

## **Gender Determination of Fowls by Using Bio-acoustical Data Mining Methods and Support Vector Machine**

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### **ABSTRACT**

Sexing is a difficult task for most birds (especially ornamental birds) involving expensive, state-of-the-art equipment and experiments. An intelligent fowl sexing system was developed based on data mining methods to distinguish hen from cock hatchlings. The vocalization of one-day-old hatchlings was captured by a microphone and a sound card. To obtain more accurate information from the recordings, time-domain sound signals were converted into the frequency domain and the time-frequency domain using Fourier transform and discrete wavelet transform, respectively. During data-mining from signals of these three domains, 25 statistical features were extracted. The Improved Distance Evaluation (IDE) method was used to select the best features and also to reduce the classifier's input dimensions. Fowls' sound signals were classified by Support Vector Machine (SVM) with a Gaussian Radial Basis Function (GRBF). This classifier identified and classified cocks and hens based on the selected features from time, frequency and time-frequency domains. The highest accuracy of the SVM at time, frequency and time-frequency domains was 68.51, 70.37 and 90.74 percent, respectively. Results showed that the proposed system can successfully distinguish between Hen and Cock hatchlings. The results further suggest that signal processing and feature selection methods can maximize the classification accuracy.

**Keywords:** Gender determination, Non-invasive sexing, Animals behavior, Fowls vocalization, Signals processing.

### **INTRODUCTION**

In most bird species (including ornamental birds), males and females cannot be distinguished morphologically. This is especially important for poultry hatchery owners. Fowl sexing is essential from different aspects including development, poultry growth and research (Griffiths, 2000). The apparent sex is determined based on a series of physical properties related to each sex.

There are common methods for bird sexing like cloacal examination, laparoscopy and genetic testing. Although cloacal sexing is an applied technique because it provides immediate results and doesn't need special equipment (Volodin *et al.*, 2009; Bazzano *et*

*al.*, 2012), there are some negative effects to these methods like traumas, stress and bleeding (Malago *et al.*, 2005). Laparoscopy is based on surgery and is very invasive (Richner, 1989). Genetic testing is very much reliable but this method is expensive, needs special laboratories and time for considering bird sexing (Morinha *et al.*, 2012). In these procedures, birds receive topical anesthesia, and this violent, expensive procedure requires specialists and specific equipment.

A number of factors can change bird-generated signals including diseases, weakness and species. Since it is possible to detect vocalization signal features, different types of analyses can be performed.

In a review study, which is done by Volodin *et al.* (2015), it has been considered that sexing

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by voice represents a feasible alternative to classical sexing techniques. This study is based on spectroscopy analysis of vocalization (Volodin *et al.*, 2015). Besides, different research studies have been carried out on Biosystems based on artificial intelligence and data mining methods. Banakar *et al.* (2016) designed an intelligent device for diagnosing avian diseases based on chicken's sound. They could detect the Newcastle, infectious bronchitis and avian influenza based on signal processing methods and Dempster-Shafer evidence theory with accuracy of 91.15% (Banakar *et al.*, 2016). In another research, Sadeghi *et al.* (2015) diagnosed avian clostridium perfringens based on chicken's vocalization. They demonstrated the usefulness and effectiveness of intelligent methods for diagnosing diseases in chickens based on sound signals (Sadeghi *et al.*, 2015). Acevedo *et al.* (2009) used SVM to identify and classify 3 bird and 9 frog species based on their vocalizations. They used decision trees and Linear Discriminant Analysis (LDA) for further studies, where the SVM recorded a 95% accuracy in classification. Accordingly, the decision tree and LDA classified 89 and 71% of the cases, respectively (Acevedo *et al.*, 2009). Huang *et al.* (2009) used both the K-Nearest Neighbors (KNN) algorithm and SVM to develop an automated frog detection using vocalization characteristics. In this study, spectral centroid, signal bandwidth and threshold-crossing rate were the inputs of both classifiers, and the SVM performed better with 90.30% accuracy. The KNN also classified 89% of the cases (Huang *et al.*, 2009).

Animal vocalizations can communicate different messages. For example, a call may be used to signal readiness to mate, to warn conspecifics of a predator, to keep in touch with other members of the group, or it could be an expression of pain or need. In animals too, vocalization can be an expression or communication of an emotional state or reaction to an event, and eliciting emotional states in others. Thus, analysis of vocalizations has been suggested as a non-invasive method for studying the emotional state of an animal (Tikhonov A., 1986; Volodin *et al.*, 2015).

This study introduced an artificial intelligence by signal processing approach to fowls sexing based on their vocalizations. vocalization was analyzed in three time, frequency and time-frequency domains and classified by support vector machine.

## MATERIALS AND METHODS

The study experiments were carried out in the Agricultural School of Tarbiat Modares University, Tehran, on a group of male and female fowls to develop an intelligent fowl sexing system. One-day-old Ross 380 hatched in an incubator were first sexed based on appearance difference (including wing differences) and Cloacal examination, and were then divided into two groups of sixty. Every single subject chicken was placed in a separate box. Recordings were made after 5 minutes of being in the box by a microphone (Microphone diameter: 9.7×6.7 mm, Impedance:  $\leq 2.2\text{K}\Omega$ , Frequency response: 100 ~ 16 kHz and Sensitivity:  $-58\pm 3$  dB) and a PC to minimize stress. After recording, the chicken sounds were separated and saved in the "wav" format using wavePad Sound Editor software version 5.98 and were analyzed at time, frequency and time-frequency domains in MATLAB 2015a. A total number of 360 vocalization signals were collected from 120 male and female samples. Since it was impossible to visually extract information from unprocessed signals, features were extracted from signals in the three domains. The IDE method was used to score and select the best features and also to reduce the classifier's input dimensionality.

### Signal Processing

Using good signal processing and analysis, can extract useful information from signals and therefore prepare them for classification (Zhan and Makis, 2006). Besides noise removal, transforming signal from time to frequency or time-frequency domain can help obtain useful details since a requirement of

signal processing is to provide a proper signal for the data-mining stage (Wang *et al.*, 2010). In this study, three signal processing methods in three different domains (time, frequency and time-frequency) were used.

### Time Domain Signals

The vocalization sensor capture signals first in the time domain. Time-domain signals have a special importance (Sadeghi *et al.*, 2015). Any secondary analysis and data mining, in fact, can be performed based on the signals in this domain.

### Frequency Domain Signals

The frequency nature of time-domain signals cannot be identified, therefore frequency-domain analyses are required to obtain data on their cyclic nature (Zhu *et al.*, 2009). Additionally, the frequency content of a signal may better carry information for identifying that signal (Duhamel and Vetterli, 1990). FFT is the most common signal processing method in this domain, which is defined as follows (Zhu *et al.*, 2009) :

$$x(f) = \int_{-\infty}^{+\infty} x(t)e^{-j\omega t} dt, \quad \text{when } \omega = 2\pi f \quad (1)$$

Where  $t$  and  $f$  are time and frequency, respectively, and  $x(f)$  is the Fourier transform of the time-domain signal  $x(t)$ . FFT confirms whether a frequency is dominant while giving no information about the time interval in which the frequency is dominant. The signal's time transparency is zero in this method.

### Time-frequency Domain Signals

FFT perform poorly when dealing with unstable signal with time-varying frequencies (Wu and Liu, 2009) because time transparency is zero in FFT (Iyer *et al.*, 2012). On the other hand, frequency-domain and time-domain analyses fail to deliver

simultaneous information on a signal's time and frequency. Discrete Wavelet Transform (DWT) is a 2-dimensional signal analysis used for achieving simultaneous time and frequency transparencies and is a highly effective method in signal analysis. Unlike FFT, Wavelet Transform (WT) do not treat all frequency components of a signal similarly, however, its main objective is to present an accurate time-domain and inaccurate frequency-domain transparency for rapid variations, and an inaccurate time-domain and accurate frequency-domain transparency for slow variations (Misiti *et al.*, 1996). This important advantage of WT makes it suitable for status monitoring application (Wu and Liu, 2009). WT inherently removes noise, therefore it is suitable for analyzing noisy signals (Iyer *et al.*, 2012). Two types of WT are common for signal processing purposes, discrete and continuous. Since a continuous signal has infinite number of values which are difficult to be entered into the WT equation and make calculations more complicated, to load and code WT on a computer, the discrete method is used which is defined as follows (Banakar and Azeem, 2008, Saravanan and Ramachandran, 2010) :

$$DWT_{\psi}^x(j, k) = \Psi_{\psi}^x(j, k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-2^j k}{2^j}\right) dt \quad (2)$$

$\Psi$  in Equation (2) is a function characterized with a determined length, an average of zero and a cyclic behavior, which is totally transient and responsible for signal windowing. In fact  $\Psi$ , known as the mother wavelet, is a model for reconstructing the primary signal. DWT divides each signal into two components of high and low frequencies. Equation (2) serves as two high-pass and low-pass filters to decompose the signal into approximation and detail coefficients. In the DWT method, the approximation coefficient represents the main signal, whereas the detail coefficient shows high frequency intervals hidden in the main signal (Misiti *et al.*, 1996). DWT was used in this study to process the signals from



hatching recordings. There are several reports of successful DWT applications in, for example, fault location and monitoring (Gong *et al.*, 1997). This study used the first-order Daubechies mother wavelet to process signals up to four levels. Figure 1 presents a DWT up to 4 levels. In this figure, each signal is divided into two sections of approximation and details coefficient. In the next step, each approximation is divided into two other sections and continues.

### Data Mining

#### Feature Extraction

WT coefficients (or outputs of any other signal processors) cannot be directly used as classifier's inputs. Because these values include a large group of raw data with no specific physical-mathematical translation. Feature functions are those which define a state of a signal and convey information which can be used as the classifier's inputs. These features are defined for signals processed at all three domains -- *i.e.* time, frequency (FFT) and time-frequency (DWT)-- and are applied to obtain a better understanding of the signal. Table 1 presents all 25 used features (for example maximum values of signal, root mean square, crest factor, standard deviation and etc.) (Lei *et al.*, 2008; Khazaei *et al.*, 2013). In this table,  $x(n)$  is a signal for  $n$  data points ( $n = 1, 2, \dots, N$ ).

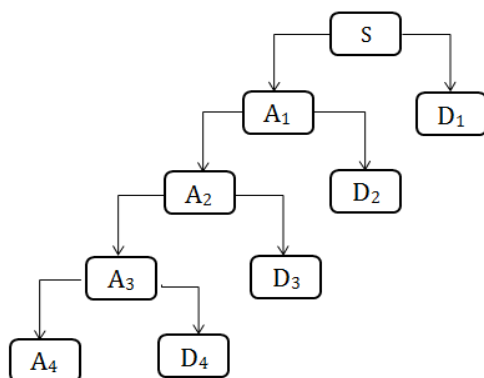


Figure 1. DWT up to 4 levels.

#### Feature Selection

Qualitative and quantitative aspects should be considered during feature selection. Selecting several feature functions can complicate the classifier, making it incapable of distinguishing between two groups of extracted features from two signal classes (Bagheri *et al.*, 2010). The feature quality is important as it should be useful in recognizing a signal. The IDE method was used for selecting the best features. (Lei *et al.*, 2008)The method's parameters were:

$$\{q_{m,c,j}, m = 1, 2, \dots, M_c; c = 1, 2, \dots, C; j = 1, 2, \dots, J\} \quad (3)$$

Where,  $q_{m,c,j}$  is the eigenvalue of the  $j$ th feature from the  $m$ th sample of class  $c$ .  $M_c$  represents the number of samples in the  $c$ th class, and  $J$  stands for the number of features in each class. Using the above-mentioned parameters, IDE relations are defined as follows:

Step 1: Computing the mean distance between samples in a given class:

$$d_{c,j} = \frac{1}{M_c \times (M_c - 1)} \sum_{l,m=1}^{M_c} |q_{m,c,j} - q_{l,c,j}| \quad (4)$$

$l, m = 1, 2, \dots, M_c, \quad l \neq m;$

Finding the mean distance values of a feature for each class:

$$d_j^{(w)} = \frac{1}{C} \sum_{c=1}^C d_{c,j} \quad (5)$$

Smaller mean feature distances within a class show that the feature is less scattered in that class; in other words, the smaller this parameter is for a feature, the more suitable that feature is for recognizing a signal related to that class.

Step 2: Defining the variance corresponding to  $d_j^{(w)}$  based on the equation 6:

**Table 1.** Primary features extracted.

Feature's Formula		
$F_1 = \frac{\sum_{n=1}^N x(n)}{N}$	$F_{10} = \sum_{n=1}^N (x(n))^2$	$F_{19} = \frac{\sum_{n=1}^N (x(n) - F_1)^4}{N-1}$
$F_2 = \max  x(n) $	$F_{11} = \frac{\sum_{n=1}^N (x(n) - F_1)^2}{N-1}$	$F_{20} = \frac{\sum_{n=1}^N (x(n) - F_1)^5}{N-1}$
$F_3 = \sqrt{\frac{\sum_{n=1}^N (x(n) - F_1)^2}{N-1}}$	$F_{12} = \frac{N}{\sum_{n=1}^N \frac{1}{x(n)}}$	$F_{21} = \frac{\sum_{n=1}^N (x(n) - F_1)^6}{N-1}$
$F_4 = \left( \frac{\sum_{n=1}^N \sqrt{ X(n) }}{N} \right)^2$	$F_{13} = N \sqrt{\prod_{n=1}^N x(n)}$	$F_{22} = \frac{F_{19}}{F_{11}^2}$
$F_5 = \sqrt{\frac{\sum_{n=1}^N x(n)^2}{N}}$	$F_{14} = \frac{F_3}{F_1}$	$F_{23} = \sum_{n=1}^N (x(n))^2$
$F_6 = \frac{F_{18}}{F_3^3}$	$F_{15} = \frac{\sum_{n=1}^N  x(n) - F_1 }{N-1}$	$F_{24} = \frac{3 \times (F_1 - \bar{X})}{F_3}$
$F_7 = \frac{F_2}{F_5}$	$F_{16} = \frac{\sum_{n=1}^N (x(n) - F_1)^3}{(N-1) F_3^3}$	$F_{25} = \frac{F_5}{F_1}$
$F_8 = \frac{F_2}{\frac{1}{N} \sum_{n=1}^N  x(n) }$	$F_{17} = \frac{\sum_{n=1}^N (x(n) - F_1)^4}{(N-1) F_3^4}$	
$F_9 = \frac{F_5}{\frac{1}{N} \sum_{n=1}^N  x(n) }$	$F_{18} = \frac{\sum_{n=1}^N (x(n) - F_1)^3}{N-1}$	

$$D_j^{(w)} = \frac{\max(d_{c,j})}{\min(d_{c,j})} \tag{6}$$

Step 3: This step involves computing the intra-class mean distance values of features. Before this, the mean feature value of each class is defined as follows:

$$u_{c,j} = \frac{1}{M_c} \sum_{m=1}^{M_c} q_{m,c,j} \tag{7}$$

Then, the mean distance between intra-class features is determined:

$$d_j^{(b)} = \frac{1}{C \times (C-1)} \sum_{l,m=1}^{M_c} |u_{e,j} - u_{c,j}|, \tag{8}$$

$c, e = 1, 2, \dots, C_c, \quad c \neq e;$

This step, in fact, determines the distance between the feature values of two classes. Larger distances present better criteria for distinguishing between two classes.

Step 4: Defining the variance corresponding to  $d_j^{(b)}$  based on the following



equation:

$$v_j^{(b)} = \frac{\max(|u_{e,j} - u_{c,j}|)}{\min(|u_{e,j} - u_{c,j}|)} \quad (9)$$

**Step 5:** Defining and computing the reward factor:

$$\lambda_j = \frac{1}{\frac{v_j^{(w)}}{\max(v_j^{(w)})} + \frac{v_j^{(b)}}{\max(v_j^{(b)})}} \quad (10)$$

**Step 6:** Features are scored based on the  $d_j^{(b)}$  to  $d_j^{(w)}$  ratio, considering the reward function described below:

$$\alpha_j = \lambda_j \times \frac{d_j^{(b)}}{d_j^{(w)}} \quad (11)$$

Equation (11) implies that the highest score is given to the feature with the largest intra-class and the lowest inter-class differences.

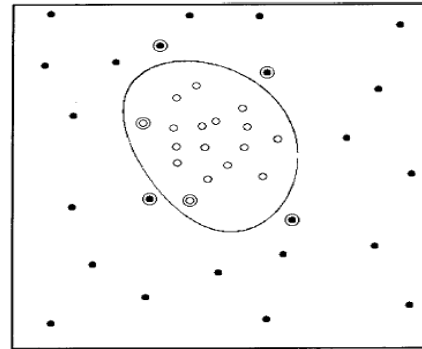
**Step 7:** Finally, the following equation was used to normalize the score of each feature, and the best feature was selected regarding an arbitrary threshold:

$$\bar{\alpha}_j = \frac{\alpha_j}{\max(\alpha_j)} \quad (12)$$

### Support Vector Machine

SVM is a robust classifier first introduced by Cortes and Vapnik in 1995 building on the Statistical Learning Theory (Cortes and Vapnik, 1995). The main idea is to separate classes using a hypothetical hyperplane (Singla *et al.*, 2014). Figure 2 clearly depicts the concept of hyperplane. This classifier intends to maximize the margin between two classes. Depending on the relationship between data of classes, the classifier type can be varied including the linear, quadratic and Gaussian Radial Basis Function (RBF) classifiers (Joachims, 1998). RBF was used in this study as both the separator and the hyperplane. RBF is defined as follows (Burges,1998):

$$K(x, y) = \exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right) \quad (13)$$



**Figure 2.** Concept of hyper plane in SVM (Scholkopf *et al.*, 1997).

If there is 1 objection, each observation consist of a pair: a vector  $x_i \in R^n$ ,  $i= 1,2,\dots,l$  and the associated “truth”  $y_i$ .  $\sigma$  is hyperplane width in Equation (13). The performance of the classifier can be calculated by computing SVM’s statistical parameter like sensitivity, specificity and the total classification accuracy. Consider the followings:

- a) *Sensitivity:* The number of true positive decision/number of actually positive cases.
- b) *Specificity:* The number of true negative decision/number of actually negative cases.
- c) *Total Classification accuracy:* The number of correct decisions/total number of cases. Figure 3 shows the different stages used for fowl sexing based on vocalization features.

## RESULTS

### Obtained Signals

Here, the signals obtained at each domain (time, frequency, and time-frequency) are presented. Figure (4-a) shows vocalization samples of hen and cock in the time domain. As shown in the figure, hen vocalization signals are more regular than signals generated by cocks. To extract more information from time-domain vocalization signals, FFT was performed to move signals into the frequency domain. Figure (4-b) presents a sample of fowl vocalization in the frequency domain.

For the next step, time-domain signals were transformed into the time-frequency domain through DWT. Figure 5 shows

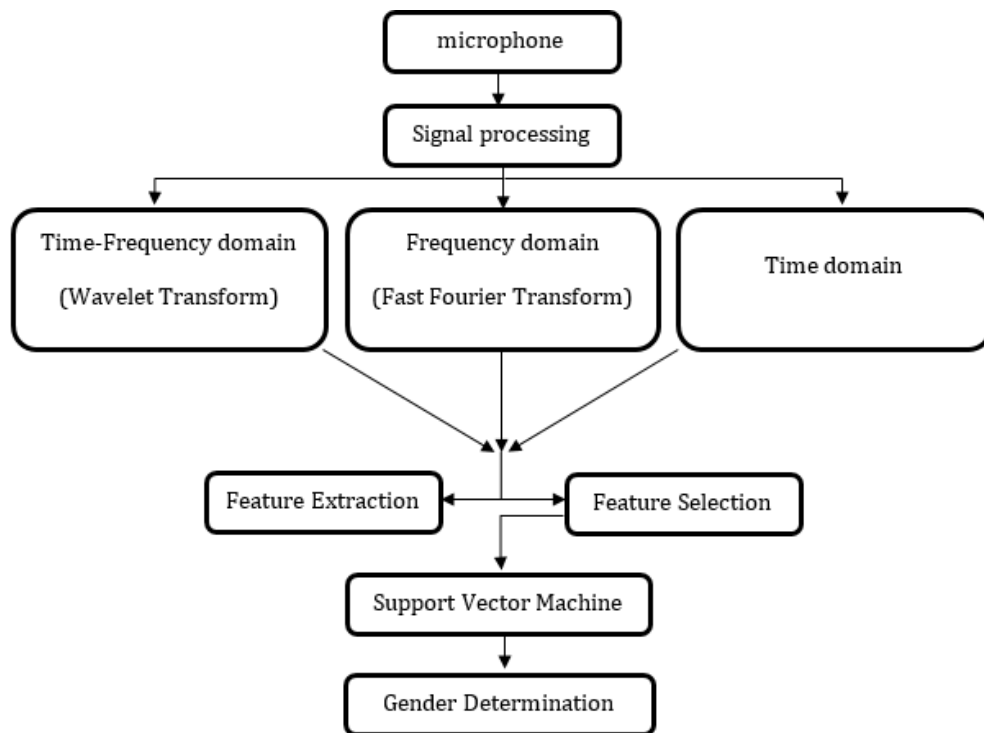


Figure 3. The different stages used for fowl sexing.

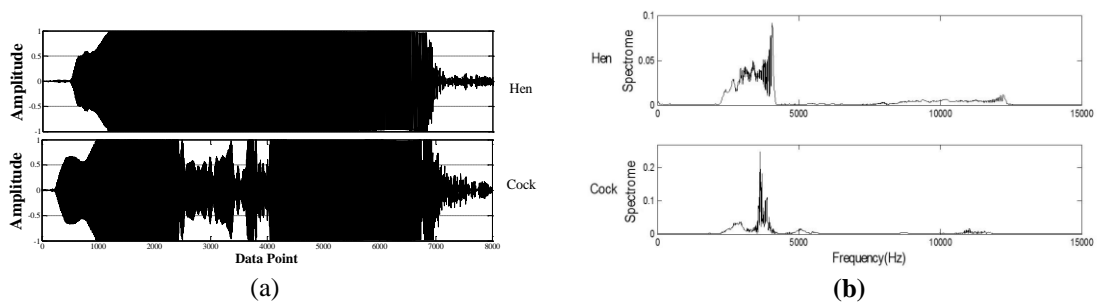


Figure 4. Fowl vocalization in the (a) time (b) frequency domain.

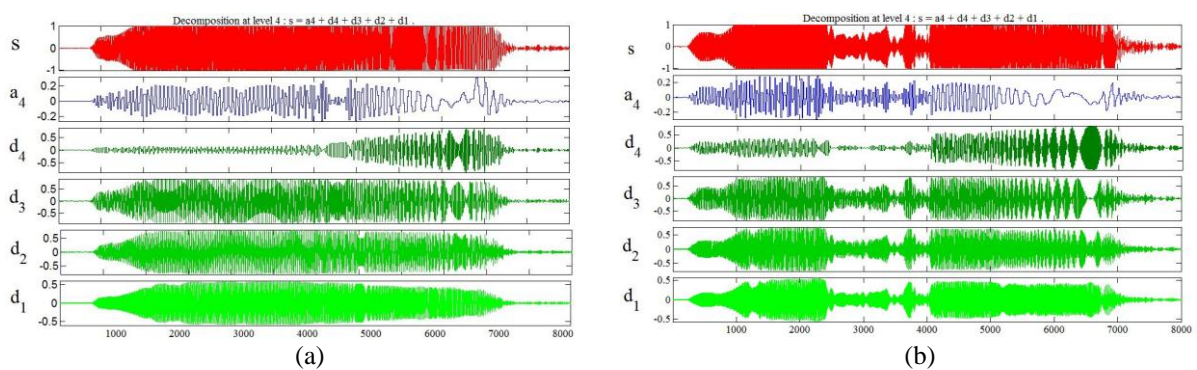


Figure 5. Approximation and details (a and d<sub>j</sub>) of DWT signals for (a) female, (b) male vocalizations.



female and male signals in the time-frequency domain, respectively, produced through four levels of DWT. According to Figure 5, the approximate coefficient behavior at the fourth DWT level for female vocalizations (which represents the original respective signal form) is completely different from that of male vocalizations. In this figure),  $S$  is the original signal,  $a_4$  stands for approximation coefficient of signal in 4<sup>th</sup> level of wavelet transform. The approximation has low frequency information of signal.  $d_4$  to  $d_1$  stands for details coefficient of signal in 4<sup>th</sup> to first level of wavelet transform. The details have high frequency information of signal.

These figure are just two instances of fowl's vocalization and data mining methods are necessary for having a good sexing classification. So it is impossible to classify just by figures.

### Data-Mining Results

By using time-domain and frequency-domain signals, 25 features were extracted separately (Table 1). In the time-frequency domain, the wavelet decomposition of each vocalization signal resulted into 125 features. Twenty five  $F_1(AP4)$ - $F_{25}(AP4)$  features were statistical parameters of the approximation coefficient; twenty five  $F_1(DE1)$ - $F_{25}(DE1)$  features were statistical parameters of the first-level detail coefficient; twenty five  $F_1(DE2)$ - $F_{25}(DE2)$  features were statistical parameters of the second-level detail coefficient; twenty five  $F_1(DE3)$ - $F_{25}(DE3)$  features were statistical parameters of the third-level detail coefficient; and twenty five  $F_1(DE4)$ - $F_{25}(DE4)$  features were statistical

parameters of the fourth-level detail coefficient (Bagheri *et al.*, 2010).

Each feature was scored based on the IDE method, and data with the highest scores were adopted as the best features, which were entered as SVM inputs. This study had 2 data classes, 180 samples in each class, and 25 time-domain and frequency-domain features, and also 125 features in the time-frequency domain in first-order and level four Daubechies wavelet transform. Figure 6 shows the features extracted from the time-domain signal.

As shown in the figure, there was a significant distance between  $F_{19}$  and  $F_5$ . Therefore, the threshold for selecting the best time-domain features was 0.7. Accordingly, eight features of  $F_{23}$ ,  $F_4$ ,  $F_{15}$ ,  $F_2$ ,  $F_8$ ,  $F_{11}$ ,  $F_{21}$  and  $F_{19}$  were selected as the best time-domain features of signals for SVM inputs.

Figure 7 shows the feature scores extracted in the frequency domain. As shown in the figure, there was a significant distance between  $F_{14}$  and  $F_{15}$ . With a threshold of 0.6, seven features of  $F_{12}$ ,  $F_{10}$ ,  $F_{13}$ ,  $F_{23}$ ,  $F_4$ ,  $F_{25}$  and  $F_{14}$  were selected as the best frequency-domain features of signals for classifier inputs.

Time-frequency features were scored in the next stage. Table 2 shows the feature scores extracted from wavelet coefficient at the fourth level.

According to Table 2, the threshold was set at 0.5 and 25 features were accordingly selected as the best inputs of SVM ( $F_{23}$ ,  $F_4$ ,  $F_{15}$ ,  $F_{17}$ ,  $F_{22}$ ,  $F_{11}$ ,  $F_8$ ,  $F_5$ ,  $F_3$ ,  $F_{13}$ ,  $F_7$ ,  $F_{19}$ ,  $F_{73}$ ,  $F_{29}$ ,  $F_{54}$ ,  $F_{65}$ ,  $F_{33}$ ,  $F_{58}$ ,  $F_{21}$ ,  $F_{61}$ ,  $F_{67}$ ,  $F_{72}$ ,  $F_{69}$ ,  $F_{53}$  and  $F_{55}$ ). As it shows, 13 features, out of 25 features which are selected from Table 2, are related approximation's coefficient of wavelet transform. So it can be said that more important information are related to the low frequency part of signal.

Table 3 shows a relative comparison between some of the most important features which were selected in data mining method.



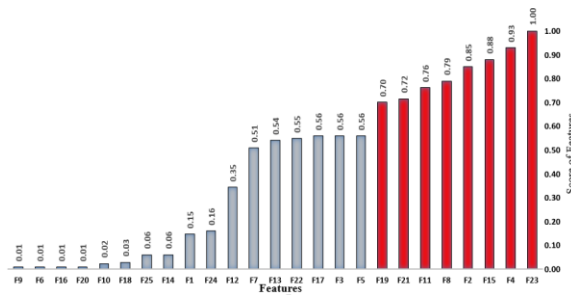


Figure 6. Time domain features and their scores.

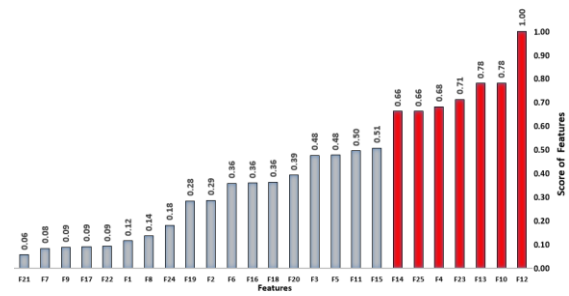


Figure 7. Frequency domain features and their scores

Table 2. Time- Frequency domain features and their scores.

Feature	Score	Feature	Score	Feature	Score	Feature	Score	Feature	Score	Feature	Score
F <sub>23</sub>	1	F <sub>72</sub>	0.53	F <sub>74</sub>	0.30	F <sub>16</sub>	0.24	F <sub>120</sub>	0.16	F <sub>101</sub>	0.02
F <sub>4</sub>	0.99	F <sub>69</sub>	0.53	F <sub>87</sub>	0.30	F <sub>6</sub>	0.24	F <sub>122</sub>	0.16	F <sub>109</sub>	0.02
F <sub>15</sub>	0.98	F <sub>53</sub>	0.53	F <sub>27</sub>	0.30	F <sub>115</sub>	0.24	F <sub>10</sub>	0.16	F <sub>59</sub>	0.02
F <sub>17</sub>	0.92	F <sub>55</sub>	0.53	F <sub>18</sub>	0.29	F <sub>64</sub>	0.23	F <sub>24</sub>	0.16	F <sub>35</sub>	0.01
F <sub>22</sub>	0.92	F <sub>40</sub>	0.41	F <sub>104</sub>	0.29	F <sub>75</sub>	0.23	F <sub>49</sub>	0.15	F <sub>41</sub>	0.005
F <sub>11</sub>	0.89	F <sub>71</sub>	0.41	F <sub>116</sub>	0.29	F <sub>60</sub>	0.23	F <sub>45</sub>	0.15	F <sub>31</sub>	0.005
F <sub>8</sub>	0.89	F <sub>57</sub>	0.40	F <sub>92</sub>	0.29	F <sub>118</sub>	0.23	F <sub>43</sub>	0.13	F <sub>100</sub>	0.003
F <sub>5</sub>	0.89	F <sub>12</sub>	0.39	F <sub>97</sub>	0.29	F <sub>56</sub>	0.21	F <sub>32</sub>	0.13	F <sub>89</sub>	0.003
F <sub>3</sub>	0.89	F <sub>110</sub>	0.39	F <sub>106</sub>	0.28	F <sub>66</sub>	0.21	F <sub>85</sub>	0.12	F <sub>39</sub>	0.003
F <sub>13</sub>	0.82	F <sub>108</sub>	0.39	F <sub>117</sub>	0.28	F <sub>93</sub>	0.21	F <sub>26</sub>	0.12	F <sub>50</sub>	0.003
F <sub>7</sub>	0.79	F <sub>114</sub>	0.38	F <sub>125</sub>	0.28	F <sub>124</sub>	0.21	F <sub>91</sub>	0.12	F <sub>103</sub>	0.08
F <sub>19</sub>	0.74	F <sub>42</sub>	0.35	F <sub>123</sub>	0.28	F <sub>95</sub>	0.20	F <sub>81</sub>	0.12	F <sub>96</sub>	0.05
F <sub>73</sub>	0.71	F <sub>47</sub>	0.35	F <sub>28</sub>	0.28	F <sub>88</sub>	0.20	F <sub>25</sub>	0.12	F <sub>76</sub>	0.05
F <sub>29</sub>	0.70	F <sub>51</sub>	0.35	F <sub>90</sub>	0.28	F <sub>9</sub>	0.19	F <sub>14</sub>	0.12	F <sub>70</sub>	0.04
F <sub>54</sub>	0.63	F <sub>107</sub>	0.35	F <sub>82</sub>	0.25	F <sub>86</sub>	0.19	F <sub>94</sub>	0.10	F <sub>84</sub>	0.04
F <sub>65</sub>	0.60	F <sub>20</sub>	0.34	F <sub>77</sub>	0.25	F <sub>119</sub>	0.18	F <sub>63</sub>	0.10	F <sub>99</sub>	0.04
F <sub>33</sub>	0.57	F <sub>98</sub>	0.32	F <sub>121</sub>	0.25	F <sub>38</sub>	0.18	F <sub>52</sub>	0.09	F <sub>68</sub>	0.04
F <sub>58</sub>	0.55	F <sub>83</sub>	0.32	F <sub>30</sub>	0.25	F <sub>80</sub>	0.18	F <sub>1</sub>	0.09	F <sub>44</sub>	0.03
F <sub>21</sub>	0.55	F <sub>48</sub>	0.30	F <sub>36</sub>	0.25	F <sub>78</sub>	0.18	F <sub>111</sub>	0.08	F <sub>46</sub>	0.03
F <sub>61</sub>	0.54	F <sub>79</sub>	0.30	F <sub>37</sub>	0.25	F <sub>112</sub>	0.17	F <sub>62</sub>	0.08	F <sub>113</sub>	0.03
F <sub>67</sub>	0.53	F <sub>102</sub>	0.30	F <sub>34</sub>	0.24	F <sub>2</sub>	0.16	F <sub>105</sub>	0.08		

Table 3. Mean values of the most important features.

Row	Feature	Female samples	Male samples
1	RMS	0.32	0.53
2	SD	0.30	0.62
3	Variance	0.10	0.25

In this table the mean values of three features [Root Mean Square (RMS), Standard Deviation (SD) and variance] have been calculated for all female and male samples. RMS of vocalization was higher in male than female chickens. These values indicate that the intensity of male's samples vocalization is higher

than of female's. SD and Variance showed signal uniformity. In fact, if the uniformity of signal decreases, the SD and Variance of this signal would be higher (McEnnis *et al.*, 2005). These values indicated that female's vocalization was more uniform and less dispersed than that of the males. This



concept can also be seen in Figure 5.

### SVM Accuracy

The selected features at this stage were used as the SVM inputs. Study data include 360 recordings of hen and cock vocalizations, 70% of which (252 vocalization signal samples) were selected in a completely random fashion for SVM training purposes. The rest (30% or 108 samples) were used for testing the SVM to determine its sexing accuracy. Table 4 shows the performance of SVM for the best features selected from time-and-frequency domain signals. Table 5 shows the performance of SVM based on all-and-best extracted features from approximation and details of DWT signals at the fourth level. The best result was obtained by  $\sigma = 1$ .  $\sigma$  is related to the hyper plane width. The larger  $\sigma$ , the more general hyper plane and the smaller  $\sigma$ , the more local hyper plane (Burges, 1998). Based on results

in Tables 3 and 4, the maximum SVM accuracy was achieved through WT. The highest SVM accuracies in the time, frequency and time-frequency domains were 68.51, 70.37 and 90.74 percent.

Table 6 shows the confusion matrix on the testing data in time, frequency and time-frequency domains. In time domain, SVM wrongfully classified 24 cocks out of 54 as hen and 10 hens out of 54 as cock. In frequency domain, SVM wrongfully classified 18 cocks out of 54 as hen and 14 hens out of 54 as cock. Based on table 6, the best recognition accuracy occurred at the time-frequency domain while using the fourth-level WT, where SVM managed to correctly recognize 6 cocks out of 54 and 4 hens out of 54. In general, by reflecting on Tables 4 and 6, it can be suggested that the sexing problem can be solved with a combination of signal processing, data-mining and artificial intelligent methods.

**Table 4.** The performance of SVM for the best features selected from time and frequency domains.

Domain	Number of inputs features	Representation (RBF)	SVM classifier accuracy (%)	
			Train	Test
Time domain	8	$\sigma = 1$	87.88%	68.75%
		$\sigma = 0.8$	96.97%	65.63%
		$\sigma = 0.6$	98.48%	65.63%
		$\sigma = 0.4$	100%	56.25%
Frequency domain	7	$\sigma = 1$	93.94%	71.88%
		$\sigma = 0.8$	93.94%	68.75%
		$\sigma = 0.6$	99.24%	59.38%
		$\sigma = 0.4$	100%	59.38%

**Table 5.** The performance of SVM based on all-and-best extracted features from approximation and details of DWT signals at the fourth level.

Number of inputs features	Representation (RBF)	SVM classifier accuracy (%)	
		Train	Test
125	$\sigma = 1$	100%	50%
	$\sigma = 0.8$	100%	50%
	$\sigma = 0.6$	100%	50%
	$\sigma = 0.4$	100%	50%
25	$\sigma = 1$	100%	90.63%
	$\sigma = 0.8$	100%	81.25%
	$\sigma = 0.6$	100%	65.63%
	$\sigma = 0.4$	100%	56.25%

**Table 6.** Confusion matrices of SVM for testing data in time, frequency and time-frequency domains.

		Cook	Hen	Sensitivity (%)	Specificity (%)	Total Classification Accuracy (%)	
						Train	Test
Time Domain	Cook	30	24	55.55 %	64.7 %	87.88 %	68.51 %
	Hen	10	44	81.48 %	75 %		
Frequency Domain	Cook	36	18	66.66 %	68.69 %	93.94 %	70.37 %
	Hen	14	40	74.07 %	72 %		
Time-Frequency Domain	Cook	48	6	88.88 %	89.28 %	100 %	90.74 %
	Hen	4	50	92.59 %	92.30 %		

## DISCUSSION

For the study of animal behavior, conservation of avian species, life history and prosperous breeding of birds, gender identification is so important. Gender identification can be done by many techniques such as cloacal examination, laparoscopy and genetic testing. Some of these methods need special equipment and others are invasive and need special laboratories (Richner, 1989, Volodin *et al.*, 2009; Bazzano *et al.*, 2012; Morinha *et al.*, 2012). However, vent sexing is the most common method (Harz *et al.*, 2008), but it needs well-trained experts. Cerit and Avanus (2007) identified avian gender by using DNA typing methods which can perform avian gender determination in as little as 24 hours (Cerit and Avanus, 2007) but this time it is longer for gender determination. Fowl gender determination by using vocalization is a rapid, accurate, and noninvasive procedure which can be used in poultry industry. Some researchers have also introduced an intelligence method. Volodin *et al.* (2015) identified bird's gender by analysis of computer images of vocalization. In their study, the potential of noninvasive

sexing for adults and chicks was compared and was concluded that the potential for voice-based sexing of chicks seems to be very limited (Volodin *et al.*, 2015). In the present research, an intelligence method has been designed based on signal processing and data mining methods which can identify one-day-old fowl's gender (Ross 380) with the accuracy of 90.74%.

The results of this research indicate that the wavelet transform outperformed other signal processing methods. Other authors also reported that WT performed relatively better than other signal processing methods (Akin, 2002; Peng *et al.*, 2005). In the another research, Turkoglu *et al.* (2003) have also presented a pattern recognition based on wavelet neural network which classified the Doppler signal of heart valve disease with accuracy of 94 percent (Turkoglu *et al.*, 2003). In the present research, Support vector machine was used as a classifier for avian gender determination. SVM is a powerful classifier and other researches have also confirmed the performance of SVM in classification tissues. Huang *et al.* (2009) have also confirmed that the performance of SVM is better than of KNN to develop an automated frog species detection using vocalization characteristics. In their research, the SVM-



and-KNN accuracy were obtained 90.30 and 89 percent, respectively (Huang *et al.*, 2009). In another study, Acevedo *et al.* (2009) have also used three classification methods (SVM, DT and LDA) to identify and classify 3 bird and 9 frog species based on their vocalization in which SVM accuracy was better than another classifier accuracy. In this study, maximum accuracies of SVM, DT and LDA were obtained 95, 89 and 71 percent, respectively (Acevedo *et al.*, 2009).

Using IDE-based selection of best features positively affected the SVM accuracy. This is in agreement with findings of other papers (Manimala *et al.*, 2011). Lee *et al.* (2015) detected pig wasting disease by using support vector machine and acoustic features. In this research, 60 statistical parameters were extracted as signal indexes and the best features (RMS, Max Pitch, PSD, Peak frequency) were selected by using Acoustic Feature Subset Selection Algorithm method which was used as a classifier input. The SVM's accuracy in detection of pig wasting disease was obtained 97 and 98.4 percent for all features and best features, respectively. (Lee *et al.*, 2015). Additionally, the present research also confirms the positive effect of selecting the best features on the classification accuracy.

## CONCLUSIONS

The study analyzed vocalizations generated by male and female hatchlings in a bid to develop an intelligent fowl sexing system. For this purpose, the chicken's Ross 380 was studied and their vocalization was analyzed in three time, frequency and time-frequency domains. In the testing phase, the best SVM accuracy belonged to time-frequency domain signals. The study results showed that intelligent practices can be useful and efficient for vocalization-based bird sexing. This method can be done for another avian order and a comprehensive sexing device can be designed.

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## REFERENCES

1. Acevedo, M. A., Corrada-Bravo, C. J., Corrada-Bravo, H., Villanueva-Rivera, L. J. and Aide, T. M. 2009. Automated Classification of Bird and Amphibian Calls Using Machine Learning: A Comparison of Methods. *Ecol. Inform.*, **4(4)**: 206-214.
2. Akin, M. 2002. Comparison of Wavelet Transform and FFT Methods in the Analysis of EEG Signals. *J. Med. Syst.*, **26(3)**: 241-247.
3. Bagheri, B., Ahmadi, H. and Labbafi, R. 2010. Application of Data Mining and Feature Extraction on Intelligent Fault Diagnosis by Artificial Neural Network and K-Nearest Neighbor. *XIX International Conference on Electrical Machines, ICEM 2010*.
4. Banakar, A. and Azeem, M. F. 2008. Artificial Wavelet Neuro-Fuzzy Model Based on Parallel Wavelet Network and Neural Network. *Soft. Comput.*, **12(8)**: 789-808.
5. Banakar, A., Sadeghi, M. and Shoushtari, A. 2016. An intelligence Device for Diagnosing Avian Disease: Newcastle, Bronchitis and avian Influenza. *Comput. Electron. Agr.*, **127**: 744 – 753.
6. Bazzano, G., Leche, A., Martella, M. B. and Navarro, J. L. 2012. Efficiency of the Cloacal Sexing Thechnique in Greater Rhea Chicks (*Rhea americana*). *Birt. Poult. Sci.*, **53(3)**: 394-6.
7. Burges, C. J. 1998. A Tutorial on Support Vector Machines for Pattern Recognition. *Data. Min. Knowl. Discov.*, **2(2)**: 121-167.
8. Cerit, H. and Avanus, K. 2007. Sex Identification in Avian Species Using DNA Typing Methods. *Worlds. Poult. Sci. J.*, **63(01)**: 91-100.
9. Cortes, C. and Vapnik, V. 1995. Support-Vector Networks. *Mach. Learn.*, **20(3)**: 273-297.
10. Dubiec, A. and Zagalska-Neubauer, M. 2006. Molecular Techniques for Sex

- Identification in Birds. *Biol. Lett.*, **43(1)**: 3-12.
11. Duhamel, P. and Vetterli, M. 1990. Fast Fourier Transforms: A Tutorial Review and a State of the Art. *Signal. Process.*, **19(4)**: 259-299.
  12. Gong, W., Obikawa, T. and Shirakashi, T. 1997. Monitoring of Tool Wear States in Turning Based on Wavelet Analysis. *JSME Int. J. Serie. C.*, **40(3)**: 447-453.
  13. Griffiths, R. 2000. *Sex Identification in Birds*. Seminars in Avian and Exotic Pet Medicine, Elsevier.
  14. Harz, M., Krause, M., Bartels, T., Cramer, K., Rösch, P. and Popp, J. 2008. Minimal Invasive Gender Determination of Birds by Means of UV-Resonance Raman Spectroscopy. *Anal. Chem.*, **80(4)**: 1080-1086.
  15. Huang, C. -J., Yang, Y. -J., Yang, D. -X. and Chen, Y. -J. 2009. Frog Classification Using Machine Learning Techniques. *Expert. Syst. Appl.*, **36(2)**: 3737-3743.
  16. Iyer, S., Sinha, S. K., Tittmann, B. R. and Pedrick, M. K. 2012. Ultrasonic Signal Processing Methods for Detection of Defects in Concrete Pipes. *Automat. Constr.*, **22**: 135-148.
  17. Joachims, T. 1998. Text Categorization with Support Vector Machines: Learning with Many Relevant Features. *Mach. Learn.: ECML*, **98**: 137-142.
  18. Khazaei, M., Ahmadi, H., Omid, M., Banakar, A. and Moosavian, A. 2013. Feature-Level Fusion Based on Wavelet Transform and Artificial Neural Network for Fault Diagnosis of Planetary Gearbox Using Acoustic and Vibration Signals. *INSIGHT*, **55(6)**: 323-330.
  19. Lee, J., Jin, L., Park, D., Chung, Y. and Chang, H. 2015. Acoustic Features for Pig Wasting Disease Detection. *Inf. Process. Manage.*, **6(1)**: 37-46.
  20. Lei, Y., He, Z. and Zi, Y. 2008. A New Approach to Intelligent Fault Diagnosis of Rotating Machinery. *Expert. Syst. Appl.*, **35(4)**: 1593-1600.
  21. Manimala, K., Selvi, K. and Ahila, R. 2011. Hybrid Soft Computing Techniques for Feature Selection and Parameter Optimization in Power Quality Data Mining. *Appl. Soft. Comput.*, **11(8)**: 5485-5497.
  22. Malago, W., Medaglia, A., Matheucci, E. and Henrique Silva, F. 2005. New PCR Multiplexes for Sex Typing of Ostriches. *Braz. J. Biol.*, **65**: 743-745.
  23. Misiti, M., Misiti, Y., Oppenheim, G. and Poggi, J. -M. 1996. *Wavelet Toolbox*. MathWorks Inc., Natick, MA.
  24. McEnnis, D., McKay, C., Fujinaga, I., Depalle, P. 2005. jAudio: A Feature Extraction Library. *Proceedings of the International Conference on Music Information Retrieval*, PP. 600-603.
  25. Morinha, F., Cabral, J. A. and Bastos, E. 2012. Molecular Sexing of Birds: a Comparative Review of Polymerase Chain Reaction (PCR)-Based Methods. *Theriogenol.*, **78**: 703-714.
  26. Peng, Z., Tse, P. W. and Chu, F. 2005. A Comparison Study of Improved Hilbert-Huang Transform and Wavelet Transform: Application to Fault Diagnosis for Rolling Bearing. *Mech. Syst. Signal. Pr.*, **19(5)**: 974-988.
  27. Richner, H. 1989. Avian Laparoscopy as Field Technique for Sexing Birds and an Assessment of Its Effects on Wild Birds. *J. Field. Ornithol.*, **60**: 137-142.
  28. Sadeghi, M., Banakar, A., Khazaei, M. and Soleimani, M. R. 2015. An Intelligent Procedure for the Detection and Classification of Chickens Infected by *Clostridium perfringens* Based on Their Vocalization. *Braz. J. Poult. Sci.*, **17**: 537-544.
  29. Saravanan, N. and Ramachandran, K. 2010. Incipient Gear Box Fault Diagnosis Using Discrete Wavelet Transform (DWT) for Feature Extraction and Classification Using Artificial Neural Network (ANN). *Expert. Syst. Appl.* **37(6)**: 4168-4181.
  30. Scholkopf, B., Sung, K.-K., Burges, C. J., Girosi, F., Niyogi, P., Poggio, T. and Vapnik, V. 1997. Comparing Support Vector Machines with Gaussian Kernels to Radial Basis Function Classifiers. *IEEE T. Signal. Proces.*, **45(11)**: 2758-2765.
  31. Singla, A., Patra, S. and Bruzzone, L. 2014. A Novel Classification Technique Based on Progressive Transductive SVM Learning. *Pattern. Recogn. Lett.*, **42**: 101-106.
  32. Turkoglu, I., Arslan, A. and Ilkay, E. 2003. An Intelligent System for Diagnosis of the Heart Valve Diseases with Wavelet Packet Neural Networks. *Comput. Biol. Med.*, **33(4)**: 319-331.



33. Tikhonov, A. V. 1986. Acoustic Signalization and Ecology of Birds. Moscow University Press, Moscow, 236 PP.
34. Volodin, I., Kaiser, M., Matrosova, V., Volodina, E., Klenova, A., Filatova, O. and Kholodova, M. 2009. The Technique of Noninvasive Distance Sexing for Four Monomorphic *Dendrocygna Whistling Duck* Species by Their Loud Whistles. *Bioacoust.*, **18**: 277-90.
35. Volodin, I., Volodina, E., Klenova, A. and Matrosova, V. 2015. Gender Identification Using Acoustic Analysis in Birds without External Sexual Dimorphism. *Avian. Res.*, **6**: 6-20.
36. Wang, X., Makis, V. and Yang, M. 2010. A Wavelet Approach to Fault Diagnosis of a Gearbox under Varying Load Conditions. *J. Sound. Vib.*, **329(9)**: 1570-1585.
37. Wu, J. -D. and Liu, C. -H. 2009. An Expert System for Fault Diagnosis in Internal Combustion Engines Using Wavelet Packet Transform and Neural Network. *Expert. Syst. Appl.*, **36(3)**: 4278-4286.
38. Yang, J., Yang, J. Y., Zhang, D. and Lu, J. F. 2003. Feature Fusion: Parallel Strategy vs. Serial Strategy. *Pattern. Recogn.*, **36**: 1369-1381.
39. Zhan, Y. and Makis, V. 2006. A Robust Diagnostic Model for Gearboxes Subject to Vibration Monitoring. *J. Sound. Vib.*, **290(3)**: 928-955.
40. Zhu, K., Wong, Y. S. and Hong, G. S. 2009. Wavelet Analysis of Sensor Signals for Tool Condition Monitoring: A Review and Some New Results. *Int. J. Mach. Tool. Manu.*, **49(7)**: 537-553.

## تشخیص جنسیت ماکیان با استفاده از روش های داده کاوی سیگنال های صوتی و ماشین بردار پشتیبان

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### چکیده

امروزه تعیین جنسیت بسیاری از پرندگان، از جمله پرندگان زینتی، بسیار دشوار است و نیازمند آزمایش های گران قیمت و تجهیزات پیشرفته می باشد. در این پژوهش سامانه ای هوشمند جهت تشخیص جنسیت جوجه مرغ ها و جوجه خروس ها بر اساس صدای آن ها معرفی شده است. برای نیل به این هدف صدای جوجه مرغ ها و خروس های یک روزه توسط یک میکروفن و کارت صدا برداری ضبط شد. به منظور دسترسی به اطلاعات دقیق تر صداهای ضبط شده، سیگنال های صدای حوزه زمان توسط تبدیل فوریه سریع و تبدیل موجک گسسته به ترتیب به حوزه های فرکانس و زمان-فرکانس انتقال داده شدند. در مرحله داده کاوی از سیگنال های هر سه حوزه ۲۵ ویژگی آماری استخراج شد. برای انتخاب بهترین ویژگی ها و همچنین کاهش ابعاد ورودی طبقه بند از روش IDE استفاده گردید. با استفاده از ماشین بردار پشتیبان با جدا کننده تابع پایه شعاعی گوسی (GRBF) به طبقه بندی سیگنال های صدای جوجه ها پرداخته شد و این طبقه بند با استفاده از ویژگی های انتخاب شده از سیگنال های حوزه زمان، فرکانس و زمان-فرکانس، به منظور تشخیص و طبقه بندی جوجه های نر و ماده به کار گرفته شد. اطلاعات فرکانسی و زمان-فرکانسی سیگنال صدا به ترتیب با استفاده از تبدیل فوریه و تبدیل موجک استخراج

گردیدند. بیشینه دقت ماشین بردار پشتیبان در حوزه زمان، فرکانس و زمان-فرکانس به ترتیب ۶۸/۷۵، ۷۱/۸۸ و ۹۰/۶۳ درصد بدست آمد. نتایج نشان می‌دهند سامانه طراحی شده به منظور تشخیص جنسیت جوجه مرغ از جوجه خروس موفق عمل نموده است. همچنین نتایج تصریح می‌کنند که با استفاده از روش‌های پردازش سیگنال و انتخاب ویژگی می‌توان به بیشینه دقت طبقه‌بندی دسترسی یافت.