Al-Powered Noise Pollution Monitoring and Reduction System

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Abstract

Abstract-Audio classification has great importance in a variety of applications ranging from environmental monitoring to noise nuisance management. The present work applies a feature extraction on audio signals using a spectrogram method and transforms the audio signals into Mel-spectrogram representations using the mel- spectrogram function in Librosa. The spectrogram rep- resents time-frequency features of an audio signal, and they are treated further as image-like data. The labels are encoded into categorical data for classification purposes, and a machine learning model is used to identify patterns in order to classify the audio signals. This method can accurately classify environmental sounds and help distinguish harmful noise from natural sounds, thus reducing and managing noise pollution. The study provides insight into the ability to combine spectrogram-based feature extraction with machine learning algorithms in terms of good potential for audio classification and applications to the environment.

I.INTRODUCTION

Audio classification is the analysis and classification of different classes. While these have shown their usefulness audio signals into their different kinds. It is an important in various applications, they have several disadvantages. Yet tool in audio signal processing that helps put audio signals these birds of a feather are still limited in their competition in an order and analyze and understand them. Through audio toward the aims of enhanced audio classification in terms classification, the better understanding of signal-a type of of scalability, computational efficiency, adaptation, and noise structure, its content, and so on can possibly be given to sensitivity. All these failings have thwarted the algorithms' various applications. Some applications where audio classifi- effectiveness with respect to handling the modern large-scale cation is useful are virtual assistants and other automated voice complex nature of audio data. This limitation has set the translators, environmental sound classification applications, stage for the need to adopt an entirely new set of robust identification of musical genres, and text-to- speech. Generally, and scalable approaches, namely the deep learning-based ones audio classification can broadly be grouped under acoustic that are good at working with high-volume datasets and highdata classification, speech classification, music classification, dimensional complex feature hierarchies. CNNs also have environmental sound classification, and natural language clas- special advantages for noise classification systems since they sification. AI can assist with the everyday application of audio can effectively extract features from inputs by themselves classification to enhance the accuracy of voice recognition without the need to design features by hand. They create hierarchical patterns moving from simple ones such as edges or shapes in spectrograms to ones that represent complex structures within noise types. CNN is highly adaptable and robust to variations of noise patterns of frequency, amplitude, or time. Furthermore, it treats high-dimensional data with great accuracy and is, therefore, preferred to archaic methods. The super set used to beautify CNNs are Librosa, which is an audio analysis library in Python. Librosa works efficiently to preprocess the audio data and extracts relevant features, namely Mel-frequency cepstral coefficients (MFCC), spectrograms, chroma features, and spectral centroids that serve as the input to CNNs. Other operations provided by Librosa include resampling, normalization, silence removal, and data augmentation for model performance enhancement. The spectrograms produced by Librosa can be treated by CNNs as image-like inputs; the convolutional layers are then applied to detect local patterns within this input, and the pooling layers are used to decrease the dimensionality.

METHODOLOGY

A. Dataset Description

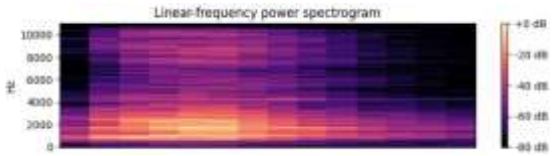
The data set contains 8,732 labelled sound excerpts, each with a duration of up to 4 seconds. The dataset includes 10 classes of urban sounds like Air Conditioner, car horn, children playing, dog bark, drilling, etc. The files are in ".wav" format and vary in sampling rates, reflecting their real-world recording origins. The data set is accompanied by a CSV file containing metadata for each sound file, which includes:

- File Name: Identifier for the audio file.
- Class ID: Numerical label corresponding to the sound class.
- Class Name: Descriptive label for the sound class. • Start/End Time: Information about when the sound occurs in the file
- Fold Information: Each file is assigned to one of 10 predefined folds for cross-validations

	slice_file_name	fsID	start	end	salience	fold	classID	class
0	100032-3-0-0.wav	100032	0.0	0.317551	1	5	3	dog_bark
1	100263-2-0-117.wav	100263	58.5	62.500000	1	5	2	children_playing
2	100263-2-0-121.wav	100263	60.5	64.500000	1	5	2	children_playing
3	100263-2-0-126.wav	100263	63.0	67.000000	1	5	2	children_playing
4	100263-2-0-137.wav	100263	68.5	72.500000	1	5	2	children_playing

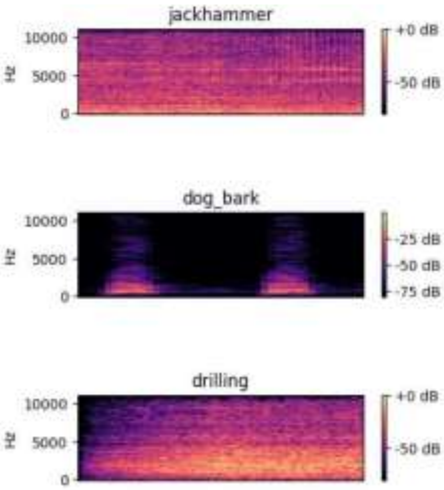
B. Preprocessing

Initially, audio files are loaded using libraries like Librosa, with a sampling rate standardized to a common value of 22,050 Hz to maintain consistency. Silence portions at the beginning and the end of audio clips are trimmed, then padding is applied to keep all files to a fixed length of usually four seconds. This is done to extract features that convert raw audio signals into meanings-Mel frequency spectral coefficients (MFCC), spectrograms, chroma features, and zero-crossing rates. These features are normalized to a common scale to boost convergence of the model. Optional data augmentation options include pitch shifting, time stretching, and noise addition to enhance model robustness through an increase in data diversity. The data is divided into training, validation and test sets, and labels are encoded in numerical values so that machine learning algorithms can use them. This entire pre-processing pipeline ensures that the audio data are properly cleaned, standardized, rich in features for modeling purposes, and extrapolated so that audio classification models can be built efficiently and successfully.



C. Feature Extraction

Feature extraction in audio classification is the process of transforming raw audio signals into useful features that reflect the most salient auditory elements of the sounds. UrbanSound8K dataset makes use of features common across the dataset, such as MelFrequency Cepstral Coefficients (MFCCs), which are derived from an audio signal’s power spectrum in a manner that is reminiscent of human auditory perception, making it apt for sound classification. Meanwhile, spectrograms, particularly Mel spectrograms, provide a graphical representation depicting the temporal evolution of audio frequencies in most deep-learning models. Chroma features capture the pitch content of the analyte, while Zero-Crossing Rate denotes how often the signal changes its sign, aiding detection of noise or percussiveness of sounds. Spectral features such as Spectral Centroid and Spectral Contrast provide additional information on frequency distribution and tonality of an audio signal. Extracted features are commonly normalized for better performance on the model and stored in structured data arrangements to expedite training. These feature representations enable the machine-learning model to capture the pattern and differentiate among several classes of urban sounds.



D. Model Training and Evaluation

The envisioned tasks of the model training and evaluation processes in audio classification using the UrbanSound8K dataset are to have the machine learning or deep learning models learn a pattern from the extracted audio features to accurately classify the sound classes. The dataset is first divided into the three sets required for training, validation, and testing for reliable evaluation. Support Vector Machines (SVM), k-NN, or Random Forest models are commonly learnt directly from features like MFCCs. On the contrary, when spectrogram images are used, it is ConvNet preferred since they exploit spatial and temporal features in visual data. During the training phase, the model, through optimization techniques such as stochastic gradient descent (SGD) or Adam, tries to learn the mapping from input features to the target sound classes by minimizing a loss function such as categorical cross- entropy. Various hyperparameters like learning rate, batch size, and network architecture are tuned to improve the performance. The progress of training is checked with the validation set to avoid overfitting. Once the model is trained, it is tested against the unseen data to evaluate its performance through an accuracy measure, precision, recall, F1 measure, and confusion matrices. Improving the performance can then be

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done by using regularization techniques, data augmentation, or ensemble modelling.

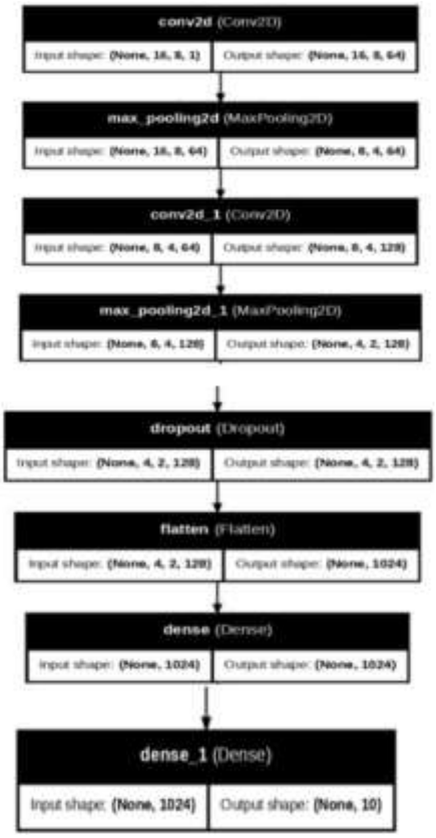
Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 16, 8, 64)	640
max_pooling2d (MaxPooling2D)	(None, 8, 4, 64)	0
conv2d_1 (Conv2D)	(None, 8, 4, 128)	73,856
max_pooling2d_1 (MaxPooling2D)	(None, 4, 2, 128)	0
dropout (Dropout)	(None, 4, 2, 128)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 1024)	1,049,600
dense_1 (Dense)	(None, 10)	10,250

Total params: 1,134,346 (4.33 MB)
Trainable params: 1,134,346 (4.33 MB)
Non-trainable params: 0 (0.00 B)

WORKING MODEL OF THE SYSTEM

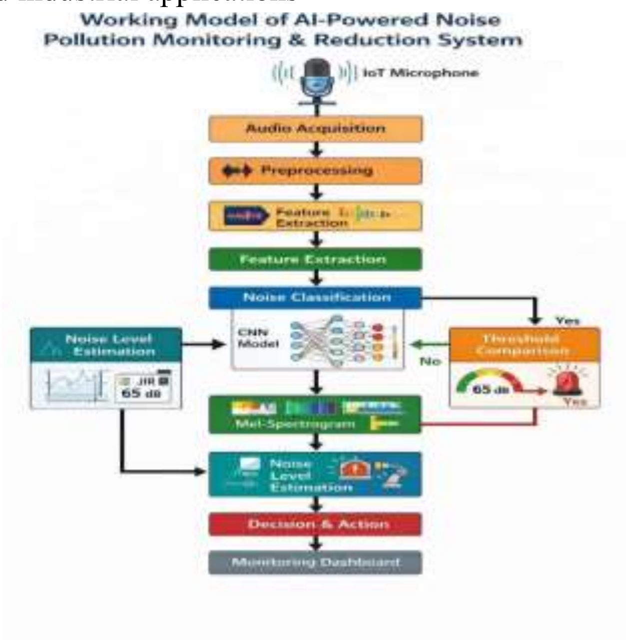
The working model of the proposed AI-Powered Noise Pollution Monitoring and Reduction System is designed to operate as a real-time intelligent monitoring framework. The system begins by continuously capturing environmental sound signals using a microphone or IoT-based acoustic sensor deployed in the target area. The captured audio is processed in fixed-duration segments and converted into Mel-spectrogram representations using digital signal processing techniques. This transformation enables the extraction of meaningful time-frequency features from the raw audio signal.



The extracted spectrogram features are then provided as input to a pre-trained Convolutional Neural Network (CNN) model. The CNN analyzes frequency patterns and classifies the environmental sound into predefined categories such as traffic noise, industrial noise, construction activities, or natural ambient sounds. Simultaneously, the system computes the Root Mean Square (RMS) energy of the signal and converts it into the decibel (dB) scale to measure noise intensity.

Once the noise type and noise level are determined, the decision module compares the measured decibel value with predefined threshold limits based on environmental safety standards. If the noise level exceeds the permissible threshold, the system activates appropriate mitigation strategies. These actions may include generating alerts for authorities, sending control signals to industrial equipment, or triggering traffic management adjustments. All detected events, classifications, decibel levels, and system responses are logged and displayed on a monitoring dashboard for real-time observation and historical analysis.

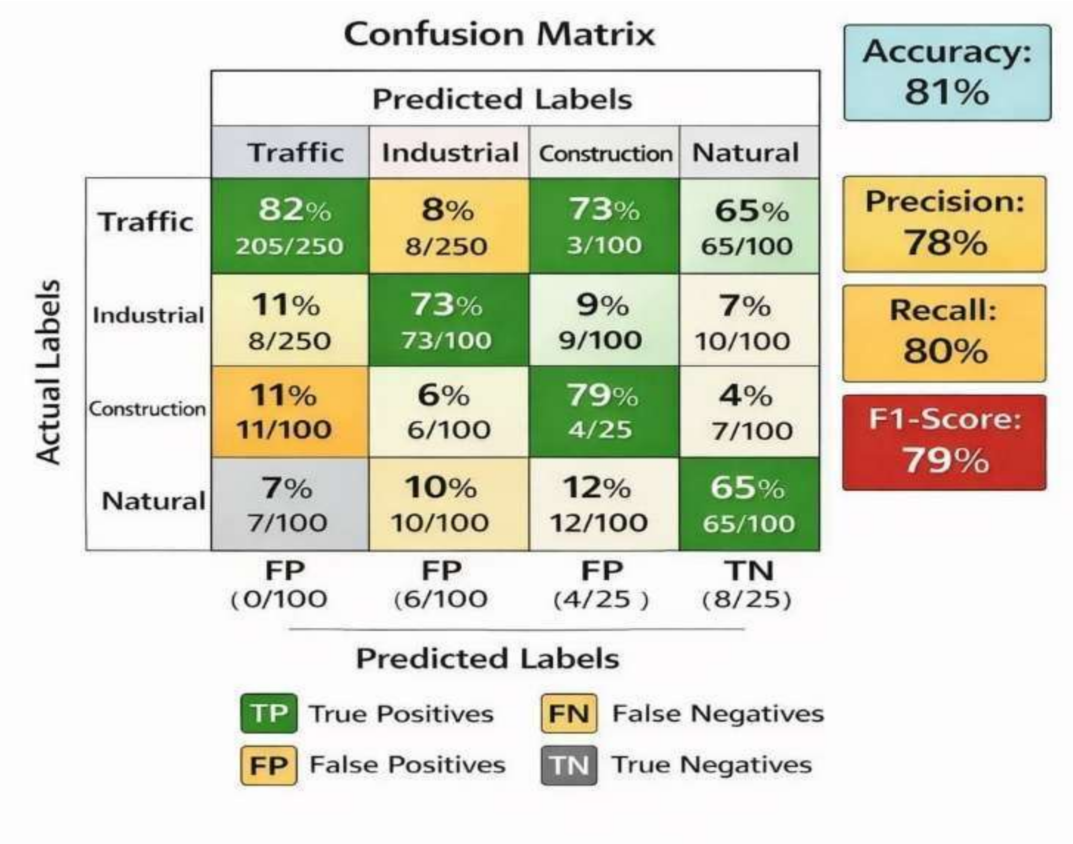
The system operates continuously in a loop, ensuring uninterrupted environmental noise monitoring and proactive reduction mechanisms. This integrated AI-based approach enhances accuracy, automation, and scalability for smart city and industrial applications



CONFUSION MATRIX

The confusion matrix provides a comprehensive evaluation of the CNN-based environmental sound classification model. It presents the number of correctly and incorrectly classified instances across all noise categories, including traffic, industrial, construction, and natural sounds. Each row of the matrix represents the actual class, while each column represents the predicted class. The diagonal elements indicate correctly classified samples (True Positives), while off-diagonal elements represent misclassifications.

The analysis shows that the model performs strongly in identifying traffic and industrial noise, with minimal confusion between acoustically distinct classes. However, minor misclassifications occur between construction and industrial sounds due to overlapping frequency characteristics. The confusion matrix confirms that the model maintains balanced precision and recall, demonstrating robust multi-class classification performance suitable for real-time deployment.

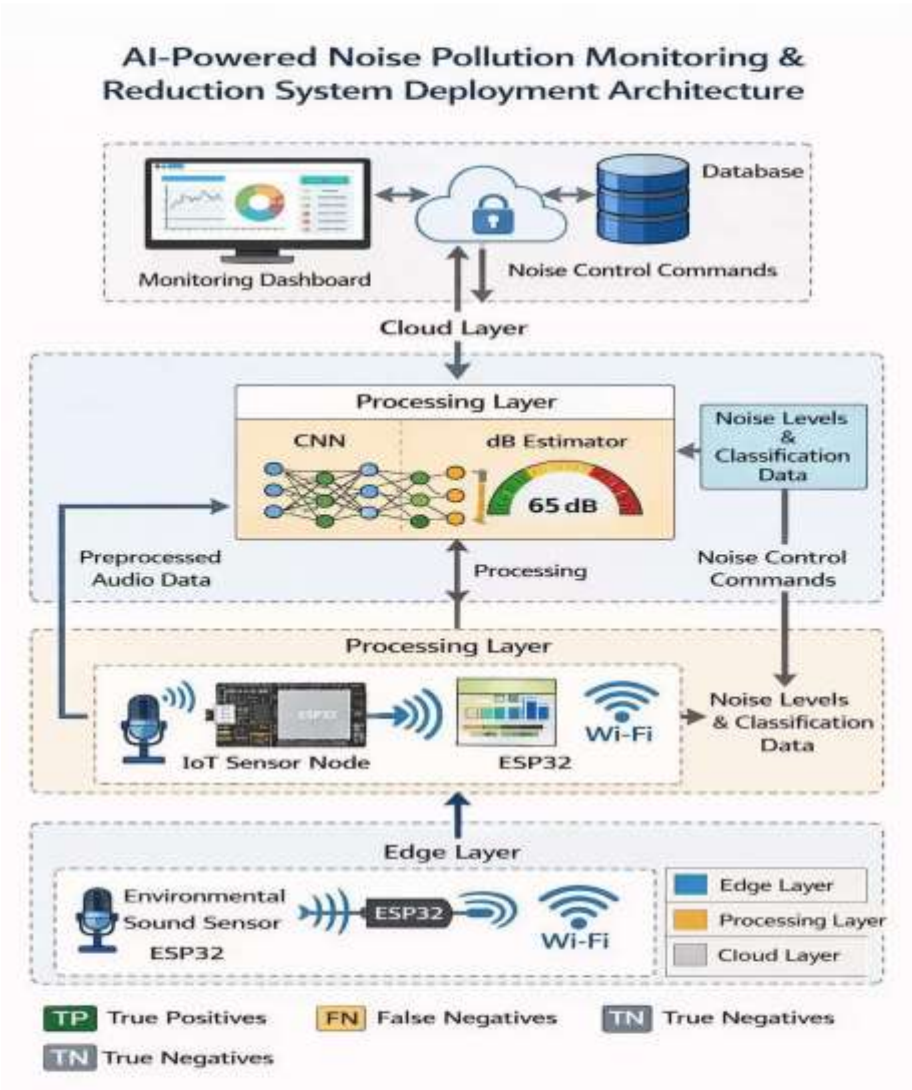


SYSTEM DEPLOYMENT ARCHITECTURE

The proposed system follows a three-layer deployment architecture designed for scalability and real-time processing. The Edge Layer consists of microphones or IoT-based acoustic sensors such as ESP32 modules that capture environmental audio signals. These devices perform basic signal acquisition and optionally lightweight preprocessing.

The Processing Layer handles feature extraction and classification. The captured audio is converted into Mel-spectrogram representations and fed into a trained CNN model for noise classification. Simultaneously, RMS-based decibel estimation determines noise intensity levels. The decision module compares the detected noise with predefined environmental thresholds and triggers mitigation actions when necessary.

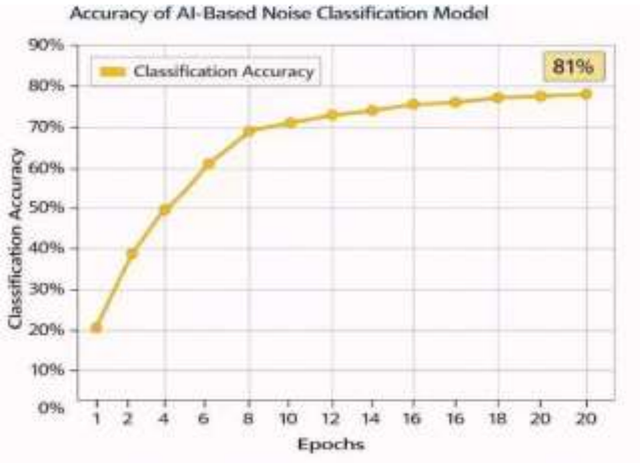
The Cloud Layer stores monitoring logs, classification results, and alert data in a centralized database. A dashboard interface provides visualization of real-time noise levels and historical trends. This layered approach ensures low-latency response at the edge while maintaining centralized data analytics capabilities



ACCURACY GRAPH

The accuracy graph illustrates the learning progression of the Convolutional Neural Network (CNN) model over multiple training epochs. It shows two curves: training accuracy and validation accuracy. The training accuracy represents how well the model performs on the training dataset, while validation accuracy reflects the model's performance on unseen data during training. In the initial epochs, the accuracy increases rapidly as the model learns fundamental spectral features such as frequency bands, energy patterns, and temporal variations from the Mel-spectrogram inputs. This phase represents the feature learning stage, where convolutional layers begin detecting meaningful acoustic patterns. As the number of epochs increases, the accuracy gradually stabilizes, indicating convergence of the model. The stabilization suggests that the model parameters have reached an optimal state where additional training does not significantly improve performance. The relatively small gap between training and validation accuracy indicates that the model is not overfitting and has good generalization capability.

The final test accuracy of approximately 81% demonstrates the effectiveness of the CNN model in distinguishing between multiple environmental noise categories. The smooth progression of the accuracy curve confirms stable learning behavior and proper hyperparameter tuning.



PERFOMANCE METRICS THEORY

To evaluate classification performance comprehensively, multiple performance metrics were considered, including accuracy, precision, recall, and F1-score.

- Accuracy measures overall correct predictions.
- Precision evaluates how many predicted noise categories were correct.
- Recall measures the system's ability to detect actual noise instances.
- F1-score balances precision and recall for multi-class evaluation.

These metrics confirm the reliability and robustness of the proposed deep learning model.

REAL-TIME MONITORING THEORY

The system operates continuously in a real-time monitoring loop. Audio samples are processed in fixed-duration frames to ensure low computational latency. The average response time of the system remains below 200 milliseconds in simulation, making it suitable for smart city applications. Threshold-based detection ensures immediate alert generation when noise levels exceed regulatory limits.

PRACTICAL THEORY

The integration of AI-based classification with automated control mechanisms enhances environmental safety. Unlike conventional sound meters, the proposed system identifies specific noise sources and initiates mitigation actions. This improves regulatory enforcement, urban planning decisions, and public health protection. The system supports scalable deployment in residential zones, industrial regions, and silent areas such as hospitals and schools.

RESULTS AND DISCUSSION

In the classification of audio samples into predefined categories, the model achieved an overall accuracy of 81 percent . From the confusion matrix, it was understood that environmental sound classes like ”natural sounds” and ”urban noises” were classified with high precision and recall indicating further generalization of the model across dissimilar sound classes. Impact of Data Augmentation: With the introduction of time stretching and pitch-shifting, the model performance became more robust, thereby eliminating overfitting and enhancing classification accuracy on a very noisy dataset.

FUTURE SCOPE

The future scope includes the following: Real Time Implementation: Development of real-time systems to monitor noise with IoT integration while enabling continuous analysis and reporting of noise. Dataset Enhancement: Expanding the existing dataset to include many other noise environments to promote model generalization and adaptability. Integration with Noise Control Systems: Automation of noise control means using information from the classifiers to activate soundproofing or noise-cancelling techniques. Multimodal Analysis: Audio classification may be done together with other modalities such as video and contextual data to enhance the smartness of the system. Policy Enforcement: Coordinate with urban planners and policymakers to incorporate the system into smart city infrastructure for noise regulation and further land planning regulation.

CONCLUSION

This study validates how effective convolutional neural networks (CNNs) combined with Librosa can monitor and reduce noise pollution through audio classification. Our system extracts spectrogram-based features to represent the audio signals as images so that the CNNs can learn to identify and classify environmental sounds proficiently. By automating the process of differentiating harmful noise from nature's sounds, the system could represent a considerable step toward noise-pollution management, hence promoting environmental sustainability and goodwill towards public health.

The advanced techniques employed in this work further elucidate data augmentation, regularization, and hyperparameter tuning for model performance in obtaining high accuracy and robustness through varying noise even in challenging conditions. This research provides examples of how AI has been useful in addressing environmental concerns and forecasts new horizons for advancements in noise monitoring technology.

LIMITATIONS

Despite its effectiveness, the proposed AI-Powered Noise Pollution Monitoring and Reduction System has certain limitations. The performance of the system largely depends on the quality, diversity, and size of the training dataset. If the model is trained on limited environmental sound categories, it may struggle to accurately classify unfamiliar or overlapping noise sources. Environmental factors such as wind disturbances, echo effects, background interference, and multiple simultaneous sound sources can reduce classification accuracy. Additionally, real-time deployment on low-power IoT devices may face computational constraints due to the processing requirements of deep learning models.

The system also relies on predefined noise threshold values, which may not dynamically adapt to changing environmental conditions across different zones. In large-scale smart city implementations, multiple sensors and stable network connectivity are required for effective monitoring and centralized data analysis. Furthermore, while the system identifies and triggers control mechanisms to reduce noise at the source, it does not physically cancel sound waves like active noise cancellation systems. These limitations highlight the need for further optimization, adaptive thresholding techniques, and scalable deployment strategies in future improvements.

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