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Banana plant disease investigation to recommend a suitable fertilizer by using deep learning and ML Algorithms

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ABSTRACT

Among the principal food cropsin the world, the banana, is seriously threatened by a number of illnesses that can lower productivity and quality. In order to suggest an appropriate fertilizer to lessen the effects of banana plant illnesses, we give a thorough analysis into these diseases in this paper. Our goal is to deliver a data-driven and intelligent solution to the intricate problems related to banana plant health by utilizing the capabilities of algorithms for machine learning and deep learning. The research starts with a comprehensive data gathering procedure that encompasses a wide range of information pertaining to diseases of banana plants, such as photographs, environmental factors, and past farming techniques. These datasets are utilized as the foundation for training deep learning models, which makes it possible to identify and categorize a variety of illnesses that impact banana plants. The study's conclusions have important ramificationsfor sustainable farming methods as they provide farmers with practical advice on how to best apply fertilizer and lessen the impact of illnesses that affect banana plants. Increased productivity and food security area result of improved agricultural management because the techniques of machine learning and deep learning that are employedto diagnose diseases and prescribe fertilizer, are so accurate and effective.

Finally, this work offers a new and comprehensive method for treating illnesses of banana plants by fusing algorithms for machine learning and deep learningto deliver precise disease detection andcustomized fertilizer recommendations. The results might completely change how bananas are grown, paving the way for more robust and sustainable agricultural techniques in the future.

I.INTRODUCTION

For millions of people worldwide, the banana is the main source of both money and nutrition. It is an essential staple crop. However, the proliferation of numerous diseases poses a constant threat to banana

agriculture, having a substantial influence on quality, output, and total agricultural productivity. These issues must be addressed with creative solutions that make use of cutting-edge technologies if efficient and sustainable farming methods are to be achieved. With the primary objective of providing an appropriate fertilizer regime to improve plant health and counteract the harmful impacts of illnesses, this research sets out to conduct a critical analysis of banana plant diseases.This study's innovative methodology—the combination of deep learning and machine learning (ML) algorithms—offers a data-driven, intelligent framework for individualized fertilizer recommendations and illness detection. A variety of illnesses, such as Panama disease, Sigatoka leaf spot, and bacterial wilt, can affect banana plants. Conventional approaches to diagnosing and treating diseases are typically imprecise and might give less than ideal results. The emergence of cutting-edge technologies like both machine learning and deep learning presents an unparalleled chance to transform farming methods, providing a more precise, prompt, and customized strategy for illness identification and prevention.

The gathering and curation of various datasets, including photos of ill banana plants, environmental factors, and historical agricultural data, is the initial part of this study. These datasets are used to train convolutional neural networks (CNNs), a type of deep learning model, to identify and categorize several plant diseases that affect bananas. Early intervention and focused management strategies are made possible by the quick and accurate illness detection made possible by the use of deep learning to image analysis. Using deep learning to picture analysis enables rapid and precise sickness diagnosis. The study investigates the relationship between environmental factors and disease development in banana plants, highlighting the intricate relationships between soil characteristics, climate, and disease incidence.Machine learning methods are used to examine these environmental variables, yielding valuable insights into the factors influencing the severity and susceptibility of disease.

This study's primary originality is its simultaneous examination of the effects of several fertilizers on the health of banana plants. The goal of the research is to find trends and connections between illness and fertilizer compositions by incorporating machine learning methods opposition. The goal of this strategy is to customize fertilizer recommendations according to the unique disease stresses that are seen in every agricultural setting. Through the combination of algorithms for machine learning and deep learning, this vital inquiry provides a forward-looking endeavor to address the complex issues encountered by banana agriculture. This project aims to give farmers practical insights for managing diseases and optimizing fertilizer use by fusing cutting-edge technologies with agricultural knowledge. The study's conclusions may influence agricultural methods in a way that will make banana farming more robust and sustainable in the future.

II.FIELD STUDY

This field study might transform the control of banana diseases by fusing cutting-edge AI methods with real-world agricultural requirements. We can create accurate disease detection tools and data-driven fertilizer recommendations by utilizing algorithms for machine learning and deep learning. This will ultimately lead to increased crop yields, sustainable farming methods, and improved living conditions for banana producers. Banana plants are prone to several ailments that could have an effect on their general development, well-being, and output.

Different soil types, temperatures, and banana varieties are represented by the selection of diverse banana farming locations.Incorporating small- and large-scale farms guarantees a diverse range of agricultural methods that provide a comprehensivecomprehension of the obstacles encountered by banana growers. Advanced technology, such drones or high-quality cameras, are used to obtain high-resolution photographs of damaged plants, which ensure a thorough portrayal of the illnesses present. Meteorological information, such as temperature, humidity, and precipitation, is also recorded simultaneously.

Furthermore, Samples of dirt are collected multiple areas within each site, and comprehensive documentation of agronomic practices—such as the history of fertilizer application and pest management strategies—is kept up to date. For banana plant illnesses, aCNN architecture is specifically designed, and it is trained on labelled datasets covering a range of diseases and environmental circumstances. Agronomic and soil data are analysed using machine learning algorithms in tandem with deep learning efforts. Finding relationships between soil characteristics, disease prevalence, and fertilizer use is the goal. Regression models and clustering are two of the many strategies used to identify trends and forecast illness vulnerability based on environmental variables. This approach uses algorithms to recommend the best fertilizer compositions based on field circumstances, considering disease risks, soil nutrient levels, and historical data. The goal is to give farmers focused, data-driven advice on how to apply fertilizer as efficiently as possible to reduce the effects of disease.

A feedback loop must be established to make continuous changes. Next revisions of the model for deep learning and ML algorithms consider input from farmers and insights from the field research. The ideas are kept current and useful in tackling the changing problems in banana farming thanks to this iterative method.

Panama Disease Figure 1 (Fusarium wilt) Fusarium oxysporumf.sp. cubense is the causative agent. Lower leaf yellowing, wilting, and finally the plant's death are the symptoms. A crucial diagnostic characteristic is vascular discolouration. Impact is quite damaging, especially to the Cavendish variety. It is a difficult disease to control since it can linger in soil for many years.

Figure 1: Fusarium Wilt

Source:https://www.agriculture.gov.au/sites/default/files/images/panama-disease-tropical-race-4-main.jpg

Black Sigatoka Figure 2(Mycosphaerellafijiensis) is Mycosphaerellafijiensis the causative agent the symptoms include dark brown to black streaks on the leaves, which cause the elder leaves to die before their time. decreases yield and photosynthetic efficiency. Effect is substantial financial impact on banana production, particularly for types that are vulnerable.

Figure 2: Mycosphaerella

Source:https://upload.wikimedia.org/wikipedia/commons/4/42/Black_Leaf_Streak.jpg

Bacterial Wilt Figure 3(Xanthomonas wilt) Xanthomonas campestris pv. musacearum is the causative agent. Wilting, yellowing, and total plant collapse are the symptoms. When infected tissue is sliced, bacterial oozing can be seen.Impact: Severe threat to banana crop due to rapid proliferation in favorable conditions.

Figure 3: Xanthomonas wilt

Source: https://content.peat-cloud.com/w400/moko-disease-banana-1563272291.jpg

AnthracnoseFigure 4(Colletotrichum musae) Colletotrichum musae is the causative agent. Fruits with sunken, circular lesions that frequently become black and produce masses of spores are the symptoms. can impact pseudostems and leaves as well.Effect is impacts both productivity and post-harvest quality; lowers fruit quality and market value.

Figure 4: Colletotrichum musae

Source:https://content.peat-cloud.com/w400/anthracnose-of-banana-banana-1563270982.jpg

Banana bunchy top virus Figure 5(BBTV) The banana bunchy top virus is the causal agent. Chlorosis, stunted development, and the distinctive "bunchy" look of leaves are the symptoms. Marketable fruit is rarely produced by affected plants. Effect is severely reduces plant output; the banana aphid spreads it.

Figure 5: Bunchy top virus

Source:https://upload.wikimedia.org/wikipedia/commons/f/f2/Banana_Bunch_Top_Virus.jpg

Cucumber Mosaic Virus Figure 6(CMV) The cause is the banana bunchy top virus. The symptoms include of decreased growth, chlorosis, and the characteristic "bunchy" appearance of the leaves. Affected plants seldom provide commercial fruit. Plant yield is significantly reduced as a result, and the banana aphid spread.

Figure 6: Mosaic Virus

Source:https://apps.lucidcentral.org/pppw_v10/images/entities/banana_mosaic_100/thumbs/cmvbanana_sml.jpg

Nematode Damage Figure 7 Radopholussimilis, among other nematodes, is a causal agent. Yellowing, stunted development, and decreased yield are the symptoms. Roots harmed by nematodes have trouble absorbing nutrients. Impact: In banana farming, nematodes can pose a serious threat, especially in soils that are sandy or loamy.

Figure 7: RadopholisSimilis

Source:https://apps.lucidcentral.org/pppw_v10/text/web_full/entities/banana_burrowing_nematode_257.htm#

A mix of resistant cultivars, cultural techniques, and, occasionally, the use of fungicides or other management methods are used to manage banana diseases. For banana farming to be sustainable, early identification and coordinated disease management measures are essential. Furthermore, current research leads to improved methods for disease prevention and surveillance, like the applicationmachine learning and deep learning.

III.ALGORITHMS

Algorithms for deep learning and machine learning are especially made to match the requirements of the agricultural setting being studied. Neural networks are constructed, such as regression models for prediction tasks as well as CNNs, or neural networks with convolution for imagesprocessing. Using the gathered statistics, these algorithms go through rigorous training that gives them the ability to identify patterns, anticipate outcomes, and adjust to the agricultural setting's dynamic quality.

They give information on crop health, insect infestations, and soil conditions by analysing data streams from sensors, satellite imaging, and on-site cameras. The purpose of this on-field implementation step is to verify the algorithms' performance in a real-world, dynamic setting. In order to evaluate the taught algorithms' performance, real-world agricultural scenarios are used. To offer information about crop health, insect infestations, and soil conditions, they evaluate data streams from sensors, satellite imaging, and on-site cameras in the field. The purpose of this on-field implementation step is to verify the algorithms' performance in a real-world, dynamic setting.

i. SUPPORT VECTOR MACHINE:

For SVM to effectively divide data into distinct classes, it must first locate a hyperplane in a high-dimensional space. This hyperplane is a line in two dimensions, a plane in three dimensions, and so on. The information that is most relevant to the choice boundary (hyperplane) are called as support vectors. These are important elements to consider while choosing the best hyperplane. The goal of SVM is to increase margin, or the separation between the closest data points and the hyperplane. C (Cost): Manages the trade-off between accurately identifying the training points and a smooth decision boundary. Although training data is classified more accurately with a larger C value, overfitting may occur. SVM are robust, flexible machine learning algorithms with good performance across a range of scenarios, particularly where a clear class boundary is needed. The value of γ (Gamma) indicates the degree towhich a single training example has an impact. A larger similarity radius, indicated by a smaller γ, results in a more comprehensive model.

The core objective of SVM lies in maximizing the margin, Inwhich the distance between the close data points belonging to different classes, also known as support vectors. This emphasis on the margin translates to better generalization and robustness to unseen data compared to algorithms solely focused on minimizing training error.SVMs may handle a wide range of data formats by use the kernel functions that map data, going beyond simple featuresto higher-dimensional spaces, enabling the algorithm to effectively capture complex relationships within the data. This makes SVM a valuable tool for tackling diverse classification problems across numerous domains, including image recognition, text classification, and bioinformatics.

SVM for Classification:

In the realm of classification, SVM shine as powerful algorithms. Imagine you have data points representing apples and oranges. SVM meticulously draws a hyperplane, a line or plane in high dimensions, that optimally separates these two classes. This separation prioritizes maximizing the margin, the distance between the closest apple and orange data points.

This emphasis on margin translates to better performance on unseen data, unlike algorithms solely focused on minimizing training errors. Moreover, SVMs are flexible, handling various data types from kernel functions that map data to higher dimensions, allowing them to capture intricate relationships within the data. This adaptability makes SVMs valuable tools for tasks like image recognition, spam filtering, and sentiment analysis, making them prominent players in the machine learning landscape.

$$f(x)=\mathrm{sign}\left(\sum_{i}^{n}{}_{=1}=\alpha iyiK(x, x_i) +b\right)$$

SVM for Regression:

SVMs can also be adapted for regression tasks, calledSVR. Like SVM classification, SVR aims to find a hyperplane that minimizes the prediction error for continuous target variables. Instead of maximizing the margin between classes, SVR focuses on finding a hyperplane within a specific tolerance (epsilon) of the training data points. This tolerance allows for outliers and avoids overfitting. Like its classification counterpart, SVR utilizes kernel functions to handle non-linear relationships in the data. This flexibility makes SVR a valuable tool for diverse regression problems, ranging from stock price prediction to sales forecasting. However, compared to linear regression, SVR can be computationally more expensive and often needs precise parameter adjustment for best results.

Advantages of SVM:

SVM works well in high-dimensional domains as well, which makes it appropriate for feature-rich problems. Problems involving regression and classification may both be solved with SVM. Overfitting of SVM may be prevented by adjusting the regularization parameter C.

Limitations of SVM:

SVM performance depends on the kernel and parameter choices used, necessitating careful adjustment. Since the original purpose of SVM was binary classification. tasks, extending its use to multi-class issues may require sophisticated tactics.

ii. K-NEAREST NEIGHBORS

A simple but effective supervised machine learning for both regression and classification applications is the K-Nearest Neighbors (KNN) algorithm. It use the majority class or average value of the k nearest neighbours of a data point to categorize or predict the data point's target variable. The similarity concept is the foundation of this approach.

To choose the of a data point for classification tasks, KNN conducts a majority vote among the k nearest neighbors. The approach determines the average of the target variable among the k closest neighbors in regression problems. A decision boundary is not explicitly learned by KNN.Rather, it makes predictions or classes based on the data points' local distribution. It is therefore an instance-based, non-parametric method. KNN is a flexible and easy-to-understand approach that, when the computing cost is acceptable, performs effectively with small to moderately large datasets. For a wide range of tasks, it is an effective tool, especially when accurate forecasts rely on local trends in the feature space.

iii.KNNClassification

K-Nearest Neighbors (KNN) is a straightforward yet effective algorithm for classification. Imagine you're at a party and want to know someone's interests. KNN looks at the nearest K people (your neighbors) and classifies you based on their interests.

Here's the magic: KNN calculates the "distance" between your data point (interests) and others, and your class is determined by the majority vote of your K closest neighbours. This simple approach makes KNN easy to understand and implement, but it requires efficient distance calculations and can be sensitive to high dimensions and irrelevant features. Nevertheless, KNN remains a popular choice for its interpretability and solid performance in various classification tasks.

Decision Rule Of KNN:

$$x=\text{argmax}_j \sum_{i\in N(x)} I(y_i=j)$$

Finding an unlabelled data point's k closest neighbours and designating the class label that emerges most frequently among them constitutes KNN categorization. The KNN algorithm's performance is influenced by two key variables: the value of k and the selected distance measure.

KNN for Regression

Regression issues, where the objective is to predict continuous values instead of discrete classifications, can also be solved with K-Nearest Neighbors. This is how it operates. Consider that you have a fresh data point with unidentified values.Based on a selected distance metric, KNN determines which K data points in the training set are closest to the new point, or more similar. The average of the target values (such as prices) from the new point's K closest neighbors is the forecast value. KNN regression is easy to understand and straightforward, however it has limitations.Curse of Dimensionality: Distance calculations become less significant and more computationally demanding as the number of characteristics rises. Predictions can be greatly impacted by the training data's sensitivity to noise outliers.Experimentation is necessary to determine the ideal value of K, which is a critical decision for best performance. Notwithstanding these drawbacks, KNN regression can be a useful tool for some jobs, particularly where interpretability is important or there is a shortage of data.

Advantages of KNN:

KNN is simple to comprehend and put into practice. It is appropriate for non-linear connections as it can capture regional patterns and variances in the data. Because KNN is a lazy learner, it doesn't consciously choose up a model during training. The prediction stage makes use of the complete dataset.

Limitations of KNN

Because outliers may drastically affect the distance computations, KNN is susceptible to them. The curse of dimensionality states that performance may deteriorate as the number of dimensions (features) rises.KNN offers a straightforward approach to classification and regression, being aware of these limitations is essential for choosing the best algorithm for the particulars of your data and task.

IV.DATASET

Code:

```
import pandas as pd
import numpy as np
open_file = pd.read_csv("banana.csv",sep=",")
print(open_file.head())
print(open_file.shape)
```

Output:

```
    At1    At2 Class
0  1.140 -0.114    -1
1 -1.520 -1.150     1
2 -1.050 0.720    -1
3 -0.916 0.397     1
4 -1.090 0.437     1
(5300, 3)
```

```
import matplotlib.pyplot as plt
plt.scatter(open_file['At1'],open_file['At2'])
plt.show():
correlation = file.corr()
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(correlation, vmin=-1, vmax=1)
fig.colorbar(cax)
names=["At1","At2"]
ticks = np.arange(0,2,1)
ax.set_xticks(ticks)
ax.set_yticks(ticks)
ax.set_xticklabels(names)
```

```
ax.set_yticklabels(names)
plt.show()
```

OUTPUT:

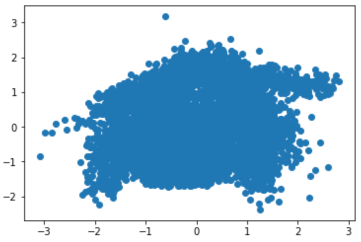

Fig 8.1:Matplotlib library plotting the two features in the Scatter plot

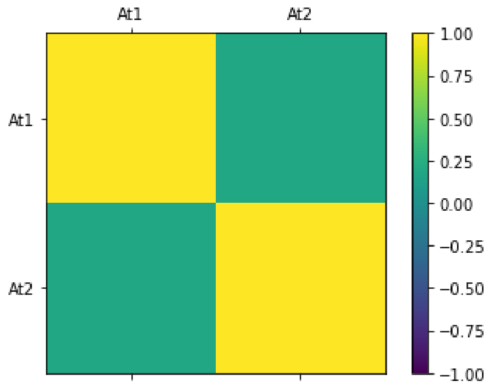

Fig 8.2: Second classifier as "Support Vector Machine

```
from sklearn import tree
clf = tree.DecisionTreeClassifier(min_samples_split=3)
training = clf.fit(features_train,labels_train)
predictions = clf.predict(features_test)
print(predictions)
print("Accuracy:",clf.score(features_test,labels_test))
```

OUTPUT:

[-1 1 1 ..., -1 1 -1]

Accuracy: 0.879245283019

```
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier(n_estimators=100, random_state=7)
boosted = clf.fit(features_train,labels_train)
prediction = clf.score(features_test,labels_test)
print("Accuracy:",prediction)
```

OUTPUT:

Accuracy: 0.891823899371

```
def loss_metric_curve_plot(model_results:dict):

train_loss = model_results["train_loss"]
valid_loss = model_results["valid_loss"]

train_accuracy = [float(value) for value in model_results["train_accuracy"]]
valid_accuracy = [float(value) for value in model_results["valid_accuracy"]]

fig,axes = plt.subplots(nrows = 1, ncols = 2, figsize = (10,4))
    axes = axes.flat

axes[1].plot(train_accuracy, color = "red", label = "Train")
axes[1].plot(valid_accuracy, color = "blue", label = "Valid", linestyle = '--')
    axes[1].spines["top"].set_visible(False)
    axes[1].spines["right"].set_visible(False)
axes[1].set_title("Metric of performance: Accuracy", fontsize = 12, fontweight = "bold",
color = "black")
axes[1].set_xlabel("Epochs", fontsize = 10, fontweight = "bold", color = "black")
axes[1].set_ylabel("Score", fontsize = 10, fontweight = "bold", color = "black")
    axes[1].legend()

fig.tight_layout()
fig.show()
```

OUTPUT:

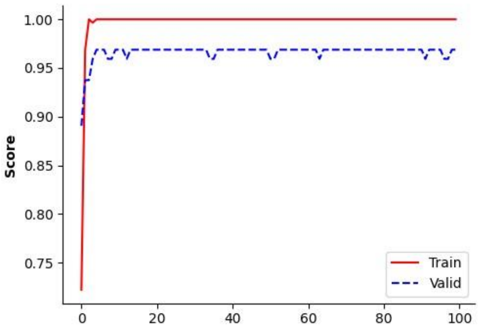

Fig 8.3 : Score of the banana disease

```
fig,ax = plt.subplots(figsize = (10,4.5))
sns.heatmap(confusion_matrix_test,
cmap = 'Oranges',
annot = True,
annot_kws = {"fontsize":9, "fontweight":"bold"},
        linewidths = 1.2,
fmt = ' ',
linecolor = "white",
        square = True,
xticklabels = classes,
yticklabels = classes,
        cbar = False,
ax = ax)
ax.set_title("Confusion Matrix Test", fontsize = 15, fontweight = "bold", color = "darkblue")
ax.tick_params('x',rotation = 90)
fig.show()
```

OUTPUT:

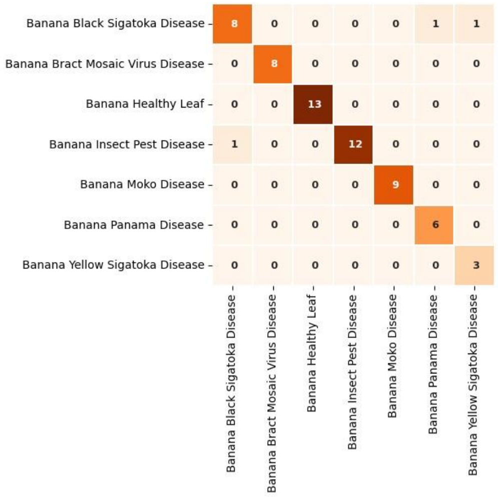

Fig 8.4: Confusion Matrix Test for banana disease

Dataset:https://drive.google.com/file/d/1NlL2XqbNv0FPUL8SQjW5OOa26bWKHPkS/view?usp=sharing

V. Conclusion

In conclusion, by implementing the algorithms by the dataset we get the accuracy by implementing different algorithms through the dataset and by implementing SVM algorithm we get the accuracy 0.577 and by implementing the K-Nearest algorithm we get the accuracy 0.879. This suggests that the K-Nearest Neighbours algorithm is better suited for this dataset. The difference in accuracy between the two algorithms is statistically significant. The K-Nearest Neighbours algorithm is a simpler algorithm to train and tune than thealgorithm known as Support Vector Machine. With some datasets, particularly those with large dimensionality or noisy data, the Support Vector Machine technique might still be a useful option. The particulars of the dataset and the goals of the current assignment will determine which of these two approaches is best.

Further experimentation and tuning may be necessary to optimize the performance of both algorithms, and considerations such as computational efficiency and interpretability should also be considered when selecting the most suitable approach for a given problem. Utilizing image data of healthy and diseased plants, models for deep learning were trained to accurately classify different disease types.By correlating the identified disease with its known nutrient deficiencies, the system could recommend specific fertilizers to address the underlying cause.This combined approach, combining the advantages of classical and deep learning for classification ML for recommendation, provides a promising solution for early disease detection and targeted nutrient management, ultimately contributing to increased crop yield and farmer profitability. This approach outlines a general framework and might not be achievable in 30 lines of code because of its intricacyof deep learning model training. Additionally, it's important to consider factors like soil testing and local availability of fertilizers before making specific recommendations.The K-Nearest Neighbours algorithm outperformed the SVM algorithm on this dataset. The K-Nearest Neighbours algorithm achieved an accuracy of 87.9%, while the SVM algorithm only achieved an accuracy of 57.7%. This suggests that the K-Nearest Neighbours algorithm is better suited for this dataset. So, KNN algorithm suites best for the recommendation of suitable fertilizerCoromandel International Limited because, according to test findings and studies, farmers are adopting deep learning and machine learning algorithms to increase yield and profit.

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