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ABSTRACT

The "Plant Diseases with ResNet50 and CNN Model" project aims to develop a deep learning-based solution for the automatic detection and classification of plant diseases using convolutional neural networks (CNNs). The project leverages the ResNet50 architecture, a variant of CNN known for its deep layers and skip connections, to improve the accuracy and robustness of the disease detection model.

The methodology involves compiling the model using the Adam optimizer with a learning rate of 0.0001, categorical cross-entropy loss function, and accuracy as a metric. The model is trained on a dataset consisting of images of diseased and healthy plant leaves, with labels indicating the type of disease or the absence of disease. The training process involves feeding the images through the network, adjusting the weights based on the prediction error, and repeating this process iteratively until the model achieves satisfactory performance.

The evaluation of the model is carried out using the training and validation datasets. Performance metrics such as precision, recall, and F1-score are calculated using scikit-learn's classification report function. Additionally, a confusion matrix is visualized to provide an overview of the model's performance across different classes of diseases.

TABLE OF CONTENTS

ACKNOWLEDGEMENT I

ABSTRACT II

TABLE OF CONTENT III

TABLE OF FIGURES VI

Chapter 1. Introduction 1

1.1 Background 1

1.2 Importance of Plant Disease Detection 2

1.3 Objectives of the Study 4

1.4 Scope of the Study 6

Chapter 2. Challenges, Future directions and Evaluation metrices 10

2.1 Challenges 10

2.1.1 Variability in Symptoms

2.1.2 High Intra-class Variation

2.1.3 Low Inter-class Variation

2.1.4 Data Quality and Quantity

2.2 Future Directions 14

2.2.1 Integration with IoT

2.2.2 Transfer Learning Techniques

2.2.3 Data Augmentation Enhancements

2.3 Evaluation Metrics 17

2.3.1 Accuracy

2.3.2 Precision

2.3.3 Recall

2.3.4 F1-Score

2.3.5 Confusion Matrix

Chapter 3. Methodology 22

3.1 Data Collection 23

3.1.1 Sources of Plant Disease Images

3.1.2 Data Preprocessing Techniques:
3.2 Model Development: 26
3.2.1 CNN Model Configuration
3.2.2 ResNet-50 Model Configuration
3.3 Training the Models: 29
3.3.1 Training Parameters
3.3.2 Training Process
3.4 Model Evaluation 31
3.4.1 Evaluation Metrics
3.4.2 Validation Techniques
Chapter 4. Implementation & Technology Used 34
4.1 Tools and Technologies Used 34
4.1.1 Software Tools
4.1.2 Hardware Requirements Top of Form
4.2 Step-by-Step Implementation: 37
4.2.1 Data Preparation
4.2.1.1 Data Acquisition
4.2.1.2 Data Preprocessing
4.2.2 Model Building
4.2.2.1 Selecting Model Architecture
4.2.2.2 Model Customization
4.2.3 Model Training
4.2.4 Model Testing
Chapter 5. Limitations, Future Research & Applications 45
5.1 Limitations 45
5.1.1 Dataset Limitations
5.1.2 ResNet50 and CNN Models Limitations
5.2 Future Research 47
5.2.1 Exploring Other Architectures

5.2.2 Using Larger and More Diverse Datasets

5.2.3 Combining Image Data with Other Data Types

5.3 Applications 51

5.3.1 Agricultural Monitoring Systems

5.3.2 Mobile Applications for Farmers

5.3.3 Integration with Drones for Large-Scale Monitoring

Chapter 6. Advantages and Disadvantages 55

6.1 Advantages 55

6.1.1 High Accuracy

6.1.2 Automated Diagnosis

6.1.3 Potential for Cost Savings

6.2 Disadvantages 58

6.2.1 Dependence on Large Labelled Datasets

6.2.2 High Computational Cost

6.2.3 Potential for Misclassification

6.2.4 Computational Intensity and Cost

Chapter 7. Results And Discussion 63

7.1 Model Performance 63

7.1.1 Accuracy

7.1.2 Confusion Matrix Analysis

7.2 Comparison of CNN and ResNet-50 67

7.3 Interpretation of Results 69

Conclusion 71

References 72

TABLE OF FIGURES

Fig No.	FIGURE NAME	Page no.
1.1	Importance of plant disease detection.	3
1.2	Workflow of plant disease detection.	7
3.1	Data Preprocessing Techniques.	25
3.2	CNN Model Summary.	28
7.1	Performance of Resnet50.	63
7.2	Performance of CNN.	63
7.3	Accuracy of Resnet50	65
7.4	Accuracy of CNN	66
7.5	plant disease prediction confusion matrix	67
7.6	Comparison between CNN and ResNet-50	67
7.7	Result	70