Neural Computing and Applications (2021) 33:16733–16744
https://doi.org/10.1007/s00521-021-06269-z

ORIGINAL ARTICLE

Classification of organic and conventional olives using convolutional neural networks

Mehmet S. Unluturk[1] · Secil Kucukyasar[2] · Fikret Pazir[2]

Received: 19 October 2020 / Accepted: 26 June 2021 / Published online: 3 July 2021

Abstract

This paper presents a convolutional neural network (CNN) to classify between the conventionally and organically cultivated Memecik varieties of green olives. The image forming method called the rising paper chromatography is utilized in preparing the images of Memecik varieties of green olives for CNN. In the rising chromatography method, 20, 30, and 40% sample concentrations were determined as the suitable concentrations for both organic and conventional olives. The concentrations of $AgNO_3$ and $FeSO_4$ were determined as 0.25, 0.5, 0.75 and 1% for both conventional and organic samples. The visual differences used for differentiation of different types of Memecik green olives are usually determined according to the regional color differences, the vivid color occurrence, the width and the frequency of bowl occurrence, the thin line, and the picks at drop zone by the expert assessors. The testing results in this study verified the effectiveness of the CNN methodology in differentiating between the organically and conventionally cultivated Memecik green olives. The newly designed neural network achieved 100% accuracy. Furthermore, this high accuracy achieved by CNN might suggest that it can be effectively used in place of the expert assessors.

Keywords Organic olive · Conventional olive · Memecik · Rising paper chromatography · Convolutional neural network

1 Introduction

Agricultural studies are important for the development of the rural parts of society. When the continuous increase in the world population is considered, it is sure that nutrition will be an important problem in the future as in the past and today. For this reason, the existing resources should be used efficiently within the agricultural activities. The use of chemical fertilizers is one of the important factors in ensuring high productivity in agriculture [1].

✉ Mehmet S. Unluturk
mehmet.unluturk@yasar.edu.tr

Secil Kucukyasar
secil.kucukyasar@hotmail.com

Fikret Pazir
fikret.pazir@ege.edu.tr

1 Department of Software Engineering, Yasar University, Izmir, Turkey

2 Food Engineering Department, Ege University, 35040 Izmir, Turkey

Since the 1950s, food production in industrialized countries has evolved into a serial production system based on external inputs such as machinery, fuel, chemical fertilizers, and various chemicals (pesticides) that human labor is significantly reduced with the intensive use of soil and water [2].

Conventional agriculture, also known as industrial agriculture, refers to farming systems that include the use of synthetic chemical fertilizers, pesticides, herbicides and other continual inputs, genetically modified organisms, concentrated animal feeding operations, heavy irrigation, intensive tillage, or concentrated monoculture production [3].

Pesticides are various chemicals used in agricultural applications to inhibit harmful organisms, to reduce or to take over control of their harm. It provides an important advantage in agriculture, as it gives better cultivation results in wide agricultural fields in a short time with less labor and expense [4]. Pesticides have become an indispensable part of modern agriculture both in the world and in Turkey as a result of increasing population and decreasing arable agricultural lands [5]. However, the pesticides can cause large amounts of residue remained in foods when used over the recommended doses, when more sprayings are done than they should be when used that not needed, or in cases where the maximum period between the last spraying period and the harvest period is not complied with. Acute or chronic poisoning may occur in humans and other living organisms who fed on these foods with high doses of pesticide residues. It may cause aroma and quality changes in some products [6].

When the pesticide consumption between the years of 2006–2018 in Turkey is examined in Table 1, it is seen that 44,126 tons of pesticides are used on average per year although there are increases and decreases among the years. In 2018, 60,020 tons of pesticides were consumed. This amount includes fungicides 38.39%, herbicides 24.64%, and insecticides 22.63% [7].

Moreover, Organic agriculture has ensued as an alternative against the negative consequences of industrial agriculture in terms of human health, economy, and environment. It adopts a form of production that prevents the use of artificial inputs and aiming to be used animal manure, green manure, crop residues, and non-agricultural organic wastes, producing human and animal food free from pests by protecting soil, water, and air [8].

Organic agriculture is expressed under different titles due to language differences by countries. For example, the titles are used such as organic in the UK, ecological (ökologisch) in Germany, and biological (Biologique) in France [9]. The countries have carried out organic agriculture independently until the 1970s and the International Organic Agriculture Federation (IFOAM) was established in 1974 to evaluate and organize organic agriculture studies in the world together [8].

Organic agriculture is defined as a holistic production management system by the International Federation of Organic Agriculture Movements (IFOAM) that prevents the use of synthetic fertilizers and pesticides, minimizes air, soil, and water pollution, and maintaining soil, ecosystem, and human health [10]. Organic agriculture is one of the sustainable agriculture systems that adopt a registered and transparent management system and is controlled by independent certification bodies and inspectors at all stages of production [9].

The development of organic agriculture has started a new period with Sustainable Development Goals. This period is called organic 3.0 that expresses sustainable production and consumption understanding. Organic 1.0 period, which expresses organic development, started with a radical change in agriculture in the early 1900s. Organic 2.0 period has started by establishing standard and legal bases in the 1970s.

Finally, the organic 3.0 period aims that organic agriculture is in a position to create solutions to the problems faced by the world from different perspectives [11]). In Table 2, it is seen that the development process of organic agriculture in Turkey has increased over the years. When the data of 2002 and 2018 are compared, it is seen that the number of organic products has increased by approximately 40% [12].

Organic olives with 12.44% of the total amount of organic products produced in Turkey were used as materials in this paper. According to the data in 2018, it is known that organic olive production is 213369 tons in Turkey [13]. Organic agriculture has emerged as an alternative to conventional agriculture and the increased consumer awareness has led to the comparison of this organic and conventional agriculture. It is seen that many studies have been carried out on topics such physical, chemical, sensory properties, nutrient content, heavy metal, pesticide residues, etc. of organic and conventional products [14–19].

Table 1 Pesticides use (in tons) [7]

Years	Insecticides	Fungicides	Herbicides	Acaricides	Rodenticides	Other	Total
2006	7628	19,900	6956	902	3	9987	45,376
2007	21,046	16,707	6669	966	51	3277	48,716
2008	9251	16,707	6177	737	351	5613	38,836
2009	9914	17,863	5961	1533	78	2302	37,651
2010	7176	17,396	7452	1040	147	5344	38,555
2011	6120	17,546	7407	1062	421	6978	39,534
2012	7264	18,124	7351	859	247	8766	42,611
2013	7741	16,248	7336	858	129	7128	39,440
2014	7586	16,674	7794	1513	149	6007	39,723
2015	8117	15,984	7825	1576	197	5327	39,026
2016	10,425	20,485	10,025	2025	259	6835	50,054
2017	11,436	22,006	11,759	2452	236	6209	54,098
2018	13,583	23,047	14,794	2486	309	5801	60,020

Table 2 Organic Agriculture Crop Production Data (Including Transition Process) [12]

Year	Number of products	Number of farmers	Cultivated area (ha)	Collection area (ha)	Total production area (ha)	Production amount (ton)
2002	150	12,428	57,365	32,462	89,827	310,125
2003	179	14,798	73,368	40,253	113,621	323,981
2004	174	12,751	108,598	100,975	209,573	377,616
2005	205	14,401	93,134	110,677	203,811	421,934
2006	203	14,256	100,275	92,514	192,789	458,095
2007	201	16,276	124,263	50,020	174,283	568,128
2008	247	14,926	109,387	57,496	166,883	530,224
2009	212	35,565	325,831	175,810	501,641	983,715
2010	216	42,097	383,782	126,251	510,033	1,343,737
2011	225	42,460	442,581	172,037	614,618	1,659,543
2012	204	54,635	523,627	179,282	702,909	1,750,126
2013	213	60,797	461,395	307,619	769,014	1,620,466
2014	208	71,472	491,977	350,239	842,216	1,642,235
2015	197	69,967	486,069	29,199	515,268	1,829,291
2016	225	67,878	489,671	34,106	523,778	2,473,600
2017	214	75,067	513,981	22,148	543,033	2,406,606
2018	213	79,563	540,000	86,885	626,885	2,371,612

There are also studies in the literature that use holistic methods (picture forming methods) to observe the differences in organic and conventional products [20]. Many components, which are determined separately by quantitative analysis, are summarized as reflecting the whole, more meaningful than reflecting the parts separately with holistic methods. Picture forming methods are three methods as “Biocrystallization”, “Capillary Rising Paper Chromatography” and “Circular Chromatography”. Picture forming methods have begun with Rudolf Steiner’s studies. According to [21], the methods are based on the principle of creating internal pictures of each substance using the aqueous extract and used to reveal the differences between the products produced by different production systems.

In this study, the Rising Paper Chromatography was used. This paper aims to evaluate the quality differences with physical and chemical analyses of the conventionally and organically cultivated Memecik type green olives and differentiation of these olives by utilizing the CNN with the help of the rising paper chromatography method. The CNN used in this study is one of the most well-known architectures and structures in deep learning, which has become very widespread in recent years and gives very successful results in many fields. Although the concept of deep learning is defined in different ways in various sources; in its simplest form, artificial neural networks can be defined as an artificial learning model with many hidden layers, more complex learning methods, and many more variables, parameters, and calculations, thus requiring high capacity memory and processors [22]. Nowadays, many problems that cannot be solved with classical artificial neural networks such as multi-layer perceptron or other artificial learning algorithms or which cannot be sufficiently successful are now solved with deep learning [23, 24].

It is mentioned that picture forming methods (biocrystallization, circular and rising paper chromatography) are used effectively in the evaluation of food quality due to their high accuracy in distinguishing organic and conventional products. The principle of the methods is based on the evaluation of the structures formed by the reaction of the food matrix with certain inorganic salts [25].

The rising paper chromatography is also known as Capillary dynamolysis. Lilly Kolisko developed this method called ’capillary dynamolysis’ for experimentally investigating the workings of the etheric forces in material substances [26].

To use the method, the $AgNO_3$ and $FeSO_4$ solutions and the sample concentration prepared from the sample extract are required. In the environment with controlled temperature and humidity (40–60% humidity, 20–25 °C temperature), the appropriate concentration of the sample is firstly absorbed into the chromatography paper until a certain height. After drying, an appropriate concentration of $AgNO_3$ solution is absorbed to a certain level and dried. In the last stage, $FeSO_4$ solution is absorbed to a certain level and dried. The patterns are occurred in the daylight [21]. The patterns obtained on the chromatography paper were evaluated by [27] in four regions. These regions are named as base zone, bowl zone, flag zone, and drop zone (Fig. 1).

In another study on organic and conventional wheat, the patterns on the chromatography paper were expressed differently. (Fig. 2) [28].

[25] studied on organic and conventional wheat to learn about the appropriateness of picture forming methods in food quality assessment. It is shown that samples taken from conventional and mineral fertilization have a lighter color and less frequent bowl structures but samples from the biodynamic, bioorganic and unfertilized control group have a darker color and more frequent bowl structures (Fig. 3).

Geier [29] showed that the differences between organically and conventionally grown potatoes in Fig. 4. It is observed that the gray-colored flags are more intense in the conventional sample but organic samples have an intense light tile red in the base zone and an intense gray color in the bowl zone.

[14] examined the organic and conventional fresh, frozen, and pulp shaped red peppers with the rising picture chromatography method. The clear pictures were obtained at 100% sample concentration with 0.5% $AgNO_3$ and 0.5% $FeSO_4$ concentration in fresh red peppers (Fig. 5). Different colors were observed in the base zone of fresh red pepper.

In the conventional samples, the presence of white flags in the flag zone is observed, while the bowl widths are higher compared to organic samples and the drop-shaped formations formed in the drop zone are darker and wider compared to the organic samples. It has been interpreted that drop-shaped formations in the drop zone are wider in conventional samples and the spaces are wavier while dark orange colored flags are seen for the organic sample compared to those of conventional in the flag zone.

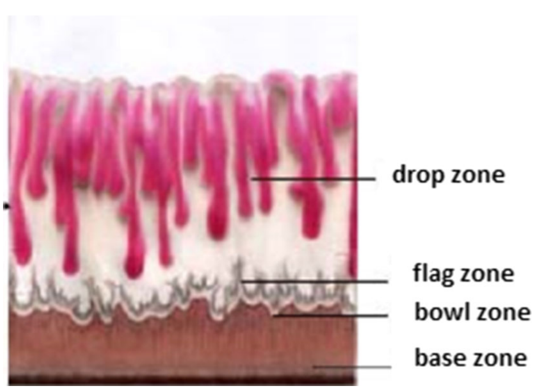


Fig. 1 Evaluation of the patterns obtained by the rising picture method in sugar beet [24]

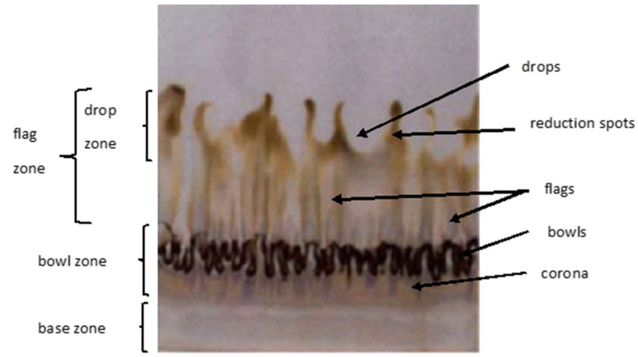


Fig. 2 Evaluation of the patterns obtained by the rising picture method in wheat [25]

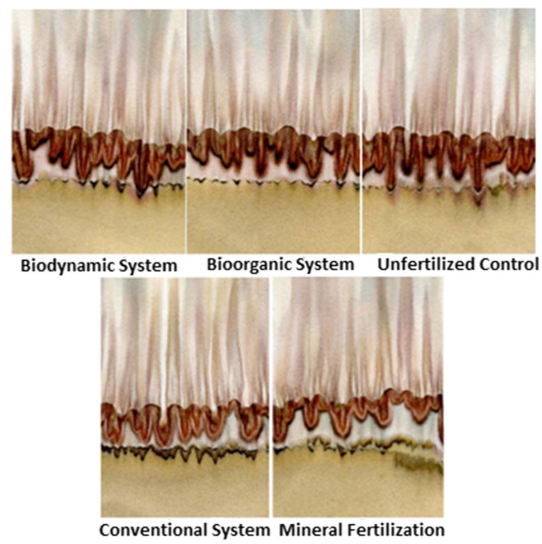


Fig. 3 Rising picture chromatograms of wheat samples [22]

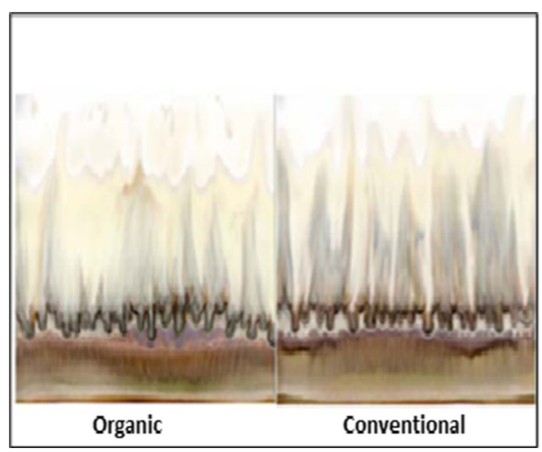


Fig. 4 Rising picture chromatograms of organic and conventional potatoes [29]

In a different study on organic and conventional tomatoes, the differences between fresh, frozen, and pulp tomatoes were observed with the rising picture method

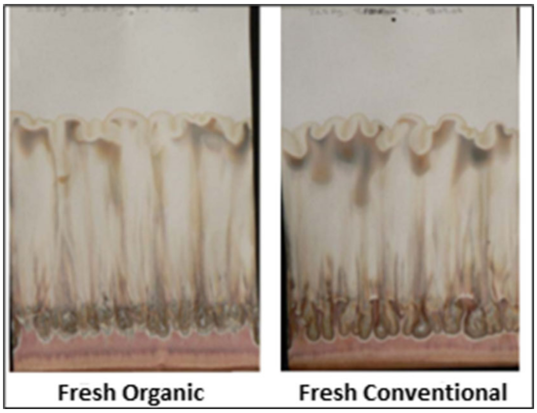


Fig. 5 Rising picture chromatograms of fresh organic and conventional red peppers [14]

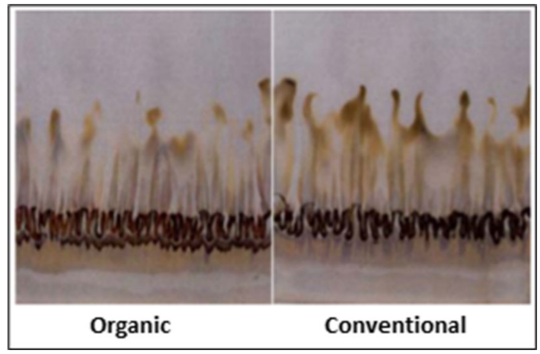


Fig. 7 Rising picture chromatograms of organic and conventional wheat [27]

[18]. The clear pictures were obtained in fresh tomatoes at concentrations of 0.5% $AgNO_3$ and 0.5% $FeSO_4$ with 30% sample concentration (Fig. 6).

In fresh organic tomatoes, it was observed that the colors and flags were more prominent and more vivid, there were color differences in the base zone, drop formations in the drop zone were a distinct gray-yellow color, and the bowls are more than conventional. It has been determined that the flags are weaker and have an indistinct structure in the conventional example.

[30] has applied the rising picture chromatography method in organic and conventional wheat and has detected differences in the pictures formed in the chromatograms (Fig. 7). The next section presents methods and data; the third section talks about the results and discussion and the final section depicts the conclusion.

2 Methods and data

In this paper, Memecik type green olives with organic product certificates in the Kemalpaşa region of Izmir and conventional Memecik type green olives obtained from the same region were used (Fig. 8). Organic and conventional olives were collected in three periods. One kg of olives simultaneously was picked from 6 different trees in each period. The maturity index method was taken into consideration before the olives were harvested. Olives between 0.5 and 1 maturity index were picked and stored in the Ege University Food Engineering Department at + 4° C and 85–90% relative humidity until analysis [31, 32].

The appropriate concentration sample is impregnated until a certain height and dried into chromatography paper. The next step is the impregnation and drying of the appropriate concentration of $AgNO_3$ solution to the chromatography paper dried in the first stage. The last stage is the impregnation and drying of a suitable concentration of iron sulfate ($FeSO_4$) solution to the chromatography paper dried in the second stage [21].

To prepare sample concentrations, approximately one kg of olives without removing the stones from freshly harvested olives were put in a cheesecloth. Then, an oil–water mixture was obtained from olives with the help of a packed press. The oil–water mixture was separated into oil and water at 4500 rpm with the help of the centrifuge device (HETTICH Universal 16R).

Olive juice was obtained by removing the oil from the top. Sample concentrations (10, 20, 30, 40, 50%) were

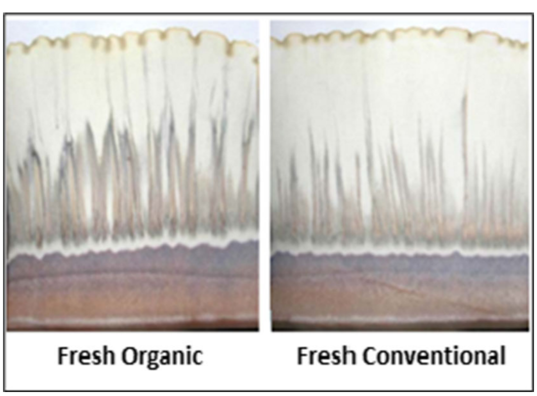


Fig. 6 Rising picture of fresh organic and conventional tomatoes [18]

Fig. 8 Pictures of conventional (left) and organic (right) green Memecik type olives

prepared from the obtained 100% olive juice with the help of tridistilled water. Sample concentrations with the most appropriate results were determined by preliminary trials. Stage 1 of the rising picture chromatography is the impregnation and drying of the sample concentration on the chromatography paper. Firstly, Whatman 2 CHR chromatography paper (10 cm width × 20 cm length) which is attached with the help of a paper clip is put in the form of a cone into the 9 cm diameter glass petri. In the first step, approximately one ml of the sample of suitable concentration is taken in glass petri. Then, a cone-shaped chromatography paper is placed into the petri dish, the concentration of the sample is absorbed up to 2 cm high from the base (Fig. 9). At the end of this stage, chromatography papers are taken and dried for 2–3 h.

In the second stage of the rising picture chromatography is the impregnation and drying of the $AgNO_3$ concentration on the chromatography paper. $AgNO_3$ concentration is impregnated into the chromatography paper obtained at the end of stage 1 and dried. The $AgNO_3$ solution in four different concentrations (0.25%, 0.5%, 0.75%, 1%) is prepared with tridistilled water. Firstly, suitable $AgNO_3$ concentration is placed inside the glass petri. Then, the chromatography paper obtained at the end of stage 1 is placed into the petri, the $AgNO_3$ concentration is absorbed until it is one cm higher than the sample concentration (Fig. 10). At the end of this stage, the chromatography papers are put away and dried for 2–3 h.

In the final stage of the rising picture chromatography, the $FeSO_4$ solution is impregnated and dried on the same chromatography paper. The $FeSO_4$ solution in four different concentrations (0.25%, 0.5%, 0.75%, 1%) was prepared with tridistilled water. The chromatography paper that has the sample concentration and $AgNO_3$ solution impregnated and dried is placed in a glass petri with the appropriate concentration of $FeSO_4$ solution. Impregnation continues until a total height of 12 cm (Fig. 11). At the end of this stage, chromatography papers are put away and dried for 2–3 h.

Fig. 9 Impregnation of sample concentration on chromatography paper in the rising picture method

Fig. 10 Impregnation of AgNO3 concentration on chromatography paper in the rising picture method

Fig. 11 Impregnation of $FeSO_4$ concentration on chromatography paper in the rising picture method

The $AgNO_3$ and $FeSO_4$ solutions used in the analysis are sensitive to light. For this reason, operations were carried out in the darkroom to prevent color change. The color was seen more clearly after drying. Under the same conditions, the pictures of the chromatograms were shot by the Nikon D-5100 camera. To have the $FeSO_4$ solution move easily, the chromatography papers are placed together with water-filled petri dish into a bell glass (Fig. 12).

10%, 20%, 30%, 40%, 50% sample concentrations were prepared from extracts from fresh organic and conventional Memecik type green olives. 0.25%, 0.5%, 0.75% and 1% concentrations were prepared for equal concentration $AgNO_3$ and $FeSO_4$. Each sample concentration was used with equal concentrations of $AgNO_3$ and $FeSO_4$ solutions. Some of the rising pictures obtained from conventional olives are presented in Fig. 13.

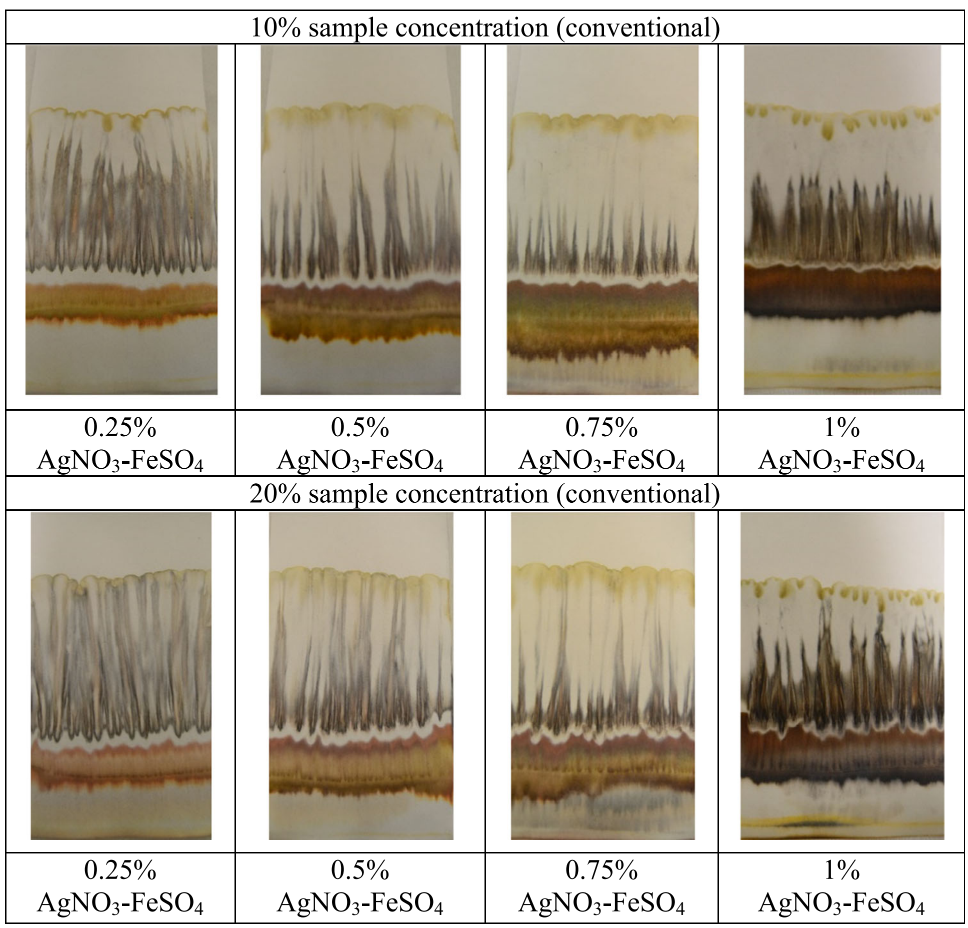
Some of the rising pictures obtained from organic olives are presented in Fig. 14.

Fig. 12 Increasing the ambient humidity in the rising picture method

Expert assessors analyze the above images and use the following rules to decide if the image of a Memecik olive belongs to an organic or a conventional class. In the rising picture chromatograms obtained from conventional samples, the base zone is usually thicker, the fine line is wider and more significant, and the bowl structures in the bowl zone are wider, infrequent, and darker. In organic sample chromatograms, the flags in the drop zone are more vivid and frequent. This study will investigate if CNNs can replace the expert assessors and achieve the correct classifications in real-time.

The CNN is a type of deep learning that can achieve very successful results, mainly in visual data and image processing, or in various hard jobs within the scope of multiple classifications. CNN was first introduced in a study for processing grid-like topological data (images and time series data) [33]. They are designed to deal with the excessive number of processes and processing complexity experienced in image preprocessing and visual data computing differently and more efficiently [34, 35]. They are the most successful, efficient, and flexible model known today in extracting new attributes and patterns from visual data such as images, videos, etc., and classifying data. There are four main stages in the process of the CNNs. In the process of convolution, which is the first stage, feature maps and patterns are obtained from input data with various image filters. In the pooling phase, a subset of the pattern of an image is obtained and the different derivatives of the image are also correctly recognized by the CNN. In the flattening phase, the multidimensional attribute set is transformed into a one-dimensional index shape and thus it is transmitted as input to the fully connected layers in the

Fig. 13 Rising pictures of $AgNO_3$-$FeSO_4$ concentrations used with 10% and 20% sample concentrations of conventional olives



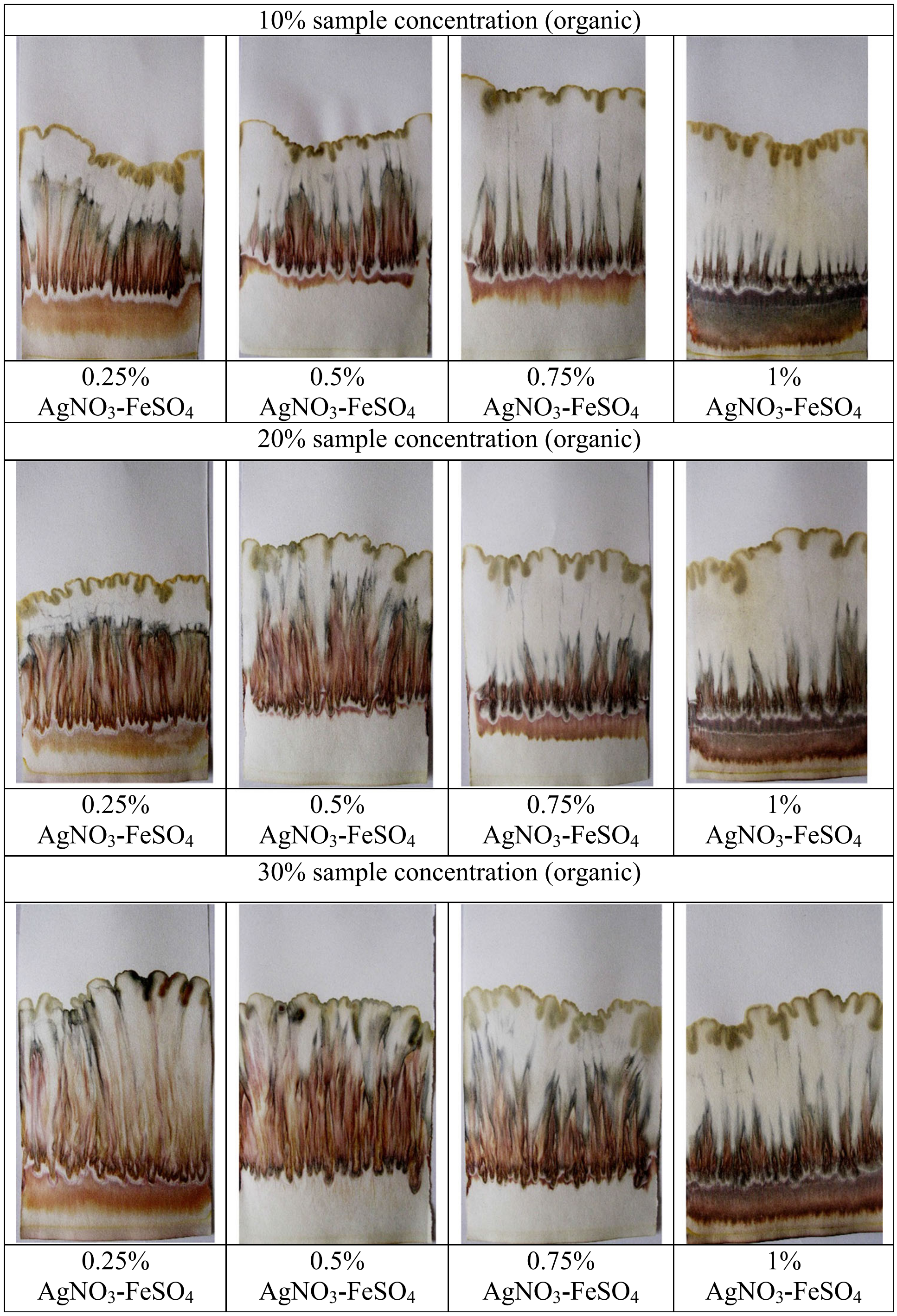


Fig. 14 Rising pictures of $AgNO_3$-$FeSO_4$ concentrations used with 10%, 20%, and 30% sample concentrations of organic olives

last stage. In the last stage, similar to the multi-layer sensor, the images are classified and the weights are updated by calculating back errors in fully connected layers consisting of one or more hidden layers [22, 23].

In CNNs; ReLU (Rectified Linear Unit) is generally used as an output activation function in convolution layers and hidden layers of fully connected layers [22, 23]. The ReLU activation function was first introduced in a dynamic network model [36]. It is the most used activation function in deep learning models and especially in CNNs, since it is not linear, it can be operated very simple and very fast and its first-order derivative can also be expressed very easily. If the input value to a node is expressed as x, the activation function ReLU can be defined as F (x) = maximum (0, x).

The Softmax function is used in the last layer of the model to estimate classes and is frequently preferred in

CNNs, especially in multiple classification processes. The output values of the Softmax function are in the range of [0, 1] and can be expressed in terms of the first-order derivative itself, and it is also a very useful function in the operations such as backpropagation of errors [16, 20]. It is defined in Eq. (1) and the Sj output value of any j input value is calculated as in the equation.

$$S_j = \frac{e^{a_j}}{\sum_{k=1}^{N} e^{a_k}} \quad (1)$$

Experiments have been conducted with many different CNN models and very different hyper-parameters, and it has been observed that the most successful results are obtained with this architecture. The dimension of the images is 3 $\times$ 70 $\times$ 70 (Fig. 15). Batch normalization was used in the input layer. In the next step; each visual is passed through two convolution layers and 8, 16, and 32 (3 $\times$ 3) filters are used in these layers, respectively. In each convolution layer, ReLU is used as the output activation function. In the ReLU processes in the first and second convolution layers, a max-pooling was used. In the next stage of our CNN model; A flattening layer is used to transform the data into a one-dimensional element. This one-dimensional element is used as the input layer of the fully linked layer and connected to hidden layer nodes. In the last stage, hidden nodes were configured as fully connected to two output layer nodes, and Softmax was used as the activation function (as well as multi-classification function) in the output layer. Our CNN model, each of the two nodes in the output layer is structured to represent one of two different classes of Memecik olive. The training was continued for a total of 30 epochs. In adjusting the learning speed, Adam's algorithm, one of the adaptive learning speed optimization models, was used [15, 16] and the initial learning speed was defined as 0.01. This structure is coded using MATLAB R2017b. Finally, the output value shows if the Memecik olive belongs to the Organic or Conventional class.

The next section presents results and discussion.

3 Results and discussions

A dried chromatography paper method was used to create 1200 images of different olive samples to detect if the image belongs to an organic olive or a conventional olive. Utilizing visual means to recognize quantifiable features from these images is a hard task for human-beings. Therefore, neural networks are strong candidates for classifying these images because of their nonlinearity.

600 images were prepared for each class namely Organic and Conventional in a lab environment (Fig. 11). Out of 1200 images, 240 images were used for testing. Results are presented in the below 2 $\times$ 2 confusion matrix (Table 3). A true positive means that CNN correctly classifies the Organic class and true negative means that CNN correctly classifies the Conventional class. Furthermore, a false positive means that CNN incorrectly classifies the

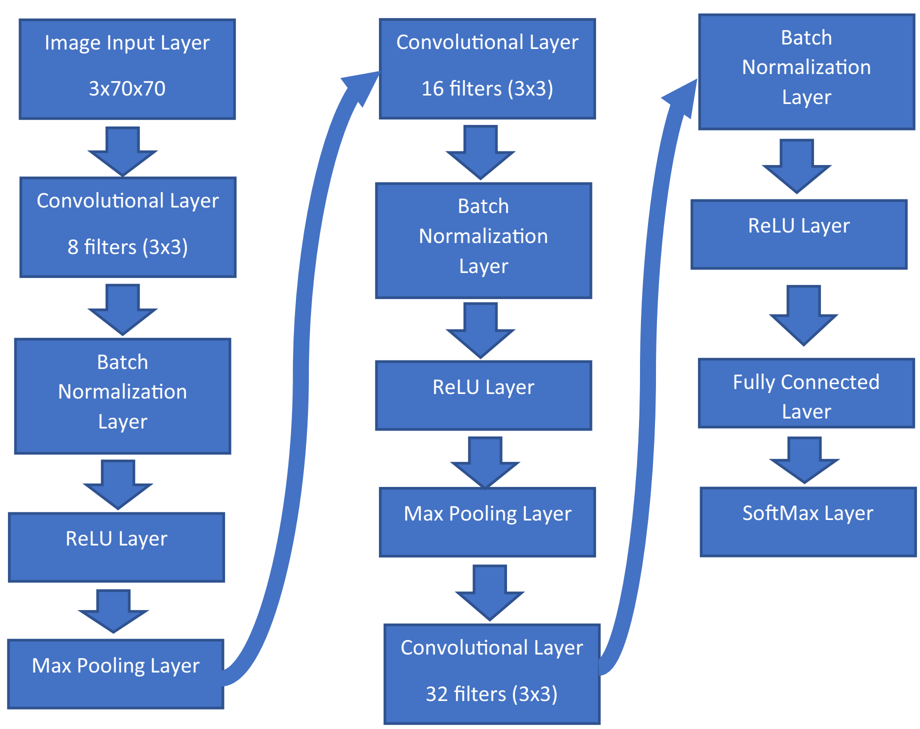


Fig. 15 Newly designed CNN for differentiating between Organic and Conventional Memecik type olive

Table 3 Confusion Matrix

		Actual	
		Organic	Conventional
Predicted Class	Organic	120	0
	Conventional	0	120

Organic class, and a false negative means that CNN incorrectly classifies the Conventional class.

Accuracy calculated as 100% for CNN using values from Table 3. This CNN can offer real-time processing of the rising picture chromatograms and can be used effectively as a digital expert assessor in deciding if a picture chromatogram belongs to an Organic or a Conventional class.

A conventional backpropagation neural network (BPNN) was also designed for the same classification problem. For each image, two calculations were performed: The mean which provides the average color properties, and the standard deviation which shows the measure of color variation inside each olive image. In an RGB image, the mean and the standard deviation were calculated for each color component which is red, green, and blue. As a result, each olive image was represented with a six-color feature vector. These features were the input to the BPNN, and the hidden layer had 20 neurons with one output node in the output layer. The same set of images were used for training this conventional neural network, and out of 1200 images, 120 images for each class were used for testing. Results are presented in the below 2×2 confusion matrix (Table 4).

The accuracy was approximately 68% which was not enough for this classification problem. To capture the spatial features which are the positioning of pixels and the relationship among them, the CNN was designed and tested instead of a BPNN. The CNN was capable of identifying different regions on the chromatography paper (Fig. 16) as well as specific features inside each region and capturing how these features were arranged in the same olive image. The CNN also utilizes a single filter across those different regions (Fig. 16) of an olive image to produce a feature

Table 4 Confusion Matrix

		Actual	
		Organic	Conventional
Predicted Class	Organic	78	42
	Conventional	35	85

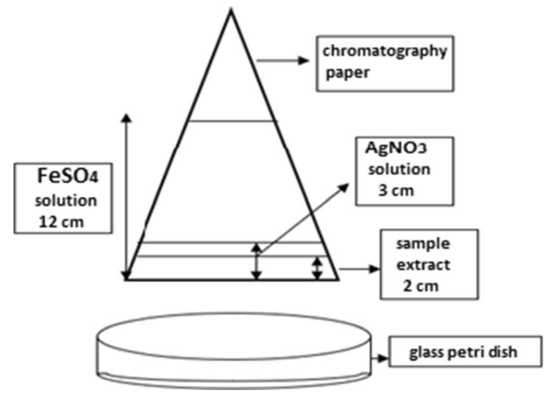


Fig. 16 The rising picture method

map. This eliminates the manual feature extraction. It can be observed that similar CNN analysis can be also used in the discrimination process of infected food products by examining the surface color and the geometrical shapes of the contaminated regions.

Although the visual examination by an expert assessor is utilized as a tool for evaluation of the olive chromatogram images, it is an expensive procedure and requires a lot of knowledge and preparation. Besides, the assessment validation procedures for assessing the quality of expert assessors are not yet to be defined. Moreover, the CNN analysis can offer a better solution in increasing the objectiveness of these picture forming methods and allow the analysis of large numbers of olive chromatogram images almost in real-time. The results of this analysis can suggest that the combined methodology which is CNN analysis with chromatography paper has the potential to be generally applied in different areas of food research for classification purposes.

4 Conclusions

In this paper, Memecik type green olives with organic product certificates in the Kemalpaşa region of Izmir and conventional Memecik type green olives obtained from the same region were used. The rising picture method is utilized to generate the olive images for the CNN. This rising method consists of three stages. In our study, the sample concentration is increased until 2 cm (about 3–5 min) from the chromatography paper base, the $AgNO_3$ solution is increased until 3 cm (about 5–8 min) from the chromatography paper base. In the final stage, the $FeSO_4$ solution is increased until 12 cm (about 8–15 min) from the chromatography paper base (Fig. 16).

A colored picture formation is expected on the dried chromatography paper. The picture formed on the

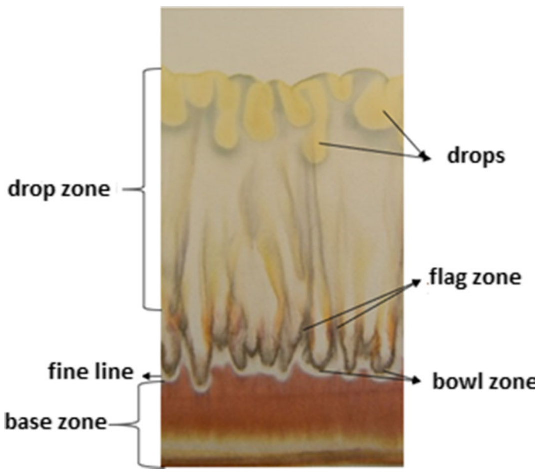


Fig. 17 Zones formed in the rising picture method

chromatography paper consisted of four different zones, namely base zone, bowl zone, flag zone, and drop zone (Fig. 17).

These images (Fig. 17) were fed into CNN and the corresponding output were the actual classifications in the training phase. For the training phase, 960 images were used and 240 images that were not part of the training phase were used to test the CNN's classification accuracy. After the testing, 100% accuracy was achieved by CNN.

The testing results (Table 3) show that the designed CNN can be used effectively to decide if the Memecik olive is cultivated organically or conventionally. The 100% accuracy shows that the optimal design of the neural network has been achieved. This neural network offers real-time processing and can be used as a digital expert assessor.

Declarations

Conflicts of interest The authors, Mehmet S. Unluturk, Secil Kucukyasar, and Fikret Pazir declare that they have no conflict of interest.

References

1. Yılmaz H, ve Demircan V, Gül M (2009) Üreticilerin kimyasal gübre kullanımında bilgi kaynaklarının belirlenmesi ve tarımsal yayım açısından değerlendirilmesi. Süleyman Demirel Üniversitesi Ziraat Fakültesi Dergisi 4(1):31–44s
2. de Kurtar ES, Ayan AK (2004) Organik tarım ve Türkiye'deki durumu. Ondokuz Mayıs Üniversitesi Ziraat Fakültesi Dergisi, Samsun 19(1):56–64s
3. Anonim, 2016, "Conventional farming", https://www.appropedia.org/Conventional_farming (Erişim Tarihi: 17.08.2018)
4. Arslan S (2016) Türkiye'de pestisit kullanımı ve çevresel etkiler, Isparta, XII. Ulusal Tarım Ekonomi Kongresi, GTHB, Tarımsal Ekonomi ve Politika Geliştirme Enstitüsü, Ankara, 2215–2224s
5. Kaymak S, ve Serim, AT (2015) Pestisit sektöründe araştırma ve geliştirme, Meyvecilik Araştırma İstasyonu Müdürlüğü, Ankara, 2 (1): 27–34 s
6. Açar, ÖÇ (2015) Pestisit analizleri, https://gidalab.tarimorman.gov.tr/gidareferans/Belgeler/B%C3%B6l%C3%BCmler/Pestisit-Egitim-Notu2015.pdf (Online Access: 10.01.2019)
7. TÜİK (2019) Tarımsal ilaç kullanımı, http://www.tuik.gov.tr/PreTablo.do?alt_id=1001 (Online Access: 13.07.2019)
8. Atlı S (2006) Orgüder ve dünyada ve Türkiye'de organik tarım uygulamaları, Türkiye 9.Gıda kongresi, Bolu, 85–88s
9. Demiryürek K (2011) Organik tarım kavramı ve organik tarımın dünya ve Türkiye'deki durumu, *Gaziosmanpaşa Üniversitesi Ziraat Fakültesi Dergisi,* 28(1): 27–36s
10. Anonim (2007) International Conference on Organic Agriculture and Food Security, http://www.fao.org/organicag/oa-specialfeatures/oa-foodsecurity/en/ (Online Access: 12.01.2019)
11. Marangoz M, ve Kumcu EH (2018) Organik üretim sürecinde organik 1.0'dan organik 3.0'a geçiş ve organik 3.0'ın temel özellikleri, *Yönetim Bilimleri Dergisi*, 16 (32):379–396 s
12. Anonim (2019) http://www.fao.org/faostat/en/#data/QC (Erişim Tarihi: 02.02.2019)
13. Anonim (2019) https://www.tarimorman.gov.tr/Konular/Bitkisel-Uretim/Organik-Tarim/Istatistikler (Online Access: 02.02.2019)
14. Mditshwa A, Magwaza LS, Tesfay SZ, Mbili N (2017) Postharvest quality and composition of organically and conventionally produced fruits: a review. Scienta Horticulturae 216:148–159
15. Suja G, Byju G, Jyothi AN, Ss V, Sreekumar J (2017) Yield, quality and soil health under organic vs conventional farming in taro. Sci Hortic 218:334–343
16. Hallmann E (2012) The influence of organic and conventional cultivation systems on the nutritional value and content of bioactive compounds in selected tomato types. J Sci Food Agric 92:2840–2848
17. Kuşçu A (2008) Organik ve konvensiyonel kırmızıbiber ve ürünlerinin ayırt edilebilme yöntemleri ve kalite özelliklerinin incelenmesi, Doktora Tezi, Ege Üniversitesi Fen Bilimleri Enstitüsü, Gıda Mühendisliği Anabilim Dalı, İzmir, Danışman: Prof. Dr. Fikret Pazır
18. Abdollahi F (2008) Organik ve konvansiyonel domates ve ürünlerinin ayırt edilebilme yöntemleri ve kalite farklarının incelenmesi, Doktora Tezi, Ege Üniversitesi Fen Bilimleri Enstitüsü, Gıda Mühendisliği Anabilim Dalı, İzmir, Danışman: Prof. Dr. Fikret Pazır
19. Ninfali P, Bacchiocca M, Biagiotti E, Esposto S, Servili M, Rosati A, Montedoro G (2008) A 3-year study on quality, nutritional and organoleptic evaluation of organic and conventional extra-virgin olive oils. J Am Oil Chem Soc 85:151–158
20. Huber MAS, Bloksma J, Van der Burgt GJ, Van de Vijver LPL (2004) Challenges for an organic food quality concept-the inner quality concept requirements demonstrated on an experimental concept, *Paper presented at Joint Organic Congress,* Odense, Denmark, May 30–31
21. Balzer-Graf U (1999) Vital-quality: quality research with picture-forming methods. 6th IFOAM Organic Trade Conference, Florence, Italy, 179–188 p
22. Goodfellow I, Bengio Y, Courville A (2016) Deep Learning. MIT Press, Cambridge
23. Buduma N, Locascio N (2017) Fundamentals of deep learning: designing next-generation artificial intelligence algorithms. O' Reilly Media Inc., USA
24. Yıldız O (2019) Derin öğrenme yöntemleriyle dermoskopi görüntülerinden melanom tespiti: Kapsamlı bir çalışma. Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi 34(4):2241–2260
25. Fritz J, Athmann M, Kautz T, Köpke U (2011) Grouping and classification of wheat from organic and conventional production

systems by combining three image forming methods. Biol Agric Hortic: Int J Sustain Prod Syst 27(3–4):320–336
26. McLean A (1980) Capillary Dynamolysis, Hermetic Journal, http://www.levity.com/alchemy/kolisko.html (Online Access: 12.11.2018)
27. Zalecka A, Skjerbaek K, Doesburg P, Pyskow B, Huber M, Kahl J, Ploeger A (2006) The Capillary Dynamolysis method as a characterized tool for crop quality determination, Paper Presented at Joint Organic Congress, Odense, Denmark, May 30–31
28. Andersen JO, Skjerbaek K, Paulsen M, Pyskow B (2004) Kvaliteten Af Udvalgte Økologisk Dyrkede Vårhvedesorter, Belyst Ved Billeddannende Metoder, Rapport nr. 2, Biodynamisk Forskningsforening, 38 p. (Kuşçu'dan, 2008)
29. Geier U (2007) Dell'intervento Del Dott, XXVI Convegno Internazionale di Agricoltura Biodinamica, Seminare Biodinamica Raccogliere Il Mondo, Firenze, Pratolino (Kuşçu'dan, 2008)
30. Schilperoord P (2004) Hat Berggetreide Besondere Qualitäten?, Einleitung Überarbeitet, 10 p., (http://www.berggetreide.ch/Archiv/VorstudieQualitaet.pdf)
31. Cebeci, Z (2007) Zeytinde olgunluk derecesi tayini, Türkiye Tarımsal Öğrenme Nesneleri Deposu: http://traglor.cu.edu.tr/objects/objectFile/zeytin_olgunluk_indeksi_2007_11_27.ppt
32. Vinha AF, Ferreres F, Silva BM, Valentao P, Goncalves A, Pereira JA, Oliveira MB, Seabra RM, Andrade PB (2005) Phenolic profiles of Portuguese olive fruits (Olea europaea L.): influences of cultivar and geographical origin. Food Chem 89:561–568
33. LeCun Y et al (1989) Backpropagation applied to handwritten zip code recognition. Neural Comp 1:541–551
34. Hanbay K (2020) Evrişimsel sinir ağı ve iki-boyutlu karmaşık gabor dönüşümü kullanılarak hiperspektral görüntü sınıflandırma. Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi 35(1):443–456
35. Arı A, ve Hanbay D (2019) Bölgesel evrişimsel sinir ağları tabanlı MR görüntülerinde tümör tespiti, Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi 34 (3): 1395–1408
36. Hahnloser R et al (2000) Digital selection and analogue amplification coexist in a cortex-inspired silicon circuit. Nature 405:947–951