A Decoder of Domestic Cat Vocalizations

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1. Motivation

In this project, we study the following problem: Is it possible to use domestic cat sounds to classify their emotional states? Pet owners frequently encounter challenges in comprehending the needs and emotions of their beloved animals, making the task of ensuring their well beings hard. This is particularly true in cats. Different domestic cats could use completely different sounds to express the same meaning. Since cats' vocalizations can vary widely and carry nuanced meanings that are often lost in communications, we want to use AI to allow people to better understand and take care of their cats.

2. Methodology

2.1 Hypothesis

A cat's emotions, such as pleasure or anger, can be directly discerned from its vocalizations. In other words, without observing its behavior or facial expression, an AI is able to tell a cat’s emotions from its vocalizations.

2.2 Goal

We aim at training an AI to accurately classify a cat’s vocalizations. Given an audio input, the AI should output one label that best describes the cat’s emotion.

2.3 Description of the Data and Data Handling

Overview of the dataset

We used a dataset of cat sounds curated for better understanding of cat behavior, or more specifically, the emotion classification of cats. This dataset is organized to include a total of 10 categories (Figure 1), each representing a different emotional state of a cat: 1.Anger, 2.Defense Behavior, 3.Fighting, 4.Happiness, 5.Hunting Desire, 6.Mating, 7.Calling for Its Mother, 8.Pain, 9.Resting, and 10.Warning. They are also used as class labels for the classifier.

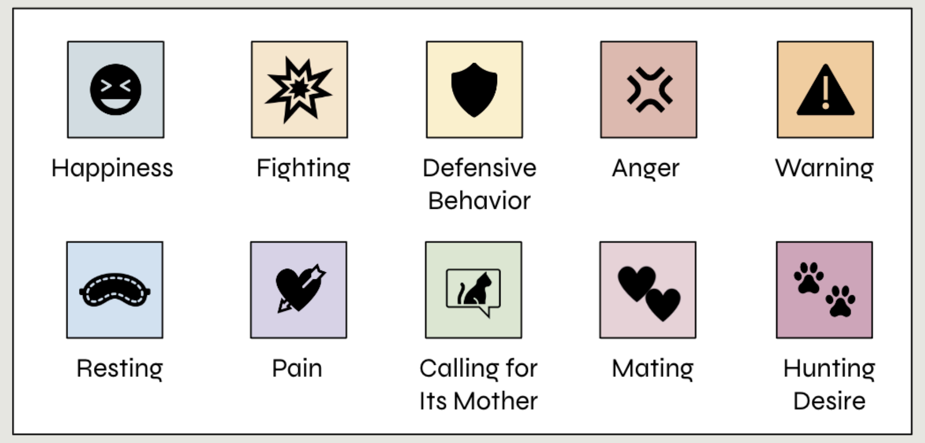


Figure 1. Labels of Cats' Vocalizations

The data sources used in this project include:

- Yagya Raj Pandeya, Dongwhoon Kim and Joonwhoan Lee, Domestic Cat Sound Classification Using Learned Features from Deep Neural Nets (https://www.mdpi.com/2076-3417/8/10/1949)
- Yagya Raj Pandeya and Joonwhoan Lee, Domestic Cat Sound Classification Using Transfer Learning (http://www.ijfis.org/journal/download_pdf.php?doi=10.5391/IJFIS.2018.18.2.154)

Data Handling

During preprocessing, we have transformed the audio in the form of .mp3 files to .wav files to comply with the python packages. We also converted the stereo input (2 channels) into mono (1 channel). There is no missingness in our dataset.

2.4 Exploratory Data Analysis

Our dataset consists of a relatively large number of audio samples, totaling 5,922 individual files. This ample sample size provides a solid foundation for training and evaluating AI models aimed at classifying cat emotions based on vocalizations.

The durations of the audio files vary significantly, ranging from as short as 0.313 seconds to as long as 16.797 seconds. This variability reflects the natural differences in cat vocalizations and adds complexity to the task of emotion classification. Moreover, the distributions of audio lengths differ across the 10 emotional classes. Histograms (Figure 2) illustrating these distributions show that certain emotions are more likely to be expressed through shorter or longer vocalizations, indicating potential patterns worth investigating further.

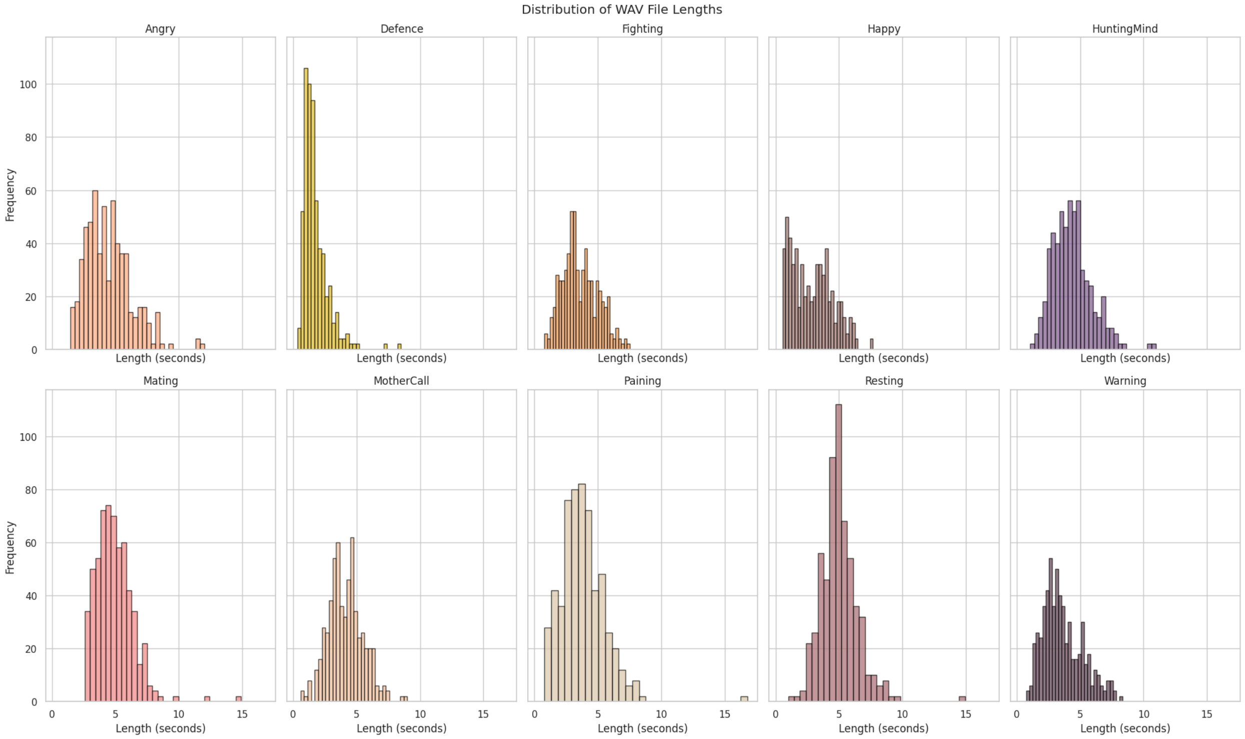


Figure 2. Distribution of WAV File Length

An important characteristic of the dataset is its class balance. The 10 emotional categories are evenly represented, ensuring that the classification model is not biased toward any particular emotion. This balance is visually confirmed through the following bar graph (Figure 3), which shows roughly equal counts for each class.

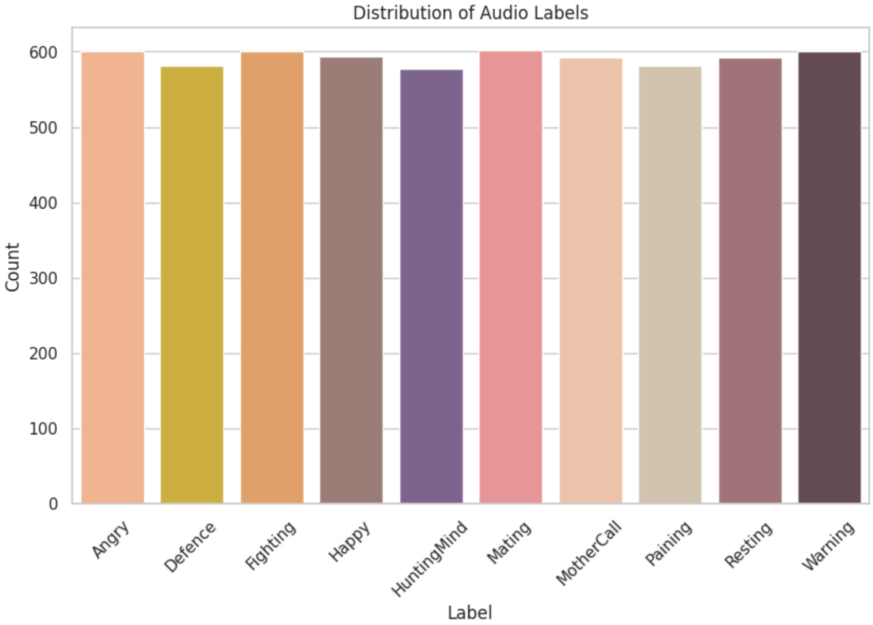
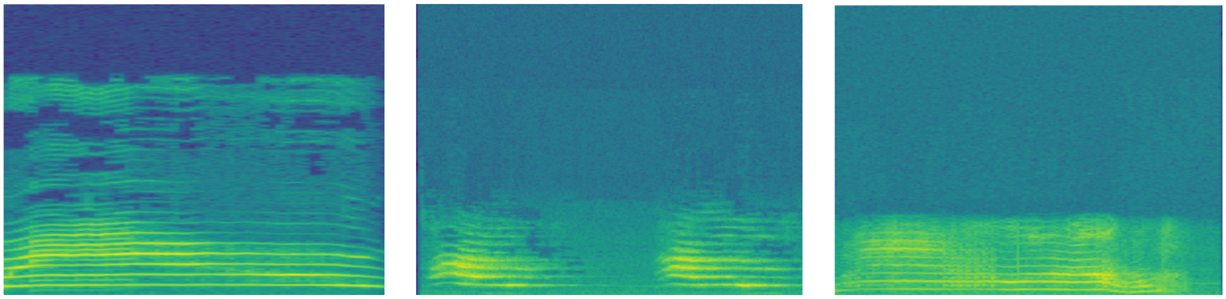


Figure 3. Distribution of Audio Labels

However, one of the key challenges revealed by our analysis is the significant variation within each emotion class, coupled with relatively small differences between some classes. This is especially evident in the spectrograms (Figure 4). For example, the first two spectrograms, though visually distinct, both represent vocalizations associated with happiness. In contrast, the last spectrogram, which closely resembles one of the happy vocalizations, actually corresponds to a cat in pain. This suggests that while there is diversity in how a single emotion may be expressed, similarities across different emotions may complicate classification, highlighting the nuanced nature of feline vocal expressions.



Happiness

Happiness

Pain

Figure 4. Spectrograms of Vocalizations from Different Categories

2.5 Modeling Approach

Given the task of classifying the emotional state based on cat sound, we decided on combining an audio feature extractor and a Convolutional Neural Network (CNN) classifier to build our model.

Audio signal processing commonly uses a set of audio features to represent the original audio effectively, and this is the traditional approach in transforming waveform into a matrix that is more compatible with machine learning models.

Our approach included the computing of:

- *Zero Crossing Rate*: Measures the rate at which audio signal changes from positive to negative or vice versa, implying the smoothness of the sound.
- *Chroma Frequencies*: Measures the harmonic content in the sound.
- *Mel-Frequency Cepstral Coefficients (MFCCs)*: Captures the timbre and texture of the audio.
- *Spectral Rolloff*: Measures the distribution of total energy, implying the brightness of a sound.
- *Spectral Bandwidth*: Quantifies the width of the band of frequencies that contain most of the energy of the signal.
- *Root Mean Square Energy (RMS)*: Measures the signal's power, reflecting its loudness.
- *Mel-Spectrogram*: Numerically represent the sound with frequencies converted to the Mel scale, a scale that approximate human ears' response to frequencies.

Such computing is implemented through a pipeline with the use of librosa, a Python module for audio and music processing. The resulting vectors were transposed and averaged over time frames to reduce the dimensionality while retaining the most significant characteristics that represent the audio sample. Finally, we concatenated these compressed statistics to form an array representative of the audio file. The array was then taken as the input to our CNN classifier to make predictions. The diagram below illustrates the pipeline of our model (Figure 5).

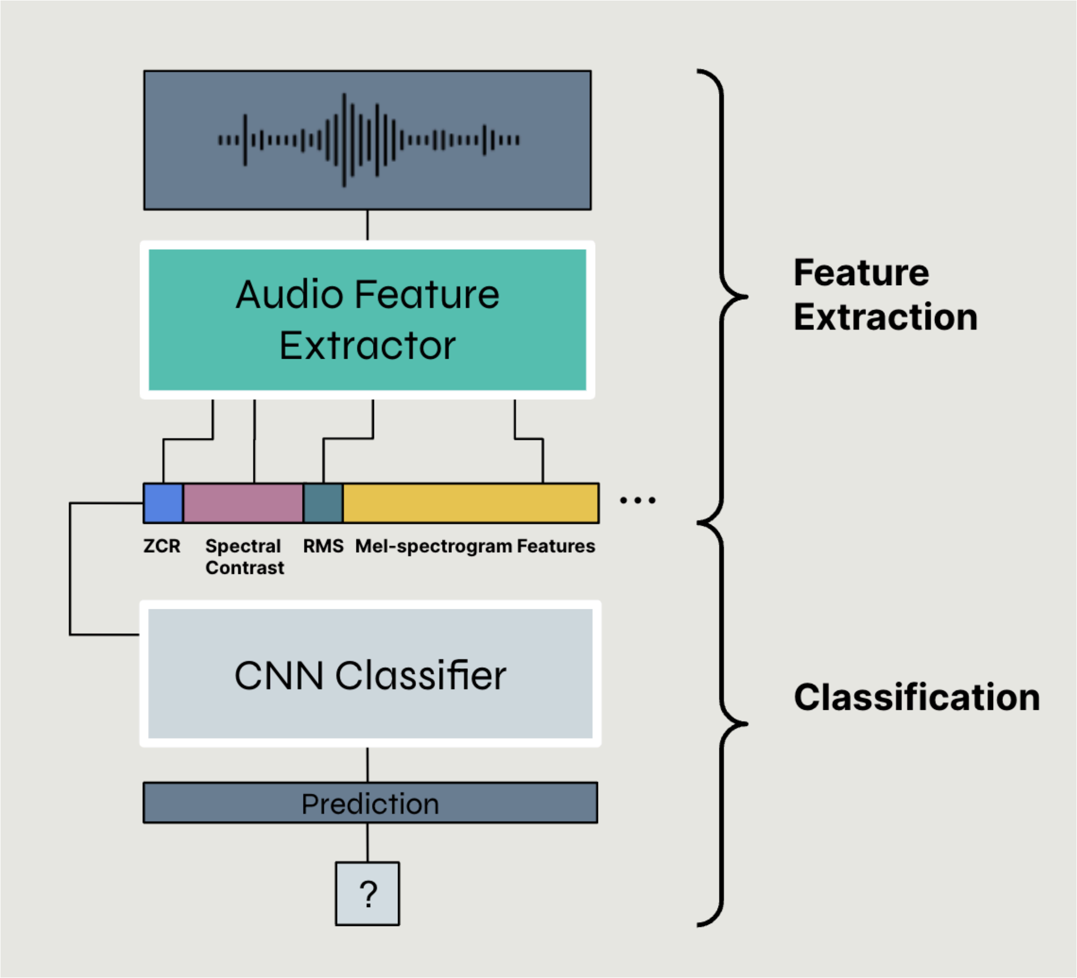


Figure 5. Model Architecture

3. Evaluation results

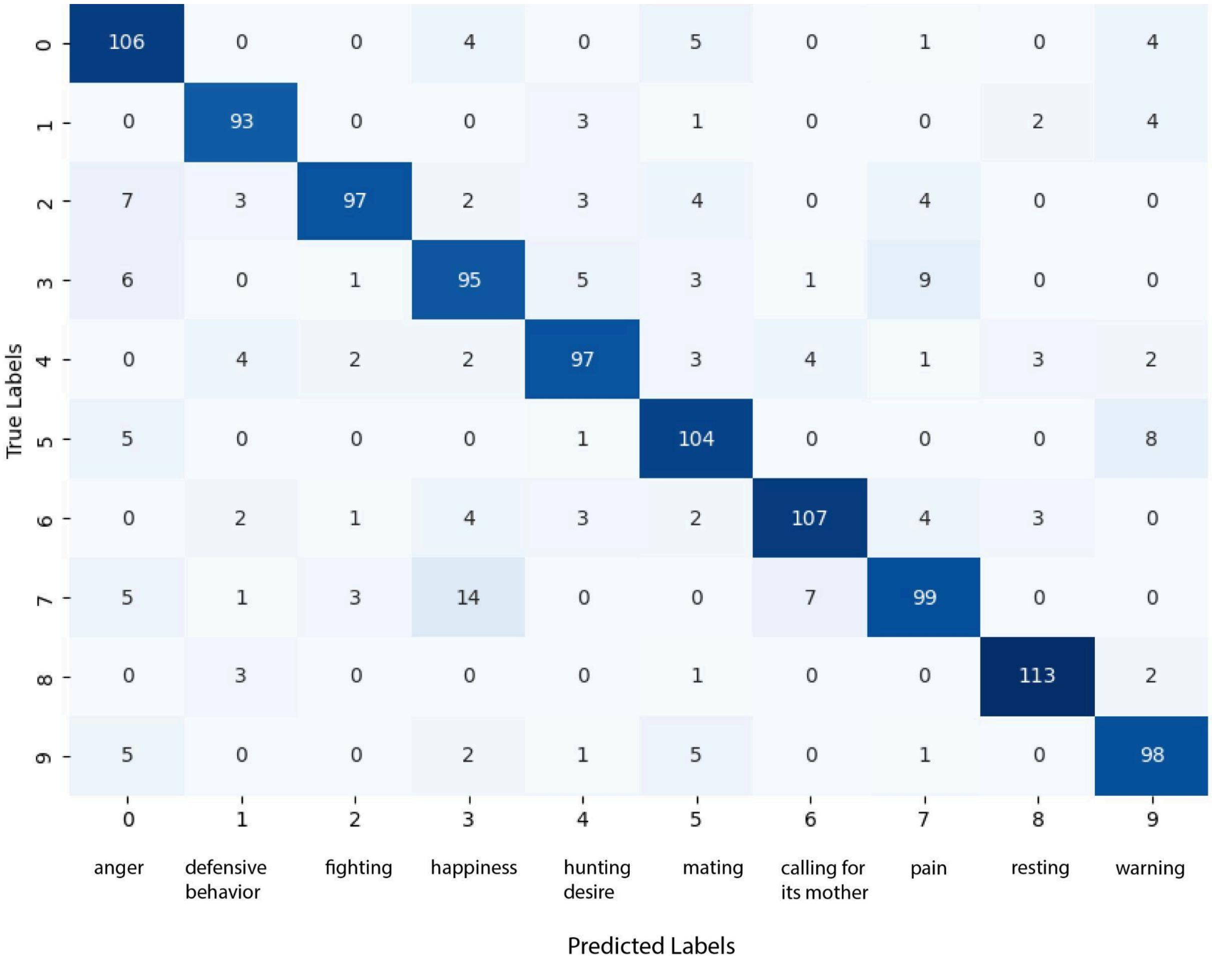
We tested our model on the test set, which contains 1185 data samples. The overall accuracy rate is 85.15%. A comparison of accuracy rates by class (Table 1) shows that our model performs the best in identifying the Fighting and the Resting sounds, both of which reach an accuracy of around 93%. It also shows that our model performs the worst in identifying the Happiness sounds, with an accuracy of around 77%, which can be explained by the large variance of this category (Figure 4).

Class	Anger	Defensive Behavior	Fighting	Happiness	Hunting Desire	Mating	Calling for its mother	Pain	Resting	Warning
Accuracy	0.79	0.88	0.93	0.77	0.86	0.81	0.90	0.83	0.93	0.83

Table 1. Accuracy Rates by Class

The confusion matrix (Figure 6) is a structured table that summarizes the outcomes of our classification task, offering a comprehensive view of the model's predictive capabilities. It highlights both its effective and deficient areas of predictions and helps us understand the bias of our model.

A clear diagonal line indicates that our model makes correct predictions for most of the categories. However, our model sometimes gets confused by the Happiness and the Pain sounds, or the Warning and the Mating sound. Such confusions are probably caused by the similarity between the sounds of Happiness ("meow-meow") and Pain ("miyoou") and that between Warning("ko-ko-ko") and Mating ("gay-gay-gay") (Pandeya & Lee, 2018). This result also matches our findings in exploratory data analysis (Figure 4). In the future study, we will focus on improving the model's ability to distinguish cats' vocalizations with similar sounds but distinct emotions.



	0	1	2	3	4	5	6	7	8	9
0	106	0	0	4	0	5	0	1	0	4
1	0	93	0	0	3	1	0	0	2	4
2	7	3	97	2	3	4	0	4	0	0
3	6	0	1	95	5	3	1	9	0	0
4	0	4	2	2	97	3	4	1	3	2
5	5	0	0	0	1	104	0	0	0	8
6	0	2	1	4	3	2	107	4	3	0
7	5	1	3	14	0	0	7	99	0	0
8	0	3	0	0	0	1	0	0	113	2
9	5	0	0	2	1	5	0	1	0	98

Figure 6. Confusion Matrix

Reference

[1] Pandeya, Y. R., Kim, D., & Lee, J. (2018). Domestic cat sound classification using learned features from deep neural nets. *Applied Sciences*, *8*(10), 1949.

[2] Pandeya, Y. R., & Lee, J. (2018). Domestic cat sound classification using transfer learning. *International Journal of Fuzzy Logic and Intelligent Systems*, *18*(2), 154-160.