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Deep Learning

Project Report

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LITERATURE

Research in agricultural development has garnered significant attention for its potential to drive economic growth and promote environmental sustainability. Utilizing advanced techniques such as deep learning and computer vision has become crucial in accelerating crop production. Several studies have capitalized on datasets like PlantVillage, a widely-used resource in agricultural research, to analyze agricultural data and enhance production quality and quantity.

Recent advancements have seen researchers like Afzaal et al. (2021) employing deep neural network models like GoogleNet and VGGNet to classify potato diseases with exceptional accuracy rates. Widiyanto et al. also demonstrated the effectiveness of convolutional neural networks in disease classification using the PlantVillage dataset.

Furthermore, VGG16 is a reliable model for detecting potato leaf diseases, while a novel approach utilizing a restructured residual dense network for tomato leaf disease identification was introduced .

These studies collectively highlight the significant strides made in agricultural research through the integration of advanced technologies, ultimately contributing to sustainable farming practices and improved crop yields

PROBLEM STATEMENT

In the domain of agricultural science, precise and timely detection of plant diseases holds paramount importance in safeguarding crop productivity and yield. Nevertheless, prevailing scholarly inquiries predominantly center on solitary model approaches, thereby overlooking the potential benefits of integrating diverse architectural frameworks .

Lacking a comprehensive approach that combines the strengths of multiple architectures,there exists a gap in the literature for an integrated model that harnesses the capabilities of both EfficientNetB0 and ResNet to improve the accuracy and efficiency of plant disease classification.

PROPOSED METHODOLOGY

Data Collection

Models are trained and assessed on a specific dataset to produce an accurate leaf classification and disease diagnosis algorithm. In this Model we have collected 2152 images from dataset PlantVillage having three classes i.e Potato early blight ,Potato late blight, Healthy Potato are gathered. Early and late blight are two frequent potato diseases, however, we also included healthy leaf as a class in
the total three classes. The dataset has been divided into 95:5 ratios for models train and test purpose that provided.

Below Table represents the exact data volume for each class.

Serial no.	Class	Sample Size	Training samples	Test Samples
1.	Healthy Potato	152	144	6
2.	Early_blight Potato	1000	950	50
3.	Late_blight Potato	1000	950	50

Image Preprocessing

In order to maintain uniformity in pixel values across the dataset and facilitate effective training of the combined EfficientNetB0 and ResNet models, a preprocessing step was implemented to resize all images to a standard dimension of 224x224 pixels.
This step is necessary to extract features from images.

Proposed Network

Model Configuration:

- Both EfficientNetB0 and ResNet50 are loaded with their top (fully connected) layers excluded (include_top=False) to enable further customization.
- ImageNet weights are utilized for initialization (weights='imagenet'), leveraging pre-trained weights learned from a vast dataset for feature extraction.

Model Input Layer:

- The input shape of the images is defined as (224, 224, 3), indicating images with dimensions of 224 pixels in height and width and 3 color channels (RGB).
- An input layer is instantiated with the specified input shape, serving as the entry point for the model.

Feature Extraction:

- The input images are passed through both EfficientNetB0 and ResNet50 models to extract high-level features. This is achieved by calling the models with the input layer (inputs), while ensuring they are in training mode (training=True)

Global Average Pooling:

- Global average pooling layers are applied to the feature maps extracted by each model. This operation calculates the average value of each feature map across its spatial dimensions, reducing the spatial dimensions to 1x1 while retaining important information.

Concatenation:

- The output features from both global average pooling layers are concatenated along axis 1 to create a unified feature representation. This allows for the combination of feature representations learned by both models.

Dense Layers:

- The concatenated feature representation is fed into a dense layer consisting of 1028 neurons with ReLU activation function. This layer facilitates the learning of complex patterns and relationships within the extracted features.

Output Layer:

- Finally, an output layer with softmax activation function is added to perform multi-class classification. In this case, the model predicts one of three classes representing different types of plant diseases.

Model Compilation:

- The model is compiled with the Adam optimizer, categorical cross-entropy loss function, and accuracy metric, setting it up for training.

RESULT

Our model achieved a commendable accuracy of 85% and a loss of 0.3. These performance indicate the effectiveness of the hybrid deep learning approach, combining the features extracted by EfficientNetB0 and ResNet50 architectures, in accurately classifying plant diseases. This level of accuracy and minimal loss underscores the robustness and efficacy of the model in handling the complexities inherent in plant disease classification tasks.