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Automatic Classification of Healthy and Sick Broilers in Terms of Avian Influenza by Using Neural Networks

Sağlıklı ve Hasta Etlik Piliçlerin Kuş Gribi Açısından Sinir Ağları Kullanarak Otomatik Sınıflandırılması

[1]Yalçın IŞIK, [2]Ahmet KAYABAŞI

[1]*Selçuk Üniversitesi, Silifke-Taşucu Meslek Yüksekokulu, Silifke/Mersin, Türkiye*
[2]*Karamanoğlu Mehmetbey Üniversitesi, Mühendislik Fakültesi, Karaman, Türkiye*

[1]isiky@selcuk.edu.tr, [2]ahmetkayabasi@kmu.edu.tr

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ABSTRACT

Poultry meat containing low fat and high protein is an important and economical protein source in providing the animal protein requirement for human nutrition. The frequent emergence of poultry diseases such as avian influenza is the feature of fast-spread in farms seriously threatens both the economy and human health. In this study, neural network (NNs) models are proposed for the classification of broiler chickens as healthy and sick for earlier detection of poultry diseases. The NNs used in the classification are artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and support vector machine (SVM). In the literature, the data set which includes seven visual features were acquired through the image processing techniques (IPTs) and was used for training, testing, and validating the process of NN models. The results point out that, the computer vision-based application using NNs successfully classifies the broilers in terms of their health conditions.

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ÖZET

Düşük yağ ve yüksek protein içeren kanatlı eti, insan beslenmesi için hayvansal protein ihtiyacının sağlanmasında önemli ve ekonomik bir protein kaynağıdır. Çiftliklerde hızlı yayılma özelliği olan kuş gribi gibi kanatlı hastalıklarının sıklıkla ortaya çıkması hem ekonomiyi hem de insan sağlığını ciddi şekilde tehdit etmektedir. Bu çalışmada, kanatlı hastalıklarının erken tespiti için etlik piliçlerin sağlıklı ve hasta olarak sınıflandırılması için sinir ağı (NN'ler) modelleri önerilmiştir. Sınıflandırmada kullanılan NN'ler yapay sinir ağı (YSA), uyarlanabilir nöro-bulanık çıkarım sistemi (ANFIS) ve destek vektör makinesidir (SVM). Literatürde, IPT'ler aracılığıyla yedi görsel özellik içeren veri seti elde edilmiş ve NN modellerinin eğitimi, test edilmesi ve doğrulanması için kullanılmıştır. Sonuçlar, NN'leri kullanan bilgisayarlı görü tabanlı uygulamanın, piliçleri sağlık koşulları açısından başarıyla sınıflandırdığını göstermektedir.

ORCID ID: [1]0000-0001-9223-5381
[2]0000-0002-9756-8756

1. INTRODUCTION

Poultry meat is seen as an important and economical protein source in providing the animal protein needs required for human nutrition with its low fat and high protein content. Poultry meat consumption has been increased in recent years due to cheaper and shorter production times than red meat [1]. Therefore, poultry meat production increased to second place after pork in meat production. To meet this need, broiler chickens are grown which are fast-growing, better utilizing than feed and producing high-quality carcass. The most important factor in poultry farming is the health and regular control of poultry. The prevalence of poultry diseases has seriously affected poultry farming in recent years. This situation poses a threat not only for economic reasons but also for human health. Today, the diagnosis of poultry diseases is performed manually with the observation of the veterinarian and using various laboratory tests. However, manual processes are time-consuming, difficult, and yet fail to detect some of the diseases. Therefore, the rapid detection of poultry diseases has become an important issue in broiler breeding. The automatic detection of broiler diseases with the help of image processing techniques (IPTs) has been an important topic in the point of fast diagnosis. For this issue, different neural networks (NNs) such as artificial neural networks (ANNs), [2-3] adaptive neuro-fuzzy inference system (ANFIS) [4-5], and support vector machine (SVM) [6-7] can be combined with IPTs.

Several studies regarding the diagnosis of broiler diseases using NNs combined IPT have been proposed in the literature [8-14] In Zhuang et al. [8], it was comparatively determined by different machine learning algorithms that the broiler chickens were healthy or sick for avian influenza disease and the most successful result was obtained with SVM. The data set used in machine learning algorithms was created by computer vision. The body weights of live broilers were estimated by using IPT analysis by Mollah et al. [9] the estimated weights and manual measurement results were shown to be very close to each other. In Matin et al. [10], different artificial intelligence techniques (AITs) were used to estimate intestinal broiler microflora. The results show that the Enterobacteriaceae population was predicted better than the lactic acid bacteria with the proposed models. A novel algorithm of image analysis was investigated for early detection of lameness for broilers by Aydin [11] and some feature variables of broilers were detected by the proposed algorithm. In Pereira et al. [12], the welfare status in commercial broiler breeders was assessed by the data mining algorithms combined with IPT, and results were obtained successfully. The NNs such as ANN and ANFIS was proposed to predict chick body mass and more successful results were achieved with ANN by Ferraz et al. [13] In Mortensen et al. [14], the weight prediction of broiler chickens five regression model integrated with 3D computer vision was used and the best result was obtained with Bayesian ANN model.

In this study, the most used NNs such as feed-forward backpropagation (FFBP) [15] based ANN (ANNFFBP), learning vector quantization (LVQ) [16] based ANN (ANNLVQ), ANFIS, and SVM are modeled to classify broiler chickens as healthy and sick in terms of avian influenza infection. In the literature, the data set includes 7 main visual feature parameters that indicate the health status of broilers were acquired through the IPTs [17]. These visual parameters are concavity, skeleton attitude angle, skeleton splicing angle, and shape features (area-linear rate, elongation, and circularity). About seven visual features, the 300 data sets were created, 150 of which were healthy and 150 of sick broilers [17]. The accuracy of the models is determined by selected 260 training, 20 testing, and 20 validating broilers data set and their performances of classification are compared to each other. In the training process, the ANNFFBP, ANNLVQ, ANFIS, and SVM models successfully classify the broilers as healthy and sick with the accuracy of 100%, 99.23%, 99.64%, and 99.92%, respectively.

2. MATERIALS AND METHODS

2.1. Data Set

The automatic classification application based on NNs is carried out through a data set reported elsewhere [17] containing 7 main visual feature parameters of broiler chickens. In the literature it is stated that, four to six weeks old broiler chickens were divided into two groups and they were placed in isolator cages [8]. Ten of the twenty R381 group broilers were vaccinated with 0.1 mL volume of 106 EID50 H5N2 avian influenza virus (R381/2008) and the other ten were intranasally injected with 0.1 mL phosphate-buffered saline (PBS). Clinical symptoms of avian influenza were observed in twenty broilers after 14 days [8]. As shown in Figure 1, the images of broilers were captured with a resolution of 640 by 480 pixels by using a Logitech C922 CCD camera, and image processing was performed using an algorithm based on VS2013 and OpenCV 2.4.13.8 To calculate the skeletal structure of the broiler, the algorithm only extracts the image of broiler from the complex background as shown in Figure 2. The eigenvectors are determined according to the features such as concavity, skeleton attitude angle, skeleton splicing angle, and shape features [8]. Briefly, the process for obtaining data on the visual properties of the broiler is shown in Figure 3 as topology.

2.2. Broiler Feature Extraction

In this section, the extraction of the features of broilers will be briefly summarized according to what is described in Zhuang et al. [8] Concavity, skeleton attitude angle, skeleton splicing angle, area-linear ratio, elongation, and circularity were named K_0, K_1, K_2, K_4, K_5, and K_6 respectively. K_3 was obtained by using the methods of skeleton simplification and skeleton splicing.

Figure 1. Image of broilers capture environment [8].

Figure 2. Image of extracted broiler from the background [8].

2.2.1. Concavity

There is a difference in the concavity between a broiler caught in avian influenza and a healthy broiler. The steepness appears in the middle of the sick broiler but this is concave in the healthy broiler. For the polygon to be convex, all inner angles of the polygon must be less than 180 degrees. For this reason, the back of the broilers with a high probability of disease is convex and K_0 is set to -1. The K_0 can be calculated as shown in Equation (1) [8].

$$K_0 = \sum_{i=1}^{n} \frac{b(s_1,s_2)l(s_1)l(s_2)}{[l(s_1)+l(s_2)]r} \tag{1}$$

2.2.2. Skeleton Attitude Angle

The angle (β) between the skeleton and horizontal plane is relatively large when the broiler is healthy [8]. Therefore, as shown in Equation (2), the skeleton can be used as a feature to separate the healthy broiler from the sick broiler [8].

$$K_1 = \sum_{i=1}^{n} \frac{l_i}{L} b \tag{2}$$

2.2.3. Skeleton Splicing Angle

As shown in Equation (3), the β angle is less than 90° (0°< β<90°). In Equation (3), K_2 is the skeleton splicing angle. After K_2 was obtained, K_3 was obtained by using the methods of skeleton simplification and skeleton splicing [8].

$$K_2 = b = arctan \frac{\sum_{i=1}^{n} |y_i^r - y_i^l|}{\sum_{i=1}^{n} |x_i^r - x_i^l|} \tag{3}$$

2.2.4. Shape Features

In addition to the skeletal features of broilers, the area-linear ratio, elongation, and circularity also reflect the shape features of broilers. The area-linear ratio (K_4), elongation (K_5), and circularity (K_6) can be formulated as follows [8]:

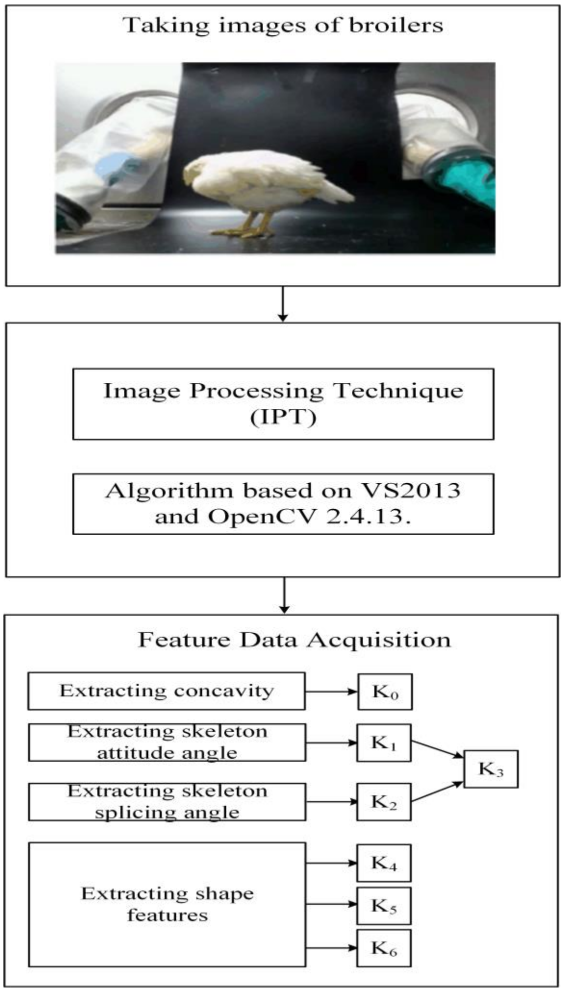


Figure 3. The topology of IPT.

$$K_4 = \frac{S}{C} \tag{4}$$

$$K_5 = \frac{H}{W} \tag{5}$$

$$K_6 = \frac{4pS}{C^2} \tag{6}$$

Where *S*, *C*, *H*, and *W* are respectively the area of the contour, the circumference of the contour, the height of the circumscribed rectangle, and the width of the circumscribed rectangle [8].

In Figure 4, 2D scattering of the broilers' features is demonstrated to show how healthy and sick broilers discriminate among each other by the feature parameters. In addition, the graphs of all feature parameters (K_0, K_1, K_2, K_3, K_4, K_5, and K_6) are plotted in Figure 5. It is observed that healthy and sick broilers distinctly cluster concerning the visual feature parameters.

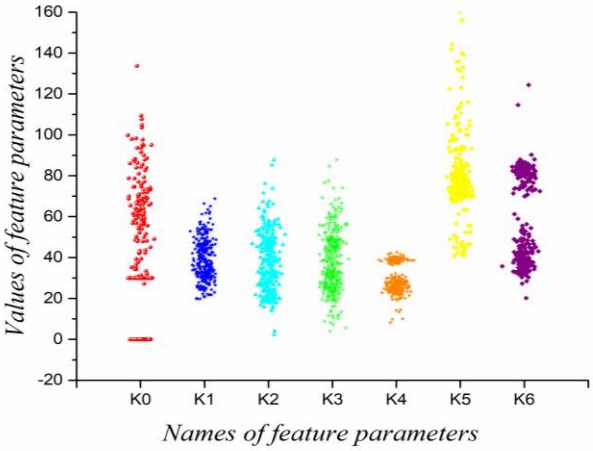


Figure 4. 2D scattering of 300 broilers according to feature parameters.

2.3. Neural Networks

The NNs such as ANN, ANFIS, and SVM are beautiful biologically-inspired programming paradigm that enables a computer to learn from observational data [2, 4, 6]. The NNs currently provide the best solutions to many problems in image recognition. The NNs interpret the raw input by labeling or clustering with a kind of machine perception. They help to group unlabeled data according to similarities between sample inputs and classify data when they have a data set labeled for training [9-14]. The modeling and training of the ANN, ANFIS, and SVM for the classification of broilers in terms of avian influenza are described below.

2.3.1. Modelling of Neural Networks

To use easier, the NNs, a graphical user interface (GUI) is prepared as seen in Figure 6 for the classification of broilers.
Before preparing the GUI, NNs are modeled and trained with appropriate set parameters according to the topology illustrated in Figure 7.
According to the results of the training, the models are updated and the training is repeated. Modeling and training processes are carried out one after the other to try to obtain the lowest classification error. The ANNFFBP, ANFIS, and SVM models numerically calculate the outputs according to mean absolute percentage error (MAPE) in given Equation (7).

$$MAPE = \frac{\sum\left|\frac{Target-Output}{Target}\right| x100}{Number\ of\ total\ data} \tag{7}$$

where the target is "1" or "2" which respectively correspond to "healthy broilers" and "sick broilers".
ANN is one of the main tools used in machine learning. The ANN consists of neurons that are organized into different layers. These neurons containing the non-linear type of functions are mutually connected by synaptic weights. These weights increase or decrease to output closer to the target throughout the training process [2]. As shown in Figure 8a and 8b, along with the set parameters given in Table 1, ANNFFBP and ANNLVQ are designed to classify the broilers into "healthy" or "sick" according to the feature parameters.
The ANNFFBP model is constructed with an input layer (7 neurons), two hidden layers (6 and 3 neurons), and an output layer (1 neuron). The "Logarithm sigmoid" function is used for both input and hidden layers while the "purelin" function is utilized for the output layer. Also, the ANNLVQ model is constructed with an input layer having 7 neurons, one hidden layer having 7 neurons and one output layer has 2 neurons.

Table 1. The set parameters of the ANN model.

Model	Parameters	Set type/value
ANN_{FFBP}	Epochs	40
	Minimum gradient descent	10^{-10}
	Momentum parameter (μ)	0.0003
	μ increment	0.3
	μ decrement	3
	Seed value	1108444055
ANN_{LVQ}	Epochs	100
	Minimum gradient descent	10^{-6}
	Learning rate	0.01
	Validation checks	6
	Output class percentage	0.5, 05

The ANFIS is a combination of two methods of ANN and fuzzy inference system (FIS) [18]. ANFIS is a fuzzy system whose membership function parameters have been tuned using neuro-adaptive learning methods similar to methods used in training ANN. ANFIS is generally formed of 5 layers that include 1 input, 3 hidden, and 1 output layer. Hidden layers consist of two membership functions (MFs) of input and output layers and one fuzzy logic rule layer [4]. The classification of broilers is constructed on Sugeno type FIS-based ANFIS, as illustrated in Figure 9, and configuration parameters of the ANFIS model, are tabulated in Table 2. The membership functions (MFs) of the ANFIS network are the Gaussian function for the input and linear function for the output [18].

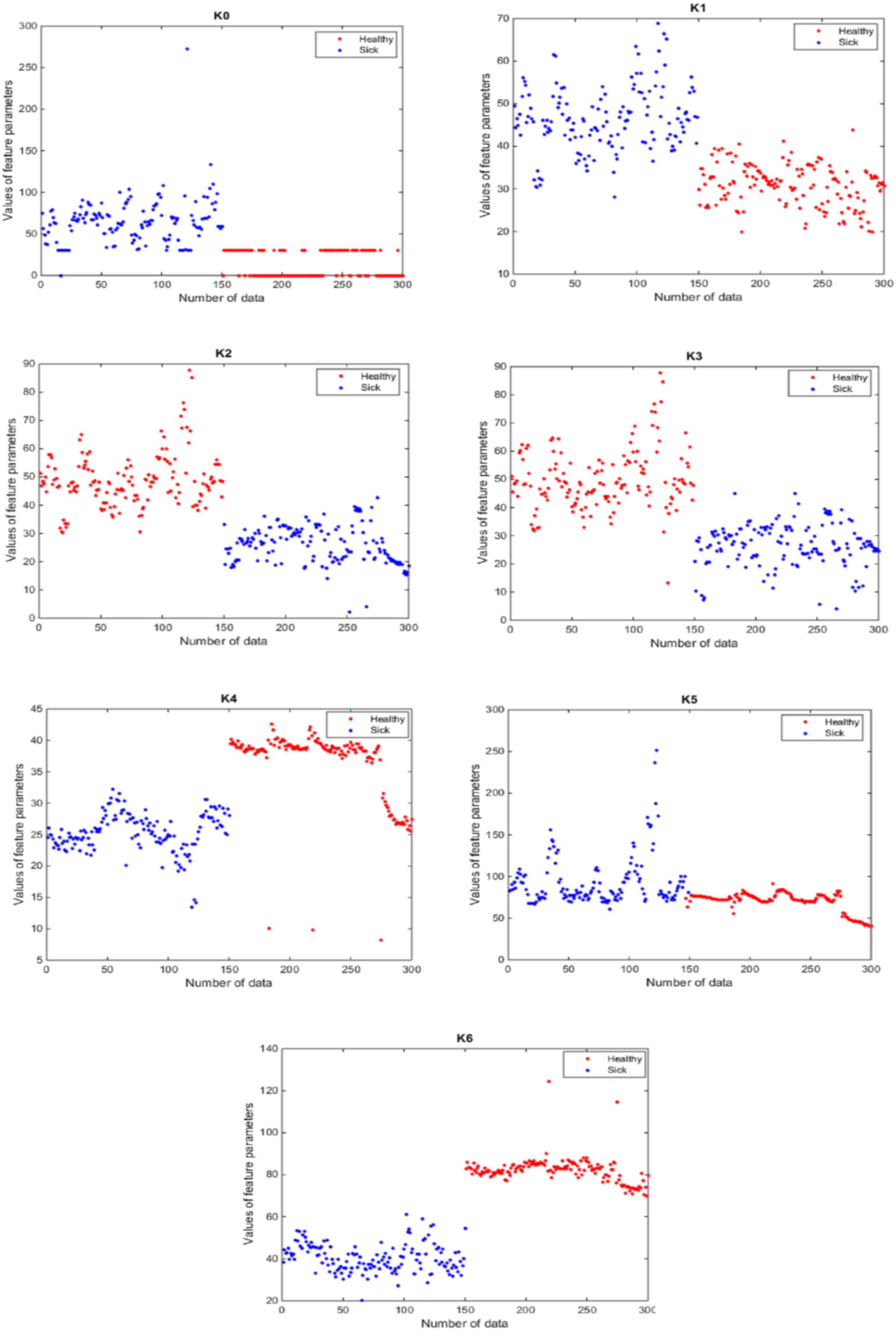


Figure 5. Separately graphs of feature parameters.

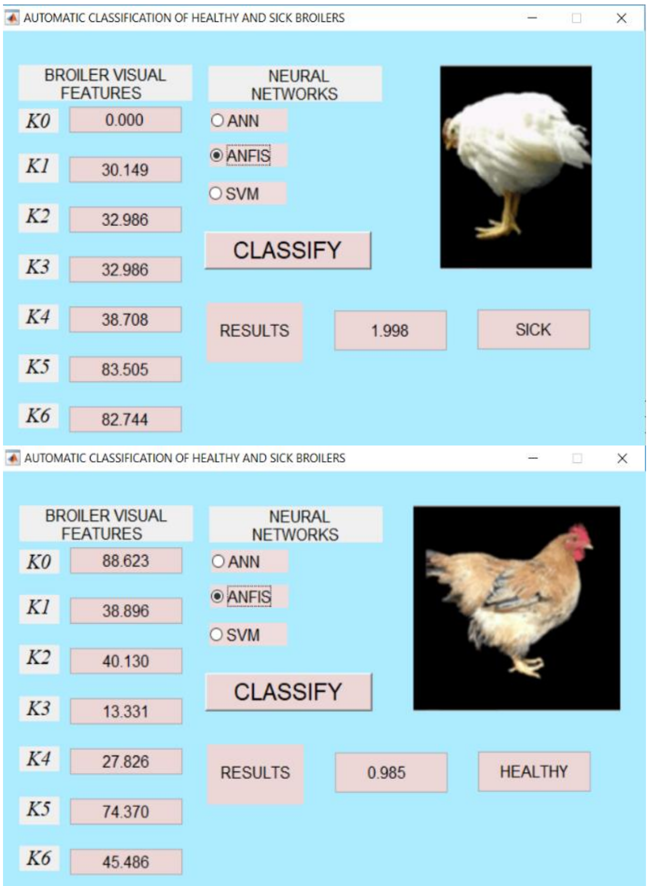


Figure 6. Screenshots of GUI for the NN models.

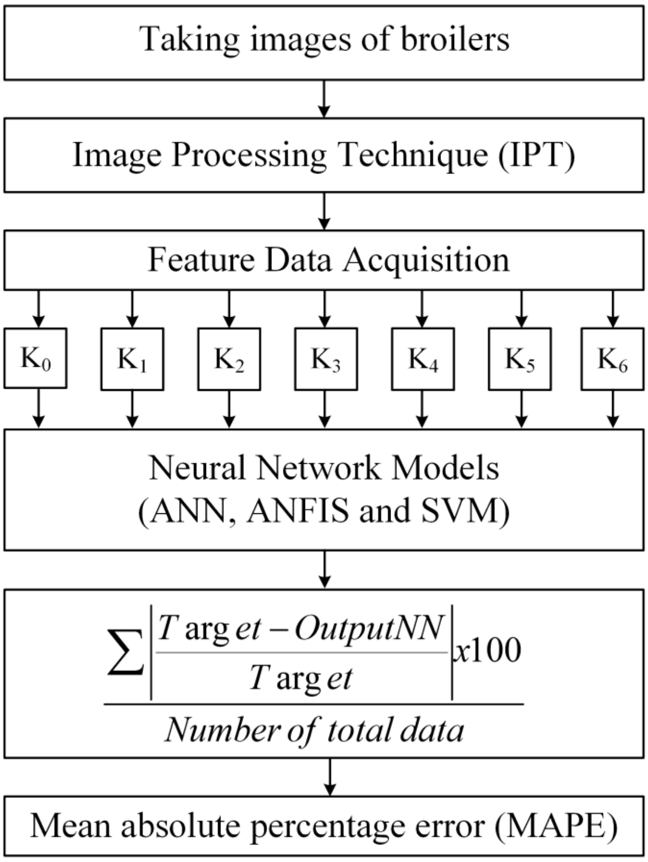
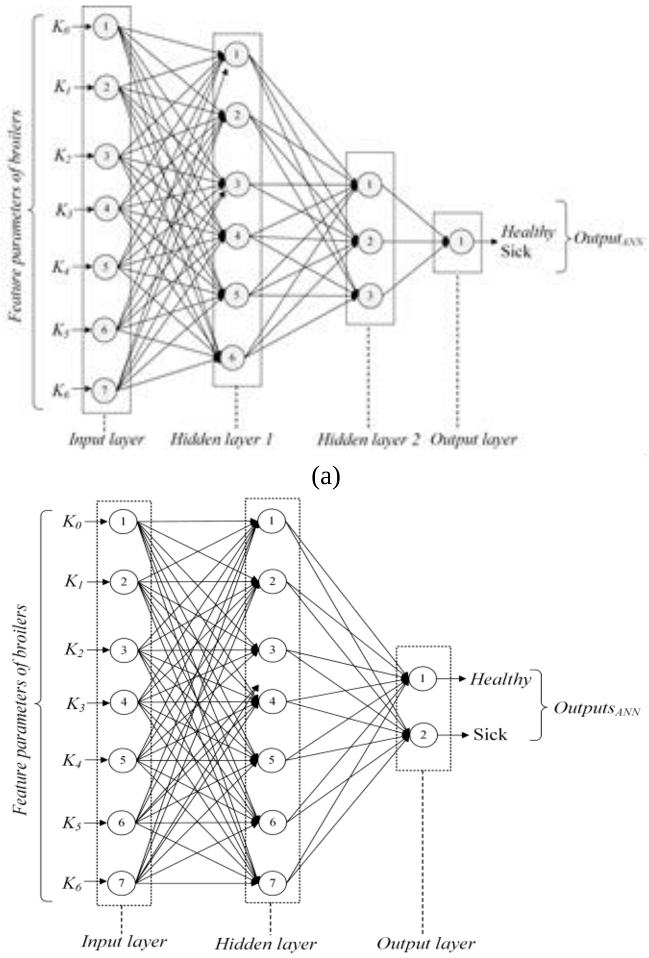


Figure 7. Topology of the NN models.



(a)

(b)

Figure 8. Topology of the NN models(a) ANNFFBP model (b) ANNLVQ model.

Table 2. The set parameters of the ANFIS model.

Model	Parameters	Set type/value
ANFIS	Epochs	150
	Range of influence	0.5
	Squash factor	1.25
	Accept ratio	0.5
	Reject ratio	0.15
	Seed value	1948281958

SVM is a supervised NN algorithm that can be used especially for classification problems. In this algorithm, each data is represented as a dot in n-dimensional space, and then it is performed classification by finding a hyperplane that separates the data very well. The data is mapped to multidimensional space by using kernel functions in multi-nonlinear problems with multi-parameter [19].

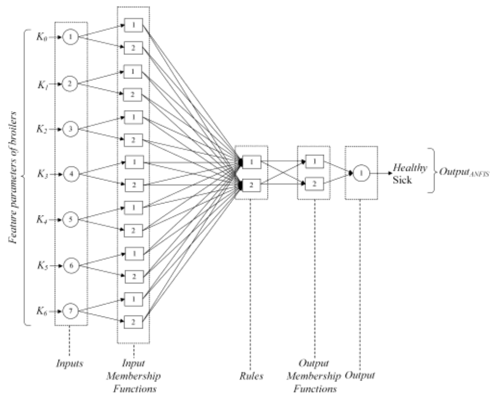


Figure 9. ANFIS model.

SVM network generally has two feed-forward layers similar to ANN. In the SVM model, the visual data of broilers is mapped to higher dimensional space using the Gaussian Kernel function [6]. SVM modeled in this study for broiler classification is illustrated in Figure 10 along with the set parameters given in Table 3.

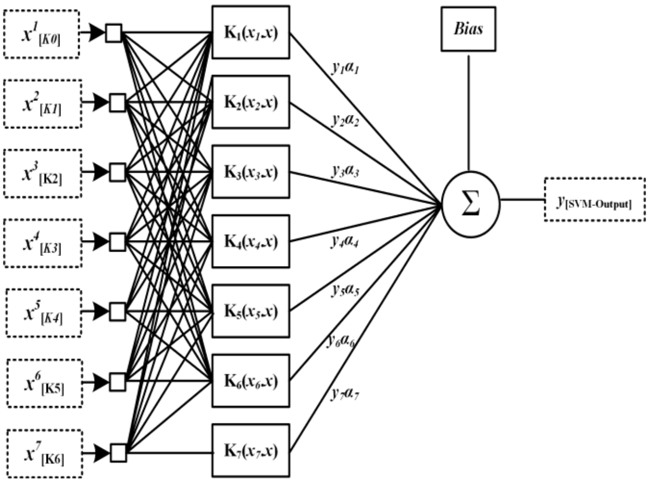


Figure 10. SVM model.

Table 3. The set parameters of the SVM model.

Model	Parameters	Set type/value
SVM	Kernel function	Gaussian
	Kernel function coefficient (σ)	10
	Penalty weight (C)	1000000

2.3.2. Training of Neural Networks

The flowchart prepared for the training of NNs is seen in Figure 11. 260 visual data of broilers randomly selected from 300 data are used for the training of NNs. To optimize the network output during the training phase, NN models are trained with different algorithms. The models of ANNFFBP, ANNLVQ, ANFIS, and SVM are trained Levenberg-Marquardt algorithm [15], random weight/bias rule [16], hybrid-learning algorithm [4], and quadratic programming algorithm [19], respectively.

As shown in Figure 12, the NNs classify broilers as healthy or sick if numerical results are in the range of 0.9-1.1 and 1.9-2.1, respectively. As a result of the training, MAPE values are calculated as 0.0001% for the ANNFFBP model, 0.356% for the ANFIS model, and 0.073% for the SVM model. Only two of 260 data sets used for the training process are incorrectly classified in the ANNLVQ model. The classification of broilers is carried out as a regression problem in ANNFFBP, ANFIS, and SVM models. But, it is carried out as a classification problem with 2 outputs in the ANNLVQ model.

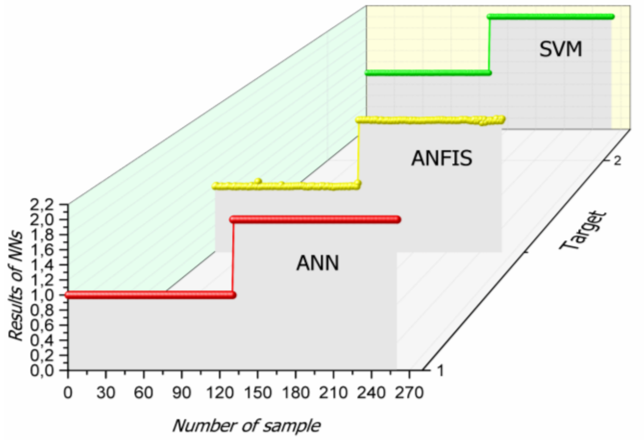


Figure 12. Numerical training results of the NN models.

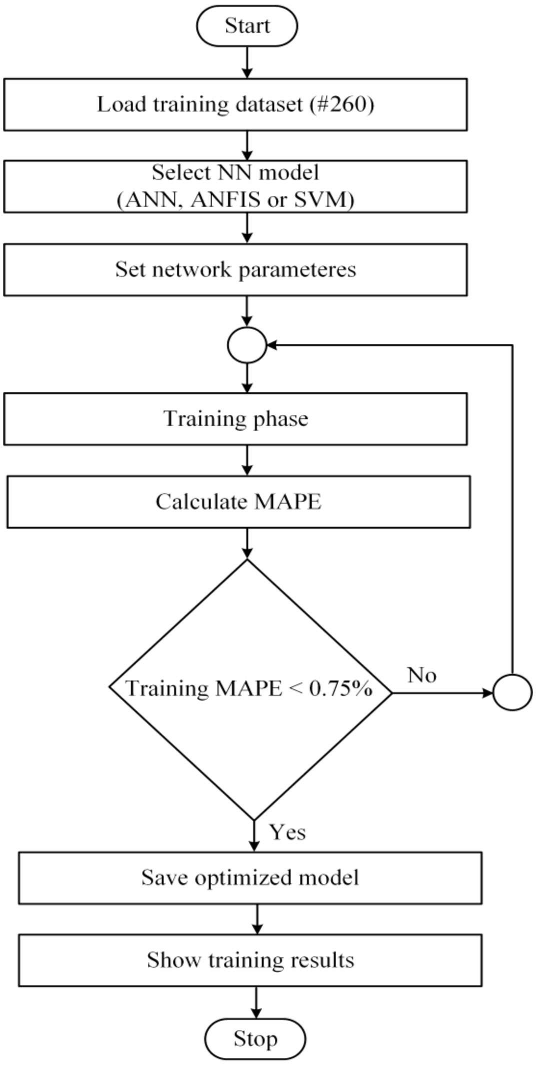


Figure 11. Flowchart of the training process of NNs models.

2.3.3. Testing of Neural Networks

The data of 20 broilers' visual features are used to test the accuracy of the NNs. The tabulated in Table 4, 20 test data are randomly selected among 300 broiler visual features and are not utilized during the training phase. The results of NNs are tabulated in Table 5 for the analysis of the testing process. The ANNFFBP, ANFIS, and SVM models numerically classify the broilers in terms of avian influenza with 0.001% (accuracy of 100%), 0.590% (accuracy of 99.41%), and 0.393% (accuracy of 99.61%), respectively. The results of the ANNLVQ model are tabulated in Table 6 for the testing process. As it is seen from the test results given in Table 5, Table 6, and Figure 13, the modeled NNs are successfully implemented to classify the broilers as "healthy" or "sick". Only one of the 20 data sets used for the testing process is misclassified in the ANNLVQ model.

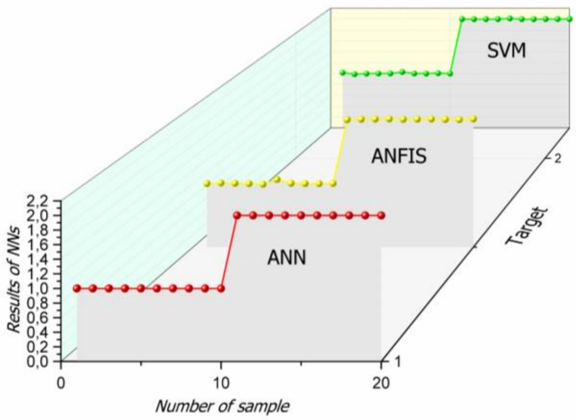


Figure 13. Numerical testing results of the NN model.

2.4. Validate and Comparison of Neural Networks

The proposed NNs are validated with the remaining 20 broiler data given in Table 7. The results of models are compared with in terms of MAPE. The design of ANN is easier and simpler than the ANFIS and SVM for this classification task in terms of the design of NNs. In the training process, the computational time is the longest in the ANFIS model, whereas it is almost the same in all models in the testing process. The data of 20 broilers not utilized during the training phase is used to validate the accuracy of the NNs. To analyze the validating process, the results of NNs are tabulated in Table 8 and Table 9. The ANNFFBP, ANFIS, and SVM models successfully classify the broilers as healthy and sick with the accuracy of 100% (MAPE of 0.001%), 99.62% (MAPE of 0.381%), and 99.31% (MAPE of 0.687%), respectively. All 20 data sets used for the validating process are correctly classified in the ANNLVQ model. As it is seen from the validating results given in Table 8, Table 9, and Figure 14, proposed models can be successfully implemented to such classification of broilers as healthy or sick.
It is seen from these results that the proposed NN models based on IPT are successful. These models can be used to automatically detect sick broilers on a farm as shown in Figure 15. In this regard, images taken at certain intervals with cameras on a farm can be analyzed using NNs. After determining the coordinate of the sick broiler, it can be taken to another area by removing the broiler with a 3-dimensional movable mechanism. In this way, early screening can be done by making an instant scan and the spread can be prevented. Also, the presented models can be easily integrated into the farm industry to automatically classify different animals.

Table 4. The used dataset in the testing process.

Sample	Broiler visual feature parameters						
	K_0	K_1	K_2	K_3	K_4	K_5	K_6
1	63.107	45.511	47.432	48.280	24.506	92.983	49.032
2	77.059	56.150	57.923	60.245	23.494	104.790	41.570
3	94.870	52.251	53.972	53.208	27.032	106.771	39.533
4	48.201	40.805	44.882	52.308	21.656	102.395	44.597
5	88.663	38.896	40.130	13.331	27.826	74.370	45.486
6	30.000	30.537	30.441	32.421	25.180	67.822	53.184
7	42.109	40.774	41.463	43.884	22.894	74.899	31.859
8	57.653	43.820	45.626	45.525	28.944	76.513	38.068
9	56.507	44.460	46.838	45.537	26.090	83.886	44.182
10	71.938	46.576	48.617	48.596	26.984	84.884	34.354
11	0.000	33.062	27.811	27.422	40.251	79.293	84.501
12	0.000	25.632	27.911	27.911	39.089	68.627	86.474
13	30.000	30.170	31.432	31.776	37.738	71.717	80.250
14	0.000	38.272	28.407	32.292	38.397	72.330	80.937
15	30.000	30.656	31.446	31.735	38.659	74.510	81.526
16	0.000	37.426	25.710	27.892	40.695	71.698	81.854
17	0.000	27.892	26.842	11.737	29.655	52.381	74.457
18	0.000	35.241	28.457	28.457	39.116	80.000	82.462
19	0.000	30.149	32.986	32.986	38.708	83.505	82.744
20	0.000	37.808	27.126	29.947	38.190	72.195	80.570

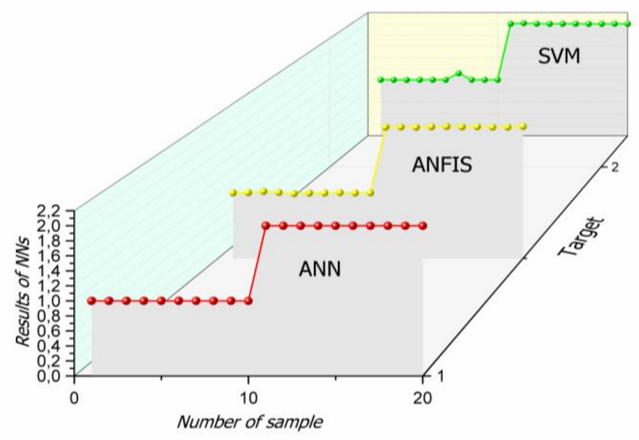


Figure 14. Numerical testing results of the NN models.

Table 5. The results of NNs in the test process.

#	Target	Neural network results								
		Numerical outputs			Absolute Percentage Error			Classification		
		ANN_{FFBP}	ANFIS	SVM	ANN_{FFBP}	ANFIS	SVM	ANN_{FFBP}	ANFIS	SVM
1	1.000	1.000	0.996	1.016	0.000	0.420	1.568	Healthy	Healthy	Healthy
2	1.000	1.000	1.005	0.988	0.000	0.494	1.168	Healthy	Healthy	Healthy
3	1.000	1.000	1.000	0.999	0.000	0.014	0.100	Healthy	Healthy	Healthy
4	1.000	1.000	0.996	1.001	0.000	0.420	0.100	Healthy	Healthy	Healthy
5	1.000	1.000	0.985	1.001	0.000	1.457	0.100	Healthy	Healthy	Healthy
6	1.000	1.000	1.060	1.029	0.000	6.031	2.851	Healthy	Healthy	Healthy
7	1.000	1.000	1.000	1.001	0.000	0.035	0.100	Healthy	Healthy	Healthy
8	1.000	1.000	0.996	1.000	0.000	0.372	0.046	Healthy	Healthy	Healthy
9	1.000	1.000	0.996	1.007	0.000	0.438	0.658	Healthy	Healthy	Healthy
10	1.000	1.000	0.999	0.999	0.000	0.077	0.100	Healthy	Healthy	Healthy
11	2.000	2.000	1.995	2.001	0.000	0.238	0.050	Sick	Sick	Sick
12	2.000	2.000	2.001	1.999	0.000	0.058	0.050	Sick	Sick	Sick
13	2.000	2.000	2.005	1.999	0.000	0.251	0.050	Sick	Sick	Sick
14	2.000	2.000	2.007	1.999	0.000	0.357	0.050	Sick	Sick	Sick
15	2.000	2.000	2.001	2.012	0.000	0.057	0.614	Sick	Sick	Sick
16	2.000	2.000	2.003	1.999	0.000	0.138	0.050	Sick	Sick	Sick
17	2.000	2.000	2.006	1.999	0.000	0.316	0.050	Sick	Sick	Sick
18	2.000	2.000	1.998	2.001	0.000	0.075	0.050	Sick	Sick	Sick
19	2.000	2.000	1.996	2.001	0.000	0.184	0.050	Sick	Sick	Sick
20	2.000	2.000	2.007	2.001	0.000	0.367	0.050	Sick	Sick	Sick
Mean Absolute Percentage Error					**0.001%**	**0.590%**	**0.393%**			
							Accuracy	**100%**	**99.41%**	**99.61%**

Table 6. The used dataset in the testing process.

#	Target		Numerical outputs		Classification
			ANN_{LVQ}		ANN_{LVQ}
1	0.000	1.000	0.000	1.000	Healthy
2	0.000	1.000	0.000	1.000	Healthy
3	0.000	1.000	0.000	1.000	Healthy
4	0.000	1.000	0.000	1.000	Healthy
5	0.000	1.000	0.000	1.000	Healthy
6	0.000	1.000	1.000	0.000	Sick
7	0.000	1.000	0.000	1.000	Healthy
8	0.000	1.000	0.000	1.000	Healthy
9	0.000	1.000	0.000	1.000	Healthy
10	0.000	1.000	0.000	1.000	Healthy
11	1.000	0.000	1.000	0.000	Sick
12	1.000	0.000	1.000	0.000	Sick
13	1.000	0.000	1.000	0.000	Sick
14	1.000	0.000	1.000	0.000	Sick
15	1.000	0.000	1.000	0.000	Sick
16	1.000	0.000	1.000	0.000	Sick
17	1.000	0.000	1.000	0.000	Sick
18	1.000	0.000	1.000	0.000	Sick
19	1.000	0.000	1.000	0.000	Sick
20	1.000	0.000	1.000	0.000	Sick

Table 7. The used dataset in the validating process.

Sample	Broiler visual feature parameters						
	K_0	K_1	K_2	K_3	K_4	K_5	K_6
1	73.249	42.214	44.400	45.639	27.376	77.211	31.599
2	35.776	47.980	49.050	49.021	25.439	79.237	38.477
3	32.124	33.947	36.189	36.621	28.928	71.260	47.783
4	69.812	53.009	56.221	56.280	19.768	112.752	39.254
5	88.663	38.896	40.130	13.331	27.826	74.370	45.486
6	50.140	36.713	38.415	41.469	30.807	77.000	38.730
7	63.107	45.511	47.432	48.280	24.506	92.983	49.032
8	59.294	46.962	48.768	48.673	25.266	73.646	32.114
9	48.201	40.805	44.882	52.308	21.656	102.395	44.597
10	30.000	65.139	85.255	84.659	24.316	172.881	56.283
11	30.000	24.690	23.574	23.574	39.190	70.202	86.018
12	30.000	30.656	31.446	31.735	38.659	74.510	81.526
13	0.000	30.149	32.986	32.986	38.708	83.505	82.744
14	0.000	31.578	30.196	32.819	38.687	71.212	85.141
15	0.000	37.808	27.126	29.947	38.190	72.195	80.570
16	0.000	34.013	38.177	38.177	38.914	77.500	80.801
17	30.000	30.170	31.432	31.776	37.738	71.717	80.250
18	0.000	27.487	17.788	16.077	40.307	70.531	84.474
19	0.000	35.241	28.457	28.457	39.116	80.000	82.462
20	30.000	22.279	23.376	25.104	36.441	70.202	76.827

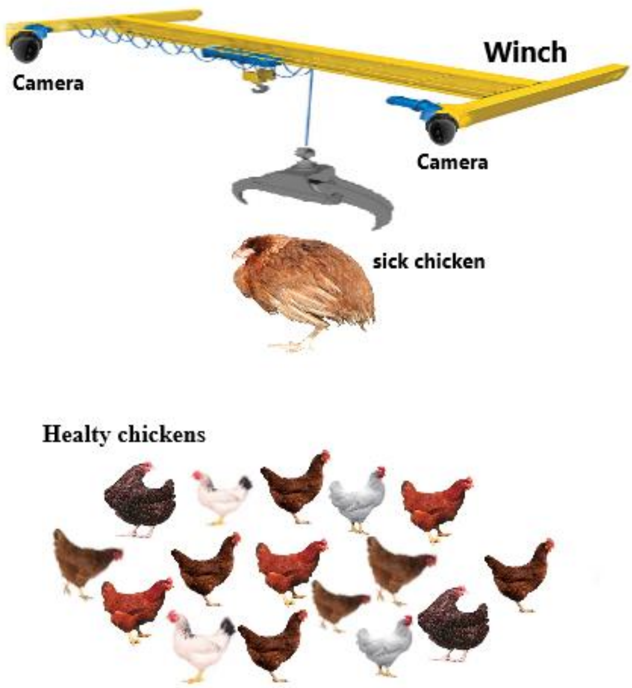


Figure 15. The system automatically detects sick broilers.

Table 8. The results of NNs in the validating process.

#	Target	Neural network results								
		Numerical outputs			Absolute Percentage Error			Classification		
		ANN$_{FFBP}$	ANFIS	SVM	ANN$_{FFBP}$	ANFIS	SVM	ANN$_{FFBP}$	ANFIS	SVM
1	1.000	1.000	0.998	1.001	0.000	0.237	0.100	Healthy	Healthy	Healthy
2	1.000	1.000	1.001	1.001	0.000	0.070	0.100	Healthy	Healthy	Healthy
3	1.000	1.000	1.020	0.999	0.000	2.014	0.100	Healthy	Healthy	Healthy
4	1.000	1.000	1.004	1.001	0.000	0.374	0.100	Healthy	Healthy	Healthy
5	1.000	1.000	0.985	1.001	0.000	1.457	0.100	Healthy	Healthy	Healthy
6	1.000	1.000	0.995	1.001	0.000	0.508	0.100	Healthy	Healthy	Healthy
7	1.000	1.000	0.996	1.118	0.000	0.420	11.805	Healthy	Healthy	Sick
8	1.000	1.000	1.002	1.001	0.000	0.190	0.100	Healthy	Healthy	Healthy
9	1.000	1.000	0.996	1.001	0.000	0.420	0.100	Healthy	Healthy	Healthy
10	1.000	1.000	0.999	1.001	0.000	0.136	0.100	Healthy	Healthy	Healthy
11	2.000	2.000	1.998	2.001	0.000	0.087	0.050	Sick	Sick	Sick
12	2.000	2.000	2.001	2.012	0.000	0.057	0.614	Sick	Sick	Sick
13	2.000	2.000	1.996	2.001	0.000	0.184	0.050	Sick	Sick	Sick
14	2.000	2.000	2.003	2.000	0.000	0.144	0.015	Sick	Sick	Sick
15	2.000	2.000	2.007	2.001	0.000	0.367	0.050	Sick	Sick	Sick
16	2.000	2.000	2.002	2.001	0.000	0.097	0.050	Sick	Sick	Sick
17	2.000	2.000	2.005	1.999	0.000	0.251	0.050	Sick	Sick	Sick
18	2.000	2.000	1.999	1.999	0.000	0.047	0.050	Sick	Sick	Sick
19	2.000	2.000	1.998	2.001	0.000	0.075	0.050	Sick	Sick	Sick
20	2.000	2.000	2.010	1.999	0.000	0.491	0.050	Sick	Sick	Sick
Mean Absolute Percentage Error					**0.001%**	**0.381%**	**0.687%**			
							Accuracy	**100%**	**99.62%**	**99.31%**

Table 9. The results of the ANNLVQ model in the validating process.

#	Target		Numerical outputs		Classification
			ANN$_{LVQ}$		ANN$_{LVQ}$
1	0.000	1.000	0.000	1.000	Healthy
2	0.000	1.000	0.000	1.000	Healthy
3	0.000	1.000	0.000	1.000	Healthy
4	0.000	1.000	0.000	1.000	Healthy
5	0.000	1.000	0.000	1.000	Healthy
6	0.000	1.000	1.000	0.000	Sick
7	0.000	1.000	0.000	1.000	Healthy
8	0.000	1.000	0.000	1.000	Healthy
9	0.000	1.000	0.000	1.000	Healthy
10	0.000	1.000	0.000	1.000	Healthy
11	1.000	0.000	1.000	0.000	Sick
12	1.000	0.000	1.000	0.000	Sick
13	1.000	0.000	1.000	0.000	Sick
14	1.000	0.000	1.000	0.000	Sick
15	1.000	0.000	1.000	0.000	Sick
16	1.000	0.000	1.000	0.000	Sick
17	1.000	0.000	1.000	0.000	Sick
18	1.000	0.000	1.000	0.000	Sick
19	1.000	0.000	1.000	0.000	Sick
20	1.000	0.000	1.000	0.000	Sick

3. CONCLUSION

In this paper, applications of IPT based NNs are successfully carried out for the classification of broilers in terms of avian influenza. The models of ANN, ANFIS, and SVM are conducted through 300 data of which visual features of broilers were acquired using IPT. The training, testing, and validation of the NN models are accomplished by using data of 260, 20, and 20 visual data, respectively. In terms of the design procedure and classification performance the ANNFFBP, ANNLVQ, ANFIS, and SVM models classify the outputs with the accuracy of 100% (MAPE of 0.001%), 100%, 99.62% (MAPE of 0.381%), and 99.31% (MAPE of 0.687%) for validating process, respectively. In the design and optimization procedure, the modeling of ANN is easier than ANFIS and SVM for classification. The proposed NN models can be integrated into a hardware system to automatically classify sick broilers on a farm. In addition, the automatic classification of broilers in terms of different health problems can be made after NNs are updated.

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Author's Contributions

The contributions of the authors is equal.

Statement of Conflict of Interest

Authors have declared no conflict of interest.

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