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CHALLENGES AND SOLUTIONS OF SEWERAGE NETWORKS IN KARBALA, IRAQ FOR FLOOD MONITORING USING SMART SENSORS AND GIS

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ABSTRACT

Floods in urban areas pose major challenges to infrastructure, especially in third world countries. The sewage network in Karbala, Iraq, faces recurring difficulties and problems from floods, especially in the rainy season, taking into account the large population density in Karbala. The design of the sewage network does not meet the need for this. This study came to build a model based on one of the artificial intelligence techniques, which is machine learning through Support Vector Machines (SVM) to analyze data coming from smart sensors and Geographic Information Systems (GIS). The classification that links variable weights is used according to the data coming from the sensors to enhance the work of the classifier and obtain a classification accuracy of up to 89.7% in real time. Enhancing smart decision-making is the most important stage in improving and building sewage networks, which are the basis of urban cities and their planning. In the future, the deep learning mechanism can be combined with machine learning to reach more accurate predictions and faster data analysis.

Keywords: *Sewage network; Smart sensors; SVM; GIS; Machine Learning; Flood Monitoring.*

1. INTRODUCTION

The Iraqi city of Karbala is a major religious and cultural center, with millions of visitors annually for religious tourism or business purposes. Thus, the population density is increasing on the one hand, and on the other hand, inadequate urban planning leads to inefficient sewage networks. Especially during the rainy season and religious seasons [1]. Floods widely affect infrastructure and cause damage, in addition to public health risks and economic losses. Current work systems are manual, inefficient, lack real-time and address rush seasons. Using modern technologies such as GIS and sensors, it is possible to reduce losses, utilize resources for the public good, mitigate the severity of floods and manage sewage.

Recently, the region has witnessed storm water and sewage management operations and enhancing decisions in this regard, to achieve long-term sustainability and maintain the health status and infrastructure [2-4]. Visualization and planning of data provided by sensors and GIS is of great importance and helps understand data patterns that contribute to making appropriate decisions [5-9]. Decision-makers and engineers can analyze data patterns when data is available but lacks real time and make appropriate and accurate decisions at the right time. This understanding and analysis of data helps to see more clearly and enhance sustainability in all its forms and manage resources effectively [10-11]. Hence, efforts are combined to build a better system for managing the sewage network that is compatible with the exploitation of rainwater. Most of the methods depended on the graph and data analysis in a way that can be concluded and know the times of floods and the tolerance of the main and secondary sewage passages [12]. Many methods worked on modeling the data in measuring the intensity of rain and the amount that causes floods and working to put time at the forefront of priorities that work to control sewage and peak times, [13]. Hence, the use of modern algorithms and models that work in real time is one of the most important things that must be taken into account. Managing and monitoring

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excess rainwater and maximizing the use of resources are among the most important goals adopted in previous studies.

Sewerage is a general term for wastewater from homes and factories, rainwater and snowmelt [14]. Population topographical changes, dynamic urban changes and agricultural land use, this changes the mechanism of sanitation and the distribution of the sewer network as it is not dynamic and changing it costs time, effort and money. Sound design based on well-thought-out decisions with models based on artificial intelligence to process data from GIS and sensors that monitor floods and congestion leads to building an urban foundation that lasts for years without the need to change it. Floods are a global problem suffered by many countries and regions [15].

Data often comes manually or human scales, which increases cost, time and inaccuracy in measurement. Many monitoring and warning systems rely on modern applications and devices such as GIS [16], which gives a realistic geographical picture of what is available or real. When building a sewage system, the general plan of the search area must be complete with all its details, such as actual dimensions, population density, agricultural areas, and areas containing obstacles such as water bodies, roads, and service pipes such as electricity and gas. In this case, this information is taken into account when building the sewage network. In the case of rain and floods that do not depend on terrain or population distribution, sensors must be installed to calculate the quantities that start with and reach their peak in order to control the pumps, especially in low-lying areas [17]. Karbala is considered one of the most important governorates in Iraq and occupies a religious and political position. It is located in the central-western part of Iraq, as shown in the Fgure1.

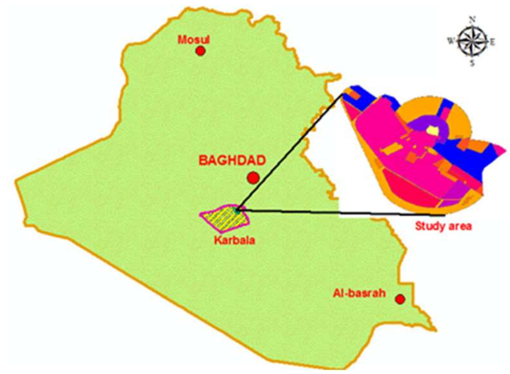

Figure 1 Karbala location in Iraq

Currently, all eyes are on emerging applications such as artificial intelligence algorithms. And now, many fields have relied on artificial intelligence for the accuracy, time and effort it provides in addition to the economic cost [18-19]. Artificial intelligence is divided into two main types, which are machine learning and deep learning, and the divisions differ according to studies. Deep learning plays a fundamental and effective role in predicting and making appropriate decisions based on the data it is fed. In most cases, the data is accurate and reliable, and to increase the accuracy of decision-making, the model is trained on real data or data that simulates real data in order to be taught and relied upon.

The main purpose of the study is to address the challenges that accompany sewage networks and find appropriate solutions through a system based on GIS and data from smart sensors.For obtaining this, we must achieve the following objectives:To build a smart model based on deep learning algorithm to manage Karbala's sewage networks.To manage data coming from GIS and smart sensors to make accurate decisions.

1.1 Challenges in the sewerage network in Karbala

1) Infrastructure constraints

A governorate like Karbala suffers from problems in the sewerage network due to the age of the pipelines, the lack of capacity and the limited maintenance. Its design is very old and does not keep pace with the rapid urban expansion and the large population.

2) Lack of monitoring systems

Automated monitoring systems are very important as they detect blockages, floods and failures in the system early. In old systems, the response time is slow and the impact is catastrophic.

3) Urban development and topography

Urban expansion leads to changes in the natural drainage paths in addition to the diversity in the topography of the region leading to complexity in drainage.

4) Climate fluctuations

The impact of unexpected rains due to climate change leads to flood risks and the old system lacks the necessary flexibility to keep pace with changing events.

One of the most important challenges is that Karbala is considered crowded with people at certain times of the year [20], so sanitary waste increases, which leads to a delay in services, as shown in the Figure 2.

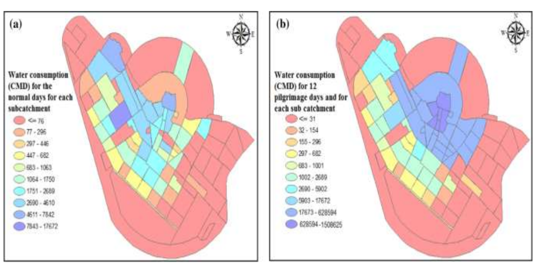

Figure 2 Distribution of water consumption in normal and pilgrimage day

1.2 Technological Solutions

1- Smart Sensors for Real-Time Monitoring

Smart sensors can be deployed within sewer networks and provide real-time measurements of water levels, flow rates, flow, blockages and obstructions. These sensors can be useful in:

- Early detection to determine flood levels, water height and their likelihood.
- Predictive maintenance by measuring wear in materials and scheduling periodic repairs to avoid breakdowns.
- Collecting data that will enable smart models to learn through a long-term database.

2- Use and integration of GIS

GIS provides a powerful tool for data analysis and spatial visualization that is useful for flood management and is useful to integrate with:

Mapping of vulnerable areas: by highlighting areas that are likely to be at risk of flooding based on historical data.

Improving resource allocation: prioritizing areas that need maintenance.

Scenario simulation: modeling and simulating flood likelihoods on historical data to draw a future plan.

3- Internet of Things (IoT) and Real-Time Smart Sensors.

The combination of IoT and GIS enhances the efficiency of data processing and sharing using AI and machine learning models. IoT-enabled sensors feed real-time data to central systems using an intelligent model and can be accessed by decision makers through communication channels.

2 RELATED WORK

The problem of worsening sewage in Karbala began after the population increase and the high rates of visitors to the city in certain seasons. As the sewage networks are less efficient and do not meet the city's needs. Since Karbala is located in a central region of Iraq, it is exposed to heavy seasonal rains during the winter season. Therefore, it is important to control the sewage networks and flood waters by all means in order to be able to accommodate the largest number of people at any time. Many studies have emphasized the recycling of sewage water to exploit the water scarcity in Iraq [21]. Developing sewage networks contributes to reducing pollution, especially in areas with high population density and where the concentration of pollutants such as nitrogen and phosphorus increases [22], and these elements lead to blockages and the growth of algae and reeds, and many problems are caused by them, as in the study [23].

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Currently, sewerage networks face the traditional manual system that is accompanied by effort, inaccuracy and inefficiency [24]. Many countries have adopted GIS systems in designing sewerage networks, including developed countries [25]. In addition, the Internet of Things (IoT) has played an important role in designing sewerage networks and controlling river and rain floods [26]. A study relied on GIS systems in studying sewerage networks in order to control population growth and direct sanitary water in a hierarchical manner [27]. A study was presented by [28] in order to control the flow of rainwater using smart sensors to open gates and channels according to loads.

Many previous studies have relied on linking GIS with the Internet of Things to design and improve sewage systems and networks [29]. Models based on artificial intelligence applications have been proposed to control rainwater and floods [30], in order to make the best use of natural resources. A machine learning model was used to predict rain and floods in a study presented by [31] to change the course of water transmission channels. Artificial intelligence algorithms have also been used to design sewage networks in densely populated cities [32] and to train on historical data from a dataset.

3 METHOD

In the process of improving and designing sewerage networks in Karbala, according to the proposed methodology that includes integrating one of the most important machine learning techniques, which is the Support Vector Machine (SVM), with the most famous data acquisition system, which is GIS. It includes several steps, the most important of which is data acquisition, then pre-processing it and training the model in order to choose the decision in real time. The proposed methodology can be applied to any application, whether sewerage management, flood monitoring, smart sensors for raining and flooding, etc. general framework illustrate in Figure 4.

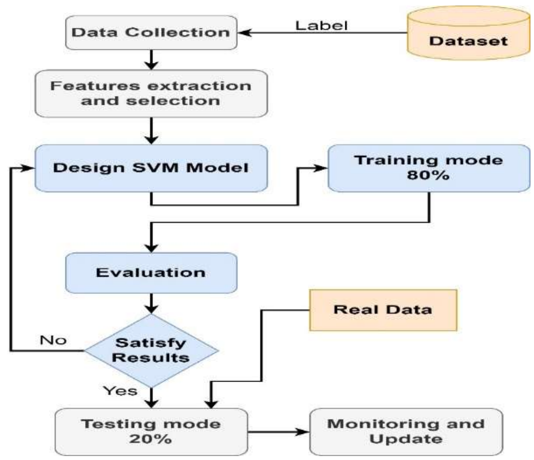

Figure 3: General framework of proposed method

The first steps in data collection are historical data recorded in a standard dataset about the topography of the land and previously recorded environmental information in addition to spatial and non-spatial information of the city's infrastructure. Data sources here are multiple, including:

GIS data such as maps and images that come via satellite and all coordinates. Which are in a dataset in addition to information from the Internet of Things (smart sensors). There is data obtained from sensor devices such as flood level and weather stations, in which the information is instantaneous. There is also fixed information available such as rain density, population density and terrain information. In general, it is of two types: historically fixed and variable in the long term, and information that occurs instantaneously in real time. As shown in Figure 4.

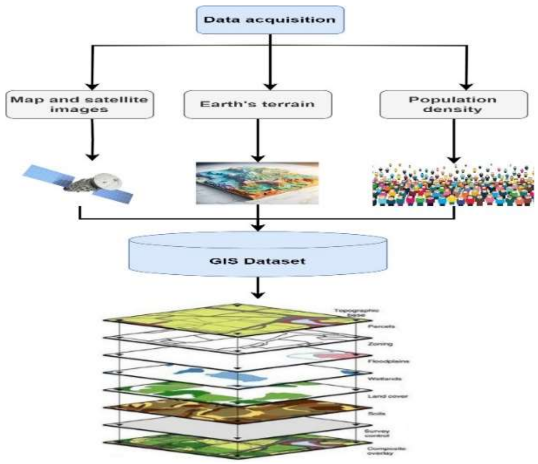

Figure 4: Type of data acquisition from dataset

Features extraction and selection represent the data before processing which are stored in vectors and these vectors are the only way to enter data into the machine learning algorithm (SVM). Vectors contain features extracted from the data in the dataset and are often in the form of a two-way vector so that the classification process can be easily done.

When the vectors containing the features are unified, the process of designing the SVM classifier begins to be suitable for classifying the features in the vectors. The training process begins on the data in the dataset and the classification is binary, for example, flood density is either high or low (true or false) or sometimes it is multi-class as in the land selection classification.

Then the kernel function is chosen for linear separation between the classes and here comes the contribution so that the weights help classify the class so that the classification is as close as possible to the margin boundaries. The classifier draws a map of the distribution of features on the two classes and which one belongs to the other class.

There are a set of steps that the classifier takes to determine feature classes. In order to train the classifier, samples are taken from the known classes to determine the unknown ones that do not contain a label. Therefore, when the pre-trained classifier is executed on unknown or new activities, it is known which class it belongs to. Repeating training leads to increasing the accuracy of the output and thus creating a fully classified class. Classification takes the form of statistical calculations, utilizing the acquired information, and determining the feature's belonging to any class.

First, the classes and their belonging to any group are identified in training, and they are used through the classifier to analyze them by features. As following:

$$D = \{(x_i.y_i)|x_i \in \mathcal{R} \,.\, y_i \in \{-1.1\}\}_{i=1}^{n} \quad (1)$$

Such as each x_i considers an n-dimensional real feature vector and y_i considers either +1 or -1 refers to the classes by which the feature of x_i is included. This helps to determine the best-split line (in terms of linear) or curve (non-linear) that groups the features including $y_i = 1$ (belong class A) and those of $y_i = -1$ (belong class B). The best separate line between two classes can be found in the case of training data is linearly behavior Figure 5.

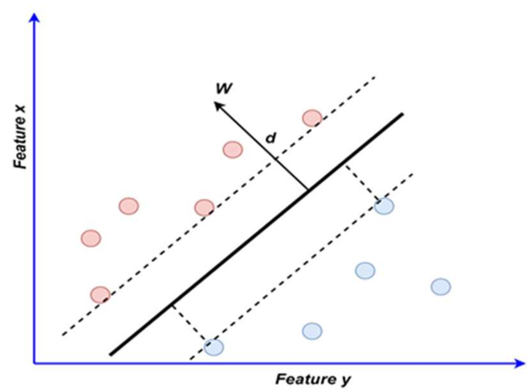

Figure 5: Linear classifications of selected class

Next step the weight w_i belong the feature can be found. During sorting features in certain vector <*w_1.w_2.....bn*> then can calculate the weight cent red in each class by,

$$\hat{C} = \frac{1}{W}\sum w_i x_i y_i \quad (2)$$

In this step, we can group similar features in order to separate them into specific categories. The process continues for all categories, including non-overlapping categories that can be easily separated by a straight line. It is separated into two classes A or B. The matching strategy was adopted in non-linear classification, which contains a section of features that overlap between

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classes such that their place is in a certain class while in reality it belongs to another class. The boundaries of the categories can be preserved to predict the best dividing line to unify the network paths in the distribution of data. As shown in Figure 6.

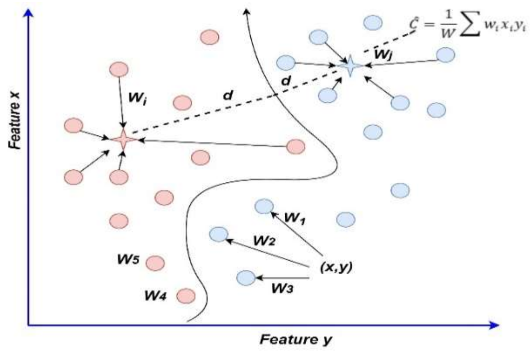

Figure 6: Non-linear classifications of features

After the algorithm is trained on 80% of the selected samples from the dataset until we reach good percentages of results and expectations according to the label attached to the sample. We test the algorithm without labels on the remaining 20% to evaluate it and know its optimal performance. The prediction accuracy, precision and recall are calculated to evaluate the proposed algorithm based on the weights of SVM and to know the algorithm's ability to classify flood level or predict sewerage network congestion, which will be discussed in the next section of the results.

In designing cities, the terrain is taken into consideration in order to determine the flow of water in the sewage networks. In Karbala, there are two main types of water flow according to the terrain, as shown in Figure 7. They are in red and green, and the governorate is divided into two parts. Water collection points are determined as shown in the drawing, and they are primary and secondary. These points contain smart sensors that give us the amount and quantity of water at that point and the speed of water flow. Then comes the role of the SVM classifier, which depends on the weights coming from all points and classifies them and gives priorities to be primary or secondary points according to the gates that control them.

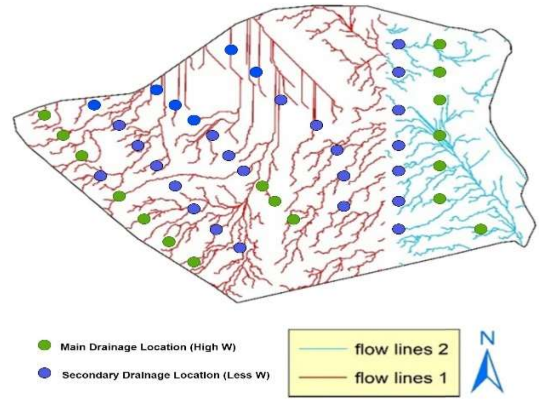

Figure 7 Distribution of drainage according to topography of the area

The data actually comes from two main sources, which are smart sensors that save the history of measurements and GIS according to seasonal changes. The data is then stored in a database and during processing, the data is taken and features are extracted from it to enter the SVM processing phase in order to start the classification process and predict the areas where discharge starts quickly or slowly. This classification leads to sound decisions that can be inferred from the results in the following section.

4 RESULTS AND DISCUSSION

The practical part of this study is very important, through which the work is evaluated and whether the proposed algorithm can be relied upon. First, we note that the algorithm is trained on real data derived from a standard dataset that contains various types of data. We divide the original data into two branches, training and testing (Figure 8). Therefore, the training group is also divided into two parts: training and validation. The final division of the data is in order to verify the validity of the test data set. The division necessarily has a set of restrictions, and in order for the test data to be good, we do this procedure. When the test data is large, the data must be verified before starting the test, and hence training depends on the labeled data, which often contains all the features of the network or any path in it.

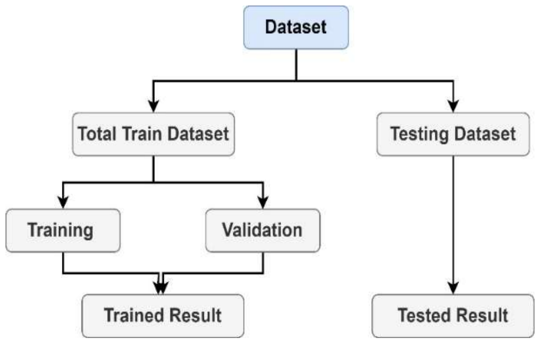

Figure 8: Architecture of dataset

Features are extracted from GIS information in a given dataset in order to be classified into vectors for work on them. Each feature has an understanding of the proposed algorithm in order to work on it.

The data is collected in order to be interpreted later, and the collection mechanism represents one of the most important processes that must be adhered to. It works on the basis of data derived from the GIS, such as the topography and terrain, environment changed, and the population density. *clusters_model= array ([1,0,4,…,0,0,4], dtypeint=32).*

In classification in general, it is important to determine the performance evaluation, and it is very useful, especially in the difference in classifications during the training phase, and it is a measure of the accuracy of the work of the proposed classifier and the extent of its success. The confusion matrix, or as it is called the contingency table, measures the accuracy of the classifier through the columns that represent the predicted and the rows that represent the actual. As shown in Figure 9.

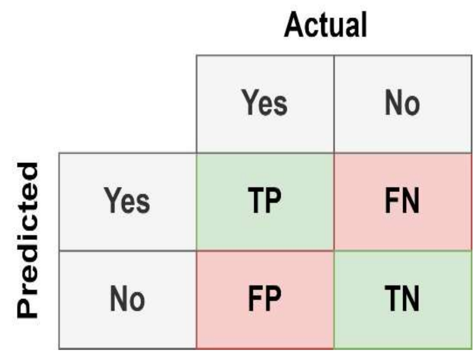

Figure 9 Confusion Matrix representation where (TP) is True Positive , (TN) is True Negative, (FP) is False Positive and (FN) is False Negative

The accuracy can be find by the Equation:

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

Precision tells us what proportion of proper path in the sewer network and can calculated by the Equation:

$$Precition = \frac{TP}{TP+FP} \quad (4)$$

The results can be translated using the confusion matrix to be clearer, realistic, and compared to the predicted results. As in Figure 10.

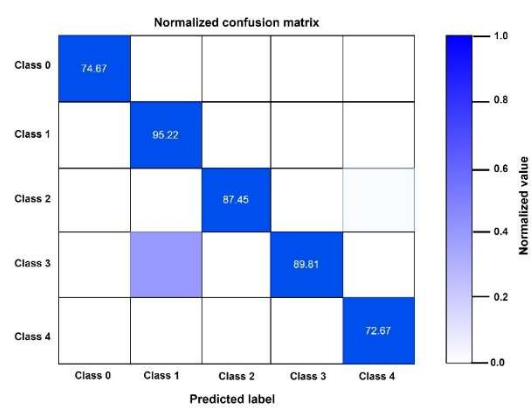

Figure 10 Confusion matrix of proposed algorithm

The dataset contains 2467800 samples, which represents 80% of the dataset during training. And the rest 20% will be in testing mode.

Classification was performed by the well-known SVM classifier for multiple classes. Classification in case of binary class is in the form of a damaged class and a non-damaged class. The results are used to examine the strong flow in sewerage networks. It is based on the time that can determine the possibility of information reaching the teams that care for the information on external variables, weather and climate. Training is done on the pre-processed data and then the changes are saved and then the test is performed on another part of the data. Table 2 shows the training on 2467800 sample given from dataset.

Table 1: Performance of SVM classifier with binary and multiclass

Classification type	Accuracy %	F-measure %	Recall %	Precision %
Binary classification	72.2	61.6	62.8	59.8
Multiclass	81.3	76.9	75.3	73.1
Weighted classification	89.7	78.8	77.4	78.3

In the Table 1, results such as precision, recall and average were obtained for data that can be interpreted in more than one way and for the areas most affected by the information change. Among the expectations are the location of the sensors to be changed according to the new predictions and considering the change in topography and the management of energy sources to be changed according to the predictions we get. The data that was trained on was the most consistent with the real data so that in the test stage there is a conviction that the results are almost real and can be relied upon. When classifying using the binary class method, the result is weaker and adding weight to the classifier increases the accuracy of the result.

The sources of water discharged in different areas of Karbala are varied and include rain, flood water, sewage water and water coming from the diversity of terrain. The statistics conducted by previous researchers in the past years are shown in Figure 11. After applying modern techniques in geographic information systems and applying weight to SVM, Figure 12 shows the method of training the system starting from 102354 samples from the data set until it reached 3277161 samples.

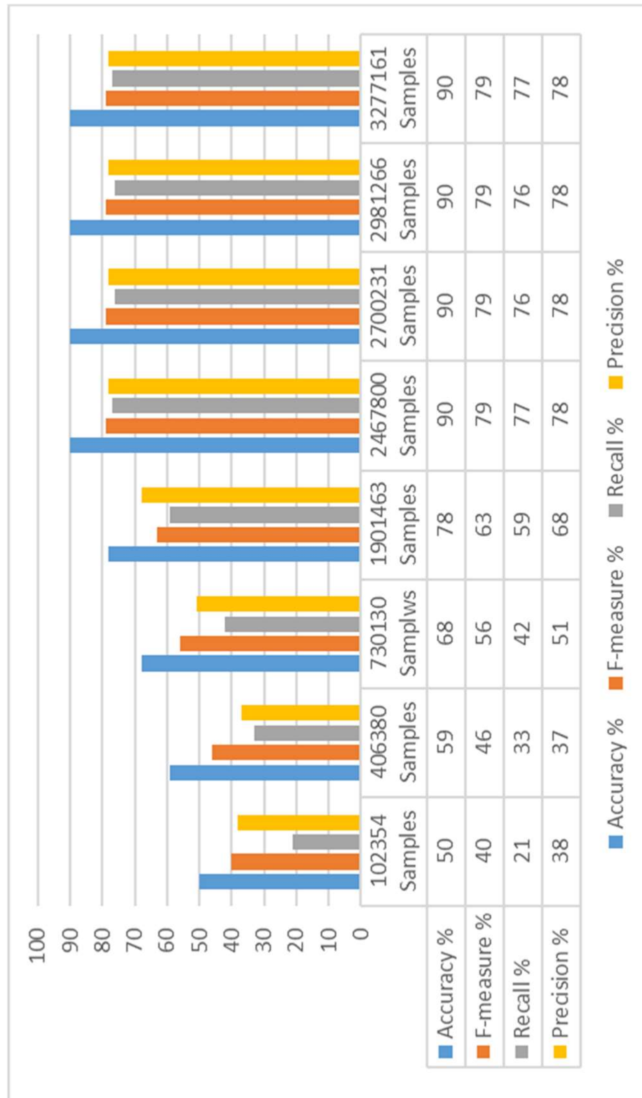

Figure 11: Evaluation of algorithm within different samples from dataset in training mode

We see that the specified number of training data is that the more data that is trained on, the more efficient the result becomes until it reaches saturation. Any increase does not serve the system but only

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increases the time used for training, which is very long during the training phase and goes 12 hours and 34 minutes when executing 2467800 samples of data and increases logarithmically after this number. As for the time taken for execution in test mode, it is negligible because the algorithm is pre-trained. The time consumption in training mode can be illustrated in Figure 11 explains how the training takes time when processing.

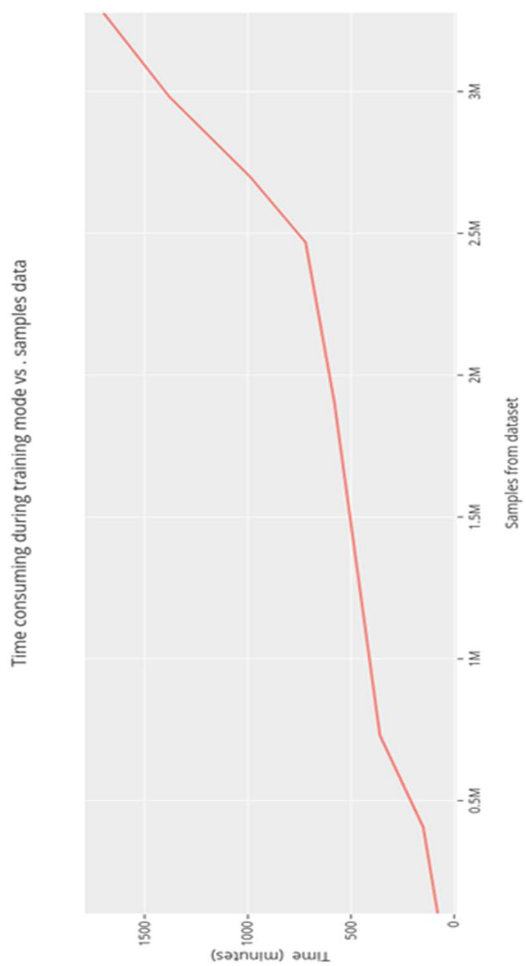

Figure 11: Excution time of proposed algorithm

5 CONCLUSION

Many challenges face the sewerage network in Karbala, Iraq. Due to the old infrastructure and lack of monitoring systems, this leads to increased flood risks. Therefore, it requires fundamental and innovative solutions to build and improve the sewerage network. In this study, we focus on integrating smart sensors and with the help of data coming from GIS to analyze the data through SVM and provides a different approach applicable to such issues. Flood monitoring through smart sensors that provide real-time and instant data and enables predictive and accurate maintenance. The pilot implementation on Karbala schemes has shown good results in reducing time and accuracy of up to 89.7% in prediction and giving appropriate priorities in precautionary measures. In this model, a strong and durable sewerage system can be built to mitigate the effects of floods resulting from climate change. In future studies, hybrid systems based on new artificial intelligence techniques such as deep learning can be used and combined with machine learning for better and more accurate predictions.

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