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Model of Combined IPT and NNLVQ for Classification of Healthy and Sick Broilers In Terms of Avian Influenza

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ABSTRACT

Poultry meat is an important and economical protein source in providing the animal protein requirement for human nutrition. The poultry diseases such as avian influenza that are a feature of fast-spread in farms seriously threatens both the economy and human health. Avian influenza must be detected early because it spreads rapidly. Earlier detection of poultry diseases has become more possible with the development of systems combining image processing techniques (IPTs) and artificial intelligence techniques (AITs). In this study, the neural network (NN) based model using learning vector quantization (LVQ) structure is proposed for the classification of broiler chickens as healthy and sick. In the literature, seven main visual feature parameters that indicate the health status of broilers were acquired through the IPTs. The data set includes seven visual features is used for training, testing and validating process of the NNLVQ model. The classification performance of the neural network (NN) using learning vector quantization (NNLVQ) is compared with IPT concerning its efficiency and accuracy. In the training process, the NNLVQ model classifies the broilers in terms of avian influenza with an accuracy error (AE) of 0.384%. The results point out that, the IPT based application using NNLVQ is successfully classified the broilers in terms of their health conditions.

1. INTRODUCTION

The 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, 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, the neural network (NN) using learning vector quantization (LVQ) can be combined with IPTs.

The several studies regarding the diagnosis of broiler diseases using NNs combined IPT have been proposed in the literature [2]–[8]. In [2], 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 a support vector machine (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. [3]. The estimated weights and manual measurement results were shown to be very close to each other. In [4], 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 and some feature variables of broilers were detected by the proposed algorithm [5]. In [6], 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 artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) were proposed to predict chick body mass and more successful results were achieved with ANN by Ferraz et al. [7]. In [8], the weight prediction of broiler chickens five regression model integrated with 3D computer vision was used and the best result was obtained with the Bayesian ANN model.

In this study, the NN using LVQ (NNLVQ) is 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 [9]. 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 [9]. 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 NNLVQ model successfully classifies the broilers as healthy and sick with an accuracy of 99.616%.

2. DATA SET

The automatic classification application based on NNs is carried out through a data set reported elsewhere [9]. containing 7 main visual feature parameters of broiler chickens. In the literature, four to six weeks old broiler chickens were divided into two groups and placed in isolator cages [2]–[9]. 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 [2]-[9]. 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 [2]. To calculate the skeletal structure of the broiler, the algorithm only extracts the image of the 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 [2]–[9]. Briefly, the process for obtaining data on the visual properties of the broiler is shown as topology in Figure 3.

Figure 1. Image of broilers capture environment [2]

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

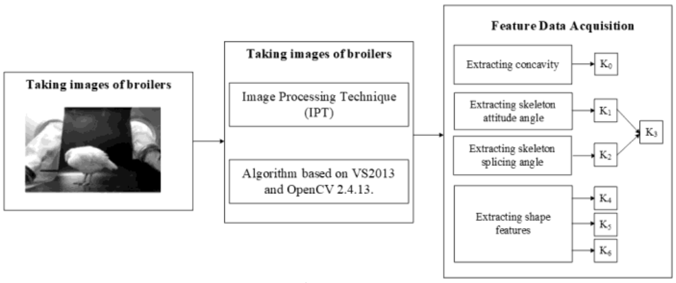

Figure 3. Image The topology of IPT

2.1. 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. [2]. 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 [2]. K_3 was obtained by using the methods of skeleton simplification and skeleton splicing [2].

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

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

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

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

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

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

In the Figure 4, 2D scattering of the broilers features is demonstrated to show how healthy and sick broilers

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discriminate among each other by the feature parameters. In addition, the graphs of all feature parameters (K_0, K_1, K_2, K_4, K_5 and K_6) are plotted in Figure 5. It is observed that healthy and sick broilers distinctly cluster for the visual feature parameters.

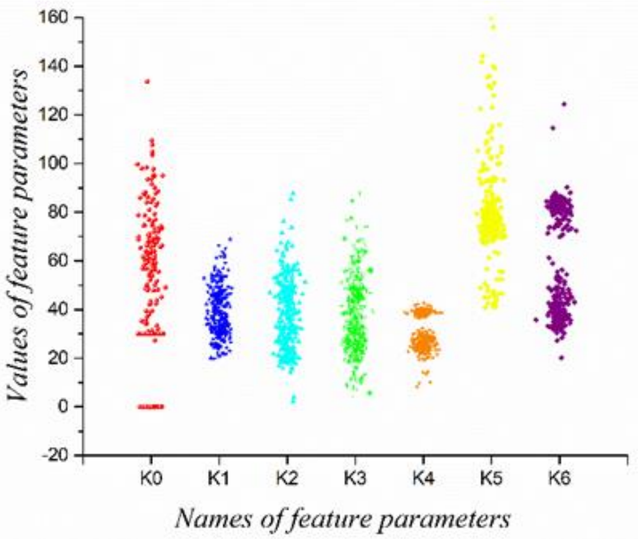

Figure 4. 2D scattering of 300 broilers according to feature parameters

3. NEURAL NETWORK

The NN currently provides the best solutions to many problems in image recognition. The NN interprets the raw input by labeling or clustering with a kind of machine perception. It helps to group unlabeled data according to similarities between sample inputs and classify data when they have a data set labeled for training [2], [3], [13], [4]–[8], [10]–[12]. The modeling and training of the NNLVQ for the classification of broilers in terms of avian influenza are described below.

3.1. Modelling and training of neural network

The NNLVQ is modeled and trained with appropriate set parameters according to the topology illustrated in Figure 6. The computer used in this study has property of Intel Core i7 CPU with 3.1 GHz and 8 GB DDR3 RAM. According to the result of the training, the model is updated and the training is repeated. Modeling and training processes are carried out one after the other to try to obtain the lowest classification accuracy error. The NNLVQ model numerically calculates the outputs according to accuracy error (AE) in given Eq. (7).

The NN consists of neurons that are organized into different layers. These neurons containing a non-linear type of functions are mutually connected by synaptic weights. These weights increase or decrease to output closer to target throughout the training process [11]–[13]. As shown in Figure 7, along with the set parameters given in Table 1, NNLVQ is designed to classify the broilers into “healthy” or “sick” according to the feature parameters. The NNLVQ model is constructed with an input layer having 7 neurons, one hidden layer having 5 neurons and one output layer have 2 neurons.

$$AE = \frac{Error\ x100}{Actual\ value} \tag{7}$$

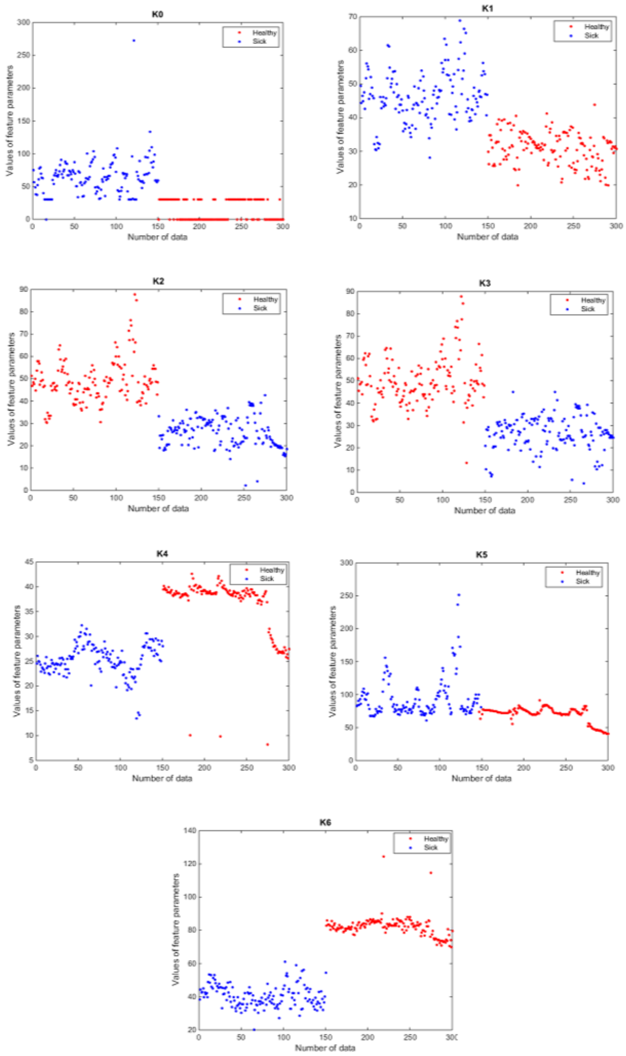

Figure 5. Separately graphs of feature parameters

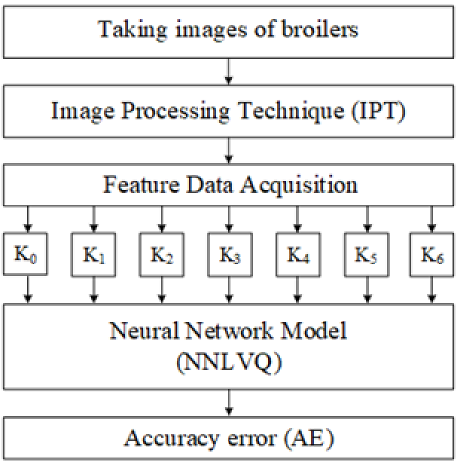

Figure 6. Topology of the NNLVQ model

TABLE I
THE SET PARAMETERS OF THE NNLVQ MODEL

Model	Parameters	Set type/value
	Epochs	200
	Minimum gradient descent	10^{-7}
ANN_{LVQ}	Learning rate	0.02
	Validation checks	7
	Output class percentage	0.5, 05

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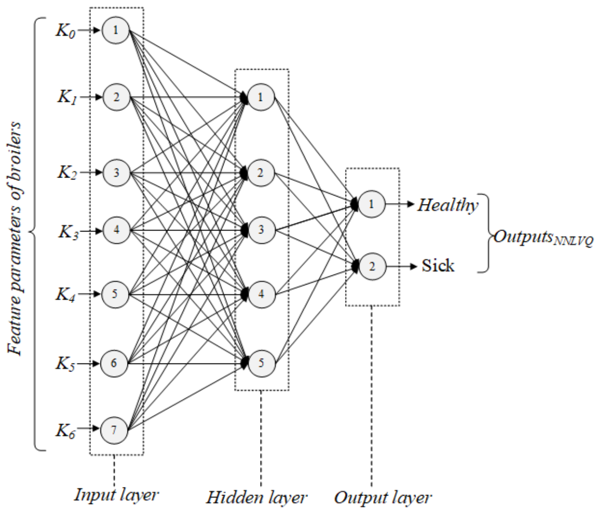

Figure 7. Structure of the NNLVQ model

The 260 visual data of broilers randomly selected from 300 data are used for the training of NNLVQ. The only one of 260 data sets used for the training process are incorrectly classified in the NNLVQ model.

3.2. Testing and validating of neural network

The data of 20 broilers' visual features is used to test the accuracy of the NNLVQ. The tabulated in Table 2, 20 test data are randomly selected among 300 broiler visual features and are not utilized during the training phase. The results of NNLVQ model are tabulated in Table 3 for testing process. Only one of the 20 data sets used for the testing process is misclassified in the NNLVQ model.

TABLE II
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

The proposed NNLVQ model is validated with the remaining 20 broiler data given in Table 4. All 20 data sets used for the validating process are correctly classified in the NNLVQ model. As it is seen from the validating results given in the Table 5, the proposed model can be successfully implemented to such classification of broilers as healthy or sick.

TABLE III
THE RESULTS OF NNLVQ MODEL IN THE TEST PROCESS

#	Target		Numerical outputs		Classification
			NNLVQ		NNLVQ
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 IV
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

TABLE V
THE RESULTS OF NNLVQ MODEL IN THE VALIDATING PROCESS

#	Target		Numerical outputs		Classification
			NNLVQ		NNLVQ
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

It is seen from these results that the proposed NNLVQ model based on IPT is successful. This model can be used to automatically detect sick broilers in a farm as shown in Figure 8. In this regard, images taken at certain intervals with cameras on a farm can be analyzed using NNLVQ. 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 farm industry to automatically classify of different animal.

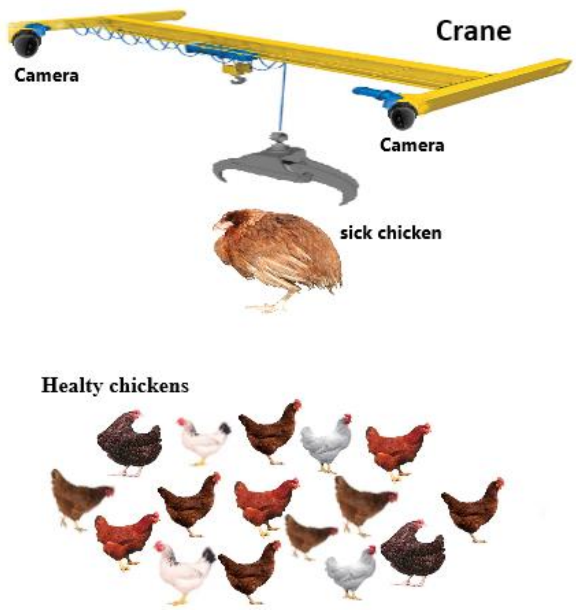

Figure 8. The system of automatically detect sick broilers

4. RESULT and CONCLUSION

The poultry diseases such as avian influenza that are a feature of fast-spread in farms seriously threatens both the economy and human health. Avian influenza must be detected early because it spreads rapidly. Earlier detection of poultry diseases has become more possible with the development of systems combining IPTs and AITs. In this paper, application of IPT based NNLVQ is successfully carried out for classification of broilers in terms of avian influenza. The model is conducted through 300 data of which visual features of broilers acquired using IPT. The training, testing and validating of the NNLVQ model is accomplished by using data of 260, 20 and 20 visual data, respectively. In the training process, the NNLVQ model successfully classifies the broilers as healthy and sick with an accuracy of 99.616%. The NNLVQ model classifies the outputs with accuracy of 100%, for validating process. The proposed NNLVQ model can be integrated to a hardware system so as to automatically classify sick broilers in a farm. In addition, automatic classification of broilers in terms of different health problems can be made after NNLVQ are updated.

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BIOGRAPHIES

Ahmet Kayabasi received his B.S. and M.S. degrees in EEE from Selcuk University, Turkey, in 2001, 2005 respectively. In 2015, he received his Ph.D. degree in electrical and electronics engineering from Mersin University, Turkey. From 2001 to 2015, he was a lecturer in the Electronics and Automation Department of Selcuk University. He has been working as Associate Professor in the Department of Electrical and Electronics Engineering at Karamanoglu Mehmetbey University. His current research interests include image processing techniques, artificial intelligent, antennas, microstrip antennas, computational electromagnetic.