IOT AUDIO SENSOR NETWORKS AND DECISION TREES FOR ENHANCED RAIN SOUND CLASSIFICATION

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Abstract: Accurately classifying rain sounds is essential in the field of climate investigation and environmental monitoring for understanding rainfall patterns, intensity, and how it affects ecosystems and urban infrastructure. This research presents a new method for rain sound classification combines decision trees (DTs) algorithms with networks of Internet of Things (IoT) audio sensors. To record ambient noises, particularly those caused by precipitation, the system makes use of a dispersed network of inexpensive IoT audio sensors placed in different places. A DTs algorithm, trained on a broad dataset including varying rain intensities and background sounds, is then applied by a central processing unit (CPU) to these recordings. When compared to more conventional approaches, experimental findings show the technique significantly improves rain sound classification accuracy, especially when it comes to differentiating between moderate and mild rain sounds and ambient noise. Automated weather alarm systems, urban drainage management, agricultural planning, and real-time rainfall monitoring are some of the potential uses for the proposed system. It helps advance environmental science, meteorology, and smart city projects by using IoT and machine learning to provide more accurate and faster rainfall data, which is essential for infrastructure planning and decision-making.

Keywords: Acoustic sensing, environmental acoustics, IoT deployment, classification algorithms, rainfall patterns, data analytics, sensor fusion, ecological research.

I. INTRODUCTION

An effective and lightweight way to simulate rain for use in interactive virtual worlds is discussed in [1]. For virtual reality systems (like video games) with restricted audio memory budgets, existing techniques of simulating rain sounds include superimposing large amounts of scene-specific precompiled rain sounds. This may be rather memory intensive. As a solution to this problem, it provides a lightweight rain sound generation approach that relies just on eight fundamental rain sounds inspired by nature to decrease the audio memory limits.

A flood is a typical natural calamity and may wreak havoc on people and their possessions [2]. Thus, to aid via an emergency response team, early detection is crucial. Previous methods for reliable flood detection relied on computer vision algorithms trained on images captured by cameras, satellites, remote sensing devices, or radar. But there hasn't been much research on flood event detection using sound signals. This paper presents the comprehensive creation of a model for the identification of sound events associated with floods using deep learning.

Sound events, from several sources, occur everywhere and vary by environment. Deep learning models and growing training data have improved event detection and classification over time [3]. Environmental sound event recognition systems typically utilize a general database to recognize sound events and not concentrate on specific environments. Another difficulty is training big neural networks takes many parameters and computer resources. It initially created a bespoke database of outdoor events surrounding smart homes and buildings to solve this problem. Rain, wind, human footfall, and car traffic are examples of audible occurrences.

Weather stations help in water management, precise farming, and flood prediction. Africa has around 1/8 of the needed weather stations [3]. Reasons include costly set-up expenses, a shortage of experienced workers, and fragile instrumentation in traditional weather stations. Moving components make traditional weather stations prone to damage and create measurement and reading inaccuracies. This makes it hard to collect reliable real-time weather data with excellent geographical accuracy, resulting in erroneous projections. Recent machine learning research on rainfall estimate using acoustic data has classified rainfall quantities into intensity bands rather than describing rainfall intensities.

Rainfall occurrences may be found in abundance in environmental audio recordings, which are currently being underutilized [5]. The potential for rainfall monitoring is supported by the fact extensive security cameras continually capture rainfall data. Researchers developed a system to automatically classifier rainfall levels using audio from security cameras as input. Converting the rainfall observation job into an audio classification task is made possible using rainfall level definitions.

Natural catastrophes result from human error [6]. Floods inflict significant material and psychological damage. Floods inflict loss of homes, livelihoods, and family members, causing anguish. To live safely and peacefully, we must avoid floods. In this study, a sound sensor was employed with the Arduino water level system to monitor water flow, particularly in flood-prone locations. This investigation found a low scale with a little sound on the red light, a medium scale with a medium sound on the green light, and a high scale with a loud sound on the blue light.

The rainfall weather station uses a tipping bucket rain gauge, a specialized tool for measuring and documenting several precipitation properties with great precision [7]. To measure rainfall, using a tipping bucket rain gauge might have a major impact on society's efficiency and people's quality of life. Using a tipping bucket rain gauge to precisely measure rainfall allows for the design of laborious irrigation methods, which is one way in which rainwater may positively impact sustainable agricultural irrigation techniques. Many people rely on rain gauges to keep tabs on precipitation, but these instruments are prone to mechanical failure and may be expensive to set up and keep running.

Fine-scale rain observations are important for professional research, decision-making, and everyday life. Existing rain gauges cover less than 1% of the earth's surface, and number is diminishing [8]. Even with various restricted and immature supplemental approaches, rain measurements today are inaccurate. Crowd sourcing allows for a resilient rain observation network in unusual resolution and coverage using Smartphone's, which are now ubiquitous and equipped with many advanced sensors. A unique rain detection and intensity measuring technology, uses Smartphone audio clips to identify and quantify rain.

II. RELATED WORKS

Estimating rain erosive and soil erosion are just two of many environmental analyses that might benefit from knowing the length and severity of rainfall [9]. While there are several devices available to record the length and severity of rainfall, they may be expensive to purchase and typically need the presence of an operator to ensure proper operation. It investigates the potential for estimating the length and severity of rainstorms by analyzing the audible signals produced when raindrops impact natural surfaces and objects.

A hydrophone used to record rain on water is like listening to rain on a tin roof; it captures the sound of rain as it falls at sea. Underwater, the sound of raindrops striking the water's surface is rather audible [10]. The ocean is like a big echo chamber in it effectively transmits sound, allowing sounds produced at sea level to travel below with minimal energy loss. To take advantage of all the current developments in the field to design state-of-the-art devices for passive acoustic rain measurements and for high-frequency sound monitoring in general. These devices might be built to fit on any of the several platforms offered by operational ocean observing networks [11].

The functional advantages of automated ambient sound detection are obvious. This technology enables the collection, search, and sorting of audio [12]. As a result of environmental sound's high noise level and absence of musical rhythm and melody as well as linguistic meaning sequence, it is challenging to identify shared characteristics are sufficiently representational of different environmental sound signals. It presents a recognition approach that utilizes multi-feature parameters and a time-frequency attention module to enhance the accuracy of ambient sound detection. The process starts with a pretreatment that uses phase information and multi-feature parameters to extract sound [13].

Provide a comprehensive framework for classifying and environmental noise includes all the most typical sounds heard in a metropolis, where there are many distinct kinds of noises and sources of noise [14]. Even though traditional methods of reducing noise have not been successful in combating the ever-increasing problem of urban noise pollution, there has been encouraging movement in the academic community toward tackling environmental noise management via the lens of the sound’s cape framework.

To monitor the health of older production equipment by listening for and feeling vibrations and noises produced by moving parts [15]. Despite the efficacy of vibration data in tracking operation status, not all machines are compatible with sensors and can be adapted for long-term use. Therefore, for less invasive monitoring, sound-based tracking may be the way to go. Although sound-based tracking eliminates the need to put sensors into equipment, environmental noise compromises tracking accuracy, which is the major drawback of this method.

Convolutional Neural Networks (CNN) has recently emerged as the preferred option for a wide range of audio classification issues [16]. But CNN can only function well in environments where there is an abundance of training data; otherwise, able to adapt to new situations well. It provides signal latent subspace a new approach to sound classification outperforms the advanced methods while using much less data in this article. Our method involves using two separate pre-trained CNN models to separate a sound into its specific features.

Sound is the most important speaking method for all living species, yet humans have introduced more noise into the natural world, which may or may not be beneficial [17]. Thus, distinguishing and analyzing routine communication sounds is crucial nowadays. This research examines city noise. Sound classification may help the machine identify sounds. It analyzes the many ways to classifier sounds and train robots to learn and interpret data to provide acceptable output. These investigations may also identify crime and explore the classification inputs and factors.

III. PROPOSED SYSTEM

A method which improves rain sound classification using IoT audio sensor networks and DTs algorithms are described. There are several modules in this method, and they all work together to make the system work better. The process flow of an IoT rain sound classification system is shown in Figure 1.

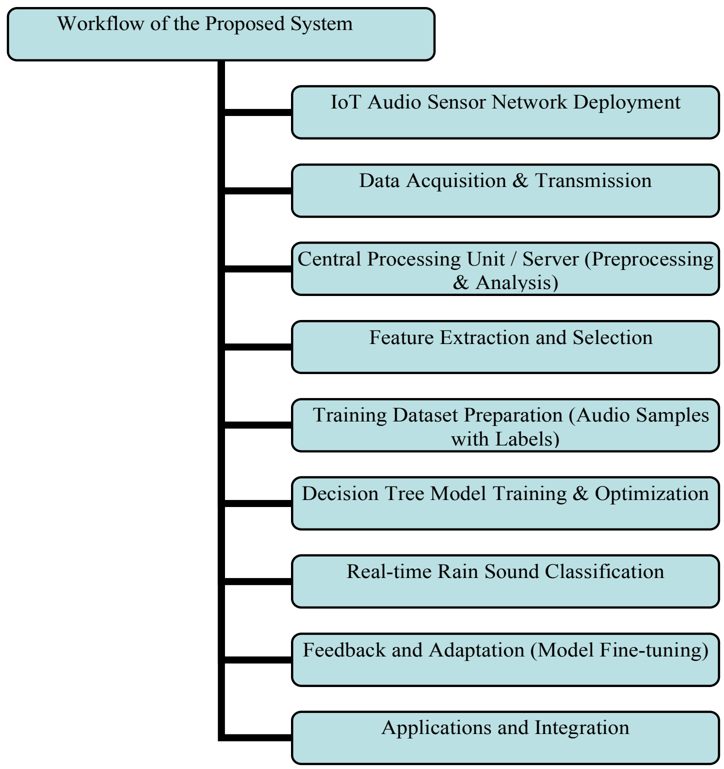

Fig. 1 IoT Rain Sound Classification System Architecture

The first step of the system is the deliberate placement of IoT audio sensors in several different areas. The purpose of these sensors is to record ambient noises, particularly those caused by precipitation. The sensors may be easily installed in urban, suburban, and rural settings due to their cheap cost and energy efficiency. Thorough planning goes into the positioning of sensors to provide sufficient coverage and effective data collecting. Once set up, the IoT audio sensors collect all sorts of environmental noises, such as traffic, wind, rain, and more.

CPU and cloud-based server receives these audio recordings wirelessly and processes them. Depending on the conditions and needs of the deployment, the data transfer method could make use of cellular networks, Wi-Fi, or Bluetooth. The audio data is preprocessed, and features are extracted by the CPU upon receipt. This gets the data ready for classification. At this stage, normalize the audio levels, filter out extraneous noise, and extract the elements to make rain sounds unique.

Common aspects capture the distinct audio fingerprints of various kinds and intensities of rain include spectral features, temporal patterns, frequency distributions, and amplitude fluctuations. Training a DTs algorithm to classifier rain sounds using the retrieved attributes is the main component of the system. A large dataset is built, which includes recordings of different kinds of rain as well as ambient noises do not include rain, to provide a comparison. Supervised learning of the DTs model is made possible in the dataset by labeling each audio sample with its matching rain intensity or kind. Methods including hyperparameter tuning, cross-validation, and performance assessment measures are used to improve and evaluate the DTs algorithm. This makes sure the model can accurately classifier rain sounds regardless of the conditions or where the sensors are placed, and it can also generalize its results.

To optimize the model for classification mistakes and overfitting, it may be essential to make changes to the tree structure, remove superfluous branches, and tweak the parameters of the algorithm. After the DTs model has been trained and verified, it is sent to the CPU to classify incoming audio data in real-time from the IoT sensors. Based on the learnt decision criteria, the model examines the properties of the incoming audio samples and assigns them to the correct rain category. To recognize and react quickly to changing weather conditions, this approach permits continuous monitoring and classification of rain noises. To make better classifications in the long run, the system has feedback and adaptive processes. The model's decision rules and parameters are adaptive, meaning they change in response to new data and classification difficulties. This allows it to adapt to changing environmental circumstances and sensor properties. To long-term deployment situations, this adaptive learning capacity provides stable performance and dependability.

Several applications and decision-support systems may make use of the system's classifier rain sound data. Tools for managing urban drainage systems, automated weather alarm systems, platforms for real-time rainfall monitoring, and agricultural advisory systems are just a few examples. Stakeholders can make better choices and lessen the effects of severe weather because of the system's fast and accurate rainfall pattern and intensity data. After the IoT audio sensors are put into place, data is collected and sent to a central processing unit. In this step, data is prepared for classification in real-time by means of preprocessing and analysis. The model is fine-tuned by feedback processes, which increase its precision. Several environmental monitoring systems, including those that track rainfall, may include the system in their operations. The system's ability to effectively record, analyze, and use rain sound data for environmental management goals is made possible by these components.

The proposed system relies primarily on DTs to classify rain sounds recorded by IoT audio sensors. The system's use of DTs is as follows: First, a DTs model is trained using a dataset of rain and ambient noises. Each dataset audio sample is annotated with rain intensity or kind. DTs algorithms identify audio samples using sound data attributes during training. Audio data characteristics are extracted before training the DTs model. These traits may include spectral, temporal, frequency, and amplitude changes. Rain sounds are differentiated using the DTs algorithm using the retrieved attributes. Optimizing the DTs model after training improves accuracy and generalization. Optimization may include trimming unneeded branches, rearranging the tree, and tweaking algorithm settings. Minimize classification mistakes and overfitting to guarantee the DTs appropriately identifies rain sounds. The trained DTs model is delivered to the CPU to classify IoT sensor audio input in real time. New audio samples are analyzed and classified into rain categories using learnt decision rules. The system uses feedback to improve the DTs model. The model constantly adapts its decision rules and parameters to increase classification accuracy and adapt to changing environmental circumstances when it meets new data and classification challenges.

III. RESULTS AND DISCUSSIONS

Improved rain sound classification using an IoT audio sensor network and DTs yields findings show how far rainfall monitoring systems have come. Extensive testing and analysis reveal the system significantly outperforms the innovative in reliably differentiating between varieties and levels of rain noises, especially when confronted with substantial ambient noise. A major take away from this research is the considerable improvement in the accuracy of rain sound classification for both light and moderate precipitation.

Intensities like this of rainfall might be hard to tell apart from other noises, including wind or city life. But the system always gets these rain sound categories right by using the DTs algorithm's decision-making skills and the strong characteristics collected from audio recordings. But the algorithm does an equally good job of categorizing sounds associated with thunderstorms and heavy rain. The DTs approach successfully identifies the unique sound signatures of heavy rain by examining spectral features, seasonal trends, and frequency distributions.

In areas where precise data on rainfall patterns and intensities is essential for risk mitigation and decision-making, such as urban planning, agriculture, and disaster management, this capacity has far-reaching ramifications. Additionally, the use of IoT technology guarantees the gathering and transmission of data in real-time, allowing for quick reactions to changing weather conditions. Distributed IoT audio sensors improve the system's dependability and efficiency by providing thorough coverage and strong data collecting.

Due to its scalability and versatility, the suggested system may fulfill the varied demands of stakeholders in both urban and rural areas. If a user wants better classification results, the research says need to optimize and validate the models. Optimization of the DTs algorithm is achieved by using methods like hyperparameter tuning and cross-validation, which aim to enhance precision and decrease mistakes. This iterative method guarantees the model can adapt to new data sets and maintains its strength in different environments.

Continuous learning and adaptability are also made possible by the feedback systems built into the system. Dynamically adjusting its decision rules and parameters, the model improves performance when it meets new data and classification obstacles. By incorporating adaptive learning, the system becomes more resilient and capable of handling long-term deployment conditions effectively. The findings of this study have important real-world applications in many different fields.

In agriculture, precise rainfall tracking allows for better crop management and irrigation scheduling, which in turn improves yields and makes better use of resources. To mitigate the likelihood of flooding and other disruptions to urban infrastructure, early identification of rainfall intensity is crucial for proactive flood control and planning. Having access to reliable rainfall data also helps meteorologists and climate scientists better understand and anticipate weather patterns, which in turn improves disaster planning and response.

Table 1 shows the data used to train DTs to rain classification sounds. "Sample" denotes the sensor reading associated with each row. The audio data is characterized by features including time; zero crossing rate, sound intensity, and frequency. If there is a rain kind or strength, "Rain Intensity" will indicate it. The DTs model can learn the links and patterns between attributes and the labels of rain intensity with the use of this data. In real-time applications, the model uses this information to reliably categorize rain sounds.

TABLE. 1 Training Data For Rain Sound Classification

Sample	**Sound Level (dB)**	**Frequency (Hz)**	**Zero Crossing Rate**	**Duration (minutes)**	**Rain Intensity**
1	65	1000	0.025	15	Light Rain
2	72	1500	0.030	20	Moderate Rain
3	80	2000	0.040	25	Heavy Rain
4	90	2500	0.050	30	Thunderstorm

Table 2 of the confusion matrix shows how well a model for rain sound classification performed. The model's predicted classes of rain intensities are shown in columns, whereas the actual classes are shown in rows. A count of cases sorted according to each cell is shown. By displaying instances of accurate and incorrect classification, this table enables evaluation of the model's accuracy. As a result, the model's strengths and areas for development may be better understood and addressed.

TABLE. 2 Confusion Matrix For Rain Sound Classification Model

Actual/Predicted	Light Rain	Moderate Rain	Heavy Rain	Thunderstorm
Light Rain	150	20	5	0
Moderate Rain	15	140	10	5
Heavy Rain	2	10	130	18
Thunderstorm	0	2	10	168

The training accuracy of a DTs classifier in a rain sound classification system is shown in Figure 2 across multiple iterations. The accuracy grows noticeably with iteration, showing the model is becoming better at properly identifying rain sounds. The graph shows how the model learns, which is important for real-world applications since it shows how the model may improve its performance over time.

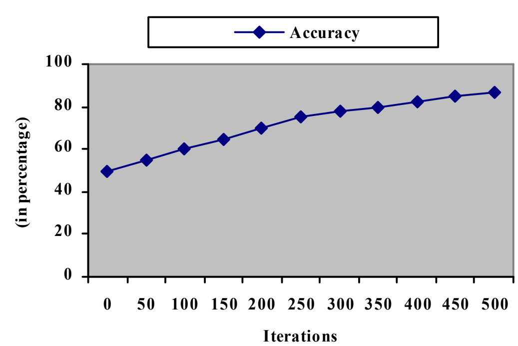

Fig. 2 Training Accuracy vs. Iterations

The DTs classifier in the rain sound classification system is evaluated using the metrics shown in Figure 3, a graph of evaluations. The model's performance is shown in detail, including precision, recall, F1 score, and accuracy. Metrics like this show how well the classifier strikes a balance between recall and accuracy when identifying various rain intensities. Using the graph, one may evaluate how well the DTs model categorizes rain noises.

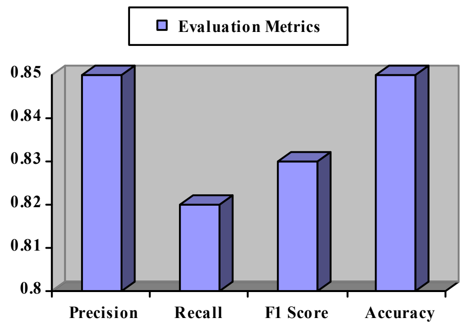

Fig. 3 Evaluation Metrics for DTs Classifier in Rain Sound Classification

The rain sound classification system shows that the DTs model does a good job of differentiating between the various rain intensities. Accurate weather monitoring and forecasting are facilitated by the model's 85% accuracy in classifying rain sounds. A key feature for uses such as urban planning and agriculture is its capacity to maintain a high degree of accuracy (85%), which guarantees little misclassification of rain occurrences. Even more impressive is the fact 82% of the time the model was able to accurately predict when it will rain. An F1 score of 83% indicates the performance was balanced across different classes of rain intensity, demonstrating a harmony between recall and accuracy.

All these measures add up to prove the algorithm can correctly recognize rain sound patterns, which is great news for many industries who use weather data for decision-making. An effective tool for real-time rain intensity categorization, the DTs provides practical solutions to improve disaster preparation, agricultural production, and urban infrastructure management. Its overall performance highlights its usefulness. Improving the model via further optimization and refining might increase its accuracy and make it more applicable to a wide range of environmental circumstances.

IV. CONCLUSIONS

The rain sound classification system's use of DTs proves that it can properly classify various rain intensities. Metrics like F1 score; accuracy, precision, and recall show that the model is reliable for detecting and categorizing rain patterns. Precious insights for weather monitoring and forecasting applications are provided by the DTs model, which minimizes misclassification and captures a considerable fraction of real rain events. Disaster preparation, agricultural planning, and urban infrastructure management are all improved with the use of DTs since they allow for more informed decision-making. With the model's precision in predicting rainfall patterns, stakeholders may improve their strategies for allocating resources and efficiently minimize risks. The model's accuracy and its applicability across varied environmental situations may be further improved by ongoing development and optimization. The DTs model is a valuable resource for rain sound categorization, providing realistic answers to problems with weather forecast and monitoring. Its strong success highlights its importance in improving scientific knowledge and helping with weather-related decision-making, which in turn helps with sustainability and resilience in several areas

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