(%)**	**Units Sold (Million)**	**Revenue(Million Rupees)**
2025	**530.81**	**0.005%**	**0.02654**	**12.27**
2026	**559.10**	**0.01%**	**0.05591**	**27.96**
2027	**582.66**	**0.02%**	**0.11653**	**58.26**
2028	**595.97**	**0.03%**	**0.17879**	**89.4**
2029	**598.69**	**0.05%**	**0.29935**	**148.68**

Example Calculations:

For 2025:

Units Sold = $530.81B \times 0.005\% = 0.02654M$ (approx. 26,540 units).

Revenue = $500 \times 26540 - 20000 =$ ₹12,27,000.

For 2029:

Units Sold = $598.69B \times 0.05\% = 0.29935M$ (approx. 299,350 units).

Revenue = $500 \times 299350 - 20000 =$ ₹1,48,68,000.

Insights and Recommendations

- **Growth Trends:** While the market is growing, the CAGR indicates a slowing pace from 2028 onward. Early penetration and scaling strategies are crucial to capture market share before saturation.
- **Break-even Analysis:** With 40 units/month, the business achieves break-even at a ₹500/unit price point:

  $$500 \times 40 - 20000 = 0$$
- **Opportunities:** Partnering with government initiatives and leveraging digital platforms can improve penetration rates.