Autoencoders for semantic segmentation of rice fungal diseases

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Abstract. In the article, the authors examine the possibility of automatic localization of rice fungal infections using modern methods of computer vision. The authors consider a new approach based on the use of autoencoders - special neural network architectures. This approach makes it possible to detect areas on rice leaves affected by a particular disease. The authors demonstrate that the autoencoder can be trained to remove affected areas from the image. In some cases, this allows one to clearly highlight the affected area by comparing the resulting image with the original one. Therefore, modern architectures of convolutional autoencoders provide quite acceptable visual quality of detection.

Key words: autoencoder, neural network, computer vision, fungal diseases.

INTRODUCTION

According to the data of the Food and Agriculture Organization of the United Nations (FAO), diseases and pests destroy 20–40% of the world's agricultural crops (Food and Agriculture Organization of the United Nations, International Plant Protection Convention, 2017). We observe no less losses when growing rice, especially in the years of epiphytoties. At the same time, fungal diseases cause enormous economic damage. The most common rice diseases are: alternaria leaf spot (causative agent is Alternaria oryzae Har. Ital); helminthosporiosis (causative agent is Helmintosporium oryzae Br. de Haan); blast (causative agent is Pyricularia oryzae Cav.); fusarium, causing root rot (causative agent is Fusarium oxysporum). Rice blast, caused by a fungus, causes lesions to form on leaves, stems, peduncles, panicles, seeds, and even roots. The potential crop losses due to this disease are enormous. That is why it is considered the most dangerous of all (Zelensky, 2016).

Farmers suffer significant financial losses every year due to fungal diseases. It is very important accurately and at an early stage to identify the symptoms of the disease in order to take the necessary measures to combat it in a timely manner. Symptoms of

fungal diseases often appear in the form of spots around the infected areas, so the initial detection of the disease is reduced to the analysis of these spots. At present, farmers mainly rely on their own experience, disease-identifying atlases or involve expert agronomists (Vimal et al., 2019). However, the identification is complicated by the fact that different diseases can have similar types of spots and vice versa, the same disease can manifest itself differently in different crops varieties and depending on growing conditions. Even nutritional deficiencies and pests can cause symptoms similar to those of some fungal rice diseases (Barbedo, 2016).

Misidentification usually results in inappropriate, untimely and sometimes uncontrolled use of pesticides. Their use is harmful to the environment and negatively affects biodiversity, including insect, bird and fish populations, as well as soil, air and water quality (Gill & Garg, 2014; Knillmann & Liess, 2019). Pesticide use also poses significant risk to human health with both acute and chronic illnesses (Bassil et al., 2007; Kim et al., 2016). In turn, the laboratory pathogen identification is a laborious process that requires time-consuming cultivation of the pathogen. In any case, both of these methods require the participation of high-level professionals in the identification process, which is often inaccessible to small farms. Automatic identification of plant diseases based on image-processing methods solves the specified problems by automatically searching for diseases or helping both farmers and experts.

The topic of intelligent processing of images of plants affected by various diseases is considered more and more often in scientific studies. The most common approach to the classification and segmentation of plant diseases, until recently, was an approach based on the application of classical machine learning algorithms (Huang, 2007; Tian et al., 2007; Zhao et al., 2007; Dong Pixia, et al., 2013; Moshou, et al., 2014; Jitesh et al., 2016; Joshi et al., 2016; Ebrahimi et al., 2017; Pantazi et al., 2017; Vimal et al., 2019). The general approaches in these studies are similar. Firstly, images of the disease are obtained using cameras or scanners. Secondly, the spots of the disease are segmented from the background. Thirdly, features of colour, shape or texture are extracted. Finally, the disease is attributed to one of the groups using classification methods such as support vector machines, K-nearest neighbors, etc.

The following authors (Baghel & Jain, 2016; Elangovan & Nalini, 2017; Gayathri Devi, et al., 2018; Guiling Sun et al., 2018, Vithiya & Santhi, 2020) use methods such as SVM, Linear Regression to classify plant diseases, and unsupervised K-means to further isolate diseased areas. In (Vinoth Kumar & Jayasankar, 2018), linear iterative clustering and k-meaths unsupervised methods are used to improve the quality of segmentation.

In a recent paper (Jayanthi & Shashikumar, 2020), the segmentation problem was solved from the standpoint of classical computer vision using physical considerations like minimization of some energy function. The alternative active contour model (ACM) built in this paper was validated with various metrics such as Jaccard index, the Dice index, and the Hausdorff distance. As a result, in (Jayanthi & Shashikumar, 2020) the authors managed to get a fairly good model without involving any data-learning algorithms.

The next step towards modeling the detection of plant diseases was the use of more progressive neural network methods of computer vision (Boulent et al., 2019). This approach has a number of advantages over both methods based on classical physical considerations. and over classical machine learning methods. First, one of the main

features of convolutional neural networks is automatic feature extraction, whereas classical machine learning methods require manual feature extraction from an image. Secondly, the quality of the model given by deep convolutional neural networks for image processing is usually significantly higher than in classical models. Finally, the recent modern neural network architectures are opening up new approaches to unsupervised segmentation of objects in the image.

The approach we propose here develops a number of researches where deep convolutional neural networks are used to solve problems of classification of plant diseases. So, in (Pardede et al., 2018) convolutional autoencoders are used to replace handcrafted features with atomatic feature inference. The paper notes the importance of both the auto-generation of features itself and the unsupevised manner of this process, which is provided by the specifics of autoencoders. The authors validate their results using the features given by the autoencoder as input to the SVM model for classifying plant diseases. The authors (Pardede et al., 2018) also note an increase in the quality given by autoencoders with convolution layers compared to conventional deep autoencoders, which is quite natural for image processing tasks.

In (Zilvan et al., 2019), autoencoders are also used to highlight signs of plant diseases and denoise. The authors note that with the help of a variational autoencoder, one can obtain even more informative features from the image. Further, as in the paper (Pardede, 2018), the signs automatically given by the encoder part of the autoencoder are used to classify plant diseases. The results (Zilvan et al., 2019) differ from those by (Pardede et al., 2018) due to the use of a more advanced autoencoder architecture, which allows, in particular, to achieve better denoise compared to conventional convolutional autoencoders.

Other studies propose modern solutions and platforms for automated crop production that cover the most important parts of the production process on the farm and include disease detection and classification models (Hakojärvi et al., 2010), as well as solutions for remote visual examination of agriculture in real time (Komasilovs et al., 2018).

Proposal of this paper and its significance

The aim of this paper is to propose a new approach to the problem of disease segmentation based on deep convolutional autoencoders, while using the autoencoder not as a regular feature extractor, as suggested in the above-mentioned papers, but as a closed unsupervised image processing system, which is able to highlight areas of plant disease damage automatically and without the participation of experts.

The rest of the paper is constructed as follows. Section 2 thoroughly previews modern methods for plant disease identification based on neural network technologies. These methods refine and automate the conventional visual detection method used by plant pathologists to identify rice diseases. Then we overview main neural network architectures suitable for solving this problem. Section 3 provides the basic methodology and gives a brief description of the basic principles of convolutional neural networks and autoencoders used in this study. We list main advantages and prospects of the chosen approach. Section 4 describes the details of the autoencoder model used as well as image post-processing. Также приведено a description of the used image dataset, as well as details of the technical implementation of the used autoencoder model. We offer a description and discussion of the main results of the performed numerical experiments.

CURRENT METHODS FOR PLANT DISEASE DETECTION

Preliminary visual analysis remains one of the most basic methods for detecting diseases in a variety of crops. Before sending samples to the laboratory, an experienced plant pathologist tries to establish the external symptoms of the disease, its degree of development and prevalence (Bidaux, 1978). This part of research is extremely important, and it is this stage that has enormous potential for automation up to the complete exclusion of human experts and their replacement with automated algorithms for determining the required defects on plants.

The main tool for such automation at present is computer vision - a set of automatic and semi-automatic approaches based on intelligent image processing (Yao et al., 2009; Xiao et al., 2018). Until recently, here the so-called classical computer vision was widely used. At present it has given way to the modern one - based on neural network architectures (Zeiler & Fergus, 2014; Wang, 2017; Zhang, 2018; Too et al., 2018).

The neural network approach to the detection of plant diseases is based on a rather simple idea to bring the work of a computer with an image closer to how the human eye does it. The vision of humans and animals generally works as follows: when a person tries to classify an object in front of him, he sequentially focuses on separate parts of the object and compares them with the forms in his memory, and does this from smaller parts to larger ones. This process is mimicked by convolutional neural networks, which began with the revolutionary work of Y. LeCun et al. (1989). In subsequent works, these ideas were significantly developed and in the last decade, convolutional neural networks confidently hold the leadership both in the competition for image detection and in solving specific applied problems. The quality of classification that neural networks currently provide is quite comparable to that of a human, and in some cases even surpasses it.

It is crucial to mention several neural network architectures, which were a kind of milestones in the history of the development of this approach and which are used in the present paper to detect the areas of rice fungal diseases. After LeCun et al. (1989) the next big breakthrough was AlexNet. It is notable for the fact that in 2012 it reached a test accuracy of 84.6% in the problem of classifying 1.2 M images into 1,000 different classes, which is a very impressive result (Alom, 2018). In 2013, He et al. (2016) significantly increased the computing power and changed the network architecture to a heavier one - VGG, while achieving the 92.7% test accuracy, which is already comparable with the visual acuity of a human eye. Further, the experts wondered whether it was possible to reduce the model without losing its quality. It turned out that using a more thought-out model, the amount of memory required for its storage can be reduced by more than 20 times, and the quality will even increase. In 2014, the GoogLeNet Inception model with 93.3% test accuracy was presented (He et al., 2016) and had only 6M parameters, instead of 138M for VGG. Subsequent improvements, ResNet (He et al., 2016), SqueezeNet (Wu et al., 2016), and DenseNet (Gao Huang et al., 2018), improved test accuracy to 96.43%.

Versatility, determined by the architecture, is the main advantage of the above-mentioned models. They cannot be directly used to identify plant diseases, since they were trained for other tasks, but they can be re-trained for the required task by showing a sufficient number of examples - images of healthy and diseased plants. The larger the number of images presented to the model, the more accurate will be its predictions in the

future. Liu et al. (2009), Phadikar et al. (2013) point out that the stage of collecting a sufficient number of high-quality images is extremely important and in fact determines the success or failure of solving the problem of detecting diseases of various agricultural crops. So, for example, if the images are very noisy, made with insufficient / excessive lighting, then this will significantly degrade the overall quality of the final model.

MATERIALS AND METHODS

Autoencoders have a special place among modern neural network image processing models. They are specific types of neural networks, a pair of neural networks actually - encoder and decoder, interconnected by a thin bottleneck (Bank, 2020).

The idea behind autoencoders is as follows (see Fig. 1): some image is fed to the input of the network, which is compressed by the first network - encoder into a vector of dimensions less than the dimension of the original image, giving it a dense representation. Further, this vector is fed to the input of the second network - decoder, which tries to decode it back into the original image.
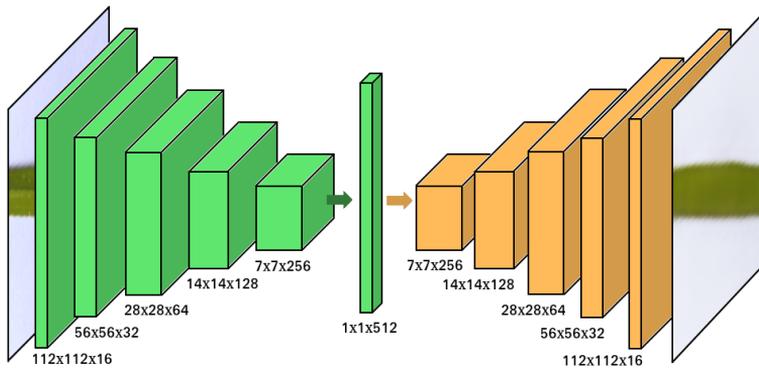

Figure 1. Autoencoder architecture: the input is a 224 × 224 image, which is encoded in the center with a 512-vector length. Then the resulting vector is decoded back into the image of the original size by a sequence of inverse operations.

Thus, at the output, the original image is compared with itself. If the original image is similar enough to the output, this has a number of advantages at once. Firstly, it has a compression effect of some sort. If we are ready to neglect some loss of image quality, then we can easily replace the image with its dense representation - the vector that gives the encoder a part of the network at the output. Indeed, in this case, we can easily restore (with some accuracy) the original image by feeding it dense to the decoder input of the neural network autoencoder part. Secondly, we extract, in an encoded form, useful features that fully or partially characterize our image. In this case, we talk about data projections - the presentation of original images in a space of a lower dimension without significant loss of information reflected on them. If we are not faced with the task of directly interpreting these vectors of lower dimension, then they may well be used further in other models, for example, predicting a specific type of disease affecting a plant or lesion size.

Thirdly, autoencoders are often used to smooth out an image noise. Due to its specificity, the autoencoder memorizes in a dense representation the most essential features of each image fed to it, and noise is usually ignored.

Ian Goodfellow and his co-authors (Goodfellow et al., 2016) used for the first time the above-mentioned concepts for conventional fully-connected neural networks in noise suppression tasks. Further, it was noticed that these ideas can be transferred without changes to convolutional neural networks, which use the convolution operation to switch between layers instead of all neurons of the previous layer. Convolution acts on the original image and subsequent layers of the neural network as a learning filter. Mathematically, it can be represented as

$$\mathrm{conv}(x) = \sum_{i,j} w_{ij} x_{i-a,j-b},$$

where x is the original image, or the output of any inner layer of the network, w are the weights of the kernel that defines the convolution, and the summation does not apply to all indices, but only to some 'window' from 0 to 2a on the first index and from 0 to 2b on the second (Murphy, 2013; Goodfellow et al., 2016). The physical meaning of such an operation is that it acts as a filter that simplifies the original image and allows to select all the necessary details in it. This is exactly what convolutional neural networks do in the course of their training - they adjust the weights of all such filters so that the final result matches the initial data as much as possible. The combination of these ideas yielded convolutional deep autoencoders, which are now widely used for intelligent image processing. One can find more information regarding convolutional neural networks in the classic books by (Murphy, 2013 and Goodfellow et al., 2016).

All the above-mentioned features of autoencoders are widely used in our study and help to get an acceptable quality of segmentation. We demonstrate that the autoencoder can be trained in such a way that it will remove the disease lesions from the original image. Thus, comparing the image at the output of the model with that supplied to the input, in a number of cases it is possible to quite clearly automatically localize the focus of the plant lesion by a fungal disease.

Finally, it is worth noting the importance of post-processing of the results of neural networks in a number of tasks. For example, in the well-known real-time object detection problem (Redmon et al., 2016), this happens for a number of reasons. Firstly, the chosen neural network may have too few parameters, and we may not want to complicate it, striving for its simplicity and lightness. Secondly, data post-processing after the operation of an algorithm can be dictated by the very nature of the problem, for example, the physics of the process. In this study, we've noticed that preprocessing in the form of overlaying additional color filters has a positive effect on the final quality of segmentation of plant diseases. In accordance with the general methodology for adjusting the parameters of models in machine learning, we configure the parameters of additional filters on lazy data sampling, thus avoiding their adjustment to the current data and increasing the generalizing ability of the model.

In this study, we use a dataset by Huy Do (2019) to train our models. It contains about 3,500 photographs of both healthy rice leaves and those affected by three types of diseases - hispa, brown spot and leaf blast. The images in this dataset are of sufficient quality for the use of computer vision; they are practically free of extraneous noise and other shooting defects.

Augmentations were applied to the input data in order to increase the generalizing ability of the model. Augmentations are various distortions and transformations such as rotations by small angles, reflections near the coordinate axes and addition of a little noise. This increased both the overall quality of the model and the confidence of its predictions.

MODEL DESCRIPTION AND TRAINING

The operation of the convolutional autoencoder used in the present study is schematically shown in Fig. 1. The original image is fed to the input of the first convolutional layer, which, using the convolution operation, transforms it into a new tensor that is half the size along the axes, but with greater depth. Then this operation is repeated, each time giving tensors of smaller and smaller resolution, until a one-dimensional vector is obtained in the very middle. This vector serves as a coded representation of the original image. The resulting vector is then converted into an image by means of inverse operations. Layer labels in Fig. 1. mean their dimensions - height, width and depth. These numbers, like the number of layers, may be different for other architectures, but the general concept remains the same.

In this paper, we considered the standard autoencoder model - Convolutional Autoencoder. It is less heavyweight than its advanced version - Deep Variational Autoencoder (Vahdat, 2020). Convolutional Autoencoder is a multilayer convolutional encoder and a convolutional decoder symmetric to it. From a number of possible architectures, we experimentally chose the following:

Encoder:
conv2d(3, 16, 8x8) → conv2d(16, 32, 8x8) → conv2d(32, 64, 8x8) →
conv2d(64, 128, 8x8) → conv2d(128, 256, 8x8) → conv2d(256, 512, 7x7)
Decoder:
conv_t2d(256, 512, 7x7) → conv_t2d(128, 256, 8x8) → conv_t2d(64, 128, 8x8) →
conv_t2d(32, 64, 8x8) → conv_t2d(16, 32, 8x8) → conv_t2donv2d(3, 16, 8x8)

Here conv2d (i, o, wxw) is a convolution layer with kernel of size wxw, which inputs a block of data of depth i and outputs a block of depth o; conv_t2d is a symmetric convolutional layer giving the inverse operations to conv2d. Between all convolutional units are ReLU activated units commonly used in image analysis tasks. The number of parameters of this model is 18.4M.

We used the PyTorch v1.6.0 framework to train the model. It is widely used due to its simplicity and functionality. Nevertheless, the architecture of the used autoencoder described above is quite simple, and it can be easily repeated on any other
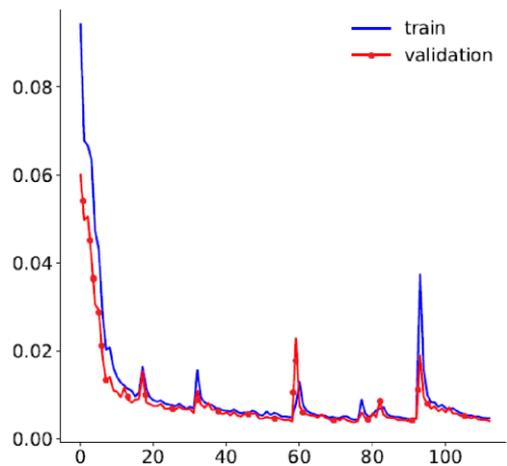

Figure 2. The process of training the autoencoder.

framework, for example TensorFlow, Caffe etc. The neural network was trained on a stationary computer with the following configuration: Core i7 / GTX 1660, GPU - GTX 1080 4 Gb.

It took about 120 epochs (approximately 6 hours of counting on the above-mentioned hardware configuration) for the model quality to reach its maximum level (Fig. 2). In the process of training, the error function experiences characteristic fluctuations due to the fact that the neural network uses minibatches for its training, but in general the error level drops. Generally, in regression problems, the values of the error function have no direct interpretation, in contrast to the usual percentage of accuracy in classification problems. In our case, one can also only observe the drop in the values of loss-function and watch when it reaches a certain plateau. After that, it is necessary to evaluate the quality of the model in general.

After training the model, the results given to it were subtracted from the original ones, and then they were subjected to additional post-processing, that is the application imposition of filters by colors and brightness for a clearer detection of the area affected by the disease. We identified the most optimal thresholds for color channels to identify the affected areas:

$$|red - r_h| < r_t, |green - g_h| < g_t, |blue - b_h| < b_t.$$

Here $r_h=0.14$, $g_h=0.29$, $b_h=0$, $r_t=0.1$, $g_t=0.1$, $b_t=0.08$. The problem of selecting such external parameters of the model, also called hyperparameters, often arises in machine learning, since almost all algorithms have such. It is crucial to select them not on the

training or test set. Otherwise, the effect of overfitting may occur, when the model adjusts well to the training set, but then works poorly on new data. It is better to adjust hyperparameters on a sample that is specially postponed in advance and is not used in training and testing. In our case, these values were selected on a deferred sample in the amount of 10% of the training sample.

Thus, the final pipeline of image processing can be represented as follows (see Fig. 3). Primarily, a 224×224 image is fed to the input of the previously trained autoencoder. This autoencoder, as described above, first converts this image into an encoded vector-512 and then expands it back to its original size.

Figure 3. The final model for highlighting the affected plant areas.

The resulting image is visually close to the original (this is the main idea of the autoencoder training), but some details are missing. After subtracting the resulting image from the original, we apply the above-described special color filters and get the final result - an image in which fine noise has been removed and areas of plant damage are clearly visible.
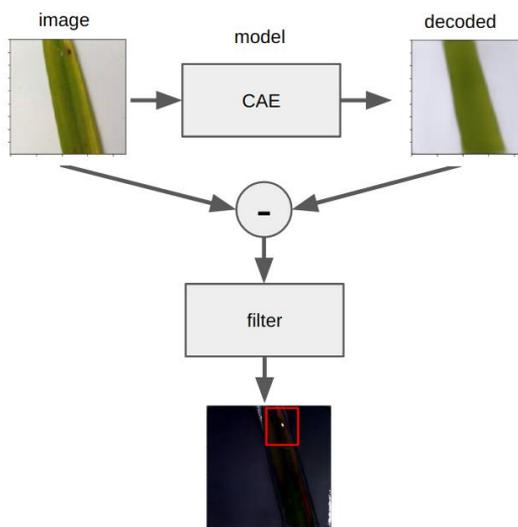
RESULTS AND DISCUSSION

Here we are not interested in the classification of plants by types of diseases, but in the presence or absence of such a disease in general. This task is easier, since it is not required to additionally train the neural network to distinguish plant diseases among themselves. However, it is solved here together with the task of determining the most affected area, which is already much more difficult. What may be obvious to a phytopathologist can be challenging for a computer.

As mentioned above, autoencoders have a number of interesting features that distinguish them from other neural networks. Thus, they allow, by compressing the data obtained from the image, to eliminate minor things that are insignificant for a given dataset. Moreover, if the lesion on the leaf is not too large, the autoencoder can, after proper training, 'erase it' from the original image. After comparing the original image with the obtained one, it is quite easy to clearly distinguish the affected area. It is noteworthy that the described image processing scheme is possible (and even preferable) precisely at the early stages of the development of the disease. This increases the value and potential benefits of the proposed approach.

The above image processing scheme (Fig. 3) contributes in a number of cases to clearly segment the image with a diseased plant, highlighting the areas of disease lesion on it Fig. 4 shows a typical example of brown spot rice as well as the result of processing it with our algorithm. Obviously, the inclusion of a neural network autoencoder along with conventional filters in the image processing pipeline, makes it possible to clearly detect the area of plant damaged by a harmful fungus.

According to our estimates, the proposed model makes it possible to automatically visualize diseased areas on rice leaves in 40–50% of cases. We consider it to be a fairly good result. Moreover, the described method is perfect in the early stages of infection, when the affected areas are still small.

Figure 4. Highlighting of the affected plant areas (black).

In this case, the autoencoder removes them from the image most accurately, taking them for insignificant noise, thereby increasing the possibility of detection of these areas after subtracting the resulting image from the original one. Thus, the method is particularly applicable for plant diseases detection at an early stage of vegetation.

Pardede and co-authors (Pardede et al., 2018) use a deep convolutional autoencoder similar to our architecture (see Fig. 1 above and Fig. 2 in (Pardede et al., 2018)). However, we are not trying to use an autoencoder to get only hidden features from images. In this study, we investigate a slightly more advanced problem of disease segmentation, where we are no longer concerned with the central layer of the autoencoder, which, in fact, reveals hidden signs. We show that an autoencoder can be useful in general, and not just as a feature extractor. This approach allows us to interpret
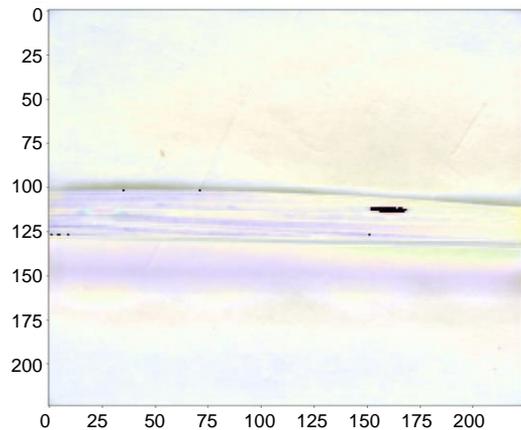
the problem of the segmentation of plant diseases in a completely unsupervised manner, without using hidden features directly.

In contrast to the study (Zilvan et al., 2019), where a variational autoencoder is also used to obtain features and subsequent classification, we use a simpler deep convolutional autoencoder architecture. Here we specifically focus on lighter architectures that can be used effectively on mobile devices if needed.

Heavier architectures require more complex solutions for implementation in production, for example, a dedicated computing server and constant access to the Internet. Our solution is designed to significantly simplify the work of phytopathologists in identifying rice diseases and detecting specific areas of plant damage.

CONCLUSIONS

In this paper, we propose a new approach to the problem of segmentation of plant diseases based on the deep convolutional autoencoder model. In this case, the autoencoder does not work like a regular feature extractor, as suggested in the above-mentioned papers, but as a closed unsupervised image processing system, which is able to highlight areas of plant disease damage automatically not involving qualified phytopathologists. The complete pipeline of image processing also includes the use of specially selected color filters that improve the final quality of the model without the use of heavier architectures such as variational autoencoders. The authors show that training of such models is quite possible without the involvement of serious computing power. The final proposed solution, due to its lightness, may well be used on mobile devices when computing resources are limited.

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