Piglets' Nursing Level Prediction

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ABSTRACT

Automatic monitoring of livestock behavior is an indispensable part of modern farming. It can assist framers in understanding the status of livestock in real-time so as to avoid risks in advance. Compared with other automatic monitoring approaches, such as video or wearable devices, using structural vibration for monitoring can ensure reliability and economy on the premise of including rich information. We propose a pipeline to detect three nursing levels of piglets based on the structural vibration using machine learning methods represented by random forest. Hundreds of features from the time domain and frequency domain with clear physical meaning are extracted at first. The model-based, outcome-oriented feature selection algorithm is implemented then to screen out the sensitive features to the nursing level. It is shown that the statistics of some frequency bands and the local variances in the time domain are essential for detecting the piglet nursing level. After validation, the features extracted through the algorithm still perform well under other common machine learning models. The detection accuracy (F1 score) of the final model with five critical features is up to 0.78 when our approach is deployed in the test set.

KEYWORDS

smart farming, structural vibration sensing, feature selection, multi classification

1 INTRODUCTION

According to Organisation for Economic Co-operation and Development/Food and Agriculture Oraganization of the United Nations [5], pig meat is the second most preferred meat for consumption since its low relative prices around the world and the production of pig meat is expected to grow by nearly 11 Mt by 2028. The pig farming industry is such a huge market that involves many people's lives at present and in the future. To reduce risk and provide more protection, farmers always want to detect the behaviors of their livestock as early as possible, Precision pig farming which means fully automated continuous monitoring of pigs [1] [2] [4], paying more attention to the individuality is helping farmers to achieve real-time detection. Many approaches have been developed for monitoring livestock. Computer vision approaches have been the main field of focus and have been used in multiple livestock behaviour analysis and classification related applications [8]. The camera-based monitoring approach has the advantage of rich information, however, it puts forward high requirements for the ambient light and equipment storage capacity [3]. Sound surveillance analysis is suitable for some health and welfare status detection related to sounds such as vocalisations and screams [10], which limits its application at the same time. Wearable sensors [6] can identify subtle behaviors such as nursing [3], however, they are vulnerable sometimes, such as violent group activities.

Structural vibration starts to be used for monitoring pigs behavior and shows great potential in the area. Structural vibration data includes rich information, and is more reliable, economic at the same time. Bonde, Amelie, et al.[3] develop the PigNet system to track pigs behavior and detect piglet nursing with structural vibration. The paper gets 85.5 percent of F1 score when detecting piglets nursing status (nursing or not). Inspired by it, we are going to develop a multi-classification model to detect the three piglet nursing levels, which can give farmers a more detailed picture about the piglets nursing status. Besides, we want to find out which features are more sensitive to the piglet nursing level, which has not been clarified before.

2 METHOD

2.1 Data Overview

Our structural vibrations data (velocity) is detected by the Geophone sensors, whose sensitivity to subtle motion just satisfies our requirement (within 10^{-4} to 10^{-3}). The sample rate of our sensors is 500 Hz, which does not have high requirement to storage capacity even if we use several sensors at the same time. We have four valid sensors in total and Figure 1 shows their layout. The time range of the data is from 03:30am to 06:00am in March 6, 2021. Besides, the camera right on the top of sensor 32 takes a picture of the pig pen nearly every five seconds. 1479 frames are extracted from the video record in this 2.5 hours. One frame can been regarded as one sample, which includes a piece of corresponding structural vibration data and a specific nursing level.

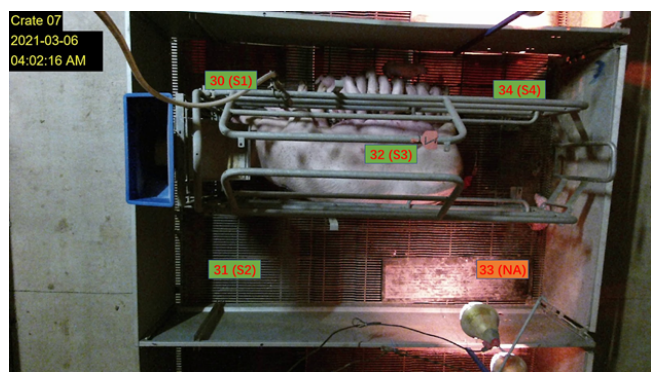

Figure 1: Sensors' Layout

Figure 2 shows an overview of the raw data. Four subplots represent four different sensors. For each subplot, the horizontal axis represents the time. The vertical axis in the left side is the structural vibration velocity and the vertical axis in the right side is the number of nursing piglets, which we count manually frame by frame. From the figure we can see that the group nursing level shows a periodic law. Most piglets nurse for nearly 30 minutes and then walk, run or sleep for nearly 15 minutes and nurse again. Besides, we can see that the structural vibration will fluctuate accordingly

when the group nursing level fluctuates, even though there seems to be a time delay sometimes. Based on the intuitive observation of the figure and practical pigs' behavior, it is shown that the nursing level can be deduced from structural vibration data.

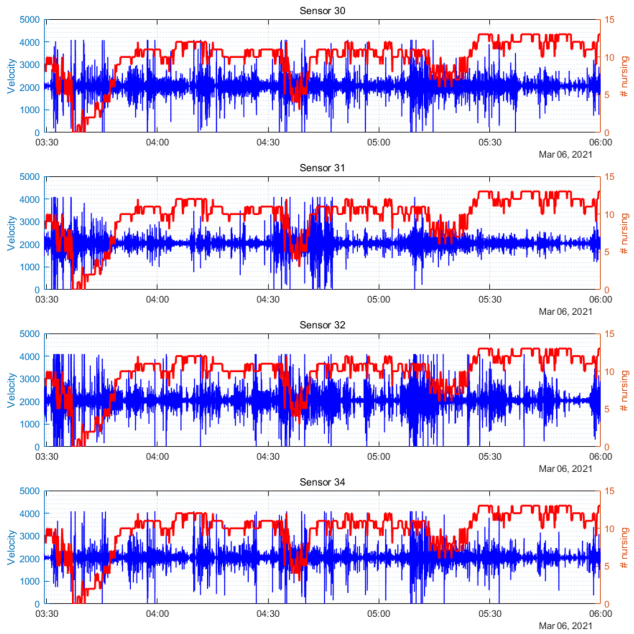

Figure 2: Raw Data Overview

2.2 Preprocessing

- `Normalize`:
  The vibration data is normalized to 0 means and 1 standard deviation (Eq.1). Because the scope of each sensor is slightly different due to the layout. On the other hand, normalization can also increase the learning speed when we training a model. In the following equation, μ and σ are the mean and standard deviation of each sensor vibration data respectively.

$$x' = \frac{x - \mu}{\sigma} \tag{1}$$

- `Clean Incomplete Data`:
  As mentioned before, each video frame corresponds a piece of vibration data. Considering that the minimum interval for each frame is 5 seconds, we decide to set the length of the piece of vibration data to 5 seconds. On the other hand, the length of five seconds can guarantee the train data and test data do not share the common part whatever we split the whole data. The accuracy of video frame time is second, however, the accuracy of vibration data 1/500 seconds. Considering the piglet behavior will change quickly sometimes, We assume the time recorded by the video frame is a whole second, based on which we can correspond an unique time (if the sensor works normally at this time). Physically, each sensor is more sensitive to the activities near its location. If we have four sensors' data at the same period, it would be more easier to detect piglet nursing level. Based on this, the five seconds of each sensor's vibration data in a sample should be complete. From figure 3 we can see that some sensors lose data sometimes. These incomplete samples are dropped and we get 789 samples. Split the samples randomly into training set with 526 samples and test set with 263 samples.

Table 1: Convert # Nursing Piglets into Nursing Level

No	Nursing Level	# Nursing Piglets
1	Light	0-4
2	Median	5-9
3	Hard	10-13

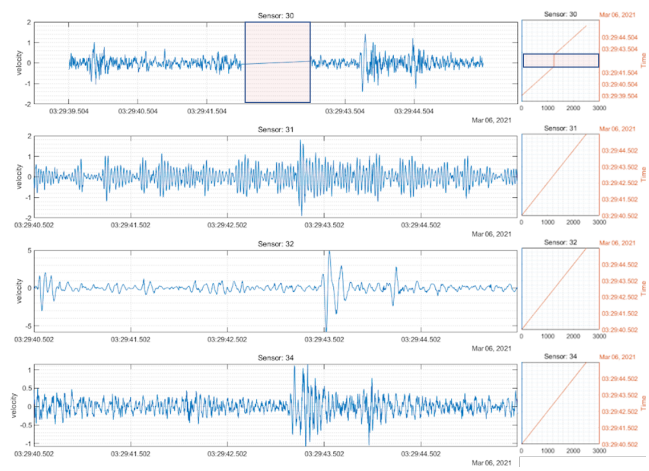

Figure 3: Missing Vibration Data for Some Sensors

- `Define Nursing Level`:
  Nursing is a concept with relatively large degrees of freedom. Valros et al. define "nursing/suckling" as any period longer than 60 seconds where at least half the piglets are suckling [9], while Thomsson et al. define "nursing/suckling" to be any time when at least five piglets are suckling [7]. It would be the best case if the nursing percentage can be predicted. However, even if our camera has a high resolution, it is not practical to exactly identify the nursing percentage based on each frame since the low frame rate of the video. According to Figure 2, three nursing levels can be a proper choice to describe the nursing status, which can promise the accuracy of labels, i.e., ground truth, and also provide more information to farmers than simple two levels (nursing or not). Table 1 shows a map between nursing levels and the number of nursing piglets.
- `Balance Nursing Labels`:
  Figure 4 shows the distribution nursing levels. From the figure we can see our labels are biased, which will cause the light nursing and median nursing samples under fitted. We repeat the unbalanced samples in the training set randomly and get 1173 training samples.

2.3 Features Extraction

It is hard to find one or two features that are obviously sensitive to the nursing level. Alternatively, we decide to extract features with

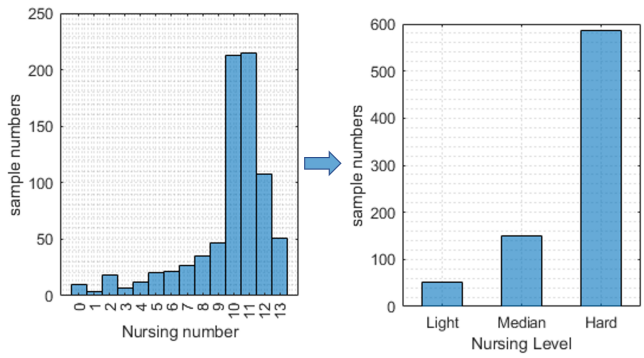

Figure 4: Unbalanced Nursing Level

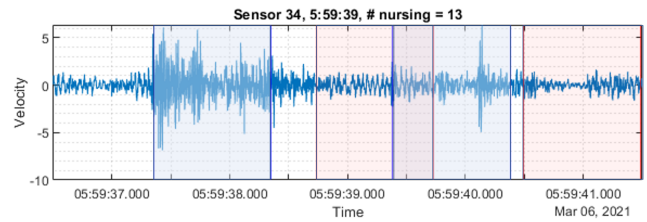

Figure 5: Local Variances in Time Domain

certain physical meaning greedily on a large scale first, and then filter out the critical features among all candidates based on their classification performance with a specific model (random forest). 390 features are extracted in the section. These features come from five categories.

- `Time Domain Statistics`:
  The mean, variance, maximum and minimum in the time domain of each sensor are extracted. These features can reflect the general activity types and intensities. 16 features can be extracted in the category.
- `Energy Domain Statistics`:
  For each sensor, the mean, variance, maximum and minimum of the vibration energy which is proportional to the square of the velocity are extracted. These features are also the indicators of general activity types and intensities. 16 features can be extracted in the category.
- `Frequency Domain Statistics`:
  The whole frequency domain (240 Hz) is split into 12 bands evenly. Different frequency bands include different activity information. For each sensor, extract the mean, variance, peak magnitude, frequency of peak magnitude, skewness and kurtosis of each band. We try to describe each frequency domain band with these six statistics. 288 features can be extracted in the category.
- `Local Variance in Time Domain`:
  Time domain statistics are calculated among the whole 5 seconds, which might submerge some important but short duration activities information. As the following figure shows, the local variance in time domain can expose this information by detecting the variances of the volatile part and the stable part through a time window with a length of one second. To be more robust, Variances of the two most unstable segments and the two most stable segments are extracted. Besides, the vibrations of other sensors might also be important when one sensor's vibration is pretty unstable or stable in the time window. Thus, 64 features are extracted in this category.
- `Peaks Features in Frequency Domain`:
  For the sensor (32) at the bottom of the sow, there always are more than one peak in low frequency domain in the light nursing level than that in hard nursing level. To quantify this phenomenon, three magnitudes with the highest prominence and their corresponding frequencies are extracted. 6 features are extracted in this category.

2.4 Random Forest

The random forest classification algorithm is as follows.
1. For b = 1 to B:
(a) Draw a bootstrap sample $\mathbf{Z}^*$ of size N from the training data.
(b) Grow a random-forest tree T_b to the bootstrapped data, by recursively repeating the following steps for each terminal node of the tree, until the minimum node size n_{min} is reached.
i. Select m variables at random from the p variables.
ii. Pick the best variable/split-point among the m.
iii. Split the node into two daughter nodes.
Let $C_b(x)$ be the class prediction of the bth random-forest tree. Then $\hat{C}_{rf}^B$ = majority vote $\{\hat{C}_b(x)\}_1^B$

Random Forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. We choose the random forests model because it often achieves higher accuracy than a single decision tree (more accurate than logistic regression in general) and also is good at handling high dimensional input. Besides, it can be used to rank the importance of variables in a regression or classification problem in a natural way.

2.5 Feature Selection

- `Algorithm Explanation`:
  As we mentioned in the introduction, we want to explore the key features that are very sensitive to nursing level. Feature selection or dimension reduction is conducted in the section. The Principal Component Analysis is used first. However, the results are not ideal. Then we turn to the new result-oriented (based on random forest) method as follow. Randomly select some features and then replace the old feature with the new feature one by one that can increase the classification accuracy.

```
Let n = number of features, best_features_list = n random features, i = 0
While i < length(features), do
    Let j = 0
    While j < length(features), do
        new_converted_set.replace(features[j])
        j += 1
    For cur_feature in new_converted_set, do
        Train new model
        If the current f1_score is the greatest, replace it
  i = i + 1
```

- `Verification of the robustness`:
  The robustness of these key features selected in this way can be validated by testing their classification performance in other models. Six models including Gradient Boosting, Logistic Regression, Linear discriminant analysis, Kneighbors, Support Vector Machine and Gaussian Naive Bayes are used here. We select 5, 10 and 20 features using this algorithm and feed them into these models respectively. F1 score is used for comparing the model performance. From the Figure 6 we can see than almost for all models, their accuracy with the selected features is higher than that with all 390 features. Even for the Support Vector Machine, the performance only drops a little when we only use selected features to train the model.
- `Selected feature explanation`:
  From Figure 6 we can see that only with 5 features we can get a relatively good accuracy. These five features are: the mean of frequency band 20 Hz 40 Hz in sensor 30, the maximum of frequency band 220 Hz 240 Hz in sensor 32, the mean of frequency band 0 Hz 20 Hz in sensor 31, the variance of frequency band 40 Hz 60 Hz in sensor 31 and the minimum local variance in sensor 31. The first four features are frequency domain features. As we mentioned in the feature extraction part, different frequency bands include different activities information. The combination of statistics in the four frequency bands can tell important information about nursing level. The last features can be understood in the this way. Compared to other sensors, sensor 31 is away from the nursing place, as Figure 1 shown. When other sensors have some unstable fluctuations in time domain, we can not tell it is because the piglets are playing around or nursing. However, when sensor 31 have some special fluctuation, we can conclude that not all piglets are nursing with relatively high confidence.

3 EVALUATION

We use F1 score to be the multi classification metric, which is defined as follow equation.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{4}$$

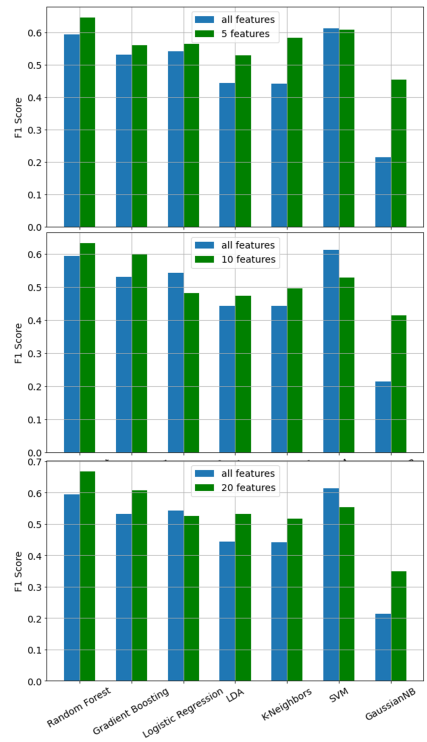

Figure 6: Prediction Performance of Features of Different Numbers in Different Models

Where TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative. From Figure 6 we can see that in general, the more features we use, the higher accuracy would be higher. Besides, random forest model can get the highest accuracy whatever features we use. So, we choose 20 features and feed into a random forest model and get a 67% F1 accuracy of test set. In order to improve the performance, train set and test set are predicted together. Because the nursing levels change continuously over time, we smooth all prediction results by a rolling windows and then evaluate the test set again. Figure 7 shows the nursing levels of training set and test set. Figure 8 shows the corresponding results after smoothing. From the figure we can see that some mispredicted values were corrected.

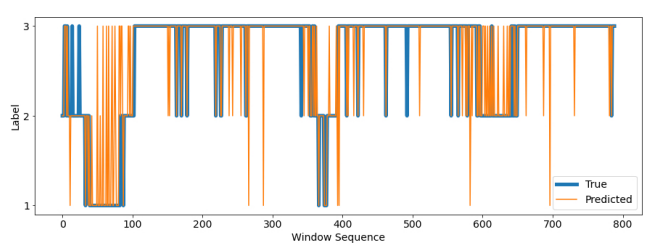

Figure 7: True and predicted value comparison before smoothing

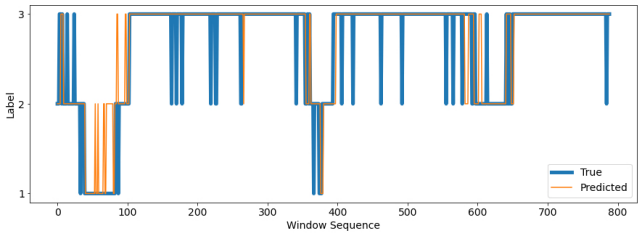

Figure 8: True and predicted value comparison after smoothing

After smoothing optimization, the model performance is up to 0.781. Figure 9 shows the confusion matrix of test data. From the confusion matrix we can see that the accuracy of Hard nursing level and Median nursing level is relatively high but the accuracy of Light nursing level is relatively low. On the one hand, it is because our selected features are still not sensitive enough to distinguish the Light and Median nursing level; On the other hand, it is because the method we use to balance our labels is not efficient enough. More work needs to be done in extracting or augmenting more samples whose nursing levels are Light or Median.

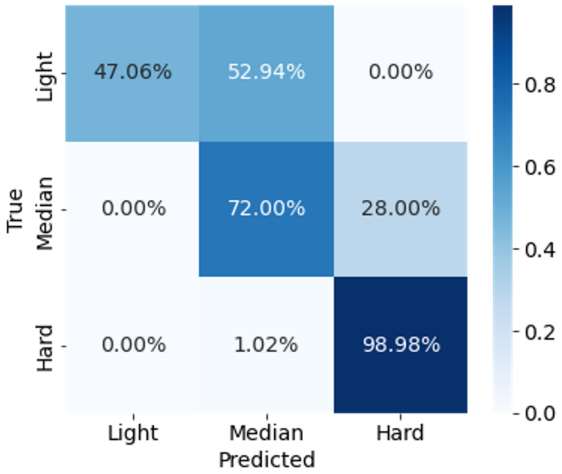

Figure 9: Confusion Matrix of Test Data

4 DISCUSSION

4.1 Method advantage over others

The goal of our project is to predict three types of piglets' nursing intensities based on vibration data, which is more practical in reality. The owner of a pig farm can know more information from our prediction results than the previous binary classification research. From the perspective of data analysis methods, the fault tolerance of the features used to predict the results is relatively high. When we extract some features, we focus on the characteristics in a band, such as the mean of a frequency band (eg. 10Hz 20Hz) or the variance of a piece of time-domain signal with extremely high/low variance. With this feature extraction method, we can get rid of the randomness and also find meaningful information at the same time. Under the premise that all the features we have contained a certain physical meaning, we use a selective algorithm to extract the 20 most effective features that reach the highest accuracy level. Besides, the prediction accuracy of the model is less dependent on a specific feature, thus, the overall reliability is higher than other models with only one or two features.

4.2 Challenges

Because of the nursing nature of new born piglets, the data reveals unbalanced nursing levels, which is harmful for the machine learning progress. The distribution of the uneven nursing level is, as shown in Figure 2:Raw Data Overview, the percentage of hard nursing nominates, and the percentage of medium nursing overweight the light nursing. The second challenge is that the asynchrony of five sensors. As presented in Figure 3: Missing Vibration Data for Some Sensors, package loss occurs in sensor 30 from 03:29:42 to 03:29:42. Then for the feature selection part. The amount of possible feature candidates and their combinations increases the feature number of the model, which requires feature selection methods to avoid over-fitting. The limited data turns out to be a challenge as well. The fragmented, limited camera data increase the difficulty of labeling and training.

4.3 Limitations and Future Work

The limitation of our work is that there is huge improvement space for the accuracy of median nursing level. This might be caused by limited labels as well as the unevenly distributed labels. Meanwhile,we need to extract features from all 4 sensors in the final model, which require that our vibration signals of four sensors should be as synchronous as possible. However, in reality, package loss occurs from time to time. The future work could be conducted on predicting the future nursing trends based on the previous vibration data, as well as predicting other piglets behavior to provide more informative suggestions to farmers.

4.4 Suggestion on the data collection

Keeping the recording continuous, which is to say, having the video continuous enough to recognize the activity change of every piglet. The resolution or fps of the camera does not need to be that high in order to save drive storage, as long as the video is recognizable for labeling and other CV analysis. What's more, the synchronization of the sensors would be helpful. If we could guarantee the synchronization of the sensors, the accuracy level could be improved greatly. Lastly, recording the other factors, such as the weather, temperature, time after the sow production and human activities influence in order to add those factors as features later.

5 CONCLUSION

The paper develops a complete workflow to predict the piglet nursing level based on the structural vibration. For the multi classfication problem, the F1 score is up to 78%. That is to say with proper features and models, the piglet's behavior can be detected in a high accuracy only based on the

6 ACKNOWLEDGMENTS

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