Piggery Ammonia Concentration Prediction Method Based on CNN-GRU

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Abstract. The ammonia concentration in piggery has a great impact on the healthy growth of pigs and breeding environment. It is of great significance to control the ammonia concentration in piggery and ensure the healthy growth of pigs by timely mastering the ammonia concentration variation trend. In order to predict the ammonia concentration in piggery, a method based on CNN(Convolutional Neural Networks) and GRU(Gated Recurrent Unit) was proposed. Firstly, the environmental data in piggery and the meteorological data outside were collected, fused and preprocessed. Then, a piggery ammonia concentration prediction model combined with CNN and GRU was established. As a result, the ammonia concentration in piggery was predicted. The result shows that the proposed method has good prediction performance. The MSE (Mean Square Error), RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) is 0.0637, 0.2524 and 0.1845, respectively. The proposed method can provide support for the early warning and regulation of piggery environment.

Keywords: Ammonia concentration; Time series data prediction; CNN; GRU.

1. Introduction

China is a major producer and consumer of pork, with pork accounting for the largest share of meat products. Pig farming is also moving towards intensification. With the application and popularization of the IOT (Internet of things) technology, many pig breeding companies have installed IOT sensors to detect the environment of the piggery. Ammonia (NH₃) is colorless gas with pungent odor in piggery, which is easy to be liquefied and attached to the skin mucous membrane and eye conjunctiva of pigs, causing irritation to pigs and being recognized as a stressor in piggery. Too much ammonia will cause a variety of inflammation in pigs, resulting in reduced production performance, resistance and piglet survival rate. Sometimes could cause self-harm and other abnormal behaviors. Environmental early warning is often adopted to solve such problems [1]. However, these methods are usually based on historical data but lack judgment on future change trend. Therefore, it is necessary to establish an effective prediction model. The prediction model provide information on future change trend of piggery and support automatic control.

Scholars at home and abroad have carried out related research on the prediction of breeding environmental parameters. These studies are mainly based on machine learning prediction algorithm. The piggery environmental data collected by the IOT sensors is used to predict ammonia concentration in piggery [2-5]. These methods can estimate the ammonia concentration in piggery without complicated
measurement and calculation, but the prediction result is greatly affected by the algorithm used. The
commonly used prediction algorithms in agriculture are mainly divided into two categories: prediction
methods based on neural network [2-7] and based on support vector regression machines [8-12]. These
algorithms have been successfully applied to the prediction of aquaculture water temperature [6],
dissolved oxygen [7, 8], pH [9] and other parameters, and the prediction of cultivated land changes [10],
the price of aquatic products [11], tensile strength of plant fiber mulch [12] and achieved good results. Neural
network and deep learning algorithm are mainly used to predict ammonia concentration in piggery. The
algorithms mainly used are BPNN [2], LM-BP [3], EMD-LSTM [4] and ARIMA-BP [5]. Through
the analysis of the literature, it was found that existing studies directly use all the collected factors to make
predictions and do not extract the features of the input data, which makes the model training
computationally expensive.
The ammonia concentration data in piggery belongs to time series data. CNN has a certain efficiency in
the feature extraction of time series data. Compared with LSTM (Long-Short Term Memory), GRU can
effectively reduce the amount of calculations during model training under the condition of ensuring
prediction performance and has higher efficiency. Therefore, an ammonia concentration prediction
method in piggery based on CNN-GRU was proposed. First, CNN was used to compress and extract
input features that have a key role in the target factor. Then, GRU was used to build an ammonia
concentration prediction model in piggery. As a result, the prediction of ammonia concentration in
piggery was realized.

2. Materials and Method

2.1. Data Collection
The data was collected in YaoSheng standardized pig farm in RuiCheng county YunCheng city ShanXi
province from March 9, 2018 to April 8, 2018. The experiment piggery with collection equipment has
20 south-north facing pens. Each of them is 6m long, 5m wide and 1.2m high. Each pen could
accommodate 5-6 sows. The piggery was equipped with slotted floor, wet curtain, fan and floor heating.
The environment of piggery is shown in Figure 1 (a).
We installed environmental sensors in the pens, set the collect frequency to 30 min, and the data
collected was reported to the server uniformly through wireless network. The collected parameters
mainly included the air temperature, air humidity, ammonia concentration and hydrogen sulfide
concentration in piggery. The collection sensor node was shown in Figure 1 (b). It was 6.2m away from
the fan. During the data collection period, the fan works 24 hours, while the floor heating does not work.

(a) environment in piggery (b) sensors installed

Figure 1. Arrangement of environmental information collection sensors in piggery.

Considering that the temperature and humidity piggery are affected by the temperature and humidity
outside, and there is a certain relationship between the ammonia concentration, the temperature and
humidity in piggery, we also collected meteorological data for the same time period, mainly including:
air temperature, the maximum temperature, the minimum temperature, relative humidity, and the
minimum relative humidity data were collected at a frequency of 1h.
2.2. Overall Process of Ammonia Concentration Prediction Method in Piggery

The process of ammonia concentration prediction method in piggery based on CNN-GRU is shown in Figure 2.

![Flowchart of Ammonia Concentration Prediction](image)

**Figure 2.** Overall flow chart of ammonia concentration prediction in piggery.

Prediction of ammonia concentration in piggery mainly includes the following steps:
1. Perform preprocessing on missing data, outliers, and normalization of the data; divide the preprocessed data set into training and test sets;
2. Use CNN to extract key features in environmental factors;
3. Build CNN-GRU prediction model;
4. Use the test set to evaluate the prediction model.

2.3. Data Preprocessing

The data collected by the IOT sensors are usually susceptible to environmental or human factors, and the problems of inaccurate data could exist. The missing values, outliers need to be processed and normalization needs to be carried out.

Arithmetic mean value was used to fill the missing values. Abnormal data were detected using the grubbs method \[13\]. The arithmetic mean value of adjacent position data was used to replace the abnormal value. In order to avoid the influence of dimension on experimental results, the data were normalized.

2.4. The Proposed CNN-GRU Prediction Method

CNN is a feed-forward neural network. It is specifically designed to process data with similar grid structures, such as time series data and image data \[14-16\]. It has the characteristics of local connection, weight sharing and pooling, which can effectively reduce the complexity of the network and the number of training parameters. CNN makes the model have a certain degree of invariance to translation, distortion and scaling. It has strong robustness and fault tolerance and it is easy to train and optimize the network structure. In this paper, the role of CNN is to compress and extract input features that have a key role in predicting target factors. Thereby effectively reducing model complexity and improving prediction accuracy. In the ammonia concentration prediction experiment, CNN can extract key input features from many environmental factors, reduce the calculation amount of model training, and improve the prediction performance of the model \[17-20\].

GRU is a variant of RNN neural network, proposed by Cho et al. In 2014, mainly used for prediction of time series data \[17\]. Its cyclic unit is similar to LSTM, but the GRU has a gating unit that can modulate
the information flow inside the unit without setting a separate storage unit. Therefore, compared with LSTM, GRU has a simpler network structure, less computation, and higher training efficiency, which makes it widely used in prediction applications of time series data \cite{21-24}. The GRU network unit is shown in Figure 3, where Input represents input data, Output represents output data, r and z represent reset and update gates, and h and \( \tilde{h} \) represent activation and candidate activation \cite{17}. In the experiments in this paper, GRU learns the input environment data inside and outside the piggery, and outputs the ammonia concentration value in piggery after 30 minutes.

![Figure 3. The illustration of GRU network unit.](image)

The main formulas and functions involved in Figure 3 are calculated as follows:

The activation function \( h_t^j \) of the GRU at time \( t \) is a linear interpolation between the activation \( h_{t-1}^j \) at the previous moment and the candidate activation \( \tilde{h}_t^j \):

\[
h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j\tilde{h}_t^j. \quad (1)
\]

The update gate \( z_t^j \) determines how much the unit updates its activation or content. The update gate is calculated by:

\[
z_t^j = \sigma(W_z x_t + U_z h_{t-1})^j. \quad (2)
\]

where \( W \) and \( U \) are weight coefficient matrices, and \( \sigma \) is a sigmoid function.

The candidate activation \( \tilde{h}_t^j \) is calculated by:

\[
\tilde{h}_t^j = \tanh(W x_t + U (r_t \circ h_{t-1})^j). \quad (3)
\]

where \( r_t \) is the GRU reset gate, and \( \circ \) means multiply by element.

The GRU reset gate, \( r_t \), is similar to the forget gate in LSTM. It can make the network forget the previously calculated state. The reset gate \( r_t \) is calculated similarly to the update gate. Its formula is as follows:

\[
r_t^j = \sigma(W_r x_t + U_r h_{t-1})^j. \quad (4)
\]

The network structure hierarchy of the CNN-GRU is shown in Figure 4:

![Figure 4. The hierarchy of CNN-GRU network.](image)
3. Experiments and Evaluations

3.1. Experimental Environment and Parameter Settings
The program of the proposed method (CNN-GRU) and the other three models of GRU, CNN and LSTM were developed in Python 3.7. The developing platform was Anaconda 2019.10 + PyCharm 2019.3. The SVR (Support Vector Regression) and LM-BP prediction program were developed based on Matlab 2018A platform. The SVR program was developed based on libsvm toolbox. The parameters of the CNN-GRU method were set as follows: the number of CNN filters was 9, each filter step size (strides) was 1. The number of GRU input layer units was 8, the number of hidden layers was 2, and the number of output layer units was 1. The number of iterations was 600 and the block size was 64.

After the data collection and data preprocessing, we fused the environmental and meteorological data and obtained a total of 1,447 data samples. Then we arranged the samples in ascending time order. The first 70% of the experiments of all models were taken as the training set and the last 30% were used as the test set [7].

3.2. Evaluating Indicators of Prediction Method
In this paper, MSE, RMSE and MAE were adopted as the evaluation criteria for prediction effect. Their calculation formulas are as follows.

\[\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y}_i)^2.\]  
\[\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y}_i)^2}.\]  
\[\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |(y_i - \bar{y}_i)|.\]

where \(y_i\) is actual value; \(\bar{y}_i\) is predict value and \(N\) is the number of predict values.

3.3. Experimental Results of Ammonia Concentration Prediction
In order to verify the effectiveness of the proposed method, the CNN-GRU and the other five prediction algorithms: GRU, LSTM, CNN, SVR, and LM-BP were used to compare the predict effect of ammonia concentration after 30 min. The evaluation indicators calculation results were shown in the Table 1.

LM-BP means use the Levenberg-Marquardt algorithm to optimize the parameters of BPNN.

| Predict method | MSE   | RMSE  | MAE   |
|----------------|-------|-------|-------|
| CNN-GRU        | 0.0637| 0.2524| 0.1845|
| GRU            | 0.0834| 0.2890| 0.2106|
| LSTM           | 0.0852| 0.2920| 0.2162|
| CNN            | 0.1003| 0.3170| 0.2358|
| SVR            | 0.0931| 0.3051| 0.2365|
| LM-BP          | 0.1036| 0.3219| 0.2405|

As can be seen from Table 1, the prediction error of CNN-GRU was lower than other methods. From the comparison of experimental results, it can be seen that the effect of CNN-GRU was better than using GRU and CNN alone. This result shows that after CNN extracts input features, the prediction error of GRU was reduced. The prediction error reduced percentage of our method(CNN-GRU) compared with other methods are shown in Table 2.
**Table 2.** The prediction error reduced percentage of our method (CNN-GRU) compared with other methods.

| Predict method | MSE↓(%) | RMSE↓(%) | MAE↓(%) |
|----------------|---------|----------|---------|
| GRU            | 23.62   | 12.66    | 12.39   |
| LSTM           | 25.23   | 13.36    | 14.66   |
| CNN            | 36.49   | 20.37    | 21.75   |
| SVR            | 31.57   | 17.27    | 21.98   |
| LM-BP          | 38.51   | 21.59    | 23.28   |

In addition to examining the evaluation indicators of the prediction model, the ability to fit the predicted value curve to the actual value curve should be evaluated. The more the predicted value curve matches the actual value curve, the more accurate the model is in judging the change trend of the curve. The practicability of the model will be better. In order to evaluate the model's ability to judge and fit the trend, this article selects some samples with large changes in the trend of the curve from the test set. The predicted-actual value curves of the proposed method and the other five models are plotted and compared respectively, as *Figure 5* shown.
From the experimental results in Figure 5, the predicted value curve of CNN-GRU, GRU and LSTM models basically agrees with the overall trend of the actual value curve. The curve fitting effect of CNN-GRU is the best. The curve fitting effect of GRU model in the range of sample numbers 40-60 is not as good as CNN-GRU, and the curve fitting effect of the LSTM model in the range of sample numbers 80-120 is also not as good as CNN-GRU and GRU model. The curve fitting effect of CNN, SVR and LM-BP is not good. The curve fitting effect of CNN model in the range of sample number 20-60 and the curve fitting of SVR model in the range of sample number 20-80 is poor. The predicted value and actual value curve of LM-BP have seriously deviated.

To sum up, from the perspective of model prediction error and prediction value-actual value curve fitting effect, compared with other prediction methods, the CNN-GRU has the best prediction effect, the lowest error, and stable prediction performance. Better qualified for prediction of ammonia concentration in piggery.

4. Conclusion

This paper proposed a method for predicting ammonia concentration in piggery based on CNN-GRU. CNN was used to extract the characteristics of the input factors, and the processed data was input into the GRU model for prediction, thereby improving the prediction effect of the model. The result shows that the MSE, RMSE and MAE of our method was 0.0637, 0.2524 and 0.1845, respectively in 30min prediction. This method has high prediction accuracy and stable performance. The prediction effect is better than the five prediction models of GRU, LSTM, CNN, SVR and LM-BP. The prediction model proposed in this paper can provide support for the early warning and regulation of the piggery. It is of great significance to improve the pig breeding environment and reduce the burden of maintaining the breeding environment.

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