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Research Article

Investigating the Causes of Deterioration in Polyethylene Pipes in the Mashhad Urban Water Distribution Network and Predicting Pipe Failure Rates Using Machine Learning

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Abstract

Urban water distribution networks are among the most critical infrastructures of society, and pipe failures pose a major challenge to the sustainability and reliability of water supply services. Polyethylene pipes are widely used because of their corrosion resistance, lightweight structure, and flexibility; however, environmental and operational factors can accelerate their deterioration and increase failures. This study investigates the factors affecting polyethylene pipe deterioration in the Mashhad water distribution network and predicts pipe failures using machine learning algorithms. Real-world data, including pipe age, diameter, length, installation depth, hydraulic pressure, and historical failure records, were collected from the Mashhad water distribution network. Environmental variables, including surface traffic and temperature fluctuations, were incorporated into the dataset. Four machine learning algorithms—Random Forest (RF), Light Gradient Boosting (LightGBM), Artificial Neural Network (ANN), and Support Vector Classifier (SVC)—were evaluated. The results showed that all models achieved high predictive performance. Among them, LightGBM produced the best results, with an accuracy of 96.1%, a recall of 95.7%, and an area under the ROC curve (AUC) of 0.980. The RF model also performed well, achieving an accuracy of 94.3%, a recall of 92.9%, and an AUC of 0.971, while the ANN and SVC models achieved accuracies of 88.4% and 89.7%, respectively. Feature importance analysis identified pipe age, temperature fluctuations, hydraulic pressure, and pipe diameter as the most influential factors affecting pipe failures. These findings provide a reliable framework for identifying high-risk pipes and supporting proactive maintenance strategies to improve urban water network reliability.

Keywords:
Polyethylene Pipes, Mashhad Urban Water Distribution network, Machine Learning, Random Forest, Light Gradient Boosting Machine

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1- Introduction

Urban water distribution networks constitute critical infrastructure for ensuring a reliable and sustainable drinking water supply. In rapidly growing metropolitan areas such as Mashhad, the long-term operation of extensive water distribution systems, combined with aging infrastructure, increasing hydraulic demands, and environmental stresses, has significantly increased the likelihood of pipe deterioration and failure. These failures not only lead to water losses and service interruptions but also impose substantial economic costs and operational challenges for water utilities. Consequently, shifting from reactive maintenance to predictive asset management has become a strategic priority for improving network reliability and reducing maintenance costs. Although considerable research has been conducted on pipe failure prediction, previous studies have primarily focused on metallic pipes, relied on limited sets of operational variables, or were developed using data from regions with different climatic and operational conditions. Furthermore, the application of machine learning techniques to predict the failure of polyethylene pipes by jointly considering operational and environmental factors remains limited, particularly for real-world water distribution systems in developing urban environments. To address these gaps, this study investigates the deterioration mechanisms of polyethylene pipes and develops machine learning models to predict pipe failure rates using operational data from the Mashhad water distribution network.

Polyethylene pipes are recognized as one of the most widely used types of pipes in water and gas transmission and distribution systems (Farajzadeh et al., 2024). These pipes have been extensively employed in water distribution networks due to their favorable mechanical behavior, long service life, and desirable properties such as corrosion resistance, flexibility, lightweight, and ease of installation (Tabesh et al., 2011). Nevertheless, polyethylene pipes are also vulnerable to certain environmental and mechanical factors, and under adverse conditions, they may suffer from premature deterioration and failure. For example, stresses caused by temperature variations (extreme heat and cold), operational pressures, water hammer, traffic loads, and soil chemical compounds can gradually lead to the initiation of creeping cracks and crack growth in polyethylene pipe walls. These creep and stress-induced cracks (the phenomenon of slow crack growth in polymers) ultimately result in brittle failure of the pipe, which is frequently observed in older polyethylene pipes (Nasiri, and Khosravani, 2023). Therefore, monitoring the condition of polyethylene pipes and predicting their failure probability before occurrence is essential for optimal management of water network assets. Accordingly, the application of modern Machine Learning methods to analyze pipe degradation patterns and predict their failure rates can enable the preventive identification of at-risk pipes and facilitate optimal maintenance planning. In the present study, focusing on the Mashhad urban water network, efforts have been made to identify the factors affecting the deterioration of polyethylene pipes and predict their failure rates with acceptable accuracy using machine learning algorithms.

In recent years, numerous studies have investigated water network pipe failures and developed prediction models for failure rates. These studies demonstrate that multiple factors contribute to pipe failures, including inherent pipe characteristics (material, diameter, and operational age), installation and operational conditions (burial depth, hydraulic pressures and their fluctuations, quality of joint execution), and environmental conditions surrounding the pipe (soil type and density, temperature and seasonal variations, and surface traffic volume). For instance, Fan et al. (2022) conducted a study to improve the accuracy of urban water pipe failure prediction, focusing on the large water distribution network of Cleveland, Ohio. Five classification algorithms—including Light Gradient Boosting, Artificial Neural Network, Logistic Regression (LR), Support Vector Machine, and K-Nearest Neighbors (KNN)—were tested. The results showed that the Light Gradient Boosting algorithm exhibited the best performance in terms of accuracy, training speed, and interpretability. Variable role analysis using the SHAP technique revealed that important factors included the number of cold days, pipe age, and the time interval between two consecutive failures, and that older, longer pipes located in cold regions, specific soil types, and made of cast iron were more susceptible to failure. Additionally, less affluent areas showed lower failure rates, likely due to reduced consumption or underreporting (Fan et al., 2022).

Omar et al. (2023) conducted studies on the water distribution network of Kitchener, Canada. In this research, six machine learning algorithms, including Random Forest, Artificial Neural Network, and Naive Bayes, were employed. The results indicated that the Random Forest algorithm demonstrated the best performance in predicting pipe failures. Evaluation of the variables affecting failure probability revealed the significant influence of pipe length, service condition index, and criticality index (Omar et al., 2023). Farajzadeh et al. (2024) designed a machine learning model for predicting failures in water distribution networks in the city of Saveh, utilizing historical data without requiring physical sensors. In comparing three algorithms, anomaly detection and the elliptical envelope algorithm showed superior accuracy and repeatability in most scenarios, although the Support Vector Machine exhibited a higher Area Under the Curve (AUC) in some cases. Sensitivity analysis indicated that certain features such as pipe length played an important role, while the removal of environmental factors in some cases led to improved model performance (Tabesh et al., 2011). Although previous studies have demonstrated the effectiveness of machine learning techniques for predicting pipe failures, several important limitations remain. Most existing studies have primarily focused on metallic water mains, have considered a limited number of operational or environmental variables, or have been conducted under climatic and operational conditions different from those of Mashhad. In addition, relatively few studies have specifically investigated the deterioration and failure of polyethylene pipes using real operational data while integrating both engineering and environmental factors. The present study addresses these limitations by developing and comparing four machine learning models (RF, LightGBM, ANN, and SVC) using real data from the Mashhad urban water distribution network. Furthermore, this study incorporates both operational variables (pipe age, diameter, length, burial depth, and hydraulic pressure) and environmental variables (traffic load and temperature fluctuations), and applies SHAP analysis to identify the relative importance of failure factors. These contributions provide a more comprehensive understanding of polyethylene pipe deterioration and support more effective preventive maintenance strategies for urban water distribution systems.

2- Materials and methods

2-1- Study domain

The city of Mashhad is recognized as the second largest and most populous city in Iran and the capital of Khorasan Razavi Province. Population estimates indicate that the city’s population was approximately 3.5 million in 2016 (1395 in the Persian calendar). The city’s drinking water supply is primarily based on groundwater resources such as wells and qanats, and to a lesser extent on surface water resources including reservoirs and dams surrounding the city. The Mashhad water and wastewater distribution network is managed by the Mashhad Water and Wastewater Company across five different service zones.

In this study, a specific area in the city of Mashhad was selected based on reports indicating a high density of pipe failure incidents in that region. This area is located in Zone 1, one of the five zones of the city. According to statistics from the Mashhad Water and Wastewater Company, the material composition of pipes used in the city’s water distribution network includes polyethylene (approximately 57%), steel (25%), asbestos-cement (10%), cast iron (7%), and other materials such as GRP at less than 1% (Figure 1).

2-2- Methods

To achieve the objectives of this study, multiple datasets were collected from various sources to construct a comprehensive database of polyethylene pipes in the Mashhad water distribution network. First, information on the physical characteristics of each pipe was extracted from the database of the Mashhad Water and Wastewater Company. These characteristics included pipe diameter, pipe length, pipe material (with a particular focus on polyethylene), installation year (used to calculate pipe age), and burial depth. In addition, hydraulic pressure, traffic load, and temperature fluctuation data were collected from the corresponding organizations and integrated with the pipe database. Records of pipe failure events during the period 2015–2024 were obtained from the maintenance and incident reports of the Mashhad Water and Wastewater Company (Mashhad Water and Wastewater Company, personal communication, 2021).

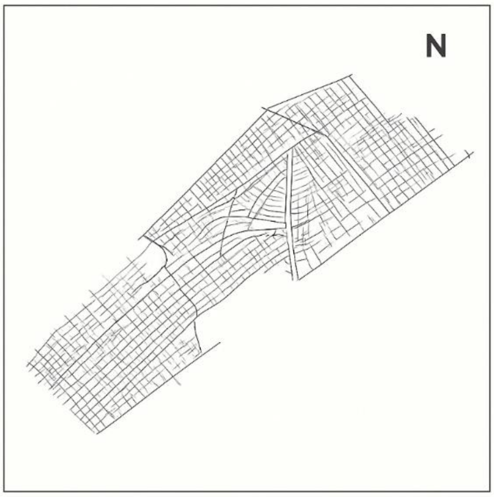


Fig. 1 Water distribution network of the study area

The target variable for the machine learning models was defined as the binary failure status of each pipe. Pipes that experienced at least one recorded failure during the study period were labeled as Failure (1), whereas pipes with no recorded failure events were labeled as Non-failure (0). The resulting dataset consisted of seven explanatory variables describing the physical, operational, and environmental characteristics of each pipe, together with the corresponding binary failure label used as the response variable in the machine learning models.

To analyze the environmental factors contributing to pipe failure, traffic load data were collected from the Mashhad Municipality Traffic and Transportation Organization, including the Average Annual Daily Traffic (AADT) on the main roads within Zone 1. The AADT values were obtained from the urban transportation yearbooks (editions 10–20), covering the period from 2009 to 2024 (1388–1403 in the Persian calendar) (Mashhad Traffic and Transportation Organization, 2021). Since the majority of the water distribution pipes in the study area are installed beneath urban road networks, traffic-induced loading was considered a potential environmental factor contributing to pipe failure. Due to the lack of detailed pipe-level traffic measurements, the total traffic volume within the study area was proportionally allocated to individual pipe segments according to their relative length within the network, as expressed in Equation (1). This approach provides an estimate of the relative cumulative traffic exposure of each pipe segment, assuming that longer pipe sections located beneath urban roads are subjected to greater cumulative traffic-induced stresses. Although this approach does not fully capture local variations in traffic intensity, it provides a practical approximation for incorporating traffic loading into the machine learning models when detailed spatial traffic data are unavailable.

$$\mathrm{AADTp} = \frac{\mathrm{Lpipe}}{\mathrm{Ltotal}} \times (\mathrm{AADTt}) \qquad (1)$$

where AADTp is the average daily traffic that each pipe endures, AADTt is the average daily traffic of vehicles in Zone 1, L_{pipe} is the length of the pipe under consideration, and L_{total} is the sum of the total length of all water distribution lines in the area.

Furthermore, climatic and temperature data for the area during the study period were collected through the Meteorological Organization (Islamic Republic of Iran Meteorological Organization, 2021). In this process, the number of days in which the average daily temperature exceeded 32 degrees Celsius or fell below zero degrees Celsius was incorporated as an important index into the pipe failure prediction models. This approach enables accurate modeling of the effects of thermal stresses and temperature fluctuations on the strength and performance of pipes. Additionally, hydraulic pressure data within the study area were recorded using pressure loggers installed at monitoring locations throughout the water distribution network. Since pressure measurements were available only at discrete locations, the hydraulic pressure distribution across the network was estimated in ArcGIS using the Inverse Distance Weighting (IDW) interpolation method. The resulting interpolated pressure surface was then used to assign a hydraulic pressure value to each pipe segment based on its spatial location within the network.

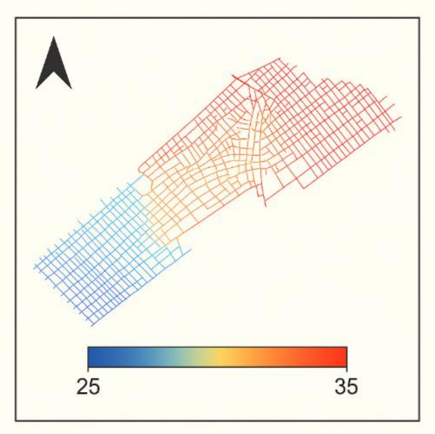


Fig. 2 Final pressure of each pipe using interpolation tools in the water distribution network of the study area

After compiling and integrating all data, given that pipe failure events were significantly less frequent and more imbalanced compared to non-failure events, the Synthetic Minority Over-sampling Technique (SMOTE) was used to balance the data distribution (Fan et al., 2022). As a result, a balanced database comprising approximately 3,000 records related to the study periods was compiled, where each record included the aforementioned characteristics of each pipe along with a label indicating whether a failure occurred or not within a specific time period.

Table 1 Sample input data for the algorithms

Diameter (mm)	Length (m)	Depth (m)	AADT (n/m.year)	AGE (day)	Climate change (day)	Pressure (m H_2o)
90	20.96	110	85	4962	189	25
90	9.45	110	45	5692	209	26
90	84.79	110	404	1673	89	27
90	33.45	110	143	4962	189	35
90	138.2	110	568	4962	189	33
110	59.91	110	285	4962	189	29
63	9	60	32	4954	185	28
90	41.37	110	197	5692	209	34
90	10.48	110	43	6390	240	25
90	49.25	110	235	4597	174	32
90	10.27	110	49	4597	174	34

In this study, four machine learning algorithms were employed to predict polyethylene pipe failures: Random Forest (RF), Light Gradient Boosting (LightGBM), Artificial Neural Network (ANN), and Support Vector Classifier (SVC). These algorithms are among the most widely used machine learning methods for classification and prediction problems (Fan et al., 2022). First, the prepared data was randomly divided into training data (80%) and test data (20%). To ensure equal distribution of failure cases in both subsets, stratified sampling was utilized in this partitioning. Subsequently, the hyperparameter tuning process for each algorithm was performed using grid search and cross-validation. An appropriate range of hyperparameters for each model was considered to select the best model for each algorithm. After training the final models on the training data, their performance was evaluated on the test data. For model evaluation, three key metrics were used: accuracy, recall, and Area Under the Curve (AUC). Accuracy represents the percentage of correct predictions by the model, recall indicates the percentage of actual failure cases correctly predicted by the model, and AUC is a measure of the model's ability to distinguish between classes (failure/non-failure) at different threshold levels. P Additionally, the TreeSHAP algorithm was employed to interpret the predictions of the LightGBM model and quantify the relative importance of the input features. TreeSHAP, implemented through the SHAP Python library, provides an efficient and exact explanation for tree-based machine learning models by estimating the contribution of each feature to the model output. The resulting SHAP values were used to rank the importance of the predictor variables and to analyze both the magnitude and direction of their influence on pipe failure prediction.

3- Results and Discussion

After training the machine learning models on the water distribution network data of the study area, their performance was evaluated based on the test data. Chart 1 presents a summary of the results obtained from the execution of the four machine learning algorithms. Based on these results, the Light Gradient Boosting (LightGBM) model, with an accuracy of approximately 0.96 and an AUC value of 0.98, demonstrated the best performance among the evaluated algorithms. Following this, Random Forest showed high accuracy with an accuracy of approximately 0.94 and an AUC of 0.97. The Support Vector Machine and Neural Network models exhibited lower performance. These results indicate the notable capability of ensemble learning methods (such as Random Forest and Gradient Boosting) in predicting pipe failure events, which is likely due to the ability of these models to combine multiple decision trees and account for data nonlinearity.

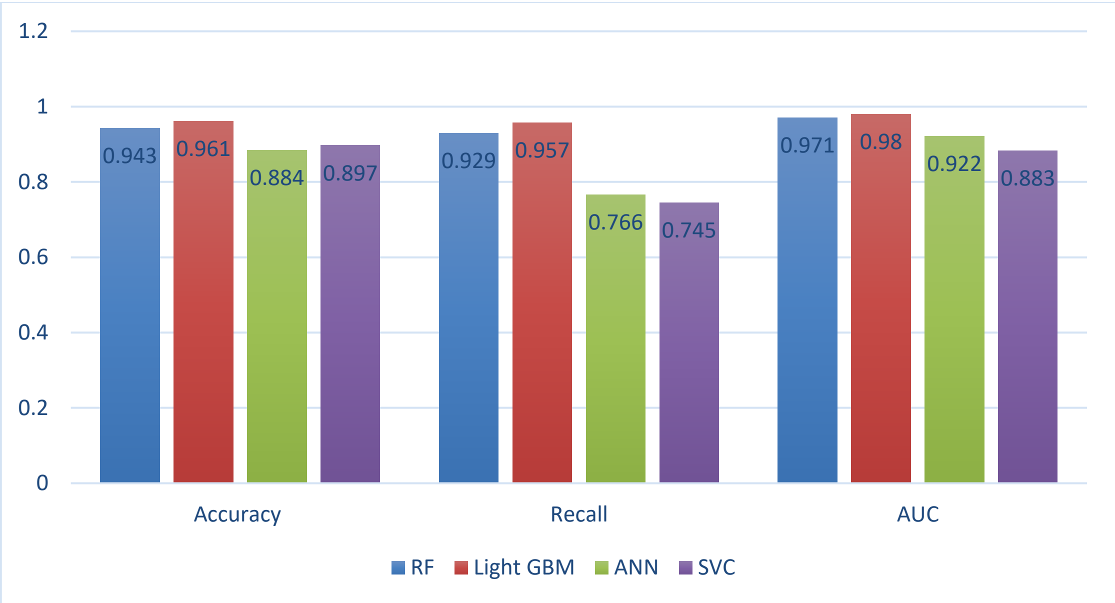


Fig. 3 Results of the four machine learning algorithms

In the next stage, to identify the factors contributing to polyethylene pipe failures, the relative importance of the input features of the models was examined. Fig. 4 presents the feature importance plot based on the output of the Light Gradient Boosting model. As observed, pipe age had the largest share in predicting polyethylene pipe failures. This result is consistent with engineering expectations and the findings of other studies, as the probability of material damage accumulation and the initiation of internal micro-cracks increases with pipe age (Barton et al., 2019). Following pipe age, climate change (temperature fluctuations) was the next most important factor. The high importance value of this factor indicates that severe temperature fluctuations (very cold winters or very hot summers) have a significant effect on increasing the probability of polyethylene pipe failure. This can be explained by thermal stresses caused by repeated expansion and contraction, as well as the increased brittleness of the polymer at low temperatures (Zheng et al., 2018). Other important factors with notable influence on system performance include pipe length, hydraulic pressure, traffic load, pipe diameter, and pipe installation depth. Each of these factors was considered in order of importance in the model, demonstrating the simultaneous role of hydraulic, physical, and environmental factors in pipe failure.

To gain a deeper understanding of the effect of each feature on the probability of pipe failure, SHAP analysis plots were also generated (Fig. 5).

These plots show how the model's predicted value for failure occurrence changes as the value of certain features increases.

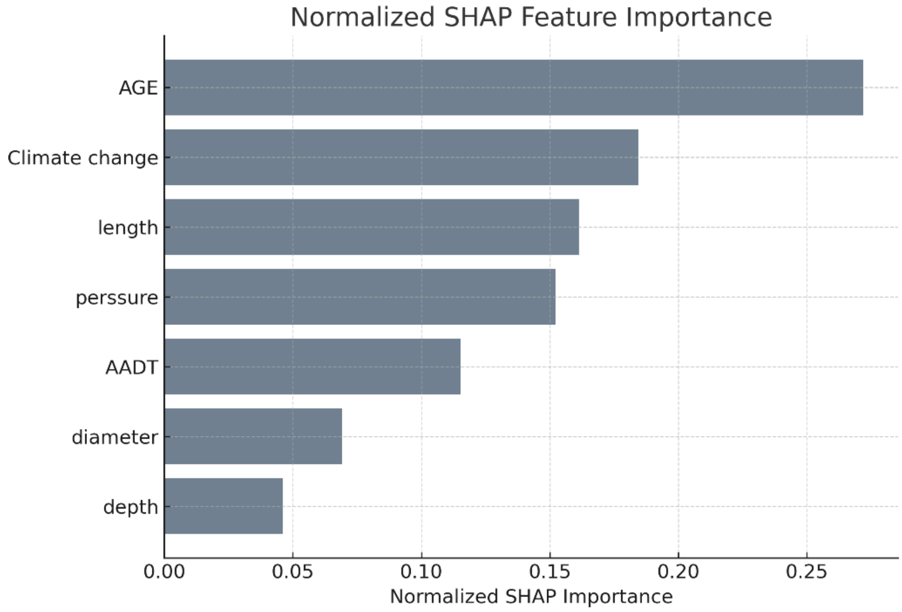


Fig.4 Feature importance plot for polyethylene pipe failure

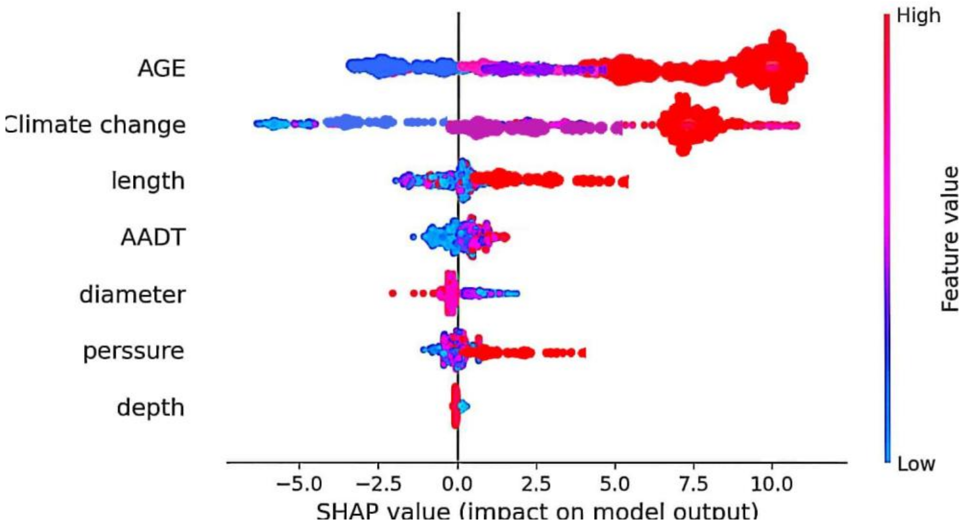
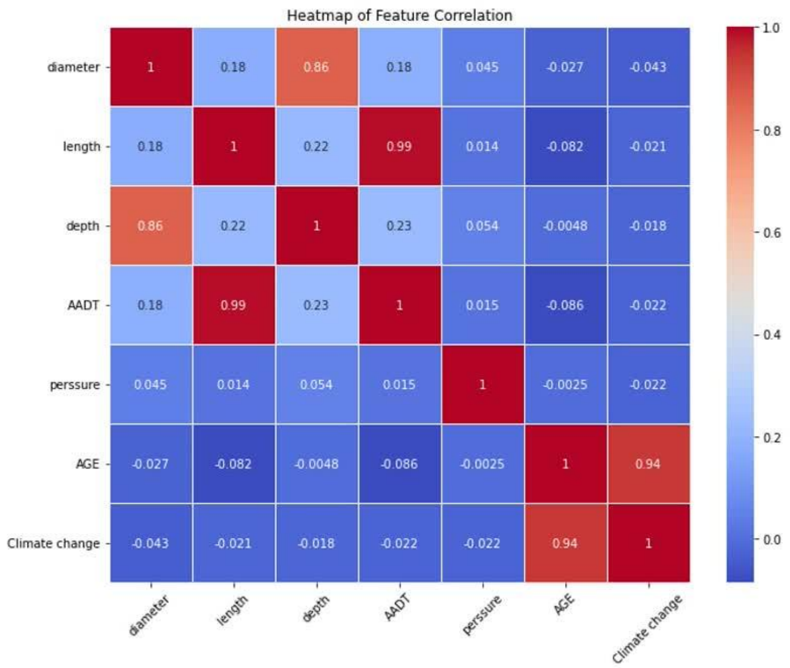


Fig.5 SHAP analysis summary plot of the Light Gradient Boosting algorithm model

Fig.5 shows the effect of pipe age on failure probability. As expected, older pipes had higher and positive SHAP values (points corresponding to older pipes in red color at the upper part of the plot), indicating the model's higher estimate of failure probability for older pipes. In contrast, newer pipes primarily had negative SHAP values (blue-colored points), exerting a reducing effect on the model output (failure probability). This trend is fully consistent with engineering realities, as over time, antioxidants added to the polymer structure degrade and the molecular chains of polyethylene undergo scission and aging, resulting in decreased material flexibility and increased pipe brittleness and susceptibility to fracture (Konstantinou and Stoianov, 2020).

In analyzing the effect of temperature fluctuations on pipe failure probability, it was observed that pipes during periods of severe temperature changes—specifically, the red points corresponding to temperatures below zero and above 32 degrees Celsius—had positive SHAP values, indicating an increased failure probability. In contrast, during the more temperate months of the year (blue points), the failure probability decreased. This finding demonstrates that the machine learning model, consistent with physical analyses, correctly identified the detrimental role of temperature in the specified range in causing pipe failures (Fan et al., 2022). In this study, the results regarding the relationship between pipe length and failure risk indicate that increasing pipe length increases the failure probability. The SHAP plot (Chart 3) confirms that longer pipes (shown in red) have more positive SHAP values, indicating the positive role of pipe length in pipe failure. Reasons for this include the increased probability of weak points such as multiple joints, welds, and variations in bed conditions, all of which can lead to stress concentration and weakness in certain sections of the pipe (Omar et al., 2023).

Increased hydraulic pressure within the water distribution network plays an important role in elevating the risk of failure. The results showed that points with high pressure (indicated in red in the plot) often had larger positive SHAP values, indicating the direct effect of high pressure on increasing internal stresses in the pipe wall. These stresses intensify particularly when the pipe is older or subject to unstable climatic conditions; consequently, increased internal pressure leads to elevated hoop stresses in the pipe wall, which directly increases the risk of brittle crack growth and sudden failure Arab, (2020). The volume of traffic passing through the study area can significantly affect the level of failure risk. According to the SHAP plot (Fig. 5), pipes located beneath routes with high traffic (red points indicating high traffic feature values) tend to have positive SHAP values, indicating an increased probability of failure. Vibrations and dynamic loads caused by passing vehicles can damage pipes over time and increase the risk of failure, especially in pipes installed at shallower depths or with greater age. On the other hand, external loads applied to the pipe that are not adequately restrained by proper and sufficient bedding can cause ring deformation and stress concentration (Fan et al., 2022).



	diameter	length	depth	AADT	perssure	AGE	Climate change
diameter	1	0.18	0.86	0.18	0.045	-0.027	-0.043
length	0.18	1	0.22	0.99	0.014	-0.082	-0.021
depth	0.86	0.22	1	0.23	0.054	-0.0048	-0.018
AADT	0.18	0.99	0.23	1	0.015	-0.086	-0.022
perssure	0.045	0.014	0.054	0.015	1	-0.0025	-0.022
AGE	-0.027	-0.082	-0.0048	-0.086	-0.0025	1	0.94
Climate change	-0.043	-0.021	-0.018	-0.022	-0.022	0.94	1

Fig.6 Correlation matrix of the variables examined in polyethylene pipe failure

To complete the analysis, Figure 6 presents the correlation matrix among the model's input features. This matrix shows the Pearson correlation coefficient among variables such as age, diameter, length, pressure, installation depth, temperature fluctuations, and traffic, determining which of these factors are directly or inversely correlated with one another. Examining these correlations helps us identify any multicollinearity in the data, which can affect the interpretability of the model's effects. The results obtained from this matrix indicate that some features are somewhat related to each other.

Overall, the correlation matrix showed that the model's input features are not absolutely independent of each other. However, no pair of variables was found with a correlation high enough to cause a serious problem due to the presence of redundant information.

4- Conclusion

In this study, the main factors contributing to polyethylene pipe failure and the corresponding failure rates were investigated through a case study of the Mashhad urban water distribution network using machine learning techniques. The modeling results demonstrated that machine learning algorithms can accurately predict pipe failures, with ensemble learning methods, particularly Light Gradient Boosting (LightGBM) and Random Forest (RF), outperforming the other evaluated models. Feature importance analysis based on the TreeSHAP method identified pipe age as the most influential factor affecting polyethylene pipe failure, indicating that older pipes are significantly more susceptible to failure. Temperature fluctuations were identified as the second most influential factor, followed by pipe length, hydraulic pressure, traffic load, pipe diameter, and installation depth. These findings highlight the importance of considering both operational and environmental factors in condition-based asset management and preventive maintenance planning. By identifying high-risk pipes before failure occurs, the proposed framework can support more efficient maintenance scheduling and reduce the economic and operational impacts of unexpected pipe failures.

Despite the promising performance of the proposed machine learning models, this study has several limitations. First, traffic load was estimated using a proportional allocation approach because detailed pipe-level traffic measurements were unavailable. Although this method provides a practical estimate of cumulative traffic exposure, it may not fully capture local variations in traffic intensity. Second, the analysis was conducted using data from the Mashhad water distribution network; therefore, the findings should be generalized to other water distribution systems with caution. In addition, several potentially influential variables, including soil characteristics, soil corrosivity, groundwater conditions, water quality parameters (e.g., chlorine concentration), and pipe installation quality, were not available and therefore could not be incorporated into the prediction models. Future studies should integrate these variables and validate the proposed framework using datasets from different urban water distribution networks to further improve the robustness and generalizability of the developed models.

Overall, this study demonstrates the potential of machine learning as an effective decision-support tool for proactive asset management in urban water distribution networks. By accurately predicting high-risk polyethylene pipes and identifying the key factors influencing pipe failure, the proposed framework can assist water utilities in optimizing maintenance strategies, reducing failure-related costs, and improving the long-term reliability and sustainability of urban water distribution systems.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors Contribution Statement

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed collaboratively. All authors read and approved the final manuscript.

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