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Exiting Hydraulic Model Based Approach To Predict Urban Water Quality

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Abstract:

Urban water quality is of great importance to our daily lives. Prediction of urban water quality help control water pollution and protect human health. However, predicting the urban water quality is a challenging task since the water quality varies in urban spaces non-linearly and depends on multiple factors, such as meteorology, water usage patterns, and land uses. In this work, we forecast the water quality of a station over the next few hours from a data-driven perspective, using the water quality data and water hydraulic data reported by existing monitor stations and a variety of data sources we observed in the city, such as meteorology, pipe networks, structure of road networks, and point of interests (POIs). First, we identify the influential factors that affect the urban water quality via extensive experiments. Second, we present a multi-task multi-view learning method to fuse those multiple datasets from different domains into an unified learning model. We evaluate our method with real-world datasets, and the extensive experiments verify the advantages of our method over other baselines and demonstrate the effectiveness of our approach. Urban water is a vital resource that affects various aspects of human. Health and urban lives. People living in major cities are increasingly concerned about the urban water quality, calling for technology that can monitor and predict the water quality in real time throughout the city. Urban water quality, which serves as "powerful environmental determinant" and "a foundation for the prevention and control of waterborne diseases", refers to the physical, chemical and biological characteristics of a water body, and several chemical indexes(such as residual chlorine, turbidity and pH)can be used as effective measurements for the water quality in current urban water distribution systems.

Keywords — **Put your keywords here, keywords are separated by comma.**

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I. INTRODUCTION

water is a vital resource that affects various aspects of human, health and urban lives. People living in major cities are increasingly concerned about the urban water quality, calling for technology that can monitor and predict the water quality in real time throughout the city. Urban water quality, which serves as “a powerful environmental determinant” and “a foundation for the prevention and control of waterborne diseases” [1], refers to the physical, chemical and biological characteristics of a water body, and several chemical indexes (such as residual chlorine, turbidity and pH) can be used as effective measurements for the water quality in current urban water distribution systems.

With the increasing demand for water quality information, several water quality monitoring stations have been deployed throughout the city’s water distribution system to provide the real-time water quality reports in a city. Figure 1 illustrates the water quality monitor stations that have been deployed in Shenzhen, China. Besides water quality monitoring, predicting the urban water quality plays an essential role in many urban aquatic projects, such as informing waterworks’ decision making (e.g., pre-adjustment of chlorine from the waterworks), affecting governments’ policy making (e.g., issuing pollution alerts or performing a pollution control), and providing maintenance suggestions (e.g., suggestions for replacements of certain pipelines).

Predicting urban water quality, however, is very challenging due to the following reasons. First, urban water quality varies by locations non-linearly and depends on multiple factors, such as meteorology, water usage patterns, land use, and urban structures. the water quality indexes (RC) reported by the three stations demonstrate different patterns. Exiting hydraulic model-based approaches try to model water quality from physical and chemical perspective, but such hydraulic model can hardly capture all of those complex factors. Moreover, the parameters in model are hard to get, which makes it difficult to extend to other water distribution systems. Second, as all the stations are connected through the pipeline system, the water quality among different stations are mutually correlated by several complex factors, such as attributes in pipe networks and distribution of POIs.

To benefit from the unprecedented data in urban areas, in this paper, we predict the water quality of a station through a data-driven perspective using a variety of data sets, including water quality data, hydraulic data, meteorology data, pipe networks data, road networks data, and POIs. First, we perform extensive experiments and data analytics between the water quality and multiple potential factors, and identify the most influential ones that have an effect on the urban water quality. Second, we present a novel spatio-temporal multi-task multi-view

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learning (stMTMV) framework to fuse the heterogeneous data from multiple domains and jointly capture each station's local information as well as their global information into an unified learning model [6].

- **Data-driven Perspective**: We present a novel data-driven approach to co-predict the future water quality among different stations with data from multiple domains. Additionally, the approach is not restricted to urban water quality prediction, but also can be applied to other multi-locations based coprediction problem in many other urban applications.
- **Influential Factor Identification**: We identify spatially-related (such as POIs, pipe networks, and road networks) and temporally-related features (e.g., time of day, meteorology and water hydraulics), contributing to not only our application but also the general problem of water quality prediction.
- **Unified Learning Model**: We present a novel spatio-temporal multi-view multi-task learning framework (stMTMV) to integrate multiple sources of spatio-temporal urban data, which provides a general framework of combining heterogeneous spatio-temporal properties for prediction, and can also be applied to other spatio-temporal based applications.
- **Real evaluation**: We evaluate our method by extensive experiments that use real-world datasets in Shenzhen, China. The results demonstrate the advantages of our method beyond other baselines, such as ARMA, Kalman filter, and ANN, and reveal interesting discoveries that can bring social good to

II. EXITING SYSTEM

Predicting urban water quality, however, is very challenging due to the following reasons. First, urban water quality varies by locations non-linearly and depends on multiple factors, such as meteorology, water usage patterns, land use, and urban structures. Existing Does not provides to take any water qualities data and make analysis on it.

- Current System comparison of water qualities in various cities is done through excel sheets.
- Did not publish that dataset on internet so we don't have that dataset but we_found Indian state water supply quality dataset.

Disadvantages

- Existing algorithms will not filtered Provides water filter data
- Existing system Manual Sheet Analysis
- No Graphical Analysis

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III.PROPOSED SYSTEM

To benefit from the unprecedented data in urban areas, in this paper, we predict the water quality of a station through a data-driven perspective using a variety of data sets, including water quality data, hydraulic data, meteorology data, pipe networks data, road networks data, and POIs. First, we perform extensive experiments and data analytics between the water quality and multiple potential factors, and identify the most influential ones that have an effect on the urban water quality. Second, we present a novel spatio-temporal multi-task multi-view learning (stMTMV) framework to fuse the heterogeneous data from multiple domains and jointly capture each station's local information as well as their global information into an unified learning model.

Advantages

- Data processing organizations are switching towards CNN and LSTM classification or prediction model due to its increasing performance and popularity.
- A significant Application for risk analysis that have been applied to qualitatively or quantitatively compute and combine 'probability of failure' and 'consequences' at different levels in water supply systems

IV.SYSTEM ARCHITECTURE

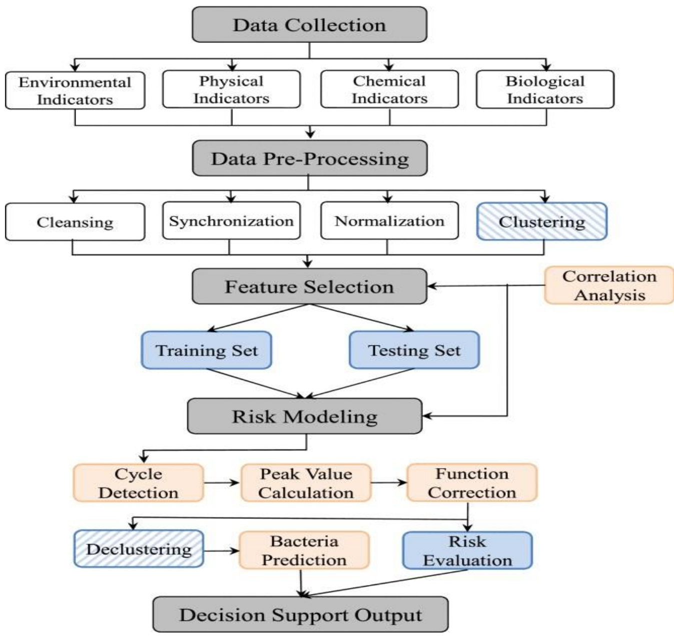
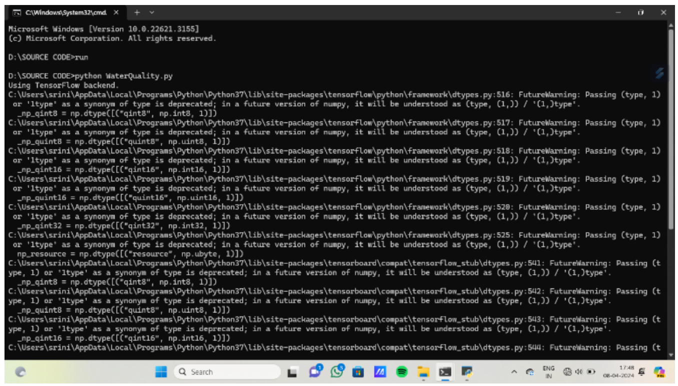


Fig: System Architecture

SAMPLE SCREENS



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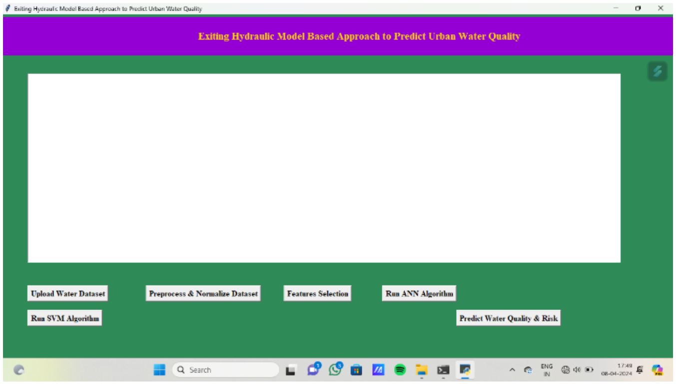

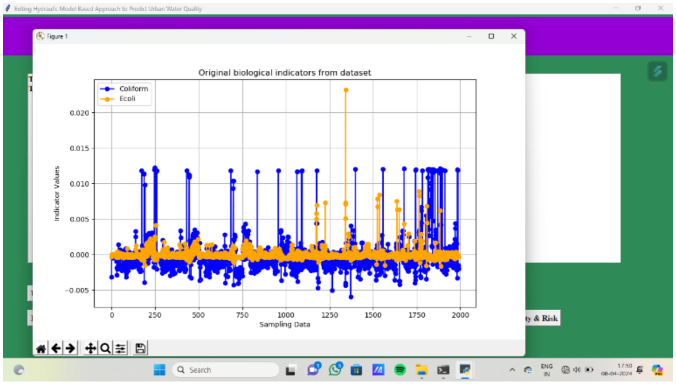

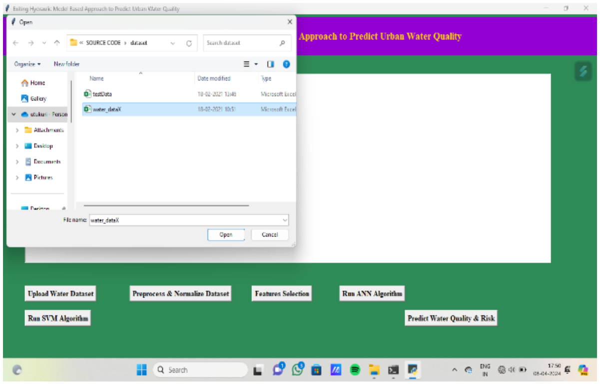

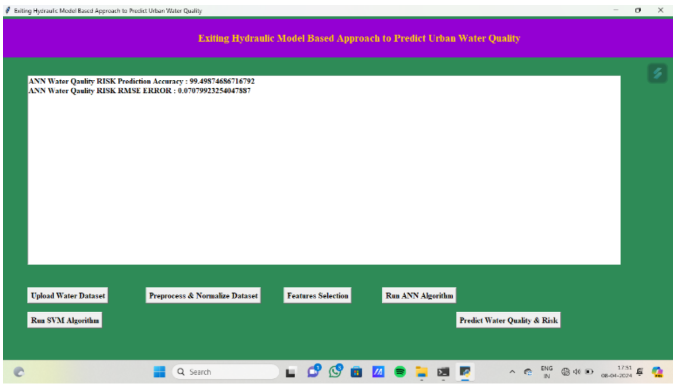

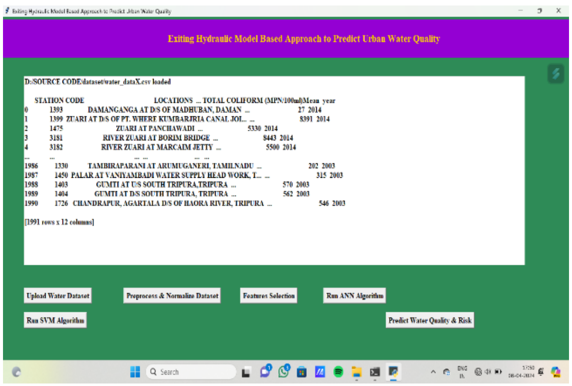

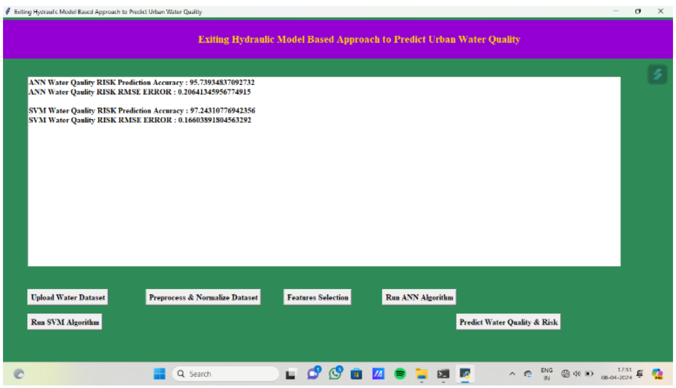

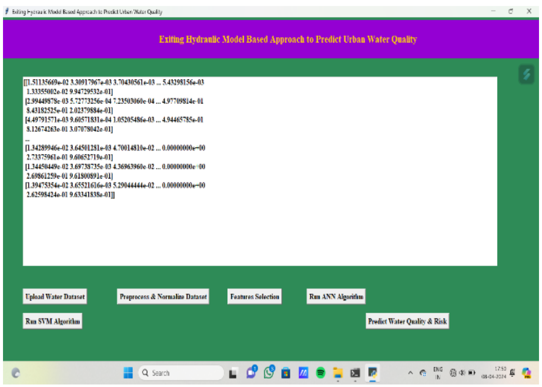

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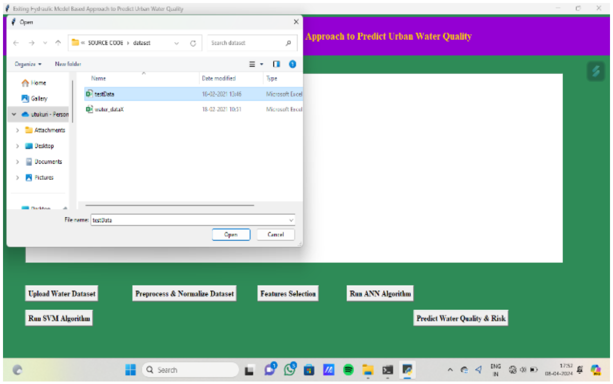

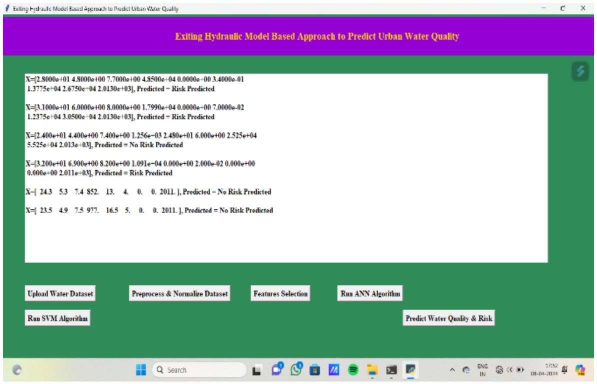

CONCLUSIONS

This paper presents a novel data-driven approach to forecast the water quality of a station by fusing multiple sources of urban data. We evaluate our approach based on Shenzhen's water quality and various urban data. The experimental results demonstrate the effectiveness and efficiency of our approach. Specifically, our approach outperforms the traditional RC decay model [2] and other classical time series predictive models (ARMA, Kalman) in terms of RMSE metric. Meanwhile, as our approach consists of two components, each of the components demonstrates its effectiveness through extensive experiments and analysis. In particular, the first component is the influential factors identification, which explores the factors that affect the urban water quality via extensive experiments and analysis in Section 3 and 4. The second one is a spatiotemporal multi-view multi-task learning (stMTMV) framework that consists of multi-view learning and multi-task learning. The experiments have shown that stMTMV has a predictive accuracy of around 85% for forecasting next 1-4 hours, which outperforms the single-task methods (LR) by approximately 11% and the single-view methods (t-view and s-view) by approximately 11% and 12%, respectively. The code has been released at: https://www.microsoft.com/en-us/research/publication/urbanwater-quality-prediction-based-multi-task-multi-view-learning-2/

In future, we plan to deal with the water quality inference problems in the urban water distribution systems through a limited number of water quality monitor stations.

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REFERENCES

[1] W. H. Organization, Guidelines for drinking-water quality, 2004, vol. 3.

[2] L. A. Rossman, R. M. Clark, and W. M. Grayman, "Modeling chlorine residuals in drinking-water distribution systems," Journal of environmental engineering, vol. 120, no. 4, pp. 803–820, 1994.

[3] Y. Zheng, "Methodologies for cross-domain data fusion: An overview," IEEE Transactions on Big Data, vol. 1, no. 1, pp. 16–34, 2015

[4] Y. Zheng, L. Capra, O. Wolfson, and H. Yang, "Urban computing: Concepts, methodologies, and applications," ACM Transactions on Intelligent Systems and Technology, vol. 5, no. 3, pp. 38:1–38:55, 2014.

[5] Y. Zheng, H. Zhang, and Y. Yu, "Detecting collective anomalies from multiple spatio- temporal datasets across different domains," 2015.

[6] Y. Liu, Y. Zheng, Y. Liang, S. Liu, and D. S. Rosenblum, "Urban water quality prediction based on multi-task multi-view learning," in Proceedings of the International Joint Conference on Artificial Intelligence, 2016.

[7] H. Cohen, "Free chlorine testing," http://www.cdc.gov/safewater/chlorineresidual-testing.html, 2014, accessed on 5 August 2016.

[8] B. D. Barkdoll and H. Didigam, "Effect of user demand on water quality and hydraulics of distribution systems," in Proceedings of the World Water and Environmental Resources Congress, 2003.

[9] P. Castro and M. Neves, "Chlorine decay in water distribution systems case study–lousada network," Electronic Journal of Environmental, Agricultural and Food Chemistry, vol. 2, no. 2, pp. 261–266, 2003.

[10] L. W. Mays, Water distribution system handbook, 1999.

[11] L. A. Rossman and P. F. Boulos, "Numerical methods for modeling water quality in distribution systems: A comparison," Journal of Water Resources planning and management, vol. 122, no. 2, pp. 137–146, 1996.

[12] W. M. Grayman, R. M. Clark, and R. M. Males, "Modeling distributionsystem water quality: dynamic approach," Journal of Water Resources Planning and Management, vol. 114, no. 3, pp. 295–312, 1988.

[13] J. Lin, E. Keogh, S. Lonardi, and B. Chiu, "A symbolic representation of time series, with implications for streaming algorithms," in Proceedings of the ACM SIGMOD Workshop on Research Issues in Data Mining and Knowledge Discovery, 2003, pp. 2–11.

[14] G. Luo, K. Yi, S.-W. Cheng, Z. Li, W. Fan, C. He, and Y. Mu, "Piecewise linear approximation of streaming time series data with max-error guarantees," in Proceedings of the IEEE International Conference on Data Engineering, 2015, pp. 173–184.

[15] E. O. Brigham and E. O. Brigham, The fast Fourier transform. PrenticeHall Englewood Cliffs, NJ, 1974, vol. 7. [16] C. S. Burrus, R. A. Gopinath,