Sound Scene Classification: Comparing the Performance of Spectrum-based and Time-based Features

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Introduction

Recognizing sound scenes in realistic soundscapes would inform machines about their setting, creating context-aware machines.

To do this, we **train "listening machines"** using audio data, which they use to **find patterns** and learn.

Machines can process *these* **features extracted** from data:

- **Frequency-based features** help machines process audio like humans hear sounds at the level of the cochlea.
- **Time-based features** quantify characteristics of the signal's time-domain plot.

Problem Statement

Since we don't know what features and classification systems are best at classifying sound scenes, we can use those features to **train classification systems** and **compare their performance**.

Research Questions

1- What **combinations** of time-based and spectrum based features will result in the best **accuracy**?

2- How will the **K-Nearest Neighbors** classifier perform compared to a **Neural Network** classifier?

Hypothesis

Classifiers will perform best with frequency-based features because they help machines process audio like humans hear sounds.

A Neural Network will perform better than the K-Nearest Neighbors classifier because it learns from its errors to understand complicated relationships.

Methods: Acoustic Features

Root Mean Square (RMS)

$$rms = \sqrt{\frac{1}{N}\sum_{n}|x(n)|^2}$$

Zero-crossing Rate (ZCR)

$$zcr = \frac{1}{T-1}\sum_{t=1}^{T-1}1_{\mathbb{R}_{<0}}(s_t s_{t-1})$$

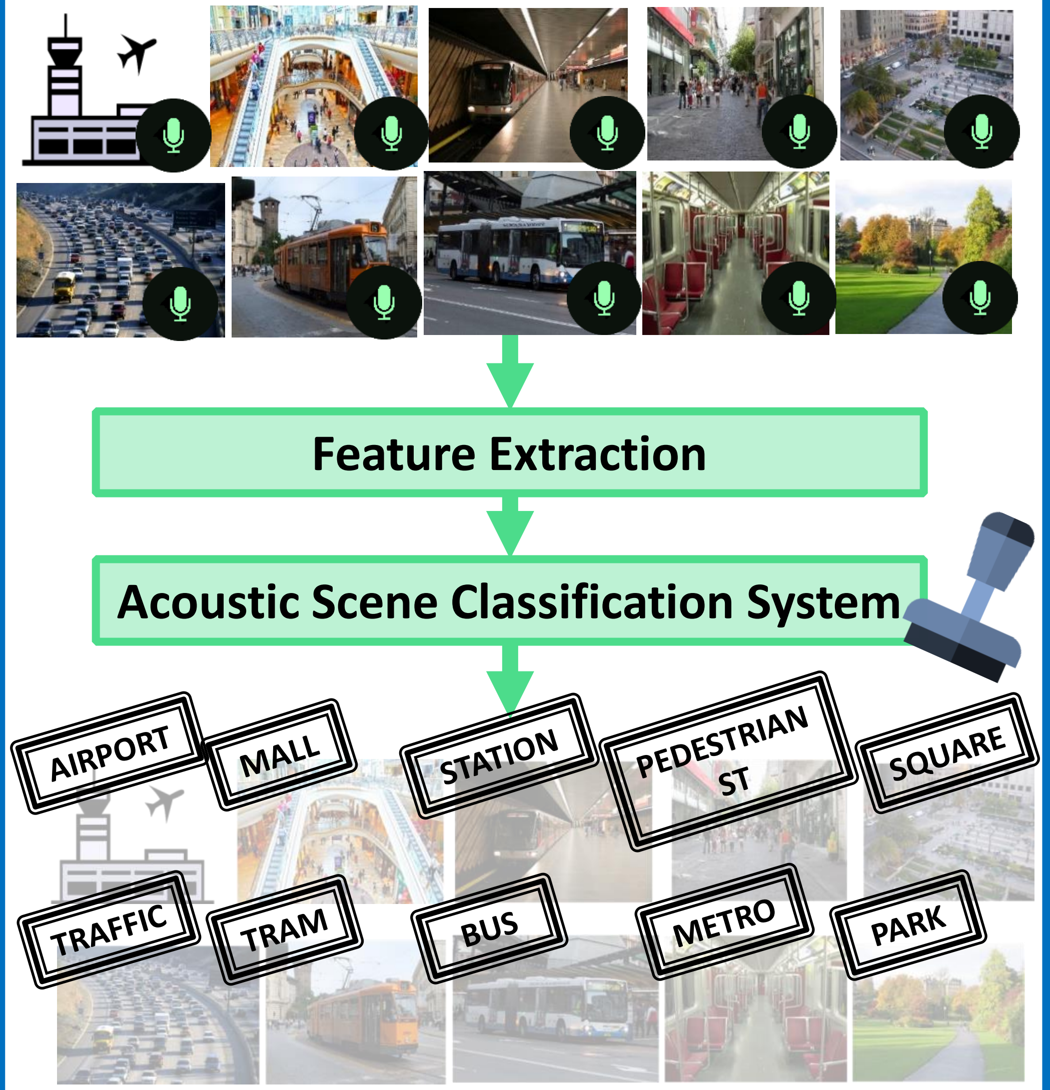
Spectral Centroid (SC)

$$c = \frac{\sum_{n=0}^{N-1} f(n)x(n)}{\sum_{n=0}^{N-1} x(n)}$$

Spectral Bandwidth (SB)

$$b = \sum_{n} S[n](f[n]-c[t])^{p^{\frac{1}{p}}}$$

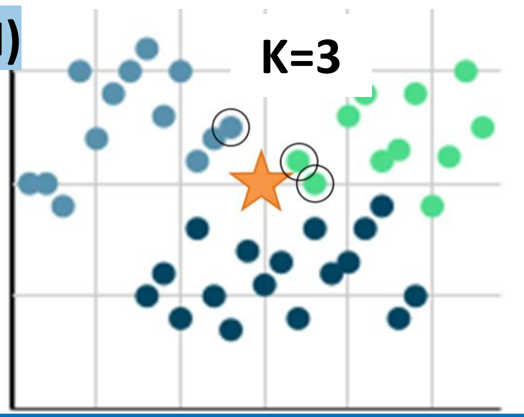
Methods

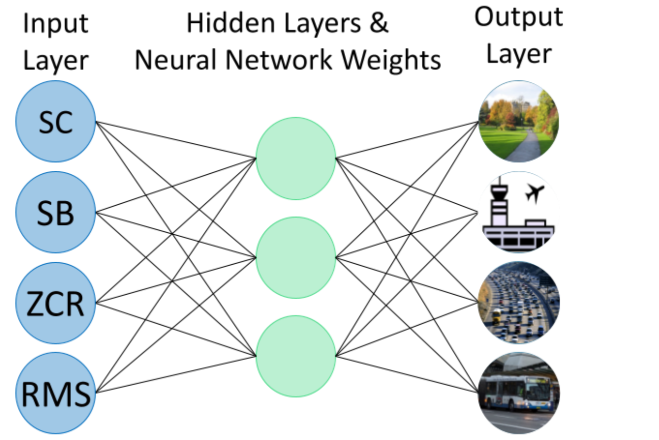


Methods: Classifiers & Cross-validation

K-Nearest Neighbors (KNN)

1. Find the k nearest neighbors.
2. Vote for classes.
3. Object is assigned to class with **majority vote**





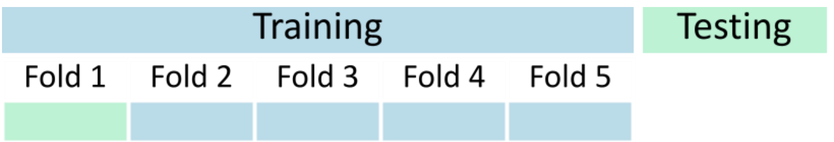
Neural Network (NN)

Error Function

$$J = \sum -\frac{1}{N}log(\sum y \cdot \hat{y})$$

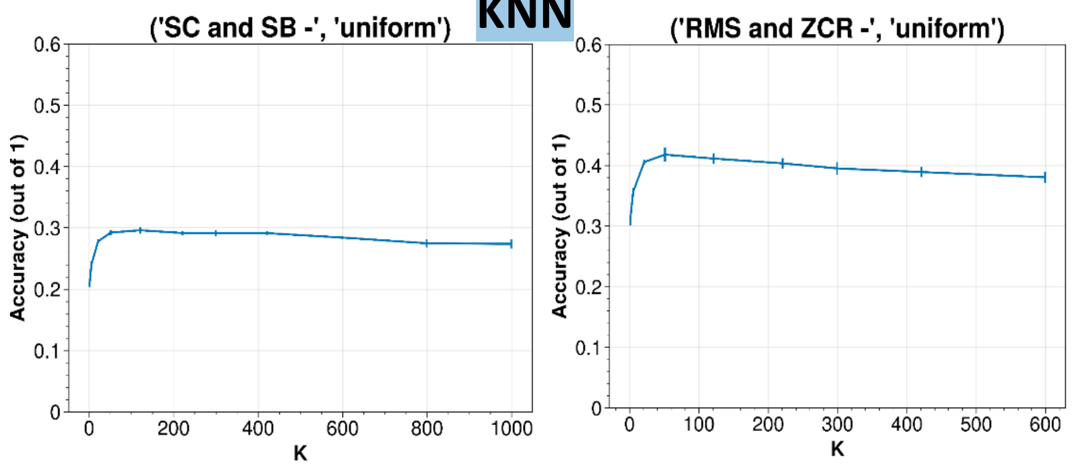
$$\hat{y} = softmax(xW)$$

Cross-validation

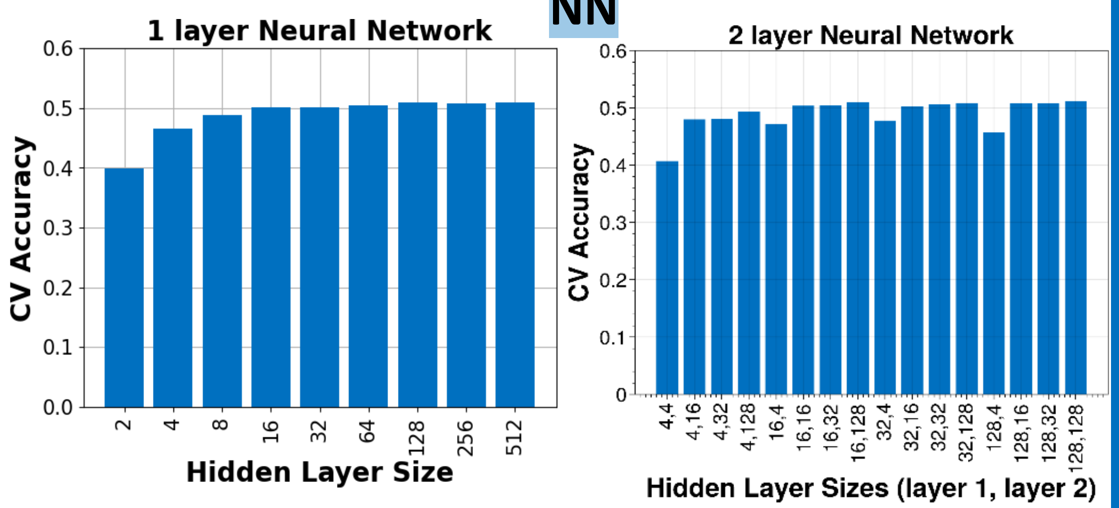


Results: Cross-validated Training

KNN

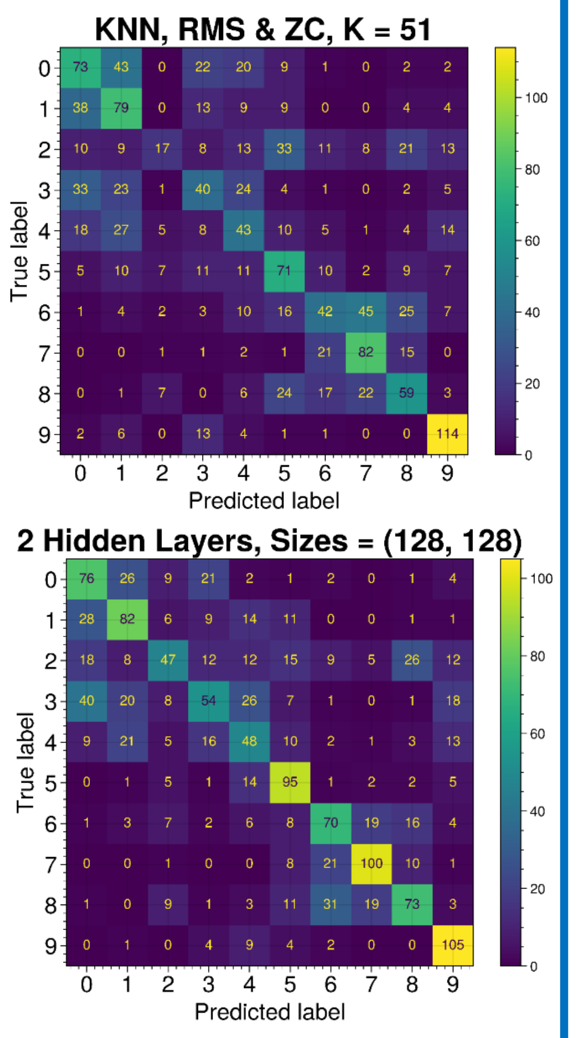


NN



Results: Performance

Model	Validation Accuracy	Test Accuracy
NN (2 layers, Sizes = (128,128))	51.4%	**51.6%**
NN (2 layers, Sizes = (16,128))	**51.8%**	51.5%
NN (1 layer, Sizes = 512)	**51.0%**	50.9%
NN (1 layer, Sizes = 2)	40.3%	39.9%
KNN (K=51, RMS & ZCR, Uniform)	**41.5%**	**41.3%**
KNN (K=221, RMS & ZCR, Distance)	40.9%	**41.3%**
KNN (K=221, SC & SB, Distance)	29.7%	29.8%
KNN (K= 221, All features, Uniform)	29.7%	29.5%
KNN (K=121, SC, SB, & ZC, Uniform)	29.7%	29.3%



Conclusion

- Overall, the performance of the Neural network increased as the sum of the sizes of the layers increased but **plateaued** quickly at around **50%**.
- The 2-hidden-layer Neural Networks with hidden layer sizes **(16,128) and (128,128)** performed the best overall at over **40% more than chance**.
- The K-Nearest Neighbors classifier performed best with a combination of the two **time-based features**, with an accuracy of **over 40%**

References

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Project Repository

https://github.com/AliaaMahgoub/sound-scenes

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