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Publications

LIST OF PUBLICATIONS

INTERNATIONAL JOURNALS

1. M. Jaithoon Bibi, and S. Karpagavalli, "**Critical Review of Deep Learning Algorithms for Plant Diseases by Leaf Recognition**" Journal of Contemporary Issues in Business and Government, Vol. 27, No. 5, P-ISSN: 2204-1990; E-ISSN: 1323-6903, DOI: 10.47750/cibg.2021.27.05.044, pp: 720 – 729, August 2021 (Web of Science & UGC Care Indexed)
2. M. Jaithoon Bibi, and S. Karpagavalli, "**Positional-aware Dual Attention and Topology Fusion GAN for Plant Leaf Disease Image Super-resolution and Classification**" LINGUISTICA ANTVERPIENSIA, 2021 Issue-3, ISSN: 0304-2294, pp-013-025, June 2021 (Scopus Indexed).
3. M. Jaithoon Bibi, and S. Karpagavalli, "**An Evolutionary Optimization of Positional-Aware Dual-Attention and Topology-Fusion Generative Adversarial Network for Plant Leaf Disease detection**" Turkish Online Journal of Qualitative Inquiry (TOJQI), Vol. 12 No. 3, ISSN: 2904-2922, e-ISSN 1309-6591, pp:2904 – 2922, July 2021 (Scopus Indexed).
4. M. Jaithoon Bibi, and S. Karpagavalli, "**Plant leaf disease image resolution classification using deep convolutional neural network**" International Journal of Natural Sciences (IJONS), Vol. 13 No. 71, ISSN: 0976-0997, pp: 40712-40722, April 2022 (Web of Science Indexed).
5. M. Jaithoon Bibi, and S. Karpagavalli, "**Pesticide Recommendation for Different Leaf Diseases and Related Pests Using Multi-Dimensional Feature Learning Deep Classifier"** International Information and Engineering Technology Association (IIETA), Vol. 28 No. 1, ISSN: 1633-1311, E-ISSN: 2116-7125, pp: 133-140, February 2023 (Scopus Indexed).

INTERNATIONAL CONFERENCES

1. M. Jaithoon Bibi, and S. Karpagavalli, "**Critical Review of Deep Learning Algorithms for Plant Diseases by Leaf Recognition**", 2nd National Conference of Education, Research and Innovation (ERI), Osmania University Center for International Program, Osmania University Campus, Hyderabad (India), June 2021, ISBN: 978-81-952307-6-1.03, pp: 114 – 122.
2. M. Jaithoon Bibi, and S. Karpagavalli, "**Plant Leaf Disease Image Resolution Classification Using Deep Convolutional Neural Network**" International Conference on Science & Technology – Computational Intelligence, Kristu Jayanti College, Bengaluru, March 2022, ISBN: 978-93-94086-07-4, pp: 12.
3. M. Jaithoon Bibi, and S. Karpagavalli, "**Plant Leaf Disease Image Super Resolution Classification Using PGANDEEP Convolution Neural Network**" in International Conference on Intelligence Computing and Technology ICICT - 2022, Sri Ramakrishna College of Arts and Science, Coimbatore, March 2022, ISBN: 978-93-91977-13-9, pp: 25-32.

Journal of Contemporary Issues in Business and Government Vol. 27, No. 5,2021
https://cibg.org.au/
P-ISSN: 2204-1990; E-ISSN: 1323-6903
DOI: 10.47750/cibg.2021.27.05.044

Critical Review of Deep Learning Algorithms for Plant Diseases by Leaf Recognition

M. Jaithoon Bibi[1], Dr. S.Karpagavalli[2] and A. Kalaivani[3]
[1] Research Scholar, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore, &Assistant Professor, Department of Multimedia and Web Technology,
KSG College of Arts and Science, Coimbatore, Tamilnadu, India
[2] Associate Professor and Head, Department of Computer Science,
PSGR Krishnammal College for Women, Coimbatore, Tamilnadu, India
[3] Research Scholar, Department of Computer Science,
PSGR Krishnammal College for Women,Coimbatore, &
Assistant Professor, Department of Computer Technology,
Nallamuthu Gounder Mahalingam College, Pollachi (India)
1 jaithoonchella@gmail.com, 2 karpagavalli@psgrkcw.ac.in, 3
kalaivanivijayan19@gmail.com

ABSTRACT
The identification and classification of the crop leaf diseases plays an essential role in the cultivation. Plants are the livelihood. Peoples depend entirely on crops for the breathing of their daily lives. Thus, suitable crop caring should take place. Most research suggests that the quality of agricultural commodities can be restricted depending on different factors. Crop diseases include microorganisms and pathogens. The leaf diseases not only reduce crop growth, the cultivation is also destroyed. Several researchers have been identified crop leaf diseases using image processing algorithms but it take more time for detection. Therefore, advanced algorithms are required to identify and classify the crop leaf diseases automatically with higher accuracy. There are different deep learning algorithms using crop leaf images developed for automatically detecting the crop leaf diseases in an efficient manner. In this article, a survey on different deep learning algorithms using image processing for detecting and classifying the crop or plant leaf diseases is presented. Also, the merits and demerits of the surveyed algorithms for crop leaves diseases identification are addressed in a tabular form. Finally, a comprehensive analysis is concluded and future directions are suggested to increase the accuracy of leaf diseases classification.
Keywords—Crop pathology, Leaf diseases, Image processing, Deep learning, Disease classification

LINGUISTICA ANTVERPIENSIA, 2021 Issue-3
www.hivt.be
ISSN: 0304-2294

Positional-aware Dual Attention and Topology Fusion GAN for Plant Leaf Disease Image Super-resolution and Classification

[1]M. Jaithoon Bibi, [2]Dr. S. Karpagavalli
[1]Research Scholar, Department of Computer Science, PSGR Krishnammal College for Women,Coimbatore, Tamilnadu, India
[2]Associate Professor and Head, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore, Tamilnadu, India

Issue Details
Issue Title: Issue 3
Received: 25 April, 2021
Accepted: 27 May, 2021
Published: 15 June, 2021
Pages: 13 - 25

Abstract

In agricultural operations, one of the main processes is to effectively identify and classify the crop leaf diseases. In the past decades, many deep learning models have been applied to feasibly and efficiently detect and classify the crop leaf diseases. Among many models, a Dual-Attention and Topology-Fusion with Generative Adversarial Network (DATFGAN) has achieved better accuracy to categorize the crop leaf diseases based on the texture features. On the other hand, the GAN aims at training a generator that models a mapping from a prior latent distribution to the real data distribution. The DATFGAN training could be accelerated highly by developing improved algorithm to coordinate generator and discriminator. Thus, it is crucial to learn the spatial relationships across a series of observations. Therefore in this article, Positional-aware DATFGAN (PDATFGAN) model is proposed to learn a coordinate manifold that is orthogonal to the latent distribution manifold. In this model, a Positional-aware GAN (PGAN) is introduced in which the generator creates images by parts according to their spatial coordinates as the condition. Once a latent vector is sampled, the generator conditions on every spatial coordinate and creates patches at every resultant spatial location. Also, the discriminator learns to decide whether neighboring patches are homogeneous and continuous across the edges between many patches. After that, the created high-resolution image patches are combined to get the full leaf image. Further, the leaf images are fed to the Deep Convolutional Neural Network (DCNN) classifier for classifying the crop leaf diseases. So, conditional coordination in DATFGAN can able to generate high-quality images than the quality of DATFGAN only. This enables the low-quality image leaf disease classification more robust. Using the generation by parts property, the PDATFGAN is greatly parallelable and intrinsically inherits the standard divide-and-conquer design paradigm which allows large field-of-view image generation. Finally, the experimental results reveal that the PDATFGAN outperform the state-of-the-art deep learning models.

Keywords—Crop leaf disease, Deep learning, DATFGAN, Conditional coordinates, Spatial correlation, CNN.

INTRODUCTION

Leaves play a crucial role in crop production for providing data about the quantity and quality of crop yield. Various factors influence food production including global warming, weeds and soil erosion. Further, the development of a number of agricultural products and a source of economic losses pose a worldwide challenge to plant and leaf diseases [1]. The inadequacy of the usage of pesticide/fungicide results in a lack of identifying the infections/bacteria/virus in plants. So, plant leaf diseases have been commonly taken into account in the research field with an emphasis on the genetic characteristics of diseases.

Precision agriculture incorporates the most sophisticated technologies for decision-making optimization. The visual analysis and biomedical examinations are typically performed by diagnosing plants when needed. But, this approach normally takes time and is economically unsuccessful. To solve these problems, advanced and intelligent techniques are required to identify the plant leaf diseases. The standard machine learning algorithms have been used in several researches to conduct the agricultural activities [2]. Nowadays, deep learning as a subcategory of machine learning has been remarkably successful in the identification and classification of real-life objects. As a result, an agricultural research has been progressed towards the deep learning-based solutions [3].

Turkish Online Journal of Qualitative Inquiry (TOJQI)

Volume 12, Issue 3, July 2021:2904- 2922

Research Article

An Evolutionary Optimization of Positional-Aware Dual-Attention and Topology-Fusion Generative Adversarial Network for Plant Leaf Disease detection

M.Jaitthoon Bibi1 and Dr. S.Karpagavalli2

1 Research Scholar, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore, Tamilnadu, India

2 Associate Professor and Head, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore, Tamilnadu, India
1 jaithoonchella@gmail.com, 2 karpagavalli@psgrkcw.ac.in

ABSTRACT

The classification of crop leaf diseases is the foremost essential task in agricultural activities since it may affect the crop productivity. To achieve this task, a Positional-aware Dual-Attention and Topology-Fusion with Generative Adversarial Network (PDATFGAN) can create super-resolution images of crop leaves robustly. Also, Deep Convolutional Neural Network (DCNN) can classify these enhanced images into different types of leaf diseases. But, the adversarial learning objectives can have non-convergent boundary sets near equilibrium which reduces the generative efficiency. Therefore this proposes a new model called PDATF-Evolutionary GAN (PDATFEGAN) by using different objectives to equally optimize the generator and create the super-resolution images for classification. In this model, an EGAN is constructed which considers an adversarial learning process as an evolutionary problem. A discriminator can act as the atmosphere and a population of generators evolve related to the atmosphere. During every adversarial iteration, the discriminator is learned to identify actual and bogus image samples. Also, the generators who act as parents execute different mutations to produce the offspring and adapt to the atmosphere. To decrease different losses between the created distribution and the image distribution providing to various mutations, different adversarial objective functions are considered. Then, the quality and diversity of images generated by the updated offspring are computed for an optimal

RESEARCH ARTICLE

Plant Leaf Disease Image Resolution Classification using Deep Convolution Neural Network

M. Jaithoon Bibi[1*] and S. Karpagavalli[2]

[1]Research Scholar, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore, Tamil Nadu, India and Assistant Professor, Department of Computer Science with Cognitive Systems, Sri Ramakrishna College of Arts and Science, Coimbatore, Tamil Nadu, India.
[2]Associate Professor & Head, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore, Tamil Nadu, India

Received: 11 Jan 2022 Revised: 23 Feb 2022 Accepted: 20 Mar 2022

***Address for Correspondence**
M. Jaithoon Bibi
Research Scholar,
Department of Computer Science,
PSGR Krishnammal College for Women,
Coimbatore, Tamil Nadu, India and
Assistant Professor, Department of Computer Science with Cognitive Systems,
Sri Ramakrishna College of Arts and Science,
Coimbatore, Tamil Nadu, India.
Email: jaithoonchella@gmail.com

ABSTRACT

In agricultural operations, one of the main processes is to effectively identify and classify the crop leaf diseases. In the past decades, many deep learning models have been applied to feasibly and efficiently detect and classify the crop leaf diseases. Among many models, a Dual-Attention and Topology-Fusion with Generative Adversarial Network (DATFGAN) has achieved better accuracy to categorize the crop leaf diseases based on the texture features. On the other hand, the GAN aims at training a generator that models a mapping from a prior latent distribution to the real data distribution. The DATFGAN training could be accelerated highly by developing improved algorithm to coordinate generator and discriminator. Thus, it is crucial to learn the spatial relationships across a series of observations. Thereforein this article, Positional-aware DATFGAN (PDATFGAN) model is proposed to learn a coordinate manifold that is orthogonal to the latent distribution manifold. In this model, a Positional-aware GAN (PGAN) is introduced in which the generator creates images by parts according to their spatial coordinates as the condition. Once a latent vector is sampled, the generator conditions on every spatial coordinate and creates patches at every resultant spatial location. Also, the discriminator learns to decide whether neighboring patches are homogeneous and continuous across the edges between many patches. After that, the created high-resolution image patches are combined to get the full leaf image.

Ingénierie des Systèmes d'Information
Vol. 28, No. 1, February, 2023, pp. 133-140
Journal homepage: http://iieta.org/journals/isi

Pesticide Recommendation for Different Leaf Diseases and Related Pests Using Multi-Dimensional Feature Learning Deep Classifier

Jaithoon Bibi Mohammed Saleem*, Karpagavalli Shanmugam

Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore-641004, Tamilnadu, India

Corresponding Author Email: jaithoonphd123@gmail.com

https://doi.org/10.18280/isi.280113

Received: 22 September 2022
Accepted: 20 November 2022

Keywords:
leaf diseases, PDATFEGAN, MFL-DCNN, pesticide, fuzzy rule, rough set, intuitionistic fuzzy approximation space, recommendation system

ABSTRACT

In agricultural applications, the most essential task is to classify leaf diseases and their associated pests from various aspects. To achieve this, a Deep Convolutional Neural Network (DCNN) model was developed to classify the leaf diseases based on the soil and climatic features. But it needs a recommendation system to control the pesticide use for controlling the leaf diseases caused by specific pests. Hence, this paper hybridizes the Multi-dimensional Feature Learning-based DCNN (MFL-DCNN) with the Rough Set (RS) on an intuitionistic Fuzzy approximation space (RSF)-based decision support system to suggest the proper pesticides for a certain crop to be planted in a particular region. First, the leaf images are augmented by the Positional-aware Dual-Attention and Topology-Fusion with Evolutionary Generative Adversarial Network (PDATFEGAN) model. Then, the multi-dimensional data such as the created leaf images, pest, soil, weather, and pesticide data are fed to the DCNN with a softmax classifier for classifying leaf diseases and related pests. Then, the RSF-based decision model is applied, which determines the correlation between leaf disease and pests to recommend suitable pesticides. Finally, the experimental results reveal that the MFL-DCNN-RSF accomplishes a maximum efficiency than all other models for recommending pesticides to control leaf diseases and pests.

1. INTRODUCTION

Crop productivity is endangered by many conditions, like environmental issues, crop diseases, and land erosion. The pathogenic illnesses of plants are worsened due to the growth of a wide range of natural commodities, and environmental degradation characteristics [1, 2]. Those illnesses are not appropriately recognized and diagnosed by human eyesight, which impacts yield productivity. To tackle this issue, Artificial Intelligence (AI) models including machine learning and deep learning algorithms have been adopted in crop/plant disease detection [3, 4]. The crop diseases are mostly identified by the leaves using a variety of methods. Many researchers have experienced the different machine learning algorithms for the detection and classification of various plant leaf diseases, including Support Vector Machine (SVM), Artificial Neural Network (ANN), random forest, and so on [5, 6]. But these algorithms need separate mechanisms for each process like pre-processing, feature extraction, feature selection, and classification. This leads to high computational time complexity.

So, deep learning algorithms have been developed for the detection and classification of crop leaf diseases from a huge number of images. Mostly used deep learning algorithms are pre-trained DCNNs [7-9], e.g., VGG, AlexNet, GoogleNet, etc. These algorithms achieved better feasibility and efficiency in identifying and classifying leaf diseases. Alternatively, images captured from farms were blurred. Poor image quality may degrade the accuracy of pre-trained classifiers, which were trained on clear high-resolution images. To increase the accuracy of leaf disease classification, low-resolution images should be regenerated into high-resolution images. For this purpose, a variety of Generative Adversarial Network (GAN) models has been employed [10], which generate more high-resolution images from the limited number of low-resolution images. Amongst, the GAN with the Dual-Attention and Topology-Fusion strategies called the DATFGAN model [11] outperformed classical GAN models in terms of sharpness and image details. It can generate sharper leaf disease images precisely by eliminating artifacts or noisy textures for increasing classification accuracy. The generated high-resolution leaf disease images were classified by the different pre-trained DCNN models to identify the types of diseases. In our previous works, the problems in the DATFGAN were solved: (a) the spatial correlation among the training images was learned with the position of disease region from the partial or whole leaf by the Positional-aware DATFGAN (PDATFGAN) model [12], and (b) the non-convergent iteration and adversarial learning ability were further improved by the Positional-aware Dual-Attention and Topology-Fusion with Evolutionary Generative Adversarial Network (PDATFEGAN) model which adopts an Evolutionary GAN (EGAN) [13]. The EGAN considers many adversarial objective values to reduce the different errors observed between the distribution of created and actual images. But the classification of leaf diseases was not only effective to enhance crop productivity.

Identification of causes for leaf diseases was also essential to control both pests and their related diseases efficiently. So, a few researchers focused on identifying pests from the leaf pest images [14, 15] of different plants using deep learning models. But, additional factors like soil and weather attributes