Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

Design and Fabrication of Acoustic Sensor with Application of Environment Monitoring.

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Abstract - Environmental acoustic monitoring requires reliable acquisition and processing of continuously varying acoustic signals to distinguish different acoustic conditions in practical environments. This paper presents the design, implementation, and experimental validation of an integrated acoustic monitoring system combining a microphone-based sensing interface, LM358-based analog signal conditioning, Arduino-based digital acquisition, and RMS-based digital signal processing. The developed sensing module incorporates microphone biasing, AC coupling, reference-voltage generation, signal conditioning, and ADC interfacing to obtain a suitable digital representation of the acquired acoustic signal. The implemented hardware was experimentally characterized using controlled acoustic inputs and laboratory measurement instruments to verify its sensing and signal-conditioning performance, followed by practical evaluation in a library environment. The acquired acoustic samples were subjected to DC-offset removal and root mean square (RMS) analysis to obtain an amplitude-domain representation of acoustic activity. An experimentally collected dataset was further analyzed using Python-based data processing to establish data-driven RMS boundaries for categorizing acoustic conditions. The resulting classification criteria were incorporated into the Arduino-based real-time processing framework, enabling continuous acoustic condition identification and local visualization through an LCD interface. The system was additionally integrated with a cloud-based data logging framework for continuous monitoring and visualization. The developed prototype demonstrates a complete engineering workflow from acoustic signal acquisition and analog front-end implementation to digital signal processing, experimental data analysis, data-driven classification, and real-time environmental monitoring, providing a practical platform for acoustic assessment in noise-sensitive environments.

Keywords - Environmental Acoustic Monitoring, Acoustic Sensors, Acoustic Signal Acquisition, Analog Signal Conditioning, Electret Microphone, Digital Signal Processing, RMS Analysis, Data-Driven Classification, Noise Monitoring, Real-Time Monitoring.

I. INTRODUCTION

Environmental noise is a continuously varying phenomenon affecting acoustic conditions in urban and indoor environments. Transportation, human activities, machinery, and other sound sources contribute to these variations, making continuous monitoring important in noise-sensitive environments such as libraries, educational institutions, and workplaces. Recent acoustic monitoring systems have incorporated embedded processing, digital acquisition, wireless communication, and IoT technologies for real-time noise measurement and monitoring [1], [2], [4], [8]. Low-cost acoustic platforms using electret and MEMS microphones have also been investigated, with emphasis on calibration, stability, dynamic range, and deployment scalability [7], [10], [14], [20]. DSP-based systems have further been developed for acoustic parameter extraction and event recognition using embedded and dedicated processing platforms [9], [11], [13]. Other studies have explored specialized sensing and acquisition techniques, including capacitive, distributed, low-frequency, and high-sensitivity acoustic sensing [3], [5], [6], [16]. Wireless acoustic sensor networks have additionally addressed large-scale monitoring, synchronization, and distributed processing [12], [18], [19]. These developments highlight the need for practical integration of acoustic acquisition, signal conditioning, digital processing, and classification.

This work presents an experimentally developed acoustic monitoring system comprising an electret microphone, an LM358-based analog signal-conditioning circuit, and an Arduino UNO for digital acquisition and processing. The analog front end incorporates microphone biasing, AC coupling, reference-voltage generation, and buffered signal conditioning for ADC-compatible acquisition. The acquired samples are processed using **RMS analysis as the primary amplitude-domain feature**, while experimentally collected data are analyzed using Python to establish data-driven RMS classification boundaries. The resulting classification is implemented for real-time operation with LCD-based indication and ThingSpeak-based data logging. Practical evaluation in a library environment further validates the developed system. The proposed system integrates **acoustic sensing, analog signal conditioning, digital acquisition, RMS-based processing, data-driven classification, and real-time monitoring** into a single experimentally implemented platform for acoustic-condition monitoring in noise-sensitive environments.

II. RELATED WORK

Recent studies have explored environmental acoustic monitoring using IoT-enabled sensing and wireless acoustic sensor networks. Electret and MEMS microphones combined with embedded platforms, digital acquisition, and

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wireless communication have been applied to real-time noise measurement, industrial noise mapping, and distributed environmental monitoring [1], [2], [4], [8], [12], [15], [19], [20]. These approaches primarily emphasize scalable deployment, communication, and remote monitoring.

Low-cost acoustic monitoring platforms based on electret and MEMS microphones have also been investigated, focusing on calibration, stability, dynamic range, and configurable deployment [7], [10], [14]. DSP-based systems have further addressed acoustic parameter extraction and environmental sound classification using embedded and wireless platforms [9], [11], [13]. Other studies have explored specialized sensing approaches, including capacitive, distributed, low-frequency, and nanofibre-based acoustic sensing [3], [5], [6], [16], along with sensor self-testing and distributed signal processing for improved reliability [17], [18].

Overall, the reviewed studies demonstrate substantial progress in acoustic sensing, DSP, and networked environmental monitoring. However, comparatively limited emphasis is placed on integrating a **practically implemented acoustic sensing interface, analog signal conditioning, Arduino-based acquisition, RMS-based digital processing, experimentally derived classification boundaries, and real-time monitoring** within a compact system. This motivates the development and experimental evaluation of the proposed platform for acoustic-condition monitoring in noise-sensitive environments.

TABLE I. COMPARISON OF EXISTING ACOUSTIC MONITORING STUDIES

Paper	Methodoly used	Frequency Range	Sampling	Accuracy/ SNR/DR
[1]	IoT + ESP32 + ADC	-	-	16 bit ADC
[2]	IoT + Zigbee + MEMS Mic	20Hz-8kHz	-	<1 dB error
[3]	Capacitive MEMS Readout Circuit	-	Upto 200kSPS	SNR 60-120 dB
[4]	Hierarchical WASN	-	8kHz	0.5-1 dB accuracy
[5]	Distributed Acoustic Sensing (DAS)	Wideband	-	High SNR
[6]	Low-Frequency Noise Measurement	Sub Hz to kHz	-	nV/√Hz noise floor
[7]	Low-cost Acoustic Sensor Network	20Hz-20kHz	Upto 48kHz	±1.5–2 dB
[8]	Wireless Acoustic Sensor Network	-	-	-
[9]	DSP-based Acoustic Sensor	63Hz-8kHz	Upto 108kHz	~80 dB dynamic range
[10]	Configurable Sensor (ARM + MEMS)	50Hz-15kHz	Upto 48kHz	SNR ~65 dB
[11]	WASN + CNN Classification	20Hz-20kHz	44.1kHz	<1 dB error
[12]	WASN Review System	Upto ~40kHz	-	-
[13]	AudioMoth + AI Algorithms	20Hz-192kHz	Upto 348kHz	F1 score ~0.98
[14]	Low-cost Noise Sensor	20Hz-20kHz	-	±2 dB accuracy
[15]	MEMS Urban Sensor Network	20Hz-20kHz	32kHz	±2 dB accuracy
[16]	Nanofibre Acoustic Sensor	20-2000Hz	-	High sensitivity (266 mV/Pa)
[17]	Self-testing Noise Sensor	80Hz-20kHz	-	Q ≈ 0.97–0.98
[18]	WASN Signal Processing	-	-	-
[19]	WSN Communication System	-	1 sec sampling	96% PRR
[20]	Low-cost Wireless Sensor	Upto 16.5kHz	33kHz16 bit	±0.86 dB accuracy

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III. PROPOSED SYSTEM

The proposed system integrates acoustic sensing, analog signal conditioning, digital acquisition, RMS-based signal processing, data-driven classification, and real-time monitoring into a single environmental acoustic monitoring platform. An electret microphone acquires the acoustic signal, which is conditioned using an LM358-based analog interface and applied to the ADC of an Arduino UNO. The acquired samples are digitally processed to obtain amplitude-domain parameters, with RMS selected as the primary feature for acoustic-condition classification.

The experimentally acquired RMS data are analyzed using Python to determine data-driven classification boundaries. The resulting thresholds are implemented in the Arduino-based processing system to categorize acoustic conditions as LOW, NORMAL, and HIGH. The classified output is displayed on an LCD, while the measured parameters are transmitted through a Python-based interface to ThingSpeak for data logging and visualization. The developed system is experimentally evaluated using controlled acoustic inputs and subsequently deployed in a library environment for practical acoustic monitoring.

IV. HARDWARE DESIGN AND IMPLEMENTATION

The developed acoustic sensing interface consists of an electret microphone, biasing and AC-coupling components, an LM358-based signal-conditioning circuit, a reference-voltage generation and buffering stage, and an Arduino UNO interface. The electret microphone is biased using a 2.2 kΩ resistor, and the acoustic signal is AC-coupled through a 1 µF capacitor. A 100 kΩ–100 kΩ resistor divider generates the reference voltage Vref, which is buffered using the second operational-amplifier stage of the LM358. The conditioned output from the first LM358 stage is connected to analog input A0 of the Arduino UNO for digital acquisition.

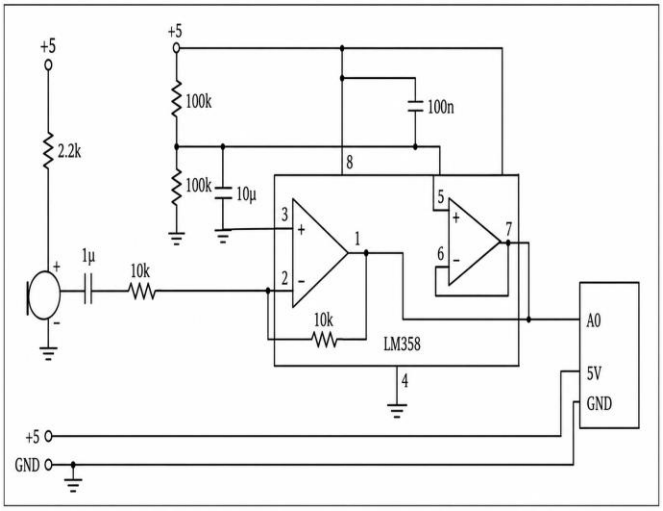


Fig. 1. Schematic of the developed acoustic sensing and signal-conditioning circuit.

The circuit operates from the 5 V supply of the Arduino UNO. Experimental measurements gave a supply voltage of approximately 5.10 V, a reference voltage of approximately 2.53 V, and a microphone bias voltage of approximately 4.45 V. The reference voltage provides the required DC operating level for the single-supply signal-conditioning stage, allowing the acquired acoustic signal to be interfaced with the Arduino ADC. The developed hardware was verified using a digital multimeter, digital oscilloscope, and function generator under controlled conditions.

A. Acoustic Signal Acquisition and Conditioning

The electret microphone converts incident acoustic pressure variations into an electrical signal. The microphone output is biased through the 2.2 kΩ resistor and coupled to the signal-conditioning stage through the 1 µF capacitor. The LM358 circuit provides the required analog signal conditioning, while the buffered Vref establishes a stable reference level for operation from a single 5 V supply. The resulting conditioned signal is applied to the Arduino ADC for subsequent digital processing.

B. Arduino-Based Data Acquisition

The conditioned analog signal is sampled through the Arduino UNO ADC at analog input A0. The acquired ADC samples are used for digital signal processing and extraction of amplitude-domain parameters. The subsequent RMS calculation and data-driven classification are described in the following sections

V. DIGITAL SIGNAL PROCESSING AND RMS ANALYSIS

The conditioned acoustic signal acquired through the Arduino UNO ADC is processed digitally to obtain amplitude-domain characteristics of the environmental acoustic signal. The acquired samples are analyzed over a fixed sampling window, and the RMS value is used as the primary feature for representing the signal amplitude. RMS provides a single quantitative measure of the signal magnitude over the observation interval and is subsequently used for acoustic-condition classification. The calculated RMS values are recorded along with other measured parameters and transferred to the data-analysis stage for threshold determination.

The RMS-based processing provides the link between the developed hardware and the data-driven classification stage. The experimentally collected RMS values are analyzed using Python to identify boundaries between three acoustic-condition categories. The threshold-generation procedure and resulting classification ranges are presented in Section VII.

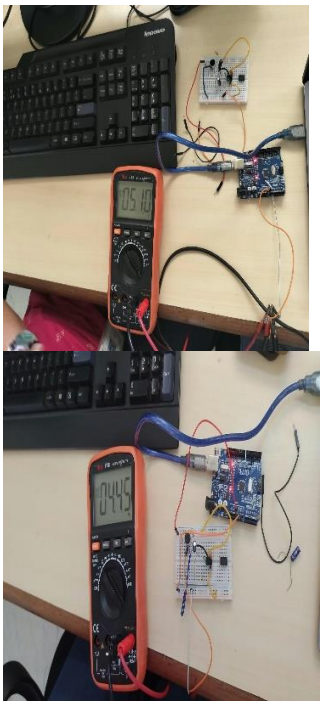
VI. EXPERIMENTAL SETUP AND RESULTS

The developed acoustic sensing interface was experimentally verified using a digital multimeter, digital oscilloscope, and function generator. The implemented circuit was operated using the Arduino UNO supply. The measured supply voltage was approximately 5.10 V, while

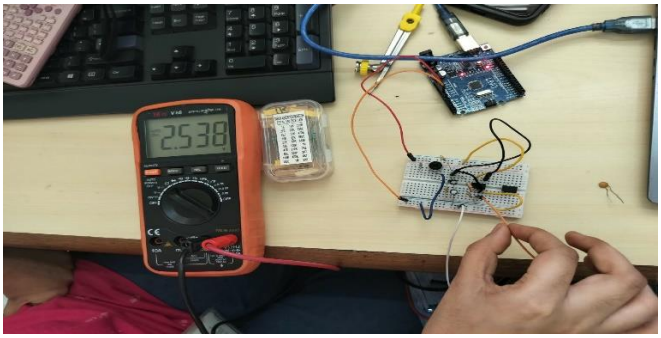
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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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the microphone bias voltage and reference voltage were measured as approximately 4.45 V and 2.53 V, respectively. These measurements verify the required electrical operating conditions of the developed sensing and signal-conditioning circuit.



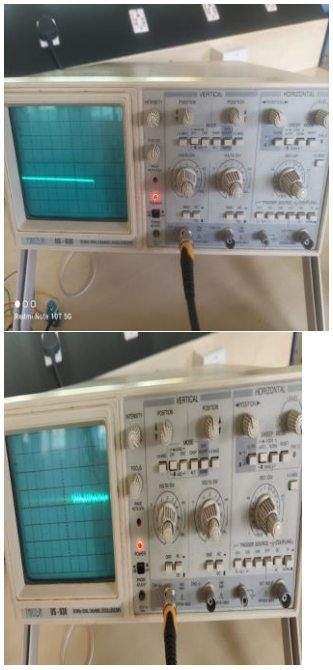
(a) (b)



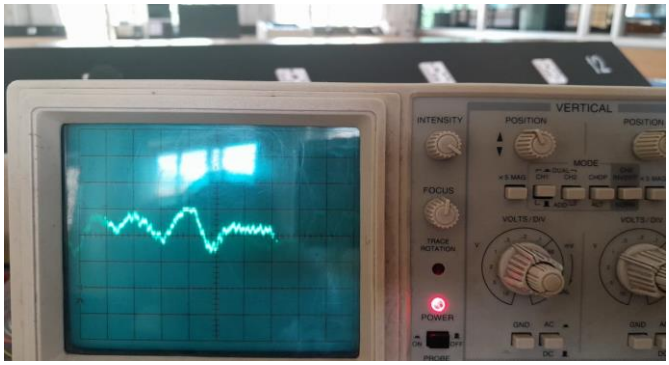
(c)

Fig. 2. Experimental measurement of the developed acoustic sensing circuit: (a) supply voltage, (b) microphone bias voltage, and (c) reference voltage.

The acoustic response of the developed sensing interface was further evaluated using a digital oscilloscope under different acoustic conditions. In the absence of intentional sound, only a small background waveform was observed due to ambient environmental noise. The measured peak-to-peak output ranges were approximately 36–44 mVpp for no sound and 308–500 mVpp for normal speech, while clap and blow inputs produced higher-amplitude responses, as summarized in Table II. The measured peak-to-peak output ranges were approximately 36–44 mVpp for no sound and 308–500 mVpp for normal speech, with higher levels observed for louder acoustic inputs. These CRO measurements were used for preliminary hardware and signal-conditioning validation and were not used for the final acoustic-condition classification



(a) (b)



(c)

Fig. 3. CRO waveforms of the conditioned acoustic signal under (a) ambient/noise condition, (b) normal speech, and (c) louder speech.

TABLE II. MEASURED ACOUSTIC RESPONSE UNDER DIFFERENT INPUT CONDITIONS

Acoustic condition	Measured Vpp
No sound / ambient	36-44 mV
Normal voice	308-500 mV
Clap	132-208 mV
Blow	~ 1.13 V

The measured Vpp values demonstrate the variation in the conditioned output with different acoustic inputs. These measurements were used for preliminary validation of the sensing interface and were not used for the final RMS-based classification.

VII. RMS-BASED DATA ANALYSIS AND DATA-DRIVEN CLASSIFICATION

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International Journal of Engineering Research & Technology (IJERT)
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The experimentally acquired measurements were logged through the Python–ThingSpeak interface and exported as a tabular dataset for offline analysis. The dataset contained approximately 300 recorded measurements, from which 237 valid RMS samples were retained after preprocessing. RMS was selected as the primary amplitude-domain feature for deriving the acoustic-condition boundaries.

A. RMS Feature Extraction

For an observation window containing N acquired samples x[n], the RMS value is defined as

$$\mathbf{R_{RMS}} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} \mathbf{x^2}\,[\mathbf{n}]}$$

..(1)

where x[n] denotes the acquired signal sample and N is the number of samples in the processing window.

The RMS values obtained from the experimental dataset were sorted in ascending order and partitioned into three approximately equal groups for data-driven characterization.

B. Experimental RMS Distribution

TABLE III. EXPERIMENTAL RMS DISTRIBUTION

Total Measurements collected	~ 300
Valid RMS samples	237
RMS groups	3
Samples per group	79
Low group mean RMS	17.13
Normal group mean RMS	43.99
High group mean RMS	92.52
Maximum observed RMS	211.04

C. Data-Driven Threshold Determination

The decision boundaries were calculated from the adjacent group limits rather than being selected empirically. The LOW-to-NORMAL boundary is given by eq (2)

$$\mathbf{T_1} = \frac{\mathbf{R_{L,max}+R_{N,min}}}{2} = \mathbf{31.38} \qquad \textbf{..(2)}$$

and the NORMAL-to-HIGH boundary is given by eq (3)

$$\mathbf{T_2} = \frac{\mathbf{R_{N,max}+R_{H,min}}}{2} = \mathbf{47.02}$$

..(3)

Where $R_{L,max}$, $R_{N,min}$, $R_{N,max}$, $R_{H,min}$ represent the corresponding boundary RMS observations of the three ordered groups.

D. RMS Classification Criteria

The resulting decision function is

$$\mathbf{C(R)} = \begin{cases} \mathbf{LOW}, & \mathbf{R < 31.38} \\ \mathbf{NORMAL}, & \mathbf{31.38 \le R < 47.02} \\ \mathbf{HIGH}, & \mathbf{R \ge 47.02} \end{cases}$$

..(4)

TABLE IV. RMS CLASSIFICATION

Criteria	RMS Range
Low/Silence	$R < 31.38$
Normal	$31.38 \le R < 47.02$
High	$R \ge 47.02$
Maximum observed RMS	211.04

The derived thresholds were subsequently incorporated into the Arduino processing logic for real-time classification.

E. RMS Distribution Characterization

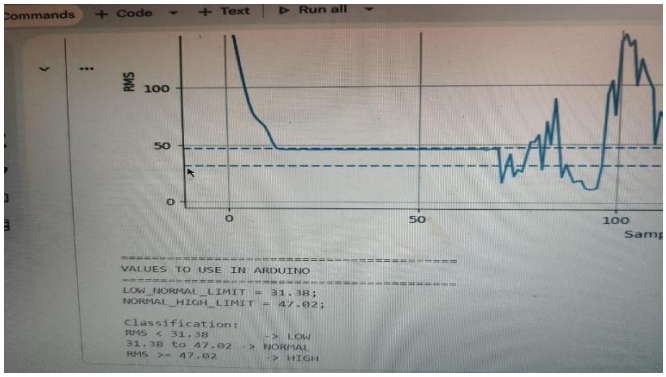


Fig. 4. RMS distribution of the experimental dataset with data-driven classification thresholds.

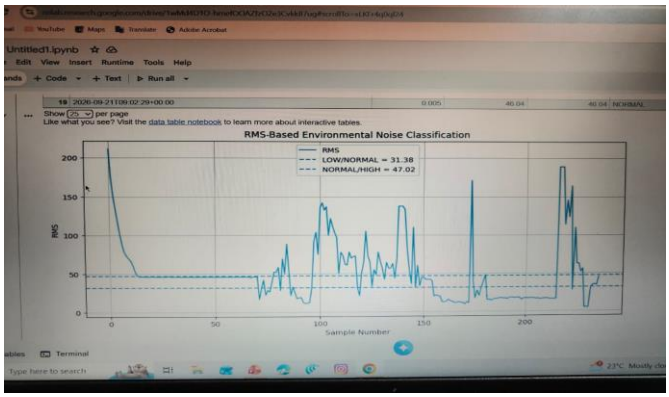


Fig. 5. RMS-based classification boundaries obtained from the experimental dataset.

VIII. REAL-TIME SYSTEM IMPLEMENTATION AND PRACTICAL VALIDATION

A. Serial Data Transfer and Cloud Logging

Since the Arduino UNO does not provide native Wi-Fi connectivity, a Python serial interface was used as an intermediate communication layer between the embedded system and ThingSpeak. The measured Vpp, RMS, mean, and intensity values were transmitted from the Arduino through USB serial communication and uploaded to ThingSpeak for time-stamped storage and visualization.

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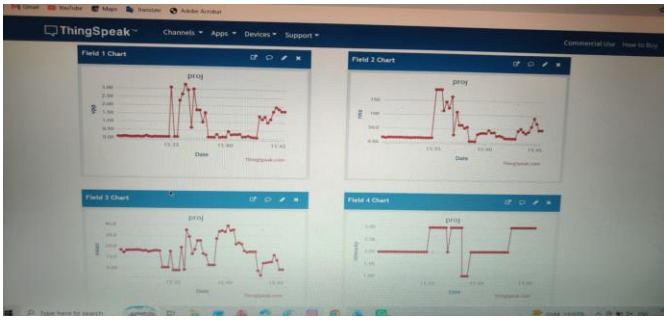


Fig. 6. ThingSpeak visualization of the measured acoustic parameters during system operation.

B. Embedded RMS Classification

The experimentally derived RMS boundaries were incorporated into the Arduino processing logic

$$\mathbf{RMS} < \mathbf{31.38} \rightarrow \mathbf{LOW}$$

$$\mathbf{31.38} \leq \mathbf{RMS} < \mathbf{47.02} \rightarrow \mathbf{NORMAL}$$

$$\mathbf{RMS} \geq \mathbf{47.02} \rightarrow \mathbf{HIGH}$$

..(5)

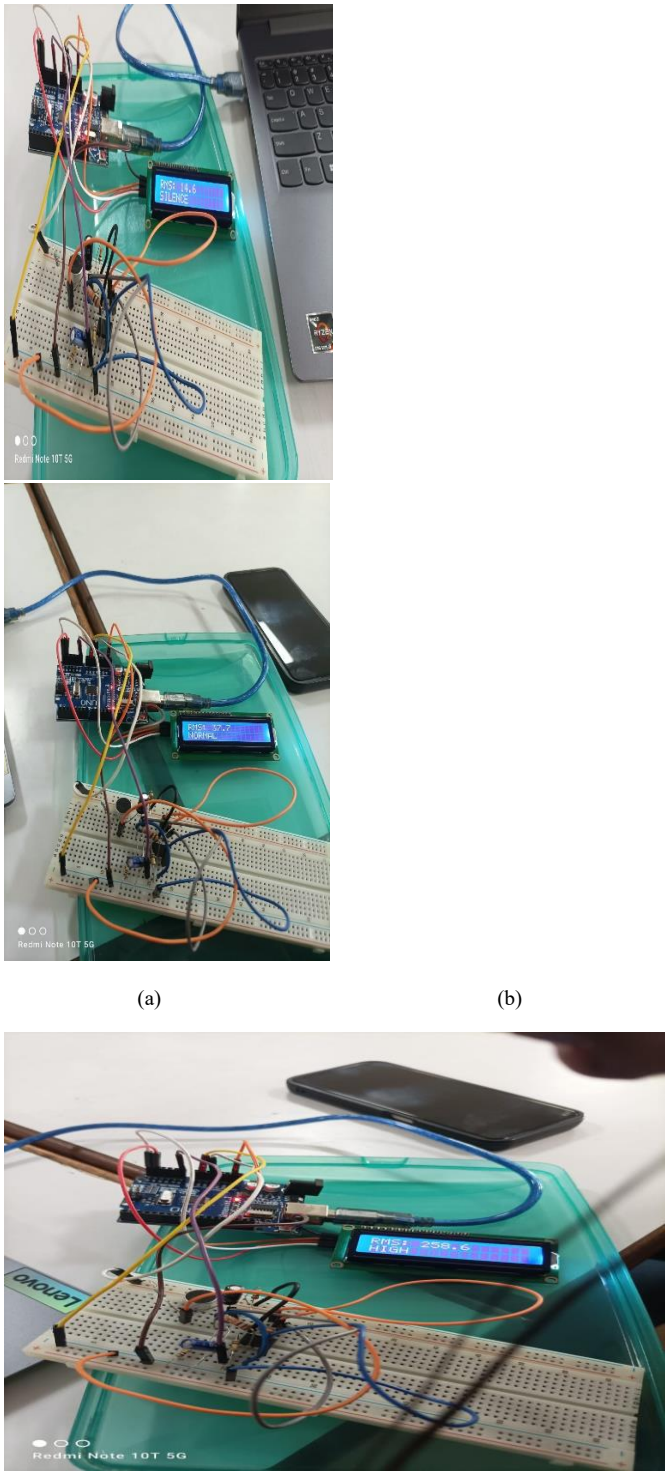
For the LCD interface, the LOW condition was represented as **SILENCE**. The processed classification dataset was also transferred to the Arduino through the Python serial interface to verify the implementation of the derived decision limits.

C. Real-Time LCD Validation

The finalized sensing system was operated using live acoustic inputs, and the calculated RMS value and corresponding classification were displayed on the LCD.

TABLE V. REPRESENTATIVE REAL-TIME RMS CLASSIFICATION OUTPUTS

RMS	LCD OUTPUT
14.6	SILENCE
33.7	NORMAL
258.6	HIGH



(a) (b)

(c)

Fig. 7. Real-time LCD outputs for (a) SILENCE, (b) NORMAL, and (c) HIGH acoustic conditions.

D. Library Deployment

The finalized prototype was deployed in a library environment for continuous acoustic monitoring. The acquired acoustic signal was processed in real time, and the resulting RMS value and acoustic condition were displayed locally on the LCD. The deployment demonstrated practical

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operation of the complete sensing, processing, classification, and visualization chain under an actual indoor acoustic environment.

IX. DISTANCE WISE RMS MEASUREMENTS

The following table presents the measurements obtained during normal speech and louder speech at different distances

TABLE VI. DISTANCE-WISE RMS MEASUREMENTS

DISTANCE	SOUND CONDITION	MINIMUM RMS	MAXIMUM RMS
5cm	Normal speech	52	55
7cm	Normal speech	7.9	10
10cm	Normal speech	9	15
15cm	Normal speech	4	8
30cm	Normal speech	8.9	9.7
30cm	Slightly louder speech	-	10
50cm	Normal speech	4.9	6.7
50cm	Shouting	35	50
75cm	Normal speech	-	6
100cm	Normal speech	-	5

The measurements indicate that the microphone responds to sound signals even when the distance between the sound source and the microphone is increased. At 5 cm, normal speech produced an RMS value between 52 and 55. At 30 cm, normal speech produced values between 8.9 and 9.7, while slightly louder speech produced a maximum RMS value of 10.

At 50 cm, normal speech produced RMS values between 4.9 and 6.7. However, when shouting was performed at the same distance, the RMS value increased to a range of 35–50. This demonstrates that the microphone output is influenced by the intensity of the sound produced, in addition to the distance from the microphone.

At larger distances, normal speech was still measurable. At 75 cm, the maximum recorded RMS value was 6, while at 1 metre, it was approximately 5. These observations indicate that the microphone can respond to normal speech from a distance of approximately 1 metre under the tested conditions.

X. RESPONSE TO OTHER ENVIRONMENTAL SOUNDS

Additional experiments were performed to examine the microphone response to different sound conditions.

TABLE VII. RESPONSE TO OTHER ENVIRONMENTAL SOUNDS

SOUND CONDITION	APPROXIMATE DISTANCE	RMS VALUE
Quiet room	-	2.2-2.8
Quiet room	-	2.7-3.3
Blowing towards microphone	30cm	52
Blowing very close	Vey close	250-300
Loud vehicle passing	10-15m	4.1-4.2
Background before vehicle	Same location	2.7-3.0
Background after vehicle	Same location	2.7-3.0

The observations show that a loud vehicle passing approximately 10–15 metres away produced a measurable increase in RMS compared with the background readings. The microphone also responded strongly when air was blown directly towards it. However, blowing is not a reliable environmental sound test because direct airflow can influence the microphone output.

The experiment demonstrates that the developed acoustic sensing system responds to sound signals at different distances. Normal speech was detected at distances up to approximately 1 metre under the tested experimental conditions. Shouting at 50 cm produced higher RMS values than normal speech at the same distance, showing the influence of sound intensity on the measured response. A passing vehicle at approximately 10–15 metres also produced a measurable change compared with the background readings.

Important experimental observation: The RMS values did not decrease consistently with increasing distance. This may be due to variations in speaking volume, microphone orientation, and room acoustics. Therefore, 1 metre should be reported as the farthest tested distance for normal speech in this experiment, not as the guaranteed maximum detection range of the microphone.

Also, keep this experiment separate from your original threshold analysis. Your original thresholds were 31.38 and 47.02, whereas most of the later normal-speech readings are below 31.38. The two datasets should not be treated as directly comparable until the RMS calculation and measurement conditions are verified.

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XI. DISCUSSION AND CONCLUSION

The experimental results establish the feasibility of the developed acoustic monitoring platform for amplitude-based acoustic-condition identification. The experimentally acquired RMS distribution provided distinct operating regions, enabling data-driven decision boundaries of 31.38 and 47.02 rather than arbitrarily selected thresholds. The derived boundaries were successfully transferred to the Arduino-based processing framework and verified using both pre-fed experimental data and live acoustic measurements.The developed prototype integrates electret-microphone sensing, LM358-based analog signal conditioning, Arduino-based digital acquisition, RMS-based processing, data-driven classification, Python-assisted serial communication, ThingSpeak data logging, and LCD-based real-time indication within a single monitoring system. Approximately 300 measurements were collected during experimental operation, with 237 valid RMS samples used for threshold determination. Representative live measurements of 14.6, 33.7, and 258.6 RMS produced SILENCE, NORMAL, and HIGH outputs, respectively, confirming operation across the defined decision regions.

The finalized system was subsequently deployed for continuous monitoring in a library environment, demonstrating the transition from experimental data characterization to real-time environmental operation. The resulting workflow provides an end-to-end implementation from acoustic signal acquisition and analog conditioning to quantitative data analysis, experimentally derived classification, embedded decision-making, cloud-assisted logging, and practical deployment.

The classification boundaries are specific to the experimentally characterized RMS distribution and therefore are not intended as universal acoustic limits. Future extensions can incorporate larger multi-environment datasets, adaptive threshold estimation, additional signal features, wireless embedded connectivity, and broader validation. The demonstrated integration of a custom-developed sensing interface with data-driven RMS classification and real-time environmental monitoring provides a practical foundation for further development of intelligent acoustic monitoring systems.

XII. LIMITATIONS AND FUTURE SCOPE

The developed prototype was experimentally evaluated using RMS-based acoustic-condition classification and practical library deployment. The classification thresholds were derived from the experimentally collected dataset and can be further refined through extended measurements across additional environments.

Future work can focus on adaptive thresholding, wireless connectivity, larger-scale data logging, and enhanced acoustic-condition classification to extend the system toward broader real-time environmental monitoring applications.

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