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Research thesis title:

IoT BASED INTELLIGENT HOUSEHOLD WATER CONSUMPTION MANAGEMENT SYSTEM

A dissertation submitted in partial fulfillment of the requirements for the award of

MASTERS OF SCIENCE DEGREE IN INTERNET OF THINGS-WIRELESS INTELLIGENT SENSOR NETWORKING

Submitted by

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February, 2022

DECLARATION

I, Mr. Gilbert Ndayisenga, hereby declare that this research report is my original work and has not been submitted before for any academic award either in this or other institutions of higher learning for academic publication or any other purpose. The references used here from other journals or materials are indicated in the references section.

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BONA FIDE CERTIFICATE

This is to certify that the research work report submitted is the original work done by **Mr. Gilbert Ndayisenga (REF:220014134)**, MSc.IoT-WISENET student at University of Rwanda /College of Science and Technology/African Center of Excellence in Internet of Things. According to my best knowledge the work reported here doesn't form a part of any other research work.

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ABSTRACT

Water is a principal resource in almost all kind of our lives like in homes; it is used for clearing, drinking and other many activities. Governments have already implemented strategic plans for this nature resource to be supplied where people live like in cities and villages. Although, there are millions of people continue living without proper access to this resources due to inadequate management and lack of its monitoring.

However, inadequate management of water resource services after it is produced and supplied can cause poor social economic development as well as poor human welfare. Consequently, this can lead to water planning or inability to the implementation of the strategic plans that the governments have already set. The decision making about water planning should also focus on the population growth of the targeted region. In the current research, we have not only designed an IoT based intelligent system that can monitor and manage household water consumption but also a predictive machine learning model that can predict the household water based on the population growth of the targeted region.

For monitoring the household water consumption, we have designed an IoT smart meter that can monitor the household consumption and connected to server in xamp platform. For machine learning modeling, we have built a predictive model in python using data merged from different institutions. Mainly 7 years water data from WASAC (2014-2021) and population data from Kigali city extracted based on two last consecutive censuses (2002-2012).

The predictive model was built using Random Forest algorithm and gave 96.1% and 91.3% of training and testing accuracies respectively. And finally the IoT based intelligent household consumption has been prototyped to monitor water consumption via dashboards by installing IoT smart water meter at household.

Keywords: Water, Machine learning, Population growth rate, Internet of Things, Mysql server

LIST OF SYMBOLS AND ABBREVIATIONS

AI: Artificial Intelligent

ACEIOT: African Center of Excellence in Internet of Things

AP: Access point

API: Application Programming Interface

CPU: Central Processing Unit

DHS: Demographic and Health Survey

DT: Decision Tree

EDPRS2: The Second Economic Development and poverty Reduction Strategy

HTTP: Hypertext Transfer Protocol

IoT: Internet of Things

ISR: Interrupt Service Routine

IP: Internet Protocol

FN: False Negative

FP: False Positive

KNN: K-Nearest Neighbors Algorithm

L: Liter

Min: Minute

ML: Machine Learning

MYSQL: My Structured Query Languages

MCu: Microcontroller

NISR: National Institute of Statistics of Rwanda

NST: National Strategic Transformation

RURA: Rwanda Utilities Regulatory Authority

RDHS: Rwanda Demographic and Health Survey

SDGs: Sustainable Development Goals

TP: True Positive

TN: True Negative

TCP: Transmission Control Protocol

UR: University of Rwanda

WASAC: Water Sanitation Corporation

WHO: World Health Organization

WISENET: Wireless Intelligent Sensor Networking

WIFI: Wireless Fidelity

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CHAPTER ONE: GENERAL INTRODUCTION

1.1 BACKGROUND

Water is one of the important resources that we cannot live without. It is a valuable resource required in numerous human life application domains like in home, it is used mainly in cooking, drinking, hygienic, agriculture, farming and manufacturing as well. Countries worldwide engage not only in water supplying but also in strategically managing this natural resource by regulating its use and protection as well. In Rwanda through the ministry of infrastructure has already elaborated a strategic plan for water and sanitation to increase the quality of life, high living standards and accelerate the implementation of national strategy transformation (NST 2018/2019-2023/2024) and SDGs (30). The strategic plan expectation is targeting to be implemented in six(6) years from 2018 to 2024 by providing water supply service and sanitation hundred percent(100%) of households [1][2]. The strategic plan also briefly highlights other stakeholders engaged in treating and managing water resources. In this background, government of Rwanda has already elaborated the water capital account, supply and management.

In[3] , NISR reported the major water use where the agriculture activities denoted as the largest consumer , mining and electricity occupy the less. The work also mentioned the household water use as the second consumer to the agriculture. The report has announced the additional demand of 2% in couple of years from 2012 due to the dramatic increase of population and hygienic enforcement. The demand of water will keep increasing as the world population continues to increase. According to the historical report since industrial revolution the world humanity got a tremendous growth where the current global estimation shows that the population has reached to 7.7 billion[4]. Proportionally the rate of urbanization has increased; where the rate was below 30% by 1951 while currently (2021) it peaks to 56%.

However, due to the increase of population, urbanization, industrialization, agriculture and farming, there is an increase of water demand to be addressed by governments and water planners. Therefore, water stakeholders and governments encourage households to manage water resources through evaluating number of variables that can impact the household water use [5].

1.2 PROBLEM STATEMENT

The estimation of WHO 2018 annual report on global water, sanitation and hygienic[6], two billion people globally drink contaminated water while 4.5 billion use inadequate sanitation system which doesn't protect universal community from harm and diseases. The report indicated that vulnerable patients and students in schools suffer from poor access on water, sanitation and hygienic. Consequently the report stated that the diseases can be reduced 10% through both improving drinking water and water resource management. Also Rwanda through its regulatory agency reported that the big challenges on water and sanitation sector are imbalance between water demand and supply. It mentioned that the adequate management of water resource service will contribute to national socio economic development and human welfare. Consequently water and sanitation sector strategic plan[1] , mentioned the need of water management to both Kigali and second cities. Water supply policy in Rwanda [2] and RURA annual report[7], to strengthen water supply and management water operator (WASAC) provide household water connection by installing water meters to monitor household consumption and set measures for water recovery. Indeed the current water meters require a period visit sometimes on monthly basis to monitor household water consumption. Apart from that water consumers must pay after that physical checking in water meter installed at the entry of the building, this also delays the payment and water operator chooses to cut off the water pipe in order to remind the household owner to complete the previous payment. So this sometimes bring complains between water provider and water users and can cause other related problems like improper hygienic. IoT based intelligent household water consumption management system will bring a solution for all said problems by using IoT smart water meters that will be installed at the entry of building's pipeline to calculates and monitor the quantity of water consumed and report it in real time remotely to the platform to facilitate the easy management and access to the digital record of used water.

1.3 OBJECTIVES

1.3.1 General objectives

In general the objective of this research is to monitor household water consumption and build a predictive machine learning model that can predict the accuracy of water consumption over population size in targeting region.

1.3.2 Specific objectives

- To design a data dashboard for household water consumption monitoring
- Implement real time system for computing household water consumption
- Evaluate machine learning model to analyze and predict the accuracy of household water consumption over population size in targeting region
- Build IoT based prototype that use real time household water consumption

1.4 Hypothesis

Using Internet of Things technology, it is possible to design an IoT smart device that can be installed to compute and timely monitor household water consumption. Also with help of machine learning models, it is possible to build and evaluate the accuracy of household water consumption.

1.5 Scope and limitation of the study

The research study was carried out to design and implement IoT based intelligent household water consumption management that deploy IoT smart water meter at household to compute and monitor water consumption on a system data dashboard.

1.6 Significance of the study

The outcome of this research will help the ministry of infrastructure through its stakeholders such as water authorities not only to monitor the household consumption but also to take adequate decision during planning and enforcement of household water management

1.6 The study organization

The dissertation is organized in six chapters as following, the first one is the general introduction, and it gives the study background, statement of the problems, objectives and study delimitation. Chapter two is the literature review; it provides the review of the literature and similar studies. It also defines the gaps ignored by other authors. The third chapter is the research methodology; it deals with data collection techniques, data analysis and interpretation of data. The fourth chapter is design and implementation of the real time system that deal with the proposed solution and findings. The fifth chapter explains and discusses the result of the study in general. Finally, the last chapter is conclusion and recommendations to country and other researchers who will be interested to work on the similar research.

CHAPTER TWO: LITERATURE REVIEW

This section briefly analysis and discusses other works similar to the current research thesis. It also investigates the problems discussed by their methodology, approaches and techniques to address the research challenges they were working on.

The researches [8][9] deal with a dynamic pricing system in water distribution system where each household equipped a smart water meter, water demand prediction for a day, the purpose was to monitor and predict water consumption during high demand hours. These researches didn't notify the consumers about water consumed nor any associated information. Also in Italy the research [10] used smart water meter to assess water losses in water distributed network (WDN). The research was based only on water loss in water distributed network and focused on monitoring the individual consumption of each household but also they didn't offer any platform for sharing the real time data on water used by consumers. Also in Australia Web based knowledge management system was proposed to link smart metering to the future urban water planning [11], this research work was used to direct architects, developers and planners, in order to understand about water consumption across urban samples. This system had some functions like collecting real time water consumption data, transfer and store data for future analysis. Indeed the interest for this project was particular for developers and city planners. It could be better if the system gave common platform via which water users could access their consumption rather than being used only for water planning.

Again on other hand some researchers [9] use to spend the time dealing with water quality monitoring as well as the cost effectiveness. For instance the researches[12][13] used IoT to provide mechanism for monitoring quality of water before it is distributed in cities and villages. These research works used different sensors to measures various parameters in water to acknowledge whether water is purified or not in IoT platform, Even if these researchers were able to measure the quality of water they didn't show any manner for household consumption nor how consumers are notified about their consumption rate. In report[14], Rwanda has committed 100% access on water supply and sanitation services by 2024 as one of the pilots to move to modern Rwanda household. In this regard the country committed to invest in water supply systems in both rural and urban area by strengthening water production capacity in the different water treatment plants available in both Kigali and six second cities.

After analyzing the similar studies, the researchers found that other authors have been interested to other thinks like monitoring the water quality and distribution activities. They have ignored the approach of its management by integrating technology that can accelerate the management of water consumption. Differently, the current research thesis used an IoT based technology that could help in real time monitoring and prediction of household water consumption. The approach could play the big role for better water monitoring and management which will generate another insight to water planners, authorities and other engaged stakeholders for future analysis.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Overview

The chapter discusses different approaches the researchers have used during conducting the research activities. It further explains various methodology and approaches used for data collection, preparation, evaluation and visualization. This chapter also demonstrates different exploratory data analysis applied using machine learning models for sorting and analyzing data gathered from the fields. Lastly the chapter comprises approaches used to design and implement IoT based real time system.

3.2 Data collection and analysis

In order to design and implement the real time system for IoT based intelligent household water consumption monitoring system, the researchers emphasizes on data gathered from two distinct institutions mainly WASAC and Kigali city in its three districts Nyarugenge, Gasabo and Kicukiro. The data gathered and modeled are household water consumed and population data in Kigali city recorded during seven year (2014-2021). The next paragraphs explain in depth how these data well collected and prepared for being used in the current research.

3.2.1 Population data

In general the historical population growth in Rwanda has significantly increased since 1975 to 2020 according the world statistics [15]. The graphical presented here bellow demonstrates the rate at which Rwanda population has grown. The below represented figure illustrates clearly the historical growth and corresponding yearly population density since the year of 1975.

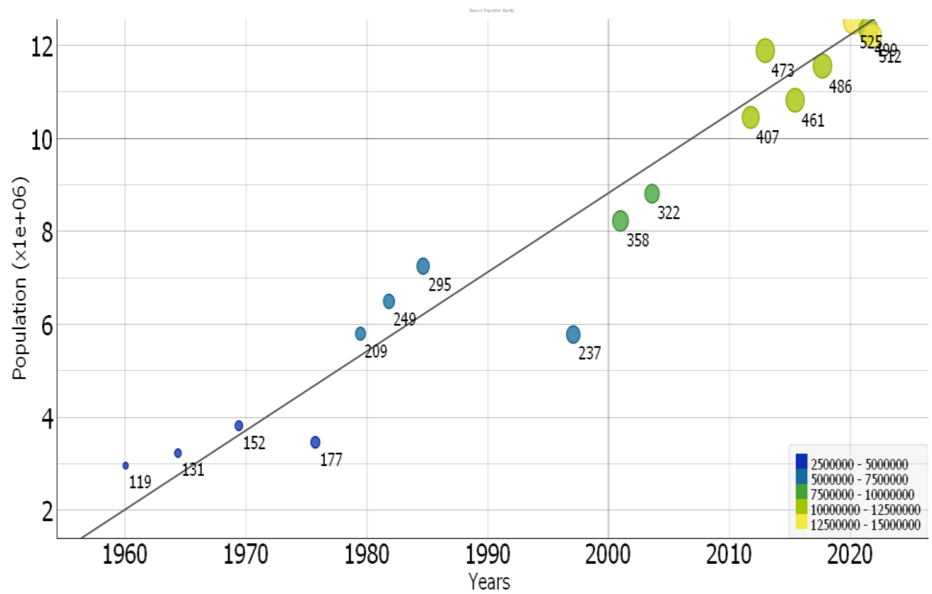


FIGURE 1:HISTORICAL POPULATION DENSITY OF RWANDA [15]

In this context, the researchers have used the average annual population growth rate (r) which is calculated by considering the change of population in two consecutive censuses that happens in every ten years. The rate is computed using the following formula [16]

$$r = \left[\left(p_t \,/\, p_o\right)^{1/t} - 1\right] \tag{1}$$

p_t is the population at the recent census

p_o is the population at previous consensus

t is interval between two censuses

r is average annual growth rate

However, the targeted population size used in this research thesis is that of Kigali city. According to 2012 consensus he population size in Kigali city continuously increases year by year and has already reached to 1,135,428 by 2012 compared to 2002 in which the size was 765,325 only. As it is illustrated by the table 1 annexed in appendix of this report the population size in the city has been almost doubled with 4.0 averaged annual growth rate from 2002 to 2012[16]. In this background the researchers have used the last consensus to estimate the next seven years population sizes of Kigali city (2014-2021) in order to be used in training and evaluating the ML model.

3.2.2 Rate of access to water in Rwanda

RURA annual report[7] shows that number of household subscribers to access water has increased in the last five years from 2015 up to 2020,the significant increase of 2,114,637 subscribers (2018-2019) to 2,300,190 (2019-2020). This makes the increase of 6.7% as shown on the figure here below.

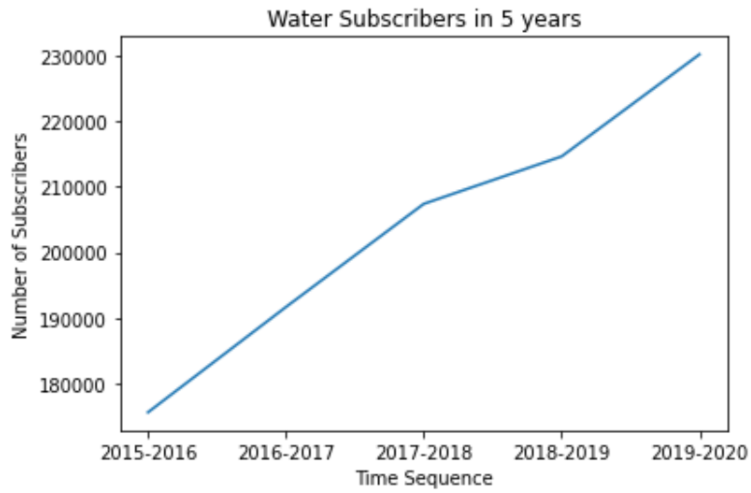


FIGURE 2: NUMBER OF HOUSEHOLD WATER SUBSCRIBERS IN RWANDA

3.2.3 Rural and urban water supply

The estimated water supply in rural area has tackled 72% progress in 2009 while it was 76% in the urban region and by that, it was estimated to reach government target of 85% by 2015[17]. In that background, the aim of Rwanda national water supply policy through EDPRC2 is to supply water in both rural and urban region at 100%. However, the need should be implement the clear strategy and schemes that will facilitate the access of water across all regions by reviewing and making a new structure of water supply promoting the creation of clustering services, maintaining and supporting the management of piped water[2]. The policy highlight that 85% of Rwandan population has accesses to improved drinking water.

According to RDHS (2019-20), 80% of Rwanda households have right access to improved water sources where in urban population 96% household uses access to clean water. While 77% households of rural population have access to improved water sources where only 36% among them uses protected spring while 31% uses public taps[18]. Also the DHS illustrated that only 55% of Rwanda population is serviced with basic drinking water while 25% of them is limited to basic drinking water.

3.2.4 Data preparation and mapping

Various data used in this research have been separately collected from different resources and were merged together to form a single research dataset. The dataset merged is composed with the important parameters, which includes population data, water data and seasonal data in form of months. For water data case, the researchers have used 84 samples recorded by WASAC during seven years mainly form 2014-2015 to 2020-2021 fiscal year and aggregated each year data on monthly basic. Similarly, the Kigali city estimated population data used has been taken from the report of NISR and aggregated in seven years on monthly basic as well. With help of data science techniques, the researchers have used both the monthly water consumption data per population averaged on monthly basic. Finally water data, population data sampled on monthly basis elapse between 2014-2015 and 2020-2021 fiscal year. The seasonal data used are 12 months of the fiscal year between 2014-2015 and 2020-2021. However, the data have been combined all together to form a single meaningful dataset, of 84 records with three input variables type defined as dependent variables and independent variables.

3.3. Predictive models

In order to build the predictive model, one should use a kind of AI and machine learning to train and evaluate the dataset. This part clarifies the machine learning classification algorithm used by researchers. For mapping dependent variables known as input variables and independent variable known as target variables, the researchers have used the different machine learning algorithms namely random forest, logistic regression, Decision Three, k-NN to select which one of them can give the best accuracy and precision. Due to the popularity and documentations available of the above models, the researchers have used them. In next paragraphs, the researchers discuss and compare in detail the different machine learning algorithms individually.

3.3.1 Decision tree

Decision tree classifier is a model of supervised machine learning used to classify and regret the data in order to predict the target variable by implementing decision rules deduced from data features. The tree is seen as the approximation approach of the models which learns data to generate the curve of the if-then-else decision[19]. The DTs is able to support both categorical and numerical data which makes it best for interpretation, understanding and visualization of the tree[20]. The machining learning model suffers not only from unstable decision tree due to some change in data which result a kind of different tree but also the bias may be created by decision tree learners due to the dominance of some class. Hence, to overcome the issue, the decision trees are assembled [21].

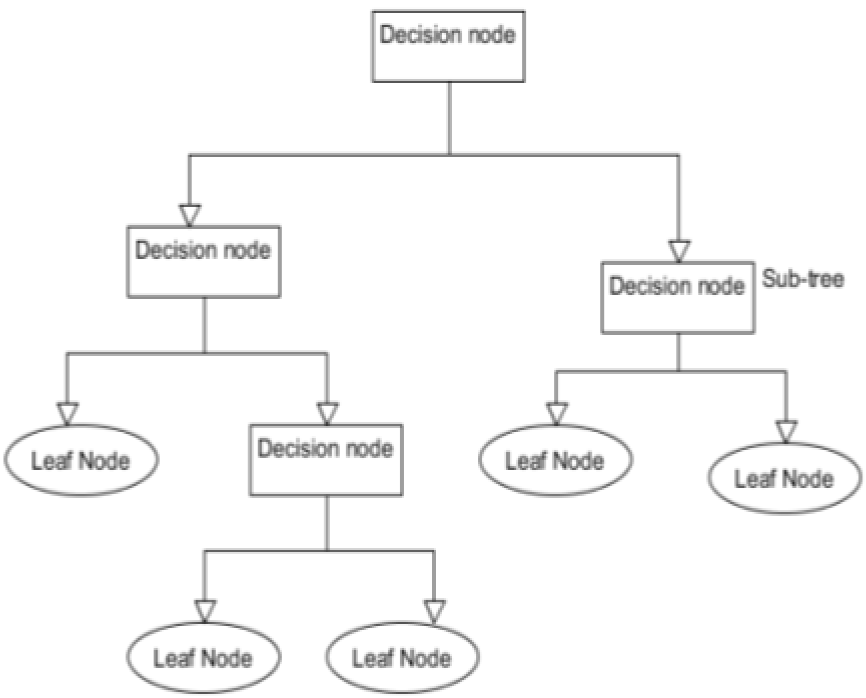


FIGURE 3: DECISION TREE CLASSIFIER

3.3.2 Random forest classifier

The random forest is one of flexible supervised machine learning algorithm which is used to classify and regret the samples taken randomly from a given dataset. The algorithm is used to construct the decision tree for predicting the result for each sample of dataset. Due to the number of decision trees in the process, the algorithm is said to be robust and accurate. Contrary to the decision tree classifier the random forest classifier doesn't get any prediction bias by taking the averaged prediction. The weaknesses of the random forest classifier, it generates prediction delay for the same input decision trees. The algorithm uses voting scheme for the same input tree which is time consuming[22]. The figure below briefly demonstrates how the random forest model works and the appendix 4 shows the python algorithm used for random Forest implementation.

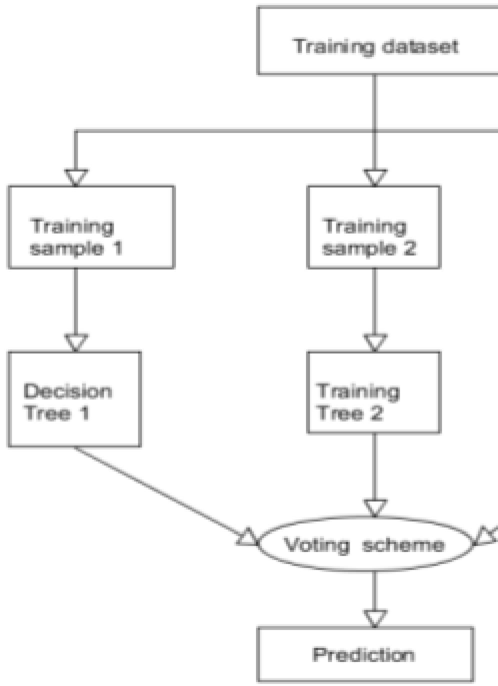


FIGURE 4: RANDOM FOREST MODELING

3.3.3 Support vector machine learning algorithm

The support vector machine learning is known to have high accuracy and handling nonlinear inputs. It has number of applications such as intrusion and face detection, for classifying the emails and recognizing the handwriting. To transform the inputs, the model uses the kernel trick to regret easily the points plotted on x and y axis [23].

3.3.4 K-Nearest Neighbor classifier

K_NN is no parametric machine learning algorithm which is used wherever the theory of mathematical assumptions are not obeyed. So, the strongest of this model is that it doesn't need the training data points. Hence it uses to save time and memory during data classification and testing. In KNN modeling, the k is the key factor for deciding the prediction and is the number of neighbor points that contribute to voting [24].To select voting points in KNN, the algorithm uses Euclidean distance between the existing point and the new point, and then the point with the list distance is selected. So the mathematical expression of the Euclidean distance is mentioned below[25].

$$d(p,q) = \sqrt{\sum_{i=1}^{n}\left(q_i - p_i\right)^2} \qquad (2)$$

p, q are two points in Euclidean n-space
q_i, P_i are Euclidean vectors starting the initial space
n is space

3.4. Model training and evaluation

One of the valuable things in model training and evaluation of dataset the researcher must be aware of is features selection. The model performance is increase similarly by reducing the cost of computation scheme through the proper selection of the features. During the raining and scoring process of the dataset some inputs are considered to be metadata, categorical data while others are numerical data. However, some inputs data have the relationship that the model takes into account. There are supervised and unsupervised techniques. One method uses the statistical measures by filtering the inputs variables with same correlations or dependencies (supervised method) [26] . Before using the whole features in ML algorithm, the random Forest ML algorithm was selected to predict water based on the population growth and the seasonal (on monthly basis) data. During training and evaluating of dataset, the main predictor used water consumed (in Kigali city).

During model training and evaluation, we have three training inputs such as water, population growth and seasonal data. The training dataset compromises 84 sample records that have the three features and one target also called class. As shown by the figure below, the data have been divided into two small subsets. One is used as testing subset while another is used as training subset. The training subset contains 90% of original dataset while the testing dataset contains only 10% of the original dataset. The training subset has been applied to the machine learning algorithms to generate the prediction model. However, to test if the predictive model does not have the over-fitting the researchers have used the testing during training and evaluation process.

So, the training and evaluation are conducted by using the software packages of anaconda distributed software to process the training.

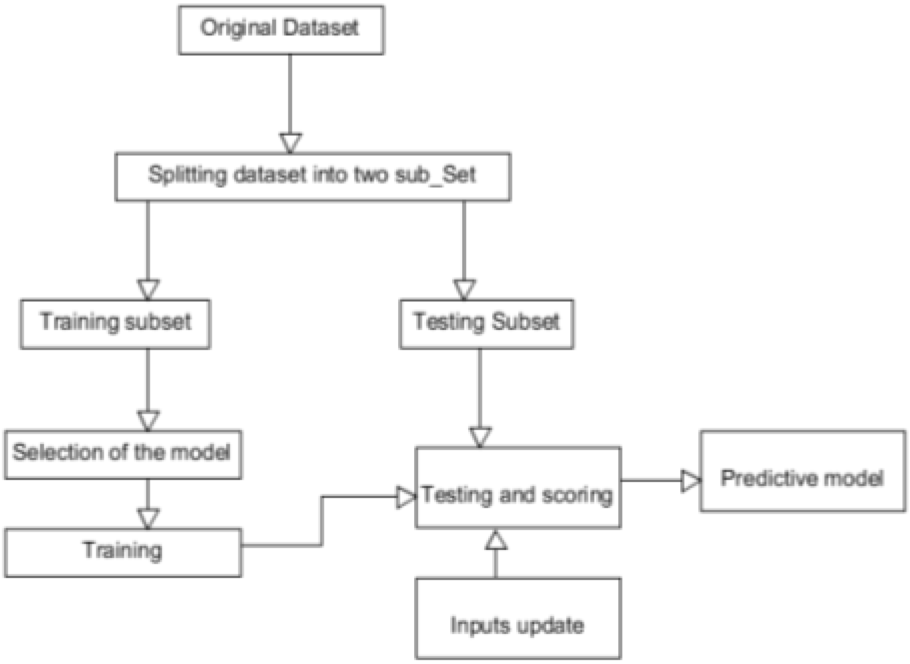


FIGURE 5: MODEL TRAINING AND EVALUATION

After completing dataset preparation, different ML models have been used to choose which one can give the best training accuracy compared to others. However, the following machine learning models such as logistic regression, decision tree, KNN and Random Forest have been applied for modeling the relationship between variables of dataset such as water, population and seasonal data. Some features of the dataset have not been used due to their nature rather they are considered to be metadata during the process of training the dataset. Due to the stability, popularity and flexibility of python codes and packages available, the python programming has been chosen for training and evaluation of dataset [27].

Finally, to select the best ML model among others, the researchers have considered some metrics that serve best to generate good predictive model such as prediction accuracy, recall and precision. The prediction accuracy means the how best the model is performing well or how much the prediction is correct and it must be greater that 70%. In addition, the accuracy can serves best only if the testing and training accuracies are close one to another [28].

CHAPTER FOUR: SYSTEM ANALYSIS AND DESIGN

This chapter mentions all techniques and approach used to design and implement IoT Intelligent household water consumption management system. The chapter illustrates both hardware and software implementation

4.1 System analysis

4.1.1 Proposed solution

The IoT solution provided has three main blocks; the first one is water counter that equips with flow rate sensor to compute real time household water consumption data and an actuator to cutoff or follow water in the pipe. The second is the gateways through which the sensor data is sent to server of xamp platform through a well programmed API that is embedded in the water counter block. Lastly there is server block that furthermore has three important parts namely MYSQL server that writes the sensor data (logs) to the data files (database), prediction sub block through which the monitoring is made on system dashboard.

4.1.2 Sensing subsystem

The subsystem illustrate the sensing part of the system .It contains a flow rate sensor that compute real time data from the environment(household) such as water being consumed by household then supply it to microcontroller ESP8266 for further processing.

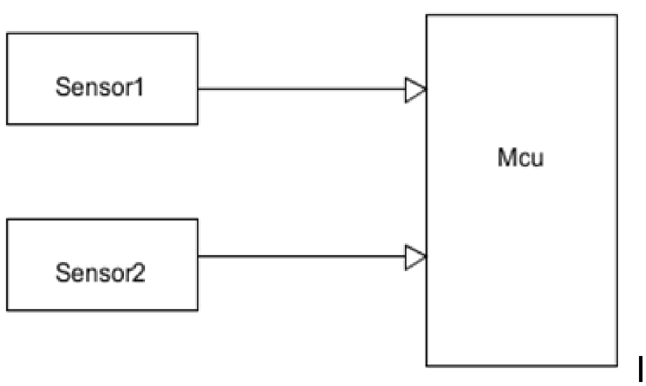


Figure 6: Sensing subsystem

Sensor is an electronic device that converts physical parameter to corresponding electrical quantity. The flow rate sensor is sort of pinwheel whose speed is proportional to the liquid flow rate passing through it. During prototyping the researchers use water flow sensor YF-S201 to calculate the total water consumed per household[29][30]. For collecting household water consumption, the flow rate sensor is connected to arduino microcontroller ESP8266 NodeMcu shown on the figure bellow. ESP8266 is WiFi built in capability board that allows connecting to the Wi-Fi using TCT/IP protocol[32]. Consequently the board operates in three mode mainly access point mode (AP), Wi-Fi station or both at the same time[33]. The work illustrated also the module to have powerful features that enable it to be integrated in many applications like real time operations and TCT/IP protocol based application where it works as either end station or soft Access point mode [35].

Additionally, the module known to work in three power saving modes, deep sleep mode, modern sleep and light sleep. The current research used to save power by using deep sleep mode where in case there is no water consumption for household the module is forced to be in sleep mode and its CPU is requested only in case of counting water and synchronized to the server once there is consumption. To achieve this technically, the researchers have used ISR function before calling the API function that updates the server the consumption.

4.1.3 Wireless communication with ESP8266 NodeMcu

The ESP8266 NoMcu microcontroller operates in three operation modes such as access point mode, Wi-Fi station mode or both[33]. Consequently during prototyping the researchers have used the board as Wi-Fi access point to connect the household sensor node to MySql server that handles all database logs. The researchers have created an application programming interface(API) using TCT/IP protocol stack to enable communication between household water meter and the remote server [36].

4.1.4 List of components and materials used

- ESP8266-12E Board
- YF-S201 Hall-Effect Water Flow Sensor
- Liquid Crystal Display
- breadboards
- Mysql server
- Jumper wires

4.1.5 System Block Diagram

The system block diagram illustrates the important part of research solution. It is composed with three important subsystems. The first one is smart meter device equipped with flow rate sensor that works as water actuator and microcontroller that serves to receive the signal from flow rate sensor and count water used. The microcontroller count water by running the function known interrupt service routine. The second part is gateway responsible to connect the water sensor subsystem to the server. Lastly the third server and monitoring part, is responsible to communicate with sensor node by receiving the flow rate sensor data which are coming from the flow rate sensor device. The subsystem also contains the dashboard on which the smart water meters are monitored.

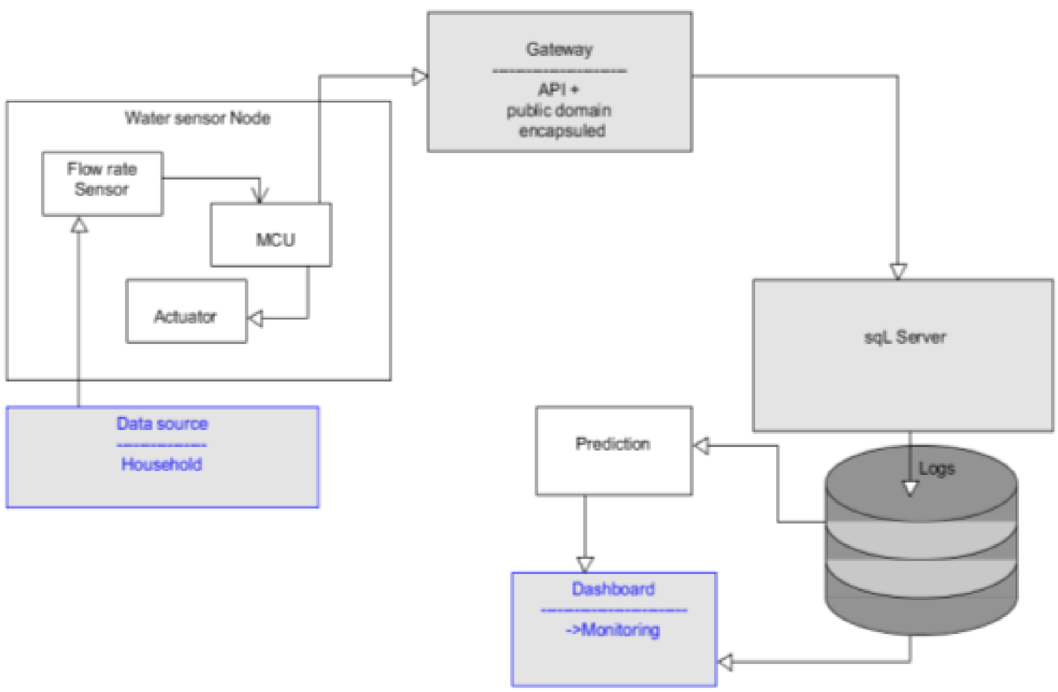


Figure 7: Detailed block diagram of household intelligent water consumption management

4.1.6 System flow chart diagram

A flowchart is a pictorial representation of an algorithm in which steps are drawn in the form of different shapes of boxes and the logical flow is indicated by interconnecting arrows. Flowcharts are also called block diagrams. The flow chart diagram illustrated bellow demonstrates how the current system works in general.

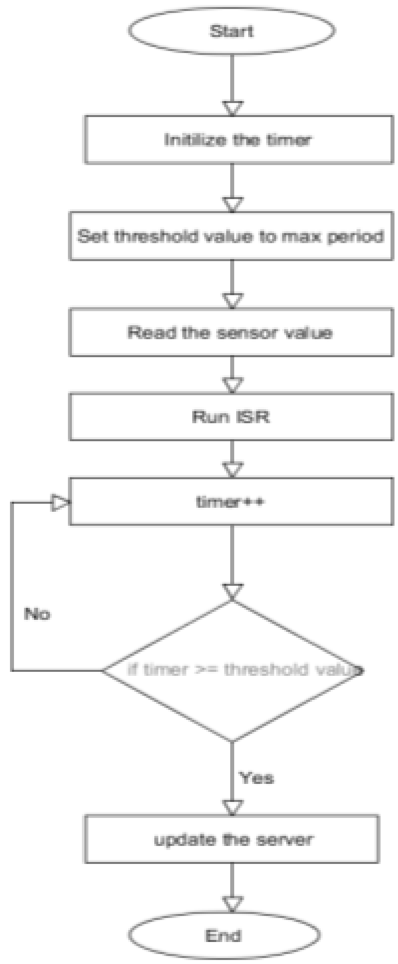


Figure 8: System flow chart

4.1.7 API design and communication protocol

To design and implement system API, the researchers enabled the Wi-Fi and assign the static IP address to the ESP8266 module. In order to address the challenge of high power consumption and internet bundle at minimum consumption rate[37], the work is to call the CPU of the module the time the flow rate sensor connected to water pipe is activated. The ESP interfaces and updates the remote server the consumption by using http communication protocol. Then sensed data is saved in database in form of table to be queried by server.

However, the server can exchange data with with microcontroller using HTTP protocol, and the communication accommodates server request method to avail the presence of data from the smart water meter. The researchers have predefined to sum up water consumption coming from the microcontroller device and update server in xamp platform.

4.1.8 System use case diagram

The part illustrates different entities and their functions to interact with real time system as mentioned on the figure below. The main users of the system are the system administrator, the entity who can perform all activities in the system after logging in. The second is water consumer or household, is the system entity who can view the individual consumption in the system after logging in. The last entity is water operator this is the system entity whose privileges are closer to the system administrator. System provides the interfaces (GUI) that can assist the users for interacting with a real time system as it is illustrated chapter five of this report.

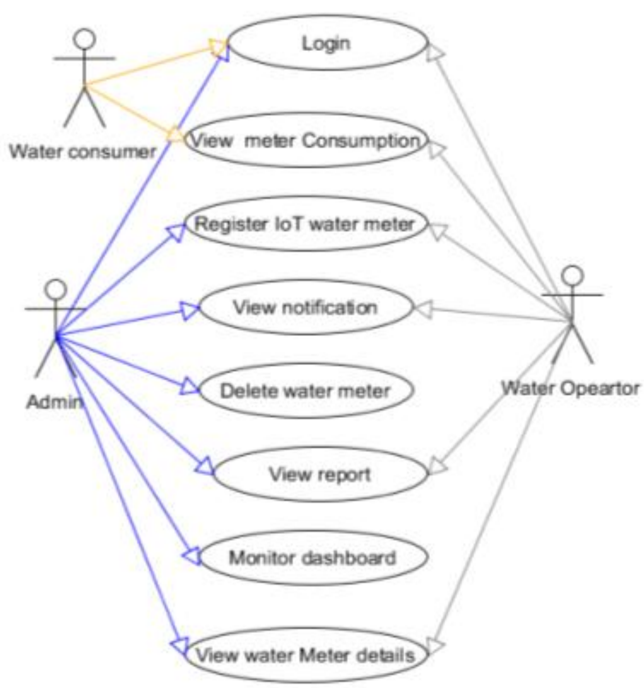


Figure 9: System use case diagram

CHAPTER FIVE: RESULTS AND ANALYSIS

5.1 Machine learning model evaluation metrics and selection

Evaluation metrics depends specifically on type of machine learning algorithms that are being evaluated. The metrics such as precision, recall, accuracy and sensitivity have been consider during model evaluations. Among other models during dataset training and evaluation, the random forest has comparatively tested and scored the highest accuracies of training and testing dataset. The import things to consider that can define the best or the worse of metrics while testing and scoring the model are the parameters which compose the accuracy such as the true positive (TP) and negatives (TN), the false negative (FN) and positive (FP). However, the precision means from the positives, how much was correct while recall means from the positives how much I found incorrect. The harmonic of precision and recall describes the imbalanced distribution of data and the specificity means how much I found in all negatives [38][39].

$$Precision = TP(TP + FP) \tag{3}$$

$$Recall = TP(TP + FP) \tag{4}$$

$$Specificity = TN(TN + FP) \tag{5}$$

$$Accuracy = (TP + TN) \ / \ (TN + TP + FN + Fp) \tag{6}$$

5.2 Training and evaluation implementation

With help of python codes and libraries, the research used various built in class of panda's package. To select the best model, the researchers have trained and tested many models and the random forest classifier gave the higher model accuracies. The prepared dataset in CSV file with 84 rows of 4 inputs each with categorical and numerical types was used to evaluate both training and testing accuracies. The trained dataset used was composed by variables which were ignored because they are metadata for dataset and two inputs taken as feature data while last input was taken as target variable.

So the water data during the training process is considered to be output or target variable whereas the population growth data and seasonal data (in months) which were transposed to numerical values (0s and 1s) were considered as feature variables. Before applying the machine learning algorithm, the data have been normalized in order to improve the prediction accuracy. Thereafter, the 90% of the original data have been used as training dataset while 10% of them have been used for testing dataset. The figures presented below are the result of model training and evaluation where the random forest machine learning algorithm is used to train the dataset and predict the output. Model training and evaluation produced 0.96 and 0.91 training and testing accuracies respectively at 0.1 of testing size with 70 of randomization factor (random state).

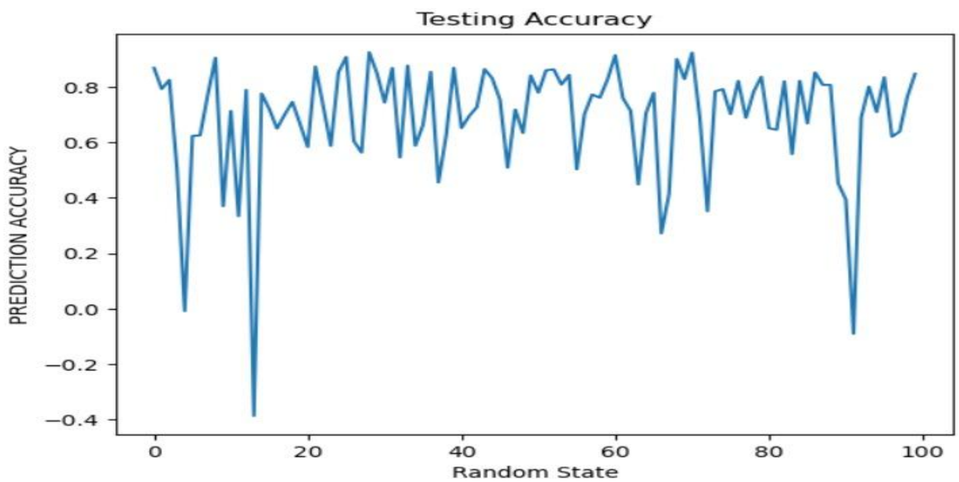


Figure 10: Testing accuracy

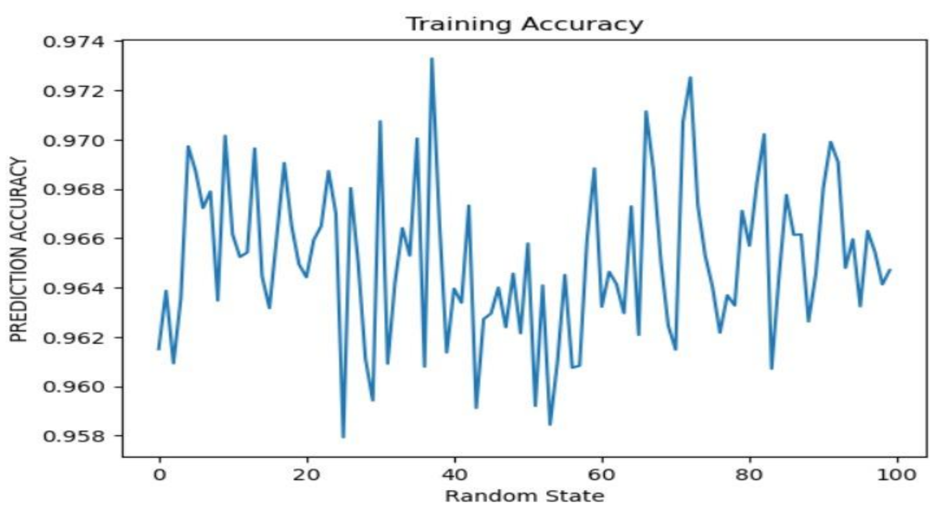


Figure 11: Training accuracy

5.2.1 Model training accuracies and evaluation

The task remain for the current work, is to select the correct random sate and testing size as key parameters to generates a good predictive model with higher prediction accuracy. After looping random sate from 0 up to 100, at 0.1 testing size, finally the researchers have evaluated the training and testing accuracies. Only at random sate of 70, the training and testing accuracies are near one to another for providing higher predictive accuracy of 0.96. This mean the system predict 96 percent of correctness as it is illustrated on the figure below.

As it is illustrated by herewith python scripts, the researchers have made a looping function for changing the randomization factor(random state) to generate a different couple of training and testing accuracies from which they select the best.

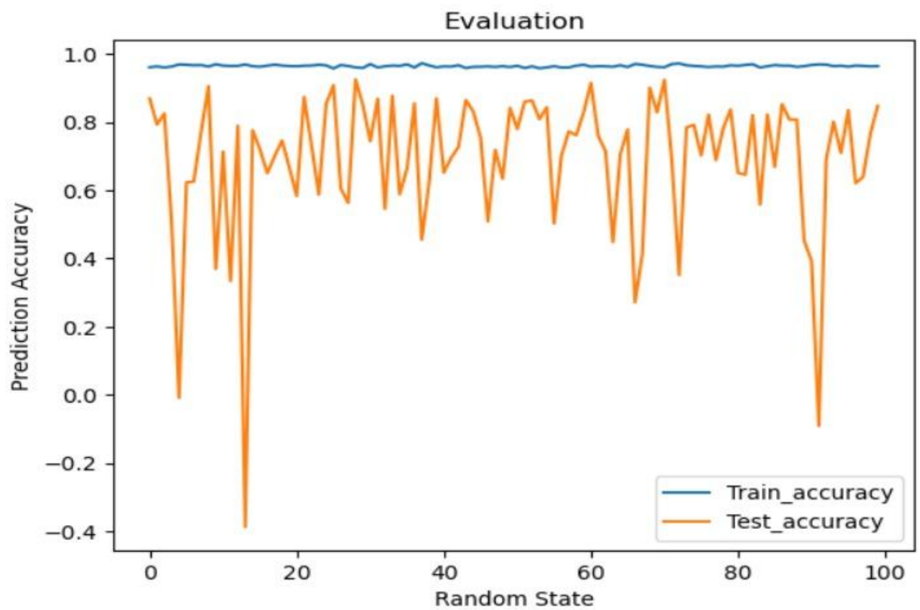
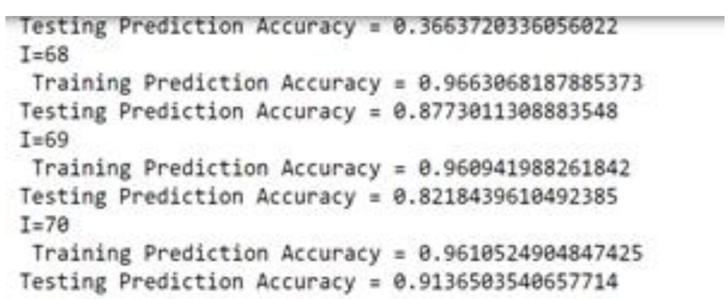


Figure 12: Prediction accuracy



```
Testing Prediction Accuracy = 0.3663720336056022
I=68
 Training Prediction Accuracy = 0.9663068187885373
Testing Prediction Accuracy = 0.8773011308883548
I=69
 Training Prediction Accuracy = 0.960941988261842
Testing Prediction Accuracy = 0.8218439610492385
I=70
 Training Prediction Accuracy = 0.9610524904847425
Testing Prediction Accuracy = 0.9136503540657714
```

Figure 13:Training and testing accuracies

5.2.3 Model predictions

After training the model, the researchers have to predict the water consumption over population size of targeted region that will be required in the future .As it is illustrated on the figure 16 there should be a great increase of water need in the next eight years as prediction illustrates, the historical water consumption shown in green between 2014-2015 up to 2020-2021 fiscal year has the maximum consumption of 1,850,8606m3 over 1,412,991 population from which the prediction is made. The prediction part is yellow notifies a small decrease of water consumption and in Kigali city (the targeted region) in 2021-2022, it is expected to be 1,685,557 m^3 over 1,449,999 population while it is expected to be increased up to 3,892,501m^3 over 1,779,987 population by 2029-2030.

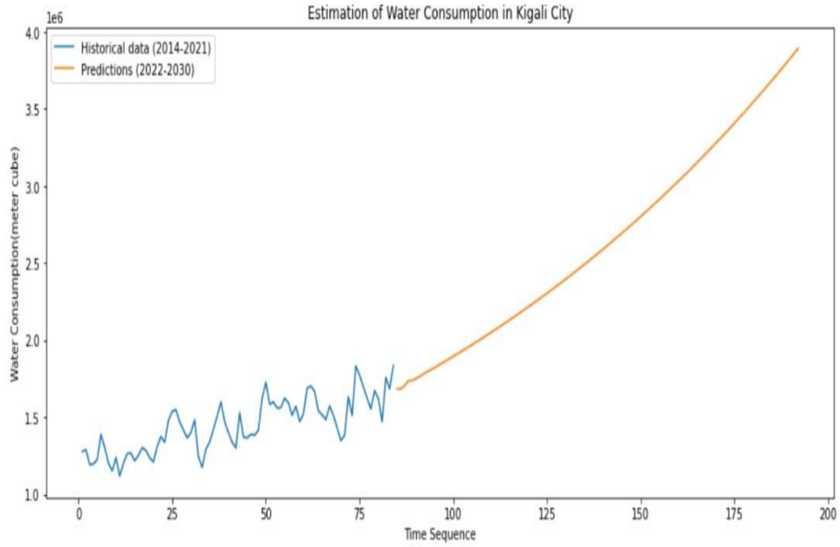


FIGURE 14: Predictions of water consumption and population size (2022-2030)

5.3 System output and dashboard

5.3.1 Registration of smart water meter in the system

The system allows the system administrator to first register the IoT water meter before it is installed at household. It auto assigns the unique number for the device which uniquely identifies throughout the system. For avoiding having two or more smart water meter in the system running into the same meter number, the system uses randomization function to generate the device numbers.

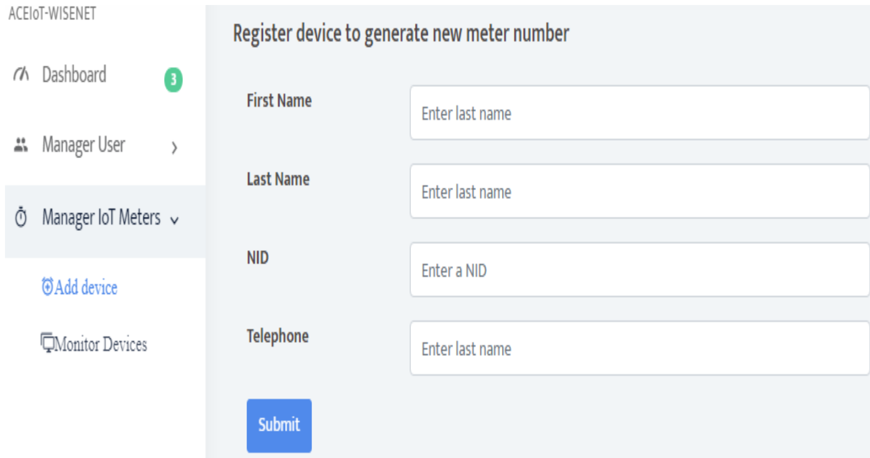


FIGURE 15: Register the IoT Water meter in system

5.3.2 Smart water meter Hardware implementation

After registering the water meter, the researchers have embedded the unique meter number generated by the system in microcontroller's API codes so that the device is identified and monitored throughout the system as it is indicated in appendix 6 of this report. Thereafter the meter is installed at household to compute and send the water consumed to the serve. The flow rate sensor of water meter installed at the entry of household is connected in between the water pipeline to compute water volume being consumed and then communicate to microcontroller for being processed. Finally after computation, the smart water meter sends the consumption to the server using http protocol.

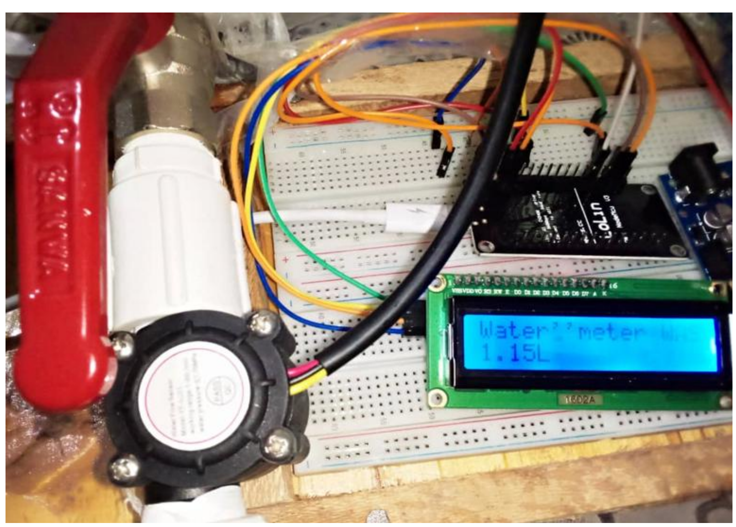
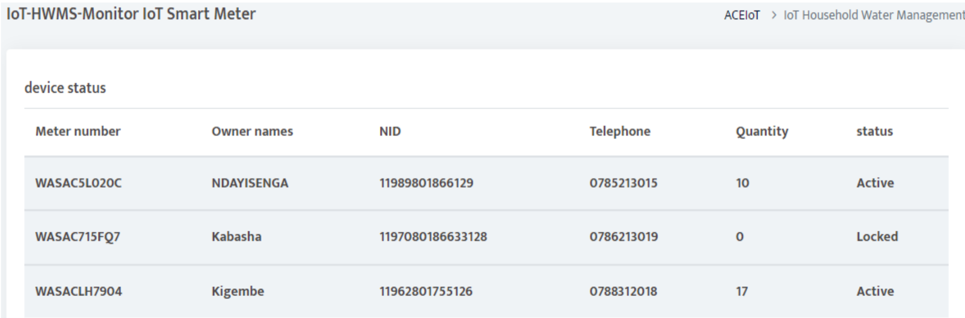


FIGURE 16: HARDWARE IMPLEMENTATION OF WATER METER

5.3.3 Water meter monitoring

The update of real time water consumption of the registered IoT water meter device installed at household could be monitored via the system dashboard by providing the right credentials such as username and password. The IOT smart water meter could remain updating the server with well established remote connection.



IoT-HWMS-Monitor IoT Smart Meter

ACEIoT > IoT Household Water Management

device status

Meter number	Owner names	NID	Telephone	Quantity	status
WASAC5L020C	NDAYISENGA	11989801866129	0785213015	10	Active
WASAC715FQ7	Kabasha	1197080186633128	0786213019	0	Locked
WASACLH7904	Kigembe	11962801755126	0788312018	17	Active

FIGURE 17: Monitoring water meters

5.3.4 Admin dashboard

The admin dashboard allows the system administrator to monitor easily system in general including water used by household and number of IoT meter devices available in the system and historical data of the system through the two sections such as device and users sections. The first section allows the administrator to view and list number of connected smart meters in the system. The second helps the admin to monitor number of users who have privileges to the system. Furthermore System administrator can easily view the detailed information of each device such as its consumption, device status as mentioned on the output figure below.

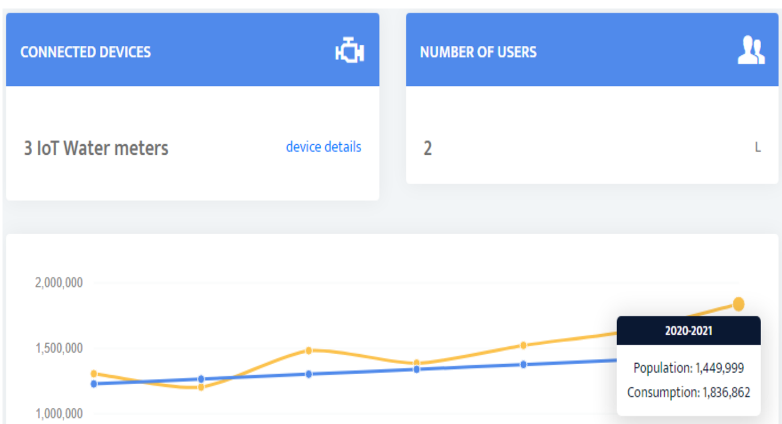


FIGURE 18: Admin dashboard

CHAPTER SIX: CONCLUSION AND FUTURE WORK

This research aimed to implement a real time monitoring of water consumption and correlate the consumption with population growth of the region under study by considering the seasonal data aggregated on monthly basis with help of one of machine learning algorithms. After exploratory data analysis of the main features of dataset, the predictive model has been correctly built to train and predict every subset of dataset. The current research outcome reveals that the water consumption could be well predicted using Random forest machine learning algorithm comparing to any other algorithms tested. The evaluation performance of the model manifested 96.1% and 91.3% of training and testing prediction accuracies respectively in Kigali city.

The model used in this study has been trained and evaluated by using 7 years (2014-2021) water, population and seasonal data from Kigali city (Rwanda). However, some parameters like precipitation or dry of different months can impact the level of demand of household water consumption supplied. For the future work we anticipate to bring into the study some advance machine learning algorithms like time series model to predict the future water demand.

Furthermore we recommend the ministry of infrastructure in collaboration with WASAC and National Institute of statistic to expand this research activity in the second cities as well, where the strain of water management is high. Secondly we recommend decision makers to help in applying IoT based intelligent water management for intensifying the water for maintaining household water access.

Finally, during this research, we focused on households water, population and seasonal data so, we recommend the future researchers to scrutinize other researches that shall include more data like industries development in the cities that shall bring the advance machine learning models Recurrent Neural Networks to address the issue of water management and prediction for long term period.

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APPENDIX

Appendix 1: Population growth by provinces (2002-2012)

Province	2002 Population			2012 Population			Population Change (2002-2012)		Average Annual Growth Rate (2002-2012)
	Male	Female	Total	Male	Female	Total	Number	Percent	
Kigali City	401,461	363,864	765,325	585,379	550,049	1,135,428	370,103	48.4	4.0
South	969,974	1,088,700	2,058,674	1,242,220	1,351,890	2,594,110	535,436	26.0	2.3
West	962,225	1,081,330	2,043,555	1,169,662	1,307,281	2,476,943	433,388	21.2	1.9
North	733,163	827,699	1,560,862	819,931	909,996	1,729,927	169,065	10.8	1.0
East	812,625	887,512	1,700,137	1,257,750	1,343,064	2,600,814	900,677	53.0	4.3
RWANDA	**3,879,448**	**4,249,105**	**8,128,553**	**5,074,942**	**5,462,280**	**10,537,222**	**2,408,669**	**29.6**	**2.6**

Appendix 2: Dataset used during training the model (2014-2021)

N/O	Year	Month	Water consumption((m3)	Population
1	2014-2015	Jul	1,280,455.00	1,194,027.00
2	2014-2015	Aug	1,290,667.00	1,197,111.00
3	2014-2015	Sep	1,196,205.00	1,200,195.00
4	2014-2015	Oct	1,200,079.00	1,203,279.00
5	2014-2015	Nov	1,227,087.00	1,206,363.00
6	2014-2015	Dec	1,391,462.00	1,209,447.00
7	2014-2015	Jan	1,305,569.00	1,212,531.00
8	2014-2015	Feb	1,204,520.00	1,215,615.00
9	2014-2015	Mar	1,153,993.00	1,218,699.00
10	2014-2015	Apr	1,240,823.00	1,221,783.00
11	2014-2015	May	1,121,033.00	1,224,867.00
12	2014-2015	Jun	1,203,771.00	1,227,951.00

13	2015-2016	Jul	1,266,622.00	1,231,035.00
14	2015-2016	Aug	1,269,687.00	1,234,119.00
15	2015-2016	Sep	1,219,298.00	1,237,203.00
16	2015-2016	Oct	1,255,984.00	1,240,287.00
17	2015-2016	Nov	1,304,830.00	1,243,371.00
18	2015-2016	Dec	1,286,475.00	1,246,455.00
19	2015-2016	Jan	1,240,071.00	1,249,539.00
20	2015-2016	Feb	1,212,566.00	1,252,623.00
21	2015-2016	Mar	1,312,596.00	1,255,707.00
22	2015-2016	Apr	1,377,479.00	1,258,791.00
23	2015-2016	May	1,340,024.00	1,261,875.00
24	2015-2016	Jun	1,481,901.00	1,264,959.00
25	2016-2017	Jul	1,539,639.00	1,268,043.00
26	2016-2017	Aug	1,551,188.00	1,271,127.00
27	2016-2017	Sep	1,472,295.00	1,274,211.00
28	2016-2017	Oct	1,420,394.00	1,277,295.00
29	2016-2017	Nov	1,367,361.00	1,280,379.00
30	2016-2017	Dec	1,403,811.00	1,283,463.00
31	2016-2017	Jan	1,484,885.00	1,286,547.00
32	2016-2017	Feb	1,246,959.00	1,289,631.00
33	2016-2017	Mar	1,177,468.00	1,292,715.00
34	2016-2017	Apr	1,295,019.00	1,295,799.00
35	2016-2017	May	1,341,473.00	1,298,883.00
36	2016-2017	Jun		

			1,422,982.00	1,301,967.00
37	2017-2018	Jul	1,510,843.00	1,305,051.00
38	2017-2018	Aug	1,600,843.00	1,308,135.00
39	2017-2018	Sep	1,473,615.00	1,311,219.00
40	2017-2018	Oct	1,403,414.00	1,314,303.00
41	2017-2018	Nov	1,340,409.00	1,317,387.00
42	2017-2018	Dec	1,302,878.00	1,320,471.00
43	2017-2018	Jan	1,532,376.00	1,323,555.00
44	2017-2018	Feb	1,374,943.00	1,326,639.00
45	2017-2018	Mar	1,367,840.00	1,329,723.00
46	2017-2018	Apr	1,391,955.00	1,332,807.00
47	2017-2018	May	1,385,750.00	1,335,891.00
48	2017-2018	Jun	1,418,975.00	1,338,975.00
49	2018-2019	Jul	1,625,699.00	1,342,059.00
50	2018-2019	Aug	1,729,371.00	1,345,143.00
51	2018-2019	Sep	1,586,416.00	1,348,227.00
52	2018-2019	Oct	1,600,730.00	1,351,311.00
53	2018-2019	Nov	1,562,443.00	1,354,395.00
54	2018-2019	Dec	1,564,529.00	1,357,479.00
55	2018-2019	Jan	1,626,131.00	1,360,563.00
56	2018-2019	Feb	1,596,598.00	1,363,647.00
57	2018-2019	Mar	1,515,130.00	1,366,731.00
58	2018-2019	Apr	1,573,394.00	1,369,815.00
59	2018-2019	May	1,474,321.00	1,372,899.00

60	2018-2019	Jun	1,521,733.00	1,375,983.00
61	2019-2020	Jul	1,689,917.00	1,379,067.00
62	2019-2020	Aug	1,704,621.00	1,382,151.00
63	2019-2020	Sep	1,669,415.00	1,385,235.00
64	2019-2020	Oct	1,544,615.00	1,388,319.00
65	2019-2020	Nov	1,517,522.00	1,391,403.00
66	2019-2020	Dec	1,486,404.00	1,394,487.00
67	2019-2020	Jan	1,575,257.00	1,397,571.00
68	2019-2020	Feb	1,515,954.00	1,400,655.00
69	2019-2020	Mar	1,434,066.00	1,403,739.00
70	2019-2020	Apr	1,350,338.00	1,406,823.00
71	2019-2020	May	1,386,123.00	1,409,907.00
72	2019-2020	Jun	1,634,374.00	1,412,991.00
73	2020-2021	Jul	1,515,288.00	1,416,075.00
74	2020-2021	Aug	1,833,464.00	1,419,159.00
75	2020-2021	Sep	1,774,535.00	1,422,243.00
76	2020-2021	Oct	1,699,035.00	1,425,327.00
77	2020-2021	Nov	1,625,758.00	1,428,411.00
78	2020-2021	Dec	1,556,554.00	1,431,495.00
79	2020-2021	Jan	1,675,183.00	1,434,579.00
80	2020-2021	Feb	1,624,045.00	1,437,663.00
81	2020-2021	Mar	1,473,847.00	1,440,747.00
82	2020-2021	Apr	1,760,187.00	1,443,831.00
83	2020-2021	May		

			1,686,449.00	1,446,915.00
84	2020-2021	Jun	1,836,862.00	1,449,999.00

Appendix 3: Python code for decision tree ML algorithm

```
#import decision tree algorithm from the sklearn library
from sklearn.tree import DecisionTreeClassifier
#instantiate the model
dec = DecisionTreeClassifier()
#Train the model with input features (X_train) and targets (Y_train)
dec.fit(X_train,Y_train)
#Making Prediction on testing data (X_test)
Y_pred=dec.predict(X_test)
```

Appendix 4: Python code of random forest algorithm

```
#import decision tree algorithm from the sklearn library
from sklearn.ensemble import RandomForestClassifier
#instantiate the model
RandF = RandomForestClassifierr()
#Train the model with input features (X_train) and targets (Y_train)
RandF.fit(X_train,Y_train)
#Making Prediction on testing data (X_test)
Y_pred=RandF.predict(X_test)
```

Appendix 5: Python codes of KNN

```
#import decision tree algorithm from the sklearn library
from sklearn.neighbors import KNeighborsClassifier
#instantiate the model
Kn = KNeighborsClassifier()
#Train the model with input features (X_train) and targets (Y_train)
Kn.fit(X_train,Y_train)
#Making Prediction on testing data (X_test)
Y_pred=Kn.predict(X_test)
```

Appendix 6: Microcontroller code to implement API

```
void updateDataServer()
{
    HTTPClient http;    //Declare object of class HTTPClient
    String id = "WASAC583U1Z";
    String postData = "my_id=" + id + "&liter=" + currentLiter+"&action=insertRecord";
  http.begin("http://192.168.43.192/scw/device_API/update.php");// update the server
  http.addHeader("Content-Type", "application/x-www-form-urlencoded");

    int httpCode = http.POST(postData);   //Send the request
     String responseData = http.getString();
     Serial.println(responseData);
    http.end();  //Close connection
}
```