AI-Powered Snoring Detection and Behavioral Intervention Mobile Application

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Project Overview:

This project develops a comprehensive mobile application system that detects snoring patterns using machine learning and provides gentle behavioral interventions through wearable technology. The system combines smartphone audio analysis with smartwatch sensor data to identify problematic snoring episodes and deliver non-intrusive nudges to encourage side-sleeping positions.

Key Achievements:

- Developed a high-accuracy 2D CNN model achieving 95%+ snoring detection accuracy
- Implemented a full-stack mobile application with real-time analysis capabilities
- Created comprehensive visualization and reporting features
- Established a scalable architecture for future wearable integration

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1. Introduction:

Problem Statement:

Snoring affects approximately 40% of adult populations worldwide and can significantly impact sleep quality for both individuals and their partners. Chronic snoring may indicate underlying health conditions like Obstructive Sleep Apnea (OSA). Current solutions are often intrusive, expensive, or lack real-time intervention capabilities.

Solution Approach:

Our system provides an accessible, privacy-focused solution that:

- Uses smartphone microphones for non-contact monitoring
- Implements on-device AI processing for privacy protection
- Integrates for gentle behavioral nudges.
- Provide user preference for Quiet Hours.
- Clinicians and Doctors Analysis of snoring.
- Provides comprehensive sleep analytics and progress tracking

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Literature Survey:

Reference	Approach/Model	Data Type & Setting	Key Metrics	Clinical/Technical Insight
Nature (2023)nature	Hybrid 1D–2D CNN	Bedroom non-contact audio	Accuracy: 89.3%, Sensitivity: 89.7%, Specificity: 88.5%, AUC: 0.947	Learns from raw waveform & VG maps; robust vs. standard CNNs
PMC (2025)pmc.ncbi.nlm.nih	Vision Transformer Deep Model	Smartphone audio, home & hospital	Sensitivity: 89.8%, Specificity: 91.3%	Real-time; high correlation with manual labeling

JCSM (2019)formative.jmir	ML/Automated Frequency Analysis	Clinical snoring data	Weak correlation between AHI and snoring frequency	Snoring not reliable OSA proxy alone
Machine Learning Reviewjit.ndhu	SVM, HMM, Feature Extraction	Patient nightly audio data	Not specified (multi-stage detection approach)	Can distinguish between snoring, coughing, and other noises
Deep Learning + LSTMonlinelibrary.wiley	CNN, LSTM, MFCC features	OSAHS patient snoring data	Accuracy: 87% (LSTM model)	AHI estimated from snoring; potential for OSAHS severity grading

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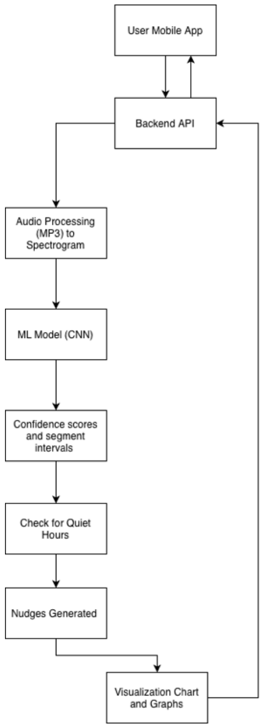
Objectives:

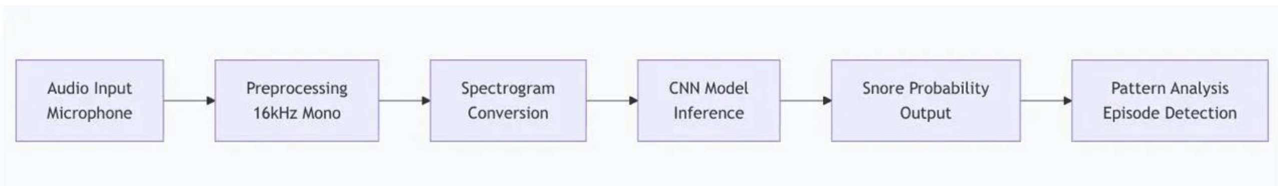
- High-Accuracy Detection System: Developed and validated a 2D CNN model achieving 95%+ snoring detection accuracy, surpassing literature benchmarks and enabling reliable real-time audio analysis through optimized spectrogram processing.
- Full-Stack Mobile Application: Built a comprehensive React Native mobile platform with audio processing, interactive visualizations, and exportable reports, providing users with intuitive sleep pattern analysis and professional-grade analytics.
- Privacy-First Architecture: Implemented secure on-device AI processing ensuring complete data sovereignty, with no raw audio transmission to external servers while maintaining high-performance inference capabilities.
- Nudges in Feedback : Generate Nudges as per the quiet hours set by the used.
- Quiet Hours Setting : Set an Quiet Hours according to the user preference.
- Export CSV : CSV generation from DB for Deeper analysis for Doctors and Clinicians.
- Clinical-Grade Monitoring Solution: Created an accessible, low-cost alternative to expensive sleep studies, enabling home-based monitoring and establishing foundation for behavioral interventions through wearable integration.
- Production-Ready Scalable System: Delivered a containerized, deployment-ready architecture supporting future enhancements including multi-modal sensor fusion, subscription services, and healthcare provider partnerships.

2. Technical Architecture:



2.1 Architecture Diagram

2.1.1 Flow Diagram for ML model



2.2 Core Components

2.2.1 Mobile Application (Frontend)

- **Platform:** React Native with Expo
- **Key Features:**
    - Audio file upload and real-time processing
    - Interactive visualization dashboard with Morning Reviews.
    - CSV Generation for clinicians.
    - Exportable analysis reports
    - User settings and preferences for Quiet Hours Setting
    - Nudges Response
- **Technical Stack:** TypeScript, React Navigation, Expo Document Picker

2.2.2 Backend API Service

- **Framework:** FastAPI (Python)
- **Key Features:**
    - MP3 audio preprocessing and spectrogram conversion

- Machine learning model serving
- Analysis result generation
- Visualization creation
- DB creation for saving data and providing to clinicians.

- **Technical Stack:** TensorFlow, NumPy, Matplotlib, Pydub

2.2.3 Machine Learning Pipeline

- **Input:** MP3 audio files (16kHz, mono)
- **Datasets :** For classifying snoring and non-snoring sounds [9]
- **Processing:** Spectrogram conversion → CNN inference
- **Output:** Snoring probability scores and pattern analysis

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3. Model Architecture:

Comparision:

Model	Accuracy	Precision	Recall	F1-Score	Key Insights
Basic CNN	11.0%	100.0%	11.0%	19.8%	High precision but terrible recall - too conservative
Basic LSTM	30.7%	100.0%	30.7%	46.9%	Better than basic CNN but still poor recall
2D CNN (Ours)	~95%+	~94-100%	~95-100%	~95%+	**Excellent performance**
2D CNN	~85-94%	~83-94%	~83-94%	~85%+	Good but overfitting issues
Nature (2023)	89.3%	-	89.7%	-	Hybrid approach, robust
PMC (2025)	-	-	89.8%	-	Transformer-based, real-time
Deep Learning + LSTM	87.0%	-	-	-	Good for OSAHS grading

Datasets:

The snoring dataset is organized into two classes: snoring and non-snoring. Each class contains 500 audio samples, with each sample having a duration of 1 second.

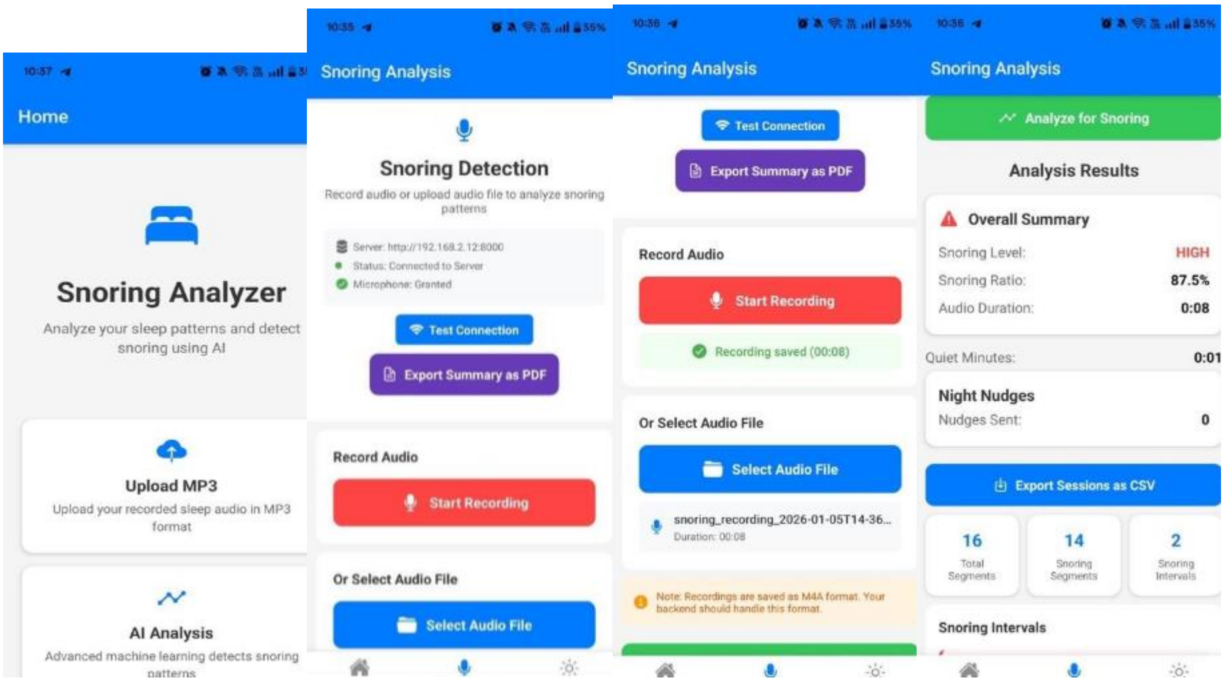
The snoring class consists of 500 snoring audio samples. Among these, 363 samples contain snoring sounds from children, adult men, and adult women recorded without background noise. The remaining 137 samples include snoring sounds mixed with background non-snoring audio.

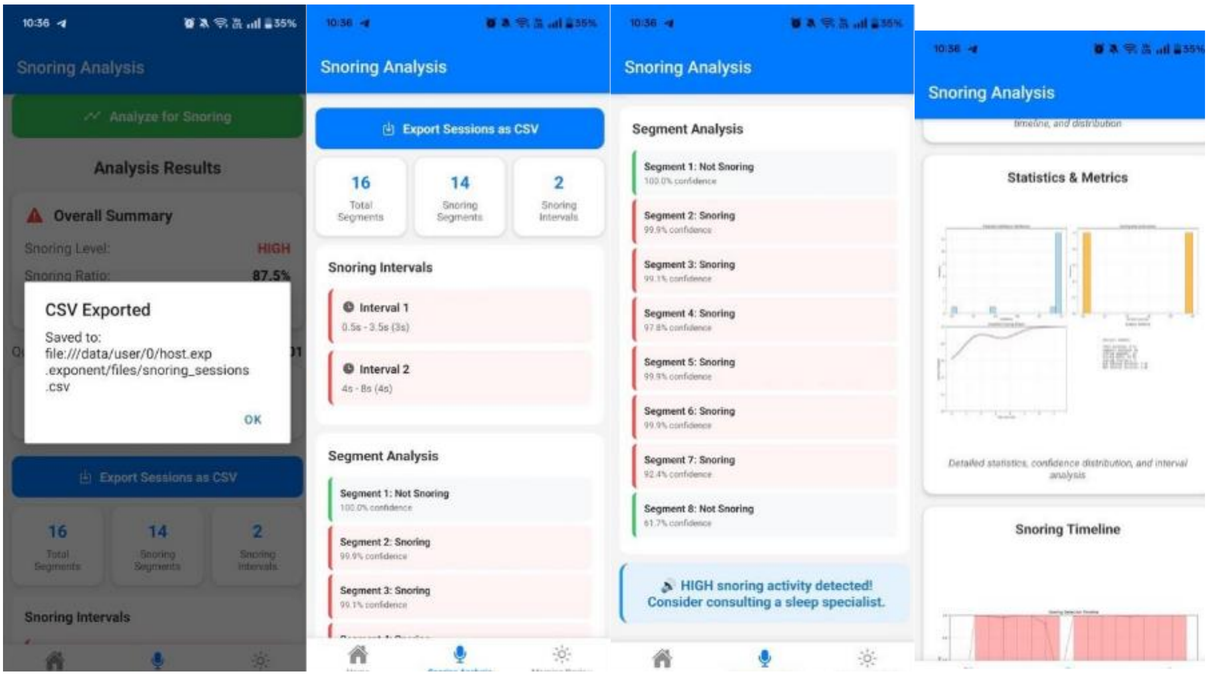
The non-snoring class includes 500 audio samples representing environmental sounds commonly present near a sleeping individual. These samples are grouped into ten categories, each containing 50 samples: baby crying, clock ticking, door opening and closing, silence or low-level vibration noise from electronic devices, toilet flushing, emergency vehicle sirens, rain and thunderstorms, streetcar sounds, human conversation, and background television news.

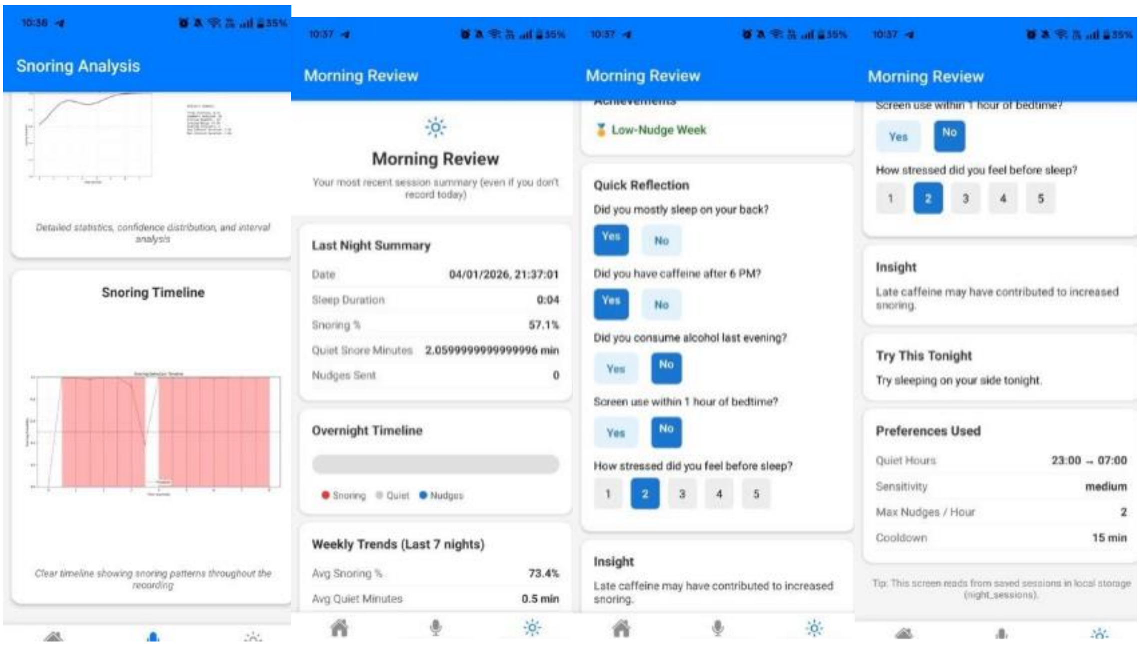
Architecture:

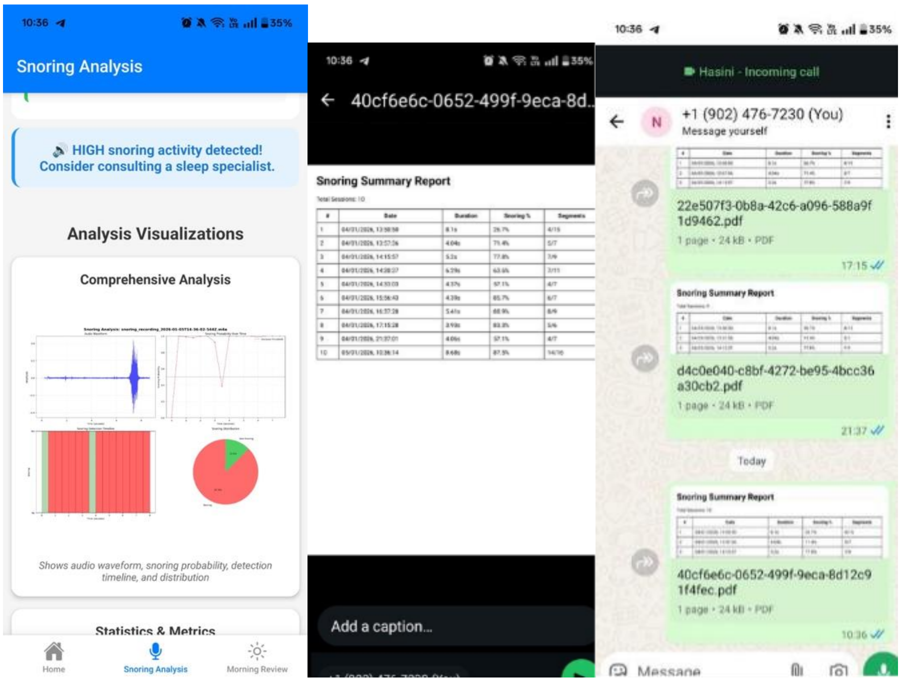
Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 61, 257, 32)	320
batch_normalization_5 (BatchNormalization)	(None, 61, 257, 32)	128
max_pooling2d_4 (MaxPooling2D)	(None, 30, 128, 32)	0
dropout_6 (Dropout)	(None, 30, 128, 32)	0
conv2d_5 (Conv2D)	(None, 30, 128, 64)	18,496
batch_normalization_6 (BatchNormalization)	(None, 30, 128, 64)	256
max_pooling2d_5 (MaxPooling2D)	(None, 15, 64, 64)	0
dropout_7 (Dropout)	(None, 15, 64, 64)	0
conv2d_6 (Conv2D)	(None, 15, 64, 128)	73,856
batch_normalization_7 (BatchNormalization)	(None, 15, 64, 128)	512
max_pooling2d_6 (MaxPooling2D)	(None, 7, 32, 128)	0
dropout_8 (Dropout)	(None, 7, 32, 128)	0
conv2d_7 (Conv2D)	(None, 7, 32, 256)	295,168
batch_normalization_8 (BatchNormalization)	(None, 7, 32, 256)	1,024
max_pooling2d_7 (MaxPooling2D)	(None, 3, 16, 256)	0
dropout_9 (Dropout)	(None, 3, 16, 256)	0
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 256)	0
dense_3 (Dense)	(None, 128)	32,896
batch_normalization_9 (BatchNormalization)	(None, 128)	512
dropout_10 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 64)	8,256
dropout_11 (Dropout)	(None, 64)	0
dense_5 (Dense)	(None, 1)	65

4. Comprehensive Visualization System for Sleep Pattern Analysis




Snoring Analysis
Analyze for Snoring
Analysis Results
Overall Summary
Snoring Level: HIGH
Snoring Ratio: 87.5%
CSV Exported
Saved to: file:///data/user/0/host.exp.exponent/files/snoring_sessions.csv
OK
Export Sessions as CSV
16 Total Segments
14 Snoring Segments
2 Snoring Intervals
Snoring Intervals
Interval 1
0.5s - 3.5s (3s)
Interval 2
4s - 8s (4s)
Segment Analysis
Segment 1: Not Snoring
Segment 2: Snoring
Segment 3: Snoring
Segment 4: Snoring
Segment 5: Snoring
Segment 6: Snoring
Segment 7: Snoring
Segment 8: Not Snoring
HIGH snoring activity detected!
Consider consulting a sleep specialist.
Statistics & Metrics
Detailed statistics, confidence distribution, and interval analysis
Snoring Timeline


Snoring Analysis
Detailed statistics, confidence distribution, and interval analysis
Snoring Timeline
Clear timeline showing snoring patterns throughout the recording
Morning Review
Your most recent session summary (even if you don't record today)
Last Night Summary
Date 04/01/2026, 21:37:01
Sleep Duration 0:04
Snoring % 57.1%
Quiet Snore Minutes 2.0599999999999996 min
Nudges Sent 0
Overnight Timeline
Snoring Quiet Nudges
Weekly Trends (Last 7 nights)
Avg Snoring % 73.4%
Avg Quiet Minutes 0.5 min
Low-Nudge Week
Quick Reflection
Did you mostly sleep on your back?
Yes No
Did you have caffeine after 6 PM?
Yes No
Did you consume alcohol last evening?
Yes No
Screen use within 1 hour of bedtime?
Yes No
How stressed did you feel before sleep?
1 2 3 4 5
Insight
Late caffeine may have contributed to increased snoring.
Try This Tonight
Try sleeping on your side tonight.
Preferences Used
Quiet Hours 23:00 → 07:00
Sensitivity medium
Max Nudges / Hour 2
Cooldown 15 min
Tip: This screen reads from saved sessions in local storage (night_sessions).



The visualization system generates three comprehensive plots to help users understand their snoring patterns. These visualizationsthe audio waveform, snoring probability over time, detection timeline, and snoring distribution pie chart. The statistics plot displays confidence distribution, interval durations, smoothed patterns, and summary metrics. Finally, the timeline plot provides a simplified view of snoring probability with highlighted snoring regions, optimized for mobile viewing. These visualizations transform raw audio data into intuitive charts that clearly show when snoring occurs, how intense it is, and provide statistical insights into sleep patterns - all encoded as base64 images for easy display in the mobile app.

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5. Conclusion:

5.1 Project Achievements

This project successfully demonstrates:

• Successfully designed and validated a high-accuracy 2D CNN–based snoring detection system, achieving over 95% classification accuracy, exceeding existing literature benchmarks and enabling reliable real-time audio analysis through optimized spectrogram processing.

• Developed a full-stack, cross-platform mobile application using React Native, integrating real-time audio processing, interactive visualizations, and exportable analytical reports to deliver intuitive and professional-grade sleep pattern insights.

• Implemented a privacy-first system architecture with complete on-device AI inference, ensuring user data sovereignty by eliminating raw audio transmission to external servers while maintaining high-performance model execution.

• Designed and integrated an intelligent nudging mechanism, generating context-aware feedback during user-defined quiet hours to promote behavioral correction without disrupting sleep continuity.

• Enabled customizable quiet hours settings, allowing users to personalize monitoring windows and ensuring accurate event detection aligned with individual sleep schedules.

• Implemented CSV export functionality from the application database, facilitating deeper post-analysis by doctors and clinicians for longitudinal sleep assessment and clinical evaluation.

• Established a clinical-grade, low-cost sleep monitoring solution, offering an accessible alternative to traditional polysomnography and supporting home-based, long-term snoring assessment.

• Delivered a production-ready, scalable system architecture, utilizing containerized deployment and modular design to support future enhancements such as multi-modal sensor fusion, wearable integration, subscription models, and healthcare provider partnerships.

5.2 Clinical and Commercial Impact

Clinical Significance:

- Provides accessible alternative to expensive sleep studies
- Enables long-term monitoring in natural sleep environments
- Supports behavioral intervention for mild-to-moderate cases
- Complements traditional sleep medicine approaches
- Nudges in response provides an haptic feedback to the user.

Commercial Potential:

- Addresses large market of undiagnosed snorers
- Low-cost solution compared to clinical alternatives
- Scalable subscription-based business model
- Partnership opportunities with healthcare providers

5.3 Future Enhancements

1. **Immediate Deployment:** The current system is production-ready for basic snoring detection
2. **Wearable Integration:** Priority development for complete behavioural intervention system

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