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Analysis effects of multiple factors on pig fattening based on neural network data mining

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Abstract. To improve the accuracy of analytical algorithm for pig fattening effect, an analytical method based on **regional-integration convolutional neural network** mining for pig fattening effect is proposed. Based on the minimum distance measurement of regional integration structure, the representation form of character subset is optimized. By the high order relation among entities in real world, it shall be represented with more significant form to achieve data reduction and aimed at the optimal character subset, recognition shall be carried out with the recursive fashion of regional integration Helly character and the classification analysis shall be carried out for pig fattening effect with residual **convolutional neural network** (CNN); by the experimental simulation, it shows that the method proposed is superior to the control methods selected on the computational accuracy and the computational efficiency, which has reflected the effectiveness of algorithm.

Key words. Convolutional neural network, Pig fattening, Data mining, Data reduction.

1. Introduction

The pig's category & breed, daily feeding status and normal temperature measured in pig house are all categorized as the influential points. In fact, only when the optimal comprehensive conditions are created in this period of pig fattening, can the weight increase velocity be improved. Properly select the most suitable individual to be fed in different group and add the feed and control the humidity and temperature in the pig house in accordance with the strength and weakness of group subdivided. The environment in the pig house shall be kept clean, the normal inspection on pig house shall be added and the fattening effectiveness shall be improved from comprehensive perspective

There are many factors affecting the pig fattening effect, which mainly are: (1)

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animal's inherent factor. The factors in fattening period include the original inherent factor, such as, pig's category and inherent multiple breeds. If there is inherent difference, both fattening character and available economic effect shown by each category of pigs will not be equal. It can be seen in details that the lean-type category can get more favorable feeding reward. Compared with fat-type pigs, it is easier for the lean type to highlight faster daily gain. According to multiple fattening characters to screen and feed, the optimal fattening status can be acquired in this way. It can be seen that fattening can not be short of provenance. (2) Feeding factor. During the pig fattening, only when the sufficient nutriment added is acquired can the weight of feed mixed be increased and the various nutrient subdivided shall be matched properly. In various feeds, the intake protein and the total energy got through feeding can be seen as the essential factor. It can be seen from the conventional view that if more existing energy has been ingested, the feed conversion can be improved; however, at the same time, higher fat will be accumulated fast in the body. Within the given scope, the existing gain can be recognized in accordance with the accurate amount of protein measured. Aimed at fattening approach, the protein keeps Helium acids under balanced stance; if some Helium acid can not be acquired, the unbalanced growth tendency will be highlighted. The fattening flow can not be short of vitamin added and sufficient minerals, etc, either, which is because if the unsaturated acid with higher ration is contained in feed, it will directly be protected for sedimentation when it goes through pig's stomach and becomes the fat in body. The fat will become softer over time, but can not be kept long. Prior to being put into market and slaughtered, the existing amount of unsaturated fatty acid should be able to be reduced. (3) Daily environment factor. The fattening can be helped by crossbreed, because crossbreed has a prominent strength, which can improve the true efficiency of fattening from the origin. More robust descendants can be acquired through crossbreed, from which not only the fattening time consumed has been shortened, but also the feed can be fully protected for calling. The fattening feed needs to control the conventional intake during the ordinary days and limit the normal intake. If they are indulged for ingestion, the pigs will fast accumulate the noumenal weight and there will be fatter. The optimal temperature and the temperature in pig house during fattening should be able to be controlled. If it is slightly hotter or colder, the follow-up weight gain will be hindered. (4) Improvement of fattening standard. It can be got through analysis that: under different environment, the effect got from fattening can also highlight the clear difference. For this, if the standard needs to be improved and more favorable economic effect needs to be acquired, it shall be comprehensively controlled in accordance with the true status represented by environment. The most proper fattening shall be ensured, so the detail control and feed shall be taken into account. During each period, the various factors involved with fattening shall all be analyzed in details and comprehensively protected for consideration. The essential feed shall be added and the fattening materials purchased shall conform to the pig's growth character in this fattening stage.

An analytical method based on **regional-integration convolutional neural network** for pig fattening effect is proposed in the Paper.

2. Experimental material

2.1. Materials and methods

Select respectively 48 for DLY and DYL crossbred pigs born on the same day and with similar birth weight, in which each combination is divided into 4 repetitions and each repetition is 12, self-help feeding and drinking water. Carry out immunity, disinsectization and castration of boar in preliminary trial period and weigh after at the end of preliminary trial period, in which 2 shall be removed in each group to adjust insignificant difference of initial weight among group, that is, while entering the experimental period, the feeding and management conditions in the whole period are in conformity. When the average weight of each group reaches 100kg, the test ends and 6 shall be randomly selected to be measured. The measurements shall all be carried out in accordance with the measurement procedure (NY/T822) of boar's production performance. The test was divided into 2 stages, carried out respectively from May to August 2015 and from October 2015 to January 2016 in Daxing District, Beijing and it was repeated twice. The diet composition and nutritional level are shown in Table 1.

Table 1. Diet Composition and nutritional level for fattening pig

Item	Content	Item	Content
Stage I (30-60kg)		Stage II (60-100kg)	
Diet composition		Diet composition	
Corn/%	59	Corn/%	62
Bean/%	25	Bean/%	21
Bran/%	4	Bran/%	5
Premix/%	12	Premix/%	12
Nutritional level		Nutritional level	
Metabolic energy/(MJ·kg-1)	13.26	Metabolic energy/(MJ·kg-1)	13.53
Crude protein/%	17.50	Crude protein/%	15.01

2.2. Feeding management

The pigs tested are fed in an open-type pig house where it is installed with cement floor and cement-slab crib, the ventilation is favorable, temperature is appropriate and they can self-help feed and drink. The pig house shall be cleaned and disinfected once a day and in the charge of the same feeder. The immunity and disinsectization shall be carried out in accordance with the feeding procedure of pig farm. Prior to the test, the weight of pigs tested shall be measured with an empty belly every morning, namely, initial weight; after the test ends, the pigs tested shall fast for 12h (self-help drinking) prior to weighing the individual weight, namely, ending weight. The feed intake shall be recorded everyday during test and the statistics for consumption of each repeated pig's feed shall be made during test, that is, the average daily feed intake (ADFI), average daily gain (ADG) and feed to gain ratio shall be calculated in accordance with each repetition. When the test ends, the thickness of backfat and eye muscle area shall be measured, in which the thickness of backfat shall be measured with B ultrasonic PrEG-ALERT on three places including the 1st rib, the 6-7th rib and finally lumbar, record the data and take the mean value; eye muscle area shall adopt the paint to measure the width and thickness of longissimus dorsi in the joint of thoracolumbar spine of the carcass and its area shall be estimated with width $\times$ thickness $\times$ 0.7.

2.3. Statistics and analysis of data

Establish the database with Excel, carry out statistic analysis with variance analysis procedure of SAS6.12 software package, inspect and compare the difference among each group by t, show the result with "mean value ±standard deviation" and show significant difference with $P < 0.05$.

3. Regional-integration convolutional neural network

3.1. Structures and characteristics of regional integration

Regional integration is the promotion of traditional graph theory, which can be represented as more significant form by the high order relation between entities of real world. In mathematics, regional integration can be defined as: $H = \{X, E\}$, where $x = \{x_1, x_2, \cdots, x_n\}$ means the non-empty limited vertex set and $E = \{E_1, E_2, \cdots, E_m\}$ represents nonempty subset of X, named as regional integration, as shown in Fig. 1. In this section, analyze the definition and characteristics of regional integration.

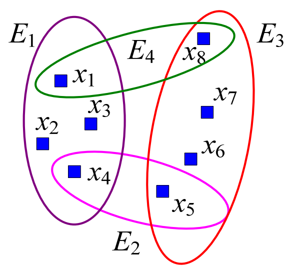

Fig. 1. Structure of regional integration

Definition 1: considering regional integration $H = \{X, E\}$, the hyperedge set with each vertex $y \in X$ and contained Y is called as the highlight of $H\left(H_y^*\right)$, as shown in Fig. 2. The degree of D_y is equal to the cardinality of H_y^*:

$$D_y = \left|H_y^*\right| . \tag{1}$$

In graph, including vertex set $x = \{x_1, x_2, \cdots, x_9\}$ and hyperedge set $E = \{E_1, E_2, \cdots, E_5\}$, if x_2 is the centre of gravity place of $H_{y_2}^* = \{E_1, E_2\}$, the de-

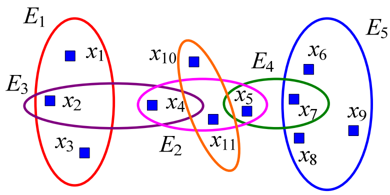

Fig. 2. Representation model of regional integration

gree of D_{y_2} is $D_{y_2} = 2$; if x_5 is the centre of gravity place of $H^*_{y_5} = \{E_2, E_4\}$, the degree of D_{y_5} is $D_{y_5} = 2$.

Definition 2: for given regional integration $H = \{X, E\}$, where an intersection clusters of H is the cluster of regional integration $E \subseteq X$, which is the non-empty intersection.

Definition 3: considering regional integration H has hyperedge set $\{E_1, E_2, \cdots, E_m\}$. If the intersection of E_i and E_j is non-empty, where $i, j \in k$ and $k = \{1, 2, \cdots, m\}$. The mutually intersecting edges of H can be divided into two conditions as follows:

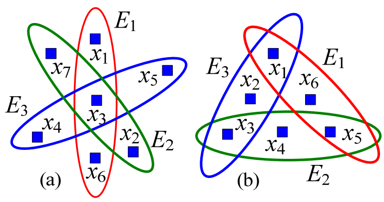

Fig. 3. Classification of mutually intersecting edges ((a) with common cross point (b) without common cross point)

Condition 1: mutually intersecting to the edges of general intersection, as shown in Fig. 3a, the vertex x_3 is served as the common point of intersection caused by mutually intersecting edge $\{E_1, E_2, E_3\}$.

Condition 2: there is no common intersection in mutually intersection, as shown in Fig. 3b, under this condition, there is no common point of intersection for mutually intersecting edge $\{E_1, E_2, E_3\}$.

3.2. Algorithm description

The main objective of any character selection technology is to reduce the dimension of data to make it maintain good classification accuracy. Many problems of pattern recognition achieve the training on learning model by text, spectrum, topology, geometric sum as well as statistical characteristic. In the case of unbalanced datasets, due to the existence of redundant characteristic, the generalization error of learning model increases. For the purpose of overcoming the above defects, obtain the recognition of optimum character subset with minimum time complexity by the representation tools of regional integration data.

The character selection algorithm (algorithm 1) proposed by the paper based on regional integration includes two phases: (1) representation of regional integration; (2) application of Helly characteristic. In the initial phase, the edge of regional integration can be obtained by the topology and geometric relationships of the sample. The edges and vertexes of regional integration respectively correspond to the sample and characteristic of dataset. For the supervised learning, the edges of each category are established by the Euclidean distance measure based on the minimum distance algorithm.

$$E_d(x, y) = ||x - y|| \,. \tag{2}$$

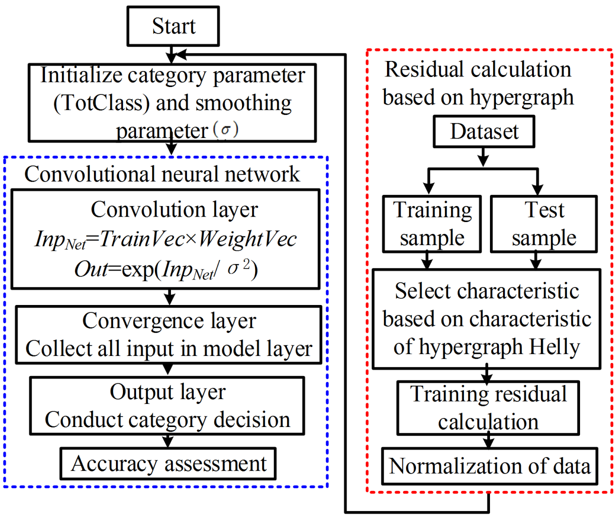

Fig. 4. Flowchart of convolutional neural network algorithm based on regional integration

In next phase, recognize the optimal reduction and apply the characteristic of regional integration on intersecting edges by recursive fashion. In the next processing procedure, ignore the nonintersecting edges. For unsupervised learning, the distance between clusters shall be furthest improved and the distance in cluster shall be furthest reduced by city block distance measure (CBD).

$$CB_d = \max(|x_1 - x_2|, |y_1 - y_2|) \,. \tag{3}$$

The complexity generated by the recognition of optimal reduction of time is the minimum by making use of the Helly characteristics of regional integration. Characteristic selection based on the Helly characteristic of regional integration and recognition process of convolutional neural network, are respectively shown in Algorithm 1 and Algorithm 2.

Algorithm 1: Characteristic selection based on the Helly characteristic of regional integration

Input: $f \leftarrow \{f_1, f_2, \cdots, f_m\}$, // give m characteristics on dataset
$S = \{S_1, S_2, \cdots, S_n\}$, // give n characteristics on dataset
$C = \{C_1, C_2, \cdots, C_k\}$, // give k characteristics on dataset
Output: $f_s \leftarrow$ optimal character subset
$HG(f, s, c, f_s)$
1.foreach$i \leftarrow 1$: k do
2. $Hyperedge[i] \leftarrow \min[E_d(f_i, f_j)]$;
3. end
4.foreach $i \leftarrow 1$: $k$begin
5. $f_s \leftarrow \bigcap_{j \in i} Hyperedge[j]$;
6.end

Algorithm 2: Recognition process based on residual convolutional neural network

Input: total of category Tot_{class}, S_{Train}, f_s, σ
Output: $Classify$ ←test the classification accuracy of vector
CNN(Tot_{class}, S_{Train}, f_s, σ)
1. Initialize parameter values
2. Calculate training residual parameter:
$Train_{Data}[i, j] \leftarrow \sum_{k=1}^{f_s} \left[\left(\frac{f_k}{\varepsilon}\right) - \left\lfloor \frac{f_k}{\varepsilon} \right\rfloor\right]$
$\forall i = \{1, \cdots, S_{Train}\}, j = \{1, 2, \cdots, f_s\}$
3. Calculate test residual parameter:
$Test_{Data}[i] \leftarrow \sum_{k=1}^{f_s} \left[\left(\frac{f_k}{\varepsilon}\right) - \left\lfloor \frac{f_k}{\varepsilon} \right\rfloor\right]$
$\forall i = \{1, 2, \cdots, f_s\}$
4.foreach $k = 1 : Tot_{class}$ begin
5. $Sum[k] \leftarrow 0$;
6. foreach $i \leftarrow 1$: S_{Train} begin
7. $p \leftarrow 0$;
8.foreach $j \leftarrow 1$ begin
9. $p \leftarrow p + (Test_{dataset}[j] \times Train_{dataset}[j][j])$

4. Experimental analysis

4.1. Experimental setting

The pig fattening dataset is used for this experiment. In each kind of category, the sample is distributed uneven. The operating condition of algorithm: Matlab2012a, with i7-7700HQ processor, 8GBddr3-1600 memory as well as win7 ultimate system. Assessment indexes include detection precision index, recalling rate index and detection stability index:

$$Precision\,(P_{value}) = \frac{T_P}{T_P + F_P}\,. \tag{4}$$

$$Recall\,(R_{value}) = \frac{T_P}{T_P + F_N}\,. \tag{5}$$

$$Stability(\%) = \frac{\text{Quantity of successful training samples}}{Totalquantityoftrainingsamples}. \tag{6}$$

In formula, T_P is the measurement that is affirmed correction, T_N is the measurement that is indentified as normal, F_P is the measurement that is misjudged as normal weight gain and F_N is the measurement that is misjudged as normal weight gain.

4.2. Analysis of experimental results

To verify the validity of algorithm, Naive Bayesian algorithm, decision tree algorithm and random prediction algorithm are selected as contrast algorithm. The results of experiment are shown in Table 2.

Table 2. Contrast of experimental results

Sample set	Index	Bayes	Decision tree	Random prediction	Proposed algorithm
	Precision	96.82	97.52	91.26	98.32
1	Recall	95.21	96.13	90.58	97.64
	Stablity	92.68	93.84	89.64	94.56
	Precision	48.76	47.53	41.62	82.16
2	Recall	50.76	51.69	48.75	81.28
	Stability	51.26	52.76	46.21	79.46
	Precision	33.21	34.27	30.69	83.64
3	Recall	36.38	35.19	32.84	82.93
	Stability	33.27	34.68	30.42	81.69
	Precision	23.16	29.16	28.94	72.59
4	Recall	23.82	30.67	27.63	73.64
	Stability	25.39	28.91	24.18	71.82

Under the experimental results of Table 2, we can know that, in the attack of sample set 1, the prediction accuracy, recalling rate index and stability index of several kinds of algorithms are all higher and can reach above 90%, which reflects the simplicity of the attack prediction of sample set 1. The proposed algorithm is superior to the selected contrast methods in above indexes. In sample set 2, the prediction accuracy, recalling rate index and stability index are the lowest and the index value of several kinds of algorithm are maintained at 20% to 30% with poor recognition effects, however, the proposed algorithm can reach above 70%, which reflects better abnormal attack recognition performance of algorithm. Contrast results for training convergence time of selected several algorithms are shown in Fig. 5.

As shown in Fig.5, in the index of operating time, the operating time of proposed algorithm is longer than Naive Bayesian algorithm and decision tree algorithm, but it is less than random prediction algorithm. Because in the attack prediction, above algorithms are adopted the method of off-line training, so the discrepant operating time is acceptable.

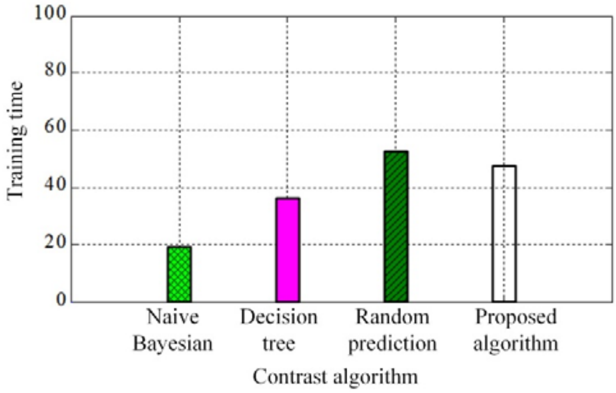

Fig. 5. Contrast on operating time of algorithm

5. Conclusion

The paper proposes a kind of pig fattening analysis method based on convolutional neural network of regional-integration characteristic reduction to optimize the representation form of character subset on the basis of the minimum distance measurement of regional integration structure and classify the data of pig fattening on the basis of residual CNN network. Experimental results show that, the proposed algorithm has advantage of prediction accuracy, although adopting the data reduction of regional integration, there is still a problem that the calculation time is slightly longer, which needs to be further optimized in the next step. Experimental results show that, the average daily gain, average daily feed intake and backfat thickness and other indexes of Du Zhangda hybrid pigs are superior to Du Zhangda with a few difference. It shows that there is a little difference between Du Zhangda and Du Zhangda hybridized combination in fattening performance. It shows that in the conditions of scientific feeding management, Du Zhangda and Du Zhangda hybridized combination can be greatly promoted in production. From the feeding time point of view, the average daily gain of ternary hybrid lean pig feeding in the autumn and winter is superior to the pig feeding in spring and summer, but the difference is not significant, which may be due to that Beijing is in a high temperature and high humidity condition in summer, it is not conducive to the growth of fattening pigs, but needs to enlarge the sample to further verify the test.

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