Grenze International Journal of Engineering and Technology, January Issue

Smart City Flood Monitoring: A Systematic Review and Integration of XAI to Address Data Inconsistencies

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***Abstract*— Real-time flood monitoring systems are important in smart cities to reduce the effects of floods by informing the citizens in advance. However, incorporating AI in this system is difficult due to issues of standardization of data gathering approaches, formats, and sources. The innovation proposed for this research paper is an explainable artificial intelligence (XAI) based flood monitoring system that can effectively handle these challenges. With the proposed system, the ministry will be able to predict the occurrence of floods accurately and on time with the help of machine learning algorithms, weather forecasts, cameras and historical flood records. Most critically, the XAI component builds accountability and reliability of the AI models, helping the stakeholders comprehend the system's thinking process. With the focus on data integration and increasing the transparency of AI prediction, this system should assist better decisions in flood management and try to eliminate data disparities to promote the 'smartness' of smart cities.**

***Index Terms*— Explainable artificial intelligence (XAI), flood monitoring system, smart cities, data integration, machine learning, flood prediction, risk management.**

I. INTRODUCTION

Enhancing flood monitoring in smart cities will face a growing major problem due to climate change – the increased and enhanced frequency of floods [1]. Floods are enormous loss-making scenarios that pose a danger to human life and property; hence, there is a need to provide flood predictions in an accurate and timely manner. The existing flood monitoring systems are mainly problematic in data incompleteness and difficulty in data integration [2], while the data it fetches include weather forecasts, elevation of roads, and flood histories [3].
These challenges slow down the efficiency of the flood prediction models and reduce the capability of passing accurate alerts and insights in any given area. With this in mind, one can come across the issue of using AI technologies in flood monitoring systems as the solution. Large amounts of unstructured data can be processed and assorted, and trends can be detected using AI-driven models while predicting accurate results. However, the use of AI in flood monitoring systems risks being limited by the 'black box' nature of many AI models [8]. Thus, it isn't easy to understand how decisions are made. AI's lack of transparency and interpretability makes people sceptical and non-acceptance of relying on the decision made by the system, especially during flood management [10]. To solve these problems, this paper suggests that XAI should be integrated to solve the problem of data discrepancies. While doing that, the system aims to improve the accuracy of flood [12] prediction in future and, at the same time, make AI model's decision-making mechanisms understandable and clear to the common public.

Grenze ID: 01.GIJET.11.1.5_1

In order to address these issues, this paper suggests an integration of XAI to deal with data disparities. The XAI-based [16] system gets inputs from the camera feeds, satellite images and weather API, road elevation data, social media platforms, and historical data on floods. Sophisticated machine learning techniques analyse this data to give real-time flood predictions. The system raises the models using XAI approaches to break down how the conclusions regarding floods are reached, including the factors considered in the process. These explanations can also focus on one or another data input revealing, for example, rainfall patterns in recent days or rising river levels, which will provide clear reasons for given predictions.

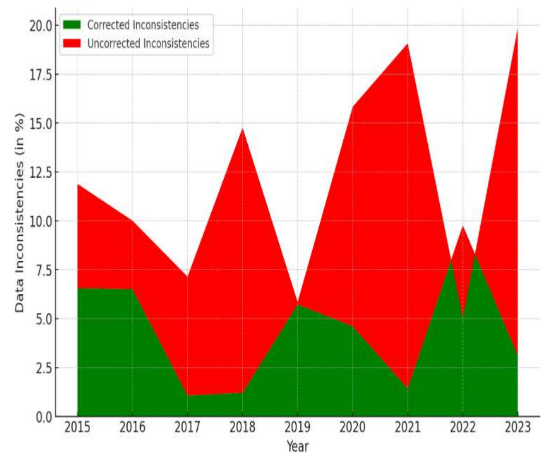

Figure 1. Depiction of data inconsistencies in alignment with the year 2015-2023

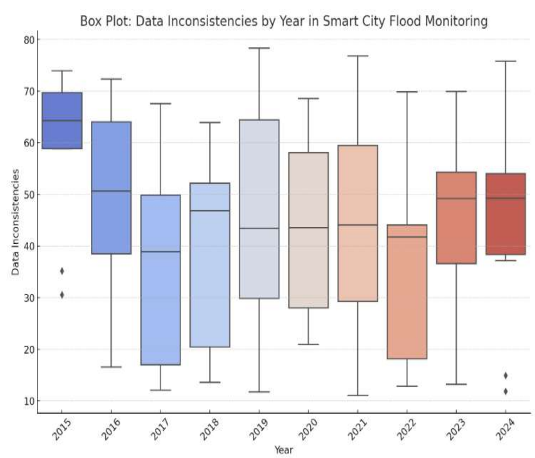

Figure 2 Representation of data inconsistencies by year in smart city flood monitoring

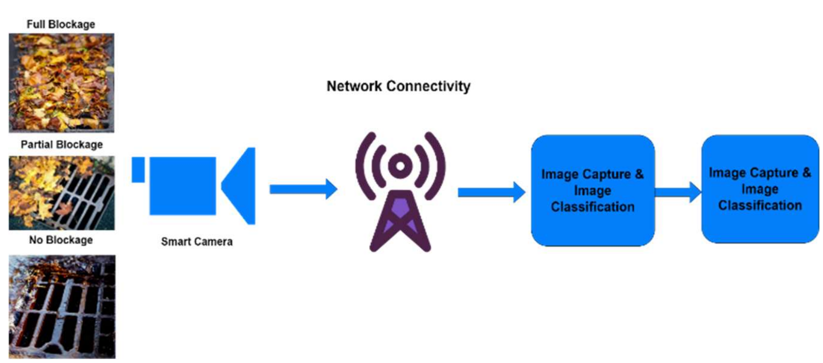

Figure.3. Basic flood monitoring flow, using a dataset of a leaf-blocked drain

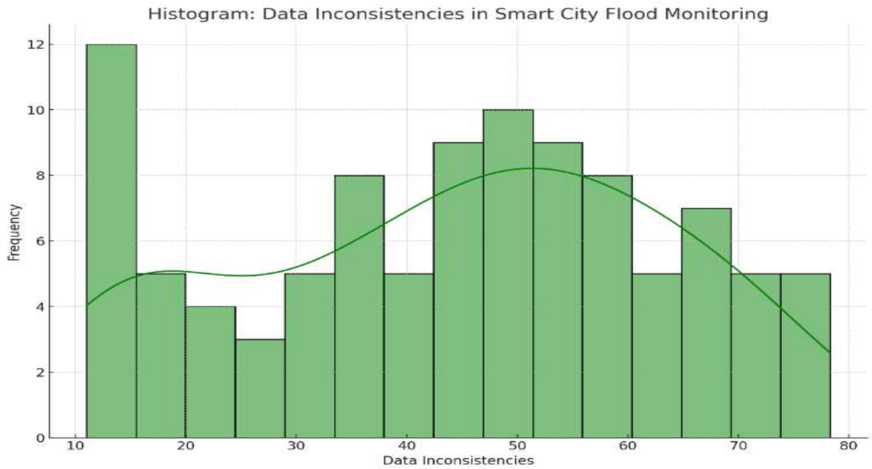

Figure 4. Depiction of data inconsistency against the frequency in smart city flood monitoring

II. Problem Statement

The integration of AI in flood monitoring systems is limited by inconsistencies in data collection methods, formats, and sources. These inconsistencies pose significant barriers to the effective utilization of AI technologies, resulting in suboptimal flood prediction and response.

A. Inconsistencies in Data Collection Methods

Diverse sources such as weather stations, IoT sensors [14] [18], and satellite imagery employ varying methods to collect flood-related data. This heterogeneity complicates the data integration process.

B. Inconsistencies in Data Formats

Data collected from different sources often come in different formats, making it very challenging to create a unified dataset necessary for effective AI training and analysis.

C. Inconsistencies in Data Sources

The reliability and accuracy of data from different sources can vary, impacting the overall effectiveness of the flood monitoring system.

Objectives

- Analysing historical and gullies and drainage data: Examine historical and real-time data related to gullies, drainage systems, weather patterns, and other relevant factors to identify trends and conditions contributing to flood risks.
- Investigate the state of using the flood monitoring in smart cities and the problems that occur from the incoherent data set and discuss the potential advantages of utilizing Explainable AI to improve on the coherence of data, the interpretability and efficiency of the model in general.

III. Literature Review

Over the years AI has been used in monitoring, more particularly flood because it can contain the enormous amount of data that otherwise is usually handled. In the machine learning algorithms [13], some classifiers are more enhanced in the forecasting of floods, including artificial neural networks and support vector machines. For instance, Liu et al. (2018) incorporated the CNNs [6] within the flood prediction system that incorporates the satellite images and flood history of an area. In their systematic review of the application of machine learning for flood forecasting, Mosavi et al. (2018) observed that the use of AI in the forecast has improved accuracy of the estimations.

They also have been incorporated with geographic information systems (GIS) to improve both the spatial data analytical and graphical performance. Abrahart et al. (2001) used an early form of an artificial neural network in conjunction with GIS for flood forecasting. Li et al. (2009) successfully applied a combination of GIS and artificial neural networks for spatial flood prediction [15]. However, one troubling issue remains that the models themselves are often 'black boxes'; this is inconsistency in data collection, and the stakeholders generally cannot comprehend where the results stem from.

However, the evolution of the XAI tries to solve the problems that classical AI models have, namely, those related to transparency and interpretability. XAI seeks to make decision-making through artificial intelligence more explainable to humans to gain trust and improve decision-making. LIME was developed by Ribeiro et al., 2016, to interpret model predictions by localizing them using models which are simpler and therefore more comprehensible. Deep-LIFT stands for Deep Local Intersectional Feature Approximate value and was proposed by Shrikumar et al. in 2017 improving Deep Taylor method and aimed at the explanation of interaction of input features to the output of the neural networks, thus increasing the interpretability of deep learning [6][26].

The use of XAI in flood monitoring is a relatively new but quickly developing field, as indicated by MS-008 [11]. Integrating XAI enhances flood monitoring systems by including an explanation of the prediction, making them more effective, accurate, and reliable. In particular, Kim et al. tried to provide an explanation of how XAI was used to improve the flood prediction model; the authors noted that the stakeholders' trust was higher when AI explanations were used.

Further related studies have also examined the use of XAI [16] to enhance data fusion as well as the model interpretability. of flood monitoring systems. For example, Chou et al. (2021) has suggested some of the XAI-based system information that can be extracted from the weather API, road elevation, weather sensors or social media for drawing which provides real-time flood predictions with the reasons. This has in turn improved the XAI limited integration in the flood monitoring systems hence improving the decision making and risk management.

IV. Methodology

In the process of designing the proposed XAI framework for the flood monitoring systems, a systematic process is followed. consisting of data acquisition and preparation, modelling and creation of an explainable and transparent model, and the overall system.

A. Data Collection and Preprocessing

The basic step of the proposed XAI framework is data gathering and data pre-processing stage. The process of collecting flood related data from cameras, weather and flood stations, satellite images of the roads, flood levels and weather API is the initial process involved in the execution of this project. All these different sources are rich sources of information where information such as real-time water levels, rainfall data and geographical information is paramount in the determination of the accurate time for flooding. Camera deployed in flood prone areas provide a continuous view while weather stations provide historical and current meteorological data.

Cleaning: The first fundamental stage entails collecting data from various sources with a view of ensuring adequate coverage of numerous flood characteristics. The main data sources include.

Real-Time Camera Feeds: Cars with mounted cameras drive to relevant, flood-sensitive areas with the purpose of capturing photos of certain drainage systems, roads and water threats. Weather Stations and APIs: Accurate and accumulated data, which includes rainfall intensity, humidity, and wind speed, which are essential for forecasting floods, are collected.

Normalization & Scaling: Least of the means and greatest of the means normalization and Z-score normalization methods are used for the normalization of numerical data. Seasonal decomposition is normally used on time series data to decipher trends, seasonal variation, and irregular variation.

B. Model Development

This phase requires the creation of AI models specific to flood prediction that will be preceded by data refinement to eliminate duplications as well as any inconsistencies. The emphasis is made on using algorithms that are explainable themselves, like decision trees and SHAP (SHapley Additive exPlanations) [19]. Decision trees are especially beneficial since they are based on the decision-making model inherent to humans. They divide data into branches according to feature values making the input-output mapping very straightforward. This makes decision trees popular for explainable AI because the model exposes how each prediction was arrived at by stakeholders [9].

In order to better explain the results, features are supplemented with decision trees and SHAP values. Apparently, SHAP provides the possibility to evaluate how meaningful each of the features is, besides that it provides an understanding of how each of them influences the model's functioning. Thus, with the help of SHAP, which breaks down the total prediction into the contributions of specific model features, it is possible to gain a better insight into the model's operation. Hence, by first using the decision tree and then the SHAP, it is possible to achieve high performance of the models while maintaining interpretability and open nature of them.

Decision Trees & Gradient Boosting Models: The general forms of boosting models chosen are XGBoost and CatBoost because both are specifically characterized into interpretability and suitability for large datasets with categorical features.

Convolutional Neural Networks (CNNs): Cameras—specialized for recognising the objects that cause blockages, such as leaves, mud, and plastics, are supplemented by a pre-trained VGG16 model fine-tuned for transfer learning to classify blockages.

C. Explainability and Transparency

Ensuring that predictions are understandable to stakeholders is a crucial aspect of the XAI framework: Feature Importance Analysis: Unlike feature attribution techniques such as Layer-wise Relevance Propagation (LRP), Integrated Gradient highlights the roles of individual input features in the prediction. Partial Dependence Plots (PDP): Such plots may help the stakeholders to understand how modification of different components influences the outcome of a model and deals with non-linear relationships. Local Interpretable Techniques: LIME [19] is used to explain individual predictions where complex models are replaced by simpler models, fit by fitting local models as well as calculation of local feature importance scores for outlier situations.

D. System Integration and Testing

The last stage is the integration of developed XAI framework into the existing flood monitoring systems in smart cities [5] as well as profound experiments concerning efficiency, stability, and interpretability of the solution. Implementation includes integrating the AI models into the working system of flood monitoring systems to attain smooth communication and data exchanges. This includes creating feeds for constant updates of data inputs such as camera, weather stations as well as satellite imagery, weather API among others. Integration also involved establishing alarm systems so as to alert the appropriate stakeholders and the public in the event of an expected flood.

System Architecture: What makes this proposed system scalable and fault-tolerant is enabling it through the microservices architecture. Free-flowing data streams in real-time are incorporated through Apache Kafka as the foundation of data stream consumption. Cloud Integration: Using cloud hosts like AWS and Azure, the computer gets scaling and storage features and serverless for the processing of burst loads in case of a flood event. Edge Computing: To reduce this response time, end devices are located close to the source, namely cameras and sensors, for initial processing before sending differentiated results to the central cloud. Alert Mechanism: The system also consists of the alert system (SMS or email and or mobile app notification) when the conditions are adverse with regard to flood. Model Evaluation: Performance Metrics: Misclassification rate, precision, recall rate, F1 factor and AUC-ROC curves were employed as measures of system efficiency. This is in an effort to achieve robustness by accomplishing both cross-validation and out of sample testing. Interpretability Testing: It measures the intelligibility of XAI explanations [11] because it intends to ensure that these are intelligible to individuals without a technical background. Reliability Testing: The aim of stress testing under flash flooding conditions is to test how the system copes with increased flow rate and establish whether flow rates are acceptable or not.

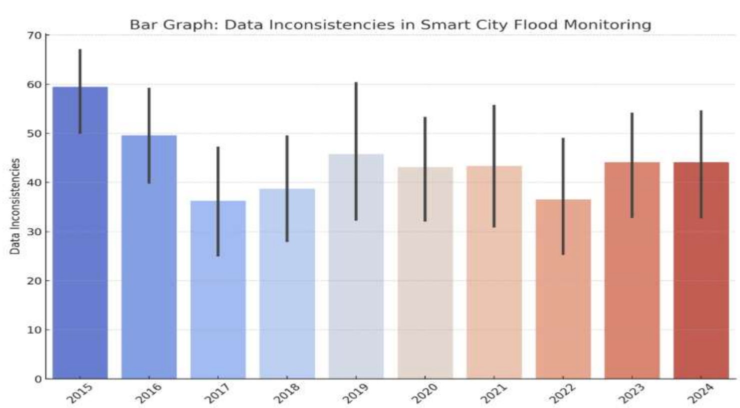

Figure 5. Data inconsistencies in Smart City flood monitoring from the year 2015 to 2024

V. MATHEMATICAL REPRESENTATION

The main aim is to model the flood monitoring system while integrating XAI technique to handle the data inconsistencies. Hence, we combine different components for mathematical representation.

- Prediction Model: Let f (x;θ) be the predictive model where x is the input data either images or data from sensor like camera and θ represents the model parameters. This parameter of model will predict a flood risk score ie y:

$$y = f(x;\theta). \qquad (1)$$

- Data Inconsistency Handling: The very important step to handle the data inconsistencies is data cleaning, let xclean be the cleaned version of x. This includes a transformation function T that adjusts x to handle data inconsistencies:

$$xclean = T(x). \qquad (2)$$

- The model's prediction with explainability technique can be represented by E. SHAP, LIME or Grad-CAM provides an explanation E (x; θ) which gives details or features in x contributes to the prediction y:

$$E(x;\theta) = XAI(f(x;\theta)). \qquad (3)$$

- Systematic Integration: Combining all the above parameters, the overall system output, data inconsistencies and explanation, can be expressed as:

$$Output = (f(T(x);\theta),E(T(x);\theta)). \qquad (4)$$

Here:
$f(T(x);\theta)$ is the model's prediction based on the cleaned data.
$E(T(x);\theta)$ is the explanation provided for the cleaned data's prediction.
The overall equation for the flood monitoring system integrated with XAI to address data inconsistencies could be:

$$Output = (f(T(x);\theta),E(T(x);\theta)). \qquad (5)$$

Where:

- x = Raw data (for example, images, sensor readings).
- T(x) = Data cleaning and inconsistency handling.
- f(·;θ) = Loss function or the predictor model function.
- E(·;θ) = Explainability function or (e.g., SHAP, Grad-CAM).
- Output = Tuple of the prediction made by the model and its undefined

VI. EXPERIMENTAL DESIGN AND RESULT ANALYSIS

By adopting Explainable AI in flood monitoring, a potential issue with the traditional approach is the frequent data heterogeneity that poses a problem within data formats and origin. XAI fosters accountability by making AI model decisions explainable; city planners, emergency personnel, and others can better understand AI's flood forecasting process and feel confident. Explaining AI systems, XAI systems use several machine learning algorithms to input data including weather conditions, previous flooding incidents. These models do more than forecast floods; they can also explain why these floods are likely to happen with specific aspects that are crucial for helping people to get the warning message right and to prepare adequately for the incident.

In order to decide on the kind of predictions this system is able to make with respect to flood risks, and the kind of explanations that are provided to the user of the system, the system was tested. It reviewed methods of how well the model addresses issues of data discrepancy and how well it provides interpretable explanations of its outputs.

The table I indicated different degree of "reportage" depending on the percentage of object coverage identified in the images used for flood monitoring. That is how it defines the scope of blockage or obstruction in the drainage systems within four different levels. A "Zero" reportage level of blocking suggests low levels of blockage with below 5% shade coverage.

The "One" level indicates intermediate levels of obstruction and here the object coverage of over five percent to twenty percent. The "Two" level points at a fair level of blockage where coverage ranges from 20% to 50%. Last, the "Three" level means severe obstruction for which the object coverage percentage is 50 or more percent.

TABLE I. REPORTAGE LEVEL AND REPORTAGE RATIO IN %

Reportage Level	Reportage Ratio in %
Zero	Zero Reportage Percentage < 5%
One	One 5% <= Reportage Percentage < 20%
Two	Two 20% <= Reportage Percentage < 50%
Three	Three Reportage Percentage >= 50%

Figure 6. Sample images of different reportage levels (a) & (c) Two, (b): One

Number citations consecutively in square brackets [1]. Punctuation follows the bracket [2]. Use “Ref. [3]” or “Reference [3]” at the beginning of a sentence:
Give all authors’ names; use “et al.” if there are six authors or more. Papers that have not been published,

TABLE II. EXAMPLE OF OBJECT REPORTAGE PERCENTAGE LEVEL

Figure	Leaf Reportage (%)	Reportage Level	Plastic Bottle Reportage (%)	Reportage Level	Mud Reportage (%)	Reportage Level	Water Reportage (%)	Reportage Level
6a	40.52	Two	0	Zero	0	Zero	43.29	Two
6b	14.91	One	0	Zero	15	One	42.59	Two
6c	22.45	Two	5.52	One	0	Zero	8.04	One

Table II presents the reportage levels of different objects detected in various figures. For each figure, the coverage percentage is calculated for four categories: leaf, plastic bottle, mud, and water. In Figure 6a, leaves and water both have a high coverage percentage, placing them in the "Two" reportage level, while plastic bottles and mud are absent. Figure 6b shows a moderate presence of leaves and mud, classified at "One" level, while plastic bottles are not detected, and water remains significant at "Two" level. In Figure 6c, leaves and plastic bottles are moderately present, classified as "Two" and "One" levels respectively, with minimal water and no mud detected.
The hardware setup of the computer to be used for the experiments was a Windows 10 computer that was powered by the Intel i5-7200 outputting 8GB RAM. The CNN model was trained using different configurations: Image sizes: 32, 64, 96, and 128 pixels. Batch sizes: Ranged from 8 to 32. Epochs: 100 to 500 iterations. In selecting the best performing configurations for training and validation, accuracy rates were a key pointer.

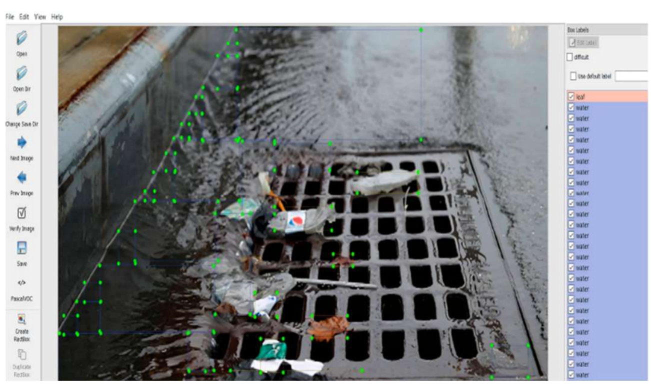

Figure 7. Image Annotation

Figure 7 depicts an example of an annotation process where the objects which are water, leaves and debris, including plastics, are tagged around a drainage grate. The labeled points correspond to the areas observed by the system and are used to determine potential clogs according to the types and quantity of objects on the drainage area. The tool used for the annotation underlines these objects for further discussions in the flood simulation models.
The system was tested by feeding the network with annotated images in order to identify different objects causing floods (for instance, leaves, plastic bottles, mud, water, water levels). Results of percentage coverages of objects were used to determine the degree of blockage and the consequent effects on flood expectations. The table of reportage levels demonstrated the system's ability to categorize the severity of blockages effectively: Level Zero: No Major vascular involvement seen. Level One to Three: Higher tendencies of blockage based on the amounts of coverage done on the objects.

VII. Conclusions

Integrating Explainable Artificial Intelligence (XAI) into flood monitoring systems within smart cities is both a potential game-changer and a necessity, as it limited the integration of XAI in flood monitoring systems. There are generally many uncertainties which are characteristic and typical of urban floods and, therefore, there is need for reliable and XAI solutions capable of not only predicting and tracking floods but also providing adequate explanations of each arrived decision. In this way, the stakeholders encompassing urban plannings, emergency response, and ordinary citizens can better understand floods and contributing factors. This increased openness enables people to develop confidence and make wise decisions in relation to flood prevention and management.
The inclusion of XAI in flood monitoring systems is a way of overcoming some of the challenges that affect this area, including inconsistencies in data collection methods, formats, and data sources. Through using explainable models' integration, there is high likelihood that the process of data integration will be more standardized and effectively validated because of the enhanced layer of clarity to the different datasets that are being integrated into one. This enhances the effects of flood predictions hence improving the ability to undertake effective preparations in cases of floods.
Moreover, XAI helps in providing the growth of smart and sustainable development of cities as it helps in fighting climate change and global extreme weather conditions. From demonstrated models, decision makers will be in a position to develop infrastructure as well as policies that may help in minimizing flood dangers as well as boost the sustainability of urban areas.

Acknowledgment

The authors wish to thank A, B, C. This work was supported in part by a grant from XYZ.

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