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Early detection of anthracnose in common bean using vegetation indices and leaf spectral information

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ABSTRACT:The objective of this study was to developan artificial neural network classifier to discriminatebetweeninfectedandhealthyleaveswitht hefungusC. lindemuthianumatanearlystageofinfection, usingleafreflectance data. The electromagneticspectrumwasdividedintofivespectral bands. In each band wasmade a principal componentanalysisandwiththefirst principal componentweregeneratedthe scores ofeachspectral band. Artificial neural networks havebeentestedwithvarious input variables: hyperspectralandmultispectralvegetation indexes andvaluesof scores ofeachspectral band. Threecultivarsof common beanandthreelevelsofseveritywereused. The vegetationindicesusedwerenormalizeddifferencevegetation index (NDVI), differencevegetation index (DVI), greennormalizeddifferencevegetation index (GNDVI), modifiedchlorophyllabsorption in reflectance index (MCARI), relativedifferencevegetation index (RDVI) andtransformedchlorophyllabsorptionreflectance index (TCARI). The most eficiente classifierusedthe DVI multispectral index as input variableandtwoneurons in thehiddenlayer. Thisclassifierobtained Kappa coefficientof 32% and overall accuracyof 79%. The classifierdetectedanthracnosethreedaysbeforethefirstcharacteristicsymptomsbecomevisible in the three beancultivars.

KEYWORDS: Remote sensing, reflectance, anthracnose, common beans, disease.

I. INTRODUCTION

In Brazil, the common bean (Phaseolus vulgaris) is cultivated throughout the year and several factors limit or reduce its production. The occurrence of diseases is one of the main causes of reduced productivity [12]. Among the main common bean diseases, anthracnose, caused by the fungus Colletotrichum lindemuthianumstands out [22].

Control of anthracnose is done using resistant cultivars. However, these cultivars may have lower agronomic characteristics than susceptible ones, mainly in terms of yield potential. Thus, one of the main anthracnose control measures is the application of fungicides [12]. It is recommended that the fungicide be applied when the first symptoms of the disease appear. Anthracnose is a disease that appears in small areas of the bean crop and over time it spreads throughout the entire plantation. Thus, it is necessary to develop techniques capable of identifying the initial stages of infection of the disease. Having determined the places where the first foci of infection occur, it is possible to apply the fungicide at a variable rate, which can promote greater savings and less damage to the environment.

Among the technologies used in precision agriculture, remote sensing has shown to be very promising in identifying diseases in the early stages of infection. [20] used reflectance data to detect and classify, at early stages of infection, three fungal beet diseases. [14] used spectral responses and vegetation indices in beet crops, detailing the progress of diseases observed at the level of cellular structure of the leaf.

Hyperspectral measurements present hundreds of reflectance measurements at different wavelengths, the use of multivariate statistical techniques makes it possible to reduce the number of wavelengths, without significant loss of information and without compromising the spectral characterization of the target [23][13]. There are several techniques of multivariate statistics for dimensional reduction. However, estimating the number of samples as a function of the number of variables is a difficult task [21]. There are authors who suggest that the number of samples vary from 2 to 20 times the number of variables [10][21].

A multivariate technique widely used to reduce the dimensionality of data and select variables is principal component analysis (PCA). [1] used ACP to reduce the number of original variables and determine four wavelength intervals of the electromagnetic spectrum: 500–533 nm, 560–675 nm, 682–733 nm and 927–931 nm, which allowed to discriminate wheat plants infected with fusarium with an accuracy of 91%, before the first symptoms became visible.

Vegetation indices (VI) are used to estimate vegetation parameters. IVs are algebraic operations between reflectance values involving two or more spectral bands. Its objective is to extract and expand information about vegetation. [20] used eight IVs to aid in the early detection of three fungal diseases in beet plants. [29] used IVs to determine early stress in soybean plants caused by the use of glyphosate.

This study aimed to: (1) select the most representative IVs of the total variance of the data, which will be used as input variables for the classifier; (2) develop and compare artificial neural network classifiers to discriminate leaves infected with anthracnose.

II. MATERIAL AND METHODS

The experiments were conducted in a greenhouse, from October to December 2013, with a temperature of 24 ± 1 ^{o}C and relative humidity of 80 ± 5%, in the city of Viçosa, latitude 20º 45' 14" South and longitude 42º 52' 55" West, in the state of Minas Gerais. To collect the spectral responses of bean leaves, experiments were conducted using three bean cultivars representing three commercial groups: carioca (cv. Rudá), preto (cv. Supremo) and vermelho (cv. Vermelhinho), given the economic importance of each group and susceptibility to anthracnose. In each pot, two plants were grown in 0.415 L of substrate (Tropstrato HT©, Vida Verde, Mogi Mirim, SP, Brazil).

One experiment was carried out for each cultivar. the delineation. The experimental design was completely randomized, with four concentrations of conidia/mL [zero (control), 1.2 x 10^4 (low), 1.2 x 10^5 (medium) and 1.2 x 10^6 (high) conidia/mL], with six replicates. The experiment was repeated from January to March 2014.

Inoculation With Colletotrichum Lindemuthianum

The inoculum of C. lindemuthianum, race 65, obtained at the Institute of Biotechnology Applied to Agriculture (BIOAGRO/UFV), was multiplied in test tubes containing sterilized pods and partially immersed in agar agar medium. The tubes were kept for approximately ten days at 24 ± 1 ^{o}C, for the production of conidia. In a greenhouse, 30 seeds of each common bean cultivar were sown in styrofoam trays (68 x 35 cm) with 128 cells. Four days after planting most seeds germinated. Six days after planting, the bean plants were transplanted into plastic pots. Inoculation was performed three days after transplanting the seedlings into plastic pots, atomizing the conidial suspension on both surfaces of the primary leaves, with the aid of a manual atomizer.

Plants were evaluated daily after inoculation, based on the 1 to 9 scale described by [15], in which: 1 = absence of symptoms; 2 = up to 1% of the veins showing necrotic spots, perceptible only on the abaxial side of the leaf; 3 = higher frequency of foliar symptoms described in the previous grade, up to 3% of affected veins; 4 = up to 1% of the veins showing necrotic spots, noticeable on both sides of the leaves; 5 = higher frequency of foliar symptoms described in the previous grade, up to 3% of veins affected; 6 = necrotic spots on the veins, noticeable on both sides of the leaves, presence of some lesions on the stem, branches and petioles; 7 = necrotic patches on most of the veins and much of the adjacent mesophyll tissue that ruptures; presence of abundant lesions on the stem, branches and petioles; 8 = necrotic spots on almost all of the veins, causing rupture, defoliation and reduced plant growth; abundant lesions on the stem, branches and petioles; and 9 = most plants dead.

Measurement Of Spectral Responses Of Common Bean Leaves

In each pot, four fully developed leaves were chosen for spectral reflectance measurements, made daily after inoculation until complete leaf fall, in the same period of the day, between 10:00 and 14:00 h. During the experiment, 2,342 reflectance measurements were performed, 555 of which were from healthy plants and 1,787 from infected plants.

Leaf spectral reflectance was measured with the ASD FieldSpec Pro FR spectroradiometer (Analytic Spectral Devices, Boulder, USA), with the “plant probe” probe for leaf contact measurements. This probe has an integrated 100 W halogen lamp, which was turned on 90 minutes

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before each data collection for its stabilization. The spectroradiometer has a spectral range between 350 - 1100 nm and the useful reading range was between 400 and 900 nm, discarding noisy spectral data at the extremes. Calibration of the spectroradiometer using the blank reference, with a Spectralon plate (Labsphere, North Sutton, USA), was performed at the beginning of each data collection and then at regular intervals of 15 minutes. The measurement time for each reading was adjusted to 544 ms, and each reflectance collection, on each leaf, was the average of 10 readings taken by the spectroradiometer.

CLASSIFIER DEVELOPMENT

The original data had a large number of variables (751 wavelengths) in relation to the number of repetitions (2342 repetitions). There are literatures that recommend at least 20 repetitions per measured variable [10][21]. To reduce the number of variables, the original data set was divided into five spectral bands, according to the spectral bands of the RapidEye satellites (Table 1).

The use of these five spectral bands was due to the direct relationship that each band has with constituent parts of bean leaves. In the visible spectrum (380-760 nm), the change in the spectral response of the leaf is due to the variation in the content of organelles, such as carotenoids and chlorophyll. And in the near infrared (760–1,200 nm), variations in spectral responses are due to variations in the physical structure of the leaf, such as water content [1].

As in the same spectral band there is a strong correlation between the variables, this makes it possible to apply PCA in each band to reduce the dimensionality of the data. PCA generates new, uncorrelated variables called principal components. Most of the variance of the original data is expected to be retained in a few principal components. With these principal components, scores were calculated for each sample of the data set for each band. These score values were the characteristics used as input vectors for the artificial neural network (ANN). Before performing principal component analysis, all data were mean-centered. Thus, each variable has zero mean, that is, the coordinates are moved to the center of the data,allowing differences in the relative intensities of the variables to be easier to perceive [25].

Table 1. Spectral bands with their respective wavelength ranges and number of variables

Spectral bands	Wavelength range (nm)	Number of variables
Blue	440 – 510	70
Green	520 – 590	70
Red	630 – 685	55
Red edge	690 – 730	40
Near infrared	760 – 850	90

With the reflectance data of healthy and infected leaves, Manova and Hotelling's T^2 mean test were performed to verify whether the separation between the classes of interest was significant, at the 5% level of significance.

Multivariate analysis of variance (Manova) was performed to verify whether there was a significant difference between treatments, using the Wilks criterion.

VEGETATION INDICES

Six vegetation indices common to hyperspectral and multispectral spectrometry were calculated (Table 2), given by: Normalized Difference Vegetation Index – NDVI [19]; Green Normalized Difference Vegetation Index – GNDVI [27]; Difference Vegetation Index – DVI [26]; Modified Chlorophyll Absorption Reflectance Index – MCARI [7]; Transformed Chlorophyll Absorption Reflectance Index – TCARI [9]; Relative Difference Vegetation Index – RDVI [18].

The blue (B), green (G), red (R), rededge (RE) and near infrared (NIR) spectral bands for calculating the multispectral indices were obtained by determining the average reflectance within each wavelength range.

Table 2. Plant indices used in hyperspectral and multispectral data

Indices	Hyperspectral	Multispectral
NDVI	$(R_{800} - R_{670})/(R_{800} + R_{670})$	(NIR - R) / (NIR + R)
DVI	$R_{800} - R_{680}$	NIR - R
GNDVI	$(R_{800} - R_{550})/(R_{800} + R_{550})$	(IR - G) / (IR + G)

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MCARI	$[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})].R_{700}/R_{670}$	[(RE - R) –0.2(RE - G)].RE/R
RDVI	$\sqrt{NDVI.DVI}$	$\sqrt{NDVI.DVI}$
TCARI	$3[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550}).(R_{700}/R_{670})]$	3[(RE - R) –0.2(RE - G).(RE/R)]

Rx = Reflectance value at wavelength x; R = red reflectance; G = reflectance in green; RE = red-edge reflectance; NIR = Near Infrared Reflectance.

ARCHITECTURE OF ANNS

In this work, Multi-Layer Perceptron (MLP) ANNs were trained to classify common bean leaves using reflectance data. The ANNs were trained using the ANN tools package of the Matlab computational program (MathWorks, Natick, USA). Different ANN architectures were tested. The spectral band score values were tested, individually and combined, as feature vectors used as input to the ANN.

The six hyperspectral and multispectral IVs were tested, individually and combined, as classifier input variables. All ANN architectures were tested with one and two intermediate layers and two neurons in the output layer (two classes: healthy and infected). For ANNs with two intermediate layers, the numbers of neurons tested, both in the first and in the second layer were: 2, 4, 6, 8 and 10. For ANNs with only one intermediate layer, the number of neurons tested ranged from 1 to 25. The activation function of the first and second hidden layers was the hyperbolic tangent and the output layer was the sigmoid. The error backpropagation algorithm was used, with the variation proposed by Levenberg-Marquardt [8].
Three types of feature vectors used as input in the ANN were tested:

1) The spectral bands score values tested individually and combined;
2) The six hyperspectral IVs tested individually and in combination;
3) The six multispectral IVs tested individually and in combination.

The best ANN architecture was the one with the highest Kappa coefficient value. To evaluate the difference between two Kappa indices, the Z test was used, according to [5], at a significance level of 5%.

TRAINING, VALIDATION AND TESTING OF ANNS

The dataset of 2342 samples was divided into: 1390 for network training, 478 for validation and 474 for testing. All datasets were chosen so that reflectance measurements of healthy and infected leaves would be present. The “early stop” method, described by [11], was used to stop ANN training. This method uses the validation set to interrupt the update of the free ANN parameters during training and, thus, avoid overfitting the data (“overfitting”). During training, mean squared error (MSE) is calculated with the training vectors and with validation vectors. Training is stopped when the validation NDE starts to increase [11]. The number of iterations used to confirm the NDE increase trend depends on the problem [17], and in the present work ten iterations were used.

At the beginning of training, the ANN parameters are randomly generated and these values can influence the final training result. In this way, each architecture was trained ten times. Among these ten trained ANNs, the one with the highest Kappa index with the test sample was chosen. To evaluate the difference between two Kappa indices, the Z test was used, according to [5], with a significance level of 5%. From this test set it was possible to construct the classification confusion matrix and determine the Kappa index [4][24] to evaluate the performance of the ANN classification.

EARLY DETECTION OF ANTHRACNOSE

For the detection of anthracnose, before its first symptoms became visible, the ANN that statistically presented the highest Kappa index was used. A dataset with 24 samples of healthy plants and 20 samples of infected plants was used for each level of infestation, totalling 84 samples. The samples from this dataset were not part of the ANN training, validation or test set.

III. RESULTS AND DISCUSSION

DISEASE DEVELOPMENT

Common bean plants not inoculated with the pathogen (control) remained healthy throughout the data collection period. The inoculated plants remained without showing any characteristic symptoms of anthracnose during the latency period of the disease.

TEST BETWEEN VECTORS OF CLASS MEANS

The difference between the mean classes of infected and healthy leaves was significant at the 5% probability level by Hotelling's T^2 test (Table 3). This shows that the development of a classifier to discriminate between the two classes can be feasible. Manova tests were significant for treatments ($\Lambda = 0.0002$, $F = 4.24$ and $p < 0.0001$).

Table 3. Calculated F value (Fc) for Hotelling's T^2 test, to compare means of infected or healthy leaves

	Hotelling's T^2	Fc
Value	5.51	1.10

Fc = calculated value of the F statistic corresponding to Hotelling's T^2 statistic.

PRINCIPAL COMPONENT ANALYSIS

The PC1 of each band retained at least 88.9% of the total data variance (Table 4). With PCA, there was a reduction of 751 original variables to five new independent variables – five main components, retaining more than 88% of the total variance of the original data. With these main components, the scores of each band were generated. These score values were used as ANN input vectors.

Table 4. Values, in percentage, of data variance retained by the first principal component (PC1) of each spectral band

	Blue band	Green band	Red band	Red edge band	Near infrared band
PC1	88.9	99.3	96.2	94.1	98.9

Visual Classification Of Anthracnose

The results of the daily visual assessments were based on the scale proposed by Pastor-Corrales (1992) (Table 5). For cv. Rudá, the first symptoms of anthracnose became visible from the fourth DAI onwards and by the ninth DAI all the plants were dead. In cv. Supreme, the characteristic symptoms of anthracnose became visible from the third DAI onwards, reaching a score of 1.1 and on the seventh DAI the average score was 8.6, indicating the susceptibility of this cultivar to the disease. In the eighth DAI all bean plants were dead. In cv. Vermelhinho, the first symptoms of the disease became visible in the third DAI, and in the tenth DAI the average of the scores was 8.7 and in the eleventh DAI all the plants were dead. Among the three cultivars studied, all were susceptible to anthracnose, however, in cv. Vermelhinho the evolution of the infection was slower than in cultivars Rudá and Supremo.

Table 5. Mean severity of anthracnose in the three common bean cultivars in relation to the number of days after inoculation (DAI) of the pathogens

Cultivars	DAI										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Rudá	1.0	1.0	1.0	1.3	2.3	3.9	8.1	8.4	-	-	-
RBS Supremo	1.0	1.0	1.1	2.7	4.3	7.8	8.6	-	-	-	-
Vermelhinho	1.0	1.0	1.1	1.8	2.8	4.0	6.4	7.1	8.4	8.7	-

Mean disease severity, based on the use of a scale from 1 to 9, according to the methodology proposed by Pastor-Corrales (1992).

CLASSIFIER BY ARTIFICIAL NEURAL NETWORKS

Two types of ANNs were trained: with one and two intermediate layers. For each type of ANN, at each combination of the five input vectors, 25 different architectures were trained. There were 31 combinations of the five input vectors, with no repetition of input vectors in the same combination. Thus, for each type of ANN, 775 different architectures were trained. The best ANN was the one that statistically presented the highest value of the Kappa coefficient by the Z test. There was no significant difference between the Kappa values for the 100 best ANNs. There were 31 combinations, without repetition, of the five input variables. Among the 100 ANNs, with two hidden layers, which presented the highest values of the Kappa coefficient, with values ranging from 34.2% to 44.4%, the highest frequencies occurred for the scores of the blue, red and near infrared bands (Table 6).

Table 6. Frequencies with which the scores of each spectral band contributed to each combination of ANN input variables with two intermediate layers

Spectral bands	Frequency
Blue	21
Green	11
Red	32
Red edge	10
Near infrared	26

For the top 100 RNAs with a middle layer. The highest frequencies occurred for the scores in the blue, red and near infrared bands. Among the 100 ANNs that presented the highest values of the Kappa coefficient, ranging from 33.7% to 41.4%, the results in the classification were better than those at random by the Z test at 5% significance. The highest frequencies occurred for the scores in the blue, red and near infrared bands (Table 7).

Table 7. Frequencies with which the scores of each spectral band contributed to each combination of ANN input variables with an intermediate layer

Spectral bands	Frequency
Blue	26
Green	8
Red	30
Red edge	12
Near infrared	24

The scores of the spectral bands with the highest frequencies were blue, red and near infrared (Tables 6 and 7). The blue and red bands are part of the visible region of the electromagnetic spectrum. The relevance of these bands can be justified by the fact that pathogens cause deterioration of photosynthetic organelles, such as chloroplasts, reducing the amount of pigments involved in the photosynthesis process. Chlorotic lesions and necrosis on the leaf surface affect reflectance in the visible spectral region. A decrease in the concentration of chlorophyll in the leaf causes an increase in the reflectance value in the red spectral region [28]. In the near-infrared spectral band there is little absorption of electromagnetic radiation and considerable internal scattering due to the interaction of incident energy with the internal structure of the sheet. Infected leaves showed an increase in reflectance values, due to the reduction in the amount of biomass, due to the pathogen attack. In general, the more gaps the internal leaf structure, the greater the reflectance [16].

ANNs that used six IVs, obtained from simulated hyperspectral and multispectral data, as input variables were also trained (Table 2). Two types of ANNs were trained: with one and two intermediate layers. For each type of ANN, at each combination of the six input vectors, 25 different architectures were trained. There were 63 combinations of the six input vectors, with no repetition of input vectors in the same combination. In this way, for each type of ANN, 1,575 different architectures were trained. The best ANN was the one that statistically presented the highest value of the Kappa coefficient by the Z test. Also, there was no significant difference between the Kappa values for the 100 best ANNs. The highest frequencies occurred for the IV DVI, indicating that the DVI was the most sensitive index to detect changes in the reflectance of infected leaves (Table 8).

Table 8. Frequencies with which each hyperspectral IV contributed to each combination of ANN input variables with two intermediate layers

Hyperspectral vegetation indices	Frequency
NDVI	24
GNDVI	9
MCARI	9
TCARI	7
DVI	33
RDVI	18

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NDVI = vegetation index by normalized difference; GNVDI = normalized green difference vegetation index; MCARI = modified chlorophyll absorption index; TCARI = transformed chlorophyll absorption index; DVI = vegetation difference index; RDVI = relative difference vegetation index.

There were 63 combinations, without repetition, of the six IV obtained from hyperspectral data for classifiers with a hidden layer. Among the 100 ANNs with the highest Kappa coefficient values, for ANNs with an intermediate layer, the highest frequencies occurred for IV DVI (Table 9).

Table 9. Frequencies with which each hyperspectral IV contributed to each combination of ANN input variables with an intermediate layer

Hyperspectral vegetation indices	Frequency
NDVI	20
GNDVI	7
MCARI	9
TCARI	10
DVI	37
RDVI	17

NDVI = vegetation index by normalized difference; GNVDI = normalized green difference vegetation index; MCARI = modified chlorophyll absorption index; TCARI = transformed chlorophyll absorption index; DVI = vegetation difference index; RDVI = relative difference vegetation index.

In the 63 combinations, without repetition, of the six IV obtained from multispectral data. Among the top 100 ANNs, with two intermediate layers, the highest frequencies occurred for DVI (Table 10). The DVI vegetation index was the most representative for the classification of anthracnose, as it was present in all combinations of input variables, both for hyperspectral IR and for multispectral IR (Tables 8, 9, 10 and 11).

Table 10. Frequencies with which each multispectral IR contributed to each combination of ANN input variables with two intermediate layers

Multispectral vegetation indices	Frequency
NDVI	21
GNDVI	8
MCARI	8
TCARI	9
DVI	38
RDVI	16

NDVI = vegetation index by normalized difference; GNVDI = normalized green difference vegetation index; MCARI = modified chlorophyll absorption index; TCARI = transformed chlorophyll absorption index; DVI = vegetation difference index; RDVI = relative difference vegetation index.

The DVI is the difference between the reflectances of the near-infrared and red bands. The red band (630-685 nm) is part of the visible spectrum, it is directly related to the variation in the spectral response of the leaf due to the variation in the content of organelles, such as chloroplasts. Chlorophyll is located inside the chloroplasts; the relevance of this band can also be justified by the fact that pathogens cause a reduction in the chlorophyll content in the plant due to necrosis or chlorotic lesions [6][1]. The near infrared band (760 to 850 nm) is a spectral range that indicates stress in plants. Variation in the spectral response of this band is due to variations in the physical structure of the plant, such as a decrease in biomass and water content [1]. Chloroplasts use water to carry out photosynthesis and the anthracnose pathogens cause a reduction in the content of these organelles, with a reduction in the water content in the leaves, causing a change in the spectral response of the infected leaf.

The DVI was the vegetation index with the highest frequency for both hyperspectral and multispectral data, proving to be more sensitive in the discrimination of anthracnose.

Table 11. Frequencies with which each multispectral IR contributed to each combination of ANN input variables with an intermediate layer

Multispectral vegetation indices	Frequency
NDVI	16
GNDVI	9
MCARI	12
TCARI	10
DVI	41
RDVI	12

NDVI = vegetation index by normalized difference; GNVDI = normalized green difference vegetation index; MCARI = modified chlorophyll absorption index; TCARI = transformed chlorophyll absorption index; DVI = vegetation difference index; RDVI = relative difference vegetation index.

There was no significant difference between the values of the Kappa coefficients for ANNs using as input vectors the values of scores of the spectral bands (Kappa values ranging from 33.7% to 41.4%,), hyperspectral IV (Kappa values ranging from 30.1% to 42.9%,) and multispectral IR (Kappa values ranging from 31.9% to 44.2%). Multispectral data have few spectral bands, characterizing a simpler system compared to hyperspectral data. Since smaller ANNs generalize better, the neural network using multispectral data with 1 input variable (the DVI), a hidden layer with 2 neurons, being simpler, was used to discriminate between healthy leaves and those infected with anthracnose. The best ANN, for multispectral data, presented architecture 1 – 2 – 2, used the DVI vegetation index as input vector and obtained a Kappa coefficient of 32%. A better analysis of this ANN can be done using its confusion matrix (Table 12).

Table 12. Confusion matrix with Kappa coefficient, producer accuracy and global accuracy, obtained with the ANN test sample, for multispectral data

	Diseased leaves	Healthy leaves	Kappa (%)	Overall accuracy (%)
Diseased leaves	340	78	32	79
Healthy leaves	20	36		
Producer accuracy(%)	94	32		

To verify whether the selected ANN had a better classification than the random one, the Z test was applied (Table 13). The calculated Z value (Zc) for this ANN was greater than the tabulated Z value at 5% significance (Zt = 1.96), indicating that the ANN classification was better than a random classification.

Table 13. Kappa coefficient, calculated Z (Zc) and variance values for the ANN architecture trained with data and multispectrals as input vectors

Data Types	Multispectral
ANN architecture	1 – 2 – 2
Kappa (%)	32
Variance	0,0033
Zc	5,48

EARLY DETECTION OF ANTHRACNOSE

Leaf spectral data proved to be useful in detecting diseases in common bean plants. Based on the results obtained in this work, it was demonstrated that the early discrimination of anthracnose in common bean was possible. The disease was detected one day after the inoculation of the pathogen with Global Accuracy of 67%, 77% and 64%, in the cultivars Rudá, RBS Supremo and Vermelhinho, respectively, three days before the first characteristic symptoms of the disease became visible, not importing the level of concentration of conidia mL- 1 (Table 9). Results similar to those found by other researchers using fungal diseases in beet plants [2][3][20]. The results showed that there was no advantage in using the score values of the five proposed spectral bands, nor the IV of hyperspectral data, as input variables of the classifier. The values of the Kappa coefficients for the classifiers were statistically equal. The input variable for the best classifier was the IV DVI obtained from multispectral data.

Table 9. Results, in percentage, of the classification of diseased and healthy leaves according to the day after inoculation (DAI), for ANN with architecture 1 – 2 – 2, using the multispectral DVI vegetation index as an input variable

Cultivars	Classes	DAI									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Rudá	**D.L.**	72	77	82	88	100	92	97	90	-	-
	H.L.	54	46	54	50	29	59	59	79	-	-
	Kappa	24	22	36	41	37	54	62	68	-	-
	O.A.	67	68	74	77	80	83	87	79	-	-
RBS Supremo	**D.L.**	90	93	97	92	98	88	85	-	-	-
	H.L.	46	38	28	58	78	75	83	-	-	-
	Kappa	39	36	31	53	75	63	64	-	-	-
	O.A.	77	77	81	82	91	85	84	-	-	-
Vermelhinho	**D.L.**	73	78	85	92	93	98	100	97	95	90
	H.L.	42	38	41	46	46	54	58	67	79	88
	Kappa	15	16	28	42	44	60	67	68	76	75
	O.A.	64	67	73	79	80	86	88	88	90	89

DVI = vegetation difference index; D.L. = diseased leaves; H.L. = healthy leaves; O.A. = overall accuracy.

IV. CONCLUSIONS

The vegetation difference index (DVI) proved to be more efficient in capturing the total variance of reflectance data from leaves infected with anthracnose.

The results of this work indicated that vegetation indices obtained from hyperspectral data did not provide significant improvement in leaf classification, when compared with IV from multispectral data.

The RNA classifier proposed in this work is effective in detecting anthracnose in common bean leaves at early stages of infection. At all three levels of conidial concentrations mL^{-1}, the classifier achieved good results in discriminating infected leaves on the first day after pathogen inoculation, three days before the first symptoms of anthracnose became visible.

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