Paddy Disease Classification using Convolutional Neural Networks

Importance of Rice as a Staple Food Crop:

Provides sustenance for over half of the world's population
Grown in over 100 countries, with 90% of the total global production from Asia
Can be a good source of nutrients, including magnesium, phosphorus, manganese, selenium, iron, folic acid, thiamin, and niacin
Can be processed into white or brown rice, with regional and cultural preferences determining market availability and final consumption

Impact of Diseases on Rice Production:

Diseases can significantly reduce rice yield and quality

Common rice diseases include bacterial leaf blight, brown spot, sheath blight, and leaf smut

Diseases can be spread through seeds, soil, water, and air, making them difficult to control

Climate change and environmental factors can exacerbate the spread and severity of rice diseases

Accurate and early disease detection is crucial for effective disease management and prevention

Motivation

behind the project !

- Accurate and early disease detection is essential for effective disease management and prevention
- Early detection can help farmers take appropriate measures to prevent or control the spread of diseases
- Appropriate measures can lead to higher yields and reduced losses
- Farmers can benefit from a user-friendly and accessible tool for rice disease detection

Objectives

1. Develop a CNN-based models for classifying paddy diseases
2. Evaluate the performance of the model in terms of accuracy
3. Provide a user-friendly and accessible tool for rice disease detection for farmers and agricultural experts

Background

types of paddy diseases and their symptoms

- Blast (Pyricularia grisea or P. oryzae)
  - Leaf Blast:
    - Irregular brown or black spots on leaves
    - Spots may have a "bull's eye" appearance
  - Neck Blast:
    - Black or brown lesions on the neck of the rice plant
    - Can cause the plant to break and lodge
  - Nodal Blast:
    - Black or brown lesions on the nodes of the rice plant
    - Can cause the plant to break and lodge
- Bacterial Leaf Blight (Xanthomonas oryzae pv. oryzae)
  - Healthy leaf:
    - Green and healthy appearance
  - Infected leaf:
    - Long, water-soaked lesions that turn yellow or brown
    - Lesions may have a wavy or jagged appearance
- Rice tungro disease (Rice tungro virus or RTSV, RTBV)
  - Healthy leaf:
    - Green and healthy appearance
  - Infected leaf:
    - Yellowing or discoloration of leaves
    - Stunted growth and reduced tillering

types of paddy diseases and their symptoms

- Brown Spot (Helminthosporium oryzae)
  - Small, dark brown or black spots on leaves
  - Spots may have a yellow halo
- Sheath Blight (Rhizoctonia solani)
  - Infected sheath:
    - Gray or tan lesions on the leaf sheath
    - Lesions may have a "frog-eye" appearance
  - Infected leaves:
    - Yellowing or browning of leaves
    - Reduced tillering and plant height
- Sheath Rot (Sarocladium oryzae)
  - Dark brown or black spots on panicle
  - Glumes and grains may be affected
- False Smut (Ustilaginoidea virens)
  - White or greenish-white masses on panicles
  - Masses turn brown or black as they mature
- Grain discoloration (fungal complex)
  - Discoloration of grains
  - May affect grain quality and yield
- Leaf streak (Xanthomonas oryzae pv. oryzicola)
  - Long, narrow lesions on leaves
  - Lesions may be yellow, brown, or orange

THE DATASET

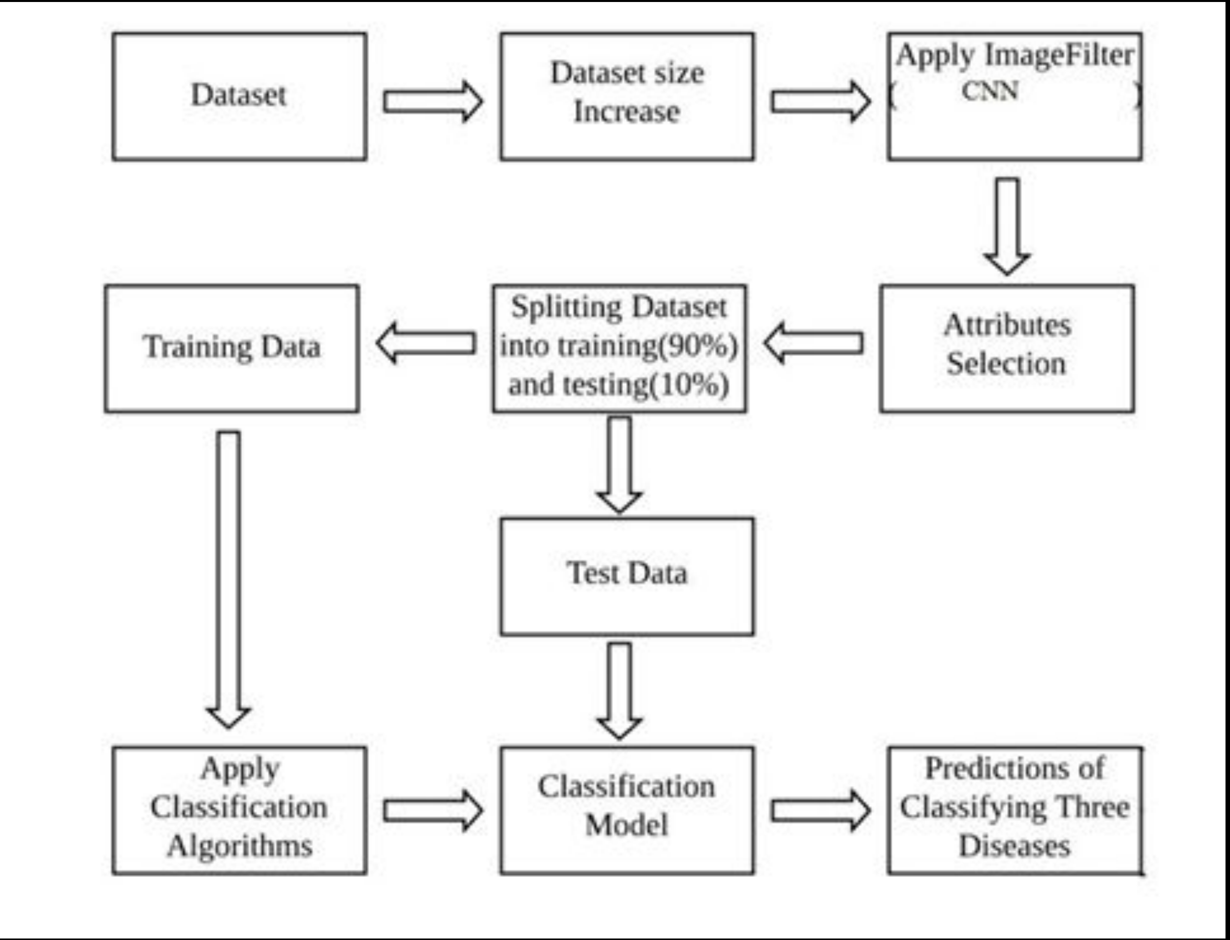
The dataset contains images of 10407 classes of rice diseases, including leaf blast, false smut, neck blast, sheath blight, bacterial stripe disease, and brown spot.

The dataset is split into training, validation, and testing sets with a ratio of 70:15:15, respectively.

The training set contains 8326images, the validation set contains 2081 images, and the testing set contains 3469 images.

The images are resized to 224x224 pixels and normalized using mean and standard deviation values.

The labels of the dataset are one-hot encoded to represent the ten classes of rice diseases.


Dataset
Dataset size Increase
Apply ImageFilter (CNN)
Attributes Selection
Splitting Dataset into training(90%) and testing(10%)
Training Data
Test Data
Apply Classification Algorithms
Classification Model
Predictions of Classifying Three Diseases

Model Architecture 1

```
Input -> Conv2D(64, 3, activation='relu') -> MaxPooling2D() ->
    Conv2D(32, 3, activation='relu') -> MaxPooling2D() ->
    Dropout(0.25) -> Flatten() -> Dense(64, activation='relu') ->
    Dense(num_classes, activation='softmax')
```

Model Architecture 2

```
Input -> Rescaling(1./255) ->
    Conv2D(64, 3, activation='relu') -> MaxPooling2D() ->
    Conv2D(32, 3, activation='relu') -> MaxPooling2D() ->
    Conv2D(32, 3, activation='relu') -> MaxPooling2D() ->
    Conv2D(32, 3, activation='relu') -> MaxPooling2D() ->
    Dropout(0.25) -> Flatten() ->
    Dense(128, activation='relu') ->
    Dense(64, activation='relu') ->
    Dense(num_classes, activation='softmax')
```

Evaluation metrics: Accuracy

Loss function: Categorical Cross-Entropy

Training procedure:

Split the dataset into training, validation, and testing sets.

Preprocess the dataset, normalization, and resizing.

Define the CNN architecture, including the number of layers, filters, and activation functions.

Compile the model with the optimization algorithm, loss function, and evaluation metrics.

Evaluate the model on the validation and testing sets.

experimental results

The proposed CNN model achieved an accuracy of 73% on the testing set.

The precision, recall, and F1-score for each class are as follows:

experimental results

The proposed CNN model outperforms other state-of-the-art methods for paddy disease classification, achieving a higher accuracy and F1-score for each class.

The proposed CNN model can be used as a decision support tool for farmers and agricultural experts to detect and classify paddy diseases in a timely and accurate manner.

Conclusion

Developed a customized CNN architecture for paddy disease classification
Achieved an accuracy of 73% on the testing set

Outperformed other state-of-the-art methods for paddy disease classification

Utilized data augmentation techniques to prevent overfitting and improve model performance

Implemented transfer learning to leverage pre-trained models and improve training time

Provided a user-friendly and accessible User Interface for rice disease detection for farmers and agricultural experts

Contributed to sustainable agriculture by minimizing yield losses and promoting efficient resource utilization

Highlighted the potential of AI-driven technology in fortifying agricultural resilience and ensuring global food security.

Future Work

Improving the model architecture

Collecting more data to increase the diversity and representativeness of the dataset, including images from different geographical locations, growth stages, and environmental conditions

Applying the model to other crops, such as wheat, corn, or soybean, to demonstrate its generalizability and versatility

Collaborating with agricultural experts and organizations to validate the model's performance and promote its adoption in practical settings

Exploring the use of unsupervised or semi-supervised learning techniques to reduce the reliance on labeled data and improve the model's robustness and adaptability.

THANK YOU