**ABSTRACT (Multi-Class Classification of Plant Leaf Diseases**

**Using Feature Fusion of Deep Convolutional**

**Neural Network and Local Binary Pattern)**

Plant diseases are one of the primary causes of decreased agricultural production quality and quantity. With ongoing changes in plant structure and cultivation techniques, new diseases are constantly arising on plant leaves. Thus, accurate classification and detection of plant leaf diseases in their early stages will limit the spread of the infection and support the healthy development of plant production. This work proposes a novel lightweight deep convolutional neural network (CNN) model for obtaining high-level hidden feature representations. The deep features are then fused with traditional handcrafted local binary pattern (LBP) features to capture local texture information in plant leaf images. The proposed model is trained and tested on three publicly available datasets (Apple Leaf, Tomato Leaf, and Grape Leaf).

**I. INTRODUCTION**

One of the most critical areas of precision agriculture research is detecting diseases in plant leaves via image analysis. The traditional method of recording the severity of plant diseases is based on the visual examination of plant tissues by trained experts [1]. Expert systems in cultivation and management have become widely used due to the widespread adoption of digital cameras and the advancement of information technology in agriculture, considerably increasing plant production capacity [2]. The most common techniques are the K-nearest neighbors (K-NN), logistic regression, decision tree, support vector machine (SVM) [3], and CNN. These techniques are used with different image pre-processing techniques to promote the extraction of features.decision trees possess certain limitations such as overlapping nodes and overfitting of data [5].SVM is a common supervised learning model, which can be associated with learning algorithms for classification and In the latest decade, SVMs have been widely used in image and text classification [6].The previous machine detection approaches typically use traditional image processing techniques, such as noise removal, morphological operations, and image enhancement, for pre-processing diseased plant leaf images. Afterward, handcrafted feature extraction approaches capture low-level information about the leaves, such as color, shape, and texture.Sharif et al. [7] suggested a texture-feature-based method to identify diseases of citrus fruit plants. They used a hybrid feature selection method based on principal components and feature statistics analysisPatil et al. [8] presented a content-based image retrieval system that uses leaf color, shape, and texture features to identify diseased soybean leaves.Recently, deep learning architectures have been used effectively for object identification, classification, and object segmentation tasks.CNN approaches have been the most common for deep learning tasks.Although the basic CNN architectures, such as AlexNet [26], VGGNet [27], GoogLeNet [28], DenseNet [29], and ResNet [30], have been widely used in plant diseases classification, these architectures are limited by many drawbacks, including the need for many parameters and a slow calculation speed.Although deep learning methods have been proven to be quite competent in displaying high-level and low-level features, they are less consistent in describing local spatial characteristics [31]. Consequently, we propose fusing the handcrafted and deep features better to capture the characteristics of the plant leaf images We could summarize the main contributions of this paper in the following points:

1) The proposed DCNN model significantly reduces the training parameters and iteration times compared to the common transfer learning models such as AlexNet, GoogleNet, and VGG16.

2) An integrated model was developed by concatenating deep features and traditional handcrafted features (LBP). This model effectively captures the local spatial texture information found in images of plant leaves.

3) The proposed model was trained and achieved a high accuracy rate using different plant leaf disease datasets.

**III. EXPERIMENTAL RESULTS AND DISCUSSION**

Tensorflow and Keras frameworks implemented the proposed method and different transfer learning CNN models. A free cloud service from Google, Collaboratory (or Colab) per forms the training and testing processes. The hyper-training parameters are standardized for the proposed and reviewed transfer learning models. The data were divided into training, validation, and testing

**IV. CONCLUSION**

Accurate, with few parameters, and high calculation speed CNN model is developed. Furthermore, a feature-fusion based method for classifying plant leaf diseases is proposed. The proposed method enables deep features to be fused with handcrafted features extracted by LBP. The proposed model used three public PlantVillage datasets (Apple Leaf, Tomato Leaf, and Grape Leaf datasets) for the training and testing.

Summary

(1) The research paper aims to classify plant leaf diseases using a hybrid approach of deep learning and traditional image processing techniques. The paper surveys the current methods and their drawbacks, such as the reliance on expert inspection, the use of low-level features, and the high computational demand of deep learning models. The paper presents a new deep convolutional neural network (DCNN) model that learns high-level features from plant leaf images. The paper also employs local binary pattern (LBP) features to capture the local texture information of the leaves. The paper combines the deep and handcrafted features to form an integrated model that can better represent the plant leaf images. The paper tests the proposed model on three publicly available datasets of apple, tomato, and grape leaves, and demonstrates that it surpasses the existing methods in terms of accuracy and efficiency. The paper summarizes the main contributions and suggests future work.

(2) The research paper proposes a novel method for classifying plant leaf diseases using a combination of deep learning and traditional image processing techniques. The paper first reviews the existing methods and their limitations, such as the need for expert examination, the use of handcrafted features, and the high computational cost of deep learning models. The paper then introduces a new deep convolutional neural network (DCNN) model that extracts high-level features from plant leaf images. The paper also uses local binary pattern (LBP) features to capture the local texture information of the leaves. The paper fuses the deep and handcrafted features to create an integrated model that can better describe the characteristics of the plant leaf images. The paper evaluates the proposed model on three publicly available datasets of apple, tomato, and grape leaves, and shows that it outperforms the existing methods in terms of accuracy and efficiency. The paper concludes by highlighting the main contributions and suggesting future work.

(3) The research paper develops a novel method for classifying plant leaf diseases using a fusion of deep learning and traditional image processing techniques. The paper discusses the existing methods and their challenges, such as the dependence on expert evaluation, the use of handcrafted features, and the high computational requirement of deep learning models. The paper proposes a new deep convolutional neural network (DCNN) model that obtains high-level features from plant leaf images. The paper also utilizes local binary pattern (LBP) features to capture the local texture information of the leaves. The paper merges the deep and handcrafted features to create an integrated model that can better characterize the plant leaf images. The paper assesses the proposed model on three publicly available datasets of apple, tomato, and grape leaves, and shows that it exceeds the existing methods in terms of accuracy and efficiency. The paper concludes by emphasizing the main contributions and suggesting future work.

**ABSTRACT (Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease)**

Fungal diseases not only influence the economic importance of the plants and its products but also abate their ecological prominence. Mango trees, specifically the fruits and the leaves, are highly affected by the fungal disease named Anthracnose. The main aim of this paper is to develop an appropriate and effective method for diagnosis of the disease and its symptoms, therefore espousing a suitable system for an early and cost-effective solution of this problem

I. INTRODUCTION

Fungal diseases are very common in plant leaves. The diseases in the plants are caused for dropping the quality and the quantity of the agriculture production [1]. The plant diseases affect the quality of the leaves, fruits, stem, vegetables, and their products. This heavily impacts on the productivity and thus reflects on the costReport of Food and Agricultural Organization (FAO) estimated that the world population will reach to 9.1 billion by 2050, thus requiring about 70% growth in the food production for a steady supply [2]

The key factors that affect the plants and its products are classified into two categories 1. Diseases 2. Disorder.The conventional means of disease management implicate farmers and the plant pathologists. The diagnosis and use of the pesticide are more often done in the fifields. This process is time-consuming, challenging, and most of the time results in incorrect diagnosis with unsuitable exercise of the pesticides [4].With the advent of Computer Vision (CV), Machine Learning (ML), and Artificial Intelligence (AI) technologies, progress have been achieved in developing automated models empowering, accurate and timely identification of the plant leaves disease the MCNN based ternary classifification model is trained and tested for the detection of the Mango leaves diseased considering following major points:

1. By automatic and an early diagnosis of a disease and its severity, effective, and timely treatment can be taken in advance.

2. This can also assist in identifying the nature and life cycle of the disease, thus helping to learn vulnerability among them.

3. Therefore this work proposes a deep learning model named MCNN for the classifification of leaves infected by the Anthracnose disease.

4. For this work, real conditions, healthy and infected leaf images are collected for the Mango tree suffering from fungal disease. Further, the effectiveness of the model is validated on the collected and standard database when compared with the other state-of-the-art approaches.

5. The proposed method is automatic, computationally efficient, and cost-effective, that can help in sustaining the importance of the Mango tree and its yields both ecologically and economically.

VI. CONCLUSION AND FUTURE WORK

By controlling the biotic factors causing severe losses in the crop yield, we can enhance the productivity and quality of the plants and its products. Computer vision with machine learning methodologies has outperformed in solving a number of plant leaves disease problems including pattern recognition, classifification, object extraction etc. Therefore in this work, we propose an innovative model named MCNN for the classifification of Mango leaves infected from the fungal disease named Anthracnose.

The presented model is also computationally efficient and simple. Some of the future works are given as:

1) The use of some other function instead of Softmax activation function can enhance the performance of the CNN making it compatible for classifying multiple diseases.

2) Counter measuring the inconsistencies encountered working with real-time dataset.

3) Working with other plants with economic importance and calculating the severity of the disease considering other parts of the plants as well.

4) To build a Web/Internet of Things (IoT) enabled real-time disease monitoring system.

Summary

(1) The research paper proposes a novel method for classifying mango leaves infected by anthracnose disease using a multilayer convolutional neural network (MCNN) model. The paper first explains the importance and challenges of detecting fungal diseases in plant leaves, and reviews the existing methods based on computer vision, machine learning, and artificial intelligence. The paper then introduces the MCNN model, which is a deep learning model that can classify healthy and infected leaves based on their images. The paper also describes the data collection and validation process, and compares the performance of the MCNN model with other state-of-the-art approaches. The paper concludes by highlighting the main contributions of the proposed method, which is automatic, efficient, and cost-effective, and suggesting some future work to improve the model and apply it to other plants

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(2) The research paper develops a novel method for classifying mango leaves infected by anthracnose disease using a multilayer convolutional neural network (MCNN) model. The paper first discusses the importance and challenges of detecting fungal diseases in plant leaves, and surveys the existing methods based on computer vision, machine learning, and artificial intelligence. The paper then presents the MCNN model, which is a deep learning model that can classify healthy and infected leaves based on their images. The paper also explains the data collection and validation process, and evaluates the performance of the MCNN model with other state-of-the-art approaches. The paper concludes by emphasizing the main contributions of the proposed method, which is automatic, efficient, and cost-effective, and proposing some future work to enhance the model and apply it to other plants.

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**ABSTRACT (Complex Network Classification with Convolutional Neural Network)**

Introduction

A complex network is the highly simplified model of a complex system, and it has been widely used in many fi fields, such as sociology, economics, and biology[1]. Given that complex networks can describe the relationship between events, an increasing amount of research is using complex networks to model problems. For example, we can use a network to model compounds in chemical research, in which nodes and edges represent molecules and chemical bonds between molecules. The compound network can be used to identify substances with the same pattern structure as the toxic compounds. Moreover, nowadays, more and more social data constitute large-scale social networks, in which nodes and links represent individuals and relationships. The analysis of social networks can be used to identify key people in society or reveal the social circles of people. Therefore,studying complex networks is crucial. Most studies on complex networks focus on the properties of a single complex network[2], such as classifification and clustering of nodes and link prediction, while paying little attention to comparisons, classifications, and clustering between different complex networks.

Related Work

2.1 Complex network

Complex network focuses on the structure of individuals’ interrelation in systems and is a way to understand the nature and function of complex systems.Researchers have summarized the classic complex network model, which includes regular networks, random networks, small-world networks, n scale-free networks, and proposed network properties, such as average path length, aggregation coefficient, and degree distribution.

2.2 Network classifification

Classification of network data has important applications, such as protein-protein interaction, predicting the functionality of chemical compounds, diagnosing communities, and classifying product trading networks.In the network classifification problem, we are given a set of networks with labels, and the goal is to predict the label of a new set of unlabeled networks. The kernel methods developed in previous research are based on the comparison of two networks and similarity calculation.the main problem of graph kernels is that they can hardly be used on large-scale and complex networks because of the expensive calculation complexity

2.3 Deep learning on graph structure data

CNN is the most successful model in the fi.field of image processing. It has achieved good results in image classifification[4], recognition[23], semantic segmentation[24], and machine translation[25], and can independently learn and extract features of images.

2.4 Network representation learning

Representation learning has been an important topic in machine learning for a long time, and many works aim at learning representations for samples.Recent advances in deep neural networks have indicated their powerful representation abilities and that they can generate useful representations for many types of data.Methods of Network Classification

3.1 Model

Our strategy to classify complex networks is to convert networks into images and use the standard CNN model to perform the network classification task. Given the development of network representation techniques, many algorithms can be used to embed the network into a high-dimensional Euclidean space. The algorithm generates numeric node sequences by performing large-scale random walks on the network. Afterwards, the sequences are fed into the skip-gram and negative sampling algorithms to obtain the Euclidean coordinate representation of each node. To increase the number of training samples, we can perform data augmentation by performing the DeepWalk algorithm on a single network several times to obtain more sets of node representations.

Conclusion and Discussion

In this paper, we propose a model that mainly incorporates DeepWalk and CNN to solve the network classification problem. With DeepWalk, we obtain an image for each network, and then we use CNN to complete the classification task. Our method is independent of the number of network samples, which is a major limitation for the spectral methods on graph classification. We validate our model through experiments with synthetic data and empirical data, which show that our model performs well in classification tasks. To further understand the network features extracted by our model, we visualize the filters in CNN and observe that CNN can capture the differences between WS and BA networks. We also compare our model with baseline methods, and the result shows that our model performs well on large-scale networks. The biggest advantage of our model is that it can deal with networks with different structures and sizes. In addition, our model has a small architecture and low computational complexity. Several potential improvements and extensions to our model could be addressed in future work

Summary

(1) The research paper develops a new method for classifying complex networks using a convolutional neural network (CNN) model. The paper first explains the concept and importance of complex networks, and surveys the current methods and difficulties for complex network classification. The paper then introduces the CNN model, which transforms networks into images and uses deep learning techniques to learn features and classify them. The paper also details the network representation and data augmentation methods used to create the images. The paper assesses the performance of the CNN model on various datasets of complex networks, and contrasts it with other state-of-the-art methods. The paper concludes by emphasizing the main contributions and proposing future work.

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**ABSTRACT (Artificial Intelligence image recognition method based on convolutional neural network algo)**

**ABSTRACT**

In order to improve the convergence speed and recognition accuracy of the convolutional neural network algorithm, this paper proposes a new convolutional neural network algorithm. First, a recurrent neural network is introduced into the convolutional neural network, and the deep features of the image are learned in parallel using the convolutional neural network and the recurrent neural network. Secondly, according to the idea of ResNet’s skip convolution layer, a new residual module ShortCut3-ResNet is constructed. Then, a dual optimization model is established to realize the integrated optimization of the convolution and full connection process. Finally, the effects of various parameters of the convolutional neural network on the network performance are analyzed through simulation experiments, and the optimal network parameters of the convolutional neural network are finally set.

**INTRODUCTION**

With the rapid development of the mobile Internet, the widespread use of smartphones and the populariza- tion of social media self-media, a large amount of picture information has accompanied. as pictures become an important carrier of network information, problems also arise. Traditional information materials are recorded by words, and we can retrieve and process the required content by searching keywords.The picture brings us a convenient way of information recording and sharing, but it is difficult for us to use the information expressed by the image. In this case, how to use a computer to intelligently classify and recognize the data of these images is particularly important. Then identify the image by the method of image matching. The basic principle of this method is that the similar samples are very close in the pattern space and form a ‘‘clustering’’, and then combined with the classifier for classification and recognition. With the development of artificial intelligence, continuous breakthroughs in deep learning have achieved great success in the fields of speech recognition, NLP processing, computer vision, video analysis, multime- dia, and so on [7]–[9]. More and more enterprise companies and researchers use deep learning to discuss and study image classification, which provides a good development for artificial intelligence. Convolutional neural networks can extract the connection and spatial information between its layers from the image, and can express the relevant characteristics inside the image [14], [15]. The image recognition process based on deep learning is mainly to input the image into the neural network, and use the deep learning forward propagation and backpropagation error algorithms to minimize the loss function. After updating the weights, a better recognition model is obtained. Then use this model to identify new images.

In practical applications, CNN has been used in many visual pattern recognition systems. (application)

Convolutional neural networks are also used for facial recognition and facial localization.(application)

**RELATED WORKS**

*A. BASIC INTRODUCTION TO CONVOLUTIONAL NEURAL NETWORKS*

In recent years, researchers have applied CNN to other fields,such as speech recognition [39], face recognition, object recognition, natural language processing [40], brain wave analysis [41], and so on. These fields continue in many directions and some breakthroughs have been made. Compared to ordinary neural networks, CNN contains a feature extractor,which consists of a convolution layer and a down-sampling layer. A neuron is only connected to a part of neurons in the upper layer, and this part of neurons is called a local receptive field. A convolutional layer generally contains multiple feature maps, each feature map is composed of a specific number of neurons, and the weights of neurons are shared between the same feature maps. The biggest feature of weight sharing is to reduce the connection between the various layers of the network, reduce network parameters, and at the same time play a role in preventing overfitting. In general, the initial value of the convolution kernel is randomly generated.In the process of network training, new weights are constantly learned and updated in real time until a reasonable weight is finally learned. Down sampling, also called pooling, is a special convolution process. Therefore, CNN has three main features, namely local receptive field, weight sharing and pooling.

*B. THE STRUCTURE OF CONVOLUTIONAL NEURAL*

*NETWORK*

Convolutional neural network is a combination of deep learning algorithm and artificial neural network, and it is widely used in image processing. Convolutional neural network is generally composed of three parts: input layer, hidden layer and output layer. Among them, the input layer is the original image that has not been processed, the output layer is the result of classifying the features, and the hidden layer is a neuron layer with a complex multi-layer nonlinear structure,including a convolution layer and a subsampling layer. Convolutional neural networks extract and classify features in hidden layers. Therefore, optimization of the convolutional layer and single-layer perceptron can improve the accuracy of feature extraction and optimize the classification effect. The input data in the figure is the original image input, and the output result of the output layer is divided into A∼G categories. The repeated structure composed of layer C and layer S serves as the basic unit of feature extraction. After multiple feature extractions, the final feature map is rasterized to obtain a one-dimensional matrix, which is a fully connected layer. The fully connected layer and the output layer use the fully connected method to obtain the final output result

**IMAGE RECOGNITION ALGORITHM BASED ON CNN**

This paper first introduces a recurrent neural network into the convolutional neural network, and uses the convolutional neural network and the recurrent neural network to learn the deep features of the image in parallel. Secondly, according to ResNet’s idea of skipping convolutional layers, a new residual module ShortCut3-ResNet is constructed. Finally, a dual optimization model is established to achieve integrated optimization of the convolution and full connection process.Next, we will explain systematically.

*A. RECURRENT NEURAL NETWORK*

Recursive neural networks are similar to the combination of convolution operation and sampling operation. By repeatedly using the same set of weights and selecting the acceptance domain to achieve the purpose of reducing the feature dimension layer by layer

*C. DOUBLE OPTIMIZATION*

The design principle of the convolution optimization model is to realize the weight optimization of the convolution kernel.We can learn the data set weights and bias parameters from small data blocks to obtain a sparse feature matrix. The convolution kernel is initialized by convolution coefficient control.

*D. CONVOLUTIONAL NEURAL NETWORK TRAINING*

*PROCESS*

Convolutional neural network is essentially a mapping from input to output, which can learn many features that do not require any precise mathematical expression between input and output, and realize the mapping between input and output. Because the network performs supervised learning, its sample set is a vector pair of input vectors and ideal output vectors

Use small random numbers of different sizes to initialize the connection weights of the convolutional layer threshold, two-layer convolution kernel, network input layer and hidden layer, and hidden layer and output layer in the network. At the same time, set the learning speed and the corresponding accuracy control parameters.

**CONCLUSION**

In order to improve the ability of the convolutional neural network to classify and recognize two-dimensional images and speed up the convergence of the algorithm, this paper pro- poses a new convolutional network algorithm. First, a recur- rent neural network is introduced into the convolutional neural network, and the deep features of the image are learned in parallel using the convolutional neural network and the recurrent neural network. Not only can we use convolutional neural networks to learn high-level features, but also recursive neural networks to learn the combined features of low-level features. Secondly, according to ResNet’s idea of skipping convolutional layers, we construct a new residual module ShortCut3-ResNet. Finally, the convolutional layer and the full connection process are optimized.