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TOMATO DISEASE RECOGNITION BASED ON OPTIMIZED CONVOLUTIONAL NEURAL NETWORKS

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Abstract

With the advent of resistant varieties and hybrids of tomato, vegetable growers are less likely to encounter diseases on tomatoes. To prevent crop loss, it is important to identify unhealthy tomato leaves and separate them from healthy leaves. Early detection of tomato diseases through deep learning can help decrease the adverse effects of diseases, and also helps surmount the drawbacks of continuous human monitoring. This study examined the performance of modern convolutional neural network classification architectures, such as ResNet18 with a standard algorithm, as well as using optimization parameters and InceptionV3, on 11,000 images of tomato leaves for the classification of tomato diseases. The accuracy of training in Inception V3 was 80.9%, and the accuracy of validation was 71.8%. ResNet architecture training with the momentum parameter demonstrated a high recognition result with 97.7% accuracy. The recognition results were compared using the optimization parameter with values 0.5, 0.7 and 0.9. The influence of the optimization parameter on the quality of training was observed. It can be concluded that using the momentum optimizer with a higher value gives the best results by minimizing fluctuations and increasing accuracy.

Keywords: agriculture, tomato recognition, disease detection, classification, convolutional neural network.

Аннотация

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РАСПОЗНАВАНИЕ БОЛЕЗНЕЙ ПОМИДОРОВ НА ОСНОВЕ ОПТИМИЗИРОВАННЫХ СВЕРТОЧНЫХ НЕЙРОННЫХ СЕТЕЙ

С появлением устойчивых сортов и гибридов томатов овощеводы реже сталкиваются с болезнями томатов. Чтобы предотвратить потерю урожая, важно выявлять нездоровые листья томатов и отделять их от здоровых листьев. Раннее обнаружение болезней томатов с помощью глубокого обучения может помочь уменьшить неблагоприятные последствия болезней, а также помочь преодолеть недостатки постоянного мониторинга со стороны человека. В этом исследовании была изучена производительность современных архитектур классификации сверточных нейронных сетей, таких как ResNet18 со стандартным алгоритмом, а также с использованием параметров оптимизации и InceptionV3, на 11 000 изображениях листьев томатов для классификации болезней томатов. Точность обучения в Inception V3 составила 80,9%, а точность валидации - 71,8%. Обучение архитектуры ResNet с параметром momentum продемонстрировало высокий результат распознавания с точностью 97,7%. Результаты распознавания сравнивались с использованием параметра оптимизации со значениями 0,5, 0,7 и 0,9. Наблюдалось влияние параметра оптимизации на качество обучения. Можно сделать вывод, что использование оптимизатора импульса с более высоким значением дает наилучшие результаты за счет минимизации колебаний и повышения точности.

Ключевые слова: сельское хозяйство, распознавание томатов, выявление болезней, классификация, сверточные нейронные сети.

Аңдатпа

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ОҢТАЙЛАНДЫРЫЛҒАН КОНВОЛЮЦИЯЛЫҚ НЕЙРОНДЫҚ ЖЕЛІЛЕР НЕГІЗІНДЕ ҚЫЗАНАҚ АУРУЛАРЫН ТАНУ

Қызанақтың төзімді сорттары мен будандарының пайда болуы көкөніс өсірушілердің қызанақ ауруларымен сирек кездесуіне әкелді. Егіннің жоғалуын болдырмау үшін қызанақтың зиянды жапырақтарын анықтап, оларды сау жапырақтардан ажырату қажет. Терең оқыту арқылы қызанақ ауруларын ерте анықтау аурудың жағымсыз әсерлерін азайтуға, сондай-ақ адамның үнемі бақылауындағы кемшіліктерді жеңуге көмектеседі. Бұл зерттеу стандартты алгоритмі бар ResNet18 сияқты конволюциялық нейрондық желілерді жіктеудің заманауи архитектураларының жұмысын, сондай-ақ қызанақ ауруларын жіктеу үшін қызанақ жапырақтарының 11000 кескінінде оңтайландырылған ResNet18 және InceptionV3 параметрлерін қолдана отырып зерттеді. Inception V3-те оқу дәлдігі 80,9%, ал валидация дәлдігі 71,8% құрады. Momentum параметрі бар ResNet архитектурасын оқыту 97,7% дәлдікпен танудың жоғары нәтижесін көрсетті. Тану нәтижелері оңтайландыру параметрінің 0,5, 0,7 және 0,9 мәндерімен салыстырылды. Оңтайландыру параметрінің оқыту сапасына әсері байқалды. Жоғары мәні бар импульсті оңтайландырғышты қолдану тербелістерді азайту және дәлдікті арттыру арқылы жақсы нәтиже береді деп қорытынды жасауға болады.

Түйін сөздер: ауыл шаруашылығы, қызанақты тану, ауруларды анықтау, жіктеу, конволюциялық нейрондық желілер.

Introduction

The demand for tomatoes is growing, and they are gradually becoming an important food item in people's daily lives. Therefore, tomatoes play an extremely important role in the agricultural production of vegetables. Being one of the most widely cultivated vegetables in the world, the tomato has not only high yield, wide adaptability, but also high nutritional value. But, like other crops, tomatoes are affected by various diseases and pests during growth. Untimely control can lead to a decrease in yield or even crop failure.

The use of information technology provides new methods and ideas for the detection of diseases of crops. Using deep learning to detect tomato diseases can significantly reduce workload and reduce identification time [1]. A complex network structure and huge data samples are the most important characteristics of deep learning. Instead of exhausting steps such as image preprocessing, feature extraction and feature classification in the traditional method, an end-to-end structure is used to simplify the recognition process and solve the problem that it is difficult for a manually developed object extractor to obtain the feature expression closest to the natural attribute of the object [2]. Based on the application of the deep learning object detection method, it not only can save time and effort, but also allows you to obtain judgments in real time, significantly reducing the huge losses caused by diseases and pests, which has important research value and significance.

The purpose of our work is to study classification problems for various variants of CNN architecture for multiclass classifications of tomato diseases. The architecture of the ResNet convolutional network was trained without using optimization, also using stochastic gradient descent optimization parameters. In addition to this architecture, the Inception V3 neural network model was trained in order to compare the accuracy of recognition of tomato diseases. The performance achieved in this work using the ResNet architecture surpasses some existing modern work in this area.

Literature review and problem statement

The development of machine learning and deep learning technology opens up new opportunities for the recognition of diseases of crops. Many researchers around the world have studied various machine learning technologies [3, 4], deep learning [5, 6] to automate the detection of plant diseases.

In the research paper [7], to classify tomato diseases, the performance of various convolutional neural network architectures, such as ResNet18, MobileNet, DenseNet201 and InceptionV3, was studied. Comparative effectiveness was determined by binary classification, as well as by multiclass classification of six and ten classes of healthy and diseased tomato leaves. As a result, the InceptionV3 architecture demonstrated high performance for binary classification with 99.2% accuracy. The classification accuracy for the six ResNet18 classes was 96.8%, and for InceptionV3 – 97.6%. The authors claim that this study can help in the early and automatic detection of diseases in tomato crops using advanced technologies such as robotic platforms. The idea of combining with a feedback system that provides relevant information, methods of treatment, disease prevention and control, which leads to an increase in crop yields, is also proposed.

The article [8] suggests a tool for early detection of banana diseases using a deep learning approach. Five deep learning architectures, namely VGG16, Resnet 18, Resnet 50, Resnet152 and Inception V3, were used to develop models for detecting banana diseases, which allowed achieving high accuracy ranging from 95.41% for InceptionV3 to 99.2% for ResNet. Inception V3 was chosen for mobile deployment because it requires much less memory. The developed tool was able to detect diseases with a high reliability of 99% on captured leaves from the real environment, can also help farmers to carry out early detection of diseases and increase their productivity.

In [9], a system was proposed to improve the quality and quantity of tomato products by detecting plant diseases. The system involves the use of deep and convolutional neural networks. They experimented with 6 varieties of sick tomatoes from the Plant Village database. A study conducted in [10] describes a method that consists in using 5 CNN deep learning architectures (AlexNet, GoogLeNet, InceptionV3, ResNet18, ResNet34) to classify tomato plant diseases. They used a learning transfer with the following hyperparameters: a batch size of 32, 30 epochs and a Plant Village database (a tomato plant with 9 different classes of diseases and one class of healthy tomatoes) with 18,160 images. The results are evaluated based on five criteria (precision, accuracy, sensitivity, specificity, F-score) with an accuracy of 99.72%.

Another work was devoted to the comparative analysis of convolutional neural network architectures in the classification of tomato diseases [11]. The DenseNet, ResNet 50, ResNet 30, ResNet 18, SqueezeNet and VGG.Net architectures were used in the study. The accuracy of recognition using ResNet18 reached a result of 99.1%. Due to such high classification rates, the authors of this work concluded that it is possible to rely on CNN to increase the accuracy of determining diseases of tomato plants.

The high result of the accuracy of detecting diseases of tomato plants by the ResNet architecture is explained by the fact that this architecture was created to overcome learning difficulties, since learning takes quite a lot of time and is limited to a certain number of levels [12]. The advantage of this model compared to other architectural models is that the performance of this model does not decrease, even though the architecture becomes deeper. The ResNet model is implemented by skipping connections at two or three levels containing ReLU and batch normalization among architectures. Thus, the ability to teach improves and the complexity of calculations decreases.

The study [13] considers the solution of the problem of detection/diagnosis of diseases using a fast and consistent reliable method. ResNet and Inception V3 were used to extract signs and adjust parameters for the detection and classification of diseases of tomato leaves. The basic models were tested on two data sets: a laboratory data set and self-collected field data. Inception V3 is recognized as the most efficient algorithm for both datasets with 99.6% accuracy.

Previous work shows that deep convolutional neural networks are good at recognizing plant diseases. But the methods indicated in many of the above works are not able to detect the disease at an early stage of leaf growth. The researchers also trained conventional neural network architectures without trying to improve performance and reduce training time.

The aim and objectives of the study

The aim of the research work is to develop a system capable of identifying healthy and unhealthy tomato leaves, as well as classifying types of tomato diseases using ResNet18 and InceptionV3 neural network architectures. In order to achieve this goal, a number of specific tasks were set that require urgent solutions:

- Evaluation of the quality of recognition and classification of tomato leaves diseases and improvement of recognition quality by the accuracy metric;
- Comparative analysis of the work of two deep learning architectures on the same dataset;
- Investigation of the influence of the optimization parameter on the quality training.

Research methodology

ResNet18

The ResNet18 network architecture represents a good compromise between computing time and performance [14]. As shown in Fig. 1, it includes five stages of convolution. The architecture has 17 convolution layers and 1 fully connected (FC) layer.

The size of the input image will be changed to 224×224. The first stage of convolution consists of a single convolution layer with 64 filters (7×7). The following convolution blocks consist of two residual blocks. Each residual block consists of two convolution layers with the same number of 3×3 filters. Each convolution block will reduce the image size by half and increase the object size (number of filters) by two. Unlike traditional CNN, an additional fast connection is added to each pair of 3×3 filters.

Inception V3

Inception V3 is a 42-level deep learning network with fewer parameters (Fig. 2). Parameter reduction is performed using convolution factorization [15]. For example, a 5×5 filter convolution can be performed using two 3×3 filters.

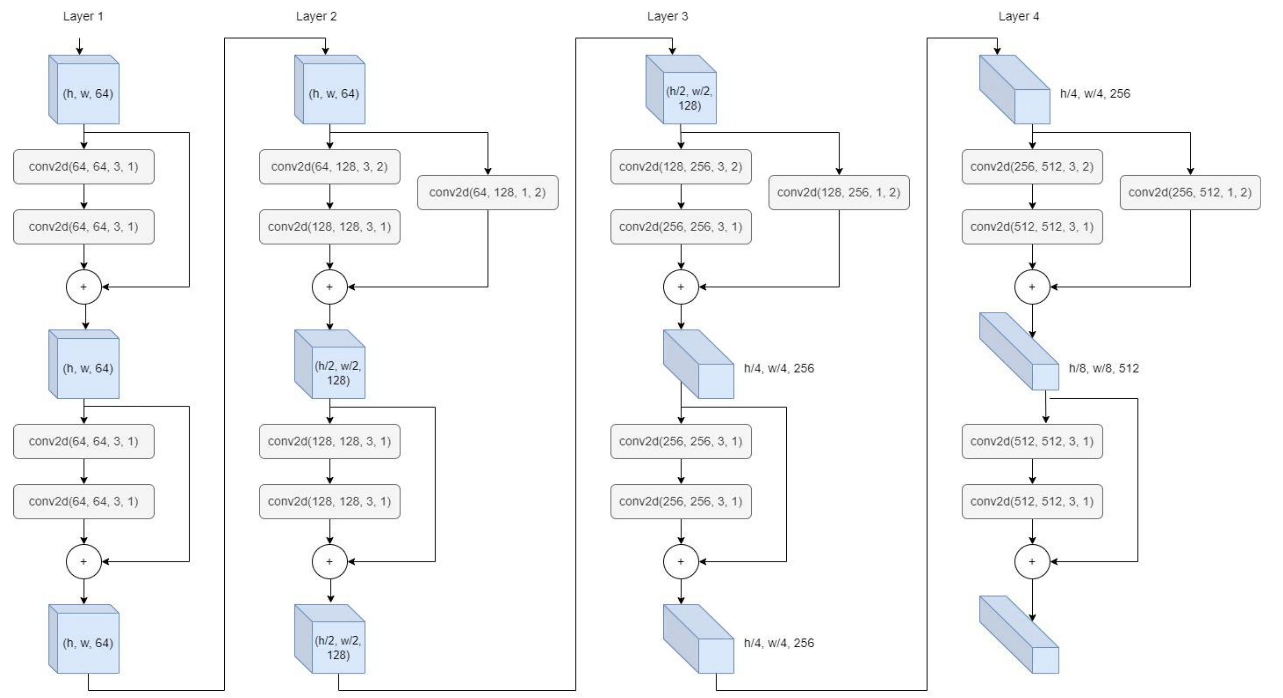


Fig. 1. ResNet 18 neural network architecture

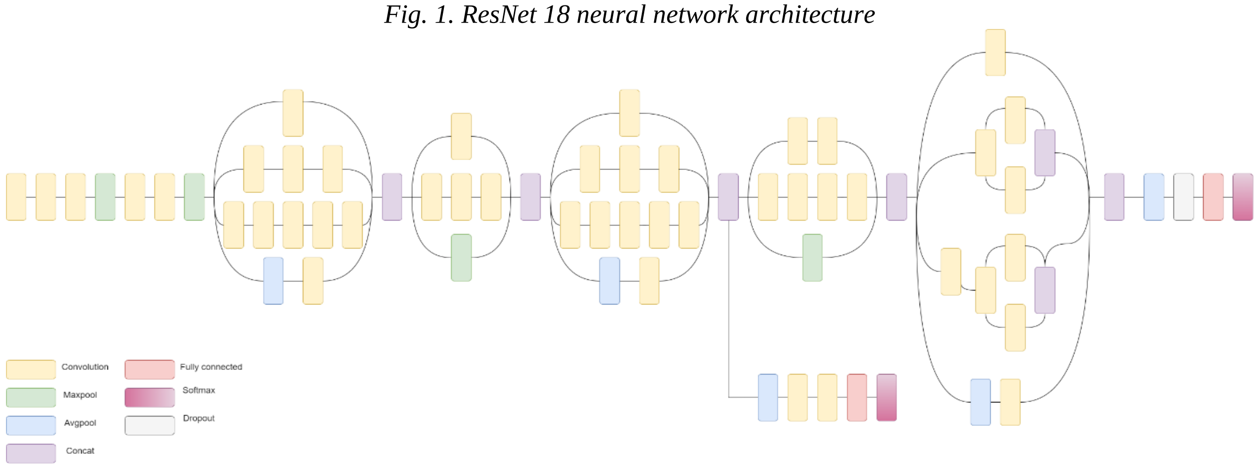


Fig. 2. The architecture of the neural network Inception V3

The parameters in this process decrease from 5x5 = 25 to 3x3+3x3 = 18. Thus, this leads to a reduction in the number of parameters by 28%.

Dataset description

As data were taken 11 000 images of tomato disease from the Tomato leaf database *(https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf)*. The images were divided into 10 classes, where there is one healthy type and nine classes (Fig.3) of unhealthy type.

Bacterial spot of tomato (Fig.3, *a*) is a potentially devastating disease that, in severe cases, can lead to unmarketable fruit and even plant death. The first symptoms of black bacterial spotting are found on the leaves in the form of small indented brown spots of irregular shape. The spots increase in size to 1-2 mm, then blackening appears in their center. They cover most of the leaf plate. Symptoms of bacterial spotting appear on the ovaries, leaves, stems, and fruits of tomatoes. On the affected fruits, dark convex spots in the form of ulcers are first formed and surrounded by a watery border. Gradually they increase in size to 3-4 mm. The affected fruits remain underdeveloped, quickly rot. High average daily air temperature causes a massive spread of the disease.

The spread of early blight (Fig.3, *b*) begins with the lower leaves of tomatoes. As the infection spreads, the spots become larger in size. The lower part of the leaves is covered with a light coating of fungus, like a spider web. Gradually, the leaf cover turns yellow, twists, dries and dies.

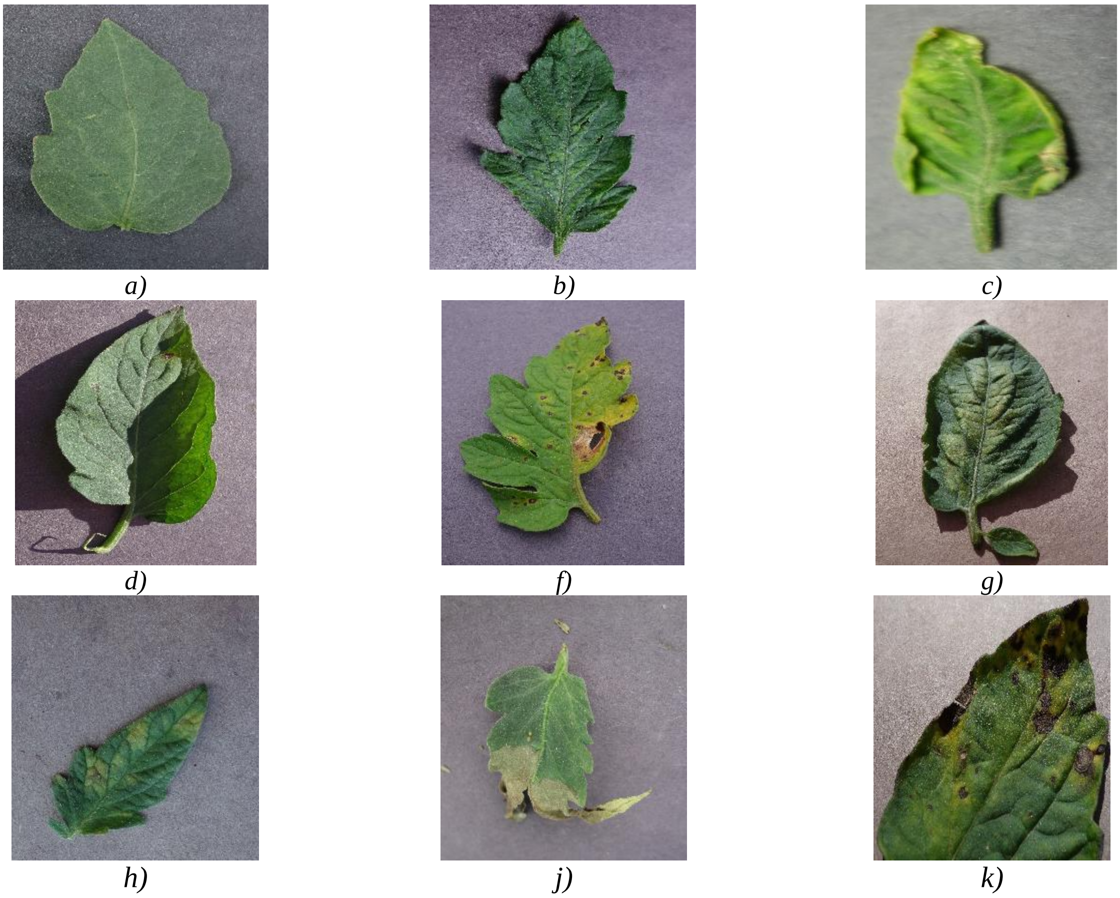


Fig. 3. Types of unhealthy tomato leaves: a – Bacterial spot; b – Early blight; c – Late blight; d – Leaf mold; f – Septoria leaf spot; g – Spider mites; h – Target spot; j – Yellow leaf curl virus; k – Mosaic virus

Leaf mold disease mainly affects only the leaves and is not dangerous for other parts of plants (Fig.3, *d*). The infection spreads from the bottom up along the leaf blades of tomatoes. An olive bloom appears on the underside of the leaf, and yellow spots spread out on the top, which damage the leaf surface through and through. Over time, the spots turn brown and spread throughout the leaf. It turns dark brown on top. Gradually, the disease rises up to the point of growth, causing the fall of dried leaves.

The white spotting or septoria of tomatoes (Fig.3, *f*) is manifested by the appearance on the leaves of the plant of small smooth round spots of dirty white or brown color, bordered by a brown stripe. Over time, these spots "spread out" to the point that they can occupy the entire surface of the leaf. On the spots of these leaves on both sides, you can also notice numerous dark dots-mushroom pycnids – it is from these fruit bodies that infectious fungal filaments – hyphae spread into the plant tissue. The disease begins to spread from the lower old leaves, then moves higher and affects the stems, flowers, and fruits of the plant. In the case of a severe lesion, these organs not only change color, but later twist, bend and dry up. The tomato is not only deprived of mature leaves and shoots, but in the future, it is forced to spend all its efforts on the formation of new ones, and not on fruiting.

Tomato red spider mite (Fig.3, *g*) produces webbing, especially on the undersides of leaves (Figure). In high infestations, dense webbing can mummify plants. Leaf defoliation follows infestation and plants may die in severe attacks.

When tomato plants are infected with the yellow curl virus of tomato leaves (transmitted by whiteflies), the new leaves acquire a cup-shaped shape and turn pale green (Fig.3, *j*). In addition, the entire plant may experience growth retardation, yellowing of the edges of the leaves, purple streaks on the underside of the leaves and a decrease in fruit yield.

Tomato mosaic virus (Fig.3, *k*) symptoms can be found at any stage of growth and all parts of the plant may be infected. They are often seen as a general mottling or mosaic appearance on foliage. When the plant is severely affected, leaves may look akin to ferns with raised dark green regions. Leaves may also become stunted. Infected plants may have a severe reduction in fruit set and those that do set may be dotted with yellow blotches and necrotic spots while the interior of the fruit is brown.

All of the above tomato diseases are the most serious and extremely contagious diseases that can lead to crop loss. Therefore, a system has been developed to identify and classify healthy and unhealthy tomato leaves using deep learning architectures.

Research results and discussion

The main task was to analyze the quality results of the two neural networks, since we trained it several times in ResNet18 itself:

1. Learning without stochastic descent
2. Training of stochastic descent with momentum parameters 0.9, 0.7 and 0.5.

The Stochastic Descent algorithm with a momentum looks like this:

$$\begin{cases} w^{t+1} = w^t + \alpha \cdot v^t \\ v^{t+1} = v^t \cdot \beta - \nabla f \end{cases} \qquad (1)$$

where, w^t – the vector of weights at the present moment of time;

w^{t+1} – the vector of weights at the next moment of time;

v^t – the speed at the present time;

v^{t+1} – the speed at the next moment in time;

α – the learning rate;

β – momentum, which we will change depending on the results.

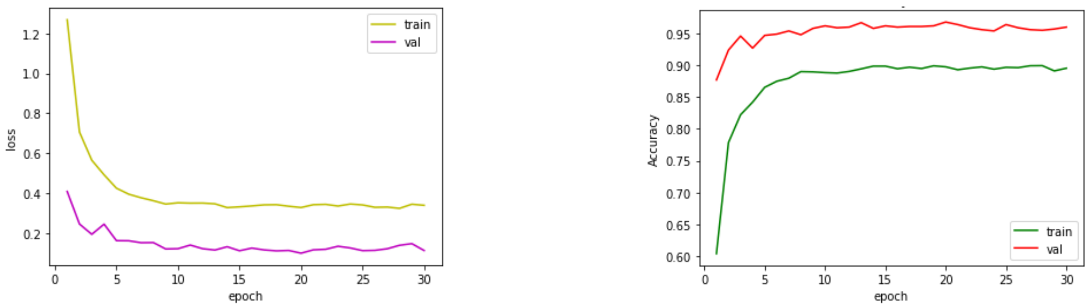
In addition, the pytorch StepLR framework method was used during the training. This function was necessary to reduce the learning rate of each group of parameters by the value of the epoch y by the step size parameter. The values of all parameters were selected as follows:

Table 1. The value of training parameters

Parameters	***Value***
α	*0.001*
γ	*0.1*
step_size	*7*
last_epoch	*-1*

ResNet18

First, the neural network was trained without the use of optimization algorithms, that is, with the usual gradient descent algorithm. As a result, the accuracy metric value showed a value above 0.95 (Fig. 4), and according to the error function graph, we see that there is no effect from retraining:



a) *b)*

Fig. 4. The value of the gradient descent ResNet learning metrics: a - loss; b - accuracy

The next step was to train the same architecture but using stochastic gradient descent (SGD) optimization. 3 parameters of β (momentum) were taken (Fig. 5-7). The learning outcomes for each are as follows.

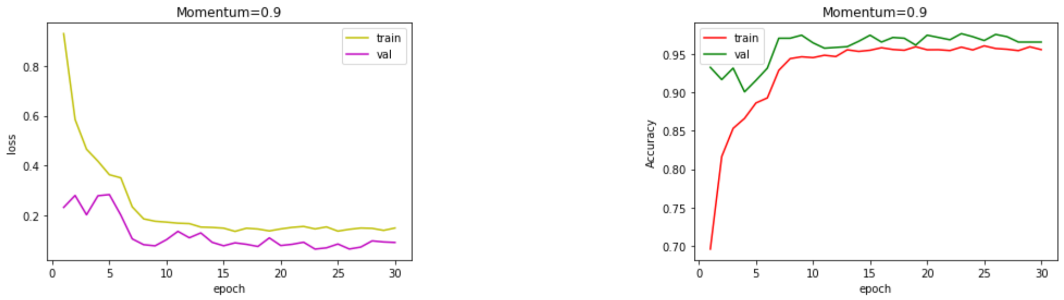


Fig. 5. The value of SGD learning metrics at β=0.9: a - loss; b - accuracy

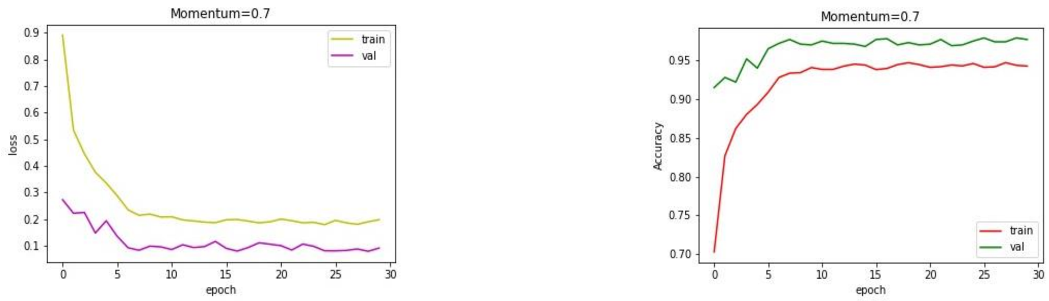
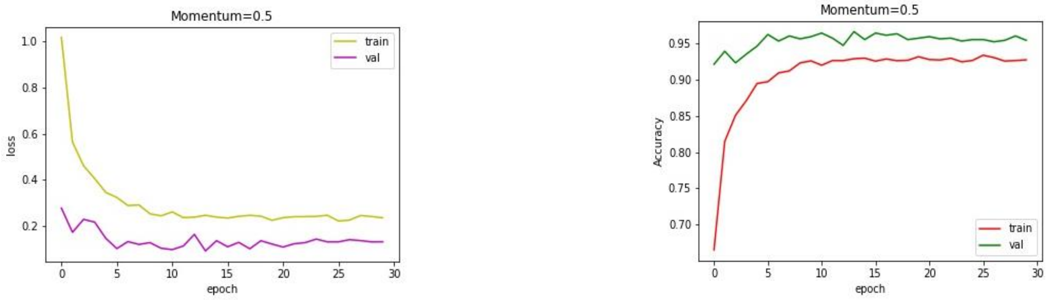


Fig. 6. The value of SGD learning metrics at β=0.7: a - loss; b – accuracy



a) *b)*

Fig. 7. The value of SGD learning metrics at β=0.5: a - loss; b – accuracy

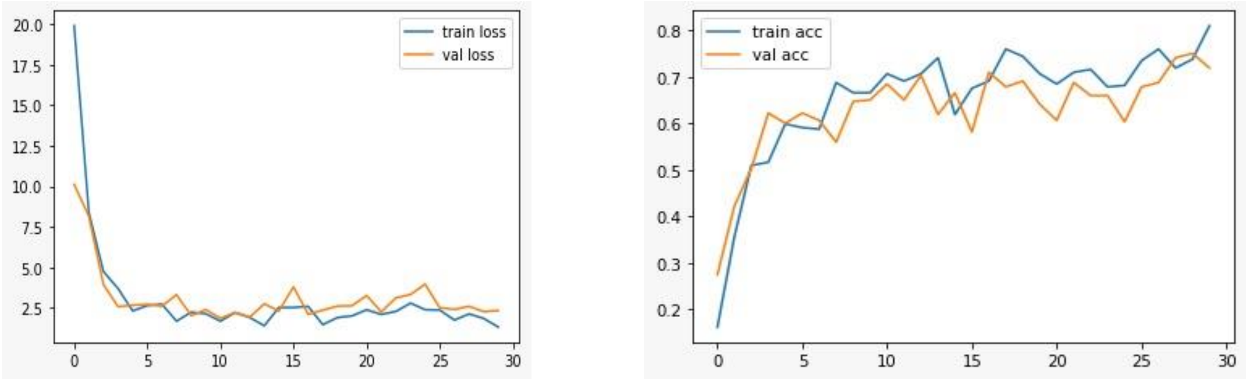
Table 2. Results of accuracy of the ResNet18 architecture

ResNet18	*Max_train Accuracy*	*Min_train Accuracy*	*Max_validation Accuracy*	*Min_validation Accuracy*
Without momentum	*0.8995*	*0.604*	*0.968*	*0.877*
β = *0.9*	*0.9611*	*0.6957*	*0.977*	*0.901*
β = *0.7*	*0.9471*	*0.703*	*0.979*	*0.915*
β = *0.5*	*0.9335*	*0.6654*	*0.966*	*0.921*

As can be seen in Table 2, the largest accuracy value on train was shown by training with a momentum value of 0.9, and on validation, training with a momentum of 0.9 and 0.7 showed almost identically 0.97. This parameter with a value of 0.5 shows the worst accuracy result out of three trained with stochastic gradient descent optimization on both train and validation at points 0.9335 and 0.966 respectively.

Training without SGD on train shows the worst result of all. You can see a significant difference in values between regular training and with SGD. If three trained with a momentum varied between 0.93 and 0.96 per train, then simple training showed a value of 0.89.

Inception V3



a) *b)*

Fig. 8. The value of InceptionV3 learning metrics: a - loss; b - accuracy

Table 3. Results of accuracy of the InceptionV3 architecture

Max_train Accuracy	*Min_train Accuracy*	*Max_validation Accuracy*	*Min_validation Accuracy*
0.8094	*0.3562*	*0.7188*	*0.2750*

Training on the InceptionV3 architecture on train showed the best result of 0.8094, and on data validation gave the result of 0.7188.

When conducting a review on similar tasks [7, 8], it was found that the recognition accuracy of our system based on Inseption V3 was comparatively less. But more emphasis was placed on learning the ResNet architecture and optimizing using the momentum parameter. Based on the results obtained, a comparative analysis was carried out for different values of the optimization parameter. Architecture variations were evaluated by accuracy and loss function metrics. The problems of forming a training sample often have a decisive impact on the quality of the algorithm and can serve as a limitation of the study. In our work, a balanced data set was used, which for each class had 1100 images of tomato leaves. This is one of the important factors, since in the learning algorithms, quality metrics are optimized in the learning process, which are a simple sum of errors for all training examples, and this amount will depend on the ratio of the number of training examples of different types. In the future, it is planned to expand the data set with the addition of other types of tomato plant diseases. With the increase in the amount of data, there is a great need for complex calculations with excellent performance specifications. The convergence of high-performance computing and deep learning for processing frames, reducing training cycles and improving accuracy is considered.

Conclusion

Work was carried out on training two neural networks ResNet18 and InceptionV3. Optimization using stochastic gradient descent showed an accuracy value greater than normal gradient descent. On average, for 30 epochs, training with SGD showed 1.05% more accuracy on the training sample. The high value of the momentum parameters training ResNet18 showed the best result of all. The recognition accuracy of InceptionV3 is significantly less than ResNet18 on the same data set. For the InceptionV3 architecture, it was concluded that with fewer parameters, the model will be less overloaded and, consequently, increase accuracy.

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