Towards Predicting Blockages in Urban Stormwater Drainage Systems with Machine Learning

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Abstract –
Occurrences of blockages in stormwater drainages could be a significant issue, especially in urban areas, due to various challenges for infrastructure operation and maintenance. Predicting blockage occurrences is a complex problem that involves numerous parameters and an adequate understanding of their impacts, interactions and the nonlinear behaviours of certain parameters. This research study aims to develop a data-driven predictive model-based framework for potential urban stormwater drainage blockages. The framework would be using selective explainable machine learning methods with a focus on improving model transparency. This paper presents an interim summary of employing some machine learning models, such as K-nearest neighbours, logistic regression, random forest, artificial neural networks, and XGBoost. The prototype framework discussed in this paper has been developed and evaluated using a set of practical datasets obtained from historical maintenance records of a local city council in Victoria state of Australia, along with some climatic, environmental, socio-economic and asset-related datasets compiled from various sources. In the pilot testing of models of prototype framework, XGBoost demonstrated the best predictive performance, showing a strong ability to capture non-linear relationships in the data. The SHAP global feature importance analysis was used to explore the importance of chosen model parameters, which revealed that specific rainfall and vegetation cover in the catchment zones are the key influencing parameters for predicting potential occurrences of blockages in stormwater drainage systems. Hopefully, the study outcomes at the outset would demonstrate that explainable machine learning can support the development of a smart stormwater drainage asset management digital twin infrastructure.

Keywords – Stormwater infrastructure, Blockage Prediction, Machine Learning, Explainable AI, Predictive Maintenance, Asset Management

1 Introduction

Urban stormwater drainage systems are essential components of modern cities, providing protection against flooding, safeguarding public health, and supporting other operational urban activities. However, these systems face significant challenges due to ageing infrastructure, climate change, growing urbanisation, and expanding cities[1]. Under these conditions, drainage blockages have become a major operational challenge, which reduces the drainage capacity and significantly increases the likelihood of urban flooding[2]. Stormwater blockages are caused by tree root intrusion, sediment deposition, debris and litter accumulation[3, 4]. Therefore, managing these challenges requires effective maintenance strategies that can support informed decision-making in stormwater asset management.

Current stormwater maintenance, such as manual inspections and CCTV inspections, is mostly reactive or schedule-based, where inspections and cleaning activities are driven by public complaints, costly and time-consuming[5, 6]. Consequently, researchers and local councils have increasingly focused on developing proactive approaches that can identify potential blockage issues before failures occur. Such approaches can help enhance system efficiency, prioritise high-risk assets, and reduce the likelihood of unexpected blockage-related failures.

Recent advances in machine learning have led to the development of data-driven prediction models for urban drainage systems. Using historical maintenance data, these models can predict drainage issues at the asset level, enabling proactive maintenance planning [7]. Machine learning techniques are well-suited to capture complex and non-linear relationships between input and output variables, which helps in understanding how key influencing factors contribute to drainage blockage occurrence[8]. According to [9], Predictive models can achieve substantial cost savings, including reductions of up to 60% in preventive maintenance costs through a 39% decrease in preventive maintenance frequency. Despite their strong predictive performance, one of the main challenges of these models is the lack of transparency, as many high-performing machine learning models are often treated as “black boxes”[10]. Explainable artificial intelligence (XAI) helps transform black-box machine learning models into transparent models by explaining how factors and their contributions affect the final output. This transparency enables decision makers to trust predictions, justify maintenance priorities and allocate resources effectively across infrastructure like drainage networks [11].

Therefore, this study uses classical machine learning models, together with explainable AI methods, to predict and interpret the occurrence of drainage blockages. Historical maintenance data and environmental and climatic variables are used to develop an explainable prediction framework. The study aims to assess model performance, improve understanding of model behaviour, and show how the results can support proactive and risk-based asset management. In future applications, the developed models can be integrated into proactive drainage management frameworks, including digital twin systems, where explainable predictions can support monitoring, maintenance prioritisation, and informed decision-making.

2 Background of Research

Blockage formation in urban drainage systems is a complex process governed by the interaction of physical, environmental, climatic, operational, and socio-economic factors. This complexity limits the effectiveness of traditional analytics approaches, such as statistical approaches to capture nonlinear relations between factors and blockage formation. For example, Statistical models for predicting blockages in drainage systems have several limitations, particularly related to data availability and model assumptions. These models are highly dependent on the quality and resolution of input data, and inaccurate or incomplete records can significantly reduce prediction reliability. For example, Markov chain models require large and consistent datasets describing pipe condition and blockage history, which are often unavailable in municipal records, leading to reduced prediction accuracy [12]. While Log Gaussian Cox models are capable of representing spatio-temporal patterns, they are computationally intensive and require a long simulation time [13]. Similarly, Cox proportional hazards models rely on assumptions that may not adequately represent the nonlinear behaviour. As a result, the applicability of these models remains limited in practical drainage management contexts.

A wide range of machine learning (ML) and deep learning (DL) models have been applied in previous studies to diagnose and predict failures within urban sewer systems. Classical ML approaches, including decision trees, random forests, logistic regression, and support vector machines, have demonstrated strong predictive capability for blockage prediction trained on historical asset and inspection data [14-16]. More recently, deep learning models, such as neural networks, graph-based neural networks, and autoencoder-based frameworks, have enabled the integration of spatiotemporal data and large feature sets to predict deposit accumulation, siltation severity, and cleaning requirements with improved accuracy [17-20]. Despite these advances, most existing predictive models focus on wastewater or combined sewer systems, with limited attention given to stormwater drainage systems. Tran [21], developed a neural network model to assess serviceability conditions of stormwater drainage, but predictive modelling for stormwater-specific blockage behaviour remains underdeveloped.

Many existing studies use a limited set of input variables, mainly focusing on pipe attributes such as diameter, length, age, material, depth, and soil type, as well as population and property density. Although these inputs are commonly used, environmental and catchment-related factors such as land use, vegetation cover (e.g., NDVI), impervious area, and the number of dry days preceding a blockage event are employed in only a limited number of studies. These factors strongly influence runoff, debris movement, and sediment build-up in stormwater systems. Their effects on stormwater blockages are still not well studied, highlighting a clear research gap in stormwater blockage prediction. Moreover, some of these studies try to understand important features from feature importance, but systematic use of model explainability to interpret predictions is also limited in existing literature. This study incorporates stormwater-specific variables into blockage prediction, which have been rarely considered in previous studies. In addition, it introduces the use of explainable machine learning in drainage infrastructure blockage prediction to improve model interpretability. SHAP-based analysis is applied to provide transparent and interpretable insights into how different variables influence blockage formation, supporting more informed maintenance decision-making.

3 Methodology

This section describes the methodology adopted to develop an explainable machine learning framework for predicting stormwater drainage blockages. The overall workflow includes dataset preparation, model development and the use of explainable machine learning for interpreting model outputs. Each component of the methodology is described as shown in Figure 1.

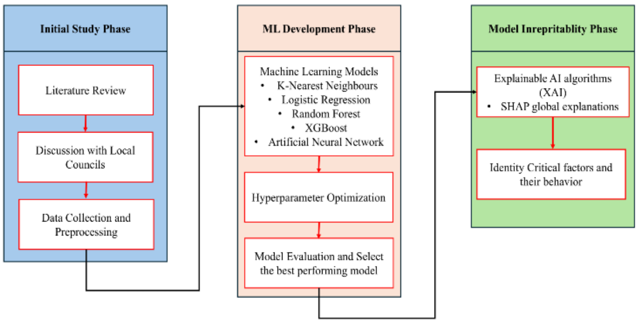

Figure 1. Research Methodology

3.1 Dataset and Variables

The dataset used in this study was provided by the Frankston council in Victoria, Australia. It comprises historical stormwater maintenance records collected between 2019 and 2025, totalling 4407 records. The stormwater drainage network includes 40,083 pipes, totalling about 1,059 km, culverts, and open drains, connected by around 41,003 stormwater pits. Pipe diameters range from 150 mm to 3,300 mm, representing both local collection pipes and larger downstream conveyance pipes. A key limitation of the dataset is that blockage information is primarily recorded at the pit level, which limits the direct use of detailed pipe attributes, such as diameter, length, and slope, as input parameters.

The factors considered in this study were identified through a comprehensive review of existing literature and experts' discussions with the local council based on their operational experience and practical knowledge of stormwater drainage management. The input factors used in this study, along with their corresponding data sources, are summarised in Table 1.

Table 1. Factors Considered in this Study

Input factor	Unit	Description
Rainfall	mm	Rainfall amount before the blockage event
Number of dry days	Days	Days without rainfall before the blockage event
Land Use	%	Impervious land use in the catchment
Number of Connections	-	Number of pipes connected to pits
NDVI	-	Vegetation cover across the area
Network density	(km/km^2)	Drainage network length per area
Population density	($Persons/km^2$)	Population per unit area

Rainfall is the cumulative rainfall before a blockage event as an indicator of stormwater runoff. The number of dry days was defined as the consecutive days with rainfall less than 1 mm before a blockage, representing dry-weather periods that influence debris accumulation [22]. Some variables, such as land use and population density, were assumed to remain constant throughout the year due to the lack of high-frequency temporal data. Vegetation cover (NDVI) was derived from Sentinel-2 satellite imagery, providing spatial information on vegetation conditions across the study area.

3.2 Model Development

3.2.1 Types of Models

Classical machine learning models, including K-Nearest Neighbours (KNN), Logistic Regression, Random Forest (RF), XGBoost, and an Artificial Neural Network (ANN), were developed to predict the occurrence of stormwater blockages using the prepared dataset. These models were selected because they have been widely applied in previous studies for prediction and classification problems [23, 24]. Thus, their predictive accuracy and reliability have been well-suited for drainage infrastructure and asset management problems.

3.2.2 Training and Optimization

Model training was performed using historical data, with the dataset divided into training and testing subsets. The dataset consists of 1669 blockage records (37.9% of total records) and 2738 non-blockage records (62.1% of total records). Given this relatively moderate class distribution, no specific class imbalance handling techniques were applied in this study. Hyperparameter tuning was conducted using a grid search (GS) approach to optimise model performance and prevent overfitting. Five-fold cross-validation (5-fold CV) was applied during training to ensure model robustness and generalisation across different data samples. The optimal model configuration was selected based on consistent performance across validation folds. Additionally, a simple baseline model (logistic regression) was trained without hyperparameters to assess the performance gains of hyper parameterized models. Table 2 shows the optimized hyperparameters used for each model.

Table 2. Optimized hyperparameters of each model

Model	Hyperparameters	Optimum
XGBoost	Max depth	6
	Estimators	400
	Learning rate	0.1
RF	Estimators	400
	Max depth	20
	Minimum sample split	5
KNN	Weights	Distance
	Neighbours	15
	Metric	Manhattan
LR	C	0.7
	Penalty	L1
ANN	Number of hidden layers	2
	Number of neurons per layer	(64,32)

3.2.3 Model Evaluation

The performance of the trained models was evaluated using multiple evaluation metrics obtained from testing data split to assess prediction accuracy (see equations 1-5).

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{1}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{2}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{3}$$

$$F1score = \frac{(2 \times Precision \times Recall)}{(Precision+Recall)} \tag{4}$$

$$ROC - AUC = Area\ under\ the\ ROC\ curve \tag{5}$$

Where TP is true positives, and FP are false positives. TN is true negatives, and FN are false negatives. The evaluation metrics were obtained using a 70/30 training and testing data split for each model to identify the most accurate model performance. A comparative analysis was conducted across all models, and the best-performing model was subsequently selected for further analysis.

3.3 Explainable AI

To address the black-box nature of machine learning models, explainable artificial intelligence (XAI) techniques were incorporated. SHAP-based global interpretation analyses were used to provide how environmental, climatic, and asset-related factors influence stormwater blockage occurrence. This interpretability enhances confidence in the model predictions and supports transparent, data-driven decision-making for drainage asset management.

4 Results

4.1 Model Performance Evaluation

The trained machine learning models were systematically evaluated to assess their predictive capability. This evaluation is critical to ensure (a) the ability of the proposed machine learning framework to capture complex and non-linear relationships among climatic, environmental, and related other factors under limited data availability, and (b) the robustness of the trained models in accurately predicting blockage occurrence for previously unseen (test) data. Following model training and hyperparameter optimization, performance was assessed using an independent test dataset, as shown in the table 3 below. Table 3 presents a comparative evaluation of the five classification models using Accuracy, F1-score, and ROC–AUC on the test dataset.

Table 3. Results and Model Comparison

Model	Accuracy	F_1 Score	ROC-AUC
XGBoost	0.81	0.74	0.88
RF	0.80	0.74	0.87
KNN	0.77	0.71	0.85
ANN	0.72	0.56	0.76
LR (With hyperparameters)	0.61	0.55	0.66
LR (Baseline model)	0.66	0.35	0.65

According to Table 3, among all models, XGBoost achieved the best overall performance, with an accuracy of 0.81, an F1-score of 0.74, and the highest ROC–AUC value of 0.88. Random Forest showed comparable performance (accuracy = 0.80, ROC–AUC = 0.87), indicating that ensemble tree-based models are also effective for capturing the complex and non-linear relationships governing stormwater drainage blockages. KNN demonstrated moderate predictive capability (accuracy = 0.77, F_1 = 0.71, ROC–AUC = 0.85), while Logistic Regression (F_1 = 0.55, ROC–AUC = 0.66) and ANN (F_1 = 0.56, ROC–AUC = 0.76) showed comparatively lower performance, especially in terms of F1-score and ROC–AUC. ANN models typically require larger datasets to effectively capture complex patterns and avoid overfitting. In contrast, classical machine learning algorithms such as Random Forest and boosting models (e.g., XGBoost) often perform better with less training data and require less extensive hyperparameter tuning [25]. Moreover, a baseline Logistic Regression model without hyperparameter tuning was implemented to provide a simple benchmark for comparison of optimized models over traditional ML models. The baseline model produced performance (accuracy = 0.66, F1 = 0.35, ROC–AUC = 0.65). In terms of accuracy, it has a slight accuracy improvement over the Logistic Regression with hyperparameters, but overall performances of optimized models outperforming traditional ML models. Figure 2 shows ROC–AUC curves for the tested models, illustrating their classification performance on the test dataset.

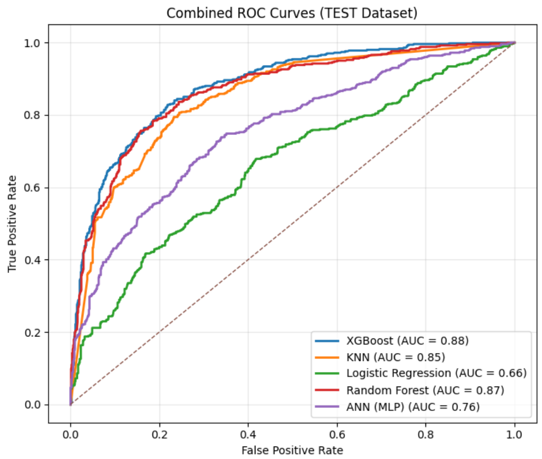

Figure 2. ROC-AUC Curves for each model

In addition to standard evaluation metrics, the confusion matrix for the best-performing model was analysed to better understand the model's misclassification patterns, as shown in Figure 3. The presence of false positives indicates that some non-blockage cases were predicted as blockages, which may lead to unnecessary inspections or preventive maintenance actions. Conversely, false negatives are cases in which actual blockages were predicted as non-blockages, potentially leading to undetected issues in the drainage network.

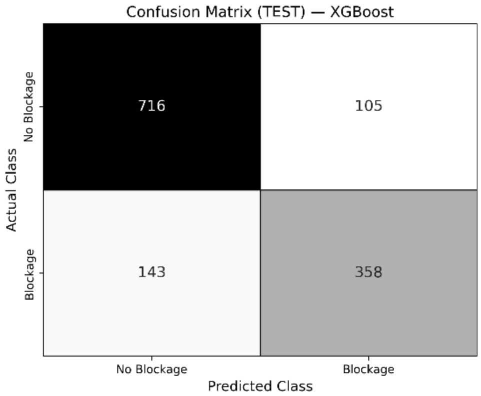

Figure 3. Confusion Matrix for test data set for XGBoost model

According to the figure, most samples are correctly classified compared to misclassified cases, indicating that the model performs well in distinguishing blockage and non-blockage events.

4.2 SHAP Explanation

To interpret the best-performing model, SHAP-based explainable AI analysis was applied to the XGBoost classifier. The explanation is shown in Figure 3.

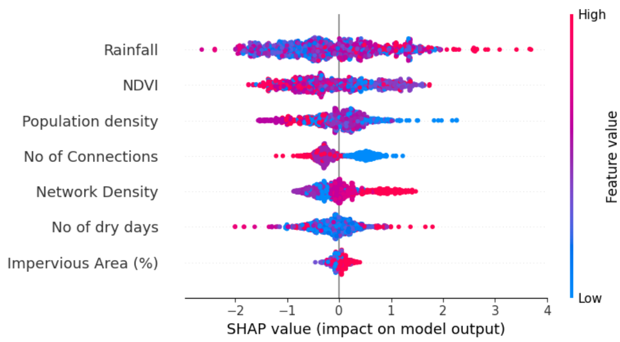

Figure 4. SHAP Summary plot

The SHAP summary plot reveals that rainfall is the most influential predictor of blockage occurrence, followed by NDVI, population density, and the number of connections. Higher rainfall values generally increase the likelihood of blockages because rainfall generates higher runoff that carries debris and sediment into pits and pipes. The SHAP results for NDVI indicate that higher and mean NDVI values are associated with an increased likelihood of blockage, likely due to greater vegetation coverage, which contributes organic debris to the drainage system. Although higher population density generally increases blockage likelihood, the SHAP plot shows that low population density can also contribute to higher blockage risk in certain cases. This occurs when low-density areas may interact with other dominant factors, such as high rainfall, NDVI, etc. Network characteristics (e.g., network density and number of connections) also exhibit significant contributions, highlighting the influence of infrastructure complexity on blockage formation. Higher values of antecedent dry days and impervious area percentage increase blockage risk, but their influence is relatively smaller. These results not only enhance model transparency but also provide physically and operationally meaningful insights to support decision-making.

5 Conclusions and Future Works

This paper developed and evaluated a data-driven predictive framework for the occurrence of stormwater drainage blockages, focusing on model performance and interpretability. Among the machine learning approaches, the XGBoost model achieved the best predictive performance, capturing complex, non-linear relationships between drainage blockages and external influencing factors. The use of explainable artificial intelligence helped address the black-box nature of the model by clearly identifying the key factors influencing blockage predictions. The results show that rainfall and vegetation indicators (NDVI) are the dominant factors, and other environmental factors have a strong influence on blockage occurrence. The outputs of this study can be integrated with decision-support systems such as multi-criteria decision-making (MCDM) methods to support inspection prioritization, maintenance scheduling, and resource allocation. For instance, explainable blockage risk factors can be translated into criteria weights or constraint rules within MCDM frameworks, enabling transparent ranking of assets that require priority maintenance or inspection. Moreover, the direct effect of pipe attributes is limited in this study; they are still useful when combined with environmental and climatic factors. The main reason for this is that maintenance data are recorded at the pit level rather than for individual pipes. Therefore, methods such as pit–pipe mapping link each pit to its connected pipe segments based on the network topology, allowing pipe attributes such as diameter, length, slope, and material to be incorporated indirectly into the model and could improve predictive performance up to a certain level in future versions. Overall, these findings demonstrate both the strengths and limitations of the proposed approach and support its use as a data-driven tool for risk-based stormwater drainage asset management.

Future work focuses on extending the proposed predictive framework to improve interpretability, robustness, and practical applicability. This includes incorporating local explanations and feature dependency analysis using explainable AI to better understand how blockages vary across individual cases and operating conditions. The model can be integrated with additional input variables, such as traffic intensity, soil type, humidity, and temperature, which influence debris accumulation, sediment transport, and moisture conditions within the drainage network. In addition, the current occurrence-based prediction will be extended towards a risk-based formulation by incorporating blockage frequency and severity to predict the blockage risk for a better understanding of critical drainage assets. Also, future studies could extend the current model by incorporating graph-based or hybrid deep learning approaches, such as Graph Neural Networks (GNNs), which can explicitly capture spatial dependencies, network connectivity, and upstream–downstream interactions within urban drainage systems, since the input variables in the current model are treated independently and do not explicitly represent network relationships.

The framework will also be extended to incorporate real-time sensor data, including water level and flow measurements, to enable early blockage detection and warning alerts. In addition, coupling the predictive model with hydraulic modelling will enable scenario-based assessment of system performance under different rainfall and blockage conditions. By integrating real-time sensor data with physics-based hydraulic models, this model can be improved as a data analytics layer of a digital twin environment of stormwater drainage systems. Furthermore, 3D BIM visualisation will be used for asset condition monitoring to represent critical drainage assets under various predicted blockage risks to enhance visualisation capabilities.

6 References

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