AI-Powered Crop Disease Detection and Diagnosis System for Agriculture

BY- RUDRANSH KAUSHIK

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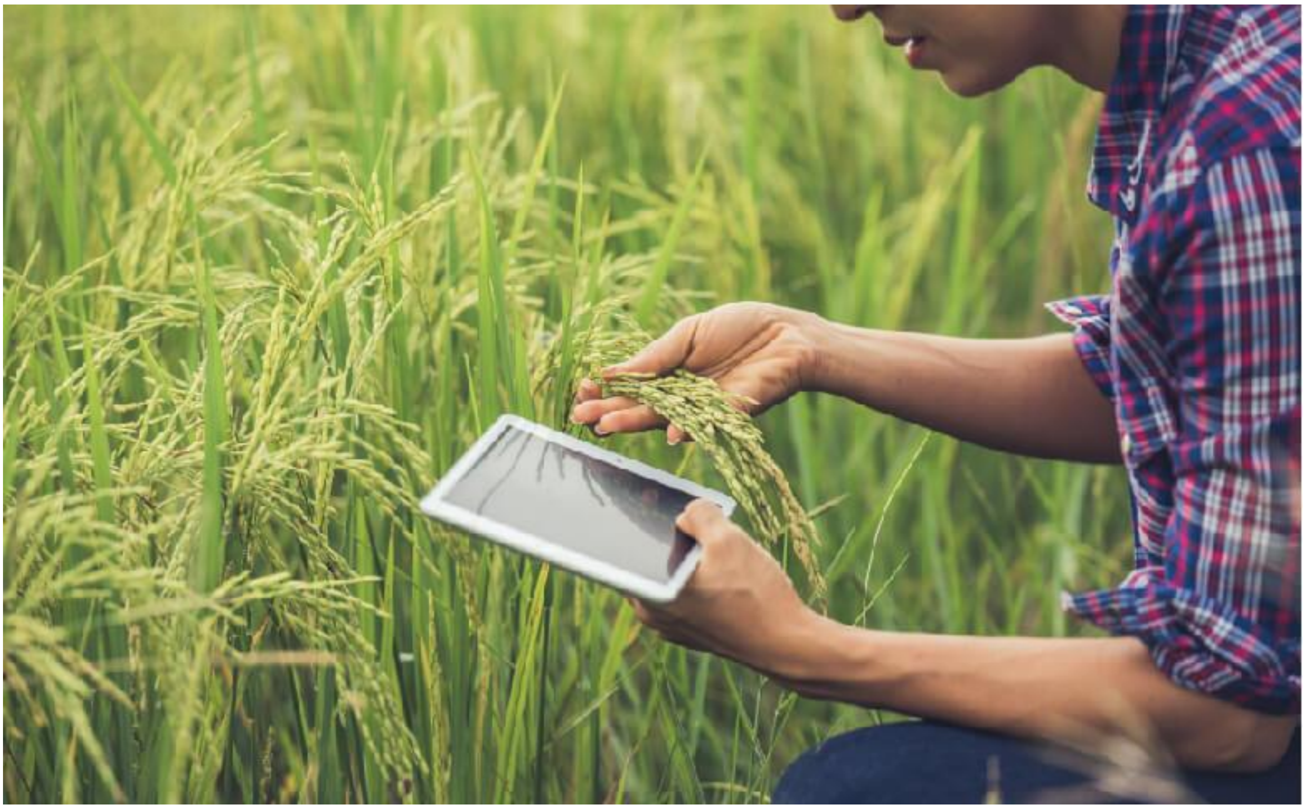
TASK-3

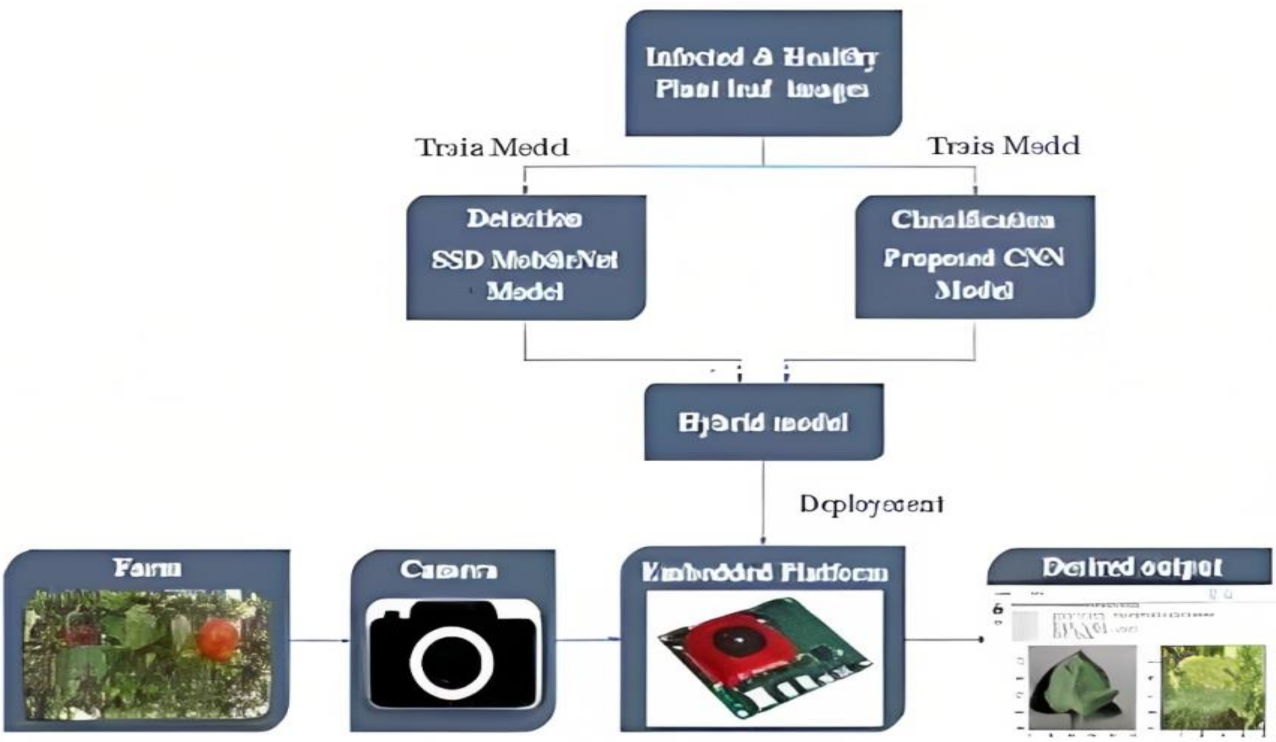


1-Introduction:

The agriculture industry plays a vital role in ensuring food security and sustainable livelihoods. However, crop diseases pose a significant threat to agricultural productivity, resulting in substantial economic losses and food scarcity. Timely detection and accurate diagnosis of crop diseases are crucial for implementing effective disease management strategies and minimizing the impact on crop yields. Unfortunately, many farmers, particularly small-scale ones, face challenges in accurately identifying and diagnosing crop diseases due to limited resources and expertise. Traditional methods of manual inspection and reliance on subjective observations are time consuming, prone to errors, and often inadequate for early disease detection. As a result, farmers may experience delays in implementing appropriate treatment measures, leading to increased crop losses and financial hardships. To address this pressing issue, an innovative solution that harnesses the power of machine learning and artificial intelligence has emerged – an AI-powered crop disease detection and diagnosis system. By leveraging computer vision algorithms, deep learning techniques, and vast databases of disease patterns, this system automates the process of detecting and diagnosing crop diseases. It analyzes images of crops captured using digital devices, extracts relevant features, and applies advanced algorithms to identify the presence of diseases or abnormalities. Subsequently, the system employs machine learning models to diagnose the specific crop disease based on patterns, symptoms, and contextual information.

2-Problem Statement:

Crop diseases pose a significant challenge to agricultural productivity and food security. Timely and accurate detection and diagnosis of these diseases are crucial for effective disease management. However, farmers, particularly small-scale ones, often lack the necessary expertise and resources to identify and diagnose crop diseases with precision. Manual inspection methods are time-consuming, subjective, and prone to errors, leading to delays in treatment, increased crop losses, and economic hardships. There is a pressing need for an advanced solution that leverages machine learning and artificial intelligence to automate the crop disease detection and diagnosis process, providing farmers with accurate and timely insights to mitigate the spread of diseases and minimize crop losses.



3-Market/Customer/Business Need Assessment:

3.1. Market Assessment:

The market for an AI-powered crop disease detection and diagnosis system is significant and promising. The agriculture industry, including small-scale farmers, faces persistent challenges in effectively managing crop diseases. The demand for accurate and timely disease detection and diagnosis solutions is high, as farmers seek to protect their crops, maximize yields, and minimize financial losses. The market potential extends globally, encompassing both developed and developing regions where agriculture plays a vital role in the economy.

3.2. Customer Assessment:

The primary customers for the AI-powered crop disease detection and diagnosis system are farmers, particularly those engaged in crop production. This includes small-scale farmers, agricultural cooperatives, and larger agricultural enterprises. The solution caters to a wide range of crops and can be customized to suit various regional and crop-specific requirements. The target customers are motivated to adopt such a solution to enhance their disease management practices, improve crop yields, and optimize their agricultural operations.

3.3. Business Need Assessment:

The business need for an AI-powered crop disease detection and diagnosis system is driven by several factors:

a. Enhanced Disease Management: Farmers need reliable tools to effectively manage crop diseases, as they directly impact crop productivity and economic viability. By automating the detection and diagnosis process, the solution addresses a critical business need of ensuring timely and accurate disease identification.

b. Cost Optimization: Crop diseases can result in substantial financial losses due to reduced yields and the need for excessive pesticide use. The solution assists farmers in optimizing costs by enabling early disease detection, targeted treatment strategies, and reducing unnecessary pesticide applications.

c. Sustainability and Environmental Impact: Adopting an AI-powered solution aligns with the growing emphasis on sustainable agricultural practices. By minimizing the use of pesticides through accurate disease diagnoses, farmers can reduce their environmental footprint and promote eco-friendly farming methods.

d. Efficiency and Time Savings: Manual inspection methods are labor-intensive and time consuming. The solution offers significant time savings by automating the disease detection and diagnosis process, allowing farmers to allocate their resources more efficiently to other critical farming activities.

4-Target Specifications and Characterization:

1. Accuracy:

The AI-powered crop disease detection and diagnosis system should strive for high accuracy in identifying and diagnosing crop diseases. The system should be able to achieve a high level of precision, minimizing false positives and false negatives to ensure reliable results.

2. Speed and Efficiency:

The system should be designed to provide timely results to farmers. It should process the images of crops quickly and deliver disease detection and diagnosis insights within a reasonable time frame, allowing farmers to take prompt action.

3. Scalability:

The solution should be scalable to accommodate different farm sizes and crop types. It should be capable of handling a large volume of image data and cater to the needs of both small-scale farmers and larger agricultural enterprises.

4. User-Friendly Interface:

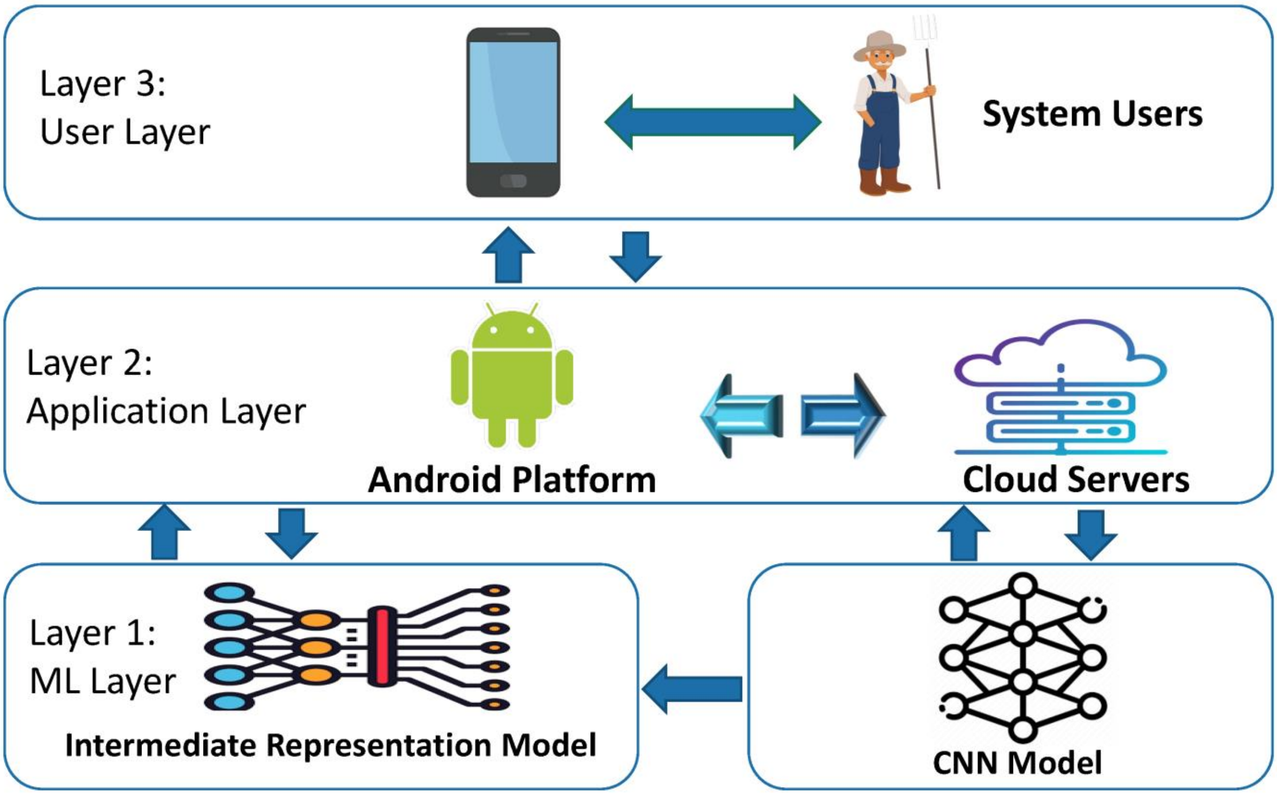
The system should have an intuitive and user-friendly interface that can be easily navigated by farmers with varying levels of technical expertise. The interface should provide a seamless experience for capturing and uploading images, accessing disease detection results, and receiving actionable recommendations.

5. Adaptability:

The system should be adaptable to different geographical regions, crop varieties, and disease profiles. It should be capable of recognizing and diagnosing a wide range of crop diseases, allowing farmers to address the specific challenges they face in their local contexts.

6. Integration and Compatibility:

The solution should be designed to integrate with existing digital platforms and agricultural technologies commonly used by farmers. Compatibility with mobile devices, smartphones, and other digital devices is crucial for ease of use and accessibility.



5-Prototype Development :

First we will import the required libraries and packages for the development.

```
import tensorflow as tf
from tensorflow.keras.models import Sequential,Model
from tensorflow.keras.layers import Dense,Flatten,Conv2D,MaxPooling2D
from tensorflow.keras.layers import AveragePooling2D
from tensorflow.keras.layers  import Concatenate
from tensorflow.keras.layers import AveragePooling2D, Dropout, Input,
BatchNormalization, Flatten
from tensorflow import keras
```

```
from tensorflow.keras import layers
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import classification_report, confusion_matrix
from PIL import Image
from tqdm import tqdm
import urllib
from tensorflow.keras.preprocessing import image
from sklearn.metrics import precision_recall_curve,roc_curve, auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
import os
from sklearn.metrics import log_loss, brier_score_loss
from sklearn.metrics import cohen_kappa_score
import matplotlib.cm as cm
from sklearn.metrics import matthews_corrcoef
import pandas as pd
import seaborn as sns
import numpy as np
import cv2
from sklearn.preprocessing import label_binarize
from sklearn.metrics import average_precision_score
from tensorflow.keras.utils import to_categorical
%matplotlib inline
```

Now we will import the datasets for training and testing

```
image_path="../input/new-plant-diseases-dataset/New Plant Diseases
Dataset(Augmented)/New Plant Diseases Dataset(Augmented)/train/"
train_image_path="../input/new-plant-diseases-dataset/New Plant Diseases
Dataset(Augmented)/New Plant Diseases Dataset(Augmented)/train/"
valid_image_path="../input/new-plant-diseases-dataset/New Plant Diseases
Dataset(Augmented)/New Plant Diseases Dataset(Augmented)/valid/"
test_image_path="../input/new-plant-diseases-dataset/test/"
```

Plotting the confusion matrix that will show the relation between actual and predicted classes in the form of a heatmap.

```
plt.figure(figsize=(40,40))
confusion = confusion_matrix(true_data, final_predict)
sns.heatmap(confusion, annot=True, fmt='d',
cmap='jet',xticklabels=class_names, yticklabels=class_names,lw=6)
```

```
plt.xlabel('Predicted',fontsize=20,color="black")
plt.ylabel('True',fontsize=20,color="black")
plt.title('Confusion Matrix\n',fontsize=20,color="black")
plt.show()
```

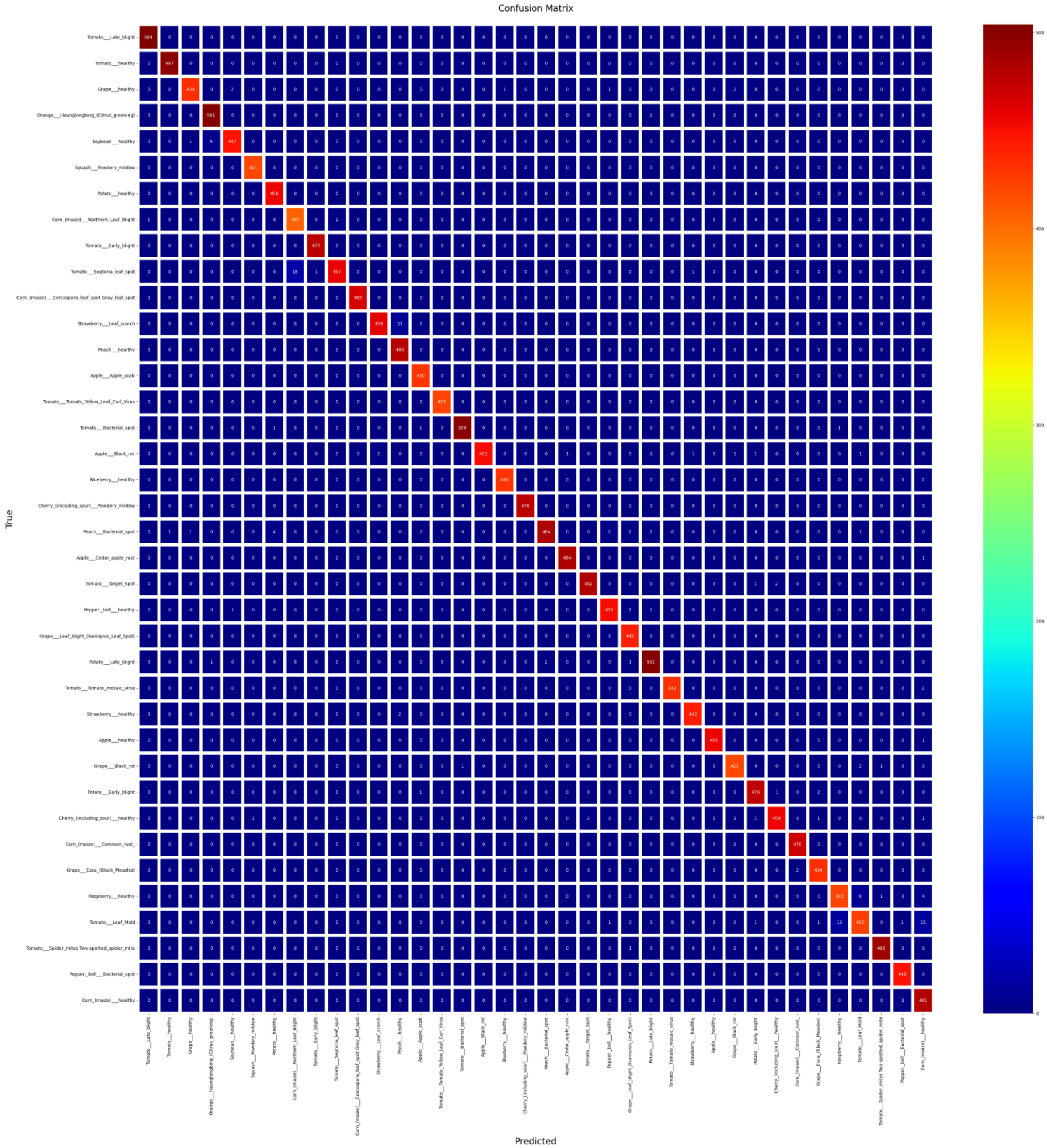


Image pre-processing and results

```
plt.figure(figsize=(5, 5))

img_url = "https://cdn.britannica.com/89/126689-004-D622CD2F/Potato-leaf-blight.jpg"

filename, headers = urllib.request.urlretrieve(img_url)
img_path = os.path.join(os.getcwd(), filename)
img = Image.open(img_path)
img = img.resize((120, 120))
img = np.array(img) / 255.0
img = np.expand_dims(img, axis=0)
probs = model.predict(img)[0]

# Get the predicted class index and name
pred_class_prob = np.argmax(probs)
pred_class_name = class_names[pred_class_prob]

max_prob = np.max(probs)
print(f'Predicted class: {pred_class_name}')
print(f'Maximum probability: {max_prob}')

# Display the image with the predicted class and probability
plt.imshow(img[0])
plt.axis('off')
plt.text(5, 15, f'Predicted class: {pred_class_name}\nMaximum probability: {max_prob:.2f}', fontsize=10, color='red', bbox=dict(facecolor='white', alpha=0.8))
plt.show()
```

The output in the above image shows the plant condition.

<u>6-Business Modelling :</u>

6.1. Subscription Tiers:

Offer different subscription tiers tailored to the needs and budgets of various customer segments. For example, a basic tier could provide essential disease detection and diagnosis features, while a premium tier could include additional services such as personalized recommendations, expert consultations, and access to advanced analytics.

6.2. Usage-based Pricing:

Implement a pricing structure based on the usage of the platform. Consider charging a base fee for access to the platform and additional fees based on the number of crops, images analysed, or area of farmland covered. This pricing approach ensures scalability and caters to the diverse needs of farmers with different farm sizes and operational capacities.

6.3. Value-added Services:

Introduce value-added services that complement the core disease detection and diagnosis capabilities. For instance, offer customized disease management plans, real-time weather data integration, or pest forecast alerts for an additional fee. These services provide additional value to farmers and generate additional revenue streams.

6.4. Partnerships and Integrations:

Collaborate with other agricultural technology providers, such as farm management software companies, sensor manufacturers, or agrochemical suppliers. Integration with their platforms and tools can create mutually beneficial partnerships, allowing for cross-promotion and revenue sharing opportunities.

6.5. Data Insights and Analytics:

Leverage the aggregated data and insights generated by the platform to provide anonymized, aggregated reports and analytics to agricultural organizations, research institutions, and government agencies. These stakeholders can gain valuable market insights and contribute to the sustainability and improvement of agricultural practices.

6.6. Training and Consulting:

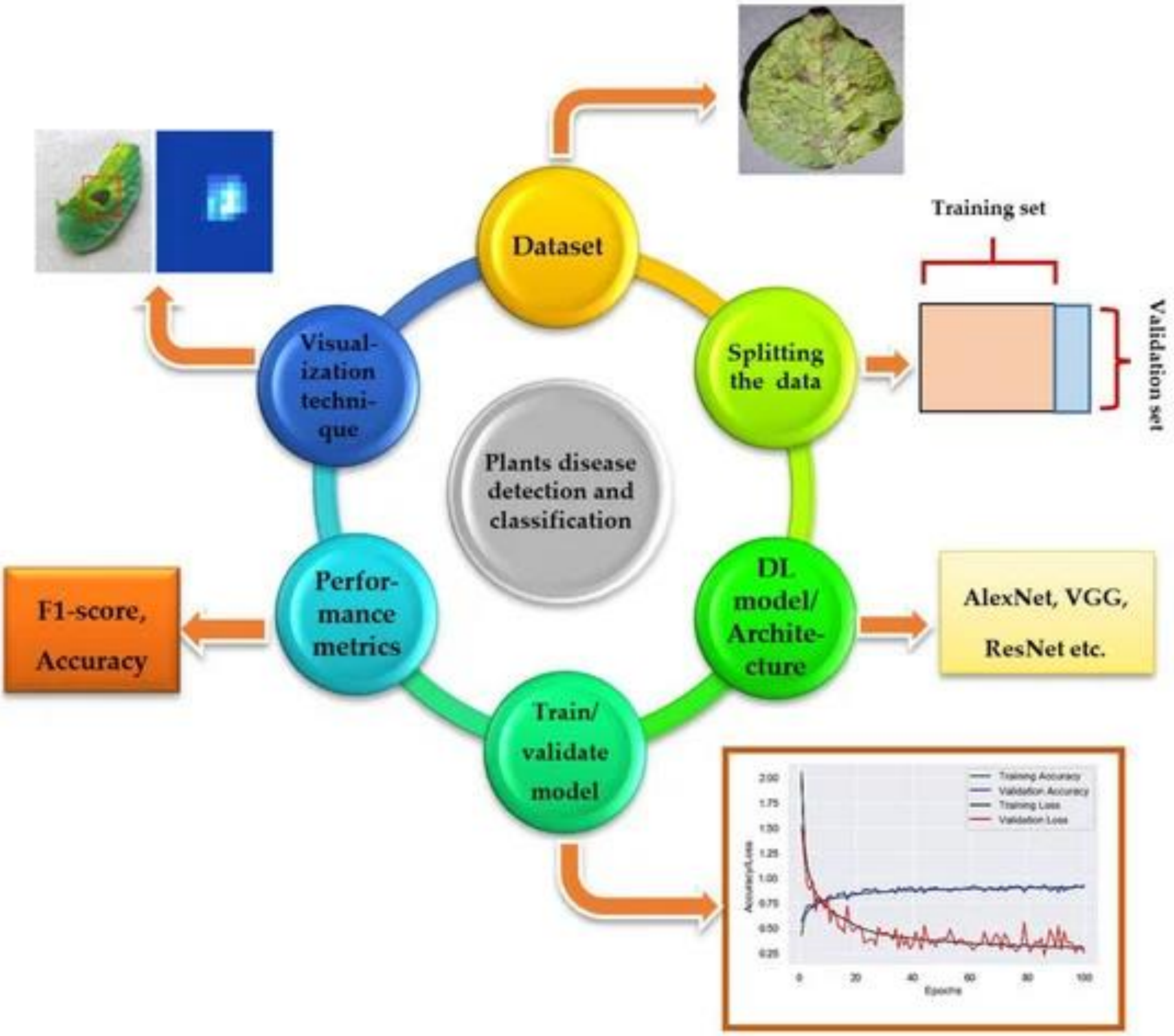
Offer training programs, workshops, and consulting services to farmers and agricultural professionals who require additional support in understanding and utilizing the AI-powered platform effectively. Charge fees for these value-added services, providing an additional revenue stream.

6.7. Market Expansion:

Consider expanding into new geographic markets and adapt the pricing strategy to suit the local context. Tailor subscription pricing, features, and value-added services to cater to the specific needs and affordability of farmers in different regions.

6.8. Research Grants and Funding:

Explore opportunities to secure research grants or funding from agricultural institutions, government agencies, or venture capital firms interested in supporting AI-driven innovations in agriculture. These funds can contribute to the development and improvement of the platform while ensuring financial stability.



7-Concept Generation:

1. Identify Industry Challenges:

Begin by understanding the challenges and pain points faced by farmers and stakeholders in the agriculture industry. Conduct market research, engage with farmers, and analyze industry reports to gain insights into the specific problems related to crop disease detection and diagnosis.

2. Technology Exploration:

Explore the capabilities of AI, machine learning, and computer vision in the context of crop disease detection and diagnosis. Investigate research papers, industry publications, and case studies to understand the latest advancements and potential applications of these technologies in agriculture.

3. Brainstorming Sessions:

Conduct brainstorming sessions with a multidisciplinary team consisting of experts in agriculture, data science, machine learning, and software development. Encourage free-flowing idea generation, allowing team members to contribute their thoughts, perspectives, and potential solutions.

4. Market Analysis:

Analyse the target market and customer segments. Identify their needs, preferences, and pain points related to crop disease management. Consider the specific crops, geographical locations, and farming practices prevalent in the target market to tailor the solution accordingly.

5. Ideation Techniques:

Utilize ideation techniques such as mind mapping, SCAMPER (Substitute, Combine, Adapt, Modify, Put to another use, Eliminate, Reverse), or the Six Thinking Hats method to stimulate creative thinking and generate diverse ideas. Encourage team members to think outside the box and explore innovative approaches.

6. Competitive Analysis:

Study existing products, services, and technologies in the field of crop disease detection and diagnosis. Identify their strengths, weaknesses, and gaps in the market that can be addressed with an AI-powered solution. Consider how to differentiate the proposed concept from existing offerings.

7. Feasibility Assessment:

Evaluate the feasibility of each idea based on technical, financial, and resource constraints. Consider factors such as data availability, hardware requirements, algorithm complexity, development costs, and scalability. Narrow down the ideas to those that are technically achievable and economically viable.

8. Prototyping and Validation:

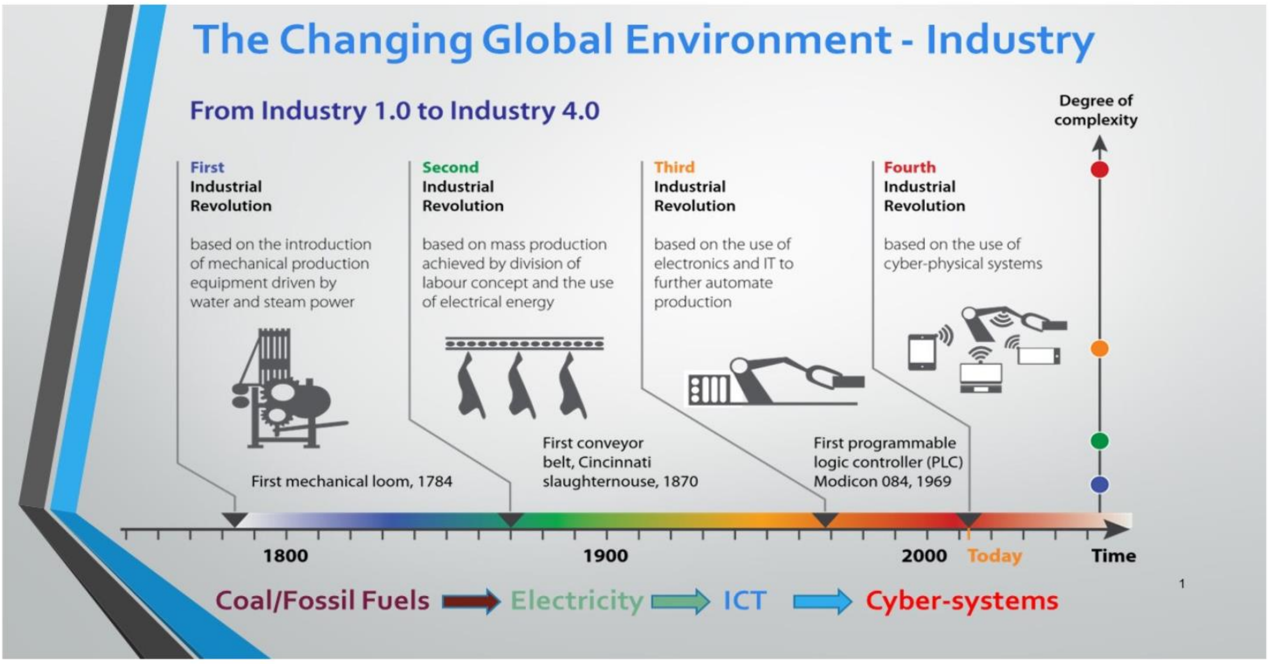
Develop a conceptual prototype or a proof-of-concept to demonstrate the potential functionality and value of the AI-powered crop disease detection and diagnosis platform. Validate the concept through feedback from farmers, agricultural experts, and potential customers to refine and iterate the idea.

9. Business Model Consideration:

Integrate the concept with a suitable business model that aligns with the target market, revenue generation, and scalability goals. Evaluate various monetization strategies such as subscription-based models, value-added services, partnerships, or data monetization opportunities.

10. Iterative Refinement:

Continuously refine the concept based on feedback, market dynamics, and technological advancements. Adapt to changing customer needs, emerging trends, and regulatory requirements to ensure the concept remains relevant and competitive



<u>7-Applicable Regulations:</u>

1. Data Privacy and Security:

Regulations related to data privacy and security may govern the collection, storage, and use of farmer data, including images of crops. Compliance with data protection laws and obtaining informed consent from farmers for data usage may be required.

2. Intellectual Property and Patents:

Companies offering AI-powered crop disease detection solutions may need to comply with intellectual property laws, especially if they have patented algorithms or technologies.

This includes protecting their own intellectual property rights and respecting the rights of others.

3. Biotechnology and Genetically Modified Organisms (GMOs):

In some cases, the use of genetically modified crops or organisms may be involved in disease resistance strategies. Such applications may be subject to regulations specific to biotechnology and GMOs in agricultural practices.

4. Agriculture and Pesticide Regulations:

The use of AI-powered crop disease detection systems may impact the use of pesticides and other agricultural chemicals. Compliance with regulations regarding pesticide application, usage limits, and safety measures may be essential.

5. Technology Standards and Certification:

Depending on the country, there might be technology standards or certification requirements for agricultural technologies, including AIbased solutions, to ensure their safety, reliability, and interoperability.

6. Environmental Impact:

Companies providing AI-powered crop disease detection solutions should consider potential environmental impacts resulting from pesticide reduction or other agricultural practices. Compliance with environmental regulations related to sustainable farming practices may be important.

7. Import and Export Regulations:

For companies operating globally, it's essential to consider import and export regulations for agricultural technologies. Compliance with international trade laws and customs requirements may be necessary

8-Conclusion:

In conclusion, the development of an AI-powered crop disease detection and diagnosis platform using machine learning and artificial intelligence has significant potential to address the challenges faced in the agriculture industry. By leveraging advanced algorithms such as Convolutional Neural Networks (CNNs), Random Forest, or K-Nearest Neighbors (KNN), we can effectively analyze crop images and classify them into different disease categories. Implementing such a solution would require a robust data collection process, including the acquisition of diverse crop images annotated with disease labels. The selection and optimization of appropriate algorithms and frameworks, such as TensorFlow for CNNs or scikit-learn for Random Forest and KNN, are essential for accurate disease detection and classification. Furthermore, assembling a skilled team comprising data scientists, machine learning engineers, and domain experts in agriculture would be crucial to developing and maintaining the AI platform. The team's expertise would ensure proper data preprocessing, algorithm selection, model training, and evaluation, ultimately leading to a reliable and effective solution. Additionally, factors such as space requirements, budget constraints, and compliance with applicable regulations should be considered during the development and deployment of the platform. The monetization of the platform can be achieved through various means, such as offering subscription-based access to the AI services, providing customized solutions to agricultural businesses, or partnering with agricultural organizations to integrate the technology into their existing operations.

Datasets and references

https://www.kaggle.com/code/rishithakalluri/fork-of-plant-disease-detection-using-google-net/input

https://www.kaggle.com/code/rishithakalluri/fork-of-plant-disease-detection-using-google-net/input?select=test

https://news.mit.edu/2019/algorithm-growingagriculture-0403

http://www.fao.org/digital-agriculture/en/

Github link :

https://github.com/Rudranshkaushik/feynn_labs_intern