Pet Behavior Classification based on Graph Attention Network

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Abstract. CCTV and wearable devices for companion animals that can effectively take care of companion animals are being researched and developed. In this paper, we propose a companion animal behavior classification technique using LSTM (Long Short-Term Memory) and GAT (Graph Attention Networks) to identify daily activity through sensors collected from pet wearable devices. The final goal of the proposed technique is to classify static and dynamic behaviors through acceleration and gyro sensors. LSTM is used as an encoder to extract features from sensor data, and this is used as input data for GAT. It is expected that the proposed technique will be able to identify the activity level of companion animals and inform the guardian of the lethargy of companion animals more quickly.

Keywords: Graph Neural Networks, Behavior classification, Deep learning, Sensor data, Companion animal, Time series data

1 Introduction

Recently, as the pet humanization phenomenon, in which pet owners treat their pet as if they were their children, has accelerated, researches and developments are being actively conducted to provide higher-quality IoT (Internet of Things)-based services to pets[1, 2]. Among them, the wearable device market is continuously growing, and a method of processing sensor data is becoming important due to the characteristics of the wearable device.

Healthcare services through wearable devices are being widely serviced for people. Typical services include fail detection through accelerometer and gyro sensors, and heart rate identification using ECG(Electrocardiogram). Healthcare services for people are basically being used for the purpose of assisting medical care because communication is possible. However, in the case of companion animals, communication is impossible, so accurate analysis of sensor data is required for the pet owners to recognize the problem.

In this paper, we propose GAT (Graph Attention Networks)-based companion animal behavior classification technique for accurate analysis of sensor data. Data is collected from the wearable device consisting of accelerometer and gyro sensors and reconfigured as a node to be input of the GAT through LSTM (Long Short-Term Memory). Then, the behavior of companion animals is classified using GAT.

2 Relative Works

2.1 Behavior Classification

Since companion animal behavior classification is the most basic process for providing automated services, related studies are steadily continuing[3-5]. Many methods, such as Skeleton Modeling, SVM (Support Vector Machine), and DeepLabCut, have been tried for recognizing the behavior of animals, and mostly behavior classification through images. Among them, as a behavior classification method using sensor data, LSTM, a type of RNN (Recurrent Neural Networks), is mainly used.

LSTM is explicitly designed to avoid the problem of long dependency periods. Due to these characteristics, it is used in combination with various models for analysis of time series data. In particular, in order to classify behaviors by collected sensor data, feature extraction through LSTM, which shows strength in time series data, is widely used[6].

2.2 Graph Classification

Research to extend neural networks to handle graphs of various structures continued, and initially, RNN was used to handle graph-structured data. GNN (Graph Neural Network) have also been introduced as generalized version of RNN. After that, GNN was developed into Spectral Representation and Spatial Representation.

The representative method of Spectral Representation is to perform convolution operation defined in the Fourier domain that calculates the eigen decomposition of Graph Laplacian. Through this operation, a non-spatially localized filter can be created. Although it is specialized to reflect more detailed structure and feature characteristics, it has a disadvantage in that it is difficult to respond to graphs or nodes of new structures[7].

Spatial Representation is a method of directly applying convolution to a graph and performing operations on neighboring groups. A representative example is GraphSAGE, which is evaluated as an effective access to data with a large range[8].

GAT has an attention-based structure to perform node classification on graph-structured data[9]. It is possible to obtain a feature only with the information on the adjacent node of the corresponding node, and it is even possible to use a completely unconfirmed graph as a test set. Based on these advantages, this study intends to classify the sensor data collected from wearable devices into static and dynamic behaviors of companion animals using GAT.

3 Pet Behavior Classification

In this paper, we implemented LSTM and GAT-based model to classify dynamic and static behaviors of companion animals from sensor data. To classify any “behavior” of companion animals, a certain period is required. In this study, the 3-seconds window size and the 5-seconds window size were compared to clarify the period. Fig.1. below is an overview of the proposed model.

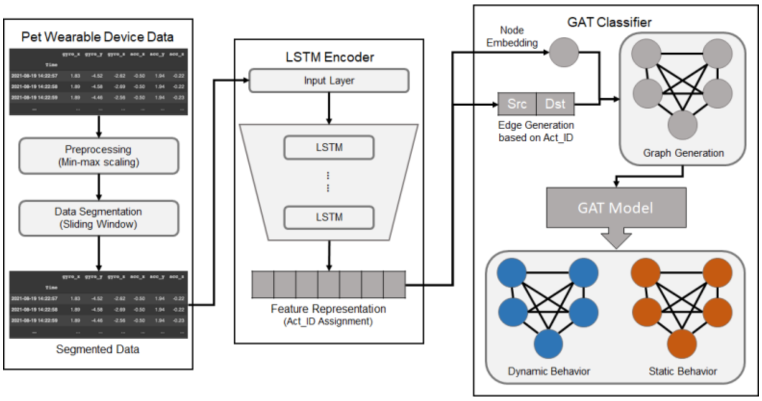

Fig. 1. Overview of proposed model.

Data collected from companion animals has a total of 7 columns consisting of 3 axes of gyroscope, 3 axes of acceleration, and the state of behavior. The collected data goes through preprocessing process based on min-max scaling, and segmented data is extracted through the window, which is sized of 5 seconds. Segmented data extracts feature through LSTM Encoder and assigns Act_ID. LSTM Encoder utilizes 3-Layer LSTM because it can solve nonlinear problems more efficiently. The feature represented data goes through the process of Node Embedding of GAT, and the edge of the graph is generated based on the assigned Act_ID. In the edge of the graph, the source and destination are determined according to the information labeled in the data. To train the model, nodes with the same label are completely connected to each other. This is to more clearly identify the features that can be seen in each behavior along with feature extraction from time series data through LSTM. Graph is created through the edges and nodes created in this way, and the behaviors are classified based on the GAT model.

4 Experiment

4.1 Data Collection

The dataset to be used for the experiment was collected from one companion animal. Sensor data was compared with the video recorded at the time and divided into dynamic behavior and static behavior.

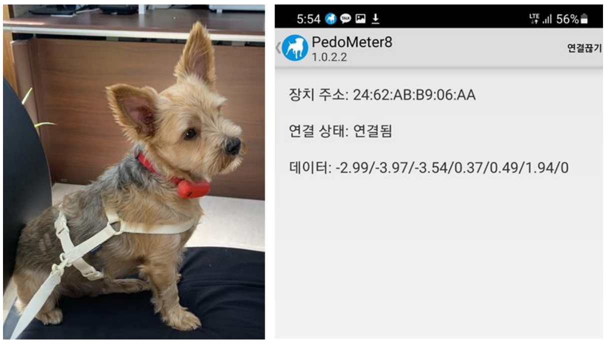

Fig. 2. Pet wearing a wearable device (*left*), screen of the smartphone collecting data (*right*)

Data collected from the wearable device can be checked in real time on a connected smartphone. As shown in Fig.2. above, the connection status with the device can be checked through the smartphone, and the collected data can be checked in the order of Gyro X, Y, Z, Acceleration X, Y, Z, and Pedometer.

4.2 Experimental Result

The experiment was performed as a comparison when 3 sized window and 5 sized window were input to the same model. Both window sizes were compared in the same experimental environment. In this study, we used early stopping for the setting of epoch, a method of stopping learning when performance in the hold-out validation set, which is a commonly used method, no longer increases at this specific point in time.

The Fig.3. below shows the training graph of each sliding windows' size.

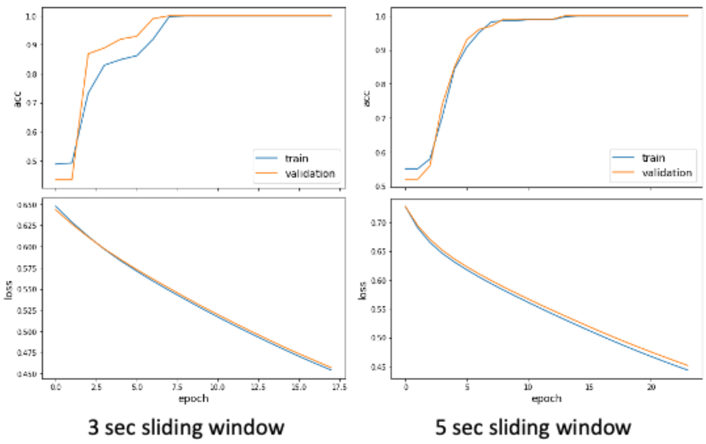

Fig. 3. Training graph of 3 seconds sliding window (*left*), Training graph of 5 seconds sliding window (*right*)

Tab 1. Below is the result of predicting 10 test data, respectively.

Table 1. Result of the experiment

Test data number (3 sec answer / 5 sec answer)	Answer probability % (3 sec)	Answer probability % (5 sec)
1 (Dynamic / Dynamic)	65.746	57.236
2 (Static / Static)	50.882	59.936
3 (Dynamic / Dynamic)	65.710	61.059
4 (Dynamic / Static)	64.850	54.793
5 (Static / Dynamic)	53.253	55.023
6 (Dynamic / Dynamic)	65.018	61.479
7 (Static / Static)	51.653	60.065
8 (Static / Static)	53.251	59.934
9 (Dynamic / Static)	63.716	59.937
10(Dynamic / Dynamic)	64.423	61.844

The model accuracy in the sliding window of 5 seconds showed an accuracy of 98.8%, but overfitting was confirmed when looking at the aspects of the learning graph and the accuracy graph in the sliding window of 3 seconds. The form of the graph currently input to the GAT has the form of a fully connected graph, and it was confirmed that the accuracy changes as the shape of the edge connected between the nodes is adjusted.

5 Conclusion

In this paper, it was possible to confirm the accuracy of the proposed model, which varies according to the size of the sliding window. This is meaningful in determining how much time to use when trying to understand an animal's behavioral pattern through sensor data. Since the overfitting was discovered during the experiment, in future research, the preprocessing before being input to the LSTM Encoder is to solve the overfitting through various preprocessing methods such as z-score rather than simple min-max scaling. Through this, the shape of the graph to be input to the GAT will be made clearer, and the best preprocessing method for resolving the overfitting will be confirmed through experiments.

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References

1. Kim, S.K., Kim, H.T., Ji, Y.G., Lee, J.Y.: A Study on the Acceptance Factors of the Introduction of a Smart IoT Technology for Well-being Companion Animal. The Journal of Society for e-Business Studies. 24, 143--163 (2019)
2. Van Der Linden, D., Zamansky, A., Hadar, I., Craggs, B., Rashid, A.: Buddy's wearable is not your buddy: Privacy implication of pet wearables. IEEE Security & Privacy. 17, 28--39 (2019)
3. Fang, C., Zhang, T., Zheng, H., Huang, J., Cuan, K.: Pose estimation and behavior classification of broiler chickens based on deep neural networks. Computers and Electronics in Agriculture. 180, 105836 (2021)
4. Fujimori, S., Ishikawa, T., Watanabe, H.: Animal Behavior Classification Using DeepLabCut. 2020 IEEE 9th Global conference on Consumer Electronics (GCCE). 254--257 (2020)
5. Tran, D. N., Nguyen, T. N., Khanh, P. C. P., Trana, D. T.: An iot-based design using accelerometers in animal behavior recognition systems. IEEE Sensors Journal. (2021)
6. Zhao, H., Deng, K., Li, N., Wang, Z., Wei, W.: Hierarchical Spatial-Spectral Feature Extraction with Long Short Term Memory (LSTM) for Mineral Identification Using Hyperspectral Imagery. Sensors. 20, 6854 (2020)
7. Cao, D., Wang, Y., Duan, J., Zhang, C., Zhu, X., Huang, C., Tong, Y., Xu, B., Bai, J., Tong, J., Zhang, Q.: Spectral Temporal Graph Neural Network for Multivariate Time-series Forecasting. arXiv preprint arXiv:2103.07719 (2021)
8. Hamilton, W. L., Ying, R., Leskovec, J.: Inductive representation learning on large graphs. In Proceedings of the 31st International Conference on Neural Information Processing Systems. 1025--1035 (2017)
9. Veličković, P., Cucurull, G., Casanova, A., Romero, A., Lio, P., Bengio, Y.: Graph Attention Networks. arXiv preprint arXiv:1710.10903 (2017)