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**SOUND SIGNAL PROCESSING-BASED AND
AI-POWERED WATER GUARD SENSOR
FOR FAUCETS AND FLUSHES: WAGUSE**

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Abstract

In daily life, clean water waste increases in areas such as sinks and bathrooms due to mechanical failures or users forgetting to turn off faucets. Considering institutions, businesses, schools, and households worldwide, the overall rate of water waste is significantly high. Existing solutions to prevent water loss, such as sensor-activated faucets, leak detectors, and flow rate monitoring systems, are often expensive and require complex installation. These systems typically require the installation of a sensor on each faucet and power supply via batteries or cabling. In this context, using a contactless approach, we designed WAGUSE (Water Guard Sensor) to detect water waste from faucets in shared sinks. This sound-based processing method is more cost-effective and easier to install than existing technologies. The project aims to develop a system that detects water loss using sound signal processing algorithms via a single sensor placed in a commonly used sink area and enables prompt intervention by a responsible staff member. The developed water sound recognition algorithm was tested in different sinks; in each case, various faucets allowed water to run lightly for 10 seconds. In 75 repetitions of this test, WAGUSE achieved an accuracy rate of 77.3%. In subsequent experiments, it was observed that a lightly running toilet flush without the sensor wasted 15.25 litres of water over 135 minutes. In addition, we collected a total of 120 sound samples, each lasting 20 seconds, from different faucets, including Hand Washing, Flushing Sound, and Water Flow sounds. We trained an artificial intelligence model to classify the sound using these collected sounds. Our AI algorithm, which uses the EfficientNet-Lite0 model, achieved a classification accuracy of 95%. However, when the sensor was used, our connected Android application allowed staff to detect the issue early, preventing this amount of daily waste. This project is a pioneering and scalable initiative in its field. The project's research question is: "Can faucet/flush-related water waste be accurately detected using a contactless sensor developed with sound signal processing and AI-based classification algorithms?"

Keywords: Water waste, Environmental Sustainability, IOT, Sound Signal Processing, Artificial Intelligence, Water Sound Classification

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2. Preliminary Matters

2a. Acknowledgements:

I would like to express my deepest appreciation to Asst. Prof. Dr. Ali Emre Ozturk from Hasan Kalyoncu University, for his invaluable guidance and support and for helping me understand complex concepts in the preparation and experimentation stages of throughout the research process. Most importantly, I would like to thank my family for their encouragement and support.

2b. Biography

Kagan Mehmet Ozkok is currently a junior student at Sanko High School. He is particularly interested in sustainability, mathematics, computer science, and physics. He is passionate about improving the world around him and solving sustainability problems through his interests in science and engineering. He attended a summer program at Harvard University, taking “Intensive Introduction to Computer Science and Data Structures” (8 College Credits) in August 2024. Kagan is the Co-Founder of his school’s AI Club, where he has tried to empower students to learn AI and realise their passions through creative applications of their learning. He also organized talks at school by inviting experienced and pioneering people in this field. He helped organize the SANMUN’24 (Sanko - Model United Nations) conference in April 2024 with the participation of more than 120+ delegates and led the Social, Humanitarian, and Cultural Committee as a chair. He also played a formative role in organizing the SANMUN’25 conference, whose theme was ”Echo the Globe,” as the Head of IT in April 2025. Helping people and solving problems makes him truly happy. He has volunteered in blanket manufacturing and distribution to reduce casualties from freezing temperatures following the earthquake in Gaziantep (7.6 magnitude) in February 2023. He coordinated meetings with undamaged factories in the Organized Industrial Region to provide shelter for downtown residents affected by the earthquake, successfully helping accommodate many people. He has chosen to attend the Young Guru Academy Summit 2024, where he was impressed with what “double wings” means. He is a licensed basketball player and won the City Championship with the school team. He is also a competitive fencer who participated in numerous tournaments and won a bronze and a silver medal in fencing in Gaziantep. He plays the guitar, loves building Legos, and reading science articles on AI.

3. Purpose

This project aims to develop a sound-based water leakage detection sensor, primarily aimed at minimizing water waste in public use areas and contributing to the efficient use of water resources. Water waste from faucets left unintentionally open poses a significant problem on both individual and societal scales. In such cases, the extent of the waste escalates rapidly until the malfunction is detected or the faucet is turned off. For instance, if an environmentally friendly faucet is left running, the water waste rate can reach 5 litres per minute (Hansgrohe, 2024). This loss becomes even more critical in high-traffic environments such as schools, public buildings, and workplaces. A single droplet is approximately 0.05 ml in volume (Martinez, 2018: 815). A faucet dripping once per second can cause approximately

1.58 tons of water loss annually. When multiplied across an entire country, these situations seriously threaten the sustainability of water resources. Only about 3.5% of the Earth's total water is freshwater, most trapped in glaciers or underground sources (Aksungur and Firidin, 2008: 9).

Current solutions such as sensor-equipped faucets, water flow sensors, and flow rate measurement systems are generally not widely adopted due to high installation and maintenance costs. Additionally, these systems often require a sensor for each faucet, making integration into existing infrastructure time-consuming and expensive. This project aims to provide an innovative solution to these challenges. Using a single, contactless device, the proposed sound-based detection sensor will identify leaks or forgotten open faucets in shared-use areas. The sensor will analyze acoustic signals to detect sound patterns specific to water leaks and transmit this data to a cloud-based system. Additionally, by using artificial intelligence algorithms to determine the class of the water sound, the system can provide more detailed information to the user. The cloud system will then send notifications about the detected leak to the technical staff's mobile device, enabling rapid response.

The project's R&D content includes the following core components: identifying acoustic signals specific to water flow and classifying them in a database; developing an algorithm capable of processing these signals; integrating sensor hardware with web-based software and smartphone applications; and presenting the results in a user-friendly format through a cloud-based control panel and mobile app.

This project aims to contribute to water conservation and sustainability by offering a low-cost, quickly deployable, and rapidly actionable solution. It also seeks to provide an alternative to current water leakage detection technologies and raise public awareness regarding water waste.

4. Introduction

Water is essential for all living beings on Earth. Therefore, the depletion of water resources poses one of the greatest threats to life's sustainability. Population growth, technological advancements, and industrialization increasingly contaminate drinking water sources. In rapidly growing metropolitan cities and slower-developing urban areas, rising environmental pollution, drought, and infrastructure issues are leading to the rapid depletion of potable water supplies. Drinking and utility water are subject to significant losses in the distribution system before they even reach consumers from treatment plants.

Although rivers, lakes, and other surface water bodies cover 70% of the Earth and may seem like abundant resources, only 0.3% of this water is usable. While highlighting the limitations of usable water resources, it is noteworthy that water consumption has increased tenfold since the 1990s. As a result, only about 1% of the total water resources on Earth are suitable for human needs (Albayrak, 2019: 4).

Water loss can be defined as the difference between the volume of water supplied to the distribution system and the volume of water actually billed to the consumers (Karakus, et al. 2010: 2). Non-revenue water losses stem from physical pipe leaks, illegal meter connections, meter reading errors, and unmetered usage. These losses not only cause severe economic damage but also lead to deterioration in water quality due to physical leakages. Studies conducted in various countries have shown that losses from physical leakages can account for 25% to 50% of total water volume. According to research conducted at different times, water loss rates were recorded as 33% in Boston (USA), 24% across the UK, 51% in India, 49% in Bangkok (Thailand), and 12% in Munich (Germany). The nationwide water loss rate in Turkey is estimated to be around 45%. Taking the 2015 population into account, the annual per capita water availability in Turkey was 1,422 m³/person. According to Turkish Statistical Institute (TSI) data, as of 2023, this figure dropped to 1,311 m³/person. Projections by TSI suggest that Turkey's population will reach 100 million by 2030. Consequently, the per capita water availability is expected to decline to approximately 1,100 m³/person, indicating that if no necessary measures are taken, Turkey may face the risk of becoming a water-scarce country by the 2030s (Gerger and Aslan, 2019: 27).

Various physical water loss and leakage detection methods have been developed in the literature. These include visual inspection for visible surface leaks, acoustic detection tools (such as ground microphones, correlators, permanent systems, and listening rods), radar devices (ground-penetrating radar), and frequency-based leakage detection techniques (Republic of Turkey Ministry of Environment, Urbanization, and Climate Change, 2021: 26–33).

More modern approaches have focused on image and signal processing technologies. Image processing can detect physical water movements to identify leaks; however, due to its high hardware costs and complex infrastructure requirements, it is not suitable for every setting. In contrast, sound-based detection methods analyze acoustic signals produced by flowing and dripping water. These approaches offer the potential for contactless measurement with lower cost and faster deployment.

Unlike previous studies, which mainly focused on underground leak detection, this project emphasizes above-ground water losses, particularly losses resulting from human or technical errors during daily faucet use. This approach aims to minimize individual water waste and promote more efficient water use. In this respect, the project presents an innovative solution to a common everyday issue.

In addition to the literature reviewed above, there are also studies focused on water-saving technologies and electronic faucets. Technologies that optimize both individual and industrial water consumption and help prevent water losses have become an important area of research. In this context, modern technologies such as acoustic listening devices, infrared (sensor-based) faucets, and smart water meters stand out:

Acoustic Listening Devices are advanced technologies used to detect water and gas leaks. Systems like Sewerin provide early detection through components such as test rods, compact receivers, and ground microphones. These devices identify leakage points by detecting acoustic or ultrasonic noise emitted by leaks (Enarmak, 2024).

Infrared (Sensor-Based) Faucets operate with advanced infrared sensor technology. A dark-colored filter on the faucet houses a transmitter and a receiver beneath it. The transmitter emits infrared beams at intervals, and the receiver detects the reflections from the user's hand via the filter, activating the water control mechanism to allow water flow (Öz, 2023: 58).

Smart Water Meters or digital meters continuously analyze water usage and alert users in case of abnormal consumption. These meters are particularly effective in large-scale water systems for quickly identifying and responding to leaks. They collect consumption data periodically and analyze it using automation and mathematical algorithms. With the help of consumption graphs and dedicated software, leaks or excessive use caused by pipe faults can be easily identified (Nisanci, 2021: 36).

The main goal of our project is to instantly detect the water loss caused by leaking or left-open faucets and alert the user. This project's scope includes sensors capable of real-time leak detection and a software infrastructure to analyze this data. The sensors continuously monitor water leakage from faucets and collect data that is evaluated in terms of frequency and continuity. If a leak persists for a specific period, the system will send instant notifications to users to prompt intervention. This way, users can recognize potential water losses and immediately take action. Our project makes a significant contribution to reducing technically induced water losses and improving individual behavior regarding water use.

In summary, this project aims to offer an innovative approach to the existing gap. It seeks to answer the question: "Can faucet/flush-related water waste be accurately detected using a contactless sensor developed with sound signal processing and AI-based classification algorithms?" By utilizing sound-based detection methods, the project targets developing a low-cost, easy-to-install, and environmentally noise-resistant water leakage detection system for shared usage areas. The target audience includes public institutions, restaurants, schools, dormitories, hotels, and households.

5. Method

The proposed solution is to develop a sensor that utilizes an Internet-of-Things (IoT) approach based on sound signal processing and to build a system that detects water losses and reports them to a central platform. The system consists of electronic hardware and software components. This structure is planned under three main categories: the electronic circuit (hardware), a smartphone application, and web server software. Classifying detected water sounds as hand washing, flushing, or continuous water flow is advantageous for improving the system's user-friendliness. Therefore, we collected sound data—Hand Washing (HW), Flushing Sound (FS), and Water Flow (WL)—from various restrooms and different types of faucets.

The collected data was used to train an AI model for sound classification using the EfficientNet-Lite0 architecture (Liu, 2020). The trained model was then deployed on a Raspberry Pi 5, where it successfully performed real-time sound classification.

Figure 1 shows the overall structure of the system and its operational steps. The sensor placed near the sink continuously monitors ambient sound and analyzes it; when it detects the sound of running water, it sends this information to the server software (1). Suppose the server detects the water has been running longer than a user-defined threshold. In that case, it will notify the relevant technical staff about the leak's location and direct the staff to

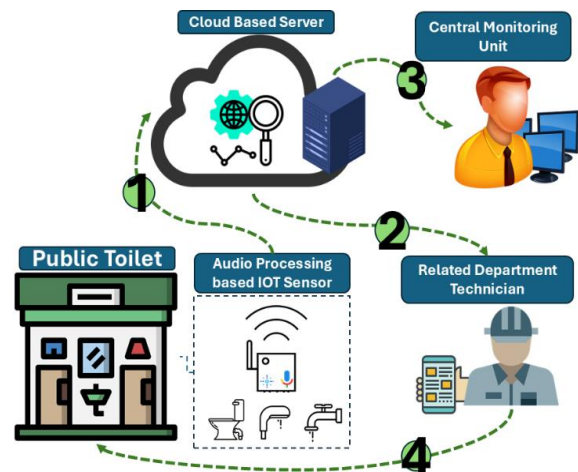


Figure 1. System Workflow and General Overview

the malfunctioning or forgotten faucet (2). The technician will then proceed to the designated area and resolve the issue (4). Simultaneously, the central monitoring unit will also be

informed (3).

5.1. System Components

The system components consist of three main sections, which are Water Guard Sensor (WAGUSE), Web – Based Server Software and Mobile Application (APP). These are categorized as hardware and software. Below is a detailed explanation of these sections.

5.1.1. Water Guard Sensor (WAGUSE)

Figure 2 shows photographs of the electronic components used during the sensor's development phase. The product shown is the initial prototype. Electronic components were used in modular form to minimize potential errors during the prototype development process and to reduce the time required for creating the first prototype.

The sensor was built on a single-board computer (SBC) running the Ubuntu Linux operating system. The software on the system was developed using the Python programming language. A MAX9814 microphone module was connected to the SBC, allowing the program—developed in Python—to continuously monitor ambient sound. Additionally, a Light-Dependent Resistor (LDR) was used to detect ambient light conditions, and the resistance of the LDR was measured using an ADS1115 analog-to-digital converter.

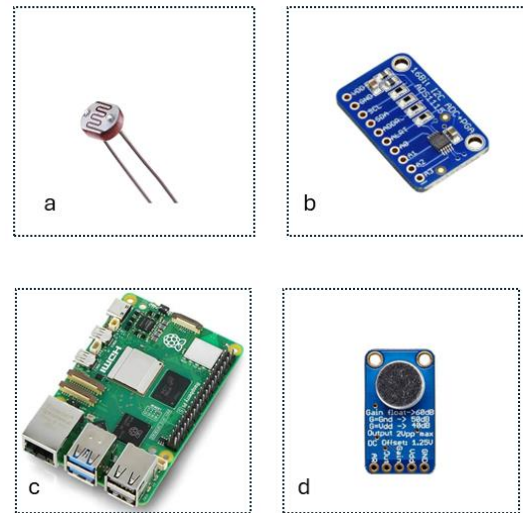


Figure 2. Components Used During the Sensor Development Phase: (A) LDR, (B) ADS1115 ADC, (C) Single-Board Computer, (D) MAX9814 Microphone

As light intensity changes, the resistance of the LDR also changes, which, in turn, causes a variation in voltage. The measured voltage values are then correlated with light levels.

Figure 2 shows the schematic representation of the electronic hardware. The Python code running on the SBC reads ambient sound through the SPI communication port, and the captured sound signal is passed through digital filters. The sound is divided into 5-second segments, and each segment is compared with previously recorded water sounds using similarity and comparison algorithms to calculate a similarity score. If this similarity exceeds 80%, the detected sound is labeled as water flow. Suppose the water sound continues uninterrupted for 3 minutes. In that case, it is determined not to be the sound of hand-washing

or everyday use but rather the sound of water waste or a forgotten faucet. Then, the information indicating a water leak is transmitted to the server via the Wi-Fi module or Ethernet port.

Figure 3 presents a schematic representation of the sound processing algorithm, including the feature weights it utilizes and the comparison methods applied. **Spectral Flatness;** Spectral flatness is a metric used to quantitatively determine whether a sound spectrum is more tone-like or noise-like. This concept is important in the field of digital signal processing (Johnston, 1988). **Temporal Consistency;** Temporal consistency has been addressed in studies examining how spectral consistency within sound sequences affects the perceptual accuracy of subdivided rhythmic patterns (Nitta, 2024). **Encoding of Natural Sounds;** How natural sounds are encoded in the human auditory cortex has explored the role of spectral and temporal resolution (Santoro, 2014). **Spectral and Temporal Resolutions;** Research on the spectral and temporal resolution of information-bearing features in acoustic signals provides significant insights into sound processing and perception (Stilp, 2015).

The results of the relevant filters are stored in an array as model features and are compared through a correlation process with previously collected water sound samples. The newly detected sound is thus associated with the most similar water sound. The sensor sends its decision based on water sound analysis to our SSL-certified server using the POST method over port 80.

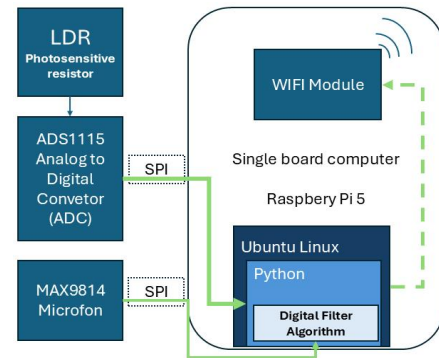


Figure 3 Schematic Representation of Hardware Specifications

The schematic representation in Figure 4 illustrates the data structure. The sensor ID is used to identify which sensor the data originates from. The data type indicates the kind of information, such as water flow, leakage, or waste. The data field contains the actual content; for example, if the data type is water waste, it specifies how long the waste occurred—for instance, 2 minutes.

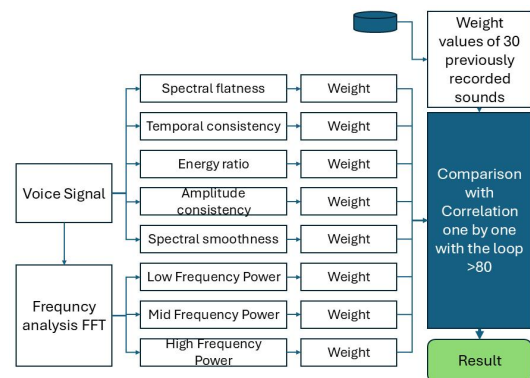


Figure 4. Sound Signal Processing Algorithm, Feature Weights, Frequency Analysis, and Schematic Representation of Weights



Figure 5. Schematic Representation of the Data Structure Sent from the Sensor to the Server, The first row shows the general format. The second row presents an example of the content.

To prevent this, a token is used; if the token does not match, the server software disregards the data. Like most electronic devices, the sensor requires an enclosure to protect it from external factors. The casing for our sensor was designed using 3D modelling software and produced with 3D printers. The flowchart of the sensor software is presented in Figure 6. The purpose of the sensor software, written in Python and running on a Linux-based system, is to measure two different environmental conditions and transmit them to the server via Wi-Fi. The software compares the sounds it hears through the microphone with 30 previously recorded sound samples and identifies the most similar one. If the similarity persists uninterrupted for 3 minutes, it sends the information to the server. The 3-minute threshold is chosen to distinguish water waste from everyday activities such as hand-washing. To differentiate the sound of water from human speech and other noises, the sound is passed through various filters beforehand, allowing the system to isolate features specific to water flow. The LDR sensor sends data to the server if a specific voltage is detected continuously for 3 minutes.

The token is generated to ensure secure communication between the sensor and the server. Without proper security, a hacker could send data to the server in the same format and cause it to be recorded in the database.

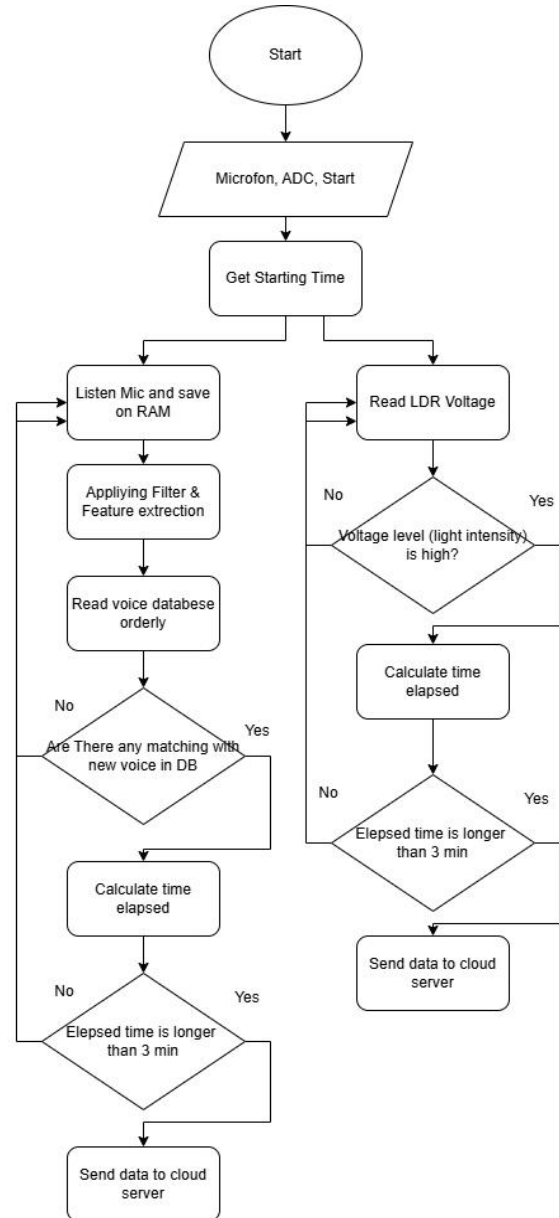


Figure 6. Flowchart of the Sensor Software

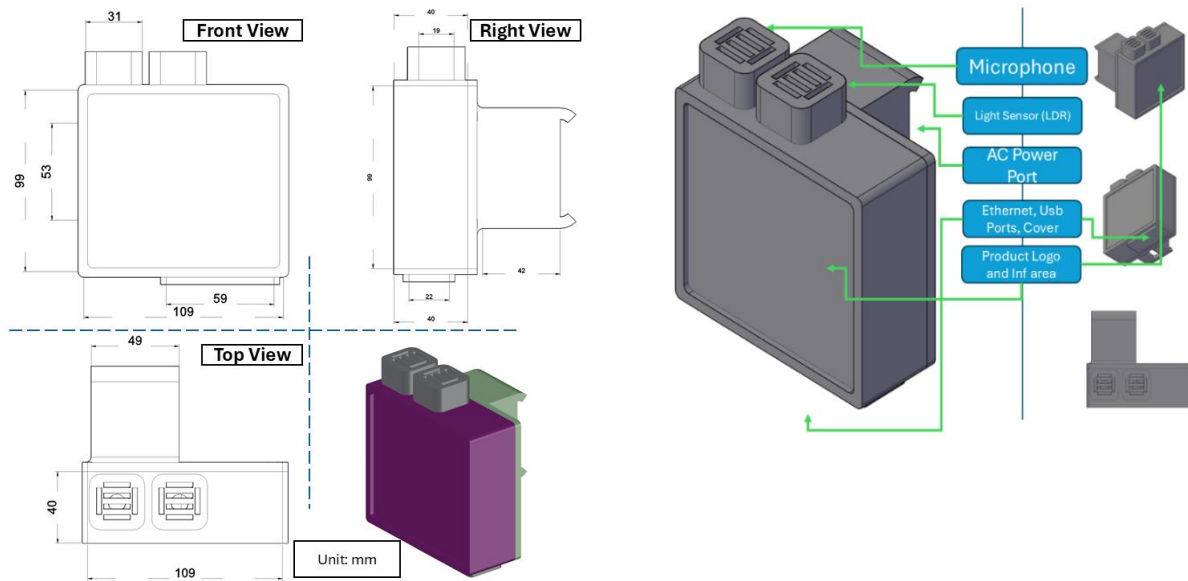


Figure 7. Sensor Enclosure Views and Dimensions (mm)

Figure 7 shows the outer enclosure dimensions and 3D models of the sensor's components. The device was designed to be easily plugged in and unplugged from a power outlet for convenient installation, resulting in a plug-and-play solution. The lower cover provides easy access to the 4 USB ports and 1 Ethernet port on the device, allowing additional sensors or devices to be connected. The cover is secured with magnetic fasteners, enabling the user to detach and reattach it as needed easily.



Figure 8. Actual Photographs of the Sensor

A plastic enclosure to house the sensor's electronic circuitry was designed using 3D modelling software and produced with 3D printers. Figure 8 shows actual images of the enclosure. The covers for the microphone, LDR, Ethernet, and USB sockets were designed with magnetic fasteners, allowing for easy plug-and-play attachment and removal. Our designed system, WAGUSE, is easy to implement, low-cost, and original - bringing a new perspective to this field.

Table 1 shows the cost breakdown for producing a single unit. Since all components were used as modules, the R&D cost is relatively high. However, if we design and manufacture our custom electronic board, the production cost per unit can be reduced to as low as 40 €.

Table 1: Materials Used and Costs

Names of Materials	Number	Cost
Raspberry Pi 5	1	75 €
SD Card	1	4 €
Power supply	1	3 €
3D Print	1	4 €
Microphone module MAX9814	1	2 \$
LDR	1	0.1 €
ADC module	1	2 \$
Total Cost:		90 €

5.1.2. Web-Based Server Software

Our Internet of Things (IoT)-based sensor transmits water leakage and light-on status to the server via Wi-Fi or Ethernet port. Adding a timestamp to the incoming data and storing it in the database is essential for overall system management. The server-side software has three main functions. First, it securely verifies whether the incoming data is from a valid sensor and records it in the database. Second, it visualizes the recorded data and presents it in a user-friendly format with graphs and visuals, enabling meaningful interpretation for the central monitoring unit. Third, it communicates with the smartphone application via web services to direct the technician to the relevant area. The server software uses PHP as the backend programming language, and MySQL was chosen for the database system. An open-source and free library called Admin LTE was used for the front end. The system can currently be accessed and reviewed through the active website **www.waguse.com**. The necessary admin information to access; **username: admin, password: admin**

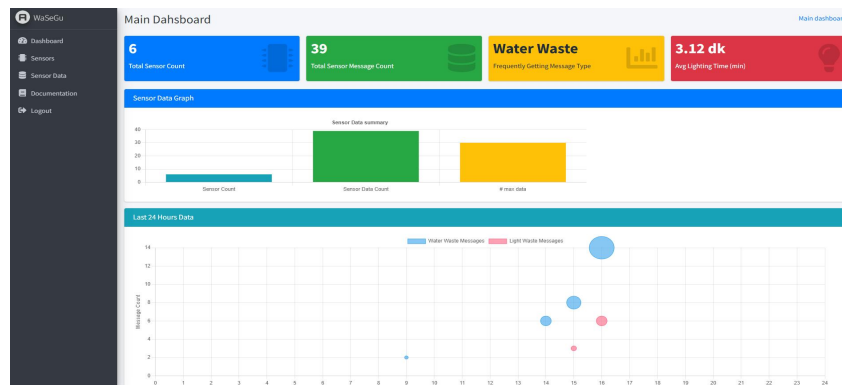


Figure 9. Server Software Data Visualization Panel — Sensor Errors and General Information Can Be Monitored Through Graphs.

Figure 9 displays the sensor data graphs from the web automation software. Graphs and labels show the number of sensors currently connected to the system, water flow, water waste, and light-on status. The server software is compatible with the Android mobile application. The Android app periodically retrieves the data recorded on the server, and if water waste is detected, the user receives a notification. The alert contains information about the leakage's location and the duration of the water waste.

5.1.3. Smartphone Software (APP)

The smartphone application reads the data sent from the sensor to the server at regular intervals. If alert records have not yet been shown to the user, a notification is displayed. The notification includes the location of the alert, the type of alert, and the duration of the alert.

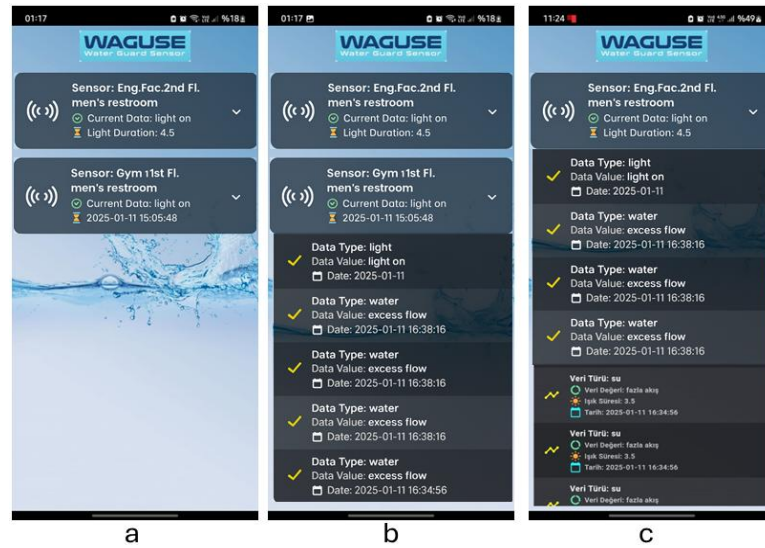


Figure 10. Smartphone Application User Interface View. (A) List of Sensors Connected to the System, (B) Data List for Sensor 2, (C) Data List for Sensor 1.

In Figure 10, the main screen of the mobile application's user interface displays the time and location of a detected water leakage. As shown in Figure 10-a, the user interface lists all sensors connected to the system. By clicking on a specific sensor, the user can view the list of events detected by that sensor. In Figure 10-b, a notification indicates that the lights are on in the men's restroom on the 1st floor of the sports hall. In Figure 10-c, water flow was detected in the men's restroom on the 2nd floor, and multiple alerts were received, including one showing that the lights had been left on for a prolonged period.

5.2. Project Work-Time Schedule

Kagan Mehmet OZKOK led the project, and Okan LEBLEBICI from Sanko High School supervised it. Additionally, Asst. Prof. Dr. Ali Emre OZTURK provided support in the preparation and experimentation stages of throughout the project.

Table 2. Project Work-Time Schedule

Work Package	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
Literature Review	X	X										
Prototype Development			X	X								
Test & Improvement					X	X						
Data Collection & Analysis							X	X				
AI Model Training & Testing									X	X	X	X
Reports									X	X	X	X

5.3. Experimental Results of Signal Processing Algorithms

Frequency distribution graphs were generated to identify the characteristics of the water leakage sound we aimed to detect. These graphs were used to understand the nature of two different water sound signals and to define them mathematically. Figure 11-a displays the frequency distribution graph of the water sound. Figure 11-b shows the frequency distribution graph of a speech sound. The frequency range of speech is broader compared to the water sound. We measured the effects of the filters and feature extraction algorithms mentioned in the Method Section on these two different signals and visualized the results graphically. The graphical analysis provided insights into the nature of the water sound.

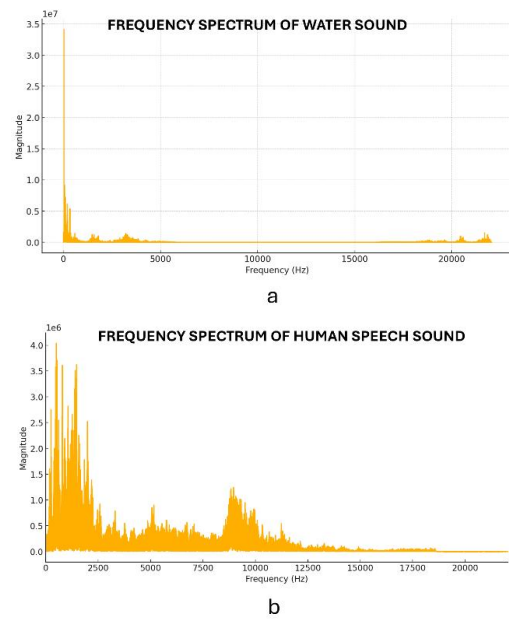


Figure 11. Frequency Distribution Graphs of Sample Sound Files, (a) A Sample Water Leakage Sound, (b) A Sample Human Speech Sound

Figure 12 displays the post-filtered graphs of water and speech sounds, as discussed in the methodology section. Comparing the input and output graphs side by side provided insights into the acoustic nature of water sounds. Compared to speech, water sounds exhibit more repetition and less frequency diversity. Among the signal features, spectral flatness, high-pass filtering, and natural sound encoding proved to be generally more discriminative. Specifically, temporal smoothing was a more distinctive feature for sounds produced when water hits the sink surface.

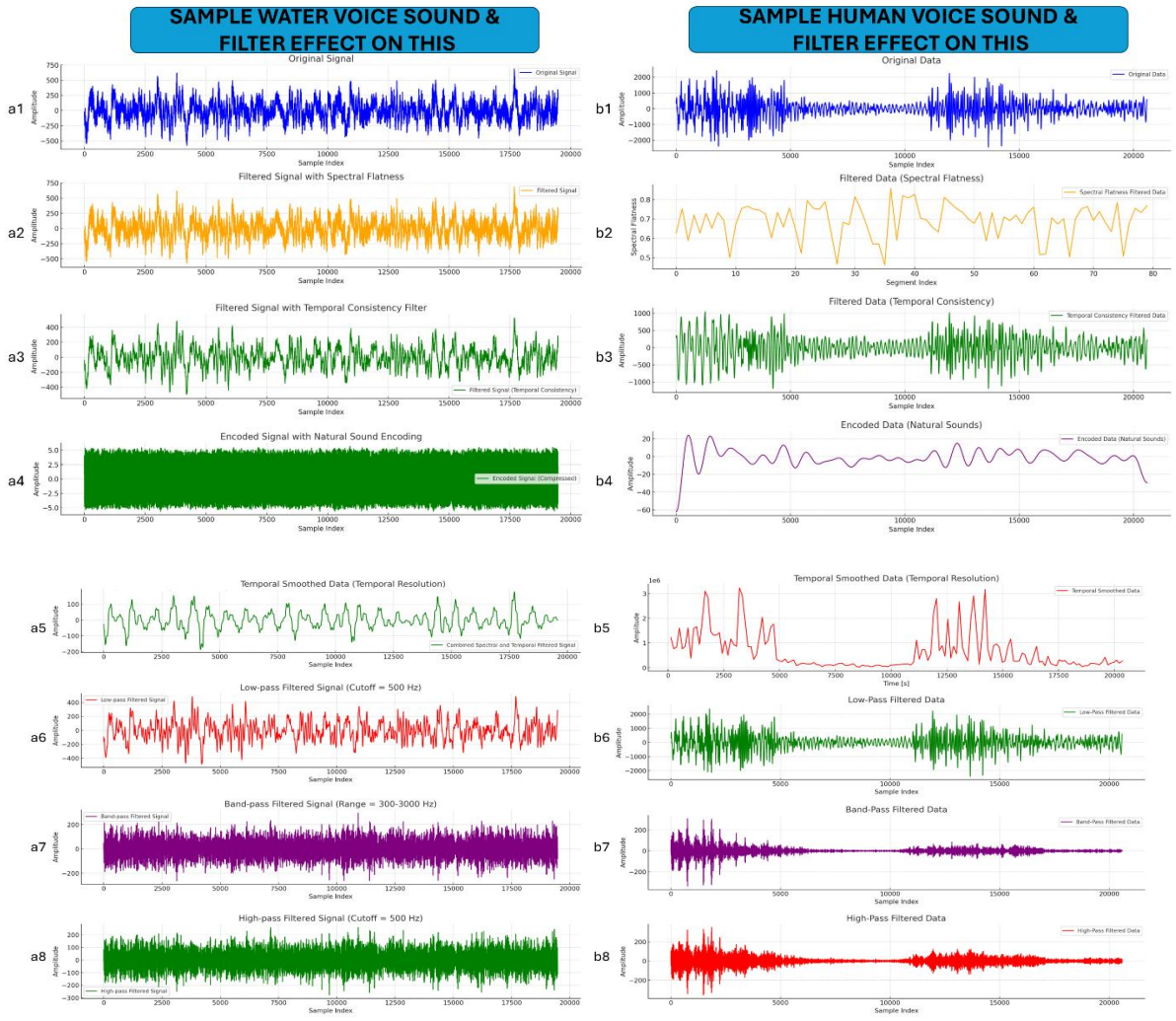


Figure 12. Comparative Graphs of Water and Speech Sample Sounds After Being Processed Through Filters. (A-X) Sample Water Sound, (B-X) Sample Speech Sound, (1) Original Signal, (2) Spectral Flatness, (3) Temporal Consistency, (4) Encoded Natural Sound, (5) Temporal Smoothed Data, (6) Low Pass, (7) Band Pass, (8) High Pass

Our observations suggest that each filter highlights unique characteristics of water in different scenarios.

Experiment 1: The water sound detection algorithm was tested across different sinks. Water was allowed to flow slightly for 10 seconds using different faucets in each trial. This test was repeated 75 times. Out of these 75 trials, the sensor successfully detected water sounds in 58 of them. **System Accuracy (%)** = $(58/75) \times 100 = \% 77.3$.

$$\text{System Accuracy (\%)} = \frac{\text{True Detection}}{\text{Total Voice Count}} \times 100$$

Figure 13 presents a graph of the data transmitted by a single sensor over one day. This data consists of detected water leaks and/or light-on statuses the sensor sends to the server. The server software visualizes these data points graphically, enabling users to interpret the information more easily.

- The **vertical axis** represents the number of detected errors (events),
- The **horizontal axis** represents the time interval from 00:01 to 23:59, labeled 0–24.

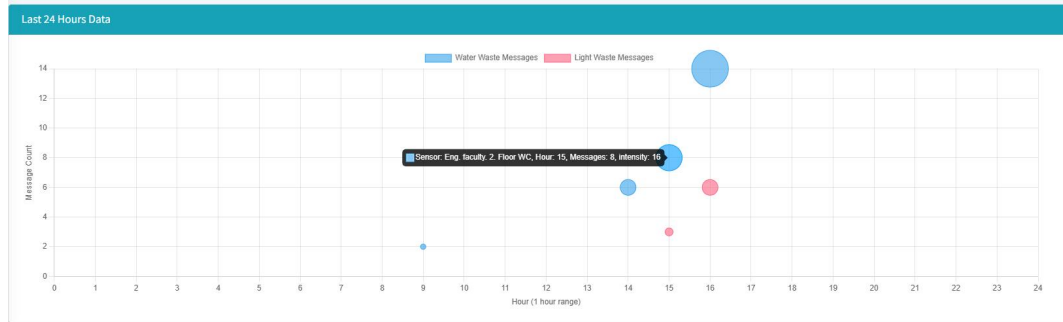


Figure 13 Graph of Sensor Data Transmitted Throughout a Day

As shown in the example, a value appearing at hour **15** indicates that **eight water leakage events** were detected between **15:00 and 16:00**. This graph was intentionally generated under controlled conditions to conduct system experiments.

Experiment 2: A sensor was placed in the men's restroom located on the second floor of a school, and data collection was performed. The experiment was conducted during weekday working hours, between 08:30 and 17:30. A phone with the Android application was given to the floor attendant, and the meaning of receiving a notification was explained.

At 09:35, the flush tap in the restroom where the sensor was located was intentionally left partially open. The aim was to observe how long it would take for the attendant to detect and address the issue. The attendant noticed the problem and turned off the flush tap at 09:48. In the graph shown in Figure 14, the data point located at vertical axis value 2 and horizontal axis value 9 corresponds to the moment this experiment was conducted.

Experiment 3: Using the same restroom and sensor, we sought to answer a different question: How long would the water have continued to flow if the sensor had not been present? To answer this, we took away the floor attendant's phone, meaning they would not receive any notifications. At 14:20, the same flush tap was intentionally left partially open again at the same low flow level. Two hours and fifteen minutes later, another staff member accidentally discovered and turned off the open tap.

The flush tap fills approximately a quarter of a 500 ml small water bottle in 1 minute, which means the water flow rate is estimated at 125 ml/min. In the first experiment, the attendant intervened after **13 minutes**. In the second experiment, the issue was resolved after **135 minutes**. Thanks to the water waste detection sensor, the water saved can be calculated as:

$$(135 \times 125 \text{ ml}) - (13 \times 125 \text{ ml}) = 15,250 \text{ ml} = \mathbf{15.25 \text{ lt of water saved.}}$$

5.4. Experimental Result of Artificial Intelligence Models

The sound signals from faucets were analyzed using classical sound processing algorithms to detect water waste. This method has proven effective in significantly reducing water wastage. Additionally, we developed a new approach by processing these sound signals with an AI-supported model to classify and distinguish different types of water sounds. That allowed us to create a preliminary projection of how AI-based algorithms might impact system performance.

As part of the study, 120 sound recordings, each lasting 20 seconds, were collected using five different sinks and flushing systems and were categorized into three main groups: **Hand-Washing Sounds (HW)**: Short-duration acoustic patterns involving intermittent water flow, soap use, and hand rubbing. **Flushing Sounds (FS)**: Intense, short bursts of water flow characterized by sudden onset and fade-out. **Running Water (Waste Condition) (WL)**: Long-duration, continuous water flow sounds (e.g., a faucet left running). This diversity enhanced the model's ability to distinguish different real-world scenarios accurately.

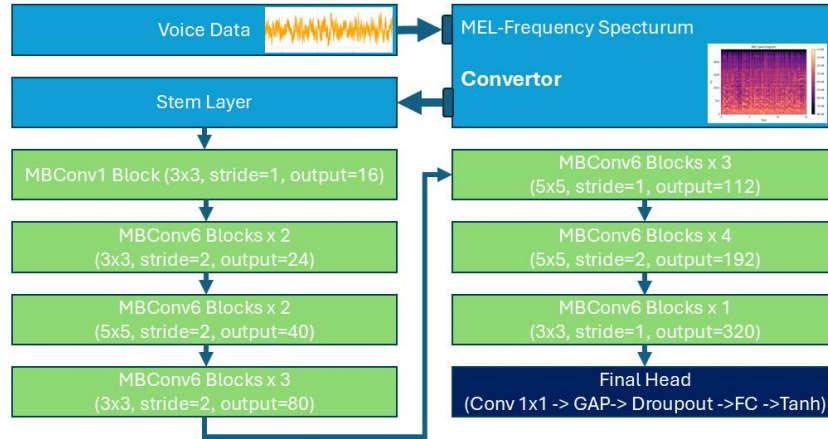


Figure 14. EfficientNet-Lite0 AI model Schematic Representation

The sound recordings were preprocessed and then trained for classification using the EfficientNet-Lite0 (Liu, 2020) deep learning model. This architecture is optimized for devices with limited hardware resources, offering high accuracy with low computational load. The model was integrated to run on a Raspberry Pi 5, transforming it into an embedded sensor system capable of real-time water wastage detection.

We evaluated the model's performance compared to the sensor that had been previously developed using classical algorithms. The model was assessed using 60 new sound recordings in the testing phase and achieved a 95% classification accuracy. Notably, the distinction between prolonged faucet flow sounds and hand-washing sounds—previously difficult to

differentiate—was successfully addressed in this study. Short and intense acoustic patterns, such as those from flushes, were also detected with high accuracy. Table 3 presents the precision, recall, and F1-score values for the three different classes the sensor recognized. **HW** represents the **Hand-Washing** class, **FS** represents the **Flushing Sound** class, and **WL** represents the **Water Flow** class.

Table 3: F1 Score Table

Class	Precision	Recall	F1-Score
HW	0.9845	0.9845	0.9845
FS	0.9190	0.9190	0.9190
WL	0.99	0.99	0.99

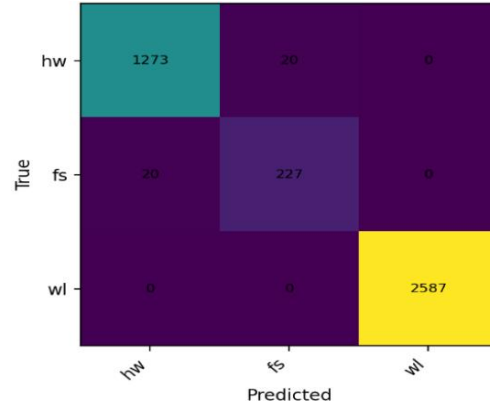


Figure 15. cross correlation of model

6. Conclusion and Discussion

The developed system operates in a loop consisting of: A Sensor (Electronic Device) → Web Software (Server) → Web Software (Central Monitoring) → Mobile Application (App).

The system's main purpose is to detect water waste in public restrooms located in schools, sports complexes, hospitals, bus terminals, airports, and similar places at a low cost, and to ensure the issue is resolved as quickly as possible.

Sensor accuracy, notification speed, server performance, and mobile application tests have all been conducted and documented. The system has been observed operating under real-life environmental conditions and supported by experiments. Experimental results including human factors and environmental variables have also been reported.

To protect the electronic sensor from environmental factors, a 3D-printed plastic enclosure was designed. This allows the device to be plugged directly into a power outlet for easy installation. The signal processing software, developed in the Python programming language and running on a Linux-based embedded operating system, successfully detected the sound of running water and identified unnecessary water flow with 77.3% accuracy.

The detected events were sent to a server, where the data was stored in a MySQL database using a back-end system developed in PHP. The mobile application communicated

with the server via APIs, displayed the information on the user interface, and directed the technical staff to the relevant area.

The experiments demonstrated that, WAGUSE could prevent **15.25 litres of water waste in 135 minutes in a single restroom** . In a scenario where the sensor is installed in hundreds of restrooms and operates continuously for **several days, tons of water** could be saved. Additionally, **real-time notifications** sent to the mobile application installed on the phones of technical personnel and custodial staff **can raise awareness**, encouraging them to be more attentive and proactive in preventing water waste.

Thanks to the **EfficientNet-Lite0 (Liu, 2020)** architecture, we analyzed sound data in greater detail and classified water waste situations in restrooms with 95% accuracy. The AI-based sensor running on the embedded system is suitable for real-time applications due to its low power consumption and great potential for field deployment.

In the next phase of system improvements, we aim to develop our own single-board computer instead of using a board like the Raspberry Pi. That will allow us to remove unused ports and make the sensor smaller and more cost-effective. System improvements will be made, and development will continue using AI-based algorithms. Following these physical improvements, we plan to **collect more data** and enhance the system to support **more complex mathematical models**. A new development phase has already begun, focusing on building a system trained and operated using **deep learning and other AI models** through systematic data collection.

To raise awareness, demo kits can be made for school children, or water waste statistics can be recorded and QR codes can be given to show how much water is saved. Additionally, a solar panel can be added to the sensor instead of using electricity to increase sustainability.

7. Referances

Aksungur, N. ve Firidin, S. (2008). Su Kaynaklarının Kullanımı ve Sürdürülebilirlik, *Sumae Yunus Araştırma Bülteni*, 8(2).

Albayrak, O. (2019). Suyun Degisen Niteligi ve Ozellestirilmesi: Dnyadan Ornekler ve Türkiye'deki Durum, Karadeniz Teknik Universitesi, SBE, Yuksek Lisans Tezi.

Enarmak, (2024). <https://enermak.com/akustik-dinleme-cihazı/?srsltid=AfmBOooXpKTqK8dG0fcWl2rv3JTrb6ThnS5fuxEnSaG4JRhTCXFuIpIh>

Gerger, R. ve Aslan, A. (2019). Sanliurfa Ili Icin Icme Suyu Kayip ve Kacaklarinin

Tespiti, *Harran Universitesi Muhendislik Dergisi*, 4(2), 26-35.

Hansgrohe, (2024). <https://www.hansgrohe.com.tr/articledetail-focus-tek-kollu-lavabo-bataryasi-100duesuek-debi-kumandasiz-31513000>

Johnston, J. D. (1988). Transform coding of audio signals using perceptual noise criteria. *IEEE Journal on Selected Areas in Communications*, 6(2), 314–332.

Karakus, C. B. et al. (2010). Sivas Kent Icme Suyu Sebekesindeki Su Kayiplari ve Kayip Oranini Azaltma Calismalari, *Selcuk Universitesi Mühendislik, Bilim ve Teknoloji Dergisi*, 25(1).

Liu, R. (2020). Higher Accuracy on Vision Models with EfficientNet-Lite. Available online: <https://blog.tensorflow.org/2020/03/higher-accuracy-on-vision-models-with-efficientnet-lite.html> (accessed on 2 July 2025).

Martinez, L. (2018). Measuring The Conductivity Of Very Dilute Electrolyte Solutions, Drop By Drop. *Quim. Nova*, 41(79), 814-817.

Nisanci, M. C. (2021). Su Kayiplari Icin Akilli Su Sayaclari ile Yapay Zeka Tabanli Otomasyon Tasarimi, Akdeniz Universitesi, FBE, Yuksek Lisans Tezi

Nitta, J., Kondoh, S., Okanoya, K., & Tachibana, R. O. (2024). Spectral consistency in sound sequence affects perceptual accuracy in discriminating subdivided rhythmic patterns. *PLOS ONE*, 19(5), e0303347.

Oz, E. (2023). https://elmor.com.tr/upload/files/content_2023-02-24_14-00-51.pdf

Ozturk, Emre. Asst. Prof. Dr., Electrical - Electronics Engineering, Faculty of Engineering, Hasan Kalyoncu University.

Republic of Turkey Ministry of Environment, Urbanization and Climate Change, (2021). Water and Loss and Leakage Monitoring Systems Technology Review Report.

Santoro, R., Moerel, M., De Martino, F., Goebel, R., Ugurbil, K., Yacoub, E., & Formisano, E. (2014). Encoding of natural sounds at multiple spectral and temporal resolutions in the human auditory cortex. *PLOS Computational Biology*, 10(1), e1003412.

Stilp, C. E., & Goupell, M. J. (2015). Spectral and temporal resolutions of information-bearing acoustic changes important for understanding speech. *The Journal of the Acoustical Society of America*, 137(2), 911–924.

TSI, (2023). Turkish Statistical Institute.