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SECTION: BS Data Science

LAB: AI

PROJECT NAME: PLANTS DISEASES

DATASET NAME: WHEAT DISEASES

PAPER NAME: Deep Learning in wheat diseases classification: A systematic review

Q1: What limitation or gap in existing CNN methods does this paper address?

Ans: No public wheat-disease datasets (mostly private). Imbalance focus limited use to advanced DL/hybrid methods. Lack of real-field images and practical evaluation.

Q2: What are the major strengths of the proposed method?

Ans: Strong systematic review Methods (multi-database search + quality scoring). Highlights best DL techniques used in studies (segmentation, preprocessing). Shows DL models outperform classical methods.

Q3: Which activation functions and loss functions are used in the proposed model?

Ans: Paper is a review No single model proposed. So, activation and loss functions are Not specified.

Q4: What CNN architectures or algorithms were used for comparison/evaluation?

Ans: AlexNet, GoogleNet, VGG16/19, ResNet, DenseNet, Overfeat, VGG-FCN, Mask R-CNN. Also, classical ML baselines: SVM Random Forest.

Q5: What dataset was used, and what are its characteristics?

Ans: Mostly private datasets, not publicly available. Image types RGB (most studies) some HIS/MSI. Largest dataset reported (83,260) images. Train/test splits & resolutions vary and are not consistently reported.

SUMMARY: Most of the research in wheat disease detection suffers from a lack of public datasets; most of the data is private and usually imbalanced, which narrows the usage of simple models and pushes the researcher towards using advanced deep learning or hybrid methods. Real-field images and practical evaluation are lacking. The paper does contribute to a strong systematic review by using multi-database searching and quality scoring. It highlights the best deep-learning techniques used across studies, including segmentation and preprocessing approaches. From the results, it is easy to tell that the DL models usually outperform classical methods. Since it is a review paper, it does not propose a new model, and therefore no activation or loss functions can be specified. Used models include AlexNet, GoogleNet, VGG16/19, ResNet, DenseNet, Overfeat, VGG-FCN, and Mask R-CNN, besides the classical baselines such as SVM and Random Forest. Most of the datasets are private, and the images are mainly RGB; the largest dataset contains 83,260 images. However, the train/test splits and image resolutions were not consistently reported.

2ND PAPER

PAPER NAME: Real-Time Plant Disease Dataset Development and Detection of Plant Disease Using Deep Learning

Q1: What limitation or gap in existing CNN methods does this paper address?

Ans: Existing CNN work lacks large real-life datasets most images are lab-controlled simple backgrounds limited disease stage weak generalization.

Q2: What are the major strengths of the proposed method?

Ans: Creates real-life, multi-stage datasets + strong preprocessing + augmentation + fine-tuning 8 CNNs + new MRW-CNN with high accuracy.

Q3: Which activation functions and loss functions are used in the proposed model?

Ans: Use ReLU in conv layers, Softmax in output trained with SGD loss implied as categorical cross-entropy.

Q4: What CNN architectures or algorithms were used for comparison/evaluation?

Ans: VGG16, ResNet50/101, MobileNet, MobileNetV2, InceptionV3, InceptionResNetV2, Xception + proposed MRW-CNN.

Q5: What dataset was used, and what are its characteristics?

Ans: Three new datasets (rice, wheat, maize), each with 5 classes, real-life + complex backgrounds, 100 images/class 25k with augmentation, 224 ×224 size 80/10/10 split.

Summary: The previous works related to CNN normally suffer from small, lab-controlled datasets with simple backgrounds and limited disease stages; this weakens real-life generalization. This paper solves this issue by creating three real-life, multi-stage plant-disease datasets of rice, wheat, and maize, each having 5 classes with complex backgrounds, expanded to 25k images through augmentation and resized to 224×224 with an 80/10/10 split. Strong preprocessing and data augmentation are used, and fine-tuning of eight CNN models such as VGG16, ResNet50/101, MobileNet, MobileNetV2, InceptionV3, InceptionResNetV2, Xception, plus new MRW-CNN are considered. Among these, ReLU is applied in convolution layers while Softmax is used at the output. Training is done using SGD with categorical cross-entropy loss.

3RD PAPER

Paper Name: Analysis of Few-Shot Techniques for Fungal Plant Disease Classification and Evaluation of Clustering Capabilities Over Real Datasets

Q1: What limitation or gap in existing CNN methods does this paper address?

Ans: The paper addresses the limitations of traditional CNNs when very few labeled images are available. Deep models normally require large datasets, so their performance drops in few-shot, real-field conditions with variables lighting, backgrounds, early-stages diseases. Metric learning is proposed to overcome this small-data gap.

Q2: What are the major strengths of the proposed method?

Ans: Uses ResNet-50 + triplet loss to learn strong embeddings with very little data, supported by data augmentation and k-NN for simple, robust evaluation.

Q3: Which activation functions and loss functions are used in the proposed model?

Ans: Activation ReLU (Standard in ResNet-50 Layers). Loss Functions Triplet Loss, Categorical cross-entropy.

Q4: What CNN architectures or algorithms were used for comparison/evaluation?

Ans: The study compares: ResNet-50 + categorical cross-entropy (traditional CNN baseline) versus. ResNet-50 Siamese network + Triplet loss(proposed) A k-NN classifier is used on learned embedding to evaluate representation quality.

Q5: What dataset was used, and what are its characteristics?

Ans: The dataset contains 121,955 real-field RGB images collected from BASF trials (2014–2019). It covers 17 fungal disease classes across five crops (wheat, barley, rice, corn, rapeseed). Images come from smartphones in natural field conditions. Multi-disease samples were removed, and images were resized to 224×224. Experiments used an 80/10/10 split and varied training sizes (4–2000 images per class) to test few-shot behavior.

Summary: The paper addresses the key limitation of traditional CNNs in real-field few-shot settings, where models struggle due to only a few labeled images and heavy variations in lighting, background, and early disease symptoms. To handle this, the authors apply metric learning using a Siamese ResNet-50 with triplet loss to learn more discriminative embeddings. This is supported by data augmentation and evaluated through a simple k-NN classifier. ReLU is used as the activation function, triplet loss as the main loss function, and categorical cross-entropy as the baseline loss function. The approach was compared with the standard ResNet-50, which was trained using cross-entropy. Experiments were done on the dataset from BASF, consisting of 121,955 real-field smartphone images, representing 17 fungal diseases across five crops, resized to 224×224, with an 80/10/10 split and different training sizes of 4–2000 images per class to investigate the performance in the few-shot setting.