Respiratory Disease Identification of Chicken Voiceprint Based on Audio Processing and Machine Learning Technology

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ABSTRACT

This study develops a device using audio processing and machine learning to identify and monitor respiratory diseases in poultry, improving automation in health monitoring, enhancing production efficiency, reducing disease transmission risk, lowering technical barriers, and optimizing farmers’ management. Achieves a 91.6% accuracy in chicken respiratory disease vocalization recognition.

1 Introduction

The poultry industry plays a vital role in the global food supply chain. To address environmental and pathogen challenges, sustainable poultry farming methods are sought. Enclosed poultry housing systems are widely used, but daily farmer entry increases disease spread risks. To monitor poultry health effectively, farmers employ environmental and body sensing technologies. Contact-based sensing detects physiological indicators through direct poultry contact. Non-contact-based sensing[1-3], like imaging and sound, captures data remotely. Sound sensing[4] is valuable for identifying respiratory diseases by analyzing specific sound patterns and vocal characteristics[5]. This study proposes a machine learning-based chicken respiratory disease recognition process using audio processing as shown in the Fig. 1, enhancing sound quality and automating data collection in commercial poultry houses. It is compared with human auditory observations by farmers.

![](Fig. 1. Overall research workflow architecture)

2 Material and method

2.1 Hardware architecture

In order to collect and build a chicken respiratory disease identification model, we set up an embedded system (Jetson Nano, NVidia, USA) as a computing unit, and connected a directional microphone (AT9947CM, Audio-Technica, Japan). Collection of abnormal health calls in commercial poultry houses and animal experiments. In animal experiments, we additionally added a camera (C920, Logitech, Swiss) as shown in Fig. 2 to improve the accuracy of voiceprint marking.

![](Fig. 2. (a) Equipment component configuration diagram. The entire equipment is equipped with dustproof and waterproof measures. (b) Equipment exterior image. A camera is additionally integrated into the equipment used in challenge trials.

2.2 Audio digital signal processing

To improve the clarity of animal sound recordings, we combined two noise reduction methods: a 4th order Butterworth bandpass filter and spectral gating algorithm. The Butterworth filter has a smooth frequency response curve in Fig. 3, effectively filtering out unwanted low and high-frequency noise to enhance the signal-to-noise ratio. Additionally, we employed spectral gating as a secondary noise reduction technique, adapting to the estimated background noise and statistical characteristics of the audio data. In commercial poultry farms, audio segmentation is crucial for analysis. We used the VAD (Voice Activity Detection) algorithm to segment the recorded audio data into individual chicken vocalizations. VAD analyzes the energy and frequency features of the sound signal, identifying periods of sound activity and non-sound activity. These methods improve the clarity and recognition of the animal sounds, enabling focused analysis and identification of chicken
vocalizations, thus enhancing the accuracy of respiratory disease recognition.

Fig. 3. Butterworth frequency and phase response curve

2.3 Voiceprint Recognition Machine Learning Model

In this experiment, we collected normal and abnormal vocalizations from chickens during the poisoning test and used time and frequency characteristics to classify these vocalizations. Each vocalization segment was transformed into a spectrogram and visually analyzed to label them as normal or abnormal. To further analyze the data, we utilized the openSMILE audio processing tool to extract vocal fingerprint features, including statistical features in the time and frequency domains, as well as speech-based features. These features provide rich information about the sound, facilitating subsequent analysis and recognition. Next, we employed machine learning methods to classify the extracted vocal fingerprint features. Common classifiers such as Support Vector Machines (SVM) and Bayesian classifiers were compared. SVM is a supervised machine learning classifier that maps data points to a high-dimensional feature space and identifies the optimal hyperplane to differentiate between different classes of data. Bayesian classifiers are based on Bayes’ theorem and conditional probability for classification. Finally, we involved farmers from commercial poultry farms in human ear recognition to compare the actual recognition performance.

2.4 Experimental field

In this study, we selected two experimental fields to test and validate our proposed method for identifying respiratory diseases in chicken voiceprints. A respiratory disease challenge test was conducted at the Veterinary Research Center of National Chung Hsing University to obtain the sound information of chickens infected with respiratory diseases. Use exhaust fans to control the air circulation in the test area, and place a dehumidifier to adjust the ambient humidity at the same time. In addition, we have installed ambient temperature, humidity and carbon dioxide sensors to monitor and adjust environmental parameters to ensure the stability of the environment. We challenged two common respiratory diseases, Infectious bronchitis (IB) and Infectious coryza (IC), respectively, against red-feathered native chickens. At the age of about 3 weeks, the chickens were divided into an experimental group and a control group, each about 30-35, and the challenge test was carried out for the experimental group. At this stage, we calculated the median infectious dose (EID50) as the basis and set it as 100 μl each time. The way of attacking poison includes eye and nose. After the completion of the IB challenge project, we conducted the IC challenge experiment about two weeks after the veterinarian confirmed that the symptoms had completely dissipated. The challenge dose was 10⁸ CUF (colony-forming units)/100 μl each time, and it was injected into the suborbital sinus. It is found in practical experience that when chickens are infected with respiratory diseases, there will be a large elongated chicken cry, which is consistent with previous literature. At the same time, there is a big difference between chicken rales and normal healthy sounds, as shown in Fig. 4, so we will build a training data set for this type of sound and the general healthy sound of chickens.

Another experimental site is Changhua Linggang Livestock Farm. The size of the site is 80mx23m. The target is also red-feathered native chickens. The male and female breeding areas are divided into two sides, and the total number of chickens falls to 18,000. We also use embedded systems for sound collection on this site and regularly record chicken sound in commercial poultry houses. These calls will be used for subsequent digital signal processing and model building. These two experimental fields will provide different environments and scenarios to verify the efficiency and accuracy of our proposed chicken voiceprint-based respiratory disease identification method.

Fig. 4. (a) Health chicken voice spectrogram (b) Sick chicken rale voice spectrogram

3 Results and discussion

3.1 Microphone performance test

In order to effectively detect the degree of signal attenuation of chicken crowing at a distance from the
microphone, we conducted a performance test of the microphone, as shown in Fig. 5, at angles of 0°, 90°, and 180° to the gun-type microphone receiving port. Carry out sound reception, as can be seen in the picture, the overall attenuation is about 5-8dB at a distance of 250 cm.

Fig. 5. Microphone directivity and intensity decay

3.2 Sound digital signal processing results

After the noise reduction process, we have successfully improved the quality of the sound signal, removed unnecessary noise, and made the subsequent analysis and identification work more accurate and reliable. As shown in Figure 6.

Fig. 6. (a) 3D spectrogram of the raw audio signal captured by the microphone (b) 3D spectrogram of the preprocessed digital audio signal captured by the microphone

After the noise reduction process, it can be seen that the background noise has been effectively removed, and the crowing of the chicken has become much clearer. After noise reduction, cutting with VAD, the cutting effect is shown in Fig. 7. The sliced archive allows for a more accurate classification of chicken calls.

Fig. 7. Voice activity detection signal extraction illustration

3.3 Identification model performance

In this study, the collected data samples were manually labeled to divide the sounds into two categories: normal calls and abnormal calls. The content of the data is shown in Table 1, and then the training of the classification model is carried out, in which there are 400 calls for normal calls and 450 calls for abnormal calls.

<table>
<thead>
<tr>
<th>Chicken breed</th>
<th>Sound type</th>
<th>Sound data source</th>
<th>Amount (record)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red feather chicken</td>
<td>Normal chicken voice</td>
<td>Commercial chicken coop</td>
<td>250</td>
</tr>
<tr>
<td>SPF layer</td>
<td>Normal chicken voice</td>
<td>Challenge trial</td>
<td>100</td>
</tr>
<tr>
<td>Red feather chicken</td>
<td>Normal chicken voice</td>
<td>Challenge trial</td>
<td>50</td>
</tr>
<tr>
<td>SPF layer</td>
<td>Rale</td>
<td>Challenge trial</td>
<td>150</td>
</tr>
<tr>
<td>Chicken abnormal voice</td>
<td>Abnormal voice &amp; rale, coughing, sneezing</td>
<td>challenge trial</td>
<td>300</td>
</tr>
</tbody>
</table>

Table. 1. Training data

After model training through the voiceprint training data set, the performance of different classifiers SVM and Bayes in identifying chicken respiratory diseases is shown in Table 2. Later, we used openSMILE to extract the 384-dimensional features of the sound. These features cover the time-domain, frequency-domain and time-frequency properties of sound.

Table. 2. Model Performance

<table>
<thead>
<tr>
<th>Model type</th>
<th>Model performance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Precision</td>
</tr>
<tr>
<td>SVM</td>
<td>91.6%</td>
</tr>
<tr>
<td>Bayes</td>
<td>80.4%</td>
</tr>
</tbody>
</table>

3.4 Field test results

We identified unknown calls received before and after the challenge. It can be seen from Fig. 8(a) that the abnormal calls began to rise 10 hours after the challenge.
at the age of 27 days. In addition, in the IC challenge test, as shown in Figure 8(b), the number of calls reached a peak on the 6th day after the challenge, and then declined.

Fig. 8. Identification of unknown chicken voice in challenge trials

In order to verify the feasibility of the equipment in a commercial poultry house, we set up the equipment in a commercial poultry house, and at the same time asked professional farmers to listen to the chickens heard during each patrol in the morning, noon and evening. The calls are graded and judged, and are divided into four levels: no abnormal calls as 0, suspected a few abnormal calls as 1, confirmed a small number of abnormal calls as 2, and a large number of abnormal calls as 3, and average the daily records to obtain daily abnormal changes.

As shown in Fig. 9. The abnormal call of the chickens fluctuated slightly on the next day at the age of 12, and the sound of the chickens began to change at the age of 33. It is speculated that the abnormal call fluctuation detected for the second time may have some relationship with the change of sound. In this period, the third abnormal call fluctuation occurred after 79 days of age. It is consistent with the results identified by farmers.

4 Conclusions

In this study, through the embedded system and the challenge test of common respiratory diseases in chickens, the sound signal of the chicken itself was obtained in a non-contact manner, and processed by digital signal processing to extract a clear single chicken cry. Labelling and acoustic feature extraction are carried out, and the identification model is established with machine learning, and the accuracy rate of the model is 91.6%. In the challenge test, the time point is the onset age of respiratory diseases. If abnormalities occur at other ages, the identification accuracy of the model may be affected, and abnormalities may not be judged. In the future, different experimental plans will be used for data acquisition, and the training data set will be collected based on the age after infection.

References