Chapter 2

Preliminaries and related work

This chapter presents the preliminaries about the various techniques used in this thesis. We also describe state-of-the-art work covering the strategies to capture different challenges encountered while assessing and monitoring the river water pollution level. We specially covers the different research works in the following sections:

2.1 Preliminaries

This section covers the overview of Internet of Things followed by knowledge distillation technique, Long Range communication Technology (LoRa), and game theory, used in this thesis.

2.1.1 Overview of Internet of Things

Internet of Things (IoT) plays a significant role in the field of water pollution assessment and monitoring. It entails a network of physical IoT devices equipped with sensors, capable of exchanging data over the Internet. These IoT devices have the capacity to measure essential water quality parameters such as pH, Dissolved Oxygen (DO), turbidity, Nitrates (NO2), Biochemical Oxygen Demand (BOD), Fecal Coliforms (FC), and more, enabling them to estimate water pollution levels accurately. These IoT devices are proficient in transmitting water quality data to a central base station via a communication network. However, a notable challenge faced by IoT devices is their constrained storage, processing, and power resources. In our research, we tackled this challenge by deploying IoT devices integrated with a compressed deep neural network, allowing us to identify water pollution levels with a satisfactory level of accuracy. In [5], the authors proposed a system for water pollution monitoring framework using sensor interfacing devices such as the Raspberry Pi. The authors introduced a system for monitoring water contamination employing IoT technology, which leverages machine learning techniques like Fast Fourier Transform (FFT) and Support Vector Machine (SVM) to detect and identify instances of water contamination in [6].

Based on numerous experiments, it is evident that the Internet of Things (IoT) has the potential to unlock novel opportunities and applications across various sectors related to the environment. Instantaneous queries can empower organizations to acquire valuable insights, make well-informed decisions, and engage with individuals in real-time. The outcomes hold significant social and economic implications across various domains, encompassing issues such as safeguarding water quality, preserving natural resources, optimizing crop management, enhancing precision in agriculture, managing agricultural expenses, improving weather predictions, and monitoring air quality [7,8].

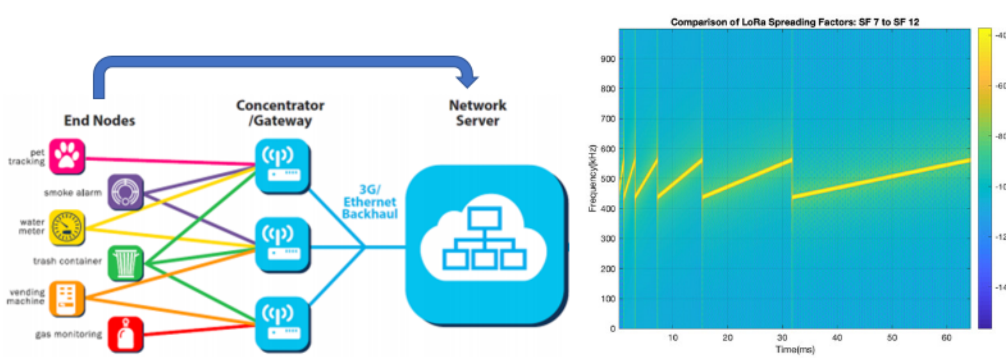
2.1.2 Overview of Knowledge Distillation

Knowledge distillation (KD) is a machine learning technique used to transfer knowledge from one model to another. It typically involves training a smaller, simpler model to mimic the behavior of a larger, more complex model. The primary goal of knowledge distillation is to transfer the generalization and knowledge learned by the teacher model to the student model, making it more efficient and practical [9, 10]. Knowledge distillation is a powerful technique for transferring knowledge from a large and complex model to a small model to improve the performance of the small models, which can be sufficient for practical deployment under real-world constraints. Knowledge distillation can significantly reduce the memory and computational requirements of a model while maintaining a performance similar to that a of cumbersome model. A small model was trained on large amounts of pseudo-data labelled by a higher-performing ensemble and optimized to match the logit of the compressed model to the logit of the ensemble to achieve compression. The logits in the DNN are the feature vectors of one layer before softmax or the last layer of the network. In other words, logits are also referred to as unnormalized predictions of a DNN. Deployment of the trained compressed network on IoT devices can achieve the desired accuracy.

Knowledge distillation is commonly used when you have a large, computationally expensive model that you want to deploy on resource-constrained devices or in applications where efficiency is crucial. By distilling the knowledge from the teacher model into a smaller student model, you can strike a balance between model size and performance. In contrast to prior research, in [11] utilized two distinct teachers in their approach. One of these teachers was trained from the beginning, guiding the student model toward the optimal pathway for reaching the final logits. The other teacher, pre-trained, was employed to emphasize a specific critical region that is relevant to the assigned task. The authors in [12] introduced a framework in which a substantial model oversaw and supervised the entire training procedure of the smaller, lightweight model. Furthermore, the lightweight model was designed to share parameters with the larger model, enabling it to directly access low-level representations from the teacher.

2.1.3 Overview of Long Range Communication Technology

Long-range communication technology (LoRa) encompasses the techniques and systems employed to transmit data or information across substantial distances, typically exceeding the capabilities of conventional short-range communication technologies such as Wi-Fi or Bluetooth. These technologies play a vital role in applications demanding data transmission across expansive geographical regions, whether for purposes like remote monitoring or the deployment of IoT solutions [13]. The architecture of a LoRa system typically encompasses a range of key components, including end devices, gateways, network servers, application servers, the LoRaWAN protocol, and cloud services. End devices refer to the data-collecting and transmitting equipment, such as sensors and IoT devices, often relying on battery power for operation. They establish communication with gateways. LoRa gateways function as base stations, acting as intermediaries between end devices and network servers. They receive data from end devices and relay it to network servers, effectively covering a considerable geographic area. Network servers play a pivotal role in managing communication between gateways and application servers. Their responsibilities include data routing, device authentication, and network configuration management. These network servers can either be hosted by a LoRaWAN network provider or deployed locally. Application servers are responsible for receiving data from network servers and processing it for specific applications or services. They can execute tasks like data analytics, triggering actions, and delivering data to end users. In some scenarios, data from application servers may be further processed, stored, or integrated with other systems through cloud services. The architecture of lora is as shown in Fig. 2.1. A new array of protocols and technologies has



(a)Architecture of LoRa (b)Spreading Factor

Figure 2.1: Architecture and spreading factor of LoRa

arisen to cater to the communication needs of the IoT, known as Low-Power Wide Area

Networks (LPWAN) [14]. In a more informal context, one could think of LPWAN as being to the IoT what WiFi was to consumer networking. LPWAN achieves this by providing radio coverage over a vast area through the use of base stations, while adjusting transmission rates, transmission power, modulation, duty cycles, and more. This results in end-devices with exceptionally low energy consumption when connected to the network [15]. In the context of LoRa (Long Range) technology, several parameters and resources are important for configuring and optimizing LoRa communication.

The Spreading Factor (SF) stands out as one of the most pivotal parameters within LoRa technology, exerting influence over the communication's range, data rate, and reliability. LoRa encompasses several key resources and parameters, including SF, bandwidth, transmit power, error coding rate, duty cycle, adaptive data rate, guard bands, acknowledgment mechanism, maximum payload size, join procedure, frequency bands, and Time-on-Air (ToA). Spreading factor, in particular, is an indispensable asset within the LoRa framework, shaping how data propagates across time and frequency. LoRa devices employ a spectrum of spreading factors, such as $SF7$, $SF8$, $SF9$, $SF10$, $SF11$, and $SF12$, with higher SF values offering extended range at the expense of slower data rates [16]. The choice of the appropriate SF plays a vital role in striking the right balance between range and data rate for a given application. Moreover, the bandwidth allocation, often specified as $125kHz$ or $250kHz$, plays a pivotal role in influencing data rates and sensitivity within LoRa devices. Narrower bandwidths grant a greater range at the cost of reduced data rates, while broader bandwidths facilitate higher data rates at the expense of a shorter range. Additionally, the level of transmit power dictates the strength of LoRa transmissions. Tweaking transmit power has the potential to impact communication range and reliability, with higher power levels extending the range while potentially consuming more energy. Simultaneously, the coding rate, represented as a fraction like 4/5, holds sway over error correction. Higher coding rates bolster error correction capabilities, albeit resulting in lengthier transmission times.

This comprehensive understanding of these resources and parameters is instrumental in optimizing LoRa networks for diverse applications.

2.1.4 Overview of Game Theory

Game theory is a mathematical and strategic framework used to analyze and model the interactions and decision-making processes of rational agents in situations where the outcome of each agent's choice depends on the choices made by others [17, 18]. In the context of game theory, there are several key entities and elements that play essential roles in analyzing and understanding games such as, players, startegies, actions, and payoffs as shown in the Fig. 2.2. Participants in a game are the individuals or entities engaged in the gameplay, with each making decisions or selections that have a direct impact on the ultimate result of the game. These participants can encompass individuals, corporations, nations, or any other pertinent entities relevant to the context. Strategies encapsulate the potential actions or choices available to each participant within the game, outlining the spectrum of viable moves at their disposal. A participant's strategy is determined by their individual preferences and goals. Payoffs, often denoted as utility, signify the consequences or rewards linked to various combinations of strategies chosen by the participants. These rewards can take the form of financial gains, utility, or any other pertinent measure of achievement or satisfaction for the participants. Game theory introduces a range of equilibrium concepts to explore stable outcomes. Some commonly employed equilibrium concepts include the Nash equilibrium, subgame-perfect equilibrium, and Bayesian Nash equilibrium, among others. Nash equilibrium stands as a cornerstone concept in the field of game theory. It represents the point of convergence for best responses, signifying that each player is strategically selecting their optimal action in response to the actions of all other players. A Nash equilibrium is inherently self-sustaining and self-enforcing, where no player finds it advantageous to unilaterally deviate from the agreed-upon strategy. It is the

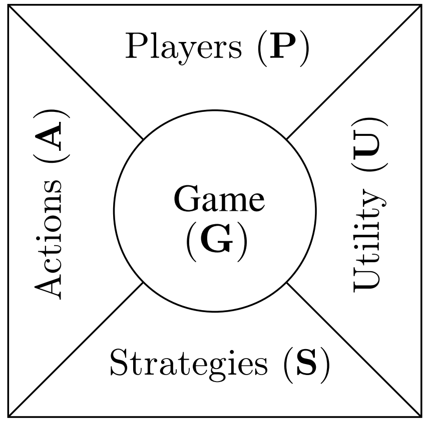


Figure 2.2: Illustration of different entities of a game.

outcome where no player possesses an incentive for independent deviation and is often regarded as a no-regret outcome. This principle is employed to determine the dynamics of best responses in strategic decision-making. A Nash equilibrium, within the realm of game theory, characterizes a scenario where every participant in a game optimally selects their course of action, factoring in the choices made by all other participants. In essence, it represents a condition where no player can gain an advantage by independently altering their strategy, assuming that the strategies of all other players remain unchanged [19]. In Nash equilibrium, every player plays a best response against the other players simultaneously. Nash equilibrium always maximizes the total utility of the two players. The decisions made by each player are considered optimal since they are aware of the other player's options. It results in a win-win situation since each player gets the result that is the best possible result, given the actions of the other player. First of all, the Nash Equilibrium assumes that players are rational enough to choose the most optimal strategy.

2.2 Related work on noisy labels in dataset

The inclusion of erroneous or noisy labels within the training dataset can have detrimental effects on the classifier's performance in the context of recognition. In this section, we explore previous research efforts aimed at integrating various techniques to address and mitigate the presence of noisy labels within the dataset. Table 2.1 provides a summary of the properties addressed by the current methodologies and highlights distinctions in the following aspects:

- Is the utilization of deep learning-based (automated) features being considered?
- Methods for addressing noisy labels, such as adapting loss functions to account for noisy labels, with the aim of enhancing performance during training with noisy data.
- Do we require information regarding the concentration of noisy labels, *i.e.*, the degree to which noisy labels are prevalent?

Authors in [20] introduced theoretically-derived loss functions designed to withstand the presence of noise in training data. These loss functions represent a more comprehensive adaptation of conventional categorical cross-entropy and mean absolute error loss functions. They asserted that these innovative loss functions have the potential to enhance the resilience of any deep neural network when faced with the challenges of noisy labels. Next, the authors in [21] effectively tackled both the issues of noise and class imbalance within the dataset simultaneously. They chose various under-sampling techniques to employ their proposed method, incorporating k-nearest neighbor-based noise filters simultaneously addressed the noise and class imbalance problems in the dataset. They selected different under-sampling schemes to implement the proposed technique using the k-nearest neighbour based noise filters. Further, the authors in [22] introduced a deep learning-based approach utilizing two concurrently trained classifiers to address noisy labels. They asserted that this approach led to a reduction in the frequency of model training updates. proposed a deep learning-based approach with two classifiers that are trained simultaneously to handle noisy labels. They claimed to reduce the number of updates during the model training. Likewise, the authors in [23] employed a collection of reliable data with pristine labels to alleviate the adverse impact of noisy labels within the training dataset. The authors in [24] introduced a method to manage noisy labels within the training dataset. The authors presented a deep learning-based joint optimization framework, which concurrently optimized the loss function and predicted labels to address the issue of noisy labels in the training dataset. They contended that noisy labels were corrected during training through a series of alternating network parameter updates. Subsequently, the authors in [25] adopted the approach of updating network parameters as a means to address noisy labels within the training data. They introduced a framework that allowed for the concurrent updating of network parameters and the estimation of class labels. In the end, the issue of noisy labels within the training data can be addressed by employing two distinct networks for class label prediction [26]. The authors in [26] aimed to minimize the disparity between the two networks used in the training process.

Table 2.1: A comparative summary of the existing work for handling noisy labels in the dataset.

Work	Year	Deep learning features	Loss Function Modification	Noise concentration information
Zhang *et al.* [20]	2018	✓	✓	✓
Kang *et al.* [21]	2017	✗	✓	✓
Malach *et al.* [22]	2017	✓	✓	✓
Hendrycks *et al.* [23]	2018	✓	✓	✓
Tanka *et al.* [24]	2018	✓	✓	✓
Yi *et al.* [25]	2019	✓	✓	✓
Wei *et al.* [26]	2020	✓	✗	✗

2.3 Related work on River Water Pollution Assessment

In this section, we discuss different water pollution assessment existing approaches used in the prior research works to assess the pollution of the river water. We mainly discuss the following research works. Menon et al. [27], considered the problem of identifying the river water quality. They proposed a mechanism for water quality monitoring by evaluating its physical parameters such as, pH, DO, temperature, turbidity and chemical parameters such as, sulphate, ammonia, and nitrate. The processing of these parameters to decide the water quality has been done ex-situ on the base station using statistical features. They have not incorporated deep learning techniques to extract the water quality parameters. Next, Randhawa et al. [28], the authors addressed the problem of identifying the water pollution from various remote sensing data of different sources. They proposed a low-cost IoT-based solution for handling the issues encountered during the assessment of water quality. The authors provided the solution by incorporating first-order correlations and the authors used moving average to filter out the noise from sensing data. They developed continuously updated water quality inversion model which makes water quality inversion an easy mean of obtaining a real-time monitoring of water using Support vector machine (SVM) regression with Radial Basis Kernel (RBF). Their approach does not include automatic extraction of the water features to decide the pollution level. Next, Gupta et al. [29] resolved the problem of water pollution monitoring by early classification of the river water using time series data and machine learning technique. The authors considered the problem of how to classify the rivers in the absence of geographical information. Here, the authors incorporated gaussian classifier and game theory based approach to monitor the river water. They do not consider the automatic annotation of the sensory data.

Furthermore, Cheng et al. [30] analyzed the impact of increasing concentration of nitrogenous pollutants on the environment, especially near the bank of the river. Finally, Kadir et al. [31] designed a smart sensor node that incorporates multiple sensing devices to accumulate several parameters associated with polluted river water. They utilized statistical methods for deciding the river water pollution and for giving flood alert messages. Next, in the previous work [32], the authors utilized Thoreau which is an Internet Of Underground Things (IoUT) testbed on an university campus that collects and curates time and geo-tagged data on an open platform on the cloud. It is based on Sigfox design and operates in the 900 MHz unlicensed bands with frequency hopped and narrow-band operation. It is also not considered automatic labelling of the sensory data. In [33], the authors addressed the problem of identifying the source of the pollution. They presented a centroidal Voronoi tessellation-based motion control method for pollutant distribution modeling using mobile nodes. They have not incorporated the deep learning method which extract the features automatically. Overall, in existing work [28, 29, 32, 33] on river water datasets, machine learning techniques (e.g., support vector machine, kNN, linear regression etc.) are employed which requires statistical features. Such dependency on the statistical features can be eluded by adopting deep learning techniques (such as long short term memory, convolutional neural network, etc.) that incorporate automatic feature extraction capability.

In the existing work [34], the authors have predicted heavy metal (*i.e.* phycocyanin concentrations) pollution in groundwater by developing stacked autoencoder deep neural network. Next, in [35] argues that integrated assessment models can provide insights that can support the development of hydroeconomic optimization models using intertemporal decision-making and economic valuation for resource systems management such as, water pollution. In the prior work [36], the authors concentrated on the problem of recognizing the source of groundwater pollution. Their research work identified whether the pollution is due to the anthropogenic activities such as, agricultural waste, untreated domestic waters, or due to natural processes such as, rock weathering, intrusion of sea water *etc.*. They developed a neural network model to identify the source of the pollution go get the clear cut view of quality of the groundwater for its specific purposes utilization. In overall, The prior studies [29, 32, 34–37] on river water do not consider any automated annotation mechanism to label the data instances. As in the absence of an automated mechanism, it is infeasible to annotate a large dataset that can improve the performance of the built classifier in learning technique. Thus, there is a need for an automated mechanism for labeling a large unlabeled dataset.

The number of water parameters plays a crucial role in determining the water pollution. Very few parameters will not be able to provide the sufficient information about pollution. In [28], the authors used only one water parameter turbidity which is not enough competent to convey the information regarding water pollution and in Gupta et al. [29], the authors incorporated four parameters such as, pH, EC, DO, and Turbidity to decide the water pollution as the data is not available for some of the parameters for Godavari, Yamuna and Ganges rivers. The research work in Cheng et al. [30] consists of six water parameters such as, temperature, pH, DO, salinity, flow rate, water level to recognize the condition of river water. Next, Tamarin et al. [37], developed an experimental platform to facilitate in situ assessment of the river water quality. They have statistically analyzed the value from a acoustic love wave sensor having a microfluidic chip. The authors included six parameters, namely, turbidity, the depth at which the sample was collected, the dissolved oxygen, the conductivity, the temperature and the pH for assigning labels to the sensory data, but it is not practical to receive the sensory values from all sensors at the same time. Further, the authors incorporates phycocyanin concentration, only one parameter in [34] to determine the water pollution.

Overall, the previous work [28, 29, 34, 37] on river dataset use various water parameters such as pH, electrical conductivity, dissolved oxygen, turbidity, *etc.*, for assigning labels to the data instances. As it is impractical to simultaneously obtain sensory values from all the sensors for a data instance. Therefore, the annotation mechanism must use a few parameters for labeling the data instances. The existing work [28, 29, 32–37] on river water do not adopt any mechanism that is capable of handling noisy labels in training instances *i.e.* model may be trained on the wrong labels by handling the noise to enhance the performance of the model. Hence, a noise handling technique must be incorporated during training that improves the performance of the build classifier. In [38], the authors addressed the accurate estimation of coastal water quality parameters (WQPs) issue developing an ensemble ML-based model. The ensemble ML model was applied to estimate chlorophyll-a (Chla), turbidity, and dissolved oxygen (DO) based on satellite images. The optimal input features for each WQP were selected from eight spectral bands and seven spectral indices. In [39], the authors investigated the water quality status of 96 deep agricultural wells using WQI and the fuzzy hierarchical analysis process of the water quality index (FAHP-WQI). The authors included three Machine Learning (ML) algorithms, namely, Gene Expression Programming (GEP), M5P Model tree, and Multivariate Adaptive Regression Splines (MARS) to predict WQI. The authors also investigated the water quality for agricultural and drinking purposes using Wilcox and Schoeller charts. In [40], the authors addressed the problem of detecting the quality of groundwater. To solve the problem the authors estimated the Weighted Arithmetic Water Quality Index (WA-WQI). The authors developed four machine learning (ML) models including artificial neural network (ANN), support vector machine (SVM), random forest (RF), and extreme gradient boosting (XG-Boost) in addition to multiple linear regression (MLR) for WA-WQI prediction of groundwater quality.

Table 2.2: A Comparative summary of the existing literature on water pollution assessment. $\#TE$, $\#TU$, $\#S$, $\#A$, $\#N$, $\#C$, $\#ORP$, $\#SA$, AND $\#FR$ denote Temperature, Turbidity, Sulphate, Ammonia, Nitrate, Conductivity, Oxygen-Reduction Potential, Salinity, and Flow Rate, respectively.

Paper Id	**Processing**		**Features**		**Data**	**Parameters**
	In-situ	**Ex-situ**	**Statistical**	**Deep**	**Sensory**	
[27]	×	✓	✓	×	✓	pH, #TE, #TU, DO, #S, #A
[41]	×	✓	×	✓	✓	#TE, pH, #C, #ORP
[37]	✓	×	✓	×	✓	#TU, DO, #C, #TE, pH
[29]	×	✓	✓	×	✓	pH, #C, #TU
[28]	×	✓	✓	×	×	#TU
[42]	×	✓	×	✓	×	#N
[43]	✓	✓	✓	×	✓	#TE, DO, pH, #SA, #FR

Table 2.2 summarizes the comprehensive overview of some of the existing approaches on river water assessment that we have discussed in this chapter. The table shows that most of the existing work considered statistical methods to extract the water parameters instead of automatic parameter extraction while solving the water assessmnet problem.

2.4 Related work on River Water Pollution Monitoring

Here, in this section, we discuss different river water pollution monitoring existing systems used in the previous research work to monitor the pollution of the river water. We mainly discuss the following research works which considered the deep neural network. Authors in [44] proposed a cost-effective remote sensing mechanism for monitoring and analyzing the quality of river water. They have used a neural network for analyzing different parameters of river water. The authors claim to solve the hurdle of monitoring the quality of river water in the logistically difficult area. In [45] authors used the neural network for predicting the quality of river water. They also developed a mechanism of artificially creating the data values for those instances that are not recorded during data collection. Zhang *et. al.* [46] utilized nonlinear autoregressive neural network to predict the concentration of bacteria named Escherichia coli near the beach site. Through experimental analysis, they claim that the use of nonlinear autoregressive neural network outperforms the existing approach for predicting bacterial concentration. Authors in [47] proposed a neural network-based model for capturing the dynamical variation in the chlorophyll value of the water. They defined an optimization problem for cost-effective on sight processing and enhancing the accuracy of prediction. Taipalmaa *et. al.* [48] presented a mechanism for analyzing river water quality using segmentation of water surface images captured using a drone camera. They utilized temporal and spatial features of the deep learning model to classify the segmented image and determine the level of pollution in the river water. Authors in [49] proposed a model for measuring the turbidity of the river water using hyper-spectral remote sensing data. They applied the random forest-based ensemble model for analyzing the hyper-spectral data.

In [50] authors developed a low-cost sensor node for estimating the quality of water. The authors deploy the sensors inside the pipe with running water to analyze its suitability for drinking. The authors also developed an event detection algorithm for recording the data of different parameters associated with the quality of river water.

Mondal *et. al.* [51] built a battery-free pH sensor tag for passively monitoring the pH of the water. The developed pH sensor tag can wirelessly transmit the data at a data rate of 0.595 Kbps. Wang *et. al.* [52] proposed a low-cost designing principle for developing a turbidity sensor using transmitted light and scattered light passed through the water. Authors have justified the cost-effectiveness and high order accuracy in estimating the turbidity of the water. Authors in [53] designed and developed a water monitoring system by analyzing different parameters. In [54] authors developed a system for collecting garbage from the river water. They proved the effectiveness of their proposed system by designing a prototype robot, which incorporates low powered IoT devices for coordination and control.

Table 2.3: A summary of existing work on water pollution monitoring.

Paper	Statistical features	Deep features	Prototype design	Experimental/ Simulation analysis	Primary goal			Communication techniques
					Cost effectiveness	Energy efficiency	Accuracy	
[44]	✓	×	×	✓	✓	×	×	×
[45]	✓	×	×	✓	×	×	×	×
[46]	✓	×	×	✓	×	×	✓	×
[47]	✓	×	×	✓	✓	×	✓	×
[48]	×	✓	×	✓	×	×	✓	×
[49]	×	✓	×	✓	×	×	✓	×
[50]	✓	×	✓	×	✓	✓	×	ZigBee/3G
[51]	✓	×	✓	×	×	✓	×	RFID
[52]	✓	×	✓	×	✓	×	✓	×
[55]	✓	×	✓	×	✓	×	×	GSM
[56]	✓	×	✓	×	✓	✓	×	Bluetooth

Table 2.3 summarizes the comparative overview of existing approaches on water quality monitoring. It illustrates that none of the existing work have simultaneously considered energy efficiency, accuracy, and low cost as its primary objective. It motivates us for this work, where, we propose a system which consumes minimum energy and gives high accuracy. Further, the system uses LoRa for long-range communication without using any addition relay, high-cost, or power-hungry networking device.

2.5 Conclusion

This chapter presented the background of how to quantify the water condition in human understandable form so that the water can be utilized for different applications. Further, the chapter presented the overview of the technologies namely, Internet of Things, knowledge distillation, long range communication technology and game theory incorporated in our research work. Next, the chapter provided the existing work on handling noisy labels in the dataset. Later, the chapter provided the existing work on river water pollution assessement. Some of the selected papers on water pollution assessment, with their objective, approach, and limitations, have been discussed in this chapter. Moreover, the chapter provided the existing work on river water pollution monitoring. Some of the selected papers on water pollution monitoring, with their objective, approach, and limitations, have been discussed in this chapter. The existing literature is grouped based on the handling of the noisy labels, river water pollution assessment and river water pollution monitoring.

Table 2.2 summarizes the comprehensive overview of some of the existing approaches on river water assessment that we have discussed in this chapter. The table shows that most of the existing work considered statistical methods to extract the water parameters instead of automatic parameter extraction while solving the water assessment problem. Not a single research work considered the automatic labelling of a huge sensory data. Moreover, the existing research work has not been considered the noisy labels during training data instances.

Table 2.3 summarizes the comparative overview of some existing work on river water monitoring that we have discussed in this chapter. The table shows that none of the existing work have simultaneously considered energy efficiency, accuracy, and low cost as its primary objective. Next, it illustrates that most of the existing work considered the communication techniques such as, ZigBee/3G, Bluetooth, RFID, GSM. But, none of the prior work has considered Long range communication technology.