A Multimodal Early-Warning Framework for Respiratory Exacerbation Prediction via Acoustic, Genomic, and Environmental Data Fusion

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Respiratory exacerbations are often detected only after symptoms become severe, limiting opportunities for early intervention. Current monitoring systems rely on clinic-based devices or single-modality data, restricting scalability and predictive accuracy. This project developed and validated a unified multimodal computational framework integrating bioacoustic cough analysis, population-level genomic risk modeling, and environmental context for early respiratory risk forecasting. The system includes two primary pipelines: (1) a bioacoustic time-series model extracting spectral and temporal features from cough audio using a CNN–BiLSTM–Attention architecture, and (2) a genomic module incorporating 42 high-impact SNPs from GWAS summary statistics to generate probabilistic population-level risk weights. Outputs were fused through a time-aware multimodal integration layer optimized for early event detection. Models were trained and validated on 310,000 cough-audio segments and 18,200 aggregated genomic risk records from independent de-identified datasets. Cross-dataset validation (COUGHVID to Coswara) achieved an AUROC of 0.93 (95% CI: 0.91–0.95) and AUPRC of 0.88. Compared to an acoustic-only baseline (AUROC 0.86), multimodal fusion significantly improved performance ($p < 0.01$). Calibration showed strong agreement between predicted and observed risk (Brier score 0.11). In longitudinal simulations, detection lead time increased from 1.2 to 3.1 days (+1.9 days) while maintaining a 5.8% false alarm rate. These results demonstrate that multimodal integration improves predictive accuracy and early-warning capability, supporting scalable, in-silico respiratory risk forecasting for remote and resource-limited settings.

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