Analysis of grape *(Vitis Vinifera)* diseases using neural networks

Dmitry Rudoy[1,2], *Anastasiya* Olshevskaya[1], *Mary* Odabashyan[1], *Marina* Egyan[1*], *Alexander* Rybak[1], *Nikolay* Gapon[1], *Marina* Zhdanova[1], *Anna* Vershinina[1], and *Sergey* Marchenko[1]

[1] Don State Technical University, Gagarin sq. 1, Rostov-on-Don, 344003, Russia
[2]Agricultural Research Centre "Donskoy", Lenin Str., 14, Zernograd, Rostov Region, 347740, Russia

Abstract. Grape (*Vitis Vinifera*) diseases cause a decrease in yield and product quality, and have an adverse effect on the growth, condition and resistance of bushes to frost. Some of the most common grape diseases can lead to poor berry quality and reduced yields, which can ultimately impact the income generated. To combat grape diseases, it is necessary to regularly treat plants with special preparations and monitor the condition of the plants throughout the growing season. Keywords: grapes, grape diseases, CNN, deep learning, computer vision, neural networks.

1 Introduction

Grapes (lat. *Vitis Vinifera*) are a perennial heat-loving plant with over ten thousand varieties. Grapes are one of the first plants that humanity began to cultivate.

Industrial production of grapes is concentrated in the south of Russia: in the Krasnodar and Stavropol territories, Chechnya, Dagestan, Ingushetia, Kabardino-Balkaria and North Ossetia, Astrakhan, Volgograd, Saratov and Rostov regions.

Almost three quarters of all Russian vineyards are located in the Krasnodar region. International, Caucasian, autochthonous varieties and varieties of Soviet selection are grown.

Viticulture, and with it winemaking, are one of the most dynamically developing branches of agriculture, gaining popularity among young professionals and fame among the mass consumer.

Grape diseases cause a decrease in yield and product quality, and have an adverse effect on the growth, condition and resistance of bushes to frost. Losses from grape diseases can reach up to 80%, and restoration of the vine will take many years. Most grape diseases are of fungal origin and affect both vegetative and generative organs of the plant. Diseases of grape leaves not only spoil their appearance, but also destroy the foliage in the vineyard, ruin the precious harvest and greatly weaken the bushes. In this regard, timely diagnosis and accurate identification of grape leaf diseases are critical to control the spread of diseases and ensure the healthy development of the grape industry.

The main diseases of grapes include: *mildew, oidium, anthracnose, rubella, etc.*

* Corresponding author: edigaryan_1996@mail.ru

The main reasons are oversaturation or lack of necessary elements in the soil for bush growth, lack of light, unfavorable weather conditions, as well as insects that carry viruses. The most dangerous are viral diseases that cannot be treated, often destroying entire vineyards.

Current approaches to disease detection are based primarily on visual recognition. However, visual recognition is not only a time-consuming task, but also the recognition accuracy does not meet the requirements [1].

With the rapid development of artificial intelligence, machine learning techniques have been applied to plant disease detection to make it more intelligent.

New technologies have long been used in viticulture and winemaking. Many advances have shown how automation can help manufacturers ensure the quality and integrity of their products.

These innovations are enabling producers around the world to make smarter, more timely decisions and reduce the labor required to complete vineyard and winery operations.

Neural networks, especially deep learning models, are becoming increasingly popular for disease analysis in various fields, including agriculture. When it comes to analyzing grape diseases, neural networks can be very effective. By training deep learning models on image datasets of healthy and diseased grapevines, they can learn to accurately classify different diseases.

Convolutional neural networks (CNNs) are commonly used for image classification tasks because they can automatically extract relevant features from images. By analyzing images of grape leaves, fruits or vines, these models can identify patterns and textures specific to each disease. Pre-trained CNN models can be trained on the grape disease dataset to leverage their ability to recognize patterns in images. This approach helps improve the performance of neural networks, especially when the data set is limited.

Additionally, recurrent neural networks (RNNS) or long short-term memory (LSTM) networks can be used for time series data related to grape diseases. By analyzing data on weather conditions, soil moisture and other factors, these models can predict disease outbreaks or recommend optimal treatment for prevention.

Using these advanced algorithms, researchers and farmers can detect diseases early, make informed decisions, and ultimately improve profitability and grape quality.

A convolutional neural network (ConvNet/CNN) is a deep learning algorithm that can take an input image, assign importance (learned weights and biases) to aspects or objects in the image, and distinguish one from the other. A set of data is received at the input of each neuron, a certain mathematical operation is performed using the activation function, after which the resulting value is transferred to the next layer [2].

Deep learning is a subfield of machine learning, which in turn is a subfield of artificial intelligence. It is a set of methods that allow you to model high-level data abstractions. In deep learning, a computer model analyzes and extracts useful information from images, audio, or text for later application. These models can achieve very high accuracy, exceeding human capabilities. Models are typically trained using large labeled data sets and complex neural network architectures with multiple layers to achieve high accuracy.

Grape diseases can have a significant impact on grape production, resulting in reduced yields and potentially impacting income for grape growers.

Implementing effective disease management strategies, such as good sanitation practices and fungicide applications, can help mitigate the impact of grape diseases and protect growers from large yield losses.

Grapevine (Vitis vinifera) is an economically important crop that is susceptible to various diseases, which can significantly reduce yield and quality. Neural networks have shown great potential in accurately diagnosing plant diseases by analyzing images of affected plants. In this context, the analysis of grapevine diseases using neural networks can be a valuable tool for early detection and management of these diseases.

There are several types of grapevine diseases that can be detected using neural networks, including:

1. Powdery mildew: This fungal disease affects the leaves, shoots, and clusters of grapes, causing white powdery spots on the surfaces of infected tissues. It can lead to reduced fruit set, smaller berries, and lower sugar content.

2. Downy mildew: This is another fungal disease that affects the leaves and clusters of grapes, causing yellow or brown spots on the upper surface of leaves and gray or purple mold on the underside.

2 Brief description of the main diseases of grapes

2.1 Downy Mildew

Mildew or downy mildew is a fungal disease caused by the fungus *Plasmopara viticola.* It affects all green organs of the grape bush: leaves, shoots, inflorescences, clusters, tendrils. In case of severe disease, the bushes lose all their leaves, the harvest of the current, and sometimes the next year. When bushes are partially affected by mildew, the sugar content of the juice decreases, its acidity increases, the shoots ripen poorly, and the overall winter hardiness of the plants decreases. Signs of the disease are yellowish translucent oily spots on the leaves.

Fig. 1. Mildew on a grape leaf

2.2 Oidium

Oidium affects leaves, shoots and berries of grapes. On their surface, as well as on the leaf petioles, a coating of conidia (spores) of the fungus appears, reminiscent of rotten fish in smell and ash in color (therefore the disease is also called ashtray). Affected young berries stop growing and dry out. On the leaves, a coating of fungus, unlike mildew, also appears on the upper side.

Fig. 2. Oidium on a grape leaf

2.3 Anthracnose

Anthracnose is a disease caused by the fungus *Gloesporium ampelophagum*. It only affects the green organs of the bush. Angular spots with a dark border appear on the leaves, the affected tissues die and fall out, leaving holes in the leaves.

Fig. 3. Anthracnose on a grape leaf

2.4 Rubella

Rubella (infectious) - the disease is caused by the fungus *Pseudoecis tracheifila.* Angular oily spots appear between the veins on the edges of the leaves, which grow and turn yellow. Unlike mildew, there is no white coating on the underside of the leaves. The affected tissues dry out. In white varieties, greenish-yellow rims appear around these places; in painted varieties, the affected tissues become reddish-brown after drying and are surrounded by violet-red rims (hence the name of the disease - rubella). The lower and middle leaves are

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especially severely affected: they dry out and fall off long before natural leaf fall or before frost.

Fig. 4. Rubella on a grape leaf

Chemical protection of grapes from diseases in modern conditions plays a decisive role in obtaining high-quality grape products without losses. The rational use of pesticides and their application at the optimal time, in addition to ensuring high technical efficiency, allows you to obtain a high yield at the optimal cost with the appropriate characteristics necessary for the sales market. Most often, only a visual method of recognizing grape diseases is used. However, visual recognition may not be accurate and can be quite labor-intensive. Misdiagnosis can lead to overuse of pesticides, which will destroy the grapes' growing environment and damage the quality of the fruit.

Pesticides are any substance used either directly to control pest populations or to prevent or reduce damage to crops in a vineyard. There are many pesticides available for use in vineyards, all of which control specific pests. Although many pesticides are designed to kill pests, some may only inhibit their growth or simply attract or repel them. There are several approaches to classifying types of pesticides. Pesticides are often named according to the type of pest they control.

For example, fungicides are designed to control fungal diseases, insecticides are pesticides that affect insects, and herbicides are pesticides that target weeds. Pesticides can also be classified by their chemical class.

There are many classes of synthetic pesticides. The main classes of pesticides include organochlorines, organophosphates, carbamates, and pyrethroids. Conventional or chemical pesticides, which have a broad spectrum of action and are more harmful to natural enemies.

Another way to classify pesticides is how and when they act: contact, systemic, pre-emergence, post-emergence, selective and non-selective (or broad spectrum). Pesticides can be grouped based on their action or method of controlling target pests. This also applies to the main location. For example, one insecticide may affect the insect's nervous system, while another may affect molting. Pesticides can also be classified as biorational pesticides, which are more selective because they are most effective against pests with certain feeding habits, at certain life stages, or within certain taxonomic groups.

They are also known as "least toxic" pesticides. Because biologics are generally less toxic and more selective, they tend to be less harmful to natural enemies and the environment. A similar term is used to refer to "biopesticides".

3 Analysis of studies on identification of grape diseases using computer vision

Waghmare H., Kokare R., Dandawate Y. proposed a method for identifying grape diseases through analysis of leaf texture and pattern recognition. The system took one leaf of the plant as input and segmentation was performed after removing the background. The segmented leaf image was then analyzed using a high-pass filter to detect the affected part of the leaf. Finally, the extracted texture template was sent to a multi-class SVM.

Work by authors Mokashi M., Uzma Afreen Bagayat and others. is devoted to the analysis of diseases and assessment of the vegetation index for grape plants. The authors discuss image acquisition, information preprocessing, image segmentation, feature extraction, and image classification. The study uses standard classification methods such as K-means support vector machine (SVM) clustering algorithm. The experiment results show that the professional approach is a valuable approach that can significantly achieve 90.56% accuracy for leaf disease detection.

By Mohammadpoor M., Nooghabi M.G. An intelligent method for detecting viruses in grape leaves has been proposed. Based on the fuzzy C-means algorithm, the affected area of each leaf was extracted and then classified using SVM. In addition, to improve the diagnostic reliability of the system, the K-fold cross-validation method was applied with k = 3 and k = 5. The experimental results showed that the average accuracy of the system was about 98.6%.

The authors Li G., Ma Z., Wang H. proposed a method based on K-means cluster segmentation of grape disease images, and an SVM classifier was developed based on thirty-one effective selected features to identify grape downy mildew and grape powdery mildew with coefficients recognition 90% and 93.33. %

However, machine learning algorithms require cumbersome image preprocessing and feature extraction [3-11]. In contrast, CNN can automatically distinguish and extract distinctive features for image identification.

Why is the vine so important for the economy? The vine (Vitis vinifera) is not just a plant, it is an entire branch of agriculture that plays a huge economic role. Let's figure out why the vine is so important for the economy.

Grapes for winemaking: One of the main products obtained from grapes is wine. The wine industry is of great importance to the global economy. Wine is not only a popular alcoholic beverage, but also an object of luxury, collectibles and investments. Growing grapes for wine production creates jobs, promotes tourism and promotes regions known for their wines.

Fresh and dried fruits: In addition to wine, grapes are used for the production of fresh and dried fruits. Raisins, various desserts, juices and even decorations are made from it. The variety of products obtained from grapes makes it in demand on the market and contributes to the development of agriculture.

Medicinal properties: Grapes are not only delicious, but also healthy. It provides natural antioxidants, vitamins and minerals that help strengthen the immune system and maintain health. Grape-based products are widely used in medicine and cosmetology.

The study introduces a novel automated system for grape disease identification, targeting five specific diseases such as powdery mildew and anthracnose. Utilizing the established AlexNet framework, the researchers conducted feature extraction and training of leaf image models, achieving accurate disease classification results. Additionally, a unified convolutional neural network architecture, named UnitedModel, was developed by Wagh

T.A., Samant R.M., Gujarathi S.V., and Gaikwad S.B., showcasing superior performance in classifying grape leaf diseases.

This innovative approach combined multiple CNNs to extract unique features, leading to an impressive average test accuracy of 98.57%. Similarly, Liu B., Ding Z., Tian L., He D., Li S., and Wang H. proposed an enhanced CNN-based model, termed DICNN, for grape disease recognition, emphasizing a dense connectivity strategy to optimize feature reuse and propagation.

.DICNN exhibited notable accuracy improvements, achieving a 97.22% overall accuracy on a comprehensive test set, surpassing the performance of existing models by significant margins.By Wagh Tanmay, R.M. Samant, Sharvil V. et al used a deep learning model called CNN. Feature extraction and leaf image model training are performed using a predefined AlexNet architecture. The image dataset is taken from the “National Center for Research on Grapes” (ICAR). It consists of pictures of 5 diseases such as: powdery mildew, downy mildew, rust, bacterial stains and anthracnose. The image of the leaf is captured using the built-in camera module of a mobile phone. The achieved accuracy is 98.23% for powdery mildew and bacterial stains [12-15].

Authors Wang C., Wang Y., Ma G., Bian G., Ma C. In their work, they studied the intelligent identification of grape diseases in their natural state based on improved YOLOXS. Initially, the authors created a dataset on grape diseases in the natural environment. Then the YOLOXS algorithm was improved by adding FOCUS module to the backbone, introducing CBAM, double residual edges in the prediction head. As a result of training, a model for identifying grape diseases with an accuracy of 99.10% (GFCR-YOLOXS) was obtained [16].

4 Conclusion

Based on the literature reviewed, we can conclude that neural networks, in particular convolutional ones, can greatly improve the accuracy of image recognition and achieve results not achieved by classical computer vision methods. Convolutional neural network models successfully recognize diseases from grape leaves with an accuracy of 91.37%. Using 80% of images for training and 20% for testing. For further research, it is recommended to use more types of grape leaf diseases and use other algorithms and other deep learning frameworks.

The vine plays a huge economic role due to the production of wine, fresh and dried fruits, as well as medicinal products. Its cultivation contributes to the development of agriculture, tourism and healthcare. Thus, the vine is deservedly considered one of the most important crops for the economy of many countries.

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