2D respiratory sound analysis to detect lung abnormalities

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In this paper, we analyze deep visual features from 2D data representation(s) of the respiratory sound to detect evidence of lung abnormalities. The primary motivation behind this is that visual cues are more important in decision-making than raw data (lung sound).

Dataset collection: In our experiments using the publicly available respiratory sound database named ICBHI 2017 (5.5 hours of recordings containing 6898 respiratory cycles from 126 subjects

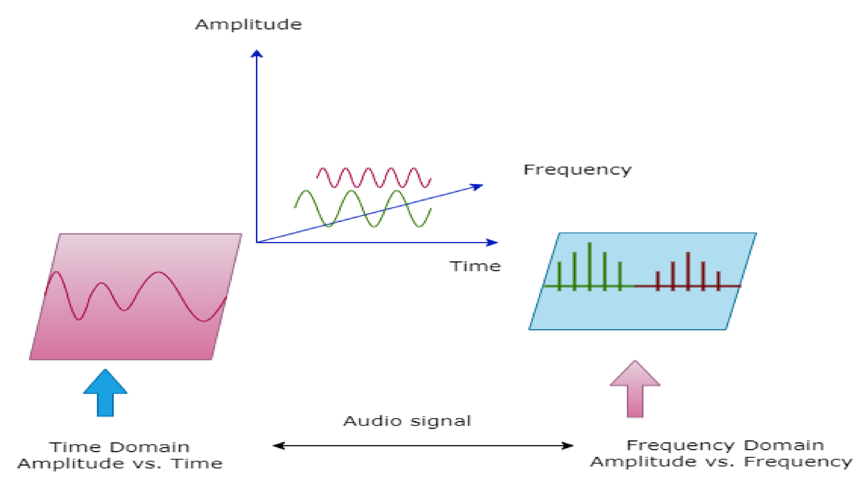
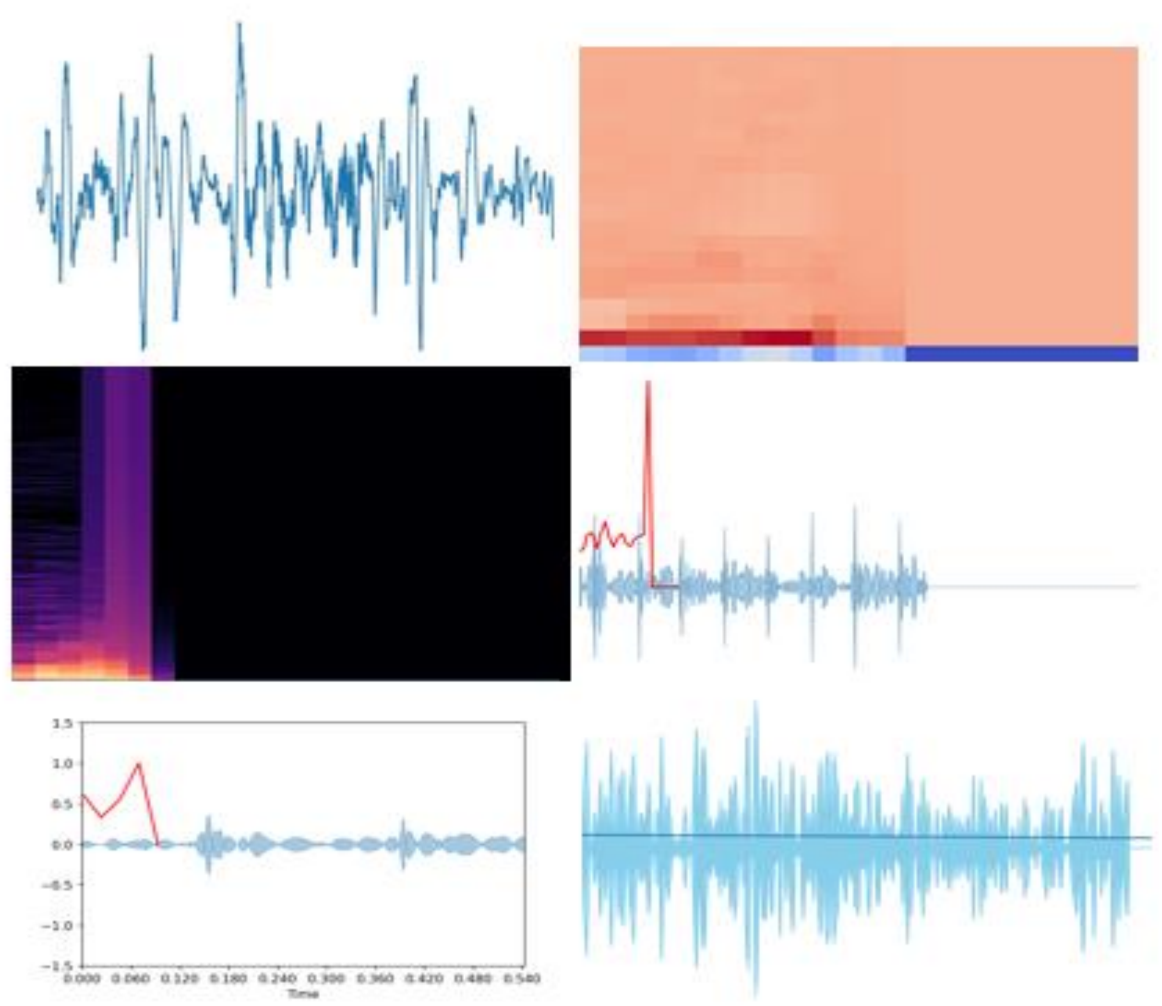


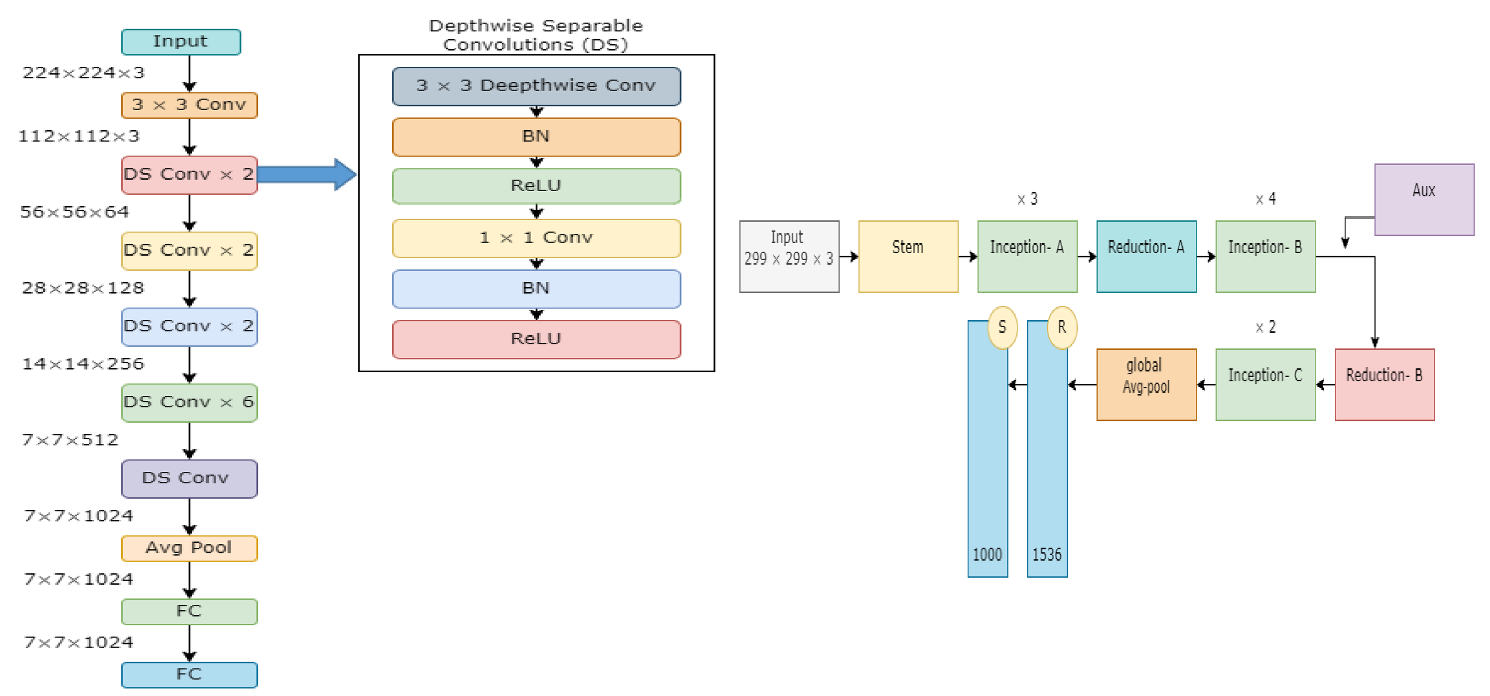
Table 1: Dataset

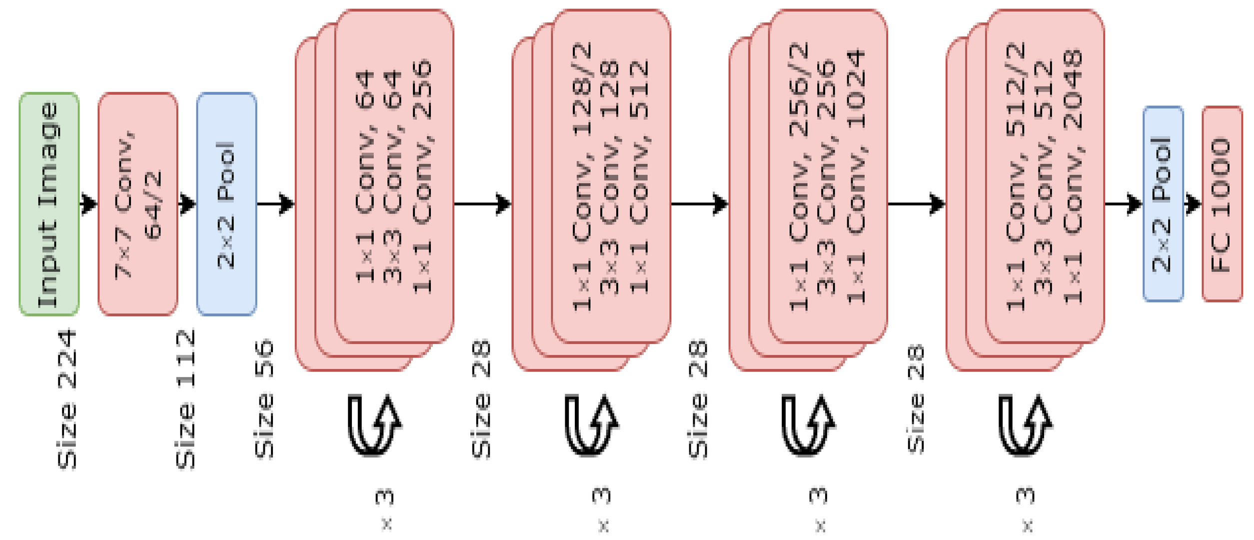
Clip type	Number of clips
Healthy	3642
Non-healthy	3256

Data Types



Different Deep learning Models





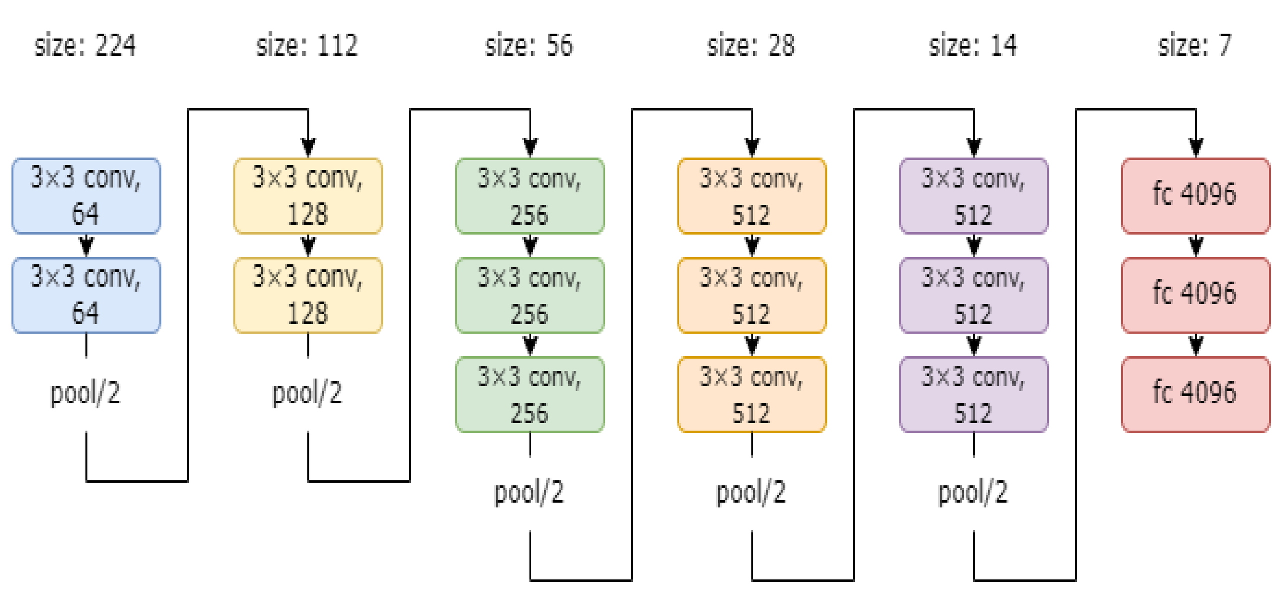


Table 2: Results and analysis

Types of Data	Model name	ACC PREC AUC SEN
Wave	VGG16	0.4697 0.4697 0.4828 0.4697
	ResNet50	0.5877 0.5882 0.5637 0.7207
	MobileNet	0.5450 0.5659 0.54554 0.6460
	InceptionV3	0.5355 0.5355 0.5000 1.0000
MFCC	VGG16	0.4545 0.4545 0.5315 0.4545
	ResNet50	0.6090 0.6900 0.7700 0.7500
	MobileNet	0.5308 0.5288 0.5150 0.9910
	InceptionV3	0.5261 0.5261 0.5000 1.0000
Spectrogram	VGG16	0.7232 0.7486 0.7930 0.6248
	Resnet50	0.6558 0.6236 0.7168 0.6876
	MobileNet	0.5592 0.5581 0.5421 0.8496
	InceptionV3	0.5355 0.5355 0.5000 1.000
Spectral centroid	VGG16	0.5655 0.5455 0.6233 0.5500
	Resnet50	0.5735 0.5533 0.7700 0.9820
	MobileNet	0.5592 0.5581 0.5421 0.8496
	InceptionV3	0.5355 0.5355 0.5000 1.0000
Spectral roll-off	VGG16	0.4091 0.4091 0.3836 0.4091
	Resnet50	0.4787 0.5031 0.4680 0.7387
	MobileNet	0.5355 0.5355 0.5000 0.1000
	InceptionV3	0.4882 0.5163 0.3673 0.6991
Zero-crossing rate	VGG16	0.4697 0.4697 0.4828 0.4697
	Resnet50	0.5261 0.5261 0.3973 1.000
	MobileNet	0.3886 0.3749 0.3749 0.1150
	InceptionV3	0.5355 0.5355 0.5000 1.0000

Table 3: Comparison with existing work

Authors	PREC	AUC	SEN	SPEC
Ma et al (2020) [10]	-	-	41.32%	63.20%
Chambres et al (2018) [12]	-	-	20.81%	78.05%
Kochetov et al (2018) [13]	-	-	58.43%	73.00%
Acharya and Basu (2020) [14]	-	-	48.63%	84.14%
Ma et al (2019) [15]	-	-	31.12%	69.20%
Proposed work	74.86%	79.30%	62.48%	-

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