CROP MANAGEMENT

MINI PROJECT REPORT

18CSC305J - ARTIFICIAL INTELLIGENCE

Submitted by

N. VIVEK [RA2011026010269]

R. AKASH [RA2011026010260]

AMRIT KUMAR[RA2011026010244]

Under the guidance of

Dr.U.Sakthi

Assistant Professor, Department of Computer Science

and Engineering

in partial fulfilment for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE & ENGINEERING

of

FACULTY OF ENGINEERING AND TECHNOLOGY

S.R.M. Nagar, Kattankulathur, Chengalpattu District

MAY 2023

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

(Under Section 3 of UGC Act, 1956)

BONAFIDE CERTIFICATE

Certified that Mini project report titled **“CROP MANAGEMENT”** is the bona fide work of **VIVEK (RA2011026010269)**, **AKASH (RA2011026010260), AMRIT KUMAR (RA2011026010244)**
who carried out the minor project under my supervision. Certified further, that to the best of my knowledge, the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

SIGNATURE	**SIGNATURE**
Dr.U.Sakthi	Dr. R. Annie Uthra
Assistant Professor	**HEAD OF THE DEPARTMENT**
Department of Computing Intelligence	Professor & Head
	Department of Computing Intelligence

ABSTRACT

The use of artificial intelligence (AI) in crop management has become increasingly popular in recent years, as farmers seek to increase their yields and reduce costs. AI can be used to gather data from various sources, including drones, satellites, and sensors, to create high-resolution maps of crop fields.

This data can then be used to optimize irrigation, fertilization, and other crop management activities, resulting in higher yields and lower costs. AI can also be used to detect crop diseases, pests, and other problems in real-time, allowing farmers to take action to prevent crop losses.

Additionally, AI can predict crop yields based on historical data, weather patterns, and other factors, providing valuable insights for optimizing planting, harvesting, and other activities. Finally, autonomous farming systems can be programmed using AI algorithms to automate various farming activities, reducing labour costs and increasing efficiency.

The use of AI in crop management has the potential to revolutionize modern agriculture and help farmers increase their profitability.

TABLE OF CONTENTS

LIST OF FIGURES

ABBREVIATIONS

IOT	Internet of Things
PIR	Passive Infrared
LCD	Liquid Crystal Diode
DHT	Distributed hash table
IR	Infra-red
UART	Universal Asynchronous Receiver/Transmitter
IDE	Integrated Development Environment

CHAPTER 1

INTRODUCTION:

Crop management is a crucial aspect of modern agriculture, and farmers are constantly seeking ways to increase their yields and reduce costs. The use of artificial intelligence (AI) in crop management has become increasingly popular in recent years, with AI technologies offering a range of benefits for farmers.

This paper will explore the various ways in which AI can be used for crop management, including precision agriculture, disease detection, yield prediction, soil analysis, and autonomous farming. The paper will also discuss the potential impact of AI on modern agriculture and how it can help farmers increase their profitability.

CHAPTER 2

LITERATURE SURVEY:

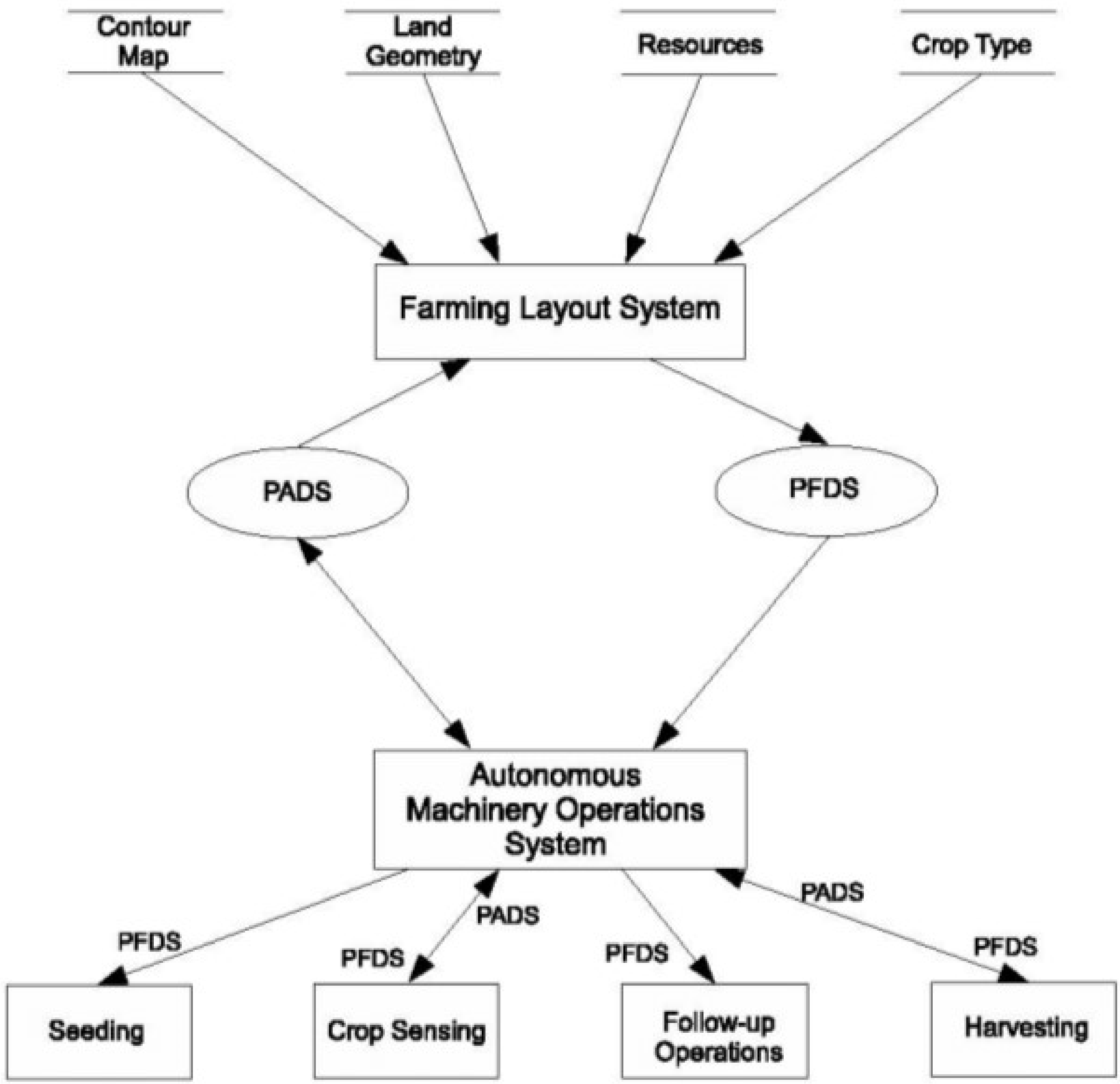
Crop management is one of the most important aspects of modern agriculture, and the use of AI technology can significantly improve crop yields and reduce costs. Here is some ways AI can be used for crop management:

1. **Precision Agriculture:** AI can be used to gather data from various sources, such as drones, satellites, and sensors, to create high-resolution maps of crop fields. This data can then be used to optimize irrigation, fertilization, and other crop management activities, resulting in higher yields and lower costs.
2. **Disease Detection:** AI can be used to identify and diagnose crop diseases, pests, and other problems in real-time. This can be done using computer vision, machine learning, and other AI technologies. By detecting problems early, farmers can take action to prevent crop losses.
3. **Yield Prediction:** AI can be used to predict crop yields based on historical data, weather patterns, and other factors. This information can be used to optimize planting, harvesting, and other activities, resulting in higher yields and lower costs.
4. **Soil Analysis:** AI can be used to analyse soil samples and provide recommendations for the optimal amount of fertilizer and other nutrients needed to maximize crop yields. This can be done using machine learning algorithms that analyse data from various sources, including satellite images, weather patterns, and soil sensors.
5. **Autonomous Farming:** AI can be used to automate various farming activities, such as planting, harvesting, and weeding. Autonomous farming systems can be programmed to operate 24/7, reducing labour costs and increasing efficiency.

6. Overall, the use of AI in crop management can help farmers increase their yields, reduce costs, and improve their overall profitability.

CHAPTER 3

SYSTEM ARCHITECTURE AND DESIGN



CHAPTER 4 - METHODOLOGY

The methodology for using AI in crop management can vary depending on the specific application and technology being used. However, here are some common steps that can be followed:

1. **Data Collection:** The first step is to gather data from various sources, such as drones, satellites, and sensors. This data can include information on soil quality, weather patterns, crop growth, and other factors that are relevant to crop management.

2. **Data Analysis:** Once the data is collected, it needs to be analysed using AI algorithms such as machine learning or deep learning. This can involve training models to recognize patterns in the data and make predictions based on this analysis.

3. **Decision-Making:** After the data is analysed, the AI system can provide recommendations for crop management activities such as irrigation, fertilization, pest management, and other tasks. The system can also provide insights into crop yields and other performance metrics.

4. **Implementation:** The final step is to implement the AI system into the crop management process. This can involve using autonomous farming equipment or using the AI system to inform manual management decisions.

It is important to note that the success of an AI-based crop management system relies on the quality and accuracy of the data being used. Therefore, it is essential to collect and maintain high-quality data throughout the entire process. Additionally, the AI system needs to be continually trained and updated to ensure that it is providing the most accurate and useful information possible.

CHAPTER 5 CODING AND TESTING

CROP RECOMMENDATION USING WEATHER AND SOIL CONTENT:

```
# Importing libraries

from __future__ import
print_function
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns from
sklearn.metrics import
classification_report from sklearn
import metrics from sklearn
import tree import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv('../Data-processed/crop-
recommendation.csv') df.head() df.size
df.shape df.columns df['label'].unique()
df.dtypes
df['label'].value_counts()
sns.heatmap(df.corr(),annot=True) features =
df[['N', 'P','K','temperature', 'humidity', 'ph',
'rainfall']] target = df['label']
#features = df[['temperature', 'humidity', 'ph',
'rainfall']] labels = df['label']

# Initialzing empty lists to append all model's name and
corresponding name acc = [] model = []

# Splitting into train and test data

from sklearn.model_selection import train_test_split
Xtrain, Xtest, Ytrain, Ytest = train_test_split(features,target,test_size =
0.2,random_state =2)
```

Decision Tree :

```
from sklearn.tree import
DecisionTreeClassifier

DecisionTree =
DecisionTreeClassifier(criterion="entropy",random_state=2,max_depth=5)

DecisionTree.fit(Xtrain,Ytrain)

predicted_values =
DecisionTree.predict(Xtest) x =
metrics.accuracy_score(Ytest,
predicted_values) acc.append(x)
model.append('Decision Tree')
print("DecisionTrees's Accuracy is: ",
x*100)

print(classification_report(Ytest,predicted_v
alues))
from sklearn.model_selection import cross_val_score

# Cross validation score (Decision Tree) score =
cross_val_score(DecisionTree, features, target,cv=5)

Score
```

Saving trained Decision Tree model :

```
import pickle
# Dump the trained Naive Bayes classifier with Pickle
DT_pkl_filename =
'../models/DecisionTree.pkl'
# Open the file to save as pkl file
DT_Model_pkl = open(DT_pkl_filename,
'wb') pickle.dump(DecisionTree,
DT_Model_pkl)
# Close the pickle instances
DT_Model_pkl.close()
```

Guassian Naive Bayes:

```
from sklearn.naive_bayes import
GaussianNB

NaiveBayes = GaussianNB()

NaiveBayes.fit(Xtrain,Ytrain)

predicted_values =
NaiveBayes.predict(Xtest) x =
metrics.accuracy_score(Ytest,
predicted_values) acc.append(x)
model.append('Naive Bayes')
print("Naive Bayes's Accuracy is: ", x)

print(classification_report(Ytest,predicted_v
alues))

# Cross validation score (NaiveBayes)
score =
cross_val_score(NaiveBayes,features,target,cv=5) score
```

Saving trained Gaussian Naive Bayes model:

```
import pickle
# Dump the trained Naive Bayes classifier with Pickle
NB_pkl_filename =
'../models/NBClassifier.pkl'
# Open the file to save as pkl file
NB_Model_pkl = open(NB_pkl_filename,
'wb') pickle.dump(NaiveBayes,
NB_Model_pkl)
# Close the pickle instances
NB_Model_pkl.close()
```

Support Vector Machine (SVM):

```
from sklearn.svm
import SVC # data
```

```
normalization with
sklearn
from sklearn.preprocessing import
MinMaxScaler
# fit scaler on training
data norm =
MinMaxScaler().fit(Xtra
in)
X_train_norm = norm.transform(Xtrain)
# transform testing dataabs
X_test_norm = norm.transform(Xtest)
SVM = SVC(kernel='poly', degree=3, C=1)
SVM.fit(X_train_norm,Ytrain)
predicted_values =
SVM.predict(X_test_norm) x =
metrics.accuracy_score(Ytest,
predicted_values) acc.append(x)
model.append('SVM')
print("SVM's Accuracy is: ", x)

print(classification_report(Ytest,predicted_v
alues))
```

Logistic Regression:

```
from sklearn.linear_model import LogisticRegression

LogReg =
LogisticRegression(random_state=2)

LogReg.fit(Xtrain,Ytrain)

predicted_values = LogReg.predict(Xtest)

x = metrics.accuracy_score(Ytest,
predicted_values) acc.append(x)
```

model.append('Logistic Regression')
print("Logistic Regression's Accuracy is: ",
x)

print(classification_report(Ytest,predicted_va
lues)) *# Cross validation score (Logistic
Regression)* score =
cross_val_score(LogReg,features,target,cv=5
) score

Saving trained Logistic Regression model:

import pickle
 # Dump the trained Naive Bayes classifier with Pickle
LR_pkl_filename = '../models/LogisticRegression.pkl'
 # Open the file to save as pkl file
LR_Model_pkl = open(DT_pkl_filename,
'wb') pickle.dump(LogReg, LR_Model_pkl)
 # Close the pickle instances
LR_Model_pkl.close()

Random Forest:

from sklearn.ensemble **import** RandomForestClassifier

RF = RandomForestClassifier(n_estimators=20, random_state=0)
RF.fit(Xtrain,Ytrain)

predicted_values = RF.predict(Xtest)

x = metrics.accuracy_score(Ytest,
predicted_values) acc.append(x)
model.append('RF')
print("RF's Accuracy is: ", x)

print(classification_report(Ytest,predicted_v
alues))
*# Cross validation score (Random
Forest)* score =

cross_val_score(RF,features,target,cv=5
) score

Saving trained Random Forest model*:*

import pickle
 # Dump the trained Naive Bayes classifier with Pickle
RF_pkl_filename =
'../models/RandomForest.pkl'
 # Open the file to save as pkl file
RF_Model_pkl = open(RF_pkl_filename,
'wb') pickle**.**dump(RF, RF_Model_pkl)
 # Close the pickle instances
RF_Model_pkl**.**close()

XGBoost:

import xgboost **as** xgb
XB = xgb**.**XGBClassifier()
XB**.**fit(Xtrain,Ytrain)

predicted_values = XB**.**predict(Xtest)

x = metrics**.**accuracy_score(Ytest,
predicted_values) acc**.**append(x)
model**.**append('XGBoost')
print("XGBoost's Accuracy is: ", x)

print(classification_report(Ytest,predicted_v
alues))

Saving trained XGBoost model

import pickle
 # Dump the trained Naive Bayes classifier with Pickle
XB_pkl_filename = '../models/XGBoost.pkl'
 # Open the file to save as pkl file

```
XB_Model_pkl = open(XB_pkl_filename, 'wb')
pickle.dump(XB, XB_Model_pkl)
# Close the pickle instances
XB_Model_pkl.close()
```

Accuracy Comparison:

```
plt.figure(figsize=[10,5],dpi = 100) plt.title('Accuracy Comparison') plt.xlabel('Accuracy') plt.ylabel('Algorithm') sns.barplot(x = acc,y = model,palette='dark') accuracy_models = dict(zip(model, acc)) for k, v in accuracy_models.items():
   print (k, '-->', v)
```

Making a prediction:

```
data = np.array([[104,18, 30, 23.603016, 60.3, 6.7, 140.91]]) prediction = RF.predict(data) print(prediction) data = np.array([[83, 45, 60, 28, 70.3, 7.0, 150.9]])
prediction = RF.predict(data)
print(prediction)
```

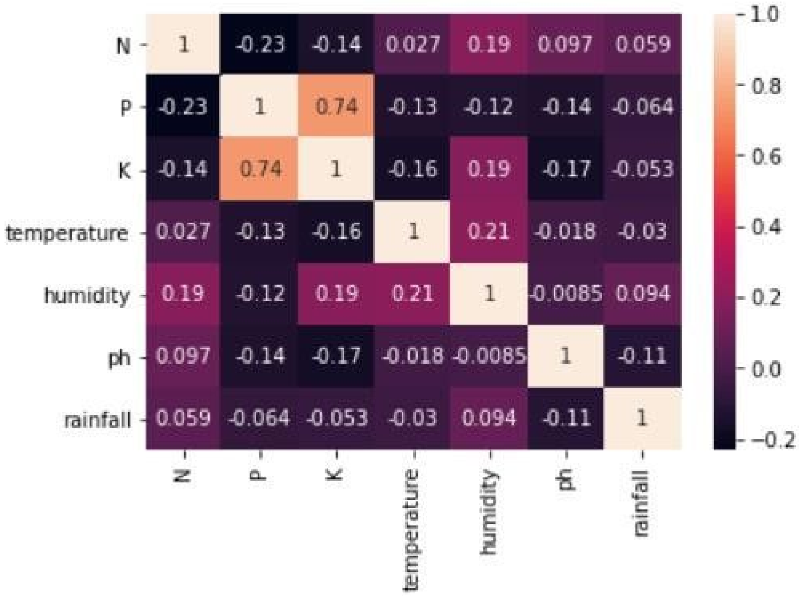
CHAPTER 6

SCREENSHOTS

AND RESULTS

Data collected from data set:

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice



Decision Tree:

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	13
banana	1.00	1.00	1.00	17
blackgram	0.59	1.00	0.74	16
chickpea	1.00	1.00	1.00	21
coconut	0.91	1.00	0.95	21
coffee	1.00	1.00	1.00	22
cotton	1.00	1.00	1.00	20
grapes	1.00	1.00	1.00	18
jute	0.74	0.93	0.83	28
kidneybeans	0.00	0.00	0.00	14
lentil	0.68	1.00	0.81	23
maize	1.00	1.00	1.00	21
mango	1.00	1.00	1.00	26
mothbeans	0.00	0.00	0.00	19
mungbean	1.00	1.00	1.00	24
muskmelon	1.00	1.00	1.00	23
orange	1.00	1.00	1.00	29
papaya	1.00	0.84	0.91	19
pigeonpeas	0.62	1.00	0.77	18
pomegranate	1.00	1.00	1.00	17
rice	1.00	0.62	0.77	16
watermelon	1.00	1.00	1.00	15
accuracy			0.90	440
macro avg	0.84	0.88	0.85	440
weighted avg	0.86	0.90	0.87	440

Gaussian Naive Bayes:

```
Naive Bayes's Accuracy is:  0.990909090909091
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        13
      banana       1.00      1.00      1.00        17
   blackgram       1.00      1.00      1.00        16
    chickpea       1.00      1.00      1.00        21
     coconut       1.00      1.00      1.00        21
      coffee       1.00      1.00      1.00        22
      cotton       1.00      1.00      1.00        20
      grapes       1.00      1.00      1.00        18
        jute       0.88      1.00      0.93        28
 kidneybeans       1.00      1.00      1.00        14
      lentil       1.00      1.00      1.00        23
       maize       1.00      1.00      1.00        21
       mango       1.00      1.00      1.00        26
   mothbeans       1.00      1.00      1.00        19
    mungbean       1.00      1.00      1.00        24
   muskmelon       1.00      1.00      1.00        23
      orange       1.00      1.00      1.00        29
      papaya       1.00      1.00      1.00        19
  pigeonpeas       1.00      1.00      1.00        18
 pomegranate       1.00      1.00      1.00        17
        rice       1.00      0.75      0.86        16
  watermelon       1.00      1.00      1.00        15

    accuracy                           0.99       440
   macro avg       0.99      0.99      0.99       440
weighted avg       0.99      0.99      0.99       440
```

Support Vector Machine (SVM):

SVM's Accuracy is: 0.9795454545454545

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	13
banana	1.00	1.00	1.00	17
blackgram	1.00	1.00	1.00	16
chickpea	1.00	1.00	1.00	21
coconut	1.00	1.00	1.00	21
coffee	1.00	0.95	0.98	22
cotton	0.95	1.00	0.98	20
grapes	1.00	1.00	1.00	18
jute	0.83	0.89	0.86	28
kidneybeans	1.00	1.00	1.00	14
lentil	1.00	1.00	1.00	23
maize	1.00	0.95	0.98	21
mango	1.00	1.00	1.00	26
mothbeans	1.00	1.00	1.00	19
mungbean	1.00	1.00	1.00	24
muskmelon	1.00	1.00	1.00	23
orange	1.00	1.00	1.00	29
papaya	1.00	1.00	1.00	19
pigeonpeas	1.00	1.00	1.00	18
pomegranate	1.00	1.00	1.00	17
rice	0.80	0.75	0.77	16
watermelon	1.00	1.00	1.00	15
accuracy			0.98	440
macro avg	0.98	0.98	0.98	440
weighted avg	0.98	0.98	0.98	440

Logistic Regression:

Logistic Regression's Accuracy is: 0.9522727272727273

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	13
banana	1.00	1.00	1.00	17
blackgram	0.86	0.75	0.80	16
chickpea	1.00	1.00	1.00	21
coconut	1.00	1.00	1.00	21
coffee	1.00	1.00	1.00	22
cotton	0.86	0.90	0.88	20
grapes	1.00	1.00	1.00	18
jute	0.84	0.93	0.88	28
kidneybeans	1.00	1.00	1.00	14
lentil	0.88	1.00	0.94	23
maize	0.90	0.86	0.88	21
mango	0.96	1.00	0.98	26
mothbeans	0.84	0.84	0.84	19
mungbean	1.00	0.96	0.98	24
muskmelon	1.00	1.00	1.00	23
orange	1.00	1.00	1.00	29
papaya	1.00	0.95	0.97	19
pigeonpeas	1.00	1.00	1.00	18
pomegranate	1.00	1.00	1.00	17
rice	0.85	0.69	0.76	16
watermelon	1.00	1.00	1.00	15
accuracy			0.95	440
macro avg	0.95	0.95	0.95	440
weighted avg	0.95	0.95	0.95	440

Random Forest:

```
RF's Accuracy is:  0.990909090909091
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        13
      banana       1.00      1.00      1.00        17
   blackgram       0.94      1.00      0.97        16
    chickpea       1.00      1.00      1.00        21
     coconut       1.00      1.00      1.00        21
      coffee       1.00      1.00      1.00        22
      cotton       1.00      1.00      1.00        20
      grapes       1.00      1.00      1.00        18
        jute       0.90      1.00      0.95        28
 kidneybeans       1.00      1.00      1.00        14
      lentil       1.00      1.00      1.00        23
       maize       1.00      1.00      1.00        21
       mango       1.00      1.00      1.00        26
   mothbeans       1.00      0.95      0.97        19
    mungbean       1.00      1.00      1.00        24
   muskmelon       1.00      1.00      1.00        23
      orange       1.00      1.00      1.00        29
      papaya       1.00      1.00      1.00        19
  pigeonpeas       1.00      1.00      1.00        18
 pomegranate       1.00      1.00      1.00        17
        rice       1.00      0.81      0.90        16
  watermelon       1.00      1.00      1.00        15

    accuracy                           0.99       440
   macro avg       0.99      0.99      0.99       440
weighted avg       0.99      0.99      0.99       440
```

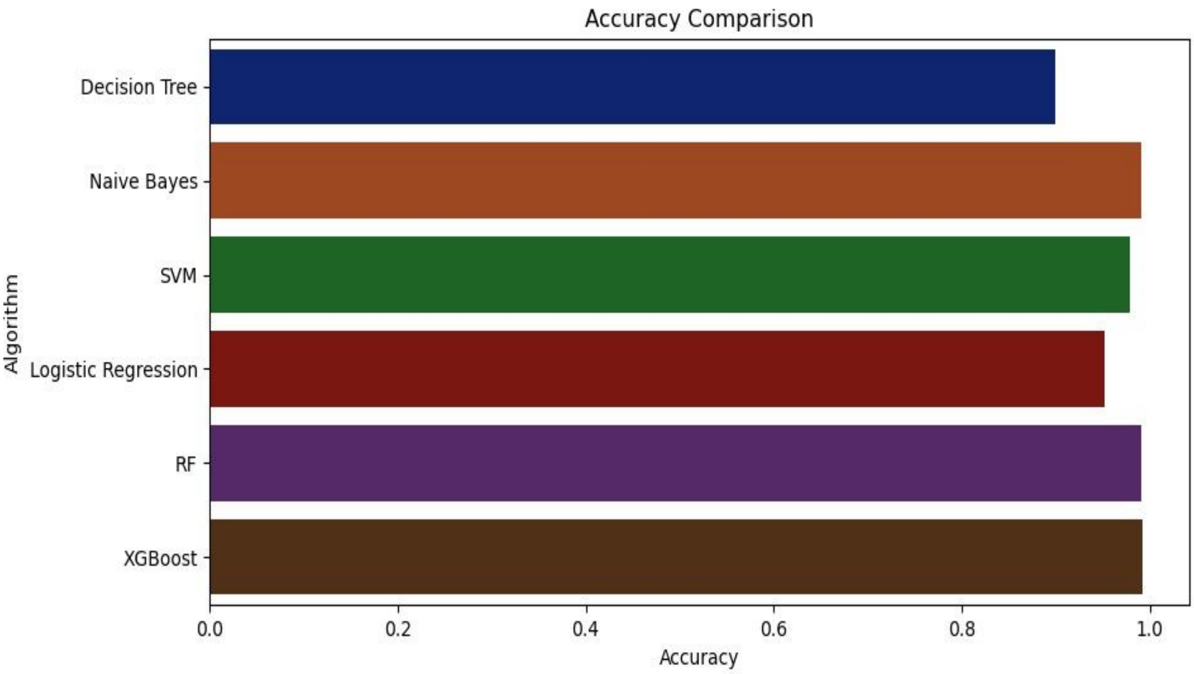
XGBoost:

```
XGBoost's Accuracy is:  0.9931818181818182
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        13
      banana       1.00      1.00      1.00        17
   blackgram       1.00      1.00      1.00        16
    chickpea       1.00      1.00      1.00        21
     coconut       1.00      1.00      1.00        21
      coffee       0.96      1.00      0.98        22
      cotton       1.00      1.00      1.00        20
      grapes       1.00      1.00      1.00        18
        jute       1.00      0.93      0.96        28
 kidneybeans       1.00      1.00      1.00        14
      lentil       0.96      1.00      0.98        23
       maize       1.00      1.00      1.00        21
       mango       1.00      1.00      1.00        26
   mothbeans       1.00      0.95      0.97        19
    mungbean       1.00      1.00      1.00        24
   muskmelon       1.00      1.00      1.00        23
      orange       1.00      1.00      1.00        29
      papaya       1.00      1.00      1.00        19
  pigeonpeas       1.00      1.00      1.00        18
 pomegranate       1.00      1.00      1.00        17
        rice       0.94      1.00      0.97        16
  watermelon       1.00      1.00      1.00        15

    accuracy                           0.99       440
   macro avg       0.99      0.99      0.99       440
weighted avg       0.99      0.99      0.99       440
```

Accuracy Comparison:



Data set:

https://drive.google.com/file/d/19jydtNyKueJEGZ7cXeVmETvmiUwGMJJ s/view?u sp=share_link

CHAPTER 7: CONCLUSION AND FUTURE ENHANCEMENT

The agricultural industry faces various challenges such as lack of effective irrigation systems, weeds, issues with plant monitoring due to crop height and extreme weather conditions. But the performance can be increased with the aid of technology and thus these problems can be solved.

It can be improved with different AI driven techniques like remote sensors for soil moisture content detection and automated irrigation with the help of GPS. The problem faced by farmers was that precision weeding techniques overcome the large number of crops being lost during the weeding process. Not only do these autonomous robots improve efficiency, they also reduce the need for unnecessary pesticides and herbicides. Besides this, farmers can spray pesticides and herbicides effectively in their farms with the aid of drones, and plant monitoring is also no longer a burden.

For starters, shortages of resources and jobs can be understood with the aid of man-made brain power in agribusiness issues. In conventional strategies huge amount of labour was required for getting crop characteristics like plant height, soil texture and content, in this manner manual testing occurred which was tedious. With the assistance of various systems examined, quick and non-damaging high throughput phenotyping would occur with the upside of adaptable and advantageous activity, on request access to information and spatial goals.

REFERENCES

[1] Zhang, X., Davidson, E. A,"Improving Nitrogen and Water Management in Crop Production on a

National Scale", American Geophysical Union, December, 2018.How to Feed the World in 2050 by FAO.

[2] Abhishek D. et al., "Estimates for World Population and Global Food Availability for Global Health", Book chapter, The Role of Functional Food Security in Global Health, 2019, Pages 3-24.Elder M., Hayashi S., "A Regional Perspective on Biofuels in Asia", in Biofuels and Sustainability, Science for Sustainable Societies, Springer, 2018.

[3] Zhang, L., Dabipi, I. K. And Brown, W. L, “Internet of Things Applications for Agriculture". In, Internet of Things A to Z: Technologies and Applications, Q. Hassan (Ed.), 2018.

[4] S. Navulur, A.S.C.S. Sastry, M.N. Giri Prasad,"Agricultural Management through Wireless Sensors and Internet of Things" International Journal of Electrical and Computer Engineering (IJECE), 2017; 7(6) :3492-3499.

[5] E. Sisinni, A. Saifullah, S.Han, U. Jennehag and M.Gidlund, "Industrial Internet ofThings:

Challenges,Opportunities, and Directions," in IEEE Transactions on Industrial Informatics, vol. 14, no. 11, pp. 4724-4734, Nov. 2018.

[6] M. Ayaz, M. Ammad-uddin, I. Baig and e. M. Aggoune, "Wireless Possibilities: A Review," in IEEE Sensors Journal, vol. 18, no. 1, pp. 4-30, 1 Jan.1, 2018.