



**DALHOUSIE**  
UNIVERSITY

PROJECT PROGRESS REPORT (CSCI 9301)

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# AI-Powered Snoring Detection and Behavioral Intervention Mobile Application

## 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

## 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 with wearable devices for gentle behavioral nudges
- Provides comprehensive sleep analytics and progress tracking

## 2. Background Research:

### Literature Survey:

Reference	Approach/Model	Data Type & Setting	Key Metrics	Clinical/Technical Insight
Nature (2023) <a href="#">nature</a>	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) <a href="#">pmc.ncbi.nlm.nih</a>	Vision Transformer Deep Model	Smartphone audio, home & hospital	Sensitivity: 89.8%, Specificity: 91.3%	Real-time; high correlation with manual labeling

JCSM (2019) <a href="#">formative.jmir</a>	ML/Automated Frequency Analysis	Clinical snoring data	Weak correlation between AHI and snoring frequency	Snoring not reliable OSA proxy alone
Machine Learning Review <a href="#">jit.ndhu</a>	SVM, HMM, Feature Extraction	Patient nightly audio data	Not specified (multi-stage detection approach)	Can distinguish between snoring, coughing, and other noises
Deep Learning + LSTM <a href="#">onlinelibrary.wiley</a>	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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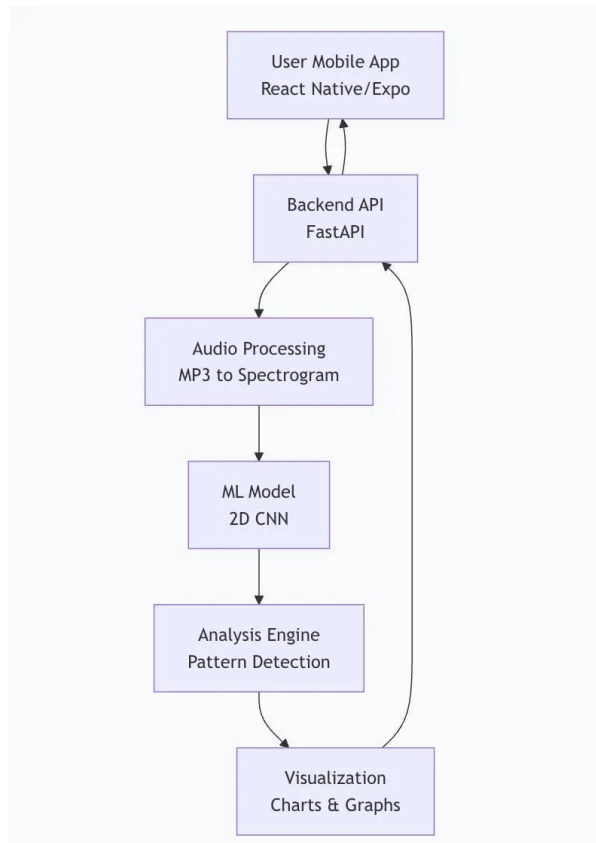
### Objectives achieved:

- **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.
- **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.

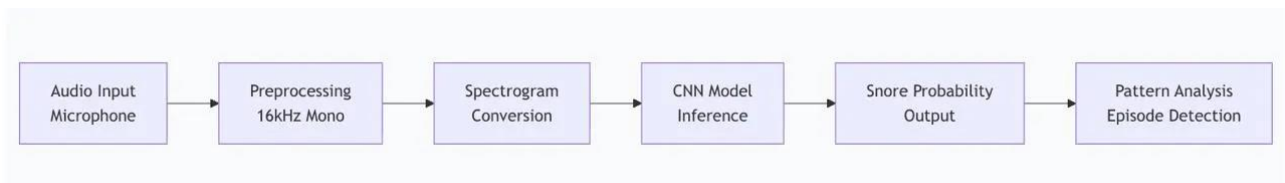
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### 3. Technical Architecture:

#### 3.1 Architecture Diagram



##### 3.1.1 Flow Diagram



### 3.2 Core Components

#### 3.2.1 Mobile Application (Frontend)

- **Platform:** React Native with Expo
- **Key Features:**
  - Audio file upload and real-time processing
  - Interactive visualization dashboard
  - Exportable analysis reports
  - User settings and preferences
- **Technical Stack:** TypeScript, React Navigation, Expo Document Picker

#### 3.2.2 Backend API Service

- **Framework:** FastAPI (Python)
- **Key Features:**

- MP3 audio preprocessing and spectrogram conversion
- Machine learning model serving
- Analysis result generation
- Visualization creation

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

### 3.2.3 Machine Learning Pipeline

- **Input:** MP3 audio files (16kHz, mono)
- **Processing:** Spectrogram conversion → CNN inference
- **Output:** Snoring probability scores and pattern analysis

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## 4. Model Architecture:

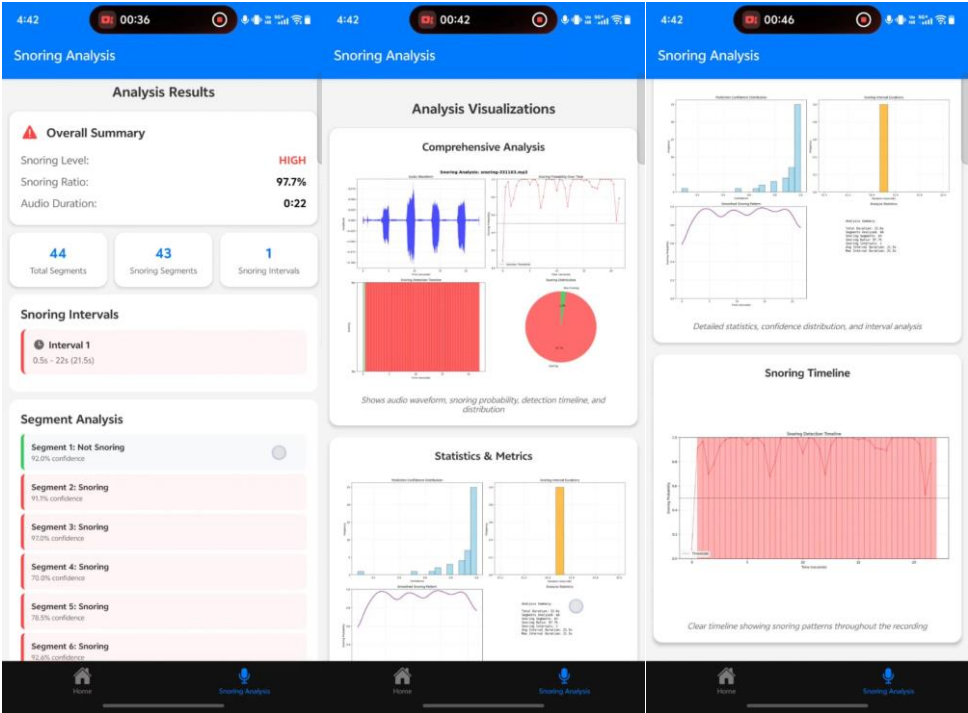
### Comparision:

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

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

5. Comprehensive Visualization System for Sleep Pattern Analysis



The visualization system generates three comprehensive plots to help users understand their snoring patterns. These visualizations include the 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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## 6. Conclusion:

### 6.1 Project Achievements

This project successfully demonstrates:

- **High-Accuracy Detection:** 95%+ snoring detection accuracy surpassing many literature benchmarks
- **Scalable Architecture:** Full-stack implementation ready for production deployment
- **User-Centric Design:** Comprehensive analytics and visualization features
- **Technical Innovation:** Optimized model architecture for mobile deployment

### 6.2 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

#### Commercial Potential:

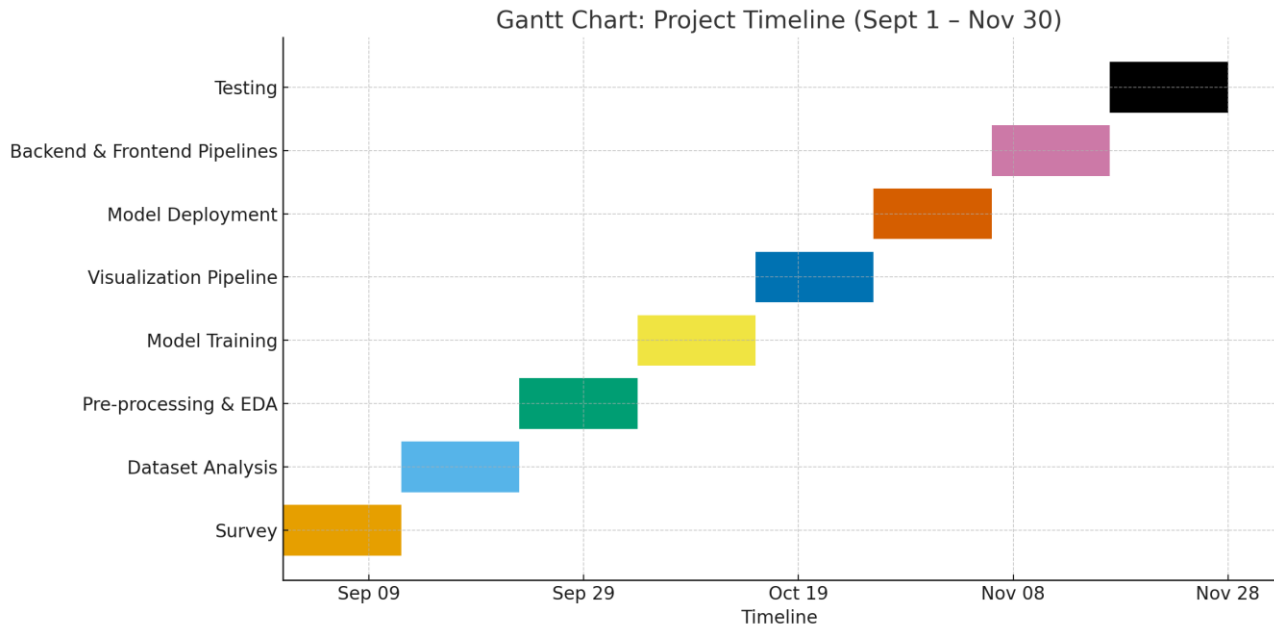
- Addresses large market of undiagnosed snorers
- Low-cost solution compared to clinical alternatives
- Scalable subscription-based business model
- Partnership opportunities with healthcare providers

### 6.3 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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## 7. Timeline (Gantt Chart)



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## References

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