

AsthmaSCELNet: A Lightweight Supervised Contrastive Embedding Learning Framework for Asthma Classification Using Lung Sounds

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Motivation

- Asthma is one of the severe chronic respiratory diseases.
- Existing diagnostic modalities (spirometry, peak flow rate) are not either dependent on patient efforts or insensitive to track minor airway obstructions.
- Asthma is often characterized by wheezing events of lung sounds.
- Existing researches only use traditional ML → incapable of extracting accurate representation of the highly varying time-frequency content of lung sound → leads to poor classification.

Key contribution

- Supervised contrastive triplet loss-based embedding extraction to provide better classification margin across the healthy and asthmatic sounds.
- Designing a lightweight embedding extraction backbone (LEEB) that exploits the paradigm of lightweight neural network architecture.
- Mel-spectrogram TFR investigation for the first time in asthma classification.

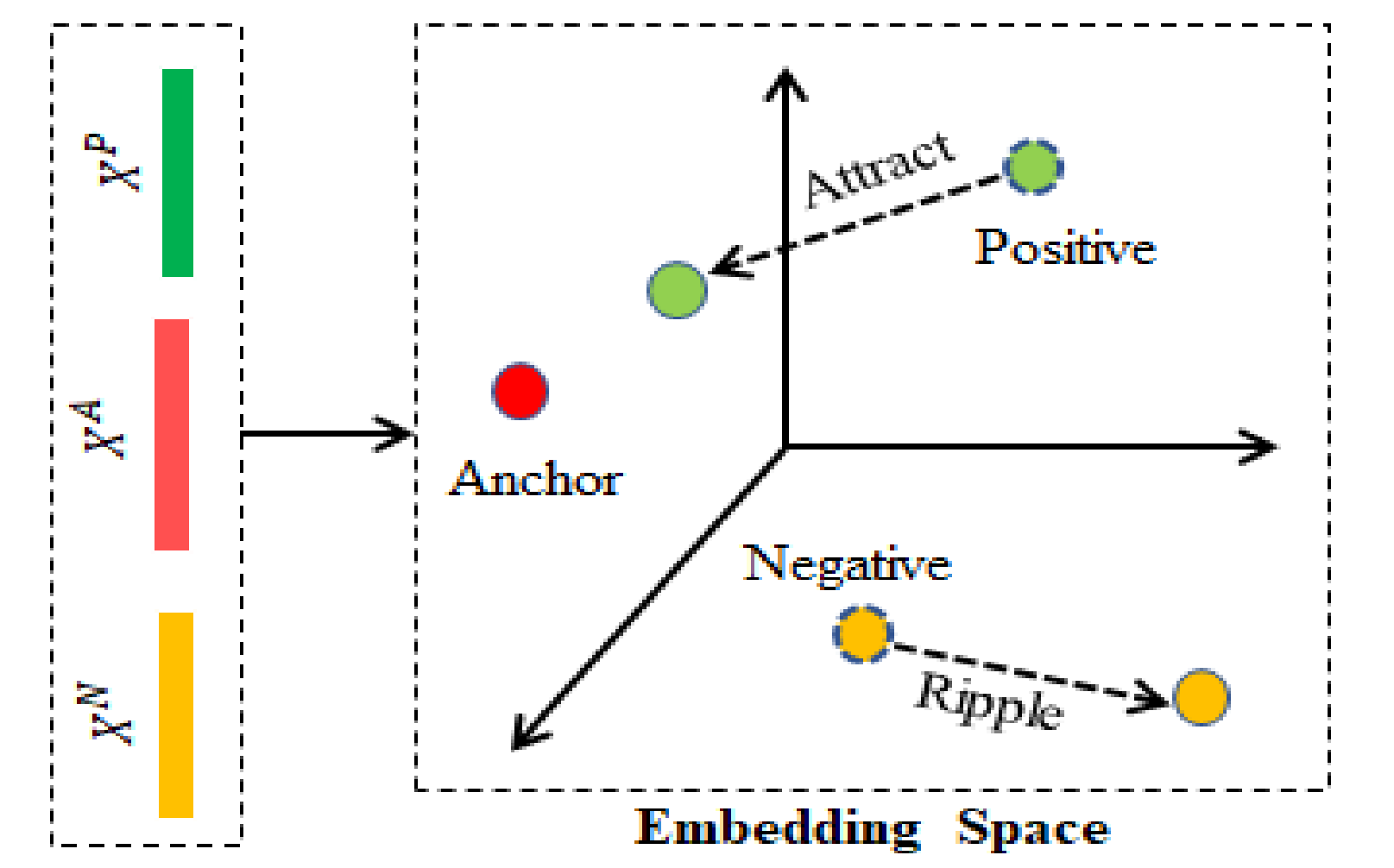


Figure 1: Basic intuition of triplet loss

Proposed AsthmaSCELNet framework for asthma classification

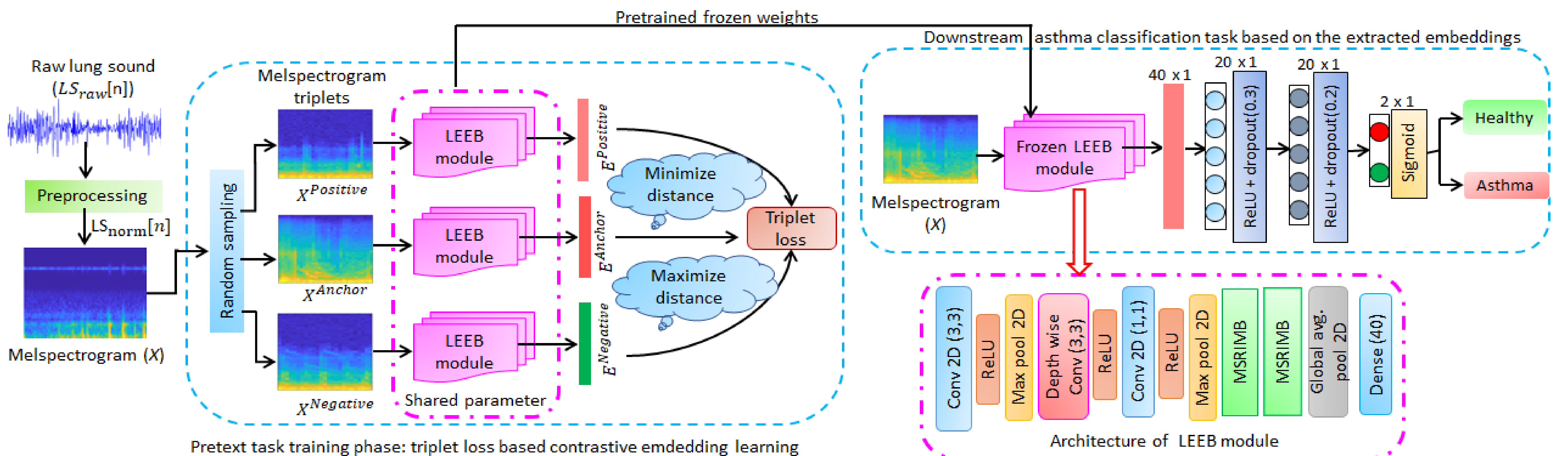


Figure 2: Block diagram of proposed AsthmaSCELNet

- Database used: **Chest wall lung sound database (CWLSD) [1]**
- AsthmaSCELNet utilizes triplet loss ($\mathcal{L}_{triplet}$)-based training to extract compact embedding from lung sounds using the LEEB module.

$$\mathcal{L}_{triplet} = \max\{0, \gamma + \mathcal{D}(E^{Anc}, E^{Pos}) - \mathcal{D}(E^{Anc}, E^{Neg})\} \quad (1)$$

γ , and $\mathcal{D}(\cdot)$ indicate the margin between two classes and the Euclidean distance operator.

- Frozen lightweight embedding extraction module (LEEB) module-based embeddings are employed in downstream asthma categorization.

Table 1: Optimal Simulation Parameters Used to Train LEEB Module and MLP Classifier

Model Simulation parameters						
	Margin (γ)	Trainable parameter	Optimizer	Learning rate	Batch size	Epochs
LEEB	0.2	18856	Adam	0.008	64	400
MLP classifier	–	1282				100
						Loss function
						Triplet loss
						Binary cross entropy

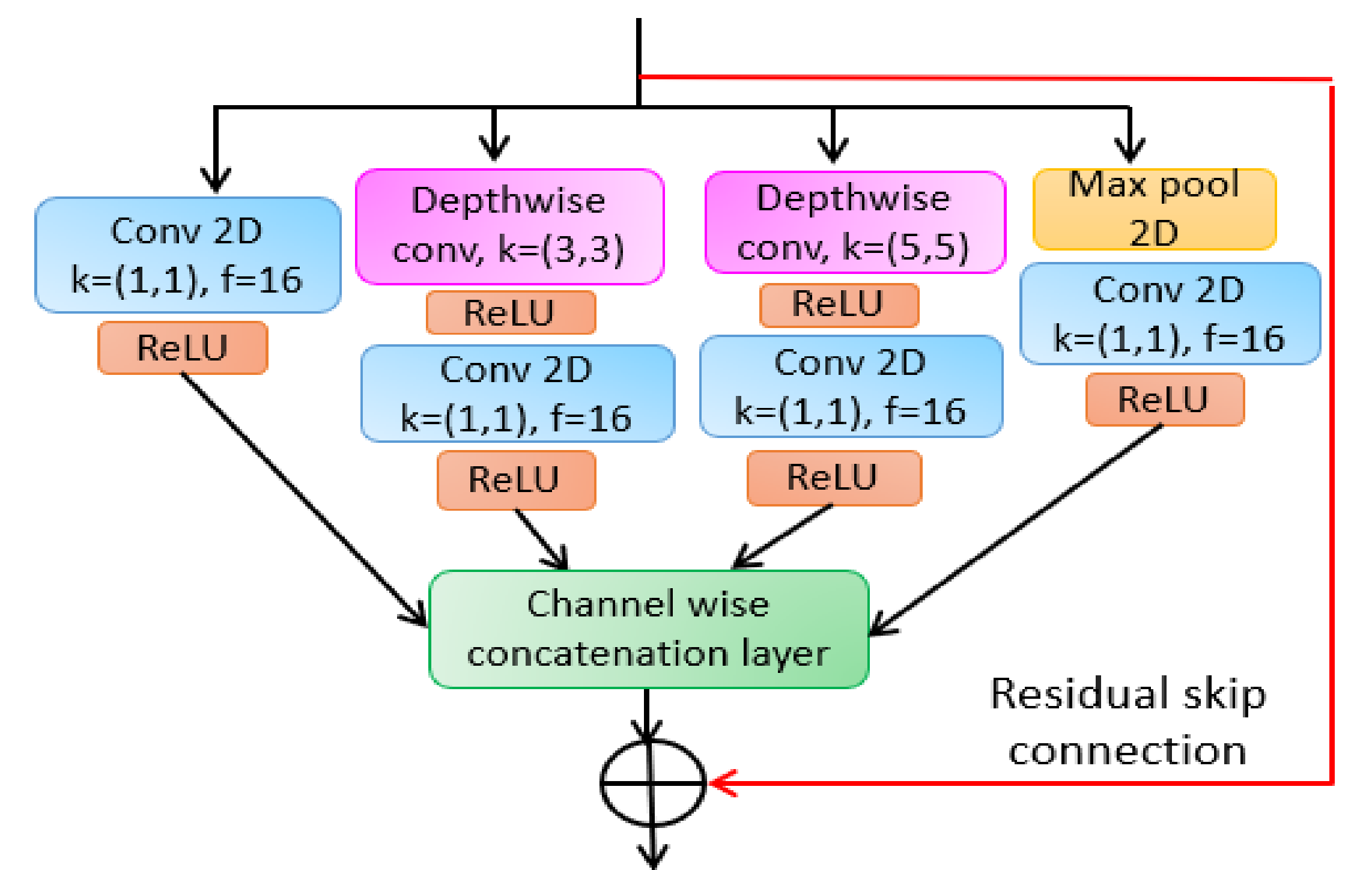


Figure 3: Multiscale residual inception mobile block (MSRIMB)

Experimental results

t-SNE based LEEB feature visualization:

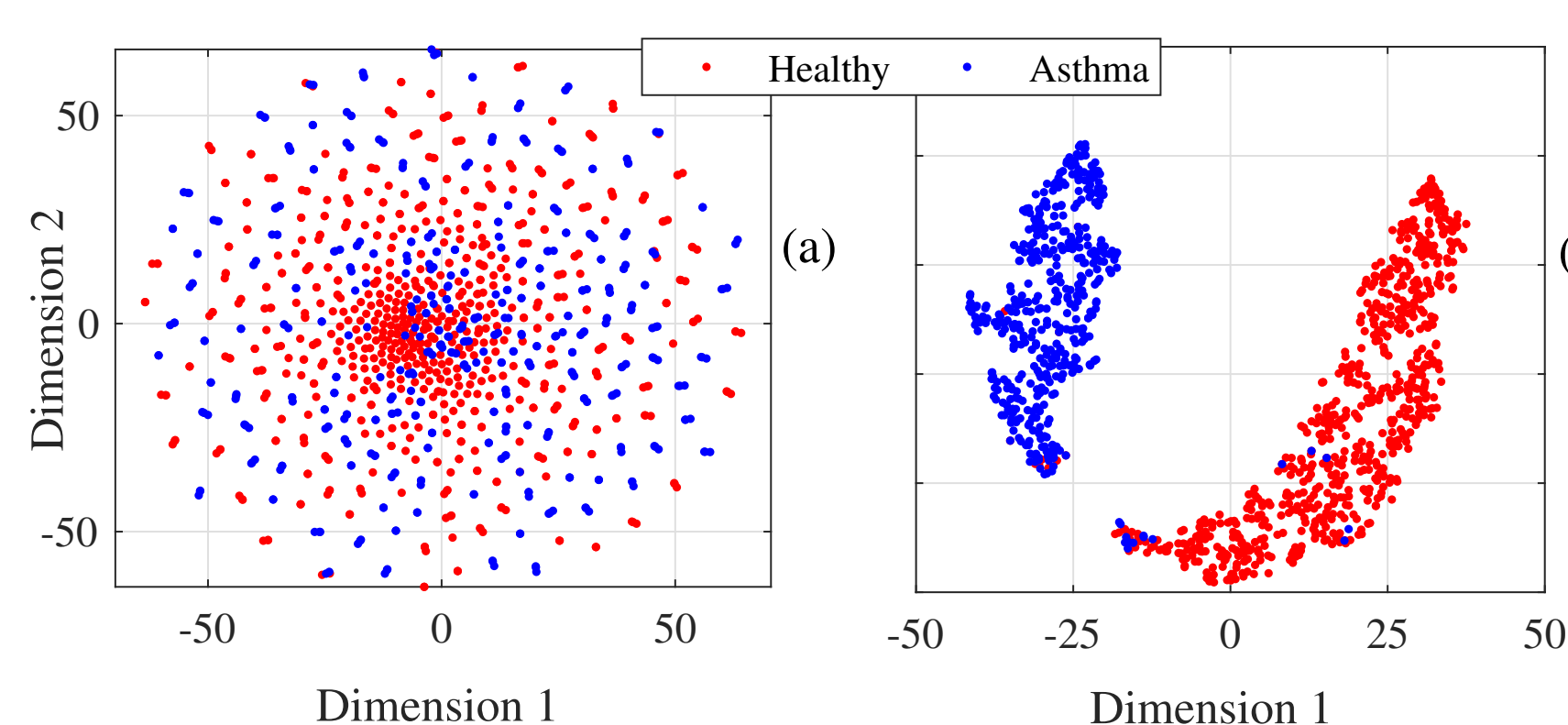


Figure 4: 2D t-SNE plot of (a) raw lung sounds, and (b) class, (b) confusion matrix embeddings extracted from LEEB module.

Classification performance

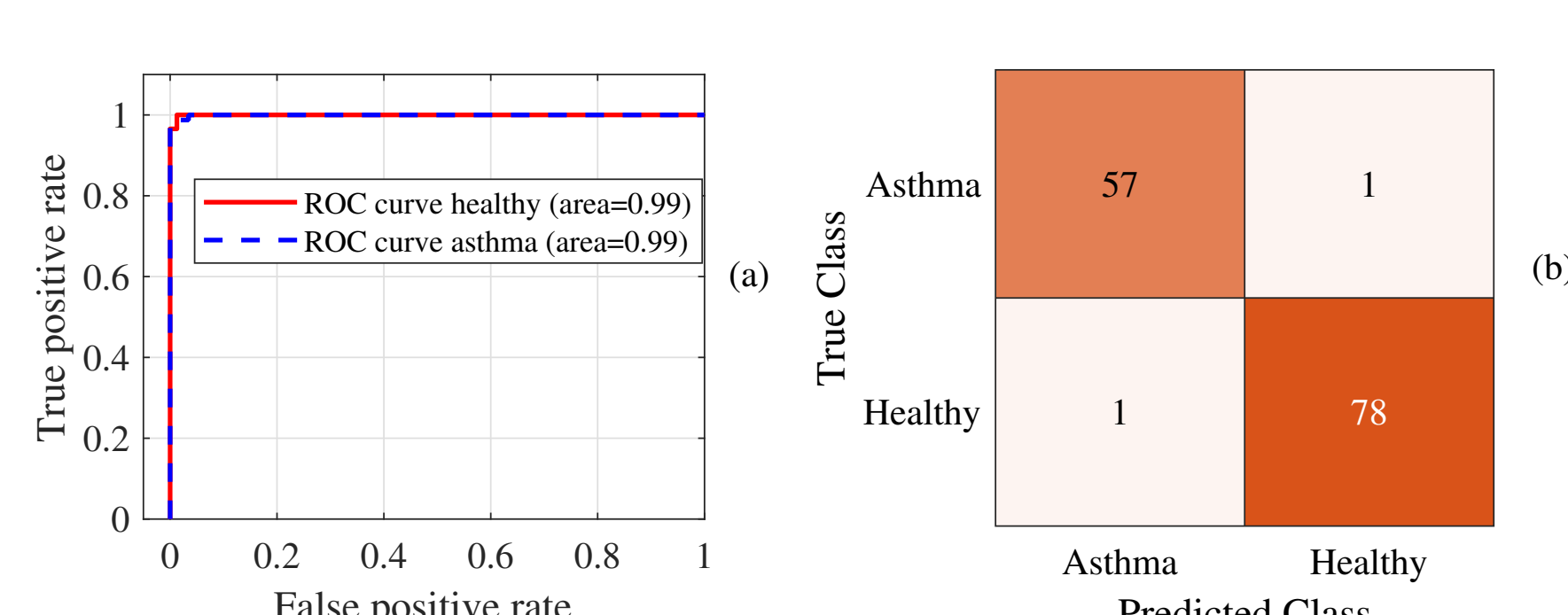


Figure 5: (a) ROC curve for both asthma and healthy, (b) confusion matrix

Table 2: Quantitative Performance Comparison of AsthmaSCELNet with Existing Methodologies

Reference	Data type (database)	Results (%)			
		acc	sen	spe	ICBHI score
Yadav et al. [2]	Speech (own)	75.4			
Altan et al. [3]	Lung sound (own)	84.61	85.83	77.11	81.47
Tripathy et al. [4]	Lung sound (CWLSD)	80.35	84.88	75.23	80.05
Proposed	Lung sound (CWLSD)	98.54	98.27	98.73	98.5

Grad-cam activation map visualization

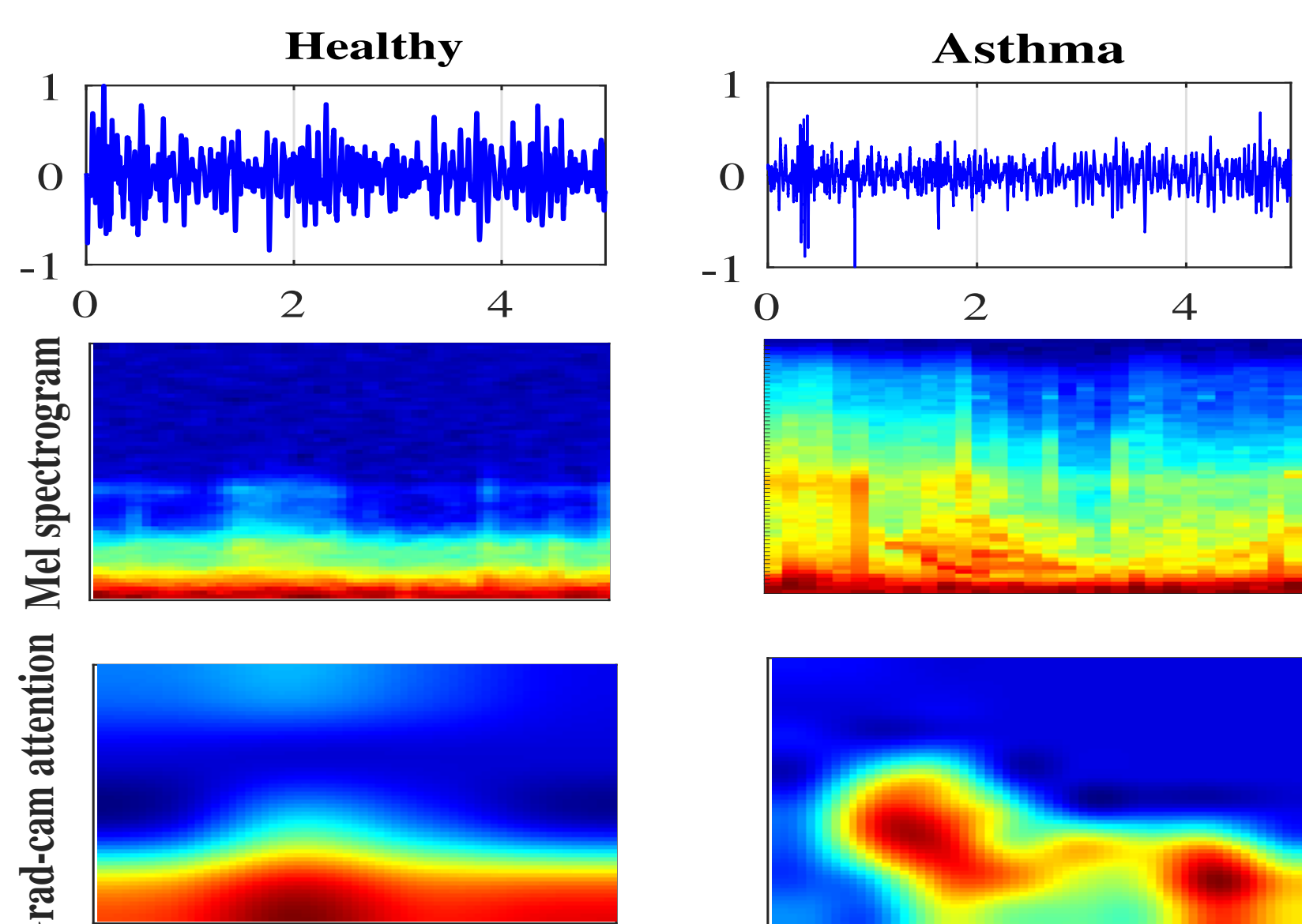


Figure 6: Activation map of healthy and asthma.

Conclusion

- We establish the efficacy of lung sounds over other modalities for asthma classification.
- Outperforms all the traditional ML approaches and reduces the burden of manual feature extraction.
- Proposed lightweight model is suitable for deployment on a low-resource-embedded processor.

References

- M. Fraiwan et al. "A dataset of lung sounds recorded from the chest wall using an electronic stethoscope," *Data in Brief*, vol. 35, p. 106913, 2021.
- S. Yadav et al. "Analysis of Acoustic Features for Speech Sound Based Classification of Asthmatic and Healthy Subjects," *ICASSP 2020*.
- G. Altan et al. "The diagnosis of asthma using hilbert–huang transform and deep learning on lung sounds," *Akilli Sistemlerde Yenilikler ve Uygulamaları (ASYU), Antalya*, p. 82, 2017.
- R. K. Tripathy et al. "Automated detection of pulmonary diseases from lung sound signals using fixed-boundary-based empirical wavelet transform," *IEEE Sensors Letters*, vol. 6, no. 5, pp. 1–4, 2022.

Project Webpage:

Code & Dataset & Model

