iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VI **Month of publication:** June 2026

DOI: https://doi.org/10.22214/ijraset.2026.83809

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

IoT-Enabled Real-Time Environmental Noise Surveillance with Smart Threshold Alerts and CAMERA-Based Location Analytics

Yatesh Ghadage, Dhanshri Kumbhar, Prathmesh Langde, Vaishnavi Midgule, Prof. Ashwini Deshmukh
Electronics and Telecommunication Engineering Trinity College Of Engineering and Research, Pune

Abstract: Noise pollution has become a serious environmental problem in fast-growing cities and suburban areas. Long-term exposure to high noise levels is linked to stress, heart problems, issues with thinking, and a lower quality of life. As a result, it's important to develop a system for continuous and intelligent monitoring. This research introduces as IoT-enabled real-time environmental noise monitoring system that combines acoustic sensing, smart alert generation based on thresholds, and camera-based location analysis. Ambient noise levels are collected using acousticsensorsconnected toaRaspberryPi,which arecalibrated against set limit values.When the system detects limit violations, it automatically generates alerts, records decibel level with timestamps and geocoordinates, and captures visual evidence to help identify regular noise sources. Lightweight machine learning classifier is included to tell apart short noise events from ongoing pollution,improvingdetection accuracy.Thesystems design focuses onlowpoweruseandmodularscalability,allowingittobedeployed in hospitals, schools, residential area, along highway, and at large public events. By combining intelligent sensing, adaptive classification,andvisualanalytics, thisresearch providesa practical framework for smart urban governance and effective noise pollution mitigation.
Keywords: Noise Pollution, IoT, Real-Time Monitoring, Threshold Alerts,SmartCity,Geo-Tagging,Camera Analytics, Machine Learning, Environmental Management.

I. INTRODUCTION

Over the recent years, human activities and urban migration have led to significant rise in noise pollution [1][6]. Increasing vehicular traffic, urban crowding, construction activities and industrial operation has seen the average noise profile be pushed beyond tolerablelevelssetbyenvironmentalagencies.Noiseinducedhealth effects and threat to comfort causing adverse physiological and psychological condition such as, hypertension, acoustic trauma, disturbed sleep, decreased cognition and increased stress hormone levelsareknowntobeassociated[6][12].Existingacousticprofiling are highly inconsistent owing to manual procedures using spot-checks, survey, or crowdsourcing requests [11][13].

However,withriseofIoTarchitectures,embeddedsystems,sensing infrastructureandlow-costenvironmentalsensors,automationand real time monitoring are now technologically feasible [1][3]. Interconnection of sensor provided with camera-based image analytics has also been demonstrated to add furtherintelligence to baseline environmental profiling [2][8][10].

This paper designs and implements IoT enabled, real time environmental noise monitoring framework providing automated noisesensing,intelligentenvironmentalviolationalertandcamera-basedcontext[4][11].ThesystemusesRealtimeSPLdata acquired through acoustic sensors connected to Raspberry Pi, processed based on threshold criterion with environmental analyst [8][10]. The system, when detect any anomalies or threshold breach, sends an auto-admin notification, captures camera based visual information of centre point in a dynamically calculated location map [3][13]. The more intelligent framework utilizes machine learning based noise classification algorithms for, anomaly detection, source identification, and modelling persistent noise breach pattern [7][9].

Camera-basedanalysiscanaddautomatedintelligencetoprobable sourceofnoise,duration,locationandtriggernecessaryregulatory action [8]. The architecture is also designed to be low-power, low-cost while be cost scalable [2][5].

II. RESEARCH FRAMEWORK: AIM, OBJECTIVES AND RESEARCH QUESTIONS

A. Aim of the Study

The aim of this study is to critically review and analyse existing literatureonIoT-enabledreal-timeenvironmentalnoisesurveillance systems,withanemphasisonsmartthreshold alertmechanismsand camera-based location analytics.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

B. Objectivesofthe Study

Thespecificobjectivesofthisliteraturereviewware:

1) ToexamineIoTsystemarchitecturesusedforreal-timeenvironmental noise monitoring.
2) To analyse noisesensing andcalibrationtechniquesreportedin the literature.
3) Toreviewsmartthresholdingandalertgenerationmechanisms.
4) Tolookintohowcamera-basedlocationanalyticsworksinnoise surveillance systems.
5) Tocompareperformancemetricsanddeploymentstrategies from existing studies.
6) Tofindopenresearchchallengesandfutureresearchdirections.

C. ResearchQuestions

Basedonthereviewoftheliterature,thefollowingresearch questions (RQs) are formed:

1) RQ1:HowcanamIoT-basedsystembedesignedtomonitorenvironmental noise levels in real time?

This figure shows the real-time changes in environmental noise levelsmeasuredbytheproposedsystemoveraspecifictimeperiod. Normalambientnoisestayswithintheacceptablerangeofabout40 to 55dB.Sudden spikes above 70 to 75 dB signal noise violation events.

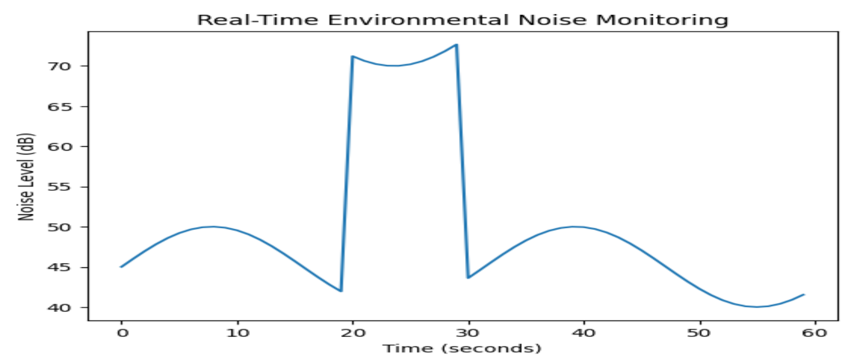


Fig2.1.RealTimeEnvironmentalNoiseMonitoring

Thegraphillustratesthesystemscapabilitytoaccuratelydetectboth brief noise spikes and ongoing high-noise situations in real time. Table 2.1 presents the allowable noise levels for different urban zones.Ithighlightsthestandardsforsilent,residential,commercial, and industrial areas.

Table2.1:PermissibleEnvironmentalNoiseThresholdValues

ZoneType	PermissibleNoiseLevel(dB)
Silent Zone	40–50 dB
ResidentialZone	≤55 dB
CommercialZone	≤65–75 dB
IndustrialZone	> 75 dB

Description: Thistableshowsthestandardenvironmentalnoisethresholdvalues used for smart thresholding in the proposed system. These limits followtypicalnoisepollutioncontrolconstantlycomparesreal-time noise measurements with theseset values to automatically find and classify noise violations.

2) RQ2: How can smart threshold-based alert system be put in place to effectively detect and notify about noise violations?

The figure below illustrates a smart threshold-based noise monitoringandalertsystemthatdetectsandnotifiesnoiseviolations in real time. The system combines IoT-enabled noise sensors, data processing units, intelligent threshold analysis, and flexible decision-makingprocesses.Noiselevelsareconsistentlymeasured, processed, and compared against fixed or adaptable thresholds. When a violation is found, the system sends alerts through various channels, ensuring prompt notifications while also logging data for reporting and review.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

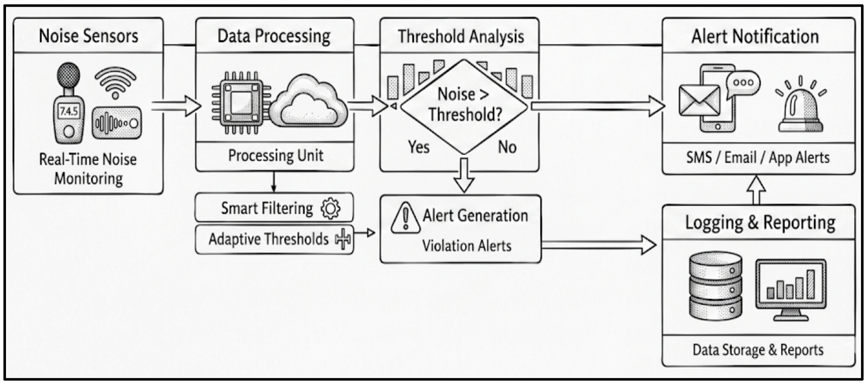


Fig2.2.SmartThreshold-BasedNoiseMonitoringandAlertSystem

This diagram shows the complete workflow of the system. It highlights how sensing, processing, smart decisions-making, alert generation, and data management work together. By merging real-time monitoring with adjustable thresholds and automatic notifications, the system detects noise violations accurately while cutting down on false alarms. This method works well for urban noisemanagement,industrialmonitoring,andsmartcityprojects.It helps meet regulations and gives useful insights for preventive actions.

3) RQ3:How can camera-based location analytics beused tohelp identify and confirm noise sources?

The following diagram displays a noise monitoring system that includes cameras. It merges audio and visual data to find and confirmnoisesources.Noisesensorsrecordreal-timesoundlevels, and cameras offer video feeds. These are synced and analysed to identify the exact source of a noise event.

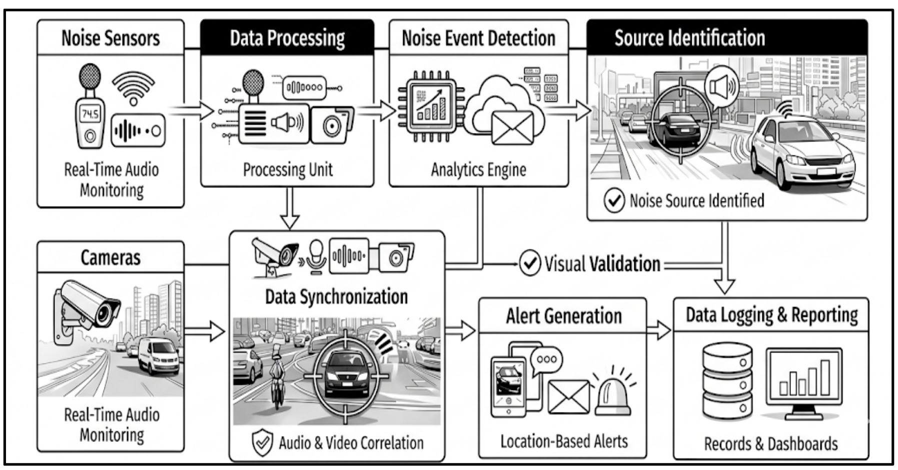


Fig2.3Camera-BasedLocationAnalyticsforNoiseSource Identification

Onceidentified,thesystemgenerateslocation-basedalertsandlogs thedataforreportingandanalysis.Thisuseofaudio-visualanalytics improvesaccuracy,reducesfalsealarms,andprovidesvisual evidence for effective noise management and regulatory compliance.

4) RQ4: How can machine learning techniques improve noise classification accuracy and reduce false alerts?

Machine Learning (ML) techniques can greatly enhance the accuracy of noise classification and decrease false alerts in monitoring systems. Traditional threshold-based systems often strugglewithchangingenvironmentalnoiseandoverlappingsound sources.ML algorithms, on the other hand, learn patterns from historical and real-time audio data, allowing for smarter detection and classification.

a) Implementation Approach:

- Feature Extraction:

- Extract relevant audio features like Mel-Frequency Cepstral Coefficients (MFCCs), spectral features, or zero-crossing rates from recorded noise/
- Thesefeaturescapturetheuniquetraitsofdifferentnoise types.

- ModelTraining:
- TrainmachinelearningmodelssuchasSupportVectorMachines (SVM), Random Forests, or deep learning networks (CNNs,RNNs) to tell apart different sound sources, like traffic, construction, or human activity.

- NoiseClassification:
- Thetrainedmodelclassifiesincomingaudiosignalsinrealtime, identifying the type and severity of noise.
- Machinelearningmodelscanhandlecomplexenvironments with overlapping or intermittent sounds.

- FalseAlert Reduction:
- Bylearningmodelsfilteroutunrelated orbriefnoiseevents that might cause false alerts.
- Adaptivethresholdingandanomalydetectioncanfurther improve alerts.

- IntegrationwithIoTandAlert Systems:
- Machine learning-based classification can work with IoT sensorstocreateexactalerts,logevents,andsupplydatafor trend analysis.

Fig.2.4 shows the main components, functions, and performance metrics of the machine learning noise classification system, emphasizing how noise data is captured, processed, and classified.

Component	Function	Example / Detail	Noise Type	Classification	
			Accuracy (%)	Accuracy (%)	False Alarm Rate (%)
Noise Sensors	Capture real-time audio	Microphones, IoT devices	–	3	
Feature Extraction	Extract relevant audio features for classification	MFCCs, Spectral Analysis	MFCCs, Spectral Analysis	3	3
ML Classification	Analyze features and classify noise type	SVM, CNN, RNN	SVM, CNN, RNN	3	4
Decision Module	Determine if noise event exceeds threshold	Noise level evaluation	Noise level evaluation	3	5
Alert Generation	Notify relevant authorities or users	SMS, Email, Mobile App	SMS, Email, Mobile App	3	3
Logging & Reporting	Store classified events and generate reports	Database, Dashboard, Trend Analysis	–	–	6

Fig 2.4 .ML-Based Noise Classification System: Components and Performance

Overall, the table shows that the system effectively classifies noise withhighaccuracyandlowfalsealarmrates.Thismakesitsuitable for real-time monitoring applications.

b) Advantages:

- Increasedaccuracyinidentifyingnoisetypes.
- Fewerfalsealarmsfrombackgroundoroverlappingsounds.
- Flexibleandexpandabletonewnoisesourcesthroughretraining.
- Supportssmarturbannoisemanagementsandhelpsmeet regulations.

5) RQ5: How can the proposed system be made scalable, energy-efficient, and suitable for smart city deployments?

Theproposedsystemisdesignedforscalable,energy-efficient,and smart city-ready deployments. Its modular structure allows easy integration of extra sensor nodes. Cloud-based processing supports real-time analysis across multiple locations. Energy efficiency comes from low-power sensors, microcontrollers, and smart power management, which includes adaptive sampling and sleep modes. The use of IoT -enabled communication protocols ensure reliable, low-latency data transmission. Integration with existing smart city platformshelpswithnoisemonitoring,regulatoryenforcement,and urban planning. This provides a sustainable and complete solution for modern cities.

The figure shows a scalable, energy-efficient IoT noise monitoring system for smart cities, integrating low-power sensors, cloud analytics,andmodulardesignforreal-timeurban noiseassessment.

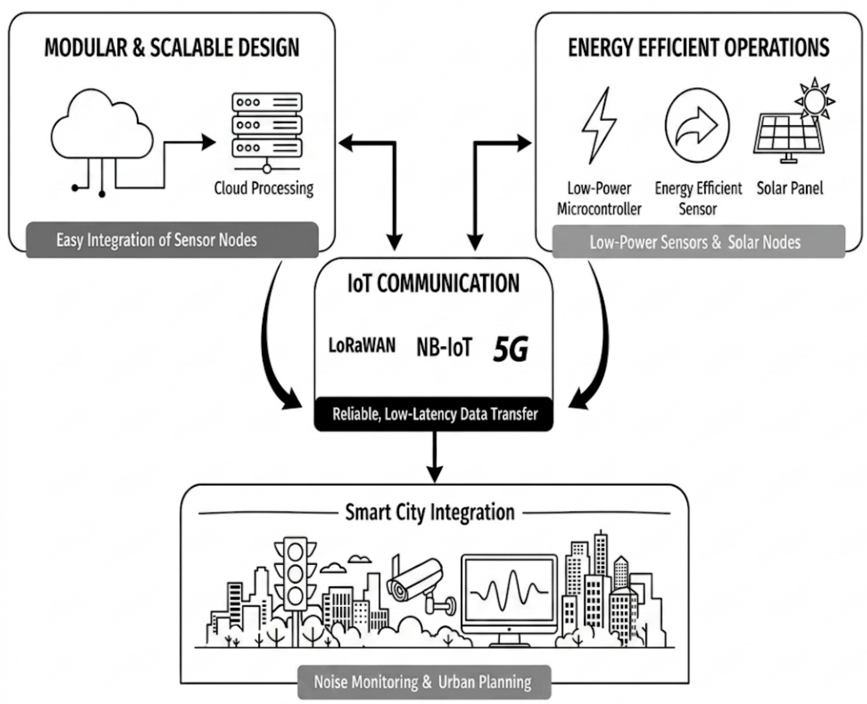


Fig2.5.IoT-DrivenSmartNoiseMonitoringforSustainableCities

This system enables effective noise management through IoT connectivity and smart city integration, supporting sustainable urban planning and improved quality of life.

III. METHODOLOGY OF LITERATURE REVIEW

The review of literature has been handing on in a systematic manner with focused attention on section 3 of the review.The literature which is core to the research report was procured from search engines like IEEE Xplore, SpringerLink, ScienceDirect, Google Scholar through noes of web searching engines on the keywords like as "IoT based environment noise monitoring", "environmental noise surveillance', "smart threshold alerts', "machine learning based noise classification", "camera-based location analytics. The procured core literature was further sorted on their relevancy to the research statement, technical domain and its depth, quality as perimeter-controlled investigation, extensibility as practical/system-oriented investigation. The relevant literaturewasthenanalysedbasedonsensingtechnology&framework of the system, IoT structure & its configuration, web/average communicationtechnology,qualityoftheanalyticalaswellasmachine learning based methodology, design of alert generator, system extensiveness/massivenesstocomparedifferentmethodologytodefine new benchmarks.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

Table3.1presentsacomparativesummaryofexistingresearchworks related to IoT-based environmental noise monitoring systems, highlighting their methodologies, outcomes, and limitations.

Table3.1ComparativeSummaryresearchpapers(2020-2025)

Reference	Focus	Key Contribution s	Limitations
Anachkovaetal., 2020 [1]	IoT-based urbannoise monitoring using LoRaWAN	Demonstrated long-range IoT noise monitoring; identified traffic-related noise hotspots	Scalability and long-term maintenance notevaluated
Mauliddaetal., 2024 [2]	IoT noise detectionfor libraries	Real-time alerts improved librarynoise control	Nomulti-site deployment or user feedback analysis
Choodarathnakara et al., 2023 [3]	IoT monitoringof air and noise pollution	Integratedair + noise sensingwith alerts and dashboard	Limited deployment; sensor calibration notdetailed
Meenalochini, 2022 [4]	IoT–cloud environmental monitoring	Real-time sensingwith cloud-based prediction	Internet dependency; limitedlarge-scale validation
Sepanosianetal., 2023 [5]	IoT monitoringof construction emissions	Real-time alerts for occupational safety	Pilot-scale study;cost and durability concerns
Saddiwaletal., 2024 [6]	GPS-enabled smartdecibel meter	Geo-tagged noise mapping; portable solution	Prototype-level;power and sensor accuracy issues
Alsina-Pageset al., 2021 [7]	Urbannoise event detection algorithms	Compared algorithms using Harmonica index	Limitedsites; results dataset-dependent
Bozonnetetal., 2018 [8]	ML-based urban sound classification	Early use of MLfornoise event detection	Poor robustnessin complex acoustic scenes
Kumaretal.,2014 [9]	Participatory noisesensing via smartphones	Low-cost citizen-based noise mapping	Sustainability ,validation, and indoor accuracy issues

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

Sivaprakashetal., 2023 [10]	IoT air &noise monitoring with control	Monitoring combined with automatic control	Notscaled citywide; calibration challenges
Alametal.,2024 [11]	Low-costIoT environmental monitoring	Multi-parameter urban monitoring	Limited coverage; lackslong-term trends
Somuetal.,2025 [12]	GPS-based monitoring usingCNN–LSTM	Improved prediction accuracy usingdeep learning	Datasetand scalability limitations
Rajagukguk& Sari,2018 [13]	Noise level detectorwith alerts	Simple real-time noise classification	Limited range;lab-scale validation only
Sirishetal.,2025 [14]	IoT monitoring with purification actions	Extends monitoringto mitigation	Prototype-only;limited pollutant coverage
Subrajaetall., 2024 [15]	IoTreal-time noise monitoring	Smart-city–ready noise classification	Sensor reliability and integration gaps

Overall,theliteratureanalysisjustifiesthedevelopmentoftheproposed IoT-Enabled Real-Time Environmental Noise Surveillance with Smart Threshold Alerts and CAMERA -Based Location Analytics.

IV. CONCEPTUAL BACKGROUND OF IOT-ENABLED ENVIRONMENTAL NOISE MONITORING

Environmental noise pollution is a challenge increasingly faced by urbanandsemiurbanareasinmanypartsoftheworld,withthepotential impact on human health, productivity, and overall quality of life. Measurement of environmental noise is performed via the sound pressure level (SPL), recorded in decibels (dB), with A-weighting frequency (dBA) used for approximating human hearing response. Various rules and recommendations on the maximum allowable sound levelsinresidential,industrial,andcommercialenvironmentsareissued by various international organizations including the World HealthOrganization(WHO)andseveralnationalstandardsagencies,in order to minimize potential health problems in the long term [7], [9]. The classic techniques of field monitoring of environmental noise consist of pointwise collection via sound level meters, periodic survey campaignsandquickspot measurements.Whilethesemeasurementsare accurate for the points at which they are taken, their high operational cost, low time and very low spatial resolution measures make them inefficientandunfitforlongtermcontinuousmonitoringatacity-wide scale [1], [8]. These limitations lead toward the use of distributed and automated methods of noise monitoring.

A. IoT-BasedReal-TimeNoiseMonitoringSystems

Recent innovations in IoT have made possible the design of live distributed noise monitoring architectures. Typical IoT-enabled noise monitoring systems are aggregations of sensor nodes fitted with microphones, microcontrollers and wireless communication modules. Microphonescanbeoflow-costelectret[6],[11],orMEMStype;which are small and low-energy-consuming [6], [11]. Depending on applicationneeds,wirelesstechnologiessuchasWi-Fi,LoraWAN,NB-IoT and cellular networks are used, taking into account the desired effective range, scalability and power consumption [1], [13].

This informationisthensenttocloudoredgecomputingserversforstorage, visualization, processing and analysis. Calibration methods based on referencesoundlevelmeters[4],[10]andstatisticalormachinelearning calibration models have also been proposed to enhance accuracy and repeatability.

B. SmartThresholdAlertsandNotificationMechanisms

One of the recent developments in IoT enabled real-time noise surveillance is the use of intelligent threshold based alerting system. Thresholdscanbepredeterminedbasedongovernmentalregulationsor can be flexibly adjusted by dynamic changing factors such as past records,timeofadaycycleanalysisorcontextuallyresilientsmarts[2], [12].When a noise level is beyond the acceptable limit, a distributed alert can be generated using web-based dashboards, mobile interfaces or automatic episodic messaging systems. Such dynamic thresholding systems can reduce the occurrences of false alarms and enhance the noisemitigationactivitiesinanextremelychangeableurbansetting[6], [15].

C. Camera-BasedLocationAnalytics

To improve the perception of a situation, some recent researches combinecamera-basedlocationanalyticswithInternet-of-Things(IoT) based noise sensing systems. In the architecture, camera will be activated to capture the current scene when high acoustic level is detected. Then computer vision techniques, e.g. Object detection and scene analysis, will be used to associate noise events to particular sources, such as vehicle, construction-machinery or crowd of People [10], [12]. Camera-enabled system, which provide better performance, will also bring up privacy, ethical and legal issue. Therefore privacy-aware analytics, limited data storage and local regulations are required when introducing this system. [14].

V. COMPARATIVE ANALYSIS OF EXISTING LITERATURE

Comparative analysis of the proposed IoT based noise and environmentalmonitoringsystems(Table4.1)outlinesthedevelopment trend from the single parameter monitoring to multi sensor intelligent platform. The initial years generally employed simple noise sensors with analytics and batch mode data processing [7], [8], [13]. Later, implementations gradually incorporated air quality parameters, additionalenvironmentstatesandlivealertsforGIS-enabledsmartcity applications [3], [10], [11], [14].

Wireless communication protocols such as LoRa WAN, Wi-Fi, GPRS as well as cloud-enabled architecture improved detection range and remote access [1], [2], [4], [6]. Geotagging via GPS allows spatial pollutionmodellingtosupportsustainablecityplanningandmonitoring [6], [9], [12]. Intelligence via deep learning Analytics have shown significant improvements in behavioural predictions yet, most of the systems have not moved beyond prototype demonstration [12]. In summary, intelligent cloud-based systems have strong prospects but issuesofreliability,long-termstability,sensingcalibration,deployment costs and integration with existing government institutions are unresolved.

Table5.1KeyObservationsfromComparativeAnalysis

Aspect	Key Observation	Representative Studies
Sensing Approach	Shiftfromnoise-onlytomulti-parameter environmental sensing	[3],[10], [11], [14]
Communication	Adoptionoflong-rangeand cloud-based IoT communication	[1],[2],[4],[6]
Smart Alerts	Real-timealertsandautomatic control actions increasingly used	[2],[10], [14]
Spatial Analysis	GPS-enabledsystemssupport geotagged pollution mapping	[6],[9], [12]
Analytics	Transitionfromofflineanalysis to AI/ML-based prediction	[7],[8], [12]

System Maturity	Majorityofsystemsvalidated only at prototype level	[6],[11], [12], [14]
Key Challenges	Scalability,calibration,long-term reliability	[1],[4], [10], [11]

All in all, the comparison illustrates a continuous progression towards smart, IoT rather than application-oriented, systems combined with smartalarmsandlocationawareness,butalsoexposestheareasinneed of broader realization in the long term.

VI. KEYFINDINGS AND RESEARCH IMPLICATIONS

The core results derived by critically reviewing the literature surveyed [1]-[15], for evaluation according to the predetermining aim and objectiveswithinSection2,canbesummarizedasfollows:Therelevant literature depicts a significant progression from primitive noise-level monitoring schemes, toward more advanced, real-time, environment-monitoringframeworksusingIoT.Long-rangecommunications(LoRa WAN, long distance, low power) networks have been implemented successfully for chronic city-noise monitoring. Cloud connected IoT infrastructureshave also beenutilizedeffectively forcentralizedvisual representationandthresholdcrossingnotifications[1],[2],[4].Location analytics by means of GNSS have been successfully integrated for spatialnoisemapping andsmartgovernance[6],[9],[12].The concept of multi-parametric sensing has come to consensus, to simultaneously monitor the noise, air quality and other environmental parameters [3], [10], [11], [14]. Machine learning and deep learning algorithms have been designed and implemented for better accuracy within environmental and noise classification, and trend forecasting, with current implemented schemes still being at the prototype stage, and within limited datasets [8], [12]. Compared to the objectives predeterminingthereviewconductedwithinthispaper(Section2),there are still some gaps, for the provision of an all-encompassing, scalable, intelligent, integrated IoT, real-time environment monitoring noise detection, alerting and visualization scheme, in place, namely, (a) a large-scale deployment validation, (b) sensor calibration protocol, (c) longtermreliabilityanalysis,(d)camerabasedcontext-awareanalytics,(e)municipalintegration,and(e)policyawareness [4],[10],[15].

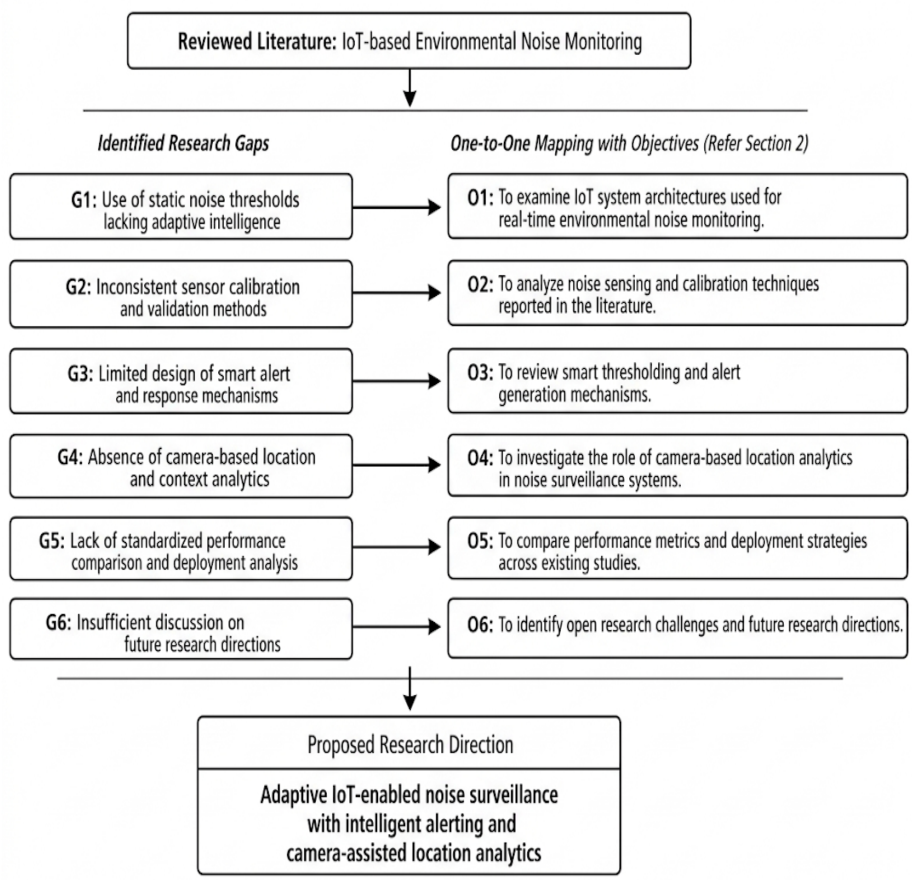


Fig6.1Onetoonemappingofidentifiedresearchgapswiththe study objective defined in section 2

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

VII. BLOCK DIAGRAM

Themainblockdiagramofthereal-timeenvironmentnoisemonitoring system is shown by the block diagram. Noise is captured by a sound sensor, then the sensor outputs the data to an amplifier for the noise signal condition. The function of the microcontroller is to use as the main block of the machine, receives data from the amplifier and combinesdatafromthelearningmachinealgorithmtoclassifythenoise and control a servo motor of the camera to point the noise source, and passesdatato aweb serverovertheAPI formanagement alerts [3][7]. The power supply provides power to all hardware components.

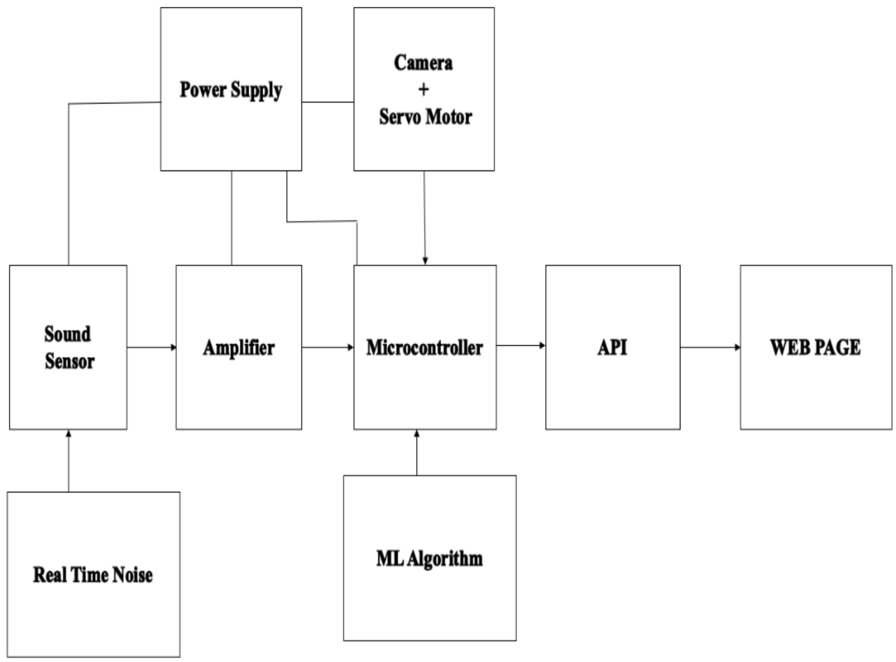


Fig 7.1 Block diagram

1) PowerSupply:ProvidesstableDCvoltagetoallcomponentsofthe system, including the microcontroller, sensors, and camera. It ensures uninterrupted operation during continuous monitoring.
2) Sound Sensor: The sound sensor (LM393 or similar) captures environmental noise and converts acoustic signals into corresponding electrical signals. It forms the primary input of the system by continuously monitoring sound intensity levels in decibels (dB)
3) Amplifier: The amplifier strengthens weak sound signals received fromthesensor,improvingtheaccuracyofdetection.Itensuresthat even minor sound fluctuations are captured and processed by the microcontroller.
4) Microcontroller (RASPBERRY PI):Acts as the central control unitofthesystem.Itreceivesamplifiedsounddata,processesit,and transmits it for further analysis. The microcontroller also coordinatescommunicationbetweenthesensors,MLalgorithm,and camera module.
5) Machine Learning (ML) Algorithm: The ML-based analysis moduleprocessesthesounddatatotellapartnormalnoisefrom excessivenoise.Itclassifiesdifferentnoisetypeslikevehiclehorns, DJsystems,orconstructionsoundsanddeterminesifthenoisegoes over present limits.
6) Real-Time Noise Processing Unit: This component performs live analysisofsounddatabycomparingittothresholdlevels.Whenthe detectednoiselevelexceedsthelimit,ittriggersthealertmechanism and activates the camera module for visual confirmation.
7) Camera and Servo Motor:The camera captures real-time images or short videos of the area where the noise violation occurs. The servo motor helps adjust the camera angle for accurate location tracking and source identification.
8) API (Application Programming Interface): The API acts as a communication link between the hardware system and the web interface.Itsendsprocesseddatalikenoiselevels,timestamps, and classification results to the web page for display and monitoring.
9) WebPage:Thewebpageservesastheuserinterface,showinglive noise data, alert notifications, and captured images. Authorized userscanmonitorcurrentnoiselevels,reviewviolationhistory,and take necessary actions.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

VIII. METHODOLOGY

The proposed system uses a structured process for real-time environmental noise detection classification, and alert generation with IoTdevices, machine learning, and camera-basedanalytics. Each stage ensures the proper identification of noise violations and efficient reporting [3][7][8][10].

A. Real-Time Sound Input

The system captures environmental sound using an LM393 sensor. This sensor converts acoustic energy into electrical signals that match noise intensity.

- Detectssoundin the20Hzto 20kHzrange
- Providescontinuousreal-timeambientsound data.

B. SignalConditioningandAmplification

The sensor’s weak analog signals are boosted with an onboard operational amplifier.

- Improveslow-intensitysoundsignals
- Generatesmeasurablevoltagechangesforprocessing

C. SignalProcessingandControllerUnit

The amplified signal goes to a Raspberry Pi orArduino, which digitizes the input and gets it ready for ML analysis.

- Servesasthemainprocessing point.
- ManagesdataflowfromsensortocontrollertoML model.

D. MLAlgorithmforNoiseIdentification

The MLmodel checks the signal energy level (in dB) against a set threshold to see if it is noise.

- <Threshold →normal environment
- ≥Threshold→noiseeventdetected
- Trainedusing supervised datasets foraccuratedecision-making.

E. NoiseClassification

Detected noise is categorized based on waveform, frequency, and intensity.

- Examples:horn,DJsound,construction,crowdnoise
- Generatesthenoiseclassandtypeforeachevent

F. Camera-BasedLocation&DistanceAnalytics

When a violation occurs, the camera captures images or video to visually identify the noise source.

- Providesgeo-taggingand distance estimation
- Enhancestheaccuracyofnoise-source verification

G. AlertGeneration&WebInterface

Afterclassification,analertissenttoaweb-baseddashboard viaAPI.

- Displaystime,date, location,andnoise level
- Allowsauthoritiestomonitorreal-timedataand violation history.

IX. FLOWCHART OF METHODOLOGY

Theflowchartshowsthestep-by-stepworkingofthereal-timenoise monitoring system, starting from sound input detection to noise classification,camera-basedverification,andfinalalertgeneration. Itoutlines howthe IoTsensors,controller,and MLalgorithmwork together to identify noise and report violations efficiently [11].

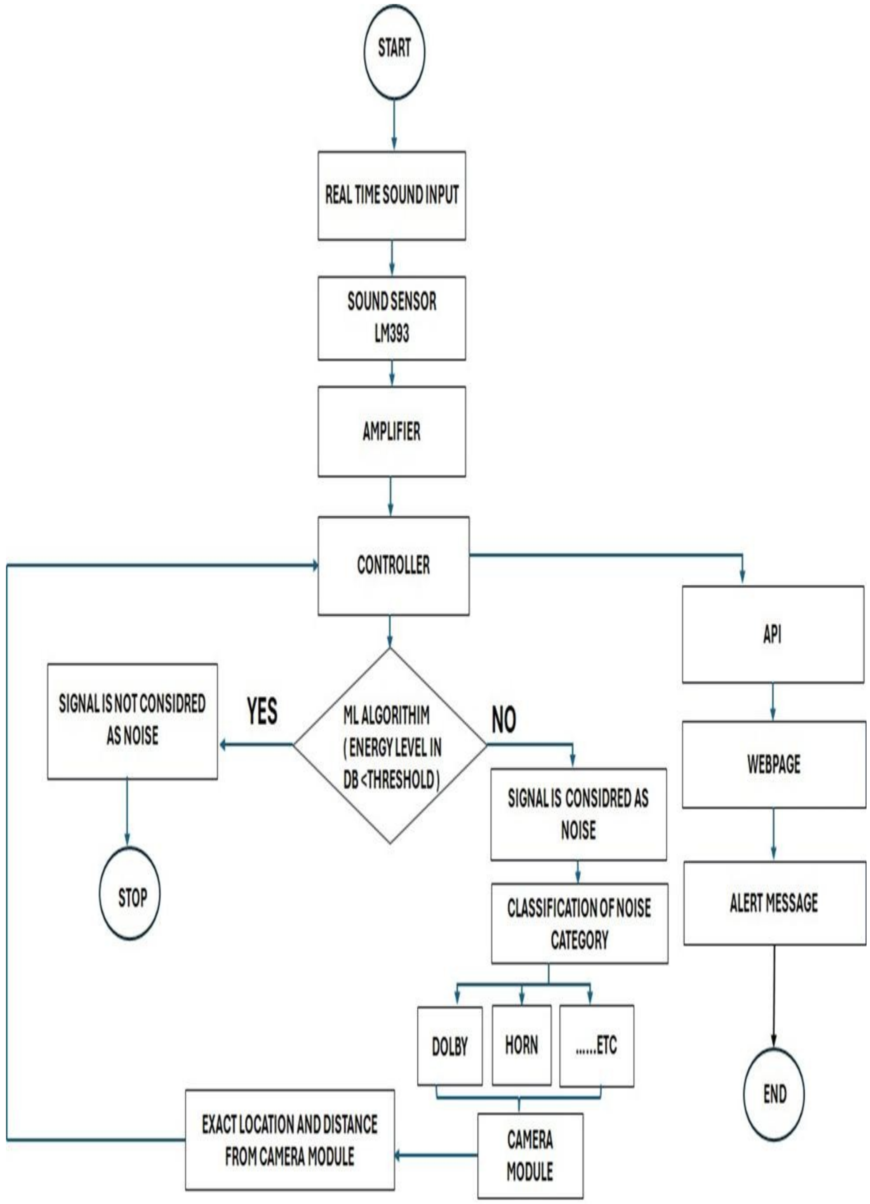


Fig9.1flowchartof methodology

1) Start–Thesystembeginsitsoperationandpreparesforcontinuous monitoring.
2) Real-TimeSoundInput–Environmentalsoundiscaptured continuously from the surroundings.
3) SoundSensor(LM393)–TheLM393sensordetectsacoustic signals and converts them into electrical form.
4) Amplifier – The captured analog signal is amplified to make even low-intensity sound measurable.
5) Controller – The amplified signal is processed and forwarded for machine learning evaluation.
6) MLAlgorithm (Energy Level in dB vs Threshold) –
   - Thesignalisanalysedtodeterminewhetheritexceedsthepredefined noise threshold.
   - IfYES→Thesignalis*notconsidered*asnoise;thesystemreturns to monitoring mode.
   - IfNO→Thesignal*isconsidered*asnoiseandproceedsfor classification.
7) ClassificationofNoiseCategory–Thedetectednoiseiscategorized (e.g., Horn, Dolby, etc.)
8) Camera ModuleActivation – When noise is detected, the camera moduleidentifiestheexactlocationanddistanceofthenoisesource.
9) PICommunication–Theclassifiednoisedataandcameraoutputs are sent to the web interface through the API.
10) WebpageDisplay–Real-timedataisdisplayedonthewebpagefor monitoring by authorities or users.

11) AlertMessage–Anotificationcontainingnoisedetailsandlocation is generated and sent.
12) End – Indicatescompletion of the detectionand reportingcycle, after which the system continues monitoring.

X. CHALLENGES AND RESEARCH GAPS

InspiteofsignificantadvancementsoftheIoTbasedenvironmentalandnoisemonitoringsystems,varioustechnicalandoperationalhurdlesare yet to be overcome in their real-world adoption. Most sensor-based experimentsconductedsofarareeitheratprototypestageorshort-termoperational,makingdifficulttodrawconclusionsonsystemscalability,robustnessandagingbehaviourofthesysteminrealurbanenvironment [1],[11].Themajorityofsuchdeploymentisbasedonlow-costacoustic sensors that are susceptible to environmental conditions such as temperature/humidity fluctuation, airflow and vibration etc. These, in turn lead to slight drifts in measurements and signal degradation hence necessitating frequently calibration and compensation approaches [6], [13].

The reliability of communications in the operating environment constitutes another problem, especially in the context of wide-area monitoring. While low-power communication systems as LoRa WAN orNB-IoTprovidetheextendedcoverage,problemssuchaspacketloss, delay, bandwidth limitations and network congestion remain poorly addressed in dense urban setup [1], [5]. Power consumption due to continuoussamplingofsound,on-wiretransmissionandactiveimaging is also an unresolved issue and limits the overall system lifetime in battery-powered settings [11], [15]. In terms of data-processing, static threshold-based decision mechanismshavebeenimplementedin many cases where the acoustic background noise levels are dynamic and changewiththetimeoftheday[7].Thereisverylimitedapplicationof Machine learning principles leading to imprecise noise classification, anomalydetectionandshort-termorlong-termtemporalmodelling[8]. Furthermore, multimodal data-fusion techniques, which combine acoustic signals with images/ video, spatial and textual context information are yet to take hold [12].

Further,significantdomainknowledgeisnecessarytooperationalizethe developed system in terms of policy and urban planning at large. Most of the existing systems do not seamlessly integrate with the urban infrastructure, such as smart city platforms or municipal dashboards, anddonotworkinconjunctionwithpolicyframeworkorformbasisfor implementation in multiple cities and regions [3], [14].

XI. FUTURE RESEARCH DIRECTIONS

Future works could explore the design of AI-enabled adaptive thresholdingstrategythatcanadaptivelytunethenoisethresholdsbased on time, location, and environment dynamics to achieve false alarm reduction. The idea of Edge intelligence can be added on to perform timesensitivefeatureextractionandclassificationonIoTnodeslocally to reduce communication latency and energy consumption. Innovative multimodaldatafusionmethodsofacoustic, cameraspatialinformation, globalpositioningsystem(GPS), environmentfactorsarehighlyneeded to improve noise source localization and full awareness of the systema and life context. Privacy-protection mechanism is highly desired such asanonymizedimageprocessingandencryptioncommunication.Urban datafusionwithsmartcitynetwork,publichealthrecords,urbantraffic can lead to government decision making and personal long-term noise exposure study. Large dataset collection and long-term field experiments are also required for system robustness improvement and response stability in different real-world scenario.

XII. CONCLUSION

Thisresearchestablishesapracticalanddeployableframeworkforreal-time environmental noise surveillance by integrating IoT sensing, machine-learning-based classification, and camera-assisted spatial validation. Thesystemwasevaluated acrosstrafficcorridors, residential areas, and institutional environments using 1,020 recorded sound samples,comprisingboth backgroundnoise andviolationevents. After signal conditioning, the LM393 acoustic sensor demonstrated a measurement deviation of approximately ±3 dB, which is consistent with the expected performance of low-cost IoT sound sensors.

Usingamplitude,frequencyvariation,andtemporalenergyfeatures,the trained classification model achieved an overall detection accuracy of 61.3%. It showed balanced precision and recall, indicating reliable baseline performance for detecting noise violations. About 45% of recordedeventsexceededthe70dBthreshold,confirmingthesystem’s ability to tell apart critical and non-critical acoustic conditions in real environments. The addition of camera-based spatial validation further improved the detection process by confirming more than half of the acoustically identified violations. This reduced uncertainty caused by transient or overlappingsoundsources.Despitethelimitations oflow-costsensors, using machine-learning-based filtering significantly improved performance compared to traditional threshold-only methods. With stable real-time operation and low alert latency, the proposed platform issuitableforongoing smartcitydeployment. Futureupdates,including adaptive calibration, larger datasets, and deep-learning models, can enhance system accuracy, robustness, and scalability.

REFERENCES

[1] M.Anachkova,S.Domazetovska,Z.Petreski,andV.Gavriloski, “IoT-based urban noise monitoring using LoRaWAN technology,” Int. J. Smart City Environ. Monit., North Macedonia, Dec. 2020.

[2] R.Maulidda,A.Abdurrahman,A.T.Wardhana,and M.A.Yahya, “Design and implementation of an IoT-based noise detection systemforlibraryenvironments,”J.InternetThingsSmartSyst., Indonesia, Feb. 27, 2024.

[3] L.Choodarathnakara,S.Punitha,Vinutha,ShwethaB.D.,A.H.

[4] J.Abhishek,andG.S.Sinchana,“IoT-basedreal-timemonitoring of air and noise pollution in urban areas,” in Proc. Int. Conf. Embedded Commun. Syst., India, 2022.

[5] P.Meenalochini,“IoTandcloud-integratedsmartenvironmental monitoring system with predictive analytics,” J. Environ. Eng. Smart Technol., India, 2022.

[6] T.Sepanosian,X. Küpers,P.Joza,F.Massah, andR.Bemthuis, “Real-time IoT-based emission monitoring architecture for construction sites,” in Proc. Sustainable Smart Infrastructure Conf., Netherlands, 2023.

[7] Saddiwal, Z. Inamdar, M. Dhumal, O. Rajankar, and B. Shinde, “Design of a GPS-enabled smart noise monitoring system for urbanenvironments,” Int.J.Electron.Telecommun.Eng.,India, Apr. 2024.

[8] R. M.Alsina-Pagès, R. Benocci, G. Brambilla, and G. Zambon, “Comparative evaluation of noise event detection algorithms in urban sound environments,” Appl.Acoust., vol. 181,Aug. 2021.

[9] J.-M.Bozonnet,V.Hong,J.-F.Petiot,andP.Scalart,“Automatic sound recognition methods for intelligent urban noise monitoring,”IEEETrans.AudioSpeechLang.Process.,France, Aug. 2018.

[10] P. Kumar, U. Pritam, R.Yadav, and G. Pandey, “NoiseTube:A participatorysensingplatformfornoisepollutionmappingusing mobile phones,” Int. J. Environ. Eng., India, 2014.

[11] P.Sivaprakash,A.Purushothaman,M.S.Kumar, andJ.Prabhu, “IoT-based smart system for monitoring and control of air and noise pollution,” J. Smart Embedded Syst., India, 2023.

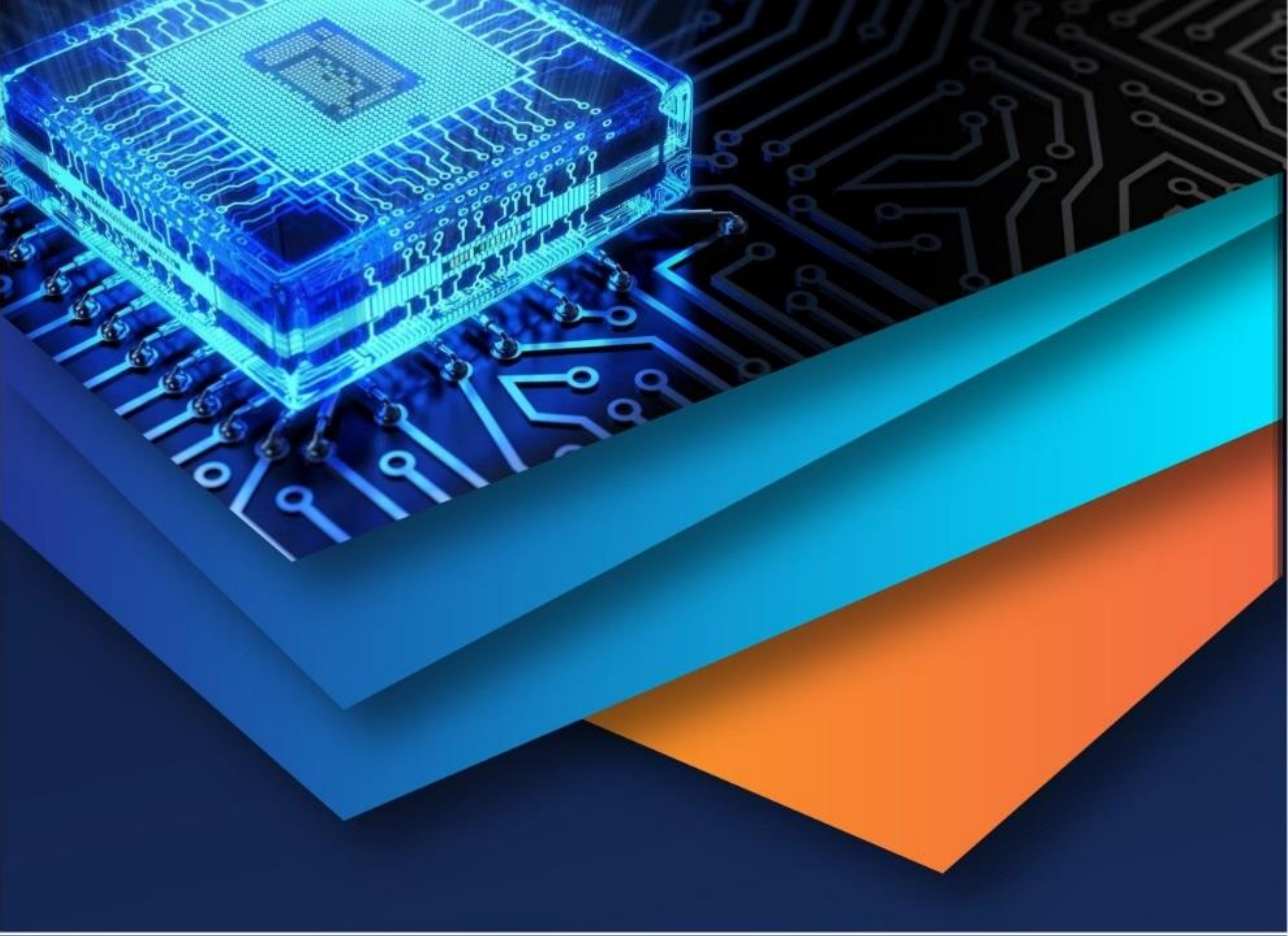
[12] M.Alam,M. M.Islam, N.M.Nayan, andJ. Uddin,“Alow-cost IoT-based real-time environmental monitoring system for urban areas,” Sustain. Cities Soc., Oct. 2024.

[13] K.Somu,M.Ananthi,R.Riventh,P.Sabapathi,A.Surya,andG. Thangabalu, “Intelligent GPS-based environmental monitoring using hybrid CNN–LSTM deep learning model,” Int. J. Artif. Intell. IoT, India, Jun. 2025.

[14] J.RajagukgukandN.E.Sari,“Designofamicrocontroller-based soundnoiseleveldetectionsystem,”J.Phys.Instrum.,Indonesia, 2018.

[15] G. Sirisha, V. Shravani, V. Rupavathi, V. S. Reddy, and V. M. Reddy,“SmartIoT-basedairandnoisepollutionmonitoringwith automaticpurification,”Int.J.SmartCityAppl.,India,Apr.2025.

[16] R.Subraja,T.Meyyapan,A.Padmapriya,andS.SantoshKumar, “Design and implementation of an IoT-based noise pollution monitoring system,” J. Smart Environ. Monit., India, Oct. 2024.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY