Recognition of Poultry Disease in Real Time using Extreme Learning Machine

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Abstract-Disease recognition is very important for successful poultry management. This paper aims to focus on real time avian pox disease recognition in poultry. In this paper, two main soft computing approaches were employed such as Support Vector Machine with Gaussian Radial Basis Function (SVM (GRBF)) and Extreme learning Machine (ELM) to detect the disease. Texture features are extracted using Gray Level Co-Occurrence Matrix (GLCM) and mean, standard deviation, kurtosis and skewness are the statistical features. The confusion matrix and Root Mean Square Error (RMSE) were used to evaluate the performance of the SVM (GRBF) and ELM. The results showed that ELM classifier provides better accuracy than SVM (GRBF).

Keywords- Avian pox disease, SVM (GRBF), ELM, GLCM, RMSE

I. Introduction

India is the third largest egg producer in the world [1]. To retain the position, to achieve the high rank and to increase egg production, we must prevent the chicken from the disease. The diseases which often affect the chicken are avian pox disease which will drop egg production. The symptoms of avian pox disease are lesions on the head, combs and wattles. Lesions will be a watt- like appearance, yellow to dark brown in color. It affects the featherless areas of the body [2]. This paper focus on real time recognition of avian pox disease. For that we acquired an image using wireless IR CCD camera. The acquired image is having some kind of random noise namely salt and pepper noise. The most popular method to removing impulse noise is median filter (MED) [3] because of its effectiveness and high computational efficiency. In this paper we used median filter to remove impulse noise. After removing the noise, statistical features were extracted using mean, standard deviation, kurtosis and skewness and GLCM were also extracted. The results of feature extraction were given as an input to classifiers. In this paper Support Vector Machine with Gaussian Radial Basis Function and Extreme Learning Machine were employed to detect the disease.

2. Related Work

Ilias Maglogiannis et al., [4] proposed an automated diagnosis system for the identification of heart valve diseases based on the Support Vector Machine (SVM) classification of heart sounds. SVM performs a very difficult diagnostic and it classifies the heart sound is healthy or not accurately. Z. Zidelmal et al., [5] proposed a support vector machine for ECG beat classification. They used a MIT-BIH arrhythmia database and used set of features are frequency information, RR intervals, QRS morphology and AC power of QRS detail coefficients is exploited to characterize each beat. The accuracy is 97.2 % with no rejection. Oral cancer is classified using support vector machine was proposed by Anuradha .K et al., [6]. In this paper features were extracted using Gray Level Co-Occurrence Matrix (GLCM). The accuracy of the proposed system is 92.5 %. T. Rumpf et al., [7] proposed an early detection and classification of plant diseases with Support Vector Machines based on hyperspectral reflectance. It detects the sugar beets leaves are diseased or not, and this paper differentiate the diseases between Cercospora leaf spot, leaf rust and powdery mildew and the proposed system identifies the diseases before the symptoms become visible. The classification is done by using support vector machine with a radial basis function as a kernel. The accuracy of the classification is 97 %. Chesner Désir et al., [8] designed an algorithm for distal lung image is pathological or normal using SVM classification with texture descriptors. The accuracy of the classification is 90 to 95%.

Runxuan Zhang et al., [9] proposed and construct an ELM algorithm for fast and efficient classification method to diagnosis a multicategory cancer problem based on microarray data is presented. They used three types of dataset such as GCM data set, the Lung data set, and the Lymphoma data set. The classification methods such as ANN, Linder's SANN, and Support Vector Machine methods like SVM-OVO and Ramaswamy's SVM-OVA and ELM were used. Among the above classifiers ELM gives comparable and better classification accuracies with reduced training time than the other classifier.

With the above literature, avian pox disease is identified with help of the classification methods such as SVM (GRBF) and ELM. This paper analyzed which classification method gives better result.

III. Materials and Method

In order to detect avian pox disease, hen images were taken and image processing techniques applied such as preprocessing (noise removal), feature extraction (GLCM and statistical features) and classification. The overall disease detection method described as in the following section. Figure 1 shows the block diagram of proposed approach.

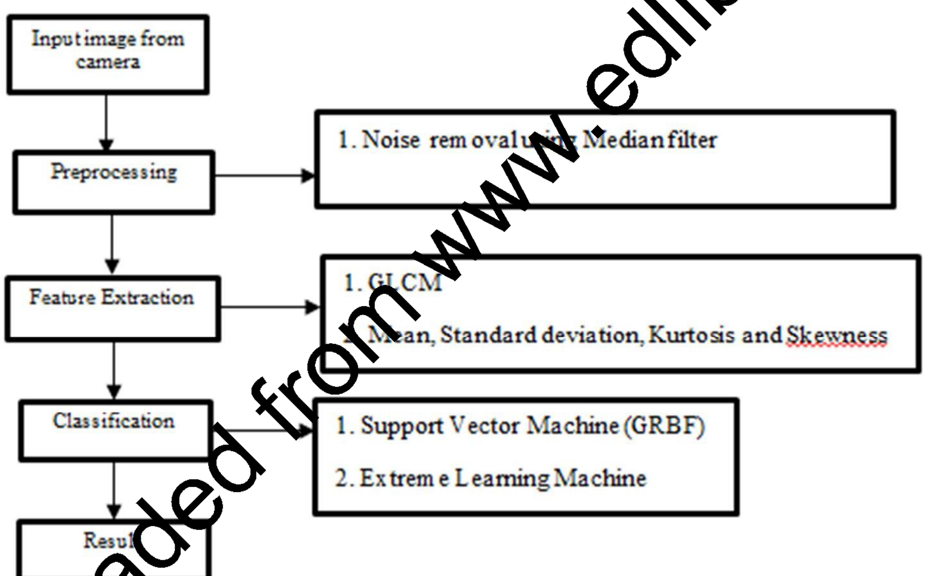

Figure 1. Block diagram of proposed approach.

A. Image acquisition

A machine vision system was applied to acquire the hen images. A wireless IR (Model: IP-702) CCD camera was fixed with raspberry pi along with a proper lighting system and this setup was placed above 50 cm with grain feeder trolley. While giving the feed to the hen this setup captures an image as a video and it was converted into number of frames using image processing techniques applied and it detects the disease.

Median Filter

The acquired image is having random noise namely salt and pepper noise and this is removed using median filter. It is a higher statistical nonlinear filter used to remove the impulse noise. It replaces the value of the center pixel, by the median of the gray levels in the image area enclosed by the filter.

B. Feature Extraction

Texture is the one of the important feature for identifying the objects in an image. In this paper texture features are extracted using most popular method called Gray Level Co-occurrence Matrix (GLCM). GLCM is a matrix which describes the frequency of one gray level appearing in a specified spatial linear relationship with another gray level within the area of investigation. It extracts the second order statistical texture feature from an image. It is also known as gray level spatial dependence matrix. Haralick et al., [10] extracted a fourteen texture features from GLCM. In this paper five important features which are contrast, entropy, energy, correlation and homogeneity were extracted from GLCM. And the statistical features such as mean, standard deviation, kurtosis and skewness were extracted.

Table I: Extracted features

GLCM features	Formula	Statistical features	Formula
Contrast	$\sum_{i,j} \|i-j\|^2 p(i,j)$	Mean	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$
Energy	$\sum_{i,j} p(i,j)^2$	Standard Deviation	$s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$
Entropy	$\sum_{i,j} p(i,j) log_2 p(i,j)$	Kurtosis	$k = \frac{E(x-\mu)^4}{\sigma^4}$
Homogeneity	$\sum_{i,j} \frac{p(i,j)}{1+\|i-j\|}$	Skewness	$s = \frac{E(x-\mu)^3}{\sigma^3}$
Correlation	$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j}$		

C. Support Vector Machine (GRBF)

The Support Vector Machine (SVM) is a widely used for classification and regression analysis. It is a supervised learning models associated with learning algorithms that analyze data and recognize the patterns. It was first introduced in the1992 by Boser, Guyon, and Vapnik [11]. An input space represented by $X = x_1, x_2, \ldots\ldots x_d$ is classified to output space, which is represented by $C_1, C_2, \ldots C_j$. To classify the data in input space, SVM tries to find the optimal separating hyperplane among all possible separating hyper planes. So, it maximizes the margin and obtains good generalization ability. A separating hyperplane is a linear function that can separate the training data into two classes (Class1=+1 and Class2=–1) in the separable feature space.The following function describes a separating hyperplane function

$D(x) = (\omega * x) + \omega_0$ ------ (1)

All separating hyperplanes must satisfy the following equation:

$Y_i[(\omega * x_i) + \omega_0] \geq 1 \quad i = 1, \ldots\ldots n$ -------- (2)

In this paper we used the kernel function while developing SVM model. Gaussian kernels are used to modify the input space into high dimensional feature space. The kernels having the following equation.

$K(x_i, x_j) = e^{-\|x_i - x_j\|^2/2\sigma^2}$ (Gaussian radial basis function kernel) ----- (3)

The values of sigma (σ) differentiate the several radial basis functions used to providing different hyper planes for the classification of data during the Support Vector Machines' calculations.

D. Extreme Learning Machine

Extreme Learning Machine (ELM) is a simple learning algorithm for Single – Hidden Layer Feed Forward Neural network (SLFN). This method is based on the Moore – Penrose generalized inverse providing the minimum Least – Squares solution of general linear systems [12].

SLFNs (with N hidden nodes) with randomly chosen input weights and hidden layer biases (and such hidden nodes can thus be called random hidden nodes) can exactly learn N distinct observations. For N arbitrary distinct samples (X_i, t_i) where $Xi = [x_{i1}, x_{i2}, \ldots x_{in}]$T ∈ R^n and $t_i = (t_{i1}, t_{i2}, \ldots t_{im})^T \in R^m$, standard SLFNS with $\widetilde{N}$ hidden nodes and activation function g(x) are mathematically modeled as

$\sum_{i=1}^{\widetilde{N}} \beta_i\ g_i\ (X_j) = \sum_{i=1}^{\widetilde{N}} \beta_i g(w_i.X_j + b_i) = oj,$

J = 1, ... ,N,

Where $w_i = [w_{i1}, w_{i2}, \ldots w_{in}]^T$ is the weight vector connecting the i^{th} hidden node and the input nodes, $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ is the weight vector connecting the i^{th} hidden node and the outputs nodes, and b_i is the threshold of the i^{th} hidden node. $w_i.X_j$ Denotes the inner product of w_i and X_j. The outputs nodes are linear.

That standard SLFNs with $\widetilde{N}$ hidden nodes with activation function $g(x)$ can approximate these N samples with zero error means that $\sum_{j=1}^{\widetilde{N}} \|o_j - t_j\| = 0$, i.e., there exist β_i , w_i, and b_i such that

$\sum_{i=1}^{\widetilde{N}} \beta_i g(w_i.X_j + b_i) = t_j$, j = 1,..., N

The above N equations can be written compactly as

Hβ = T,

Where,

$$H(w_1, \ldots w_{\widetilde{N}}, b_1, \ldots b_{\widetilde{N}}, X_1, \ldots X_N) = \begin{bmatrix} g(w_1.X_1 + b_1) & \cdots & g(w_{\widetilde{N}}.X_1 + b_{\widetilde{N}}) \\ \vdots & \ldots & \vdots \\ g(w_1.X_N + b_1) & \cdots & g((w_{\widetilde{N}}.X_N + b_{\widetilde{N}}) \end{bmatrix}_{NX\widetilde{N}}$$

$$\beta = \begin{bmatrix} \beta_1{}^T \\ \vdots \\ \beta_{\widetilde{N}}{}^T \end{bmatrix}_{\widetilde{N}Xm} \text{ and } T = \begin{bmatrix} t_1{}^T \\ \vdots \\ t_N{}^T \end{bmatrix}_{NXm}$$

Here, H is called the hidden layer output matrix of the neural network; the i^{th} column of H is the i^{th} hidden node output with respect to inputs $X_1, X_2, \ldots X_N$. If the activation function g is infinitely differentiable we can prove that the required number of hidden nodes $\widetilde{N} \leq$ N.

Algorithm of ELM:

Given a training set $\aleph = \{(X_i, t_i) | X_i \in R^n, t_i \in R^m, i = 1, \ldots, N\}$, activation function $g(x)$ and hidden node number $\widetilde{N}$

Step 1: Randomly assign input weight w_i and bias b_i , $i = 1, \ldots \widetilde{N}$

Step 2: Calculate the hidden layer output matrix H.

Step 3: Calculate the output weight β

$\beta = H^{\dagger}T$

Where $T = [t_1, \ldots . t_N]^T$

IV. Results and Discussion

The hen samples used in this paper were collected from one of the poultry farm in Namakkal district, Tamil Nadu, India. There are 110 data were collected. From which 65 data for training purpose and 45 for data used for testing purpose. The experiments are done in MATLAB 7.10 version released in the year 2010. In this paper, feature extraction results were given as an input to Support Vector Machine classifier and Extreme learning Machine. The input image, affected with avian pox disease, gray image and noise filtered image using median filter are shown in figure 2.

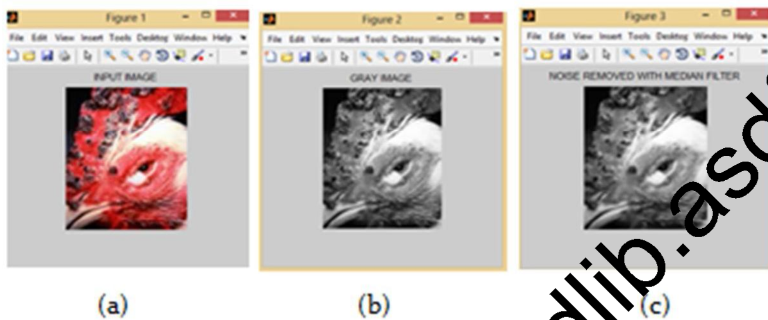

Figure 2. (a) Input image, (b) Gray image, (c) noise filtered image using median filter

Texture features and statistical features were extracted and their results were given to the classifiers. In this paper confusion matrix and root mean square error were served to evaluate the performance of the Support vector machine with Gaussian Radial Basis Function and extreme learning machine.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}; \quad Specificity = \frac{TN}{TN+FP}; \quad Sensitivity = \frac{TP}{TP+FN}$$

Table II: Confusion matrix of svm (grbf) and elm

Method	Accuracy (%)	Specificity (%)	Sensitivity (%)
SVM(GRBF)	92.77	94.93	90.8
ELM	95.01	96.59	93.75

The confusion matrix Graph for SVM (GRBF) and ELM was shown in the figure 3.

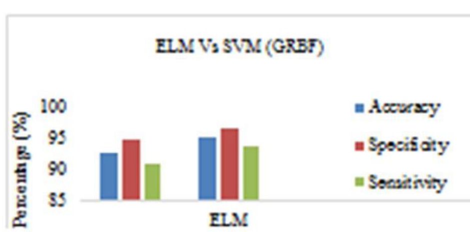

Figure 3. Confusion matrix Graph for SVM (GRBF) and ELM

From figure 3, it was observed that ELM accuracy was 95.01 % and 92.77 % for SVM (GRBF). The specificity value of ELM was 96.59 % and 94.93 % for SVM (GRBF) and sensitivity of ELM was 93.75 % and for SVM (GRBF) was 90.8 %. From the result of the confusion matrix, ELM provides better accuracy.

Table III: Root mean square error of svm (grbf) and elm

Method	RMSE (Training)	RMSE (Testing)
SVM(GRBF)	0.28	0.3
ELM	0.12	0.15

The RMSE value of SVM (GRBF) for training was 0.28 and for testing 0.3. A very small value of RMSE for ELM was 0.12 for training and REMSE of 0.15 for testing. The following figure 4 showed the RMSE of SVM (GRBF) and ELM.

Figure 4. Root Mean Square Error of SVM (GRBF) and ELM

The time is the very important factor while choosing the classifier. The training and testing time for ELM classifier is lesser than the SVM (GRBF) was shown in table 4.

Table IV: The training and testing time for of svm (grbf) and elm

Method	Training time (s)	Testing time (s)
SVM (GRBF)	2.21	1.56
ELM	1.02	0.98

The training time for SVM (GRBF) was 2.21 seconds and testing time was 1.56. The training time of ELM was 1.02 seconds and 0.98 seconds for testing.

The results observed from table II, table III and table IV, it was observed that ELM classifies avian pox disease better than SVM (GRBF) with less training and testing time.

V. Conclusion

In this paper, Extreme Learning Machine (ELM) and Support Vector Machine with Gaussian Radial Function classifier is used to classify an avain pox disease. Texture features were extracted using Gray Level Co-Occurrence Matrix and statistical features were extracted using mean, standard deviation, kurtosis and skewness. Based on the confusion matrix results, ELM gives higher accuracy against the SVM (GRBF). The root mean square error value was very small for ELM. And the training time of ELM is very less than the SVM (GRBF). According to the results given above, it was clearly obvious that ELM classifies the disease better than SVM (GRBF).

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