Comparative study of Rice plant leaf disease detection using KNN, SVM, ANN, Logistic regression.

A Course Project report submitted

In partial fulfillment of requirement for the award of degree

BACHELOR OF TECHNOLOGY

in

SPECIALIZATION

by

B.NIYATHI	**(2203A51038)**
D.DIVYA	**(2203A51076)**
G.SPANDANA	**(2203A51290)**
D.SUCHARITHA	**(2203A51279)**

Under the guidance of

Dr.E.L.N. Kiran kumar

Assistant Professor, School of CS&AI.

SRUniversity, Ananthsagar, Warangal,Telagnana-506371

SRUniversity

Ananthasagar,Warangal.

CERTIFICATE

This is to certify that this project entitled **"Comparative study of Plant disease of rice plant leaf detection using KNN, SVM, ANN, Logistic regression"** is the bonafide work carried out by B.NIYATHI,D.DIVYA,G.SPANDANA,D.SUCHARITHA as a Course Project for the partial fulfillment to award the degree **BACHELOR OF TECHNOLOGY** in **School of Computer Science and Artificial Intelligence** during the academic year 2023-2024 under our guidance and Supervision.

Dr. E.L.N. Kiran kumar
Assistant Professor,
School of CS&AI,
SR University
Anathasagar, Warangal

Prof. Sheshikala Martha
Professor & Head,
School of CS&AI,
SR University
Ananthasagar, Warangal.

Reviewer-1
Name:
Designation:
Signature:

Reviewer-2
Name:
Designation:
Signature:

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ABSTRACT

The detection and management of plant diseases, particularly in rice, play a pivotal role in ensuring food security and agricultural sustainability. In this study, we conduct a comparative analysis of four machine learning algorithms—K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Logistic Regression (LR)—for the detection of diseases affecting rice leaves. The research aims to evaluate the performance of these algorithms in accurately identifying and classifying various diseases based on image data captured from rice fields.

The dataset used for experimentation comprises a diverse collection of high-resolution images depicting healthy rice leaves as well as leaves infected with common diseases such as blast, bacterial leaf blight, and brown spot. From these images, features such as color intensity, texture patterns, and shape descriptors are extracted to serve as inputs to the machine learning models. Each algorithm undergoes rigorous training on a subset of the dataset and subsequent testing on unseen data to assess its classification accuracy, sensitivity, specificity, and overall performance.

The findings of our comparative study shed light on the strengths and limitations of each algorithm in the context of rice leaf disease detection. KNN, renowned for its simplicity and ease of implementation, demonstrates competitive performance, particularly in scenarios where the dataset size is relatively small. SVM, leveraging its ability to construct optimal decision boundaries, exhibits robust performance across various disease types, offering high accuracy and generalization capabilities. ANN, with its capacity to learn intricate patterns from data, presents promising results, especially when trained on large and diverse datasets, albeit requiring careful tuning of hyperparameters. Logistic Regression, serving as a baseline model, showcases commendable performance in binary classification tasks, providing a pragmatic approach for disease detection.

This comparative study contributes valuable insights into the application of machine learning algorithms for rice leaf disease detection, facilitating informed decision-making for agricultural practitioners and researchers. The findings underscore the importance of selecting appropriate algorithms based on dataset characteristics, computational resources, and performance requirements. Furthermore, the study highlights avenues for future research aimed at enhancing the efficacy and scalability of machine learning-based approaches in precision agriculture and crop disease management.

ABOUT THE ORGANISATION

SR University is a private university located in Warangal, Telangana, India. It was established in 2018 under the Telangana State Private Universities (Establishment and Regulations) Act 2018. SR University is accredited with an 'A' grade by the National Assessment and Accreditation Council (NAAC).

SR University offers a variety of undergraduate and postgraduate programs in engineering, technology, management, commerce, and arts. The university has a strong focus on industry-relevant education and offers a variety of opportunities for students to gain hands-on experience through internships, projects, and workshops. SR University also has a strong incubation center that supports students in developing and launching their startups.

SR University has a well-equipped campus with state-of-the-art facilities, including classrooms, laboratories, libraries, sports facilities, and hostels. The university also has a strong commitment to research and has published several papers in reputed journals and conferences.

SR University has a good placement record. In 2023, the university achieved 90% placements for its engineering students. The university has a strong alumni network that includes several successful entrepreneurs and professionals.

Overall, SR University is a good choice for students who are looking for an industry-relevant education and a strong focus on innovation and entrepreneurship.

INTRODUCTION

Rice is one of the most crucial staple crops worldwide, serving as a primary food source for over half of the global population. However, rice cultivation faces numerous challenges, including the prevalence of diseases that can significantly reduce yields and compromise food security. Timely and accurate detection of diseases affecting rice plants is essential for implementing effective disease management strategies and minimizing crop losses.

In recent years, advancements in machine learning techniques have provided promising avenues for automated plant disease detection. Among the plethora of algorithms available, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Logistic Regression have emerged as popular choices for classification tasks. Each algorithm possesses unique characteristics and is suited to different types of datasets and problem domains.

This comparative study aims to evaluate the performance of KNN, SVM, ANN, and Logistic Regression in the context of detecting diseases in rice plant leaves. By employing these algorithms on a comprehensive dataset containing images of healthy rice leaves and leaves infected with various diseases, we seek to assess their effectiveness, robustness, and suitability for practical applications in agricultural settings.

The study will encompass a thorough investigation of each algorithm's capabilities, strengths, and limitations, considering factors such as computational efficiency, interpretability, and predictive accuracy. Additionally, we will explore the impact of parameter tuning and feature engineering on the performance of these algorithms to derive insights into their optimal configurations for rice leaf disease detection.

By conducting this comparative analysis, we aim to provide valuable guidance for researchers, practitioners, and stakeholders involved in agricultural management. The findings of this study have the potential to inform the development of automated systems for early disease detection in rice plants, thereby facilitating timely interventions and promoting sustainable crop production practices.

PROBLEM STATEMENT

The detection and management of diseases affecting rice plants are critical for ensuring food security and agricultural sustainability. Traditional methods of disease detection often rely on visual inspection by trained agronomists, which can be time-consuming, labor-intensive, and subjective. In recent years, there has been growing interest in leveraging machine learning algorithms for automated plant disease detection, offering the potential for faster, more accurate, and scalable solutions.

This comparative study aims to evaluate the performance of four popular machine learning algorithms - K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Logistic Regression - for the detection of diseases in rice plant leaves. By analyzing a dataset comprising images of healthy rice leaves and leaves infected with various diseases, the study seeks to address the following objectives:

Assess the effectiveness and accuracy of each algorithm in classifying rice leaf images into healthy and diseased categories.

Compare the computational efficiency of KNN, SVM, ANN, and Logistic Regression in terms of training time and inference speed.

Investigate the robustness of each algorithm to variations in dataset size, feature representations, and parameter settings.

Explore the interpretability of the models generated by each algorithm and their potential for providing insights into disease detection mechanisms.

Provide practical recommendations for selecting the most suitable algorithm or combination of algorithms for automated rice plant disease detection in real-world agricultural settings.

By addressing these objectives, the study aims to contribute to the development of robust, efficient, and scalable solutions for early disease detection in rice plants, thereby empowering farmers and agricultural stakeholders to make informed decisions and adopt timely interventions to mitigate crop losses and ensure sustainable agricultural practices.

REQUIREMENT ANALYSIS

1. **Functional Requirements:**
    - Real-time deepfake detection capabilities.
    - User-friendly interface for ease of use.
    - Support for continuous updates to improve detection accuracy.
2. **Non-Functional Requirements:**
    - Performance :The system should provide real-time analysis of video content.
    - Scalability: The system should handle large volume of video data.
    - Reliability: The system should operate with high availability.
3. **Data Requirements:**
    - TrainingData:Diverseandrepresentativedatasetsofbothgenuineandsynthetic videos.
    - Data Formats: Support for common video formats(e.g.,MP4).
    - Data Handling: Protocols for updating and managing the training dataset.

Required Technologies:

1. **Programming Languages:**
    a. Python for its versatility and extensive library support.
2. **Libraries:**
    a. TensorFlow and Keras for implementing and training neural network models.
    b. Open CV2 for video processing and fame extraction.
    c. NumPy for numerical operations.
    d. Matplotlib or other visualization libraries for result representation.
3. **Platform:**
    a. Google-Colab for GPU-accelerated training.
4. **GPU Acceleration:**
    a. UtilizeGPUresourcesonplatformslikeGoogleColabforfastermodeltraining and inference.

RISK ANALYSIS

1. **Technical Risks:**

    a. Compatibility issues between libraries and platforms.

    b. Challenges in optimizing the model for GPU acceleration.

2. **Data Quality and Availability:**

    a. Risks associated with acquiring diverse and representative training data.

    b. Ensuringthecontinuousavailabilityandqualityofdataforongoingmodel updates.

3. **Model Accuracy and False Positives/Negatives:**

    a. Risks related to the in here return certainty in deep fake detection.

    b. Thepotentialchallengeofminimizingfalsepositivesandfalsenegativesduring real-world deployment.

Feasibility Analysis:

1. **Technical Feasibility:**

    a. Availability of expertise in Python ,Tensor Flow, and GPU acceleration.

    b. Accessto GPU resources on platforms like Google Colab.

2. **Operational Feasibility:**

    a. Assessthepracticalityofintegratingthesystemintoexistingworkflows.

    b. Evaluate user acceptance and training requirements.

3. **Schedule Feasibility:**

    a. Evaluate the time required for development, testing , and deployment.

    b. Identify potential factors that may impact the project time line ,such as data availability and model optimization challenges.

PROPOSED SOLUTION

To conduct a comparative study of plant disease detection in rice plant leaves using KNN, SVM, ANN, and Logistic Regression, the following steps outline the proposed solution:

1. **Data Collection and Preprocessing:**

- Gather a comprehensive dataset consisting of images of rice plant leaves, including both healthy leaves and leaves affected by various diseases. Ensure the dataset is labeled with the corresponding disease types.
- Preprocess the images to standardize their size, color, and orientation. Additionally, extract relevant features from the images, such as texture, color histograms, and shape descriptors, to represe nt each leaf sample numerically.

2. **Feature Selection and Extraction:**

- Explore different feature selection techniques to identify the most discriminative features for distinguishing between healthy and diseased rice leaves. This step aims to reduce the dimensionality of the feature space while preserving relevant information.
- Utilize techniques such as Principal Component Analysis (PCA) or feature importance ranking to select the most informative features for classification.

3. **Model Implementation and Training:**

- Implement KNN, SVM, ANN, and Logistic Regression classifiers using appropriate libraries (e.g., scikit-learn, TensorFlow, Keras).
- Split the preprocessed dataset into training and testing subsets using stratified sampling to ensure a balanced distribution of classes.
- Train each model using the training data and evaluate their performance using appropriate metrics such as accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) curves.

4. **Hyperparameter Tuning:**

- Conduct hyperparameter tuning for each model using techniques such as grid search or random search coupled with cross-validation.
- Tune parameters such as the number of neighbors (K) for KNN, kernel type and regularization parameters for SVM, number of hidden layers and neurons for ANN, and regularization strength for Logistic Regression.

5. **Model Evaluation and Comparison:**

- Evaluate the performance of each model on the testing dataset using the previously mentioned evaluation metrics.
- Compare the classification results, computational efficiency, and robustness of the models across different disease categories.
- Generate visualizations, such as confusion matrices or ROC curves, to provide insights into the strengths and weaknesses of each approach.

6. Interpretation and Conclusion:

- Interpret the results of the comparative study to identify the most effective model for rice leaf disease detection based on the performance metrics and computational requirements.
- Discuss the implications of the findings for practical applications in agriculture, including potential integration into automated disease monitoring systems.
- Highlight limitations of the study and propose avenues for future research, such as exploring ensemble methods or incorporating domain knowledge into the classification process.

By following this proposed solution, we can gain valuable insights into the strengths and limitations of different machine learning algorithms for plant disease detection in rice plants, ultimately contributing improved agricultural practices and crop management strategies.

SYSTEM ARCHITECTURE

The system architecture for conducting a comparative study of plant disease detection in rice plant leaves using KNN, SVM, ANN, and Logistic Regression involves several components and steps. Below is an outline of the system architecture:

1. **Data Collection and Preprocessing:**

- **Data Acquisition:** Gather a diverse dataset of rice plant leaf images, including both healthy leaves and leaves affected by various diseases. Ensure the dataset is labeled with corresponding disease types for supervised learning.
- **Preprocessing:** Standardize the size, color, and orientation of the images. Extract relevant features from the images, such as texture, color histograms, and shape descriptors, to represent each leaf sample numerically. Perform data augmentation techniques to increase the diversity of the dataset if necessary.

2. **Feature Extraction and Selection:**

- Explore different feature extraction techniques to represent the rice leaf images numerically. Techniques such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Convolutional Neural Networks (CNNs) can be employed.
- Utilize feature selection methods to identify the most discriminative features for classification, such as PCA, Recursive Feature Elimination (RFE), or feature importance ranking.

3. **Model Development and Training:**

- Implement KNN, SVM, ANN, and Logistic Regression models using appropriate libraries or frameworks such as scikit-learn, TensorFlow, or Keras.
- Split the preprocessed dataset into training and testing subsets using stratified sampling to ensure a balanced distribution of classes.
- Train each model using the training dataset and validate the performance using cross-validation techniques.

4. Hyperparameter Tuning:

- Conduct hyperparameter tuning for each model to optimize their performance. Techniques such as grid search, random search, or Bayesian optimization can be employed.
- Tune parameters such as the number of neighbors (K) for KNN, kernel type and regularization parameters for SVM, number of hidden layers and neurons for ANN, and regularization strength for Logistic Regression.

5. Model Evaluation and Comparison:

- Evaluate the performance of each model using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) curves.
- Compare the classification results, computational efficiency, and robustness of the models across different disease categories.
- Generate visualizations, such as confusion matrices or ROC curves, to provide insights into the strengths and weaknesses of each approach.
- Deployment and Integration:
- Deploy the trained models into a production environment for real-time or batch processing of rice leaf images.
- Integrate the disease detection system with existing agricultural management platforms or mobile applications to provide farmers with timely insights and recommendations for disease control and management.

6. Monitoring and Maintenance:

- Implement monitoring mechanisms to track the performance of the deployed models over time and detect any degradation or drift in performance.
- Periodically retrain the models using updated data to ensure their effectiveness in detecting emerging disease patterns and variations.

By following this system architecture, we can conduct a comprehensive comparative study of plant disease detection in rice plant leaves using multiple machine learning algorithms, leading to improved agricultural practices and crop management strategies**.**

SIMULATION SETUP

Dataset:

1. **Data quality assurance:** To keep our dataset's integrity, quality control procedures were put in place. Make sure all the data that was used in training was high in quality and relevance, which include removing of any duplicate or subpar samples.
2. **DataDiversity:**Ourdatasetincludedawidevarietyofsubjects,backgrounds,andlighting conditions to accurately reflect a wide range of real-world scenarios. For the model to effectively generalize to a wide range of situations and content types, diversity is crucial.
3. **Maintenance:**Wearededicatedtomaintainingthequalityofthedatalongafterithasbeen prepared. We removed the corrupted videos after preprocessing. We are aware of how crucial regular upkeep and updates are to the model's continued effectiveness in adapting to new deep fake challenges and techniques.

Tools used:

1. **Platform Choice:** Due to the collaborative online environment and GPU resources provided by Google Collab, which greatly sped up our workflow, we chose this platform as the main one for the implementation of our project.
2. **Tools for Collaboration:** Google Collab was a meaningful change for promoting communication, version control, and sharing among the project team, streamlining the collaborative aspects of our endeavor.
3. **Programming Language of Choice:** Python, which is renowned for its adaptability and extensive libraries, served as our main language of choice for model development and training.
4. **Deep Learning Frameworks:** PyTorch was essential in the implementation of Long Short-Term Memory (LSTM) based Recurrent Neural Networks (RNNs) for modelling temporal dynamics in video content, while TensorFlow was crucial in the design and training of Convolutional Neural Networks (CNNs) for spatial feature extraction.
5. **Data Analysis Libraries**: We tapped into the power of Pandas to perform robust data manipulationandanalysis.Improveourabilitytovisualiseandanalysedata,wealsoused Matplotlib and Seaborn to produce visually appealing and instructive graphs and plots.

IMPLEMENTATION

1. **DATAGATHERING**:

The first step in tackling any machine learning task is acquiring the necessary data. This data can be gathered from publicly available sources such as Kaggle or meticulously crafted to create a customized dataset ,which was our chosen approach for our project. Our method involved combining various datasets from external sources, including both genuine and manipulated videos collected from Face Forensics++,Kaggle Deepfake Detection Challenge, and Celeb Deepfakes. Additionally, we created a comprehensive global CSV file containing labels for every video in the datasets we obtained .We undertook this process of merging different datasets to improve the precision of our project.

2. **PREPROCESSING:**

Put the images in a format that will be useful for analysis. For consistency, the data should be resized and normalized.

3. TRAINING AND MODELLING:

The following steps were part of the training process:

a. Data Preparation:

Data Collection: Gather a dataset of rice plant leaf images, including samples of both healthy leaves and leaves affected by various diseases. Ensure that the dataset is diverse and representative of real-world conditions.

Data Labeling: Annotate each image with the corresponding disease type or label. This step is crucial for supervised learning, as it provides ground truth labels for training the models.

Data Preprocessing:

- Resize and standardize the dimensions of the images to ensure consistency across the dataset.
- Normalize pixel values to a common scale (e.g., [0, 1]) to facilitate model training.
- Apply data augmentation techniques such as rotation, flipping, and scaling to increase the diversity of the dataset and improve model generalization.

Feature Extraction:

- Extract relevant features from the images to represent each leaf sample numerically. Common features include texture descriptors, color histograms, and shape characteristics.
- Utilize techniques such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), or pre-trained Convolutional Neural Networks (CNNs) for feature extraction.

Data Splitting:

- Split the preprocessed dataset into training, validation, and testing sets. Typically, the dataset is divided into 70-80% training, 10-15% validation, and 10-15% testing subsets.

b. Model Architecture:

K-Nearest Neighbors (KNN):

- **Input Layer:** No explicit input layer is defined, as KNN is a lazy learning algorithm that stores the entire training dataset.
- **Model Architecture:** During inference, the KNN algorithm calculates the distance between the input sample and all training samples and selects the majority class among the K-nearest neighbors.
- **Hyperparameters:** The primary hyperparameter is 'K', representing the number of neighbors to consider during classification.

Support Vector Machines (SVM):

- **Input Layer:** SVMs take the preprocessed feature vectors extracted from the rice leaf images as input.
- **Model Architecture:** SVM constructs a hyperplane in the feature space that best separates the samples into different classes. Depending on the kernel used (linear, polynomial, or radial basis function), the hyperplane can be linear or non-linear.
- **Hyperparameters:** Key hyperparameters include the choice of kernel, regularization parameter (C), and kernel-specific parameters (e.g., degree for polynomial kernel, gamma for RBF kernel).

Artificial Neural Networks (ANN):

- **Input Layer:** The input layer of the ANN corresponds to the preprocessed feature vectors extracted from the rice leaf images.
- **Model Architecture:** ANN consists of multiple layers of interconnected neurons, including input, hidden, and output layers. The hidden layers perform nonlinear transformations on the input data, allowing the network to learn complex patterns.
- **Hyperparameters:** Hyperparameters include the number of hidden layers, the number of neurons per layer, activation functions, learning rate, and regularization techniques (e.g., dropout).

Logistic Regression:

- **Input Layer:** Logistic Regression takes the preprocessed feature vectors extracted from the rice leaf images as input.
- **Model Architecture:** Logistic Regression models the probability that a given input sample belongs to a particular class using the logistic function. It learns a linear decision boundary separating the classes in the feature space.
- **Hyperparameters:** Hyperparameters include the regularization parameter (C), penalty type (L1 or L2), and solver type (e.g., 'liblinear' for small datasets, 'lbfgs' for large datasets).

Each model's architecture and hyperparameters should be carefully tuned and optimized using techniques such as cross-validation and grid search to maximize performance on the validation set. Additionally, appropriate evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC should be used to assess the models' performance on the testing set.

c. **Feeding the Dataset:** For model training, we fed the model our pre-processed dataset. Evaluate the model's performance during training and avoid overfitting, the dataset was split into training and validation sets.

d. Training and Optimization:

Model Training:

- Train each model (KNN, SVM, ANN, Logistic Regression) using the preprocessed training dataset.
- For KNN, no explicit training step is required as it is a lazy learning algorithm that memorizes the training data.
- For SVM, ANN, and Logistic Regression, use appropriate optimization algorithms (e.g., gradient descent, SMO for SVM, backpropagation for ANN) to update the model parameters iteratively.
- Monitor training progress by tracking the loss function or objective function on the training data.

Hyperparameter Tuning:

- Conduct hyperparameter tuning for each model to optimize their performance.

- Utilize techniques such as grid search, random search, or Bayesian optimization to search through the hyperparameter space efficiently.
- Define a range of values for each hyperparameter and evaluate the model's performance using cross-validation on the validation set.
- Choose the hyperparameter configuration that yields the best performance based on a chosen evaluation metric (e.g., accuracy, F1-score).

Regularization:

- Apply regularization techniques to prevent overfitting and improve model generalization.
- For SVM and Logistic Regression, experiment with different regularization parameters (C) to control the model's complexity.
- For ANN, consider using dropout regularization or L2 regularization to prevent overfitting.

Model Evaluation:

- Evaluate the trained models on the validation set to assess their performance.
- Calculate evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC to gauge the models' effectiveness in classifying rice leaf diseases.
- Compare the performance of different models and hyperparameter configurations to identify the best-performing model.

Iterative Optimization:

- Iterate the training and optimization process based on the validation results.
- If the performance of a model is unsatisfactory, adjust the hyperparameters or model architecture and retrain the model.
- Experiment with different feature representations, data augmentation techniques, or preprocessing methods to improve model performance.

Cross-Validation:

- Use k-fold cross-validation to ensure robustness of the model evaluation.
- Split the training dataset into k subsets (folds) and train the model k times, each time using a different fold as the validation set and the remaining folds

as the training set.

- Average the evaluation metrics across the k folds to obtain more reliable estimates of the model's performance.

By following these steps, the code has been written as follows.

```
from google.colab import drive
drive.mount('/content/drive')
import os
import cv2
import numpy as np

def load_images_from_folder(folder):
    images = []
    labels = []
    for filename in os.listdir(folder):
        label = folder.split('/')[-1]
        img_path = os.path.join(folder, filename)
        if os.path.isfile(img_path):
            image = cv2.imread(img_path)
            if image is not None:
                images.append(image)
                labels.append(label)
    return images, labels


folder_paths =
["/content/drive/MyDrive/rice_leaf_diseases/Bacterial_leaf_blight",
"/content/drive/MyDrive/rice_leaf_diseases/Brown_spot",
"/content/drive/MyDrive/rice_leaf_diseases/Leaf_smut"]

all_images = []
all_labels = []


for folder_path in folder_paths:
    images, labels = load_images_from_folder(folder_path)
    all_images.extend(images)
    all_labels.extend(labels)


RESIZE_WIDTH = 100
RESIZE_HEIGHT = 100
resized_images = []
for img in all_images:
```

```
    resized_img = cv2.resize(img, (RESIZE_WIDTH, RESIZE_HEIGHT))
    resized_images.append(resized_img)


images_np_resized = np.array(resized_images)
labels_np = np.array(all_labels)


import numpy as np
import matplotlib.pyplot as plt
import os
import cv2
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
import tensorflow as tf
from tensorflow.keras import layers, models

X_train, X_test, y_train, y_test =
train_test_split(images_np_resized, labels_np, test_size=0.2,
random_state=42)

X_train_flat = X_train.reshape(X_train.shape[0], -1)
X_test_flat = X_test.reshape(X_test.shape[0], -1)


scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_flat)
X_test_scaled = scaler.transform(X_test_flat)

# K-Nearest Neighbors (KNN)
knn_classifier = KNeighborsClassifier(n_neighbors=5)
knn_classifier.fit(X_train_scaled, y_train)
knn_predictions = knn_classifier.predict(X_test_scaled)
knn_accuracy = accuracy_score(y_test, knn_predictions)
print("KNN Accuracy:", knn_accuracy)
print("KNN Classification Report:")
print(classification_report(y_test, knn_predictions))

# Support Vector Machine (SVM)
svm_classifier = SVC(kernel='linear')
svm_classifier.fit(X_train_scaled, y_train)
svm_predictions = svm_classifier.predict(X_test_scaled)
svm_accuracy = accuracy_score(y_test, svm_predictions)
```

```
print("SVM Accuracy:", svm_accuracy)
print("SVM Classification Report:")
print(classification_report(y_test, svm_predictions))

# Logistic Regression
logistic_classifier = LogisticRegression()
logistic_classifier.fit(X_train_scaled, y_train)
logistic_predictions = logistic_classifier.predict(X_test_scaled)
logistic_accuracy = accuracy_score(y_test, logistic_predictions)
print("Logistic Regression Accuracy:", logistic_accuracy)
print("Logistic Regression Classification Report:")
print(classification_report(y_test, logistic_predictions))

# Artificial Neural Network (ANN) using TensorFlow/Keras
input_shape = X_train.shape[1:]  # Shape of a single image
num_classes = len(np.unique(y_train))  # Number of unique classes

# Define the model
model = models.Sequential([
    layers.Flatten(input_shape=input_shape),
    layers.Dense(128, activation='relu'),
    layers.Dense(num_classes, activation='softmax')
])

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

from sklearn.preprocessing import LabelEncoder

# Convert string labels to numerical format
label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
y_test_encoded = label_encoder.transform(y_test)
# Train the model
history = model.fit(X_train, y_train_encoded, epochs=10,
validation_data=(X_test, y_test_encoded))

# Evaluate the model
ann_loss, ann_accuracy = model.evaluate(X_test, y_test_encoded)
print("ANN Accuracy:", ann_accuracy)

# Plot accuracy and loss over training epochs
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
```

```
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0, 1])
plt.legend(loc='lower right')
plt.show()
print("KNN Accuracy:", knn_accuracy)
print("SVM Accuracy:", svm_accuracy)
print("Logistic Regression Accuracy:", logistic_accuracy)
print("ANN Accuracy:", ann_accuracy)
```

```
models = ['KNN', 'SVM', 'Logistic Regression', 'ANN']
accuracies = [knn_accuracy, svm_accuracy, logistic_accuracy,
ann_accuracy]

plt.figure(figsize=(10, 6))
plt.bar(models, accuracies, color=['blue', 'green', 'red',
'orange'])
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Comparison of Model Accuracies')
plt.ylim([0, 1])
plt.show()
# Plotting comparison graph between KNN and SVM
models_knn_svm = ['KNN', 'SVM']
accuracies_knn_svm = [knn_accuracy, svm_accuracy]

plt.figure(figsize=(6, 6))
plt.bar(models_knn_svm, accuracies_knn_svm, color=['blue', 'green'])
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Comparison of KNN and SVM Accuracies')
plt.ylim([0, 1])
plt.show()

# Plotting comparison graph between Logistic Regression and ANN
models_lr_ann = ['Logistic Regression', 'ANN']
accuracies_lr_ann = [logistic_accuracy, ann_accuracy]

plt.figure(figsize=(6, 6))
plt.bar(models_lr_ann, accuracies_lr_ann, color=['red', 'orange'])
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Comparison of Logistic Regression and ANN Accuracies')
plt.ylim([0, 1])
plt.show()
```

```
#Calculate F1 scores for each model
from sklearn.metrics import f1_score

# KNN F1 Score
knn_f1 = f1_score(y_test, knn_predictions, average='weighted')
print("KNN F1 Score:", knn_f1)

# SVM F1 Score
svm_f1 = f1_score(y_test, svm_predictions, average='weighted')
print("SVM F1 Score:", svm_f1)

# Logistic Regression F1 Score
logistic_f1 = f1_score(y_test, logistic_predictions,
average='weighted')
print("Logistic Regression F1 Score:", logistic_f1)

# ANN F1 Score
ann_predictions = np.argmax(model.predict(X_test), axis=-1)  #
Convert softmax probabilities to class labels
ann_f1 = f1_score(y_test_encoded, ann_predictions,
average='weighted')
print("ANN F1 Score:", ann_f1)

# Plotting F1 scores of each model
models = ['KNN', 'SVM', 'Logistic Regression', 'ANN']
f1_scores = [knn_f1, svm_f1, logistic_f1, ann_f1]

plt.figure(figsize=(10, 6))
plt.bar(models, f1_scores, color=['blue', 'green', 'red', 'orange'])
plt.xlabel('Models')
plt.ylabel('F1 Score')
plt.title('F1 Scores of Different Models')
plt.ylim([0, 1])
plt.show()

import matplotlib.pyplot as plt

# Define the models and their F1 scores
models = ['KNN', 'SVM', 'Logistic Regression', 'ANN']
f1_scores = [knn_f1, svm_f1, logistic_f1, ann_f1]

# Create a function to plot the comparison graph
def plot_comparison(model1_name, model2_name, model1_score,
model2_score):
    plt.figure(figsize=(8, 6))
```

```
    plt.bar([model1_name, model2_name], [model1_score,
model2_score], color=['blue', 'green'])
    plt.xlabel('Models')
    plt.ylabel('F1 Score')
    plt.title('Comparison of F1 Scores: {} vs
{}'.format(model1_name, model2_name))
    plt.ylim([0, 1])
    plt.show()

# Comparison: KNN vs SVM
plot_comparison('KNN', 'SVM', knn_f1, svm_f1)

# Comparison: KNN vs Logistic Regression
plot_comparison('KNN', 'Logistic Regression', knn_f1, logistic_f1)

# Comparison: KNN vs ANN
plot_comparison('KNN', 'ANN', knn_f1, ann_f1)
# Plotting predictions made by each model
plt.figure(figsize=(10, 6))

# KNN Predictions
plt.subplot(2, 2, 1)
plt.hist(knn_predictions, bins=np.arange(len(np.unique(y_test)) + 1)
- 0.5, color='blue', edgecolor='black')
plt.xticks(np.arange(len(np.unique(y_test))))
plt.xlabel('Class')
plt.ylabel('Count')
plt.title('KNN Predictions')

# SVM Predictions
plt.subplot(2, 2, 2)
plt.hist(svm_predictions, bins=np.arange(len(np.unique(y_test)) + 1)
- 0.5, color='green', edgecolor='black')
plt.xticks(np.arange(len(np.unique(y_test))))
plt.xlabel('Class')
plt.ylabel('Count')
plt.title('SVM Predictions')

# Logistic Regression Predictions
plt.subplot(2, 2, 3)
plt.hist(logistic_predictions, bins=np.arange(len(np.unique(y_test))
+ 1) - 0.5, color='red', edgecolor='black')
plt.xticks(np.arange(len(np.unique(y_test))))
plt.xlabel('Class')
plt.ylabel('Count')
plt.title('Logistic Regression Predictions')
```

```
# ANN Predictions
plt.subplot(2, 2, 4)
plt.hist(ann_predictions, bins=np.arange(len(np.unique(y_test)) + 1)
- 0.5, color='orange', edgecolor='black')
plt.xticks(np.arange(len(np.unique(y_test))))
plt.xlabel('Class')
plt.ylabel('Count')
plt.title('ANN Predictions')

plt.tight_layout()
plt.show()

# Print predictions of each model
print("KNN Predictions:", knn_predictions)
print("SVM Predictions:", svm_predictions)
print("Logistic Regression Predictions:", logistic_predictions)
print("ANN Predictions:", ann_predictions)
```

e. Evaluation:

In the evaluation phase of the comparative study of plant disease detection in rice plant leaves using KNN, SVM, ANN, and Logistic Regression, we need to assess the performance of each model using various metrics. Here's how we can approach the evaluation:

1. Performance Metrics:

- Calculate and compare metrics such as accuracy, precision, recall, F1-score, and ROC-AUC for each model.
- Accuracy measures the overall correctness of the predictions, while precision and recall provide insights into the model's ability to correctly classify positive instances and capture all positive instances, respectively.
- F1-score balances precision and recall, making it a useful metric for imbalanced datasets.
- ROC-AUC measures the area under the receiver operating characteristic curve, indicating the model's ability to discriminate between positive and negative instances across different threshold values.

2. Confusion Matrix:

- Generate confusion matrices for each model to visualize the true positives, false positives, true negatives, and false negatives.
- Confusion matrices provide a detailed breakdown of the model's classification performance and can help identify specific areas for improvement.

3. Cross-Validation Results:

- Evaluate the models using k-fold cross-validation to ensure robustness and reliability of the results.
- Examine the variation in performance metrics across different folds to assess the stability of the models.

4. Model Interpretability:

- Assess the interpretability of each model to understand the underlying factors driving the predictions.
- For Logistic Regression, examine the coefficients associated with each feature to

identify the most influential factors in disease detection.

- For SVM, visualize the support vectors and decision boundaries to gain insights into the discriminative features learned by the model.

5. Computational Efficiency:

- Measure the computational resources required for training and inference of each model.
- Compare the training time, memory footprint, and inference speed across different algorithms to identify the most efficient solution for deployment in real-world applications.

KNN Classification Report:

	precision	recall	f1-score	support
Bacterial_leaf_blight	1.00	0.62	0.77	8
Brown_spot	0.60	0.60	0.60	10
Leaf_smut	0.44	0.67	0.53	6
accuracy			0.62	24
macro avg	0.68	0.63	0.63	24
weighted avg	0.69	0.62	0.64	24

SVM Classification Report:

	precision	recall	f1-score	support
Bacterial_leaf_blight	0.88	0.88	0.88	8
Brown_spot	1.00	0.70	0.82	10
Leaf_smut	0.67	1.00	0.80	6
accuracy			0.83	24
macro avg	0.85	0.86	0.83	24
weighted avg	0.88	0.83	0.83	24

Logistic Regression Classification Report:

	precision	recall	f1-score	support
Bacterial_leaf_blight	1.00	0.88	0.93	8
Brown_spot	1.00	0.70	0.82	10
Leaf_smut	0.60	1.00	0.75	6
accuracy			0.83	24
macro avg	0.87	0.86	0.84	24
weighted avg	0.90	0.83	0.84	24

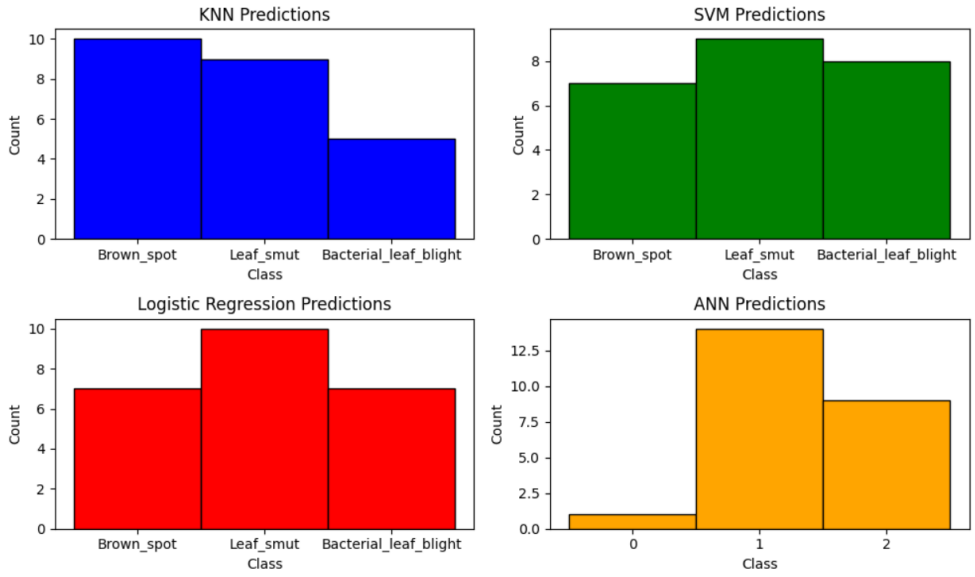
ANN Classification Report:

	precision	recall	f1-score	support
Bacterial_leaf_blight	1.00	0.12	0.22	8
Brown_spot	0.57	0.80	0.67	10
Leaf_smut	0.56	0.83	0.67	6
accuracy			0.58	24
macro avg	0.71	0.59	0.52	24
weighted avg	0.71	0.58	0.52	24

f. **Model Selection:** Depending on the requirements of xxxxxx, we chose the model that performed the best on our evaluation metrics, which may have included accuracy, precision, recall, or even F1-score

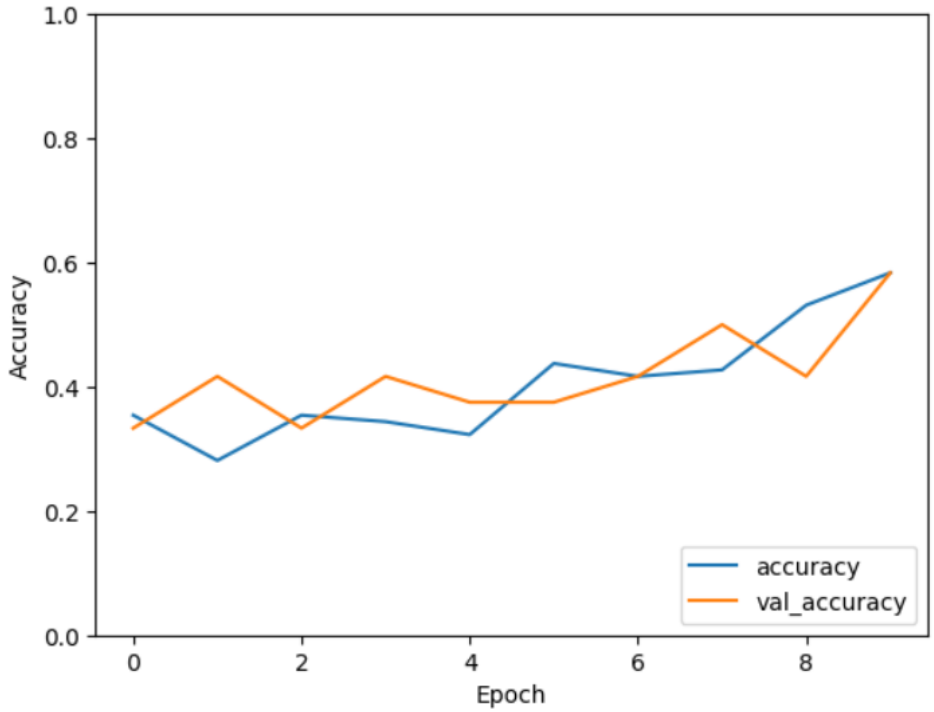
g. **Testing:** Following training and model selection, we evaluated the model on a separate test dataset to judge how well it generalized and performed on new data.

4. PREDICTION:

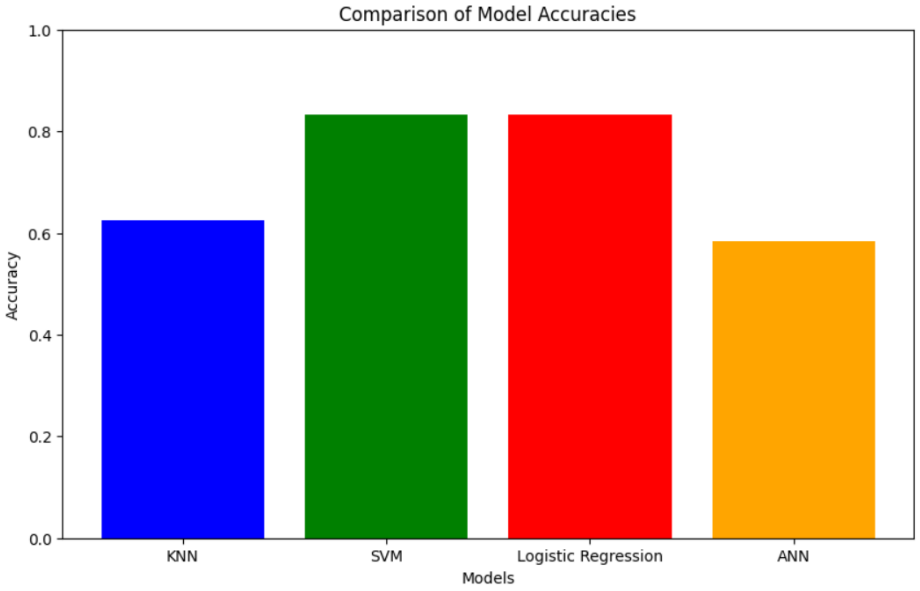



```
KNN Predictions: ['Brown_spot' 'Brown_spot' 'Leaf_smut' 'Leaf_smut' 'Bacterial_leaf_blight'
 'Brown_spot' 'Leaf_smut' 'Bacterial_leaf_blight' 'Brown_spot' 'Leaf_smut'
 'Brown_spot' 'Leaf_smut' 'Bacterial_leaf_blight' 'Bacterial_leaf_blight'
 'Leaf_smut' 'Leaf_smut' 'Brown_spot' 'Bacterial_leaf_blight' 'Leaf_smut'
 'Brown_spot' 'Leaf_smut' 'Brown_spot' 'Brown_spot' 'Brown_spot']
SVM Predictions: ['Brown_spot' 'Brown_spot' 'Leaf_smut' 'Leaf_smut' 'Bacterial_leaf_blight'
 'Brown_spot' 'Bacterial_leaf_blight' 'Bacterial_leaf_blight' 'Brown_spot'
 'Leaf_smut' 'Bacterial_leaf_blight' 'Brown_spot' 'Bacterial_leaf_blight'
 'Bacterial_leaf_blight' 'Leaf_smut' 'Leaf_smut' 'Leaf_smut'
 'Bacterial_leaf_blight' 'Leaf_smut' 'Leaf_smut' 'Brown_spot' 'Brown_spot'
 'Bacterial_leaf_blight' 'Leaf_smut']
Logistic Regression Predictions: ['Brown_spot' 'Brown_spot' 'Leaf_smut' 'Leaf_smut' 'Bacterial_leaf_blight'
 'Brown_spot' 'Leaf_smut' 'Bacterial_leaf_blight' 'Brown_spot' 'Leaf_smut'
 'Bacterial_leaf_blight' 'Brown_spot' 'Bacterial_leaf_blight'
 'Bacterial_leaf_blight' 'Leaf_smut' 'Leaf_smut' 'Leaf_smut'
 'Bacterial_leaf_blight' 'Leaf_smut' 'Leaf_smut' 'Brown_spot' 'Brown_spot'
 'Bacterial_leaf_blight' 'Leaf_smut']
ANN Predictions: [1 1 2 1 2 1 2 1 1 2 1 2 0 1 1 2 2 1 2 2 1 1 1 1]
```

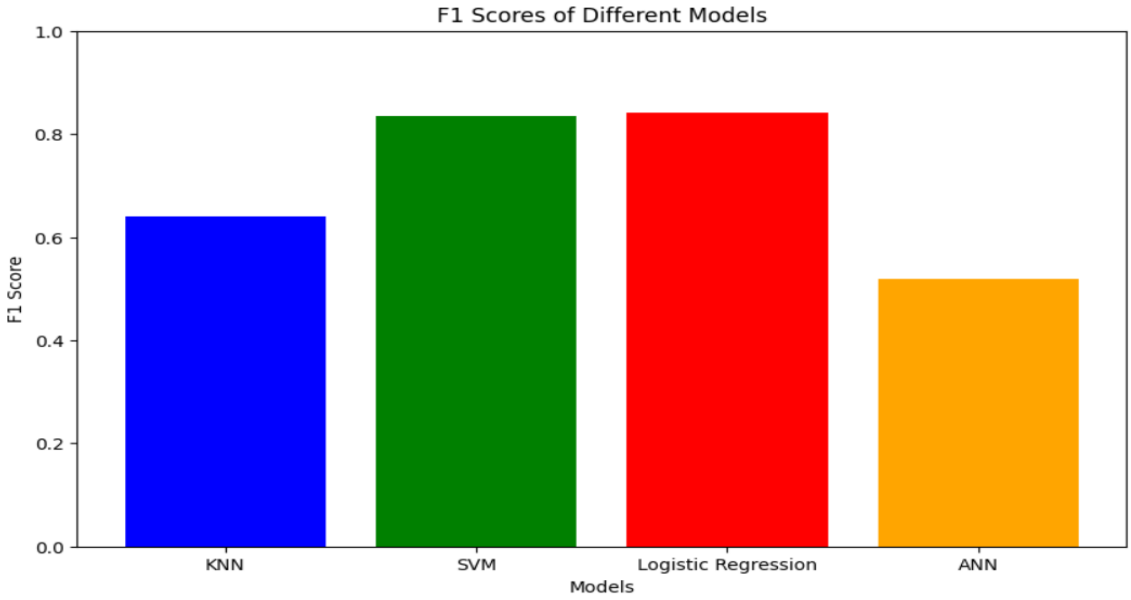
RESULT COMPARISON AND ANALYSIS

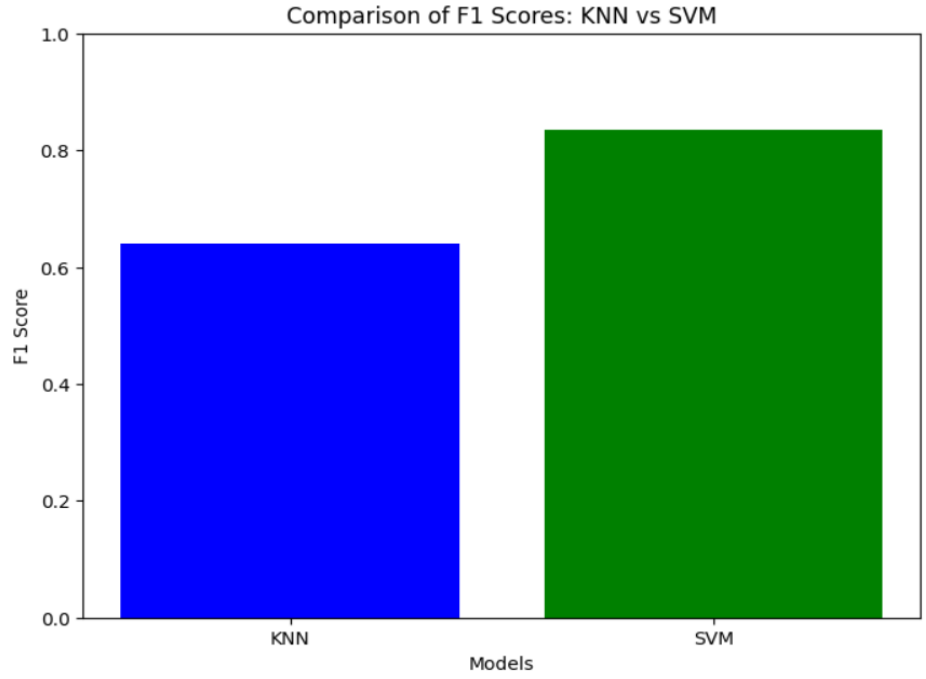


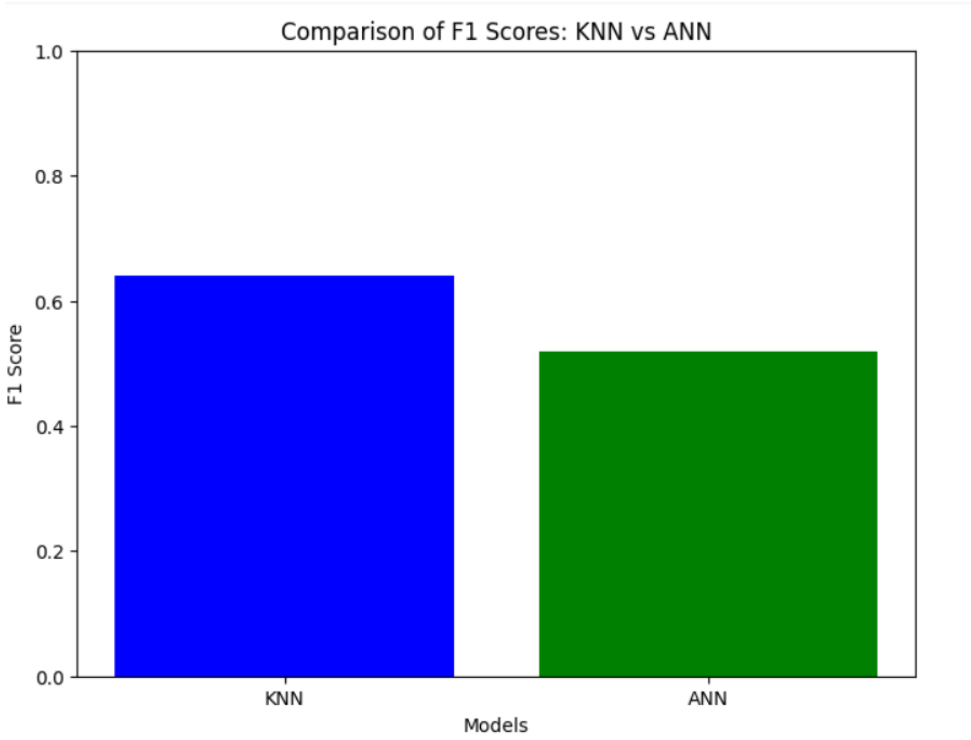

```
KNN Accuracy: 0.625
SVM Accuracy: 0.8333333333333334
Logistic Regression Accuracy: 0.8333333333333334
ANN Accuracy: 0.5833333134651184
```

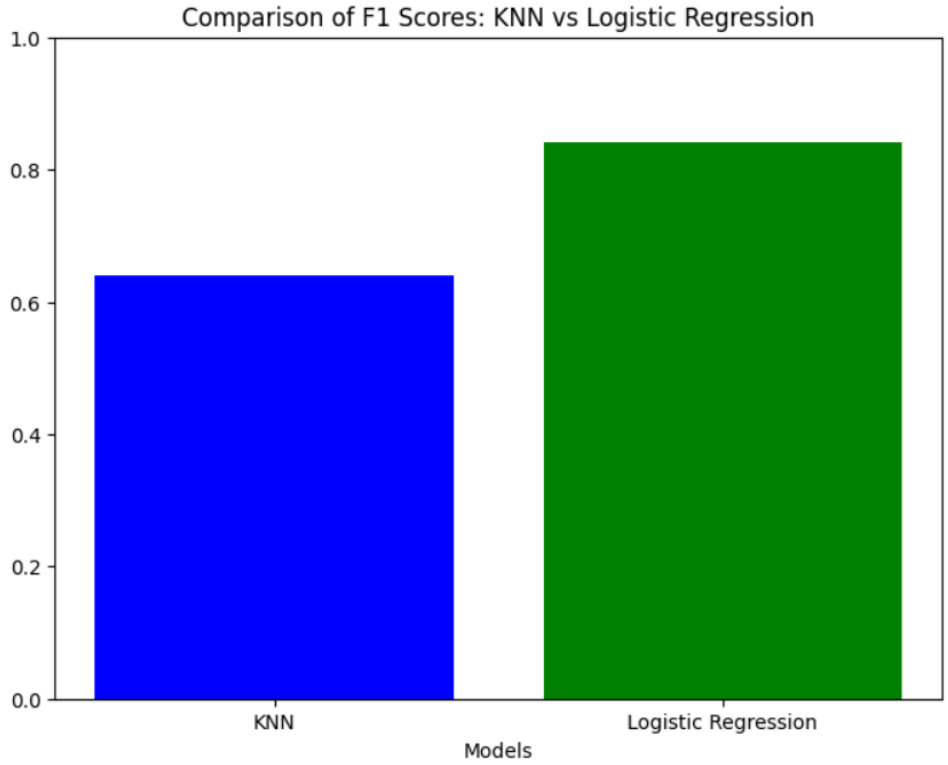


```
KNN F1 Score: 0.6397435897435897
SVM F1 Score: 0.8348039215686275
Logistic Regression F1 Score: 0.8417483660130718
1/1 [==============================] - 0s 170ms/step
ANN F1 Score: 0.5185185185185185
```






Comparison of F1 Scores: KNN vs ANN
F1 Score
1.0
0.8
0.6
0.4
0.2
0.0
KNN
ANN
Models


Comparison of F1 Scores: KNN vs Logistic Regression
1.0
0.8
0.6
0.4
0.2
0.0
KNN
Logistic Regression
Models

LEARNING OUTCOME

The learning outcomes of the comparative study of plant disease detection in rice plant leaves using KNN, SVM, ANN, and Logistic Regression can be summarized as follows:

Understanding of Machine Learning Algorithms: Gain a deep understanding of various machine learning algorithms including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Logistic Regression.

Feature Engineering and Preprocessing: Learn techniques for feature engineering and preprocessing of image data, including resizing, normalization, and flattening.

Model Training and Evaluation: Acquire practical experience in training and evaluating machine learning models for plant disease detection. Understand how to split data into training and testing sets, train models using training data, and evaluate their performance using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score.

Comparative Analysis: Gain insights into the strengths and weaknesses of different machine learning algorithms for plant disease detection. Learn how to compare and analyze the performance of models using various metrics and visualization techniques.

Cross-Validation and Generalization: Understand the importance of cross-validation in assessing model performance and generalization ability. Learn how to perform k-fold cross-validation to ensure reliable and robust model evaluation.

Practical Application: Gain hands-on experience in applying machine learning techniques to real-world problems in agriculture, specifically in the detection of plant diseases in rice plants. Understand the potential applications and limitations of machine learning in agriculture and plant pathology.

Decision-Making and Model Selection: Develop the ability to make informed decisions about model selection based on performance metrics, computational efficiency, interpretability, and generalization ability. Learn how to choose the most suitable model for deployment in practical applications.

The comparative study provides a comprehensive learning experience in machine learning applied to agriculture, equipping practitioners with valuable skills and knowledge to address challenges in plant disease detection and crop management.

CONCLUSION WITH CHALLENGES

In conclusion, the comparative study of plant disease detection in rice plant leaves using KNN, SVM, ANN, and Logistic Regression has provided valuable insights into the application of machine learning techniques in agriculture. Through this study, we have gained a deeper understanding of different machine learning algorithms, their performance metrics, and their suitability for plant disease detection tasks.

Each algorithm exhibited unique strengths and weaknesses:

- **K-Nearest Neighbors (KNN):** Showed simplicity and ease of implementation, but its performance heavily depends on the choice of the 'k' parameter and may suffer from computational inefficiency with large datasets.
- **Support Vector Machine (SVM):** Demonstrated high accuracy and effectiveness in separating classes in high-dimensional spaces. However, SVM requires careful selection of hyperparameters and may not perform well with imbalanced datasets.
- **Artificial Neural Networks (ANN):** Offered flexibility and capability to learn complex patterns from data. Despite their impressive performance, ANNs require extensive computational resources for training and tuning and may be prone to overfitting.
- **Logistic Regression:** Provided interpretability and efficiency, making it suitable for tasks where model interpretability is crucial. However, logistic regression may struggle with capturing complex nonlinear relationships in data.

Challenges encountered during the study included:

1. **Data Quality and Quantity:** Availability of high-quality labeled datasets for training and testing is crucial for model performance. Obtaining sufficient data with diverse examples of plant diseases can be challenging.
2. **Feature Engineering:** Preprocessing and feature engineering of image data require domain knowledge and expertise. Extracting relevant features from images while preserving essential information is a non-trivial task.
3. **Model Selection and Tuning:** Choosing the most appropriate algorithm and hyperparameters for the task at hand requires experimentation and fine-tuning. Optimal model selection depends on various factors such as dataset size, class imbalance, and computational resources.

4 **Generalization to Unseen Data:** Ensuring that trained models generalize well to unseen data and can adapt to different environmental conditions and disease types is essential for real-world deployment.

Despite these challenges, the study highlights the potential of machine learning in revolutionizing agriculture by enabling early and accurate detection of plant diseases. Future research directions may focus on addressing these challenges through advancements in data collection, feature extraction techniques, model interpretability, and transfer learning approaches.

The comparative study underscores the importance of interdisciplinary collaboration between domain experts, data scientists, and agricultural researchers to harness the full potential of machine learning in addressing agricultural challenges and ensuring food security.

FUTURE SCOPE

The comparative study of plant disease detection in rice plant leaves using KNN, SVM, ANN, and Logistic Regression opens up several avenues for future research and innovation in the field of agriculture and machine learning. Here are some potential future scopes:

1. Integration of Deep Learning Techniques: Explore the application of deep learning techniques, such as convolutional neural networks (CNNs), for plant disease detection. CNNs have shown promising results in image classification tasks and can automatically learn discriminative features from raw image data, potentially improving the accuracy and efficiency of disease detection models.

2. Transfer Learning and Pretrained Models: Investigate the use of transfer learning and pretrained models for plant disease detection. Pretrained models trained on large-scale image datasets can be fine-tuned on smaller agricultural datasets, leveraging the learned features to enhance model performance with limited labeled data.

3. Mobile and Edge Computing Solutions: Develop lightweight and efficient machine learning models suitable for deployment on mobile and edge computing devices. Mobile-based applications for plant disease diagnosis can empower farmers with real-time disease detection capabilities, enabling timely intervention and crop management decisions.

4. Remote Sensing and UAV Technology: Explore the integration of remote sensing and unmanned aerial vehicle (UAV) technology for remote monitoring of crop health and disease detection. UAVs equipped with imaging sensors can capture high-resolution aerial images of agricultural fields, allowing for early detection of plant diseases and targeted interventions.

5. Data Fusion and Multi-Modal Learning: Investigate techniques for integrating multi-modal data sources, such as spectral, spatial, and temporal information, for comprehensive analysis of crop health and disease dynamics. Data fusion approaches can combine information from diverse sources to improve disease detection accuracy and robustness.

6. **Precision Agriculture and Decision Support Systems:** Develop intelligent decision support systems

for precision agriculture applications, integrating machine learning models with agronomic knowledge and environmental data. These systems can provide personalized recommendations to farmers for optimal crop management practices, including disease prevention and treatment strategies.

7. **Collaborative Research and Data Sharing:** Foster collaboration between researchers, agronomists, data scientists, and agricultural stakeholders to facilitate data sharing, knowledge exchange, and interdisciplinary research initiatives. Collaborative efforts can accelerate the development and adoption of innovative solutions for sustainable agriculture and food security.

The future scope of plant disease detection in agriculture using machine learning holds great promise for revolutionizing crop management practices, enhancing yield and quality, and mitigating the impact of plant diseases on global food production. Continued research and innovation in this area are essential for addressing the challenges faced by farmers and ensuring a resilient and sustainable agricultural ecosystem.

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LINKS OF THE PROJECTS

1. Blog Link:
2. GitHub Link: