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Applications of Machine Learning Algorithms in Nitrogen Fertilizer Management of Triticale

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In this study, a new classification technique is proposed to distinguish the appropriate one from four different nitrogen (N) fertilizer doses (0, 40, 80, and 160 kg ha^{-1}) using six triticale cultivars. In the classification phase, nine yield features from 30 plants of the same cultivar were measured, that is, each dose or class has 30 feature vectors consisting of nine features. Next, six triticale cultivars were classified for each dose of N fertilizer separately by using 30 feature vectors belonging to each dose. Similarly, the same classification task was repeated by using all feature vectors taken from four doses of N fertilizer. What makes this study novel is the classification process of six triticale cultivars by taking into account their characters based on different doses of N fertilizer. The classification tasks were conducted by applying Common Vector Approach, Support Vector Machine, k-Nearest Neighbor, and Decision Trees algorithms. While satisfactory results were obtained from the training sets for all cases, the test set accuracy is relatively lower for the classification of four doses of N fertilizer and six cultivars since features extracted from different doses of N fertilizer for the same cultivar are close to each other. Furthermore, the number of feature vectors is insufficient to classify classes efficiently. Interestingly, when the common information of the classifiers was extracted with the biplot technique, useful results were obtained in selecting appropriate N doses for several triticale varieties. Combined with the results of future comprehensive studies, applicable results for the agricultural sector can be proposed.

Keywords: Cereals, Common vector approach, K-Nearest neighbor, Plant nutrition, Support vector machine

Introduction

The first cereal crop created by breeders is triticale. The triticale takes place in the low diets that are visible in some developing countries and is a desirable crop for livestock feeds due to its numerous nutritional qualities. In addition to these characteristics, the triticale is one of the most possible crops that may arise in poor agricultural settings (insufficient plant minerals, heat stress, etc.).[1]

Nitrogen (N) is the nutrient required for cereal production, which not only determines the plant growth rate and the final grain yield but also the relative contribution to dry matter associated with grain quality.[2] The use of applied N is determined based on the crop species.[3] Fertilizer N efficiency in field crops is predicted between 30% and 35%, around 60% of the global N fertilizer is used to produce wheat, maize, and rice which are three major kinds of cereal in the world.[4–5] Increased production costs and environmental awareness (surface or groundwater pollution from nitrates) encourage the development of methods to improve the efficiency of N fertilization.[6] For this reason, fertilizers and their management will be the forerunners in the measures to be taken to improve the global N balance, both short and long-term. Moreover, N has great importance in the physical properties of cereals such as grain weight per spike, grain shapes, and protein content. The most important quality parameter used to determine cereal quality is the amount of grain protein.[7] Differences in the amount of protein are largely influenced by the genetic structure and environmental factors including N fertilizer application and climatic conditions. Among the ways to minimize the losses caused by N fertilization, there are soil and plant analyses to determine fertilizer doses according to plant needs. So far, different methods have been developed for plants to maximize the intake of N fertilizer from the soil. In recent years, various sensors based on the color intensity of field

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crops have begun to be used to determine fertilization.[8] However, due to soil and plant-based problems, the use of N sensors to determine plants' N needs is not common.

Appropriate N dosage advice is usually made in the form of manual recommendations. However, as field experts offer manual recommendations, his/her judgments are based on his/her experience and may be biased and inaccurate in some cases, resulting from financial losses or impacts on crop production. An alternative to this method is to integrate smart algorithms that use historical data to make decisions automatically. It has been observed that the accuracy of the algorithm is considerably high and stable as the decision depends on historical data.[9]

Classification with computer algorithms of plant characteristics and making recommendations on cultivars and fertilization based on the predictions have been applied to real-world experiments in recent years.[10–12] The common vectors signifying the common plant features can be obtained by removing the variations in each plant.[13] Currently, machine learning, common vectors, data mining, and deep learning methods are used in various studies to obtain features from plant species, estimate crop yield and quality, and/or recommend the most suitable crop/cultivar/fertilizer for a particular land.[14–19] Romero *et al.*[16] analyzed yield estimation of durum wheat from yield characters by using classification algorithms. Bondre and Mahagaonkar[18] used machine learning algorithms like Support Vector Machine (SVM) and Random Forest on agriculture data to recommend suitable fertilizers for each specific crop.

The aim of this study is to investigate the usage of machine learning algorithms in agricultural sciences for triticale cultivar classification and fertilizer dose recommendations. Common Vector Approach (CVA), SVM, Decision Trees (DT), and k-nearest Neighbor (k-NN) were applied for the classification of N fertilizer doses and triticale cultivars. Initially, the classification of four doses of fertilizer for each cultivar separately is proposed. For this purpose, nine plant characteristics [grain length (GL), grain number per spike (GNS), grain protein content (PC), grain thickness (GT), grain weight per spike (GWS), grain width (GW), plant height (PH), spike length (SL), and spikelet number per spike (SPN)] were used in the feature vectors. These characters are taken from 30 plants of the same cultivar. Therefore, each dose or class has 30 feature vectors, and each feature vector has nine features. In this way, we can investigate whether suitable required N fertilizer doses can be recommended to each cultivar with high accuracy. Secondly, six triticale cultivars were classified for each dose of N fertilizer separately. In this case, each cultivar or class has 30 feature vectors. Thirdly, six cultivars were also classified by considering all feature vectors in four doses of N fertilizer. In this case, each class has 120 feature vectors (30 feature vectors × four doses of N fertilizer). Finally, the results obtained from the first two classifications were reprocessed with a biplot, and it was utilized to select the appropriate fertilizer dose for each genotype based on principle component analysis (PCA). The classifications of cultivars are also novel studies as in the classification of doses of N fertilizer. The proposed system comes with a model to be precise and accurate in predicting cultivars and serve the grower with proper recommendations about the required fertilizer rate.

Materials and Methods

Dataset Description

There are six hexaploid winter triticale (x *Triticosecale* Wittmack) cultivars; Melez, Presto, Sorti, Karma, Tatlicak, Mikham, and four doses of N fertilization (0, 40, 80, and 160 kg·ha^{-1} N) in our dataset. Thirty values are obtained for each of the nine characters (SL, SPN, GNS, GWS, GT, GL, GW, PH, and PC) taken from a cultivar. These samples are used to create feature vectors for each cultivar. The samples of nine characters of the cultivar Karma belonging to N0 and N40 applications are given in Table 1 and Table 2, respectively.

In the classification stage, four well-known classifiers which are CVA, SVM, DT, and k-NN are used. In addition, the classifiers were compared according to the PCA-biplot method for cultivars and N doses. Finally, proper N doses were selected for each cultivar. The machine learning algorithms used in the study are summarized below.

CVA Method

CVA is a successful subspace method that has been previously proposed.[20–22] Therefore, CVA was used to classify four doses of N fertilizer applied to six triticale cultivars, for the classification of six cultivars. In the training phase of CVA, a common vector that signifies common or invariant features of each class is determined and an indifference subspace is obtained for each class. Let us assume that $a_1^c, a_2^c, \ldots, a_m^c \in R^n$ denotes the feature vectors for the

Table 1 — Samples belonging to nine characters of Karma cv. for control (N0)

Plant no	SL (cm)	SPN (#)	GNS (#)	GWS (g)	GT (cm)	GL (cm)	GW (g)	PH (cm)	PC (%)
1	12.0	31	59	2.50	0.15	0.55	0.16	105	10.0
2	12.0	30	60	1.80	0.17	0.65	0.15	103	10.0
3	12.0	27	54	2.10	0.16	0.75	0.15	110	12.7
4	11.5	25	49	1.50	0.14	0.65	0.18	103	12.8
5	10.5	25	50	1.20	0.19	0.63	0.12	108	13.4
6	11.0	27	57	3.10	0.18	0.72	0.21	109	14.2
7	11.5	30	55	2.30	0.17	0.68	0.19	106	15.4
8	12.0	31	50	2.40	0.13	0.53	0.17	102	14.2
9	10.5	24	42	2.48	0.17	0.56	0.18	100	15.0
10	11.0	29	56	2.10	0.16	0.59	0.16	102	13.9
11	12.0	30	56	3.80	0.13	0.58	0.18	99	15.0
12	11.0	27	49	2.20	0.19	0.54	0.14	98	13.9
13	13.0	31	61	3.30	0.20	0.56	0.19	103	14.1
14	13.0	32	64	2.60	0.21	0.65	0.15	101	13.3
15	11.0	29	60	1.33	0.17	0.64	0.17	110	14.1
16	12.0	29	59	1.73	0.19	0.61	0.13	108	14.3
17	13.0	30	62	1.96	0.18	0.62	0.17	111	11.3
18	9.0	27	41	2.10	0.17	0.63	0.19	107	12.4
19	10.0	28	54	1.20	0.16	0.74	0.18	105	11.3
20	11.0	28	59	1.70	0.15	0.78	0.19	112	11.6
21	10.0	29	40	1.70	0.13	0.63	0.17	109	12.3
22	9.0	28	42	3.30	0.19	0.62	0.21	93	11.3
23	9.5	27	43	1.06	0.21	0.64	0.22	95	12.6
24	8.5	26	50	1.30	0.25	0.66	0.14	96	11.2
25	10.5	22	41	1.22	0.17	0.55	0.15	97	10.9
26	10.0	28	42	1.00	0.19	0.71	0.18	95	11.0
27	11.0	24	39	2.00	0.13	0.73	0.19	94	11.4
28	8.5	31	54	1.80	0.16	0.69	0.17	95	10.4
29	9.0	21	53	1.17	0.17	0.68	0.17	98	12.4
30	9.5	22	55	1.50	0.19	0.64	0.16	96	10.2

Table 2 — Samples belonging to nine characters of cv. Karma for N40 application

Plant no	SL (cm)	SPN (#)	GNS (#)	GWS (g)	GT (cm)	GL (cm)	GW (g)	PH (cm)	PC (%)
1	13.0	34	76	1.8	0.21	0.62	0.21	110	11.1
2	13.0	33	58	1.4	0.25	0.63	0.22	111	12.3
3	12.0	33	76	1.5	0.26	0.65	0.24	112	12.1
4	9.5	28	47	1.6	0.24	0.61	0.26	110	13.3
5	10.0	26	40	1.3	0.21	0.54	0.31	108	10.5
6	12.0	32	77	1.5	0.28	0.56	0.25	106	11.7
7	14.0	36	62	1.6	0.29	0.58	0.26	110	12.5
8	13.5	34	61	1.8	0.21	0.51	0.24	105	12.7
9	12.0	31	73	1.7	0.20	0.63	0.21	107	12.7
10	11.0	31	69	1.7	0.19	0.68	0.27	104	13.7
11	11.0	35	80	2.2	0.18	0.51	0.23	103	14.7
12	11.0	28	58	3.2	0.17	0.69	0.25	102	14.7
13	11.5	25	58	2.0	0.16	0.71	0.24	103	11.4
14	12.5	31	59	2.0	0.24	0.78	0.26	104	12.3
15	11.0	27	46	1.9	0.21	0.80	0.21	93	12.5
16	13.0	33	50	2.4	0.23	0.64	0.25	94	13.7
17	10.0	29	56	2.0	0.25	0.57	0.26	95	14.4
18	11.0	34	60	1.6	0.26	0.68	0.28	93	12.4
19	10.0	27	39	3.0	0.25	0.78	0.30	97	12.3
20	10.0	28	50	1.8	0.19	0.77	0.29	96	13.7
21	10.0	27	56	1.9	0.19	0.66	0.21	95	13.0

(*Contd*.)

Table 2 — Samples belonging to nine characters of cv. Karma for N40 application (*Contd.*)

Plant no	SL (cm)	SPN (#)	GNS (#)	GWS (g)	GT (cm)	GL (cm)	GW (g)	PH (cm)	PC (%)
22	12.0	25	65	1.6	0.21	0.62	0.2	108	12.0
23	9.0	25	37	1.8	0.24	0.61	0.24	110	12.5
24	10.0	27	45	2.6	0.29	0.58	0.25	111	13.1
25	7.0	22	36	2.4	0.28	0.63	0.22	109	12.7
26	9.0	25	40	2.7	0.27	0.62	0.23	108	12.6
27	11.0	31	53	2.8	0.26	0.64	0.21	105	13.3
28	10.0	26	41	2.1	0.25	0.68	0.26	109	12.6
29	8.0	19	29	2.9	0.27	0.75	0.21	98	11.3
30	10.0	27	42	2.1	0.24	0.74	0.23	102	11.2

c^{th} class in the training set in which $m > n$. These feature vectors are assumed to be linearly independent and they can be expressed as

$$\mathbf{a}_i^c = \mathbf{a}_{i,dif}^c + \mathbf{a}_{com}^c + \varepsilon_i^c \quad \text{for } i=1,2,\ldots,m \qquad \ldots (1)$$

where, the vector $\mathbf{a}_{i,dif}^c$ represents the differences resulting from climatic effects, alien pollination, and cultivar of plants, and the vector $\mathbf{a}_{com}^c$ is the common vector of dose or cultivar class, and ε_i^c indicates the error vector.[21] The common vector can be determined by using the following procedure. The covariance matrix for c^{th} dose or cultivar class can be written as

$$\mathbf{\Phi}^c = \sum_{i=1}^{m} (\mathbf{a}_i^c - \mathbf{a}_{ave}^c)(\mathbf{a}_i^c - \mathbf{a}_{ave}^c)^T \qquad \ldots (2)$$

where, $\mathbf{a}_{ave}^c$ is the average of the feature vectors in c^{th} class and T corresponds to the transpose of a matrix.

The non-negative eigenvalues of the covariance matrix $\mathbf{\Phi^c}$ can be sorted in decreasing order: $\lambda_1^c \geq \lambda_2^c \geq \ldots \geq \lambda_n^c$. $u_1^c, u_2^c, \ldots, u_n^c$ are the orthonormal eigenvectors associated with these eigenvalues. The eigenvectors corresponding to the largest k eigenvalues of the covariance matrix form an orthonormal basis for the difference subspace B.[22] All the eigenvectors associated with the smallest (n-k) eigenvalues span the orthogonal complement subspace $B^{\perp}$ which is called the indifference subspace. The direct sum of two subspaces B and $B^{\perp}$ covers the entire space and the intersection of them gives the null space. The value of k can be chosen such that the sum of the smallest eigenvalues is less than a particular percentage (L) of the sum of all eigenvalues[23], that is,

$$\frac{\sum_{i=k+1}^{n} \lambda_i}{\sum_{i=1}^{n} \lambda_i} < L \qquad \ldots (3)$$

In the experimental studies, if L=25% is used in the training phase, higher recognition rates were obtained when compared with other values of L. L = 25% for indifference subspace was achieved at a different number of eigenvalues for each class. These eigenvalues had an average number of 7.

The value of k is also determined from the point, where the eigenvalues of the training data start to vary slowly upon plotting the eigenvalues in descending order. In Fig. 1, this point approximately corresponds to k = 3 (= 9−7+ 1).

The common vector can be written in terms of the eigenvectors associated with the smallest eigenvalues of $\mathbf{\Phi}^c$[22], such that,

$$\mathbf{a}_{com}^c = \left\langle \mathbf{a}_{ave}^c, \mathbf{u}_{k+1}^c \right\rangle \mathbf{u}_{k+1}^c + \cdots + \left\langle \mathbf{a}_{ave}^c, \mathbf{u}_n^c \right\rangle \mathbf{u}_n^c \qquad \ldots (4)$$

Therefore, the common vector $\mathbf{a}_{com}^c$ corresponds to the projection of the average feature vector onto the indifference subspace $B^{\perp}$. The common vector signifies the common features or invariant properties of the dose or cultivar class. The common vector is sole for each class and all the error vectors ε_i^c would be minimum.

During the classification phase, the decision criterion given below is utilized:

$$distance = \underset{1 \leq c \leq S}{argmin} \left\| \sum_{j=k+1}^{n} \left\{ \left[\left(\mathbf{a}_x - \mathbf{a}_{ave}^c \right)^T \mathbf{u}_j^c \right] \mathbf{u}_j^c \right\} \right\|^2 \qquad \ldots (5)$$

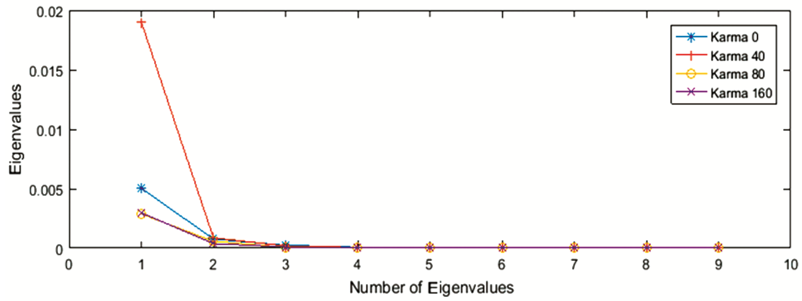

Fig. 1 — The variations of the eigenvalues of the covariance matrix obtained for Karma

where, a_x is a test or unknown vector and S corresponds to the total number of classes. If the minimum distance is obtained for any class c, the feature vector a_x is designated to that class.

The above classification procedure can be given in algorithmic notation as below:

1. [Initialize]

Take characters for each class

2. [Construct the feature vectors]

Characters $\rightarrow$ feature vectors: $a_1^c, a_2^c, \ldots, a_m^c$ while m>n

3. [Find the covariance matrix]

Feature vectors $\rightarrow$ covariance matrix: $\boldsymbol{\Phi}^c$

4. [Find the eigenvalues and eigenvectors]

Covariance matrix: $\boldsymbol{\Phi}^c \rightarrow$ eigenvalues: $\lambda_1^c,\ \lambda_2^c,\ \ldots,\ \lambda_n^c$. and eigenvectors: $u_1^c, u_2^c, \ldots, u_n^c$

5. [Find the common vector]

$$\left.\begin{array}{r} \text{average vector: } a_{ave}^c \\ \text{eigenvectors: } u_1^c, u_2^c, \ldots, u_n^c \end{array}\right\} \xrightarrow{\textit{projection}}$$

common vector: a_{com}^c

6. [Classify test vector]

$$\left.\begin{array}{r} \text{test vector - average vector: } a_x - a_{ave}^c \\ \text{eigenvectors: } u_1^c, u_2^c, \ldots, u_n^c \end{array}\right\}$$

$$\Big\} \Rightarrow \text{minimum value of projection} \Rightarrow \text{class of test vector}$$

7. [Finished]

Exit

SVM Method

Proposed as a binary classifier, SVM determines the optimal hyperplane that maximizes the distance between the optimal hyperplane and the closest sample to that hyperplane.[24–26] So it is also called the maximum margin classifier.[27] Because SVM is originally binary classification algorithm, for dealing with multi-class problems “one against all” strategy was used in this study. In this paper, the polynomial SVM classifier was preferred and it was implemented by using Pattern Recognition Toolbox (PRTools).[28] The order of the polynomial was selected as 2.

The k-NN Method

The k-NN is a lazy learning and non-parametric classifier algorithm.[29] The k-NN classifies the test data according to its similarity to training data. For the classification procedure, Euclidian distance was used and k value was selected as 5.

DT Method

A decision tree is a supervised learning algorithm that has decision nodes, branches, and leaf nodes that are referred as features, conditions, and classes, respectively.[30] When designing a classification tree, the splitting criterion should be carefully selected. For this study, Information Gain was selected as a splitting criterion.

PCA-Biplot Method

A biplot or binary plot is an exploration plot to present both the observations (sample) and the data variables- as points or vectors. Axes are typically hidden major dimensions. Biplot is often used to demonstrate principal component analysis, fitness analysis, and other multivariate methods. The principal component analysis is a method that identifies the features that contribute the most to the variation available within a group of datasets. Biplot analysis based on two principal components was performed to learn the relationships between recognition rates calculated for the genotypes and N doses obtained from the classifiers. The dataset and variables were presented in a single biplot graph to further simplify the visualization. The biplot graph was drawn with Minitab 16 statistics program.

The block diagram of classification models including all approaches for recommendations is shown in Fig. 2.

Results and Discussion

In the experimental studies, three different classification processes are carried out: i) The classification of four doses of N fertilizer each of which has 30 feature vectors, ii) the classification of six triticale cultivars by using 30 feature vectors of each dose separately, iii) the classification of six triticale cultivars by using 120 feature vectors of all doses (four doses of N fertilizer ×30 feature vectors). Each feature vector has nine features or characters, and it is standardized by subtracting the mean of all feature vectors in the training set and then dividing by the standard deviation of all feature vectors in the training set.

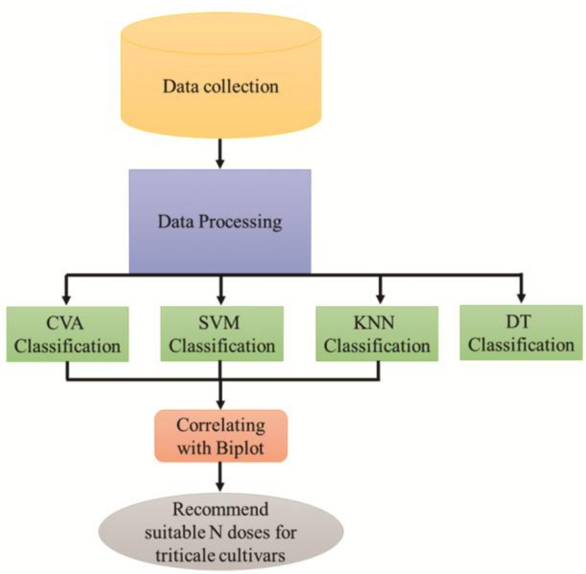

Fig. 2 — Block diagram of classification for N doses recommendation of triticale cultivars

In this paper, the classification of doses of N fertilizer is presented as a new study. Four doses (0, 40, 80, and 160) of N fertilizer applied to six cultivars (Karma, Melez, Mikham, Presto, Sorti, and Tatlicak) were classified for each cultivar separately. For this purpose, the k-NN, DT, CVA, and SVM methods were used. Each dose corresponds to one class in the classification stages and each class has 30 feature vectors consisting of nine characters or features. The five-fold cross validation approach was applied in the classification stages, namely, 24 feature vectors were utilized in the training phase, and the remaining six feature vectors were used in the testing phase in each fold. The correct recognition rates of four doses of N fertilizer for cultivars are given in Table 3 as an average of five-fold cross-validation for all classifiers.

The average scores found in the test set are low for all classifiers since characters in the feature vectors representing different doses of N fertilizer are very close to each other for the same cultivar. Therefore, common features or invariant properties of each dose cannot be properly taken out and discriminative feature space cannot be built proficiently. Meanwhile, separable dose classes cannot be constructed because samples of characters belonging to different doses are very similar. When SVM, DT, k-NN, and CVA algorithms were used to classify the feature vectors used in the training phase, the average recognition rates of 99.9%, 94.6%, 85.0%, and 87.5% were obtained for all doses and cultivars, respectively.

In another study, six triticale cultivars were classified by considering 30 feature vectors of each dose of N fertilizer by using all classifiers. Each cultivar forms one class in the classification stages. In

Table 3 — The correct recognition rates as percentage of four doses of N fertilizer for cultivars

N (*kg ha*$^{-1}$)	*Melez*				*Presto*				*Sorti*			
	SVM	DT	k-NN	CVA	SVM	DT	k-NN	CVA	SVM	DT	k-NN	CVA
0	33.3	53.3	46.7	53.3	86.7	100.0	96.7	96.7	60.0	63.3	60.0	63.3
40	73.3	70.0	80.0	70.0	53.3	70.0	70.0	70.0	46.7	76.7	36.7	70.0
80	63.3	53.3	63.3	56.7	36.7	43.3	26.7	40.0	66.7	83.3	76.7	63.3
160	53.3	50.0	43.3	36.7	86.7	53.3	63.3	73.3	76.7	93.3	100.0	96.7
Av.	55.8	56.7	58.3	54.2	65.9	66.7	64.2	70.0	62.5	79.2	68.4	73.3
N (*kg ha*$^{-1}$)	*Karma*				*Tatlicak*				*Mikham*			
	SVM	DT	k-NN	CVA	SVM	DT	k-NN	CVA	SVM	DT	k-NN	CVA
0	66.7	80.0	70.0	83.3	93.3	100.0	93.3	90.0	96.7	86.7	96.7	96.7
40	56.7	60.0	53.3	80.0	70.0	63.3	56.7	53.3	46.7	46.7	63.3	70.0
80	73.3	50.0	70.0	56.7	80.0	73.3	83.3	60.0	46.7	33.3	36.7	66.7
160	73.3	93.3	83.3	83.3	76.7	63.3	76.7	73.3	76.7	56.7	66.7	63.3
Av.	67.5	70.8	69.2	75.8	80.0	75.0	77.5	69.2	66.7	55.9	65.9	74.2

Table 4 — The correct recognition rates as percentage of six triticale cultivars for each dose separately

N (*kg·ha*$^{-1}$)	0				40				80				160			
Cultivars	SVM	DT	k-NN	CVA	SVM	DT	k-NN	CVA	SVM	DT	k-NN	CVA	SVM	DT	k-NN	CVA
Melez	53.3	40.0	60.0	63.3	53.3	36.7	63.3	63.3	26.7	33.3	56.7	46.7	53.3	13.3	60.0	43.3
Presto	86.7	80.0	86.7	80.0	76.7	76.7	80.0	80.0	53.3	56.7	50.0	60.0	76.7	83.3	83.3	83.3
Sorti	73.3	73.3	66.7	80.0	73.3	40.0	56.7	53.3	60.0	43.3	66.7	30.0	30.0	46.7	43.3	60.0
Karma	50.0	26.7	43.3	56.7	63.3	46.7	56.7	66.7	70.0	73.3	76.7	60.0	66.7	33.3	50.0	26.7
Tatlicak	53.3	56.7	53.3	60.0	76.7	73.3	76.7	93.3	80.0	76.7	80.0	76.7	60.0	63.3	76.7	66.7
Mikham	66.7	43.3	36.7	43.3	50.0	30.0	43.3	76.7	20.0	30.0	26.7	40.0	56.7	63.3	33.3	66.7
Average	63.9	53.3	57.8	63.9	65.6	50.6	62.8	72.2	51.7	52.2	59.4	52.2	57.2	50.5	57.8	57.8

this case, cultivars were classified for each dose separately. The classification of the triticale cultivars with obtained features is also a new study. The recognition rates of six cultivars are given in Table 4 as an average of five-fold cross-validation for all classifiers.

The average scores obtained in the test set are low for all classifiers because characters in the feature vectors of six cultivars are very close to each other for the same dose. When the feature vectors used in the training phase were classified by using SVM, DT, k-NN, and CVA algorithms the average classification rates of 98.6%, 92.5%, 80.6%, and 71.4% were obtained for all cultivars and doses, respectively.

In the third study, six triticale cultivars were classified by considering 120 feature vectors (four doses of N fertilizer × 30 feature vectors). The 96 feature vectors were utilized in the training phase and the remaining 24 feature vectors were checked for each class in each fold, using the five-fold cross-validation approach once more in this instance. The average recognition rates of five-fold cross-validation for six cultivars are shown in Table 5 for all classifiers.

The recognition rates are lower than the previous experiments' classification rates for all classifiers because the discriminatory power of features decreases and results in confusion when all features belonging to four doses are considered. Another reason behind the low recognition rates is that different cultivars have similar feature values which makes it more difficult to distinguish different classes with the learning algorithms.

The SVM, DT, k-NN, and CVA algorithms were used to classify the feature vectors used in the training phase, and the average recognition rates for all cultivars were 57.6%, 70.1%, 64.2%, and 47.6%, respectively.

When the feature vectors are normalized according to their average or maximum values the recognition rates decrease because the values of characters will be different from the original ones and they cannot correctly represent the yield and quality properties of the plant.

Table 5 — The correct recognition rates as percentage of six triticale cultivars when all doses are considered

Cultivars	SVM	DT	k-NN	CVA
Melez	16.7	33.3	33.3	27.5
Presto	58.3	38.3	57.5	45.8
Sorti	71.7	63.3	78.3	49.2
Karma	20.8	13.3	5.8	22.5
Tatlicak	57.5	59.2	59.2	43.3
Mikham	55.0	35.8	41.7	35.0
Average	46.7	40.6	46.0	37.2

In the last experiment, a PCA-based biplot was created to detect the combinations of cultivar and N dose with a high recognition rate by determining the correlation between the classifiers. According to the results obtained, it was expected that the combinations of the high recognition rate of the cultivars and N doses could be an effective way to separate the N doses suitable for the cultivars. When the biplot graph (Fig. 3) is examined, it is observed that there is a positive relationship between the classification models created based on both cultivars and N doses. In the classifications performed according to N doses, all classifiers were able to separate the Tatlicak cultivar at N40 and N80 doses, and the Presto cultivar at N40 and N160 doses. In the classification phase conducted under varieties, more varieties could be recognized with high accuracy. Melez was recognized with high accuracy at the N40 dose, Karma and Sorti were recognized at the N160 dose, and Tatlicak and Mikham at the N0 dose. Presto cultivar with N0 dose could be distinguished with high accuracy in both classifications.

Different plant species have been successfully classified in the literature using many popular algorithms. In particular, wheat species classification with various algorithms has become widespread for

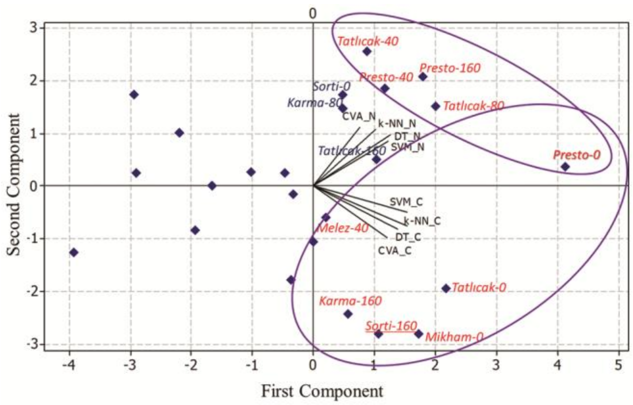

Fig. 3 — Principal component bi-plot of recognition rates obtained from cultivars and N doses between four classifiers

many years.[10,14,17,31] The wheat characters and wheat grains were also classified successfully.[14,15,32,33]

In the fertilizer classification, when the feature vectors utilized in the training phase were tested relatively higher recognition rates were obtained especially for SVM and DT methods. In the classification of training samples of six triticale cultivars, remarkable correct recognition rates were obtained when 30 feature vectors of each dose of N fertilizer were considered separately. However, low recognition rates were obtained when 120 feature vectors of all doses of N fertilizer were considered.

Some researchers have analyzed different methods to provide recommendations using machine learning and deep learning algorithms to provide accurate crop-growing recommendations at a low cost.[11,12,34,35] In this study, we examined to select the appropriate N dose for triticale varieties classified using machine learning models. Considering the biplot results, a dose of N40 can be recommended for Tatlicak, Presto, and Melez, and a dose of N160 for Karma and Sorti. Since it is understood that higher N doses cause similar effects for Tatlicak and Presto, the lowest dose (40 $kg{\cdot}N{\cdot}ha^{-1}$) may be preferred for economical fertilization. For cultivar that is not classified with a biplot appropriate N doses may be recommended based on closely related cultivars, or an average dose can be selected.

Conclusions

In this paper, the classification of both doses of N fertilizer and triticale cultivars with mentioned characters or features are newly proposed. It is concluded that all classifiers have relatively low performances in all classification stages. Nevertheless, such classifications can be very useful in the designation of unknown doses of N fertilizer for each cultivar. Also, classifications of various triticale cultivars and characters are very important in this field. It must be pointed out that the features of each dose need to be considered separately in the cultivar classification.

If more particular characters are taken out for each dose of fertilizer and each cultivar, and the number of plants increases for each dose of fertilizer, better performance can be attained from the classification procedure. Additionally, differences between the samples of the same character taken from different cultivars and fertilizer doses are very important for good performance of classification.

The results of this study introduced initial insight into estimating appropriate N doses for some triticale cultivars and will provide a background for future studies. Combining the results of this study and future comprehensive experiments will both offer a chance for researchers to develop new models and allow farmers to decide on the right fertilization preferences for growing crops. If these models can be integrated into mobile applications so that farmers can easily access recommendations for their future production, the agricultural sector can develop innovative ideas.

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References

1 Mergoum M, Sapkota S, El Doliefy A E A, Naraghi S M, Pirseyedi S, Alamri M S & Abu Hammad W, Triticale (x TriticosecaleWittmack) Breeding, *Adv Plant Breeding Strat: Cereals*, **5** (2019) 405-451, https://doi.org/10.1007/978-3-030-23108-8_11.

2 de Oliveira S A, Ciampitti I A, Slafer G A & Lollato R P, Nitrogen utilization efficiency in wheat: A global perspective, *Europ J Agr*, **114** (2020) 126008, https://doi.org/10.1016/j.eja.2020.126008.

3 Omara P, Aula L, Oyebiyi F & Raun W R, World cereal nitrogen use efficiency trends: review and current knowledge, *Agrosys, Geosci Environ*, **2(1)** (2019) 1–8, https://doi.org/10.2134/age2018.10.0045.

4 Martínez-Dalmau J, Berbel J & Ordóñez-Fernández R, Nitrogen fertilization-A review of the risks associated with the in efficiency of its use and policy responses, *Sustainability*, **13(10)** (2021) 5625, https://doi.org/10.3390/su13105625.

5 Yu X, Keitel C, Zhang Y, Wangeci A N & Dijkstra F A, Global meta-analysis of nitrogen fertilizer use efficiency in rice, wheat and maize, *Agric Ecosyst Env*, **338** (2022) 108089, https://doi.org/10.1016/j.agee.2022.108089.

6 Koutroubas S D, Fotiadis S & Damalas C A, Grain yield and nitrogen dynamics of Mediterranean barley and triticale, *Arch Agric Soil Sci*, **62(4)** (2016) 484-501, https://doi.org/10.1080/03650340.2015.1064902.

7 Malik A H, Andersson A, Kuktaite R, Mujahid M Y, Khan B & Johansson E, Genotypic variation in dry weight and nitrogen concentration of wheat plant parts; relations to grain yield and grain protein concentration, *J Agric Sci*, **4(11)** (2012) 11, http://dx.doi.org/10.5539/jas.v4n11p11.

8 Liu J, Cai H, Chen S, Pi J & Zhao L, A review on Soil Nitrogen Sensing Technologies: Challenges, Progress and Perspectives, *Agriculture*, **13(4)** (2023) 743, https://doi.org/10.3390/agriculture13040743.

9 Garg R, Aggarwal H, Centobelli P & Cerchione R, Extracting knowledge from big data for sustainability: A comparison of machine learning techniques, *Sustainability*, **11(23)** (2019) 6669, https://doi.org/10.3390/su11236669.

10 Olgun M, Onarcan A O, Ozkan K, Isık S, Sezer O, Ozgisi K, Ayter N G, Basciftci Z B, Ardıc M & Koyuncu O, Wheat grain classification by using dense SIFT features with SVM classifier, *Comput Electron Agric*, **122** (2016) 185–190, https://doi.org/10.1016/j.compag.2016.01.033.

11 Naresh V, Vatsala B R & Vidya C R, Crop yield prediction and fertilizer recommendation, *Int J Eng Sci Comp*, **10(6)** (2020) 26256–26258, https://doi.org/10.1109/CSNT57126.2023.10134662.

12 Manoj Kumar D P, Malyadri N & Srikanth M S, A machine learning model for crop and fertilizer recommendation, *Nveo-Nat Vol Essent Oils J*, **8(5)** (2021)10531–10539.

13 Aytac Z, Gulmezoglu N & Gulmezoglu M B, Application of the common vector approach on identification of winter rapeseed (*Brassica napus* L.) cultivars and their yield characters, *Int J Sustain Agric Manag Inform*, **2(1)** (2016) 66–78, https://doi.org/10.1504/IJSAMI.2016.077271.

14 Khan A, Vibhute A D, Mali S & Patil C H, A systematic review on hyperspectral imaging technology with a machine and deep learning methodology for agricultural applications, *Ecol Inform*, **69** (2022) 101678, https://doi.org/10.1016/j.ecoinf.2022.101678.

15 Zapotoczny P, Discrimination of wheat grain varieties using image analysis: morphological features, *Eur Food Res Technol*, **233** (2011) 769–779, https://doi.org/10.1007/s00217-011-1573-y.

16 Romero J R, Roncallo P F, Akkiraju P C, Ponzoni I, Echenique V C & Carballido J A, Using classification algorithms for predicting durum wheat yield in the province of Buenos Aires, *Comput Electron Agric*, **96** (2013) 173–179, https://doi.org/10.1016/j.compag.2013.05.006.

17 Onarcan A O, Ozkan K & Olgun M, Unclassified wheat identification with bag of contour fragments, In *Signal Processing and Communications Applications Conference* (IEEE) 2017, 1–4, doi: 10.1109/SIU.2017.7960305.

18 Bondre D A & Mahagaonkar S, Prediction of crop yield and fertilizer recommendation using machine learning algorithms, *Int J Eng Appl Sci Technol*, **4(5)** (2019) 371–376.

19 Meng L, Liu H L, Ustin S & Zhang X, Predicting maize yield at the plot scale of different fertilizer systems by multi-source data and machine learning methods, *Remote Sens*, **13(18)** (2021) 3760, https://doi.org/10.3390/rs13183760.

20 Gulmezoglu M B, Keskin M, Dzhafarov V & Barkana A, A novel approach to isolated word recognition, *IEEE Trans Speech Audio Process*, **7(6)** (1999) 620–628, doi: 10.1109/89.799687.

21 Gulmezoglu M B, Dzhafarov V & Barkana A, The common vector approach and its relation to principal component analysis, *IEEE Trans Speech Audio Process*, **9(6)** (2001) 655–662, doi: 10.1109/89.943343.

22 Gulmezoglu M B, Dzhafarov V, Edizkan R & Barkana A, The common vector approach and its comparison with other subspace methods in case of sufficient data, *Comput Speech Lang*, **(21)2** (2007) 266–281, https://doi.org/10.1016/j.csl.2006.06.002.

23 Oja E, *Subspace methods of pattern recognition* (John Wiley and Sons, Inc., New York) 1983.

24 Hotta K, Support vector machine with local summation kernel for robust face recognition, In: *Proc. of 17th Int. Conf. on Pattern Recognition* (IEEE) 2004, 482–485, doi: 10.1109/ICPR.2004.1334571.

25 Vapnik V, *The nature of statistical learning theory, Statistics for Engineering and Information Science* (Springer Verlag, Berlin) 2000.

26 Cevikalp H, Yavuz H S, Edizkan R, Gunduz H & Kandemir C M, Comparisons of features for automatic eye and mouth localization, In: *Proc. of the IEEE Int Symp on Innovations in Intelligent Systems and Applications* (IEEE) 2011, 576–580, doi: 10.1109/INISTA.2011.5946152.

27 Burges C J C, Tutorial on support vector machines for pattern recognition, *Data Min Knowl Discov*, **2** (1998) 121–167, https://doi.org/10.1023/A:1009715923555.

28 Duin R P W, Juszczak P, Paclik P, Pekalska E, De Ridder D & Tax D M J, *PRTools4, A Matlab tool box for pattern recognition* (Delft University of Technology) 2004.

29 Cunningham P & Delany S J, k-Nearest neighbour classifiers, *Mult Class Syst*, **34** (2007) 1–17, https://doi.org/10.1145/3459665.

30 Darooei R, Sanadgol G, Gh-Nataj A, Almasnia M, Darivishi A, Eslaminejad A & Raoufy M R, Discriminating tuberculous pleural effusion from malignant pleural effusion based on routine pleural fluid biomarkers, using mathematical methods, *Tanaffos*, **16(2)** (2017) 157.

31 Gulmezoglu M B & Gulmezoglu N, Classification of bread wheat varieties and their yield characters with the common vector approach, *International Conference on Chemical, Environmental and Biological Sciences* (Dubai, BAE) 2015, 142–145.

32 Kutlu I, Heritability of end-use quality and biofortification characteristics in line x tester bread wheat (*Triticum aestivum* L.) crosses, *Appl Ecol Environ Res*, **16(5)** (2018) 7305–7326, http://dx.doi.org/10.15666/aeer/1605_73057326.

33 Kutlu I, Gulmezoglu M B & Karaduman Y, Classifying wheat genotypes using machine learning models for single kernel characterization system measurements, *J Sci Ind Res*, **80** (2021) 985–991, 10.56042/jsir.v80i11.40757.

34 Irfan S A, Azeem B, Irshad K, Algarni S, KuShaari K, Islam S & Abdelmohimen M A, Machine learning model for nutrient release from biopolymers coated controlled-release fertilizer, *Agriculture*, **10(11)** (2020) 538, https://doi.org/10.3390/agriculture10110538.

35 Agarwal S & Tarar S, A hybrid approach for crop yield prediction using machine learning and deep learning algorithms, In *J Phy*: Conference Series, *IOP Publishing*, **1714(1)** (2021) 012012, https://doi.org/10.1088/1742-6596/1714/1/012012.