doi:10.20944/preprints202208.0387.v1

Article

Entropy as the High-Level Feature for XAI-based early plant stress detection

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Abstract: The article is devoted to solving the problem of searching for universal explainable features that can remain explainable for a wide class of objects and phenomena and become an integral part of Explainable AI (XAI). The study is implemented on the example of an applied problem of early diagnostics of plant stress, using Thermal IR (TIR) and HSI, presented by 8 vegetation indices/channels. Each such index was presented by 5 statistical values. A Single-Layer-Perceptron classifier was used as the main instrument. TIR turned out to be the best of the indices in terms of efficiency in the field and sufficient to detect all 7 key days with 100% accuracy. Our study shows also that there are a number of indices, inluding NDVI, and usual color channels Red, Green, Blue, which are close to TIR possibilities in early plant stress detection with 100% accurasy or near, and can be used for wide class of plants and in different conditions their treatment. The stability of the stress classification in our study was maintained when the training set was reduced up to 10% of the dataset volume. The entropy-like feature of (max-min) for any indices/channels have determined as a leadersheep universal high-level explainable feature for the plant stress detection, which used in interaction with some of other statistical features.

Keywords: explainable artificial intelligence; high-level explainable feature; entropy; plant stress; early diagnosis

1. Introduction

The explainability of artificial intelligence (AI) is now increasingly recognized as its necessary property. An arsenal of universal methods for increasing the explainability of a neural network solution, such as LIME, SHAP, DeepSHAP, DeepLIFT, CXplain, has been developed. It is also of great interest to search for explicable features that are simple and fundamental enough so that they remain explicable for a wide class of objects and phenomena. In this article, we study as such a trait the characteristics of plant states directly related to entropy, for its application in the early diagnosis of stress in a wide class of plants. It is these characteristics that can and should become mandatory components of Explainable AI (XAI). Various types of images used in precision farming can be presented as initial data: regular RGB; multispectral (MSI); hyperspectral (HSI); Thermal IR (TIR).

Since we chose the detection of plant stress as an applied task, we used vegetation indices that are widely used in precision agriculture for these purposes. The most popular vegetation index here is NDVI, and many others are used, for example: GNDVI, CGL, SIPI, etc. In the early detection of stress, that is, so early that it is possible to eliminate stress without loss to the crop, biologists consider the use of TIR sensors to be the leading mass method. This sensor is able to detect plant stress at an early stage by a slight increase in leaf temperature (by 0.2°C). The TIR leaf image, like the HSI channels, is a grayscale image. However, it is interesting, having found a fundamental feature, to consider it not only as a component of XAI, but also as a component of a high-level feature vector [1].

 doi:10.20944/preprints202208.0387.v1

Precision farming today widely uses artificial intelligence (AI) methods [2], [3], [4]. Most of them are deep learning methods. However, the most relevant properties of AI models used today are the reliability and explainability of decisions, which are the main features of explainable AI (XAI). In the interests of XAI, approaches have been developed that turn the curse of data dimensionality into a blessing of dimensionality [5], offering also easy-to-train and additionally trainable decision correctors during operation [6].

In this work, it was also planned to use the found fundamental explicable feature as the basis for the functionality of a simple XAI classifier / corrector. A fairly successful attempt to create a simple, easily configurable and efficient XAI network was made in a last year publication [7]. XAI-based classifier and regressor, which are simple and easily configurable under the user's task, were built on the basis of a single layer perceptron (SLP). However, the decision was largely tied to a specific experiment with plant drought in the presence of a reference (control group).

An interesting example of the use and preprocessing of initial data, including hyperspectral ones, is the state-of-the-art publication [8], which significantly overlaps, in terms of the content of the applied problem and the use of HSI at the input, with the problem solved in this publication. For HSI data, 9 vegetation indices, together with average signatures of HSI pixels and their derivatives, were studied for the sequence {0,3,6,9,12,15,18,21,24} days. A drought track was also tracked under conditions of depleted irrigation. Main conclusions of this publication:

1. 3 indices (from 9 used) CIRed-edge, mSR705, and SR have a significant difference after 3 days of water treatment. Most of the indices were sensitive to drought-induced change after 6 days of the water treatment, except for NDVI, ARI, and CCRI.
2. Indices cannot be used for quality diagnostics on all days and the best, but not ideal, result is a mixture of indices.
3. The result close to ideal is given by MLP with the use of average HSI signature curves and their derivatives, designated in [8] as DNN-Full, DNN-Deriv(atives), at the input.
4. It is argued, that due to the use of hyperspectra as features, it is necessary to train the classifier for each plant type and possibly irrigation conditions.It is interesting to take this publication as a reference.

2. Materials and Methods

2.1. Materials

An experiment was carried out to monitor the drought stress of wheat plants for 25 days with the fixation of the state of plants after 2-3 days [7]. Plants were observed in 3 boxes of 30 plant pots in each: 15 on the left were watered; 15 on the right were not watered. The state of plants was recorded from a direction of 90° to the surface using three cameras (sensors): hyperspectral (HSI) - Specim IQ (range: 400-1000 nm, spectral resolution: 7nm, channels: 204; 512x512 pix); thermal IR (TIR) - Thermal imager Testo 885-2 (320x240 pix); High resolution (5184x3456 pix) RGB. The total volume is 72.2GB. The TIR sensors were chosen to directly record the leaf temperature, an increase in which is the earliest sign of a stress condition. HSI are used primarily as a source of many vegetation indices that control the presence and condition of green mass.

During the experiment, the differences between non-irrigated and irrigated plants in temperature (according to TIR images) and in water loss (%, through plant weighing) were recorded in 1, 3, 6, 8, 10, 12, 14, 16, 19, 22 , 25 days of the experiment. The following key events and changes in the state of plants compared with the control ones were recorded: 1) after 5 days - an increase in the average temperature of plants by 0.2 degrees; 2) after 11 - the beginning of water loss by the plant (about 8% of the water volume). The first feature, a small rise in plant temperature, is the earliest evidence of drought stress, which passes without water loss and visible changes in green mass. Detection of plant

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stress before the onset of water loss meets the criterion of "early" detection. After 18 days we can observe a depletion of the plant's compensatory function, manifested by a break in the line of monotonic temperature increase.

All index and TIR images in our study are grayscale images and each is characterized at the preprocessing stage by its histogram and 4 standard statistical features: {max, min, mean, std}, supplemented with (max-min). Before these features calculation, a denoise preprocessing must be executed. For this goal we exclude a few procentiles of pixel values from the top and bottom of histogram. For more noised TIR-images it is 5 procentile, and HSI it is 1 procentile. This give us excluding the noise and increasing the robastness of the features. A single-layer perceptron (SLP) was chosen as a neural network for the study, on which the classification ability to distinguish a sequence of 6 key stress states of a plant, from no stress to deep stress, was studied: and each of the indexes separately, and each of the characteristics of the index and their paired combinations. It has been established that the most informative feature of plant stress for all indices is the max-min characteristic, which reflects the real diversity of plant states at the current time and, therefore, correlates with the entropy of their states. The state of the plant can be directly related to the entropy value through the Gray Level Co-occurance Matrix (GLCM), built for the image, as a rule, of a leaf of a plant in shades of gray, where each of the gray levels is associated with certain changes in the state of the plant. And each matrix corresponds to the entropy value [9] for the studied area of the image, as it was demonstrated in [7].

2.2. The idea using of (max-min)-feature as universal

The idea of using (max-min) as a universal attribute is based on the fact that changes in many complex natural objects and, especially, their sets are associated with a change (increase/decrease) in the number of states in which the elements of the object (set) are located. If both growth and reduction in the number of states fall into the observation period, then this becomes the cause of ambiguity in the classification assessment of the object. For an unambiguous resolution of the classification, a sign is required that differs in the nature of the behavior over the observation interval, for example, changing monotonously. On the example of abiotic stress of drought in plants, we observe: the initial essentially homogeneous state of plants; then - an increase in heterogeneity due to uneven entry into a state of stress due to heterogeneous soil moisture; then - a non-uniform entry into the state of real loss of moisture by the body of the plant and the beginning of drying; then, with an increase in the proportion of withering and withered plants, there is again a reduction in the variety of states. An example of a parallel monotonic process would be an increase in plant temperature or an increase in the yellow component in leaf color.

2.3. XAI-based classifier description

In the construction of XAI-based classifier and regressor, which are simple and easily configurable under the user's task, we following the example of [7], which realise the idea of [10], but using the 'Backyard Dog'-function as main function of the network and realizing this function via SLP (Fig.1).

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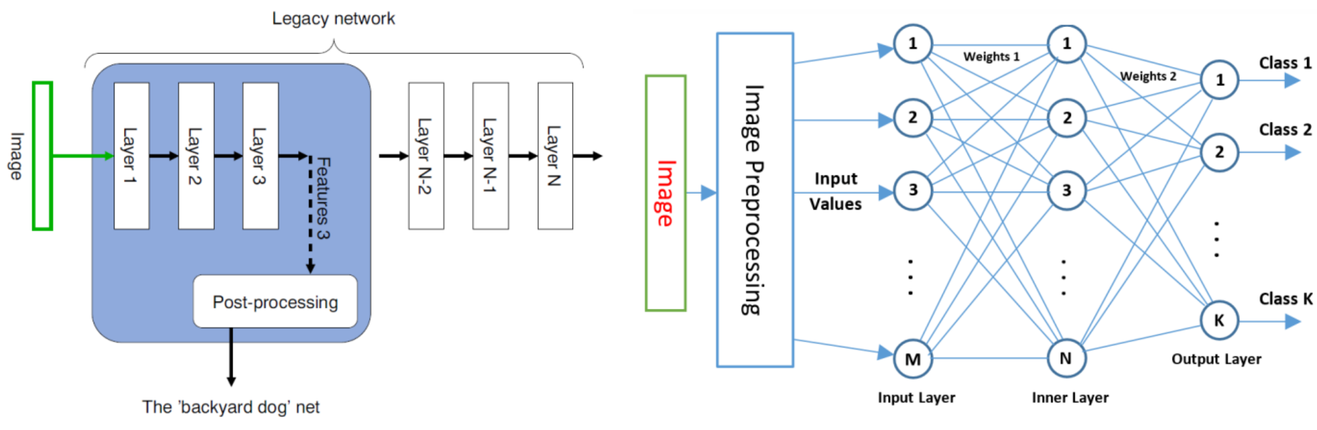

(a) (b)

Figure 1. Comparison of the designs of two neural networks: (a) the 'backyard dog' network from a given legacy network ([10], Fig.5); (b) the structure of our SLP classifier as an example of the 'backyard dog' net implementation for independent using.

The idea of using (max-min) as a universal attribute is based on the fact that changes in many complex natural objects and, especially, their sets are associated with a change (increase / decrease) in the number of states in which the elements of the object (set) are located. If both growth and reduction in the number of states fall into the observation period, then this becomes the cause of ambiguity in the classification assessment of the object. For an unambiguous resolution of the classification, a sign is required that differs in the nature of the behavior over the observation interval, for example, changing monotonously. On the example of abiotic stress of drought in plants, we observe: the initial essentially homogeneous state of plants; then - an increase in heterogeneity due to uneven entry into a state of stress due to heterogeneous soil moisture; then - a non-uniform entry into the state of real loss of moisture by the body of the plant and the beginning of drying; then, with an increase in the proportion of withering and withered plants, there is again a reduction in the variety of states. An example of a parallel monotonic process would be an increase in plant temperature or an increase in the yellow component in leaf color.

Determining N, we will take for research a separate thermal channel (TIR), a series of indices popular in precision agriculture: NDVI, GNDVI, GCL, SIPI. In addition, let's consider the capabilities of each of the channels (Red, Green, Blue) of a regular RGB image and a special index, an analogue of mNDblue, which we used to build a plant mask, which we designated as NDblue. Red, Green, Blue are interesting for precision farming due to their high resolution at a low price. However, it is generally accepted that they cannot provide sufficient accuracy in the early diagnosis of plant stress. As a result, 9 vegetation indices and individual channels were accepted for the study, and the number of neurons in the inner layer was N=9. As a result, the maximum number of inputs (M) and the maximum number of weights (Nw):

$$\begin{gathered} M = N{\cdot}h = 9{\cdot}5 = 45, \\ Nw = M{\cdot}N + N{\cdot}K = 45 \cdot 9 + 9 \cdot 7 = 468. \end{gathered} \tag{1}$$

Our SLP-classifier should provide early detection of plant stress in the absence of a clearly defined standard of a stress-free plant in the detected area.

An important condition for the successful conduct of computational experiments is the correct separation of plant pixels from the background under conditions of changing the state of the plant, soil, and other background objects. The plant mask can be built on both the traditionally used NDVI and other indices that are sensitive to chlorophyll. In connection with the study of the channels of a color image, it was interesting to build a mask on the values of the visible range, or even on the RGB values. Therefore, mNDblue is used as a base index, which is intended for high-resolution plant leaf images. [11]:

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$$mNDblue = -(\rho_{\lambda} - \rho_{450}) / (\rho_{850} + \rho_{450})\ \lambda\epsilon\{530,570,675,730\},\ \text{using}\ \lambda=550 \quad (2)$$

In order to use a constant threshold value (Th) for all plant states, the normalization in formula (2) is modified:

$$NDblue = (G_{550} - B_{450}) / (\max(G_{550} - B_{450}) - \min(G_{550} - B_{450})),\ \text{or} \quad (3)$$

$$NDGB = (G - B) / (\max(G - B) - \min(G - B)),\ \text{were G,B are RGB channels.} \quad (4)$$

Option (3) is for HSI and option (4) is for visible range. To select the type of plant mask formation index between traditional NDVI and NDblue, as well as to select the threshold value, computational experiments were carried out. The results for one of the days are shown in (Fig. 2). The NDblue index (3) was chosen and the threshold Th > 0.1 was experimentally set for the plant mask.

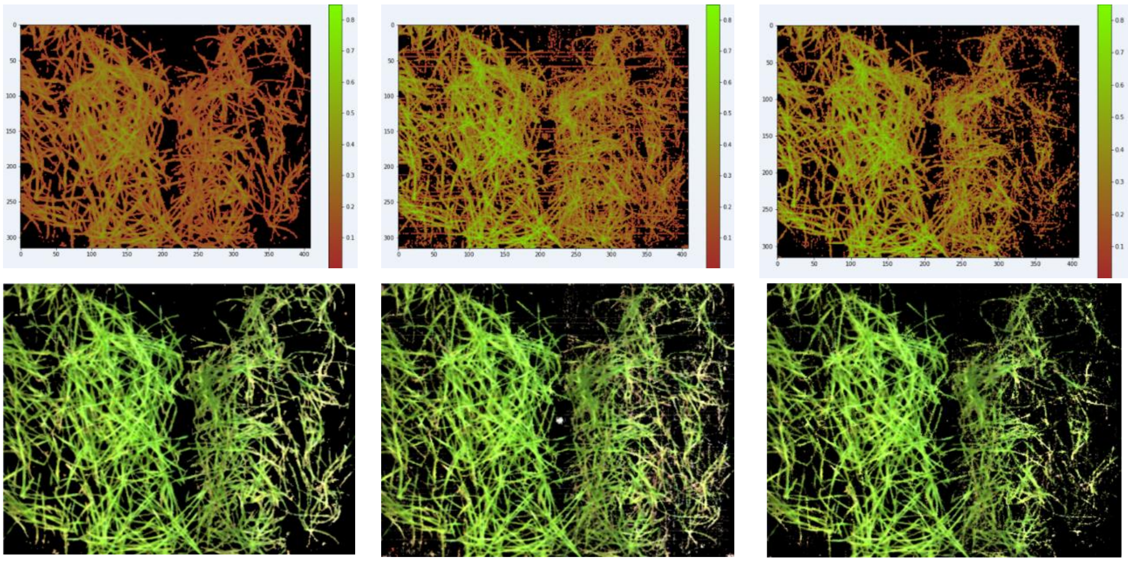

Figure 2. Upper row – day 25 images defining the mask, from left to right: 1) normalized NDblue index in pseudocolor according to the scale, threshold 0.1; 2) and 3) normalized NDVI index in pseudocolor, at thresholds of 0.15 and 0.25, respectively. Bottom row - images generated by the mask on 3 HSI channels.

The NDblue variant with a threshold of 0.1 was chosen as the most preserving the integrity of the plant without capturing background pixels and losing pixels inside the leaf when the state of the plant changes. The choice is made on all key days. The figure shows day 25, for which the changes that have occurred are most noticeable visually. The accepted normalization (3) ensures that the threshold is constant for all days.

2.4. Exploration Methods

Through the SLP-classifier (Fig.1b), our study aims to establish:

1. Which components of the input feature vector have the maximum significance for diagnosing the state of the plant with an accuracy equal to or close to the maximum.
2. The data of which vegetation indices or spectral channels best train the SLP-classifier for solving the problem of early plant stress diagnostics.
3. Is the involvement of the full feature vector necessary to achieve maximum accuracy or is there a necessary minimum set of features that contrasts the objective function of the problem
4. Is the parameter (max-min) associated with the entropy of states included in the required minimum set of features that ensures the explainability of the solution of the problem and the classifier as a whole.

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5. What is the minimum dimension of the problem and the corresponding minimum configuration of the XAI SLP classifier that solves the problem.

To solve these problems, we sequentially train the SLP classifier shown in Fig.1b, using only the required number of inputs and neurons for the current task, and then we solve the problems of classifying plant stress conditions for: 1) each of the statistical features of each of the indices/channels (hereinafter index); 2) paired combinations of features separately within each of the indices; 3) combinations of all 5 features within each of the indices separately; 4) combinations of all indices, excluding Thrmal IR (TIR} 5) combinations of all indices, including Thermal IR (TIR} Each of the tasks is solved for two cases: a short monitoring period (up to 12 days) a long monitoring period (up to 25 days) It was possible to reduce the share of data used to train the classifier to 10-20% of the plant mask area without loss of classification quality.

3. Results

3.1. Significance of each feature from the complete feature vector

Significance of each feature in the form of Confusion matrix can be seen on the Fig.3.

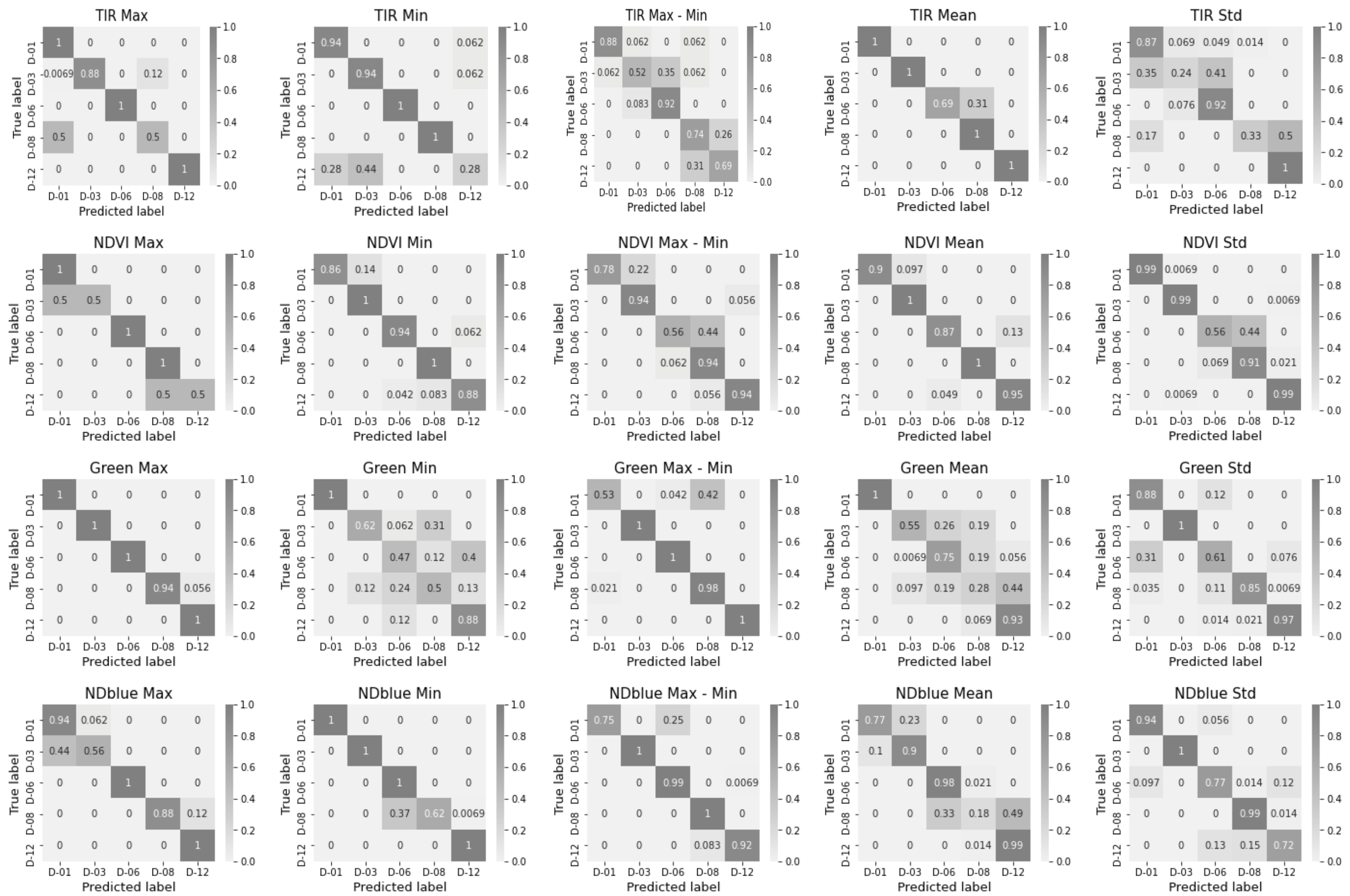

Figure 3. Training SLP-classifier with 1 scalar feature only. Period: 1-12 day. D-00 - observation days. Confusion Matrices for each scalar feature: in colomns are features max, min, max-min, mean, std; in rows are more interesting 4 from 9 indices (TIR, NDVI, Green, NDblue).

Significance of each feature in the form of Confusion matrix for the period 1-25 days can be seen on the Fig.4.

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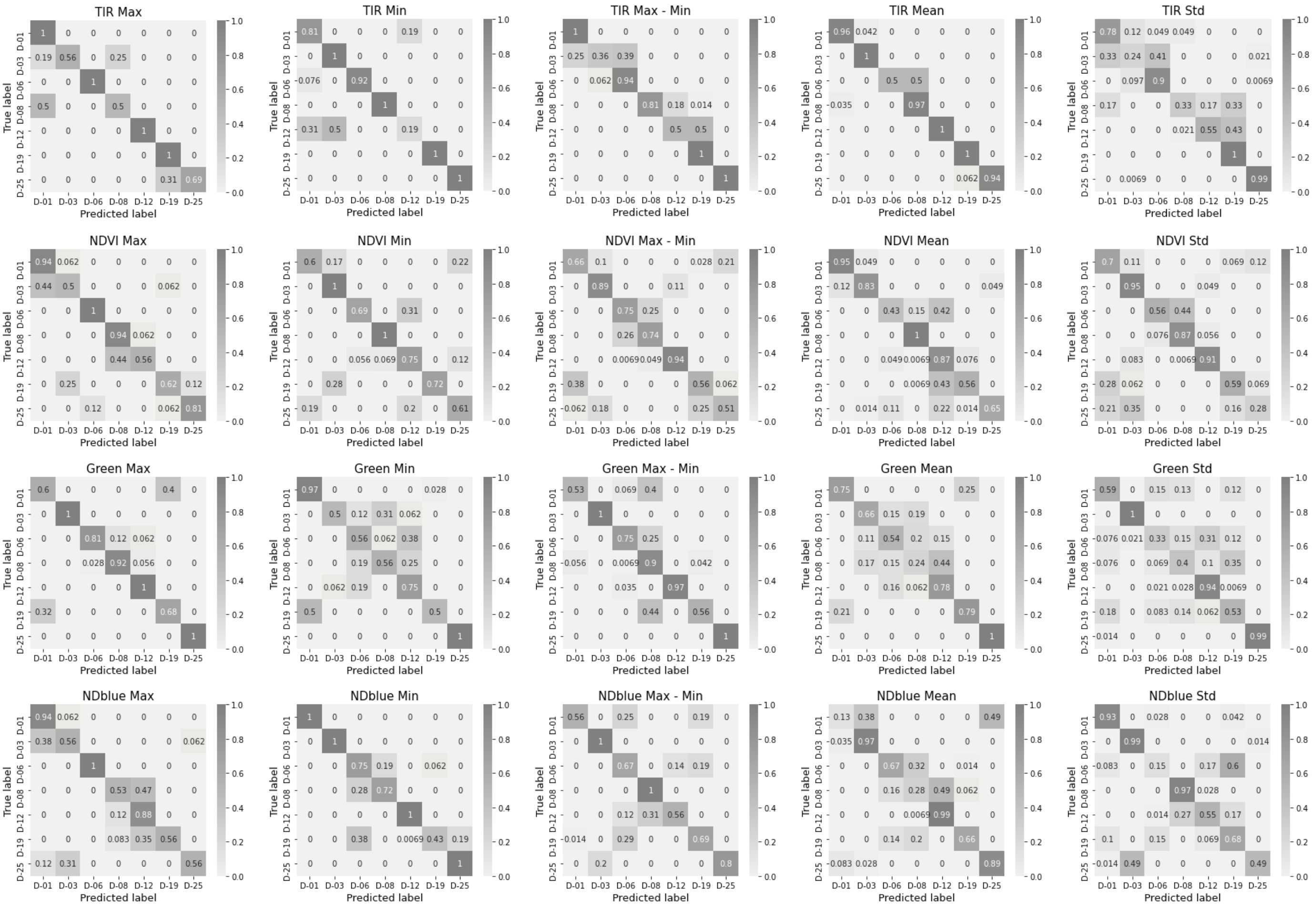

Figure 4. Training SLP-classifier with 1 scalar feature only. Period: 1-25 day. D-00 -observation days. Confusion Matrices for each scalar feature: in colomns are features max, min, max-min, mean, std; in rows are more interesting 4 from 9 indices/channels (TIR, NDVI, Green, NDblue).

On a short period (1-12 days, Fig.3), TIR shows the best diagonality (for 4 features: max, min, max-min, mean). Then NDblue (for 3: max, min, max-min) and Green (for 2 traits max and max-min). On the full period (1-25 day) it is again TIR (previous 4) and Green (max sign). Green channel (550 nm) was included in the both Fig.3 and Fig.4 as most significant channel for short period (1-12 days). This is also confirmed by the average value for 5 key days, the value of classification accuracy on the basis of Green/max = 0.99 (Tab.1). Table (Tab.1) shows the average Accuracy of plant stress classification for each of the 5 traits for 8 of the 9 vegetation indices/channels. As a rule, the classification ability of a feature for a full period decreases relative to a short period. The maximum values for each of the indices are shown in bold for both periods. The worst individual classification ability has the feature 'std'.

For TIR, the maximum classification accuracy falls on the sign of the average temperature (mean) in both periods (short and long). For GNDVI, SIPI, Green - on the sign max, for Red (630nm) - on min. For Blue (480nm) and the rest, the maximum value in the short and long periods falls on different features. The sign (max-min) is usually in the top three in terms of significance.

Table 1. Significance of each feature for SLP-classification in Accuracy value for 8 from 9 indecies.

Index/Feature	Accuracy, 1-12	Accuracy, 1-25	Index/Feature	Accuracy, 1-12	Accuracy, 1-25
TIR/max	0.88	0.82	GNDVI/max	**0.98**	**0.72**

TIR/min	0.83	0.85	GNDVI/min	0.80	0.78
TIR/max-min	0.75	0.80	GNDVI/max - min	0.79	0.71
TIR/mean	**0.94**	**0.91**	GNDVI/mean	0.85	0.83
TIR/std	0.67	0.68	GNDVI/std	0.54	0.46
NDVI/max	0.80	**0.77**	GCL/max	**0.98**	0.85
NDVI/min	0.93	**0.77**	GCL/min	0.84	0.80
NDVI/max-min	0.83	0.72	GCL/max - min	0.90	0.79
NDVI/mean	**0.94**	0.76	GCL/mean	0.79	**0.86**
NDVI/std	0.89	0.69	GCL/std	0.69	0.52
Green/max	**0.99**	**0.86**	SIPI/max	**0.91**	**0.79**
Green/min	0.69	0.69	SIPI/min	0.80	0.78
Green/max-min	0.90	0.81	SIPI/max - min	0.88	0.76
Green/mean	0.70	0.68	SIPI/mean	0.81	0.69
Green/std	0.86	0.68	SIPI/std	0.84	0.65
NDblue/max	0.88	0.72	Red/Max	0.74	0.75
NDblue/min	**0.93**	**0.84**	Red/Min	**0.90**	**0.86**
NDblue/max-min	**0.93**	0.76	Red/Max - Min	0.83	0.84
NDblue/mean	0.76	0.66	Red/Mean	0.63	0.68
NDblue/std	0.88	0.68	Red/Std	0.83	0.72

3.2. Significance of feature pairs within each index separately

The following figure (Fig. 5) contains 4 tables that demonstrate the achieved average Accuracy of classification of key stress states in plants with paired combinations of traits. It determines the significance of these combinations at a stress detection period of 12 days (above the gray diagonal) and 25 days (below the gray diagonal). More interesting results for 4 (TIR; NDVI; Green; NDblue) from 9 indices are shown. For comparison, the gray diagonal shows the accuracy for the most significant single feature.

TIR 25\12	**max**	**min**	**max-min**	**mean**	**std**
max		1.00	1.00	1.00	0.97
min	1.00		1.00	1.00	1.00
max-min	1.00	1.00		1.00	0.69
mean	1.00	1.00	1.00	0.91\0.94	1.00
std	0.98	1.00	0.73	0.98	

NDVI 25\12	**max**	**min**	**max-min**	**mean**	**std**
max		0.98	0.97	0.93	0.96
min	0.99		0.98	0.94	0.94
max-min	0.99	0.98		0.98	0.79
mean	0.96	0.93	0.98	0.76\0.94	0.96
std	0.98	0.94	0.70	0.98	

Green 25\12	**max**	**min**	**max-min**	**mean**	**std**
max	0.86\0.99	1.00	1.00	1.00	0.97
min	0.97		1.00	1.00	1.00
max-min	0.96	0.97		1.00	0.92
mean	0.83	0.93	0.91		1.00
std	0.93	0.99	0.73	0.99	

NDblue 25\12	**max**	**min**	**max-min**	**mean**	**std**
max		1.00	1.00	0.92	0.98
min	1.00	0.84\0.93	1.00	0.99	1.00
max-min	0.98	1.00		0.92	0.83
mean	0.94	0.97	0.94		0.95
std	0.93	0.93	0.63	0.88	

Figure 5. Average Accuracy values for the classification of key stress states achieved after training using pairs of features. The Accuracy values in the triangle above the gray diagonal correspond to a period of 12 days, under the gray diagonal ones correspond to 25 days.

Training SLP-classifier was executed each time using only one of 9 indices/channels and different paiers of 5 features. From Fig.5, it can be seen that already paired combinations of features give a classification accuracy equal to or very close to 1.00. For the observation period of 12 days, there are more such cases. So the value of 1.00 is achieved for 8 out of 9 indices, excluding NDVI. But upon closer examination, the average value of NDVI 0.98-0.99 is due to deviations of 3-8% only for the 1st and 12th days, and the most important days for early diagnosis 3,6,8 are detected with an accuracy of 1. Thus, during the

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observation period in 12 days, it is possible to provide early detection of plant stress with an accuracy of 1 on only two signs of any of the indices. Extreme couples with participation (max-min) are in all cases marked with a background in shades of green. Similar pairs without participation (max-min) are marked yellow in the upper triangular part, and light brown in the lower triangular part. There are 8 such pairs of features for TIR and Green, and 3 of them involve (max-min); for NDVI - 4, and 3 of them with participation (max-min); for Ndblue - 5, and 2 of them with participation (max-min).

For an observation period of 25 days, a value of 1.00 is achieved for 6 out of 9 indices, excluding NDVI, Green, Blue. At the same time, NDVI saves Accuracy=1 for 3, 6, 8 days for 2 pairs with participation (max-min) and for 3, 6 days - one at a time. Consistently high and maximum result (max-min) is paired with max, min, mean. Often a high result, but somewhat worse than the previous one, is obtained by replacing the previous version (max-min) with std. Quite often, pairs max with min or any of them paired with mean are successful. The worst pair in all cases was the pair {(max-min),std} due to the high correlation of these signs and the presence of a maximum in the middle of the observation period of 25 days.

3.3. Significance of using all 5 features within each index and using comlete feature vector for all indices excluding and including TIR

Examples of significance each of the 9 indices using all 5 features in the form of Confusion matrix for each key day classification can be seen on the Fig.6.

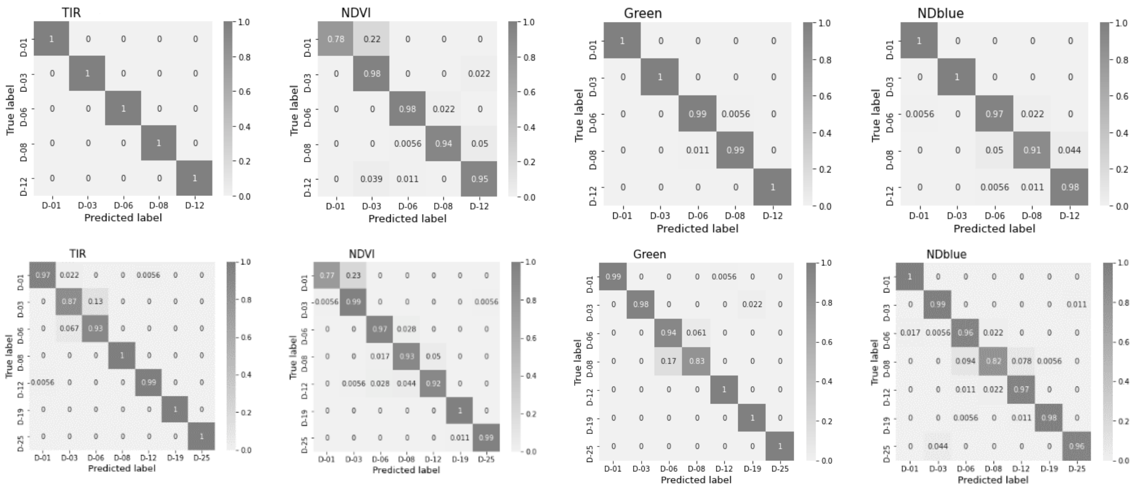

Figure 6. Accuracy values for the classification of key stress states achieved after training on all 5 features inside each of 9 indices. More interesting results for 4 indices (TIR; NDVI; Green; NDblue) are showed. Confusion matrices for each index: along Y the true classes, and along X the predicted classes are showed. D-00 - key days. First row is for observation period 12 days, second row is for 25 days.

The average, over stress states, accuracy for the classification of key stress states achieved after training using all 5 features inside each of 9 indices using separately are showed in the (Tab.2). The table demonstrates the accuracy for both periods 12 days and 25 days.

Table 2. The average classification accuracy after training using all 5 features.

Index	Accuracy, 12 days	Accuracy, 25 days
TIR	**1.000**	0.968
NDVI	0.927	0.939
NDblue	0.972	0.953

Red	0.969	0.975
Green	**0.997**	0.964
Blue	0.858	0.918
GNDVI	0.934	0.896
GCL	0.887	0.888
SIPI	0.986	**0.999**

It is clearly view, that after training SLP-classifier using all 5 features instead 2 we got some decreased resuls in the accuracy.

It is interesting that training the SLP-classifier immediately on the full vector of features, using most of the indices simultaneously, made it possible to achieve the maximum classification accuracy for all key stress days both in the 12-day monitoring period and in the 25-day one. Tested on 6 indexes TIR, NDVI, NDblue, Red, Green, Blue and 5 indices, completely excluding TIR. The possibility of reducing the number of indices under TIR exclusion conditions has been investigated (Tab.3)

Table 3. The average classification accuracy after training using the index combinations, and neaded training time.

Combination of Indices	Accuracy, 25 days	Training time, sec
GREEN + RED	**1**	**0.32**
GREEN + BLUE	**0.999**	0.64
GREEN + NDVI	0.969	1.57
GREEN + SIPI	0.997	0.46
GREEN + GCL	0.914	1.9
GREEN + NDblue	**0.999**	0.62
RED + GREEN + BLUE	**1**	**0.28**
GNDVI + GCL + SIPI	0.997	0.56
NDVI + GCL + SIPI	0.999	0.37
NDblue + GCL + SIPI	0.998	0.89
NDVI + GNDVI + GCL + SIPI	0.998	0.65
NDVI + RED + GREEN + BLUE	**1**	**0.3**
NDblue + GNDVI + GCL + SIPI	0.999	0.69
NDblue + RED + GREEN + BLUE	**1**	0.47
NDVI, GNDVI, BLUE, GCL, SIPI	**1**	0.51
NDVI, RED, GREEN, BLUE, Ndblue	**1**	0.39
TIR+NDVI, GNDVI, BLUE, GCL, SIPI	**1**	**0.21**
TIR+NDVI, RED, GREEN, BLUE, NDblue	**1**	0.3

The table shows that it is possible to build a network to classify all 7 stress states of plants with an accuracy of 1, but only for some combinations of 2, 3 and 4 indices. A combination of 5 or more studied indices provides an accuracy equal to 1. Comparison of the required training time with the error matrix shows that the shorter the training time, the closer the error matrix is to the diagonal.

4. Discussion

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 22 August 2022 doi:10.20944/preprints202208.0387.v1

The main difference and similarity between the compared experiments ([8] and our) is: plants have different stages of vegetation on the start of experiment (with a lag in development of the crown in our case for 3-5 days), but have the same start point of real water losses. But it is nevertheless interesting to compare (Tab. 4).

Table 4. The average classification accuracy after training using the index combinations, and neaded training time.

Results of [8]	Our results
3 index images (from 9 used) CIRed-edge, mSR705, and SR have a significant difference after 3 days of water treatment. Most of the indices were sensitive to drought-induced change after 6 days of the water treatment, except for NDVI, ARI, and CCRI.	We used 5 statistical features for each index intead its image, and studied individual possibilities each of 45 features and their pairs for 2 time-intervals 12 and 25 days. All indices were possible to detect plant stress states on both intervals with accuracy 1 or near.
Indices cannot be used for quality diagnostics on all days and the best, but not ideal, result is a mixture of indexes.	Indices can be used for quality diagnostics on all days, using some feature pairs. Using all 5 features is less productive, then some pairs. Using a mixture of 5 indices really guarantees the accuracy 1.
The result close to ideal is given by MLP with the use of average HSI signature curves and their derivatives, designated in [8] as DNN-Full, DNN-Deriv(atives), at the input.	Using SLP (partical case of MLP) really enough for plant stress classification with accuracy 1. Used properties of HSI signature derivatives practically equals to properties of NDVI.
It is argued, that due to the use of hyperspectra as features, it is necessary to train the classifier for each plant type and possibly irrigation conditions.	Using (max-min)-feature in pair with other suitable statistical feature we get simplest and robust XAI-classifier which independent from plant type, irrigation conditions, temperature and other external conditions.

During the study, the following questions were resolved:

An SLP-classifier has been built that has a structure adjusted by the number of neurons N used on the inner layer (by the number of indexes used), by the length of the feature vector M=m·N, where m=1,2,…5, by the number of detected states (key days) K.

The classification accuracy of key days was determined individually for each of the possible 45 features, and the classification accuracy for their pair combinations. Combinations that provide Accuracy=1 and close to it, as well as the number of such combinations for each of the indices, are determined, indexes-leaders are established.

It has been established that the involvement of the full feature vector is not necessary to achieve maximum accuracy, and there is a required minimum set of 2 features and 1 neuron on the inner layer that contrasts the solution of the problem. In this case, it is recommended to use the parameter (max-min), which is associated with the entropy of states, which ensures the explainability of the classifier as a whole and high accuracy.

Increasing the number of indexes increases the robustness of the solution, which may require up to 5 indexes.

5. Conclusions

One of the possible solutions has been found in the search for universal explainable features that can remain explainable for a wide class of objects and phenomena and become a part of XAI. As such feature, an entropy-like feature (max-min) was proposed and studied in combination with another effective feature.

For conceptual contrasting of learning and building a neural network, 9 HSI indices/channels were used, which are traditionally used to describe the state of plants in nature research and agriculture: NDVI; GNDVI; CGL; SIPI; NDblue; red; green; blue; TIR.

The network training time has been reduced to 0.21-1.9 sec. It has been established that it does not depend on N or M, but is associated with a specific combination of indices used. And the shorter the training time, the closer the confusion matrix to the diagonal form.

It is planned to study in more depth the dependence of the results on the choice of the base index and the threshold when forming the mask.

Author Contributions: Conceptualization and methodology, V.T.; software and validation, I.M., M.L.; formal analysis, V.T.; investigation, E.V., A.G; data curation, M.L.; writing—original draft preparation, M.L.; writing—review and editing, V.T.; visualization, M.L.,I.M.; funding acquisition, V.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Ministry of Science and Higher Education of the Russian Federation, agreement number 075-15-2020-808.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The used here data of a 25-day experiment on wheat drought with fixation of the state of plants in the control and experimental groups every 2-3 days using three types of sensors (HSI, Thermal IR, RGB) occupy 72.2 GB. The data can be obtained for free use upon request.

Conflicts of Interest: The authors declare no conflict of interest.

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