Using Neural Networks to Identify Technological Stress Using the Example of Crop Compaction

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Abstract
The article is devoted to the study of the use of neural networks to identify the technological stress of plantations in the technologies of precision agriculture. The study takes into account such complex aspects of sample selection as the speed of image acquisition, the effectiveness of assessing the state of crop compaction, etc. The use of neural networks makes it possible to automate and increase the accuracy of selection, to improve the quality of the analysis of plant stands, provided that the technology of evaluating soil samples is followed. The obtained results indicate the prospects of implementing this approach in modern agriculture.

Keywords
Neural network, precision farming, image recognition, education, crop density, technological stress.

1. Introduction

The promotion of energy-efficient communities is becoming an increasingly popular phenomenon in various countries, and the stench is associated with the persistent development and unleashing of many global problems (economic, social, climate and energy, etc.). Energy-efficient communities are those that have become self-sufficient in renewable energy and energy-efficient technologies. The availability of biomass (including those from agricultural production) for biogas production is determined by both the regions that do not allow access to cheap energy resources and the energy-possible regions (on butt, USA), according to Y. Niu and A. Korneev (2022) in [1] beware of the rapid development of this galusa. One of the main reasons for such respect is the possibility of effective and efficient disposal of organic surpluses since uncontrolled disposal of agricultural waste can become a serious environmental problem (J. Li et al, 2020) [2]. While for urbanized territories, such as megacities, agrarian generation can serve as an additional source of energy, then for locality with less intensity of accumulated energy such These can become an alternative to centralized energy supply measures.

With the intensification of the food crisis in the world, there is still a tendency for the growth of agricultural output as biomass sources. Thus, in Pakistan, according to the data of U. Ur Rehman Zia et al (2019) in [3], they looked at various options for the use of vegetable matter for energy production with a view to saving soil fertility. For European countries, according to the data of S. Kalenska (2022) in [4], the same trend is being guarded.

One of the most promising sources of plant biomass are crops affected by technological stress. The stresses of a technological nature include poisoning by agrochemical residues shown in N.

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Tereshchenko et al (2023) in [5], in particular the prolonged action of herbicides described by N. Pasichnyk et al (2020) in [6] and exposure to harmful organisms, respectively, in L. Murashko et al (2022) in [7] and crop compaction. The compaction of crops leads, in particular, to loss of grain quality or, in general, to lodging of plants and loss of harvest. Thickening occurs due to a malfunction or improper adjustment of the planter, errors of non-observance of technological tracks during sowing. The danger of this technological stress is that it is difficult to diagnose at the initial stages of industrial production, which leads to the irrational use of agrochemicals and incorrect assessment of the expected quality of products.

The purpose of this work is to develop methodological approaches for remote assessment of crop thickening.

2. Materials and methods

2.1. State of the problem

The issue of crop compaction and its impact on fertility was studied by agronomists in particular in the works of V.F. Zavertalyuk et al (2019) in [8] and P.V. Pysarenko et al (2021) in [9]. The methods of determining the compaction of plants used by the above authors involve the counting of plants per unit area and are used to correct the sowing technology, that is, the option of accidental compaction, that is, technological stress, is not considered. Cases of compaction of crops were recorded regularly by growers, to prevent them, they tried to improve the equipment for differentiated seed application shown in the work of A.M. Ayubov et al (2019) in [10], the accuracy of positioning in the field is shown in L.V. Aniskevich, (2018) in [11]. Such approaches contribute to avoiding the problem, but not its identification.

The assessment of seed compaction for sunflower and corn at the initial stages of vegetation was carried out in the works of D. Poleshchenko et al (2023) in [12] and Shuaibing Liu et al (2023) in [13], however, the proposed solutions are suitable only for row crops, where the sowing error it is easier to detect and purely visually. In the work of Norman Wilke et al (2021) in [14] regarding wheat, a resolution of 0.2 mm/pixel was recommended for plant counting, which is difficult to implement on an industrial scale with the existing parameters of sensor equipment for UAVs. To solve the question of industrial use, the authors proposed to identify the area of the leaf floor, which coincided with the proposals put forward in the work of V. Lysenko et al (2019) in [15]. However, this is possible only at the initial stages of vegetation, while taking into account the small dimensions of the plants, there may be problems with the reliability of the data. Taking into account the complexity of identifying the boundary between plants and soil, the approach tested in the work of N. Pasichnyk et al (2021) in [16] on high-resolution satellite images for object identification in images for GaussAmp distribution (1) is possible, where additional the parameter is the standard deviation.

$$N = A \times exp^{\frac{-(X-xc)^2}{2w^2}} \tag{1}$$

where: N is the number of pixels; X – is mathematical expectation, A – is amplitude; xc – the average value; w is the standard deviation (corresponds to the value of A/2).

Therefore, for the identification of crop compaction, it is promising to monitor crops using UAVs, taking into account distribution parameters for spectral channels or vegetation indices on field sections.

2.2. Organization of experimental studies and processing of results

Experiments were conducted with wheat during 2017-2021 on production fields in Boryspil district of Kyiv region with coordinates 50º16' N, 30º58'E 50.0347. Multispectral studies using the infrared range were carried out using the Slantrange 3p system and SlantView software (version 2.13.1.2304), specially developed for this type of sensor equipment.

The advantage of SlantView software is the ability to quickly and independently create maps of the distribution of vegetation indices even in an open field. This software also allows you to create orthophoto maps from the images, correct lighting and provide users with ready-made maps of the distribution of vegetation indices, such as different variants of NDVI. Using the built-in SlantView software tools, data can be exported to geotiff format. The analysis was carried out both by separate spectral channels and by means of vegetation indices calculated in the SlantView program. A more detailed description of the research methodology is given in N. Pasichnyk et al (2021) in [17]. For research, a part of the production field was taken, where within a single frame, plots with normal and double the number of seeds were recorded (Fig. 1).

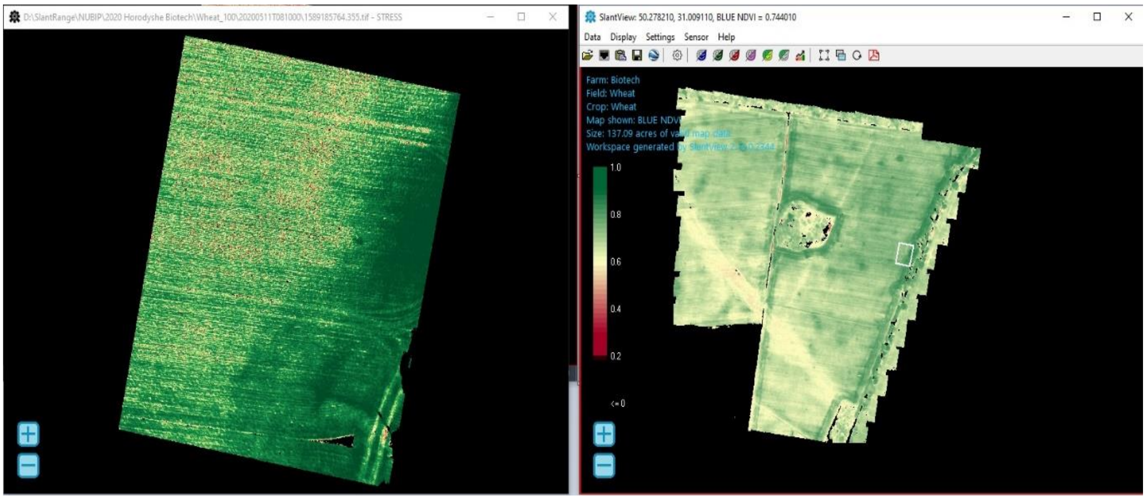

Figure 1: Technological stresses associated with the thickening of crops. Snapshot window for stress index (left) and NDVI distribution map in SlantView software (right)

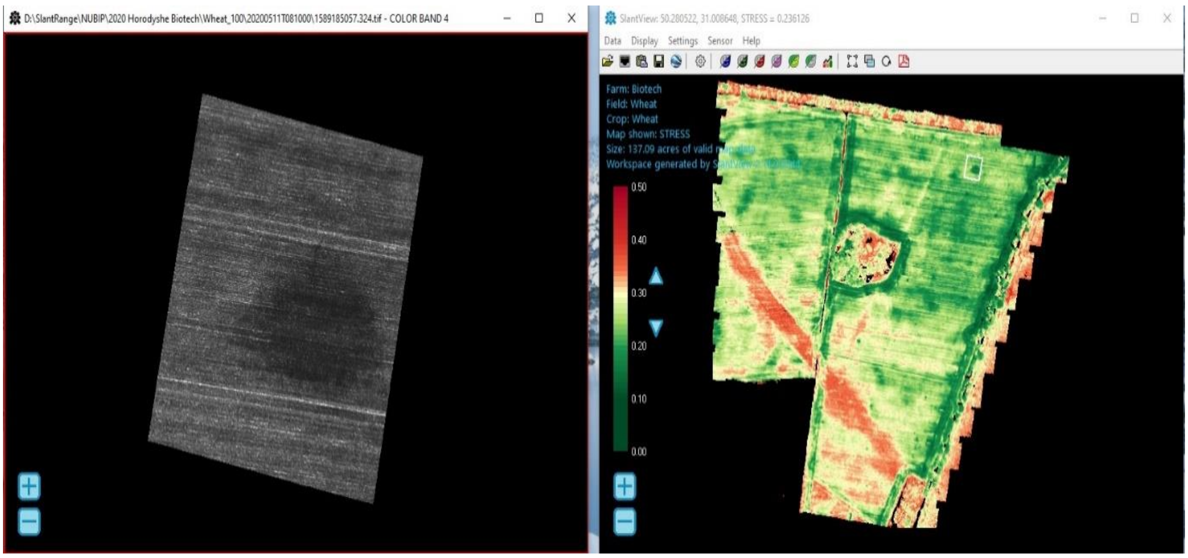

Figure 2: A picture in the IR spectrum of a field with a lowland (on the left) and the Stress map in the SlantView software (on the right)

To take into account the influence of the state of moisture, we separately considered the area in the lowland (Fig. 2), where relatively larger dimensions of plants were recorded during ground monitoring. To ensure unambiguous identification of pixels in the image, reference points were used, which were implemented in SlantView software to merge images and maps. These reference points were highlighted and displayed on both images and maps.

The software OriginPro version 8.0951 (B951), developed by OriginLab Corporation, was used for statistical processing of experimental data related to distribution parameters.

3. Results

3.1. Spectral channels

The results obtained for the green spectral channel of the Slantrange system are presented in Fig. 3. Therefore, in connection with the technological stress caused by the increase in the density of sowing, the average value, which was recorded in the sowing in the lowland with better indicators of water supply, turned out to be identical to the average value of other plots.

In other words, solutions based only on average values for this area, in our case for the GaussAmp distribution - the value of mathematical expectation, were not able to distinguish these differences. But when using a promising parameter such as standard deviation, identification was possible because the values were close to those of the reference plot with a normalized seeding rate. The results obtained using the Red, RedEDGE, and NIR channels are presented in Table 1.

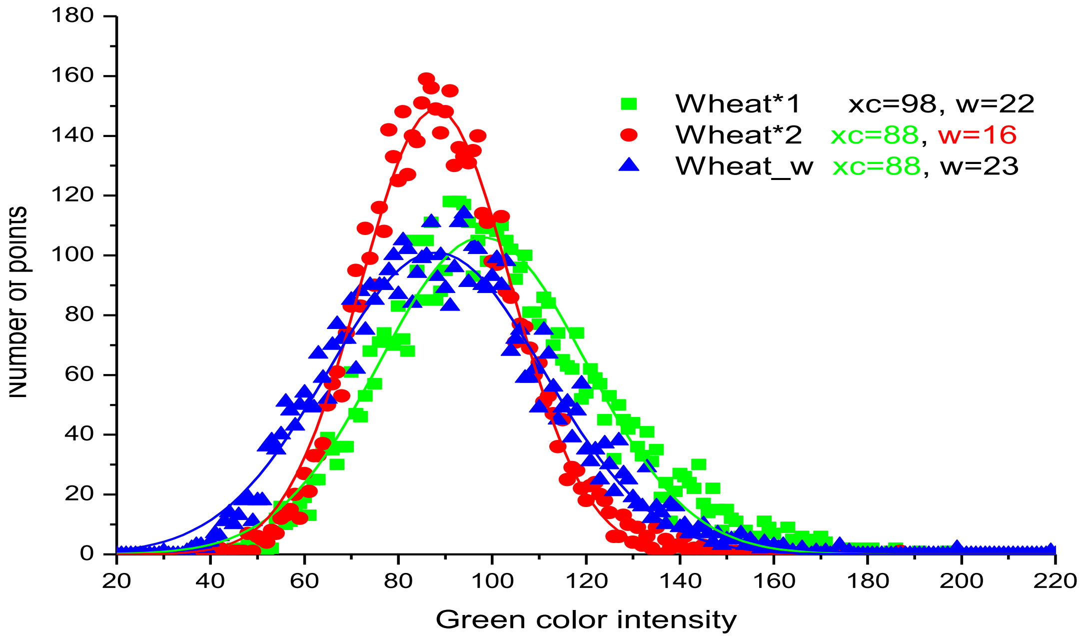

Figure 3: Dependence of the number of pixels on the value of the intensity of the green color components for normal and doubled number of seeds (Wheat*1 and Wheat*2, respectively) and with greater water supply (Wheat_w)

Table 1
Results of approximation of experimental data using GaussAmp distribution for plots of winter wheat

	Red			RedEDGE			NIR		
	wheat 1	wheat 2	wheat w	wheat 1	wheat 2	wheat w	wheat 1	wheat 2	wheat w
xc	89	69	79	65,3	61,1	65	42	50,7	48,5
w	22,2	14	18,6	15	11,2	15,7	10,7	11,3	11,3
A	101	160	121	153	208	149	217	205	202
R2	0,95	0,98	0,97	0,99	0,99	0,99	0,99	0,99	0,98

According to the obtained results, it can be said that the value of the standard deviation, which was calculated on the basis of experimental data, is a useful parameter for detecting the stress state of wheat using the Green, Red and RedEDGE spectral channels.

The small difference in xc and w parameters for the NIR channel, which is commonly used for plant identification by spectral monitoring, may be due to the fact that the plants are slightly larger due to better water availability. Despite the positive results obtained directly from the standard spectral channels of the Slantrange complex, it should be taken into account that, unlike similar complexes of other developers, the Slantview standard software does not provide the ability to calculate its own vegetation indices. Accordingly, taking into account the limited time frame for making a decision on sampling sites, it is advisable to consider those vegetation indices that can be calculated by the official Slantview software.

3.2. Combinations of spectral channels (vegetation indices)

By analogy with the spectral channels for the vegetation indices, plots with a size of 50×50 pixels were considered. To avoid binding to Slantrange equipment (Slantview software), only standard vegetation indices whose calculation formula is known, namely different variations of the NDVI index (Red NDVI - RNDVI and Green NDVI - GNDVI) will be considered. The obtained results are shown in Fig. 4. For vegetation indices, the difference in the value of mathematical expectation between compacted and normal crops was larger, for the Green and GreenNDVI channels it was 4 and 14%, respectively. The situation is similar for the standard deviation. That is, it is advisable to analyze the presence of technological stresses with vegetation indices. Similar results were obtained for stresses caused by the prolonged action of herbicides shown in the work of N. Pasichnyk et al (2021) in [17] where graphical analysis was applied to analyze the distribution map. A possible option for speeding up calculations is the graphical analysis of maps of the distribution of vegetation indices, that is, when the map itself is the object of research. When conducting research on a production field with an area of 60 ha, data processing with standard Slantview software on a computer (Core i7 6500u\16 Gb DDR3\240 Gb SSD\Quadro M500m) lasted for 80 minutes. In order to use graph analysis, the distribution map was exported and processed using proprietary software (Fig. 5).

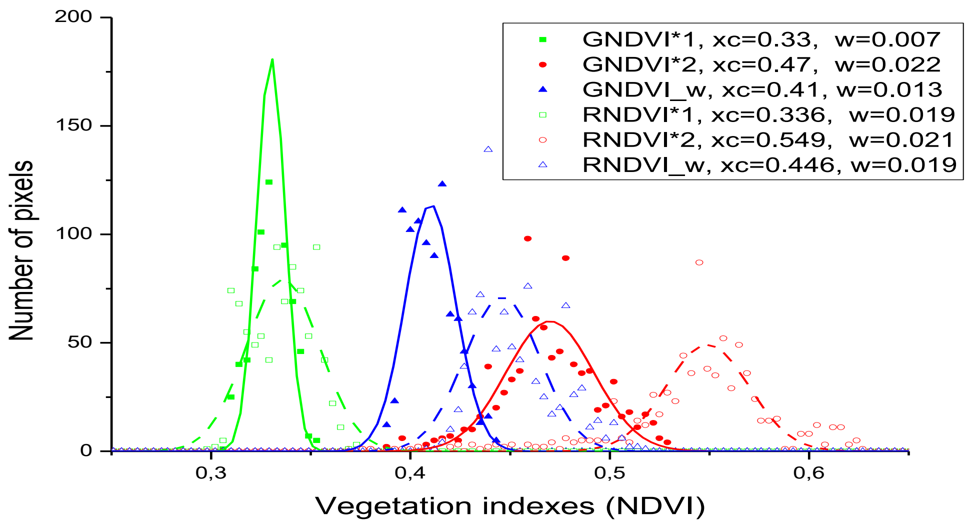

Figure 4: Dependence of the number of pixels on the value of the vegetation index GNDVI and RNDVI indices similarly to Fig. 1

The duration of the calculations was more than 50 minutes, which, at the request of the farm's production specialists, should be shortened. The issue of identifying crop compaction based on Gauss distribution analysis is complicated by the fact that compaction is possible not only due to errors in technological tracks, but also as a result of purposeful action, as an option of additional sowing along the roads is shown in Fig. 2 on the distribution map of the Stress index. It was proposed to speed up the identification process using neural networks as shown in the work of M.G. Lutsky et al (2021) in [18].

3.3. Neural networks for the analysis of maps of the distribution of vegetation indices

Deep learning has proven successful in various fields of machine learning, such as computer vision, natural language processing, audio processing, and speech recognition. Section [19] provides a detailed review of graph convolutional networks that extend the convolution operation to graph data. These networks are divided into four categories and their performance and scalability in large graph structures are discussed. Modeling and optimization of various processes in modern engineering are becoming more efficient thanks to the use of data and machine learning. Data-driven models can be updated to accurately represent the system. They are used in technological systems, although they have their limitations, especially in scaling [20].

Machine learning allows computers to learn from examples and formulate general rules from specific input data. Deep learning includes concepts such as multi-level concatenation, backpropagation, and convolution. Ultimately, it is important to note that both forms of machine learning have their own areas of application and may be optimal for different tasks.

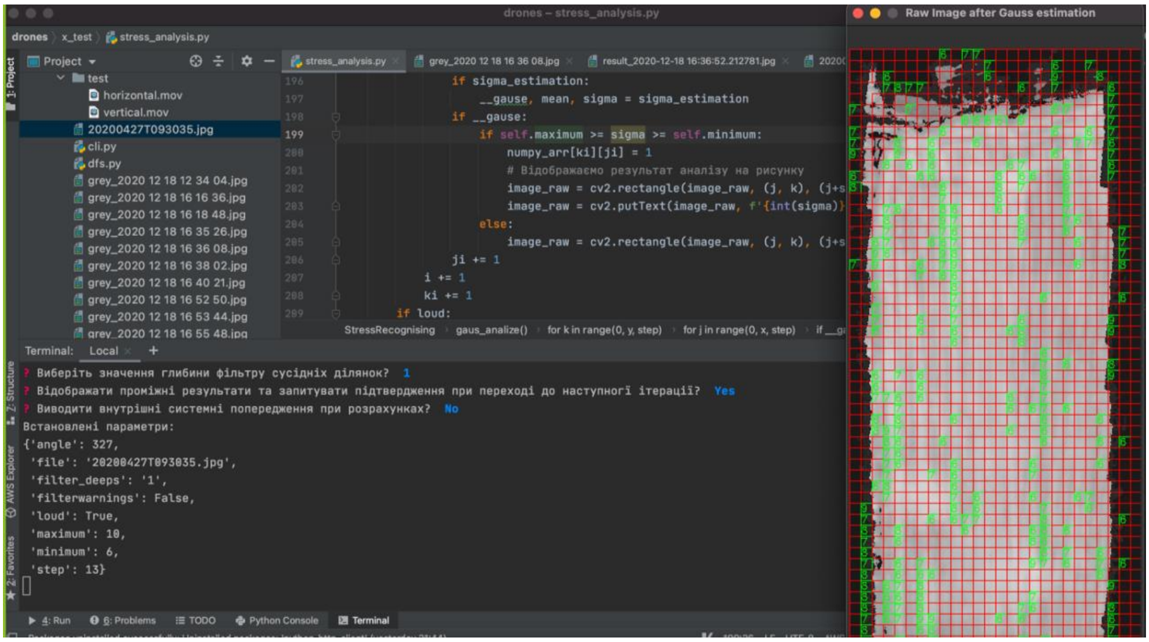

Figure 5: Image of the command line interface of the program during the operation of the program with the output of the intermediate results of the analysis (the areas highlighted in green show the value of w

In order to determine the stresses of technological training, images of fields and field sections, which were input data for training, a set of images for neural network testing were used (Fig. 6). The training of the neural network was carried out using the ML (Machine Learning) Visual Studio environment, where a number of libraries for machine learning are available. Determining the stresses of a technological nature involved the detection of straight lines and/or areas that differed in color (consolidation of crops) on photographs. Object Detection is chosen among the proposed approaches in the interface of the ML block (Fig. 7).

Since the main sign of technological stress is the presence of lines on fields or sections of fields, a corresponding code has been developed to search for such lines on images. Part of the program code is shown in Fig. 8. To quantify the line detection model, several metrics were considered: precision, recall, and F1 score. The dataset was used to evaluate the performance of this line detection approach.

The following key indicators were determined:

Precision: Proportion of detected lines that were actual lines.

$$Precision = \frac{TP}{TP + FP}$$

Recall (or Sensitivity): Proportion of actual lines that were detected.

$$Recall = \frac{TP}{TP + FN}$$

F1 Score: Harmonic mean of precision and recall, providing a balance between the two.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

True Positive (TP): A line was detected and was actually present. False Positive (FP): A line was detected but was not actually present (a false alarm). True Negative (TN): A non-line was not detected and was actually not present. False Negative (FN): A line was not detected but was actually present (a miss).

Precision: 67% of the detected lines were actual lines.

Recall: we captured 80% of the actual lines present.

F1 Score: The balance between precision and recall is 73%.

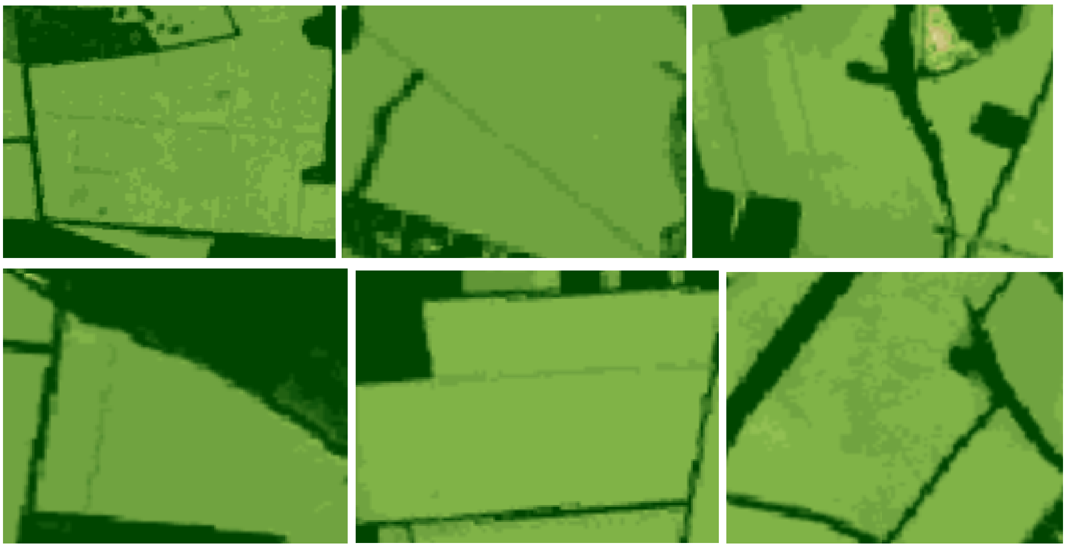

Figure 6: A set of images for training and testing the neural network

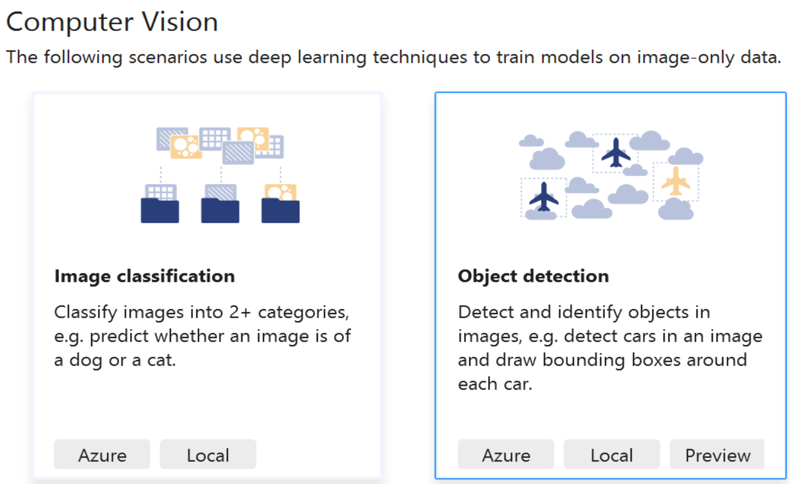

Figure 7: View of the interface of the ML (Machine Learning) Visual Studio middleware

4. Discussion

Improvement of the results of the detection of technological stresses is possible with the help of certain adaptations of these indicators for the domain, taking into account that lines (stresses) can be partially detected. Establishing a clear evaluation methodology that reflects program needs and data characteristics is also critical. In addition, there may be a need to specify a distance threshold to determine whether a correctly detected line corresponds to an actual line in real images. This is because the lines may be detected almost correctly, but slightly offset or tilted at a different angle compared to their actual location. These are some complexities that should be taken into account, but the obtained results allow us to affirm the effectiveness of this approach with the possibility of improvement and optimization. The developed neural network based on the SSD (Single Shot MultiBox Detector) architecture [21] recognizes and segments areas of the field, evaluates the object presented in the form of a photograph, classifies it and produces a result in the form of a percentage probability that he is stressed. The architecture of the used neural network model is shown in Fig. 9.

```
using System;
using Emgu.CV;
using Emgu.CV.Structure;
using Emgu.CV.CvEnum;

class Program
{
    static void Main()
    {
        // Load an image from file
        string path = "C:\Images\qw123e3.jpg";
        UMat uimage = new UMat();
        UMat uimageGray = new UMat();
        uimage = CvInvoke.Imread(path, ImreadModes.Color).ToUMat(AccessType.ReadWrite);

        // Convert it to Grayscale
        CvInvoke.CvtColor(uimage, uimageGray, ColorConversion.Bgr2Gray);

        // Use Canny algorithm to detect edges
        UMat uimageCanny = new UMat();
        CvInvoke.Canny(uimageGray, uimageCanny, 100, 200);

        // Use Hough transform to detect straight lines
        LineSegment2D[] lines = CvInvoke.HoughLinesP(
           uimageCanny,
           1, //Distance resolution in pixel-related units
           Math.PI / 45.0, //Angle resolution measured in radians.
           20, //Threshold
           30, //min Line width
           10); //gap between lines

        // Draw lines on the image
        foreach (LineSegment2D line in lines)
            CvInvoke.Line(uimage, line.P1, line.P2, new MCvScalar(0, 0, 255), 2);

        // Save or show the result
        CvInvoke.Imwrite("C:\Images\out.jpg", uimage);
    }
}
```

Figure 8: Listing of the program code for searching for straight lines as signs of technological stress

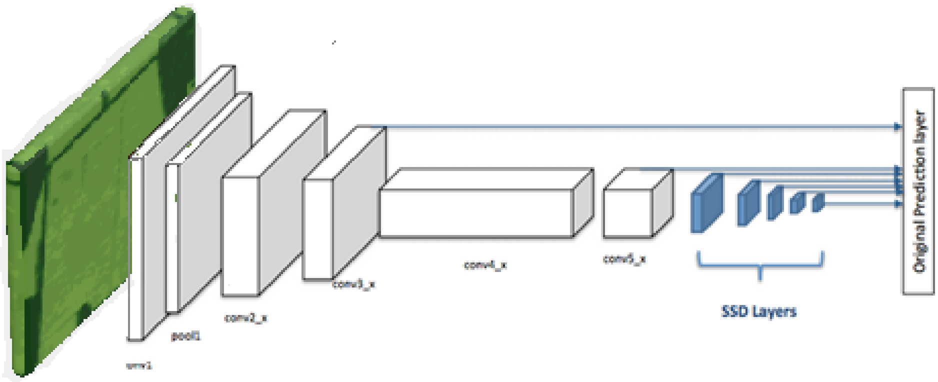

Figure 9: Scheme of the model SSD

The time required to evaluate the compaction of crops based on the statistical processing of the parameters of the distribution of vegetation indices on the site has significant limitations, both purely technical and methodical. Methodological ones include the debatable issue regarding the optimal size of the site for calculations, as it is quite possible to use equipment with different processing widths. The technical ones include limitations regarding the available spectral equipment, although there are relatively cheap samples of sensors on the market that provide video images of the distribution of vegetation indices in real-time. Therefore, it is advisable to consider other approaches to processing such large amounts of data.

In our future research, we plan to take a deeper look at the use of various neural network models for processing field images from satellites and UAVs, including for pixel-by-pixel recognition [21], compare the quality of recognition, and examine network training graphs. Also for solving classification problems. High-resolution hyperspectral images employ DCNN methods [21], which we recommend comparing with the convolutional neural networks we used.

Neural networks are also used for other operations in agriculture, for example, for monitoring apple diseases [22,23,24,25], and also as computer networks, using the Internet of Things to identify traffic and ensure information security [26,27].

5. Conclusion

To identify the technological stress of plantings caused by the compaction of wheat, from the 3 measuring channels available in the Slantrange complex, the red channel was the most effective, where the maximum difference was recorded both in terms of mathematical expectation and standard deviation. Of the considered standard NDVI vegetation indices, the GNDVI index turned out to be the most selective, the selectivity of which was greater than in the original spectral channels. The use of graph analysis for the analysis of the presence of crop compaction showed a significant calculation time, which is advisable to reduce in view of practical use on a production scale. Machine learning technologies based on a neural network ensured an acceptable quality of technological stress detection (crop compaction), while data processing and image evaluation speed were reduced to 10 minutes.

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