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Classification of Livestock Diseases Using GLCM and Artificial Neural Networks

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Abstract

In the naked eye observation, the health of livestock can be controlled by the range of activity, temperature, pulse, cough, snot, eye excrement, ears and feces. In order to confirm the health of livestock, this paper uses calf face image data to classify the health status by image shape, color and texture. A series of images that have been processed in advance and can judge the health status of calves were used in the study, including 177 images of normal calves and 130 images of abnormal calves. We used GLCM calculation and Convolutional Neural Networks to extract 6 texture attributes of GLCM from the dataset containing the health status of calves by detecting the image of calves and learning the composite image of Convolutional Neural Networks. In the research, the classification ability of GLCM-CNN shows a classification rate of 91.3%, and the subsequent research will be further applied to the texture attributes of GLCM. It is hoped that this study can help us master the health status of livestock that cannot be observed by the naked eye.

Keywords : *Machine Learning, Convolutional Neural Network, Gray Level Co- occurrence Matrix, Classification, Calf Health*

1. INTRODUCTION

With the development of Internet of Things technology, the management of livestock in the barn becomes more intelligent. Administrators can monitor the activity status of livestock through video or images [1]. All animals in the barn live in the same environment and eat the same food together. Therefore, when a disease occurs in a calf, it may also occur in other calves, so it is very important to observe the condition of livestock in the barn at any time. The observation of livestock in the barn includes recording their temperature, heartbeat, cough, nasal discharge, ocular discharge, ears and feces. Ocular discharge of the calf can be observed with reference to Table 1 and classified into four conditions: normal ocular discharge around the eye, less ocular discharge, ocular discharge of both eyes and heavy ocular discharge [2-3].

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Table 1. Calf health criteria in eyes and nasal

normal	small amount of ocular discharge	slight unilateral droop	heavy ocular discharge
			
normal serous discharge	small amount of unilateral cloudy discharge	bilateral, cloudy of excessive mucus discharge	Copious bilateral mucopurulent discharge
			

When the temperature (including around the eyes) of the calf is 37.9~39 ℃, the heartbeat is 80~158 bpm, and the humidity is 2~98%, the calf has a normal degree of cough, runny nose, organic discharge, ears, and feces, which can be regarded as the normal health of the calf. The temperature and heartbeat of calves can be detected by numerical data, and the status of cattle and feces can be detected by image data. All these detected data can be used to analyze the health status of calves [4-5].

Our ongoing research is based on the biological data of dairy cows and the environmental data of livestock houses, using machine learning technology to analyze the environmental factors that affect their reproductive capacity. Other researchers contents include the classification of cattle breeds for the operation of the livestock management system, the installation of thermal sensors to monitor the temperature of calves, and the collection of biological information for predicting the disease status of calves, so as to build a remote diagnosis and treatment knowledge base and image AI data of livestock behavior [6-8].

This paper analyzes the facial images of calves and classifies them into two groups: normal and abnormal health. The specific process is to extract six texture attributes from the images through GLCM calculation, and then use Convolutional Neural Networks to classify their health.

2. RELATED WORKS

2.1 Calf Diseases

The health of calves can be judged by whether the oral mucosa is dry, whether the eye sockets are sunken, depression, anorexia, weight loss, skin elasticity, etc. Infections are caused by bacteria and viruses, but the living environment of calves and the management of calves are very important factors that cause the disease. Predicting the transmission mode of the disease can minimize the impact of bacteria and viruses on the health of calves, and conducting health observation on calves in advance is a very effective method to speculate the transmission mode of the disease [9-10].

2.2 GLCM Algorithm

In the Text-Based classification of image data, the subject, content and file name of the text are all defined as text. And the Content-Based classification extracts and analyzes the statistical features or geometric features such as morphology, texture classification and color displayed in images and videos [11-13]. In terms of representing the texture features of the image, the given texture features are calculated by analyzing GLCM. In this way, even if the object size in the image changes or geometric changes such as rotation occur, GLCM can still perform texture classification. The texture of the image can be obtained by using the algorithm is shown in Table 2. The gray level of the image determines the size of the matrix, and the gray level will affect the analysis of texture features.

Table 2. Algorithm for GLCM Algorithm

1	Converting the color image into a grayscale image.
2	Input image is filtered by the 5×5 filter.
3	Filter image is split into blocks of 4×4.
4	GLCM Properties Definitions: energy, standard deviation, mean value, homogeneity and contrast for each block. Computation is made to these features in accordance with four directions namely diagonal(45° and 135°, vertical(0°) and horizontal(90°) directions.
5	Extracted features.

2.3 Convolution Neural Networks

The Convolution Neural Networks is composed of one or more Convolution, activation function, sub sampling, fully connected layers [14]. The convolution layer transmits the features to the next layer through the filtering and weighting sum of the input image. In this process, filtering is used as a function to determine which texture features exist in the data. When there are texture features, the result value reaches the maximum value. When there is no way to know whether there are texture features, the result value is close to 0. According to the size of the original data, the output value will be smaller than the input image value. To make up for this, you can set the surrounding of the original image to 0, and the result value will become smaller. In this way, you can effectively prevent the loss of the obtained texture features. Enter 0 in the input data, because it is necessary to prevent the original texture features from being diluted and over fitting, so 0 should be used for filling. If the feature map is extracted through filtering, it will be used in the activation function, and then the nonlinear value process of converting the feature into "yes" and "no" will be found from the activation function. If all the features extracted from the sub-sampling layer are used for judgment, capacity loss will occur, which will make it more difficult to find the features. Therefore, max pooling can be used as a pooling process. When max pooling is used as a pooling process, max pooling only transfers the maximum value in the filtering, and the rest will be ignored for sampling. Fully Connected is to put the extracted feature values into the existing neural network for learning, which is the same as the hidden layer structure of the general neural network. The function of Fully Connected is to identify and extract image features through the convolution process.

3. PROPOSAL MODEL

In this paper, the deep neural network structure which simulates human neural network is used to process the facial image data of calves to classify whether the calves are healthy or not. Figure 1 shows the process of Convolution Neural Networks used in this paper.

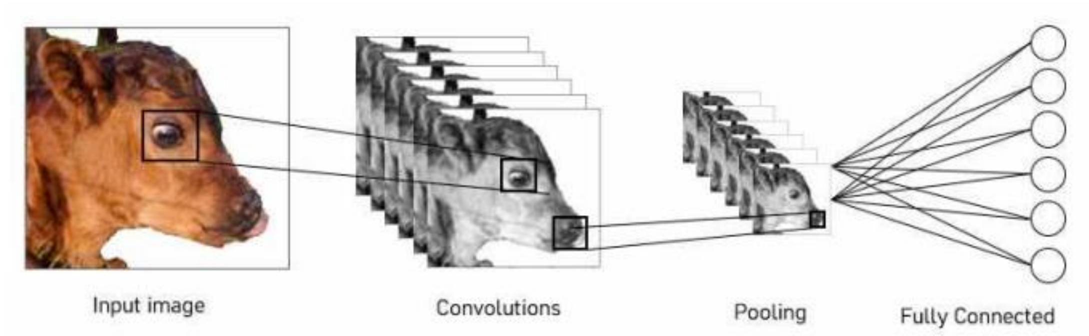

Figure 1. Structure of Convolution Neural Networks

3.1 Method

Keras and Numpy of Python library based on Tenserflow are used on GLCM (Gray Level Co-occurrence Matrix)-CNN which combines CNN and image processing. Texture is one of the most important features for identifying marked regions or objects in images because of its information related to the arrangement of surface structures. For the distance and direction set in the generation of GLCM, adjust a large distance value in the image with more detailed texture, or take the direction between a pair of pixels as the set direction, and then take a pixel as the center, then the adjacent pixels will have 8 directions. Calculate the six attribute values of CLCM: energy, contrast, correlation, entropy, homogeneity, and dissimilarity.

It can be concluded that the energy of the square sum of GLCM elements is set as Eq. 1. Energy, also known as ASM (Angular Second Moment), is a measure of whether the brightness and darkness of pixels in an image are in order. As the calculation formula for measuring the evenness of shading, if the shading changes evenly, the energy value is 1.

$$energy = \sum_{i,j} p(i,j)^2 \tag{1}$$

In the whole image, set the Contrast that can obtain the contrast between a certain pixel and adjacent pixels as Eq. 1. Contrast is used to distinguish the brightness between pixels. For pixels that are far away from each other on the diagonal of the GLCM, the Contrast value is relatively large.

$$contrast = \sum_{i,j} |i-j|^2 p(i,j) \tag{2}$$

Set the Correlation for determining the correlation coefficient between a pixel and adjacent pixels as Eq. 3. Correlation is a measure of the linear dependence of lightness and darkness between pixels, and its value can indicate the softness of an image.

$$Correlation = \sum_{i,j} \frac{(i-ui)(j-uj)\,p(i,j)}{\sigma i \sigma j} \tag{3}$$

Entropy is used to measure the randomness of the light and shade distribution, which is set as Eq. 4. Because of the large changes in brightness, if the values of each element are distributed in various places, a larger

Entropy value will be obtained, thus generating a brighter image.

$$entropy = -\sum_{i,j=0}^{N-1} p_{ij} \log(p(i,j)) \tag{4}$$

Homogeneity is used to determine the approximate value between GLCM elements and GLCM diagonal, which is set as Eq. 5. Homogeneity indicates uniformity. As GLCM elements gradually move away from the diagonal, the number of Homogeneity increases geometrically. When the diagonal is GLCM, the value of homogeneity is 1.

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1+\left|i - jvert\right|} \tag{5}$$

According to the properties of dissimilarity, it is set as Eq. 6. It is used to distinguish the shading difference between pixels. For pixels that are relatively far from the diagonal, the more pixels with large shading differences, the greater the value of dissimilarity.

$$dissimilarity = \sum_{i,j=0}^{N-1} P_{i,j} \left|i - jvert\right| \tag{6}$$

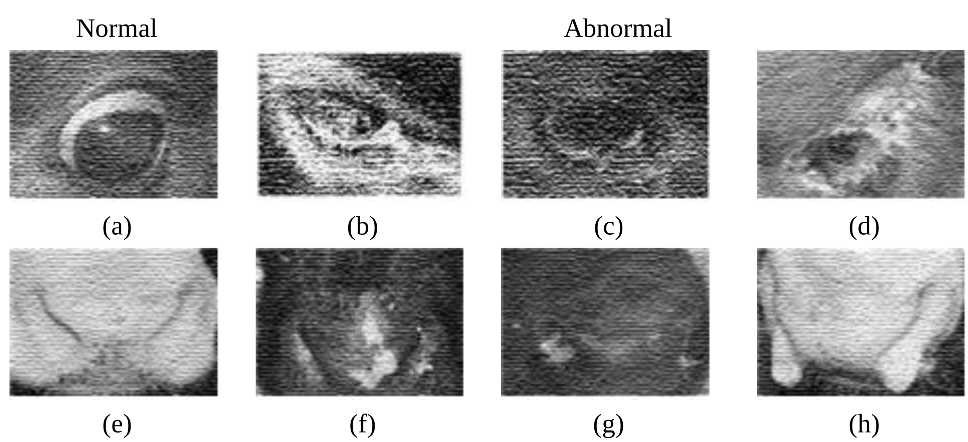

Figure 2. GLCM attribute image

Figure 2 shows the texture characteristics of the GLCM attribute image based on the image used in the experiment. Normal (a) and (e) are the images of healthy calf eyes and nose, using the features of GLCM attributes; (b)-(d), (f)-(h) are the image features of abnormal healthy calf eyes and nose.

3.2 Dataset

In order to carry out the experiment, we selected the relevant data of 177 healthy calves and 130 unhealthy calves after prior processing to establish the dataset [17]. The collected data includes 11 variables that can analyze the health status of calves. However, in this paper, the variables are set as eyes and nasal in Table 3 to classify the health status of calves.

Table 3. Data collection for calf parameters.

Parameters.	Classification
Eyes	Normal
	Small amount of ocular discharge
	Slight unilateral droop
	Heavy ocular discharge
Nasal	Normal serous discharge
	Small amount of unilateral cloudy discharge
	Bilateral, cloudy of excessive mucus discharge
	Copious bilateral mucopurulent discharge
Health	Normal / Abnormal

4. ANALYSIS

In this paper, accuracy, precision, sensitivity and F1measure, which are widely used, will be used as performance evaluation scales to evaluate the health status classification of livestock proposed in this paper.

Learning rate is a gradual transition from a very low learning rate to a very high learning rate. This process is repeated hundreds of times to achieve the goal of training the model. The higher the learning rate is, the faster the learning speed will be, but it will cause the problem that the minimum value cannot be reached or errors will occur. On the contrary, if the learning rate decreases, the learning ability will decline and can remain at a local value. Epoch refers to the number of learning times, that is, all the learning data sets are used for model training. If epoch=10, it means that the learning data set has learned 10 times. Batch size indicates how many data sets can be added at one time in an epoch. m ($m \geq 1$) block batches can be added. Iterations refer to the number of configurations required when you carry out one iterations of all data on the model. You can divide 300 pieces of data into three iterations, with 100 iterations each. For such mini configuration, 3 iterations are required for 1 epoch and 3 parameter updates are required. In all data sets, set the learning data set to 70%, the test set to 30%, the learning times (epoch) to 10, the batch size of each epoch to 1, and the iteration to 50, 100, 200.

Table 4. Classification accuracy

Iteration	EN	CT	CN	ET	H	D
50	0.827	0.891	0.847	0.718	0.762	0.778
100	0.896	0.826	0.851	0.726	0.796	0.812
200	0.913	0.839	0.893	0.871	0.823	0.83

Description of EN: energy, CT: contrast, CN: correlation, ET: entropy, H: homogeneity, D: dissimilarity

Table 4 shows that the accuracy of the contrast attribute is improved when there are fewer repetitions. The contrast attribute shows an accuracy of 83.9%. The accuracy of energy attributes increases with the increase of repetition. After 200 iterations, the accuracy of using energy image reaches 91.3%. The accuracy of homogeneity attribute increases with the number of repetitions.

The accuracy of energy, contrast, correlation, entropy, homogeneity and dissimilarity attributes using GLCM-CNN has been improved. The highest performance of GLCM-CNN is shown in Table 5, with an accuracy of 91.3%.

Table 5. Classification CA, PPV, Sensitivity, F1 of GLCM-CNN

	CA	PPV	Sensitivity	F1
GLCM-CNN	0.913	0.898	0.891	0.894

5. CONCLUSION

We presented a method for classifying the health of calves by learning by using facial images of calves for classifying the health of livestock and applying a convolutional neural network to the GLCM algorithm. The attributes of energy, contrast, correlation, amount of information, homogeneity and dissimilarity of GLCM used for image analysis were extracted, and the classification rate of normal and abnormal calves was 91.3% after learning using evolutionary neural network. It is hoped that this study can help us master the health status of livestock that cannot be observed by the naked eye. In the future, the first is to increase the number of data and scale the data for a long time, the second is to increase the attributes of GLCM for expansion, and the third is to divide the decision on unhealthy status into three stages for classification. The combination of GLCM attribute extension and Convolutional neural network will improve the accuracy to determine more detailed health conditions.

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