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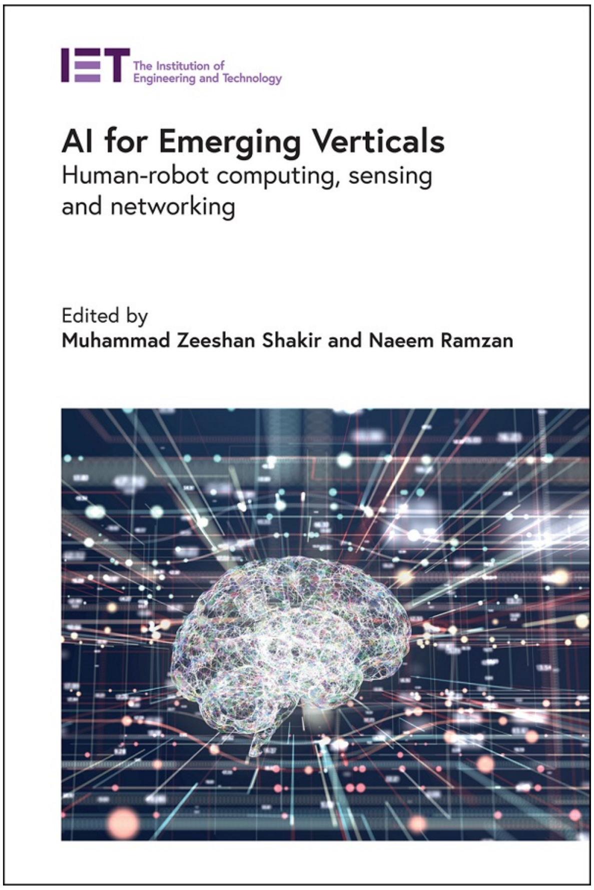

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Human-robot computing, sensing and networking

Edited by Muhammad Zeeshan Shakir, Naeem Ramzan

By specializing in a vertical market, companies can better understand their customers and bring more insight to clients in order to become an integral part of their businesses. This approach requires dedicated tools, which is where artificial intelligence (AI) and machine learning (ML) will play a major role. By adopting AI software and services, businesses can create predictive strategies, enhance their capabilities, better interact with customers, and streamline their business processes.

This edited book explores novel concepts and cutting-edge research and developments towards designing these fully automated advanced digital systems. Fostered by technological advances in artificial intelligence and machine learning, such systems potentially have a wide range of applications in robotics, human computing, sensing and networking. The chapters focus on models and theoretical approaches to guarantee automation in large multi-scale implementations of AI and ML systems; protocol designs to ensure AI systems meet key requirements for future services such as latency; and optimisation algorithms to leverage the trusted distributed and efficient complex architectures.

The book is of interest to researchers, scientists, and engineers working in the fields of ICTs, networking, AI, ML, signal processing, HCI, robotics and sensing. It could also be used as supplementary material for courses on AI, machine and deep learning, ICTs, networking signal processing, robotics and sensing.

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Chapter 17

Surface water pollution monitoring using the Internet of Things (IoT) and machine learning

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Water is one of the basic resources required for human survival. However, pollution of water has become a global problem. 2.4 billion people worldwide live without any form of water sanitation. This work focuses on case study of water pollution in Pakistan where only 20% of the population has an access to good-quality water. Drinking bad-quality water causes diseases such as hepatitis, diarrhea and typhoid. Moreover, people living close to the industrial areas are more prone to drinking polluted water and catching diseases as a result. Yet, there is no system that can monitor the quality of water or help in disease prevention. In this work, an Internet of Things (IoT)-enabled water quality monitoring system is developed that works as a stand-alone portable solution for monitoring water quality accurately and in real time. The real-time results are stored in a cloud database. The public web portal shows these results in the form of data sheets, maps and charts for analyzing data. Further, this data along with the collected data of past water quality is used to generate machine learning (ML) models for prediction of water quality. As a consequence, a model for prediction of water quality is trained and tested on a test set. The predictions on the test set resulted in a mean squared error (MSE) of 0.264.

17.1 Introduction

Water is a vital requisite for existence of life on the Earth; however, this vital resource is in danger. One out of nine people worldwide uses drinking water from unsafe sources [1], while 2.4 billion people live without any form of sanitation [1]. In this work, a case study of water pollution of Pakistan is presented. Water is of utmost importance in Pakistan due to its agronomic nature and due to unavailability of drinkable water

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to more than 80% of its population [2]. So the majority of the population remain oblivious to the consequences of drinking polluted water, i.e., development of diseases such as hepatitis, diarrhea and typhoid. People living close to the industrial areas are more prone to drink polluted water and catch diseases as a result [3,4]. Pakistan is the seventeenth country across the globe facing acute water crisis. Despite of all the efforts made by government, there has been no solution that could decrease the rate of mortality due to water pollution. In today's world of smart cities and advanced technologies that can solve most complex problems, this basic problem still remains unresolved in Pakistan. The laboratories set up by the government of Pakistan log water quality data manually and perform tests on it in chemical labs. These labs are very few and the data they produce is not used for effective analysis. This monitoring process is also expensive, non-real time and unavailable in majority of the cities of Pakistan.

To solve this problem, an IoT-enabled solution for real-time monitoring of water quality parameters is developed. It can monitor temperature, pH, dissolved oxygen (DO), conductivity and turbidity. These parameters are used to calculate water quality index (WQI) [5] that is an international unit for measuring water quality. These IoT nodes can be deployed in the form of a network at a water reservoir or any source of water for urban areas. This IoT network of water quality monitoring nodes is connected to the internet in a way that the data is continuously synchronized with the back-end web server. The users of the system can browse the website to analyze and monitor the quality of water at various source points. Meanwhile, past data of water quality is used to generate ML model for prediction of future water quality data.

17.2 Literature review

This section contains review of related literature. In [6], a system for monitoring water quality is developed. It monitors parameters such as pH and turbidity. It also uses a cloud back end to store the data. In [7], a case study is presented on the monitoring of the water quality parameters such as turbidity, total dissolved solids (TDSs) and pH. Daud *et al.* in [2] collected water quality samples from all over Pakistan. They compared different parameters of water quality against NEQS (National Environmental Quality Standards) and WHO (World Health Organization) standards. Majority of the samples indicated the presence of high total *coliform*, *fecal coliform*, *Escherichia coli* (*E. coli*) primarily due to the mix of sewerage water and secondarily due to the disposal of industrial wastes. It was recommended to install and maintain the treatment plants and ensure regular enforcement of NEQS. In [8], 46 piped water samples were collected across different places of Orangi Town, Karachi and tested for bacteriological and physiochemical analyses using WHO standards and National Standards for Drinking Water Quality that are considered to be the benchmark of comparative analysis. The statistical analysis for each of the parameters was performed and it was found that physiochemical parameters were well in limits except sulfates. However, bacteriological parameters such as total *fecal coliform* and total *coliform* counts were critically high, reflecting poor hygienic and sewerage conditions. Another research on the data set of river Ravi by sampling its data for 3 years, from Jan 2005 to Mar

2007, from 14 sampling stations is presented in [9]. In this study, 12 parameters, *COD (chemical oxygen demand), suspended solids, phosphorus, BOD (biochemical oxygen demand), DO, chloride, total nitrogen, sodium, nitrate, oil and grease, nitrite and total coliforms*, were tested.

There are several studies that used ML approaches. In [10], a research is described which is conducted on Rawal watershed, situated in Islamabad. A total of 663 water samples have been collected from 13 different stations and tested for *appearance, temperature, turbidity, pH, alkalinity, hardness as* $CaCO_3$*, conductance, calcium, TDSs, chlorides, nitrates and fecal coliforms* against WHO standards. A correlation analysis was performed to draw out the correlation among the parameters. In [11], research is conducted on the data set of 47 wells and springs (2006–13) acquired from the Ministry of Iran. The study considered 16 water quality parameters. The method used in this study was proposed by Horton (1965) to calculate WQI. There were three methodologies that were employed: artificial neural network (ANN) with early stopping, ANN with ensemble averaging and ANN with Bayesian regularization. The correlations were computed between the observed and the predicted values of WQI and were found to be 0.94 and 0.77.

Some studies used IoT-enabled systems. In [12], a generic IoT system for real-time water quality monitoring is discussed. It comprises sensors that read parameter readings, then those parameter readings are transmitted to a controller through wireless communication devices attached with sensors. The controllers, through some wireless communication technology, store those sensor readings to a data storage that are reflected in some customized application. In [13], authors proposed a general framework for IoT system for real-time water quality monitoring, demand forecasting and anomaly detection. For an IoT system, they have considered the parameters *turbidity, chlorine, ORP, nitrates, pH, conductivity and temperature* and used their sensors. Their proposed system is quite a general one and no data-set has been used to test it. In 2015, authors developed a real-time IoT-based water quality monitoring system using different water quality sensors [14]. They connected it to the Raspberry Pi minicomputer. However, the proposed system is not feasible and cost effective for large systems. In addition to that it only provides the feature of monitoring.

17.3 Methodology

In this section, we will discuss the methodology which was followed to conduct this study. The methodology can also be seen as a flow-chart in Figure 17.1.

17.3.1 Development of water quality monitoring IoT nodes

In this section, the development of the IoT nodes and all of its components is explained.

17.3.1.1 Selected parameters

Following parameters were chosen to be monitored by the system.

1. **Temperature:** Most of the water quality parameters are related to temperature; so when it is paired with other parameters, true values of these parameters can be found which are affected by temperature. In this way, it helps in WQI calculations.

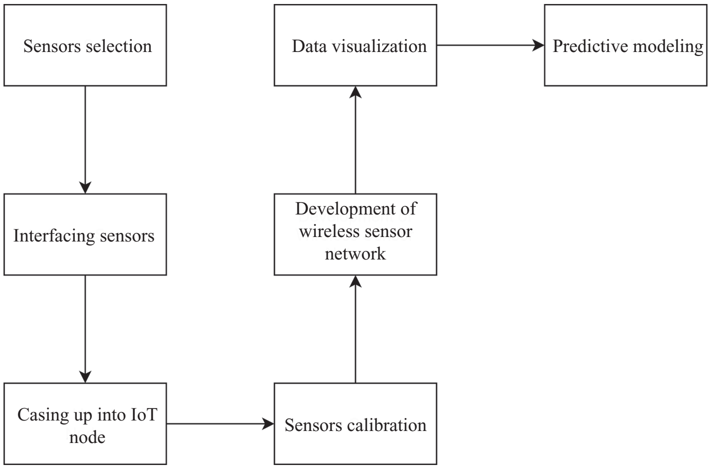

Figure 17.1 Methodology flow chart

2. **Dissolved oxygen:** It determines the health of water. Fish and aquatic animals cannot survive in water with low DO. So, it contributes to the overall WQI. It is monitored in mg/L, percent DO or ppm.
3. **Conductivity:** It measures the ability of water to conduct electricity through it. This depends upon the presence of certain ions present in the water. Pure water has poor conductivity due to the absence of impurities and ions. It is also used to calculate TDSs. It is monitored in µS/cm.
4. **pH:** It is a measure of how acidic or alkaline the water is. It can range from 0 to 14 with 0 being maximum acidic and 14 being maximum alkaline. Normal pH of drinking water lies in the range of 6–8.
5. **Turbidity:** It is the measure of haziness or cloudiness of water. Hazy or cloudy water is considered impure, so it contributes toward overall WQI. It is measured in NTU (nephelometric turbidity unit).

17.3.1.2 Sensors

Sensors are the most important part for any IoT-enabled monitoring system, as they influence the cost-effectiveness of the project. Also, the quality of sensors determines the quality of data generated by the system. Usually, there is a trade-off between the quality of sensor and its cost-effectiveness. The lower quality sensors are very cost-effective but the data they generate is not accurate. Also, these sensors are more prone to early retirement. On the other hand, the sensors from good brands are costlier, but the data they generate is highly accurate and reliable.

Research about various brands providing sensors for water quality monitoring was done for finding the perfect combination of cost-effectiveness and data accuracy. The search narrowed down to three options at the end, which were Libelium sensors, vernier sensors and locally available sensors. Libelium sensors were highly accurate but costly. On the other hand, local sensors were easily available and cheaper but they were inaccurate and unreliable. It is also found that these sensors were prone to early retirement. However, vernier sensors offered a perfect blend of accuracy and cost-effectiveness. They were accurate in readings and their error rates were comparable to that of Libelium. So, vernier sensors were chosen for this system. A brief detail of each of the sensors used is provided next.

17.3.1.3 Temperature sensor

Vernier temperature sensor monitors temperature of water in degree Celsius. The sensor as can be seen in Figure 17.2 has a probe made of steel which can be dipped in water. When powered, it generates a signal with readings of temperature in real time.

17.3.1.4 Dissolved oxygen sensor

Vernier DO sensor monitors the concentration of oxygen dissolved in water in mg/L. Similar to the temperature sensor, it is also a probe that can be dipped into water to generate readings. However, this probe has a membrane cap at the end which is filled with an electrode filling solution. The sensor can be seen in Figure 17.3.

17.3.1.5 Conductivity sensor

Vernier conductivity sensor monitors the conductivity of water in μS/cm. As can be seen in Figure 17.4, it also has a probe. The probe can be dipped into water to make the sensor generate readings. The sensor can be configured to work with different ranges of conductivity. There are three ranges of operation, thus the sensor can have three levels of sensitivity, which can be used in different types of situations. An

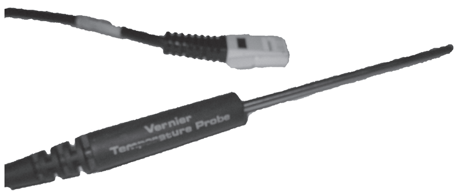

Figure 17.2 Vernier temperature sensor

Figure 17.3 Vernier dissolved oxygen sensor

Figure 17.4 Vernier conductivity sensor

Figure 17.5 Vernier pH sensor

important reason for monitoring conductivity is to calculate TDS contents in water as conductivity can be converted to TDS units quite easily.

17.3.1.6 pH sensor

Vernier pH sensor (Figure 17.5) monitors the pH level of water. It is also a probe that is dipped into water for the purpose of taking readings. The probe is stored in a 10% KCl solution. The storage solution keeps the sensor healthy and ready for instant use when it is not being used.

17.3.1.7 Turbidity sensor

Vernier turbidity sensor (Figure 17.6) monitors the turbidity of water in the range of 0–200 NTU. It has a closed chamber that contains a bottle. When the bottle inside is filled with water and the chamber is closed, the sensor monitors turbidity of this water by monitoring dispersion of light in the water.

17.3.1.8 Interfacing sensors

The sensors used here are generic sensors intended for use in laboratories. So, an interface had to be created between these sensors and the system. Arduino was used

Figure 17.6 Vernier turbidity sensor

Figure 17.7 British telecom plug

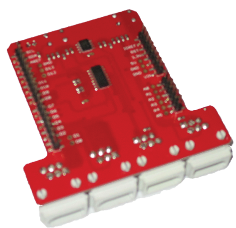

Figure 17.8 SparkFun Vernier Arduino Interface Shield

as the development platform, thus they had to be interfaced with Arduino board. All of the vernier sensors listed previously come with a British telecom plug for connection, which can be seen in Figure 17.7.

To create an interface between the Arduino and British telecom plugs of vernier sensors, SparkFun's Vernier Arduino Interface Shield was used (Figure 17.8). The shield has four British telecom sockets for vernier sensors. Two of the sockets support digital sensors, while the remaining two support analog sensors. The shield converts the readings from sensors to analog voltages ranging from 0 to 5 V. This output of shield is connected to analog ports on Arduino to record this voltage for each sensor connected to shield. As all of the sensors were analog sensors, three interface shields were needed for each node to create interface for five sensors.

17.3.1.9 Design of water quality monitoring IoT nodes

All the five sensors were connected to interface shields, and these shields were connected to Arduino. The Arduino microcontroller was programmed to calculate sensor readings from all the sensor voltages using calibration equations (explained later in the chapter). Also, ESP8266 was used as Wi-Fi module to send these values to web server. Later, the whole node was cased up for better portability. The final node after the design completion can be seen in Figure 17.9.

17.3.1.10 Sensors calibration

Now that the node is up and running, there was a need to verify and ensure that the sensors are properly configured to give accurate readings. For this purpose, the process of linear calibration was used. Vernier describes this process in its user manual for analog sensors calibration [15]. It is also explained in detail next.

For sensors provided, the values are mapped linearly from voltage values to sensor outputs using a line in XY-plane where sensor voltages are plotted on x-axis and actual parameter readings on y-axis. So, each voltage value maps to an actual parameter reading directly using this linear relation. This means that the equation of line can be used to translate between voltages and actual readings of parameters. The equation of line is

$$y = mx + c \tag{17.1}$$

where y is value with respect to y-axis, x is value with respect to x-axis, m is slope and c is intercept. Now, this equation for sensors can be rewritten as following:

$$actual\ reading = slope \times sensor\ voltage + intercept \tag{17.2}$$

Here, slope and intercept are fixed values for a sensor, as they define the line for relationship of that sensor's values with its voltage. These two values for each sensor need to be found for further evaluation of actual sensor readings (parameter

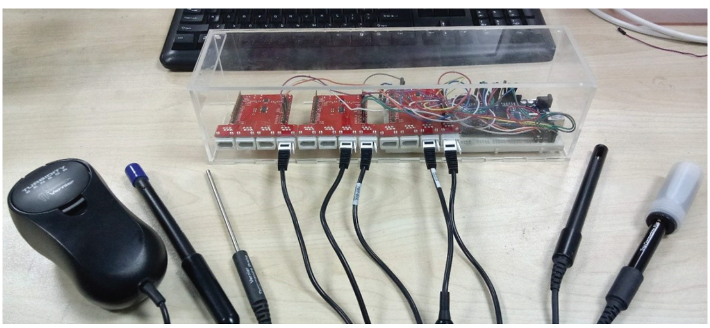

Figure 17.9 Design of water quality monitoring node

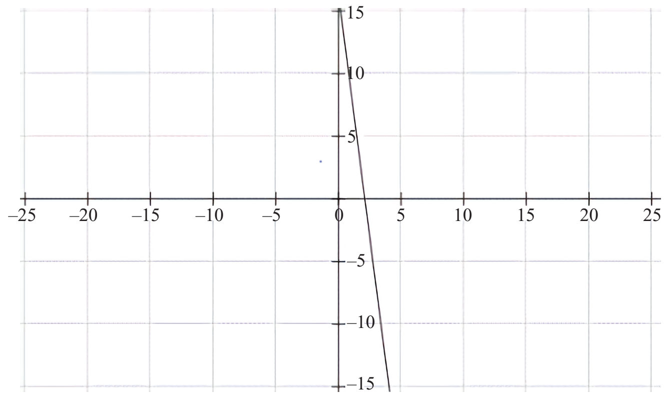

Figure 17.10 Linear calibration plot for pH

readings). For this purpose, two standard solutions are obtained whose readings are known. Then, sensor voltages are taken for these two solutions using sensors. Using these two (x, y) pairs with equation of two-variables, the system of two equations is then solved simultaneously. Hence, the values of slope and intercept for each sensor are obtained.

For example, for calibrating the pH sensor, solutions with pH 7 and 4.2 were used. Voltages of pH sensor for these two solutions were found and then the pairs of values were used to find slope and intercept of the calibration line. The calculated line for pH sensor after calibration can be seen in Figure 17.10.

It should be noted that it has to be done for each sensor unit and for each new IoT node as sensors are not sold pre-calibrated. Also, this ensures that the readings generated from all the sensors are accurate.

Linear calibration is a pre-built mechanism in monitors sold by vernier, with which sensors are attached and readings are obtained on-the-go. However, it was interfaced with an Arduino, so it had to be done separately. Two standard solutions for each parameter were used and the linear calibration equations were solved for each sensor. These equations were then programmed into Arduino. Now, it had the ability to calculate sensor readings on-the-go.

17.3.2 Development of wireless sensor network

After the development of IoT nodes, the back end to complete the wireless sensor network was created. This network of nodes followed the client–server model. The details of implementation are provided next.

17.3.2.1 Cloud back end

For any IoT system, internet connectivity is a crucial part. A cloud back end is deployed to complete the internet side of the IoT system. A PHP-enabled and MySQL-enabled web hosting server is used and an online database on the MySQL server is created. The structure of database is created in an order to support storing of all the parameters of water quality for any number of nodes simultaneously. The scripts in PHP are developed to create a RESTful API (application programming interface) on the server. The API provides data storage and data retrieval functions. The Arduino boards in the developed nodes are programmed to access this API over the internet and send sensor values to them. Thus, each node creates a packet containing values from every sensor and sends it to the API hosted at the server along with its node identification number. The API stores this data into the MySQL database. When a network of IoT nodes is deployed over a geographic area and each node has connectivity to the internet, the entire system is centralized using the web server as the common contact point. Also, the web server can be accessed anywhere in world to observe and analyze the stored data. This completes the loop of IoT-enabled monitoring. A website is also developed to display the data stored at the server. The services of this website are explained in more detail in later part of this chapter.

17.3.3 Data visualization

As the wireless sensor part is completed, there is a need to visualize the data and made it available to general public. For this purpose, a web portal is developed.

17.3.3.1 Web portal development

The web portal is developed with the following features:

1. Display **Data Sheets** for showing all the data stored at the server in tabular form. Users can access the data by node ID and see individual records.
2. Display **Maps** showing data geographically. Water quality by areas can be seen clearly in this view.
3. Display **Charts** for analyzing trend of data generated over time.

Some screenshots from the website can be seen in Figures 17.11 and 17.12.

Data Table

10 records per page

Search

Time/Date	Turbidity	pH	Disolved Oxygen	Conductivity	Temperature
2019-06-20 11:24:57	201.35	2.31	9.31	909.32	29.67
2019-06-20 11:24:57	201.35	2.31	9.31	909.32	29.67
2019-06-20 11:27:50	126.68	2.35	10.10	1022.98	29.48
2019-06-20 11:27:50	126.68	2.35	10.10	1022.98	29.48
2019-06-20 11:28:56	107.67	2.42	9.05	795.65	29.67
2019-06-20 11:28:56	107.67	2.42	9.05	795.65	29.67
2019-06-20 11:29:44	238.68	2.35	9.24	833.54	29.67
2019-06-20 11:29:44	238.68	2.35	9.24	833.54	29.67
2019-06-20 11:30:25	204.74	1.74	9.39	1136.65	29.48
2019-06-20 11:30:25	204.74	1.74	9.39	1136.65	29.48

Figure 17.11 Website snippet showing a data sheet

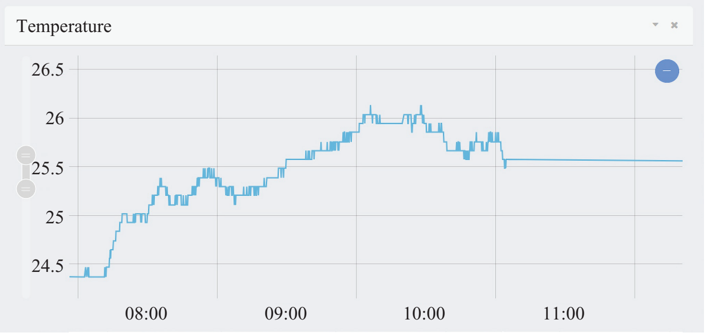

Figure 17.12 Website snippet showing a data chart for temperature

Figure 17.13 Data collection points on Rawal Dam

17.3.4 Prediction of water quality using machine learning

The prime objective of predictive modeling is to use the data generated by IoT nodes, as well as historic data from other sources to forecast the future trends of water quality. For predictive modeling, there must be an adequate size of data to be fed into the ML algorithms. For this purpose, following data was collected:

- Real-time data of water quality of 4 months (from September to December 2019) from Rawal Dam was collected. Rawal Dam is the main source of water supply to the city of Rawalpindi. This data was collected at regular intervals using the IoT nodes. The data collection points can be seen in Figure 17.13.
- The historic data of past 4 years (2015–19) of water quality was collected from Rawal Lake filtration plant. This data was combined with the IoT nodes data to make its size suitable for predictive modeling.

Table 17.1 Water quality classes

Quality class	WQI range	Description
Class 1	100–95	Excellent water quality
Class 2	94–90	Very good water quality
Class 3	89–80	Good water quality
Class 4	79–65	Medium water quality
Class 5	64–45	Polluted water
Class 6	44–0	Very polluted water

Table 17.2 Predictive model results

Error type	Error
Mean absolute error	0.276
Mean squared error	0.264

17.4 Results and discussion

The data from Rawal Dam was collected at its three inlet streams and one outlet stream for 4 months starting from September 2019. WQI of this data was calculated and it is classified according to the classes of WQI specified in literature [5]. As per the results of this classification, 0.0049% of the data lies in Class 5, while the remaining 99.9951% of data lies in Class 6 which is the poorest quality class as can be seen in Table 17.1. The average WQI is 22.99 with standard deviation of 8.52, while maximum and minimum are 61 and 6, respectively. This tells us that the quality of water that is being supplied from Rawal Dam is of extremely bad quality.

The data is then digitized and preprocessed in order to feed it into a long short-term memory (LSTM) neural network. LSTM is a recurrent-neural-network-based architecture, which has feedback points for processing the complete sequences of data instead of just one data point. LSTMs are used mainly for context-based or sequence-based data. The choice of LSTMs is due to two major reasons:

1. LSTMs are capable of finding trends in time series data. So, they have the ability to predict future values based on past data.
2. LSTMs perform better on sequential data as compared to conventional neural networks.

The neural network architecture had three layers. The first layer being the input layer contained 155 neurons, the second layer contained 200 LSTM units, while the third layer had 5 neurons. For each training iteration, data of last 31 days was fed to model for output of each day's data. So for each iteration, five parameters for

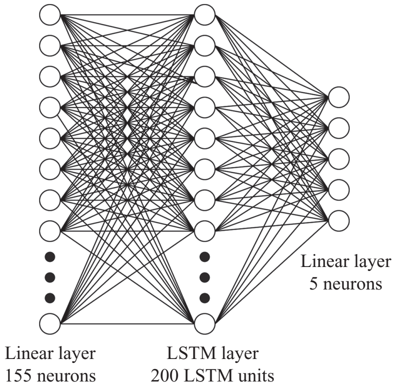

Figure 17.14 Neural network architecture

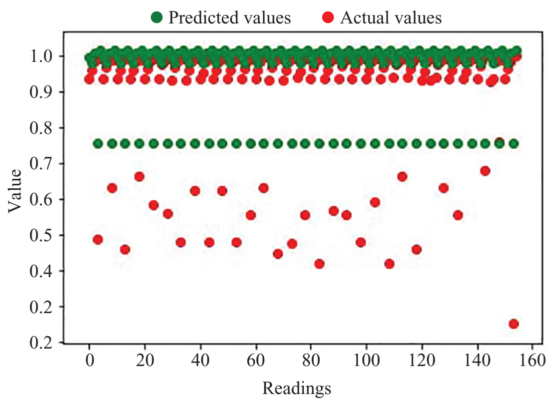

Figure 17.15 Ground truth and predicted values

31 days were used as input to forecast next day's data. This makes number of input parameters equal to 155 thus input layer's size and output parameters equal to 5 that was output layer's size. The network was not made deep to avoid over-fitting due to the low number of records in the data-set. The architecture of our network can be seen in Figure 17.14.

The framework used for training was PyTorch. For optimization, Adam optimizer was used with MSE loss function. To avoid the risks of over-fitting, the training was done only for 15 epochs. Out of the 48-month data records, the data of 47 months was used for training, while the remaining 1 month was used for testing. As per the results, the mean average error is 0.276, *R*-squared is 0.112, while MSE is 0.264 (Table 17.2). Also, the correlation between scaled actual and predicted values can be seen in Figure 17.15.

Neural networks always perform better with comparatively bigger data-sets than the one used here. However, in the absence of large amounts of data, the results produced are promising and can be used to predict water quality with good accuracy.

17.5 Conclusion and future work

The low adoption of modern techniques due to the lack of literacy, institutional capability to deliver technology and economic constraints has made Pakistan reliant on traditional system. The traditional tools for water quality monitoring are manually controlled, based on human intervention, rather than technology. Quality assessments are usually carried out in research laboratories where data is processed in non-real time. Toward such end, the development of an IoT-based system to monitor the quality of water in Pakistan is a promising alternative to traditional complex and ineffective approaches, thus providing a proper and near real-time assessment of water to the community. In order to ensure an accurate and reliable analysis in monitoring water quality, we need a large number of water samples where IoT resolves such issues of data collection, analysis and communication. The major outcomes of this research work are the development of low-cost indigenous solution based on latest technology, a system that offers near real-time water quality status by monitoring parameters such as pH level, turbidity, temperature, conductivity and DO, as well as the development of a state-of-the-art apparatus that provides water quality data with high temporal resolution through effective data communication. Such a system is beneficial not only for the water regulating and environment protection authorities but also for the research community and public at large.

An extension and future work of this research is predictive healthcare. For this purpose, the data of patients suffering from water borne diseases will be acquired. This data will be collected from a government hospital, where this data will help us to identify regions of poor water quality. It will also support us to get an insight of the seasonal variations affecting the water quality, the surroundings of the patient residence degrading the water quality and the time period when more cases with water borne diseases are reported to the local hospital. For predictive modeling, ML algorithms will be applied. The selection of the algorithm will be part of the research.

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