# 摘要

音频场景分类（Acoustic Scene Classification）是一项通过音频分析使设备能够理解其所处环境的任务，属于计算机听觉场景领域的一个分支。目前该技术已经广泛使用于智能可穿戴设备、机器人导航系统、上下文感知服务等应用场景。得益于近年来深度学习热潮的掀起，将深度学习中的方法应用到音频场景分类中的例子越来越多。通过引入诸如卷积神经网络等手段，使场景分类准确率有了可观的提升，甚至能使机器超过人类水平。为了探究卷积神经网络在领域音频场景分类的适用性并探究系统性能的提升方法，本文中设计了几组系统并进行实验以验证，主要工作及贡献如下：

（1）针对普通单声道模型不能有效利用音频中空间信息导致分类准确率不佳的问题，文中使用了双耳表示法及谐波-冲击源分离法对原始音频进行处理，使其在具有明显空间特征的场景中分类准确率得到了明显的提升。（2）针对一般卷积神经网络应对不同数据泛化能力不佳的问题，本文尝试借鉴图像识别领域中的VGGNet结构，在增加卷积神经网络深度的同时增加了系统的灵活性，最终在不同的数据上取得了更好的泛化效果。（3）本文还尝试使用集成学习领域中流行的Stacking方法将多个基于不同特征的独立模型融合，融合后的系统相比其中的子系统分类性能又有了进一步的提升。（4）本文还在卷积神经网络训练时参数调整阶段将训练时间考虑到系统性能评估的要素中去，使得系统在性能逐渐提升的同时训练时间也处于可控范围内。

本文先从设计基于MFCC和GMM的基线系统开始，用传统机器学习的方法构造了一个典型的基线系统作为之后系统的对照组。接着研究一般的基于卷积神经网络的音频场景分类方法与原理，并实现了一个具有两层卷积结构的基本系统。训练系统时通过调整参数以发挥其分类潜力，并分析系统在各类别上的分类准确率与混淆矩阵，借此评价其优点与不足。最后，根据之前系统体现出的问题，从特征处理和网络结构两个方面进行改进，得到了最终的改进系统。在改进系统中分类的准确率相对前两个系统有了明显的提升。

最终得出的结论是，卷积神经网络相比于一般机器学习方法所需要的数据更少、学习能力更强。在设计卷积神经网络时应注意网络的灵活性，避免因参数过多而造成系统的泛化能力不佳。此外，通过引入集成学习的方法将多组模型进行融合通常可以显著的提升性能，但集成时应注意模型间的独立性。最后，在音频特征提取阶段如果能利用到立体声信息，可以提升系统对空间的感知能力，进而提升分类准确率。

关键词：音频场景分类；卷积神经网络；梅尔频率倒谱系数；集成学习

# Abstract

Acoustic Scene Classification is an

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# 致 谢

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