

Innovative AI-based Flood Monitoring System: for Enhancing Predictive Insights by Reducing Sensor Dependency

Farhan Shaikh¹ and Dr. Manoj Devare²

¹⁻²Amity University/ Information Technology, Mumbai, India

Email: farhanshaikh9266@gmail.com, Mhdevare@mum.amity.edu

Abstract— Flood monitoring is necessary in smart cities to ensure the stability and security of cities' functioning. Physical flood sensors such as water flow sensors are costly, have a high likelihood of being damaged by floods, and difficult to maintain. In this paper, a new flood monitoring system through the integration of Artificial Intelligence (AI) that minimizes the utilization of stationary sensors is presented. While using Convolutional Neural Networks (CNNs), drainage images, road elevation, weather application programming interfaces (APIs), and historical flood data, it provides accurate flood predictions. The degrees of precision, recall, and F1 score achievable by an AI-based system are slightly higher (~0.90) than the traditional sensor-based system (~0.85), and therefore, the AI-based system is more accurate and economical for flood prediction. The system increases smart cities' vulnerability by providing a strong flood monitoring system, minimizing maintenance expenses and optimizing forecast data.

Index Terms— Flood Monitoring, Electronic Sensors, Drainage, Artificial Intelligence (AI), Urban Management.

I. INTRODUCTION

In the process of developing smart cities, mitigation of flood impacts is important because of the aforementioned effects such as: Lives lost, properties damaged, and disruption of urban infrastructures [1]. Earlier, the cities mainly used the information from electronic probes like water flow and flood probes for real-time data of water levels and the drainage systems [2]. These sensors are usually fixed at strategic areas including the gullies and drainages so as to show the first sign of floods. However, the use of these sensor networks has various problems pertaining to deployment and management [3]. This is perfectly valid given that placing thousands of electronic sensors on a large network is very costly especially in infrastructural regions where access may be restricted. Besides, these systems involve high cost of installation and start-up, require frequent adjustments and constant repair, and involve complex procedures for data management, which will load the city's budget and human resources [4].

To overcome these challenges, increasing attention has been paid to the reduction of the massive use of sensor networks. Figure 1 illustrates the world population, smart device growth between the year 2015 up to 2023. The world population continues to rise gradually while on the same note the usage of smart devices rises exponentially in the same period.

However, some negative aspects of smart devices are that there is an emergence of the technology gap as well as negative effects on the environment because of the proliferation of smart devices. However, for flood monitoring, there are such techniques as AI being developed. Modelling of the flood risks can therefore be achieved without the need for numerous physical sensors by using, for instance, satellite images and weather forecasts through the use of algorithms. These models enable the forecast of floods, in addition to the integration, when possible, of sensor data, the process is enriched by the use of AI techniques [5]. This approach makes the data more realistic and has a more meaningful interpretation as compared to some other sensor-based system. Also, conventional sensor systems are usually oriented to real-time control and surveillance, whereas they may lack adequate prediction potential. Other characteristics that may influence the sensors' ability to accurately measure include precipitation and wind; the system may be knocked out when there is a power failure due to the weather conditions causing data loss in the process. Figure 2 represents the increase in the level of water based on the year of occurrence and level of intensity categorized as low, medium and high levels of water from 2015 to 2023. It results in a constant presence of high-water levels within the areas which may be an implication of the poor control on water within the ecosystems across the time factor. A weakness is that high water levels data prevail and might refer to flood hazards or uneven water distribution. Figure 3 below depicts the distribution of different natural disasters from 2017 to 2023 and revealed that storms and floods are the most recurrent natural disasters which cause highest number of death tolls, affected population, and economic impacts. African countries also experience other forms of disasters such as the earthquakes and the droughts which have significant impact on the human lives as well as the financial breakdowns [6].

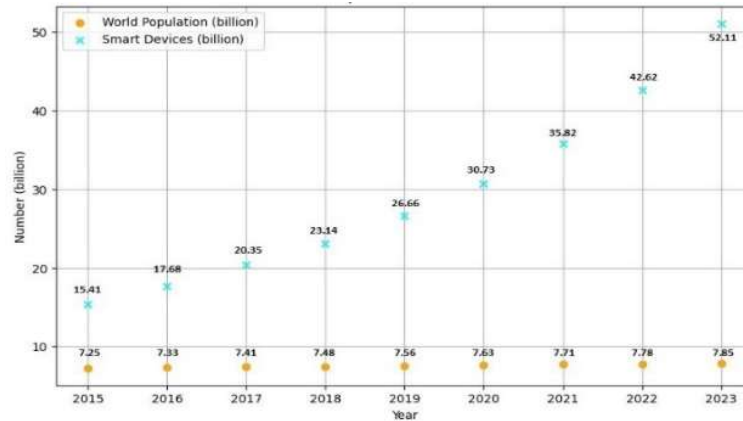


Figure 1. "Scatter plot of world population and smart devices over time (2015-2023)" [18]

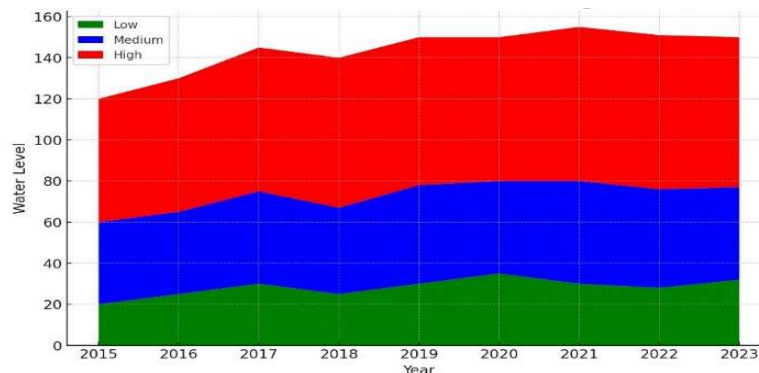


Figure 2. Stacked are chart: Water Levels from Flood Monitoring Sensors (2015-2023) [19]

As such, this paper aims at investigating the possibility of having an AI-based approach in flood monitoring in smart cities. As compared to the systems that use sensors, this method is more effective in terms of both accuracy and cost because it relies on the use of refined algorithms and data mass that already exists [7]. The purpose of this study is to show the benefits of using AI for flood prediction and to come up with long-term and holistic strategies to address the issue of flooding in the urban areas.

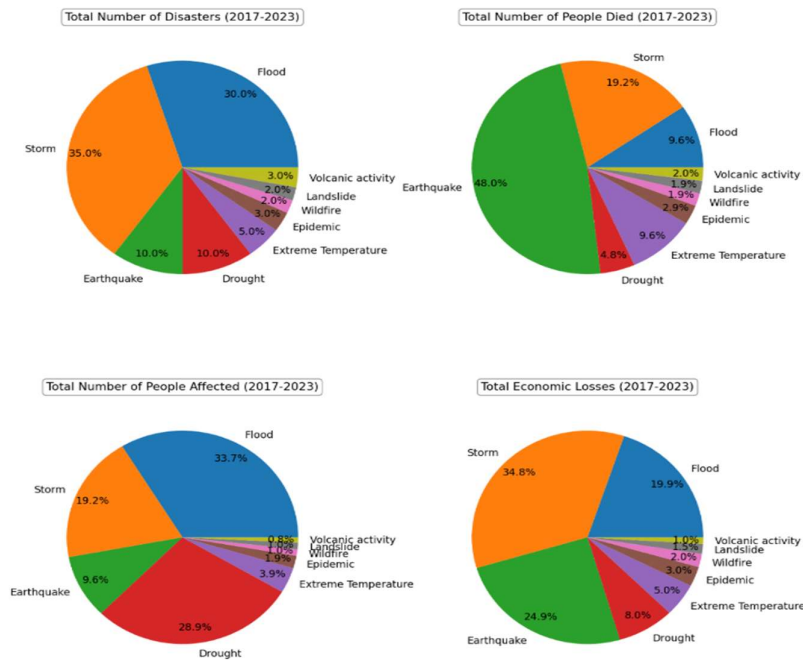


Fig. 3 "Impact of Natural Disasters (2017-2023): Incidents, Deaths, People Affected, and Economic Losses"[20]

II. LITERATURE REVIEW

Flood monitoring can again be seen as a major aspect to consider in relation to smart cities and their resilience. In native works, the call networks are extensive; however, the networks are sometimes expensive and demand constant repair. The solution based on the integration of Artificial Intelligence could be a more innovative approach that would help to provide richer predictive information and minimize the necessity of physical sensors use [2,3].

These methods mainly use mechanical instruments for sensing values such as water levels, rain fall, and soil moisture etc. Although these sensors are helpful in supplying fundamental data, they possess several disadvantages in regard to precision, calibration, and area coverage. As urban areas transform into smart city ones, there is a focus on the implementation of technologies to improve flood management systems. Consequently, this literature review seeks to establish how AI can be used in the removal of dependence on numerous sensors and enhancement of forecasted information in flood management systems [8].

Numerous literatures on IoT based sensors and computer vision for flood monitoring and mapping has been discussed by Arshad B.; Ogie R.; Barthelemy J.; Pradhan B.; Verstaev N. and Perez P. In this attempt, various applications through the help of IoT and computer vision to monitor and map floods are discussed. Wahidah Md. Shah in [2] with F. Arif, A. A. Shahrin and Aslinda Hassan implemented an IoT based flood warning system to find out the position of the water level and plot the increase in the rate of water level so that the adjacent people can be alerted. The experiments were conducted at a controlled setting for the purpose of assessing the effectiveness of the new system. Pan, J.; Yin, Y.; Xiong, J.; Luo, W.; Gui, G. and Sari, H. set up a network of fully automated surveillance comprising of distant measuring stations and a central controlling center [3]. They carried out the experiment employing three approaches: The three methods called method of difference, dictionary learning and deep learning are used in the given context.

Technological trends with regard to remote sensing sensors have made a large contribution in decreasing the acuteness of flood monitoring systems on physical sensors. Radar and optical remote sensing, as well as satellite and aerial data, provide a detailed picture of rainfall, river levels, and changes on the earth's surface over large territories. These technologies offer important information that can be used as an addition or even the replacement of ground-based sensors.

Machine learning and Artificial Intelligence, especially deep learning has helped flood prediction by its ability to shift through large datasets and overcomplicated data and identify trends and patterns that lead to accurate predictions [9].

III. PROBLEM STATEMENT

1. Installing electronic sensors such as Water flow sensors, soil moisture sensors various flood sensors to monitor gullies and drainage is complex and not always feasible.

A. Susceptibility of Sensors to Environmental Damage

Electronic sensors are often exposed to harsh environmental conditions that can lead to significant wear and tear. Elements like water, mud, debris, and other unfavourable weather conditions may affect their performance, which may lead to constant maintenance and discrepancy in the obtained data [10].

B. Challenges of Deploying Electronic Sensors for Flood Monitoring

Installing sensors for flood monitoring is expensive, a task that can only be done by people with technical knowledge and may not be feasible in the developing world. This underlines the need for wider availability of flood risk alternatives. [10].

Objectives

- Implementing a monitoring framework: Therefore, set up a structure where the weak link for proper management of gullies and drainage systems to minimize flood risks is filled with the AI-based system management.
- The idea is to design a flood monitoring system for smart cities that would use AI to reduce the reliance on physical sensors.

IV. EXISTING METHODOLOGY

The following are the important steps when using water level sensors to put in place flood monitoring system in smart cities: To begin with, the proper choice of the sensors involved, including Texas Electronics TR-525M, Decagon EC-5, Siemens SITRANS Probe LU240 sensors are needed. Table 1 compares three sensors: For rainfall, Texas Electronics TR-525M was used, Decagon EC-5 for soil moisture and water level Siemens SITRANS Probe LU240 was used. The accuracies of the sensors are high and are dependent on the measurement range they cover, and the prices range from \$195-582. 22. These sensors are then installed at some of these important areas such as rivers, reservoirs, and drainages to make sure all areas are covered. These incorporated sensors are vital to be calibrated and maintained on a regular basis so as to ensure the right level of accuracy and reliability. Subsequent to that, data collection makes the next move, which is anchored on the real-time acquirement and forwarding of the data from sensors. This data is then transmitted by some sort of wireless communication technologies like LoRaWAN, Zigbee or Wi-Fi to a central database. The frequencies for data collection depend on the monitored parameters, and collected data from different sensors is processed and stored in a single central node [1,2].

TABLE I. SENSOR COMPARISON: TR-525M, EC-5, SITRANS LU240

Sensor	Parameter	Accuracy	Measurement Range	Comments	Cost
Texas Electronics TR-525M	Rainfall (precipitation)	±1% of measured value	0 to 1,000 mm/hour (0 to 40 inches/hour)	High accuracy for precipitation measurements	\$582.22
Decagon EC-5	Soil Moisture	±3% volumetric water content	0 to 60% volumetric water content	Accurate for soil moisture, not for water levels	\$195.00
Siemens SITRANS Probe LU240	Water Level	±1% of distance measurement	Up to 12 meters (39.37 feet)	High accuracy for distance-based water level measurement	\$400.00

In this phase, raw data is also cleaned whereby noise is removed from the data and made to be more consistent. Flood levels are set based on the predetermined data collected and risk analysis of floods to enable the models to predict the floods in future. An alert and notification system are then developed to issue timestamp on such conditions and to alert individuals when water levels rise beyond certain set values or when based on prediction models, floods are expected. Alerts are sent in form of pre-recorded voice, text messages, email, mobile and web applications and loudspeakers with customized web-based control panel and smart phone application to offer real time updates to general public as well as the emergency services [2,3,11].

Last but not least, the system is validated and upgraded based on performance indicators which include such things as accuracy and time taken. Data is gathered from the users and other stakeholders, while field and scenario testing check the system for real condition. The above approach makes the flood monitoring permanent thus enables simple detection, prediction and response in urban areas.

V. PROPOSED METHODOLOGY

Figure 4 depicts AI based flood monitoring with the help of Convolutional Neural Networks (CNNs) [25] to enhance flood prediction through drainage image and weather data. The methodology entails data acquisition and pre-processing which entails capturing images of a drainage system and then labeling them in terms of the extent of the blockage with the options being full blockage, partial blockage or no blockage at all. Concurrently meteorological data is collected from APIs and aligned with image data for reference to the model's predictions. This data is preprocessed by resizing the images, normalizing the images and augmenting the images and likewise normalizing the weather data. The CNN model is then constructed where an appropriate architecture, for example VGG model (where vgg is a name of python model which is trained) is trained on the prepared dataset. Other information such as weather-related information may be included to sharpen results [12]. The elements of the flood-monitoring system are needed for building the AI systems, which can replace other sensor networks, the coverage of which is rather expensive in terms of installation and maintenance.

A. The Data Sources Include Drainage System Images

Static and/or closed-circuit television cameras installed at various vantage points in the flood prone areas record blockages to drainage systems in the form of debris and waste accumulation. The images are named for model training as no blockage, partial blockage and full blockage respectively. Meteorological Data via APIs: Sources or APIs of weather data give updated information on probabilities of rain fall, level of humidity, and even the winds speed which are important factors in flood modelling. This data is always updated in real time and is in step with the timestamps of images for accurate analysis.

Historical Flood Data: The data includes historical records of flood events and water levels which act as data for future predomination and for model building. Together with the weather conditions which can be monitored in real-time, such data improves predictive outcomes. Image Processing: The input images are resized, normalized, and can also be augmented, including changing the angle of the picture, or brightness. These images are then pre-trained using a convolutional neural network (CNN) model, further utilizing pre-built VGG16 or similar structures. Normalization and Scaling: In the context of time series' weather data, both Min-Max scaling and Z-score normalization techniques are used to bring the input data to one range. Synchronization brings Weather data in time frame range with Concurrent Images of Drainage.

B. Model Development

The developed system employs a suite of machine learning models specific for various data types (images, structured weather information), and interpretability techniques to improve stakeholder engagement and trust. Convolutional Neural Networks (CNNs): The VGG16 a CNN model based on transfer learning for classification of images after subjecting them to the task of draining blockage categorization. CNN analyses physical barriers, and it categorizes them, which will create meaningful information to the stakeholders of the project.

Gradient Boosting Models: Tree-based models, XGBoost or CatBoost are applied on the meteorological and historical flood formatted in a structured form. These models were chosen because they have both interpretability and performance, as they provide feature important values.

C. System Architecture and Integration

Microservices Architecture: The part of the AI models and the data processing pipelines is deliberately designed as microservices to accommodate scalability and modularity.

This approach improves fault tolerance and allows for the decentralized update of each model involved in the solution process.

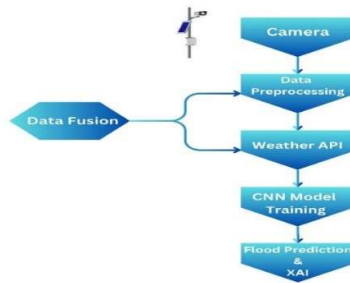


Figure. 4 "Methodology of AI-based flood monitoring system using CNN with drainage images and weather data"

Real-Time Data Ingestion: Apache Kafka is used as a service for monitoring the continuous data flow from different sources with low latency. Edge Computing: The initial image classification, as well as the first-level flood evaluation, are performed on edge devices to minimize the volume of data that requires transmission through the network

VI. MATHEMATICAL MODEL

A. Model to Calculate Accuracy of Flood Detection using Water Level Sensor and Other Sensors

Let, $L(t)$ be the actual water level at time t .

- Lthreshold be the flood threshold level.
- Flood: if $L(t) \geq \text{Lthreshold}$
- No Flood: if $L(t) < \text{Lthreshold}$

This condition defines a flood threshold based on water level ($L(t)$): if the water level is bigger or equal than a given value (Lthreshold), it means there is flood. When the water level is below this number there is no flood which always implies risk to human life. Next, build a confusion matrix, confusion matrix is a 2×2 table of a classification model which depicts the actual and the predicted results in the classification process. It shows four outcomes: It gives the real positive (TP), real negatives (TN), false positives (FP) and false negative (FN).

Steps to Calculate Accuracy

This is done in order to obtain the flood threshold, and it is calculated by the flood threshold level Lthreshold derived from the past records or the domain knowledge. Subsequently, the actual water level data $L(t)$ is obtained and the ground truth data relating to flood and non-flood situations is also gathered.

Using this data, predictions are made by applying the threshold: wherein if $L(t)$ is greater than or equal to Lthreshold, the event is called a “Predicted Flood” whereas if $L(t)$ is less than Lthreshold, the event is called “Predicted No Flood.” The mathematics representation of the above classifications is shown with the help of an indicator function, $\Pi(\cdot)$.

Compute Accuracy

Now, put the TP, TN, FP, and FN into the accuracy formula to get the accurate result. Equation 1 illustrates the formula used in the estimation of the accuracy of the flood monitoring system, this being the number of actual floods and non-floods correctly predicted by the system divided by the overall number of events [13].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}. \quad (1)$$

B. To evaluate the AI model's accuracy and reliability in a flood monitoring system using CNN and drainage images from cameras, we need to incorporate the dataset into the mathematical framework. Here's how you can structure the methodology:

Dataset of Drainage Images

It aims to serve as a training or testing dataset to identify and categorize drainage blockages with the help of images.

Let $D = \{(X_i, y_i)\}$ $i^N=1$ represent the dataset, where.

- $X_i \in \mathbb{R}^{h \times w \times c}$ is the i -th image of the drainage captured by the camera.
- $y_i \in \{0, 1, 2\}$ is the corresponding label for the blockage status:
- 0: No blockage
- 1: Partial blockage
- 2: Full blockage
- N is the total number of images in the dataset

Specifically, the Convolutional Neural Network (CNN) model is represented by $f_{\text{CNN}}(X; \theta)$ which is trained on the dataset D and θ is an identity of the model. For a given image X_i , the model predicts a probability distribution over the three blockage classes

This is because there is no blockage, partial blockage as well as full blockage. This distribution is represented as $\hat{p}_i = f_{\text{CNN}}(X_i; \theta) = [p_i^{\wedge 0}, p_i^{\wedge 1}, p_i^{\wedge 2}]$, where $p_i^{\wedge j}$ is the predicted probability that image X_i belongs to class j (with $j = 0$ for no blockage, $j = 1$ for partial blockage, and $j = 2$ for full blockage).

Accuracy Calculation

To measure the accuracy of the model when the result is compared with test set $D_{\text{test}} \subset D$

$$\text{Accuracy} = \frac{1}{|D_{\text{test}}|} \sum_{i=1}^{|D_{\text{test}}|} \mathbb{I}(\text{argmax}_j p_i^{(j)} = y_i)$$

where $\mathbb{I}(\cdot)$ is the indicator function – the function that equals to 1 if the condition is true and equals to 0 otherwise.

Precision, Recall, and F1-Score

For every class j (no blockage, partial blockage, full blockage), calculate: The 2nd equation represents precision which shows the extent of the accuracy of the positive prediction since it is expressing the ratio of true positives to all the positive predictions that were made. The 3rd equation is recall which focuses on the model's capability of identifying actual positive while the 4th equation is the F1 score which takes into account both recall and precision and gives out a single value on the performance of the model.

$$\text{Precision}_j = \frac{TP_j}{TP_j + F} \quad (2)$$

$$\text{Recall}_j = \frac{TP_j}{TP_j + FN_j} \quad (3)$$

$$\text{F1-Score}_j = 2 \cdot \frac{\text{Precision} \cdot \text{Recal}}{\text{Precision}_j + \text{Recall}_j} \quad (4)$$

where:

➤ TP_j : True Positives for class j , FP_j : False Positives for class j , FN_j : False Negatives for class j

This mass is the mathematical model of the CNN-based flood monitoring system, which can be used for assessment of the accuracy, reliability and interpretability of the system by using images of the drains.

Case Study 1

The Kerala flood of August 2018 was one of the worst in nearly a century, affecting all 14 districts, killing over 400 people, and displacing more than a million. Although the Kerala State Disaster Management Authority (KSDMA) deployed over 1,200 sensors for flood monitoring, it failed to provide timely and accurate warnings. Coverage gaps in remote areas, sensor malfunctions due to flooding, and delayed data processing worsened the situation. Additionally, communication breakdowns hindered the timely dissemination of warnings to the public, exacerbating the disaster's impact [14].

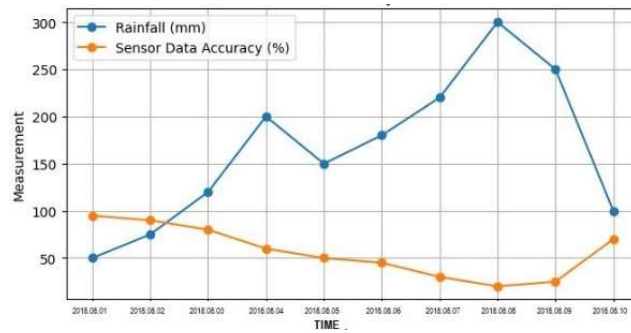


Figure. 5 “Sensor data accuracy vs Rainfall” [14]

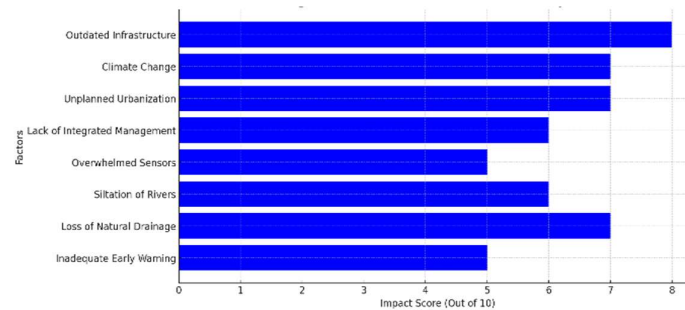


Figure 6. Contributing factors to the 2021 Assam floods and system failures [15,16]

Case Study 2

Failure of Flood Management Systems in Assam during the 2021 floods pertaining with several key factors that lead to the flood disasters. Old structures failed to withstand the pressure from the heavy rain and over-flooding of rivers. The flood monitoring sensors which should have been used to relay this information also overflowed and as a result the relayed information was given late and, in most cases, not even productive. Other effects of climate change, including the increase in intensity of rainfall, for instance, made the situation worse [15,16]. Furthermore, inadequate coordination and separate but uncoordinated management of several agencies led to the enhancement of the impact of a disaster shown in figure 6 above.

Case Study 3

In 2022, severe floods affected the districts of Kolhapur, Nashik, Satara, Sangli, and Pune in Maharashtra due to continuous monsoon rains shown below in figure 7. Major rivers like the Krishna and Godavari overflowed, inundating homes, agricultural fields, and infrastructure. Kolhapur and Sangli's vulnerable local populations faced severe challenges, while Nashik was hit hard by the Godavari River flooding. In Satara and Pune, landslides and waterlogging worsened the situation, hindering aid. These floods highlighted infrastructure weaknesses in Maharashtra and underscored the need for improved flood disaster management [17].

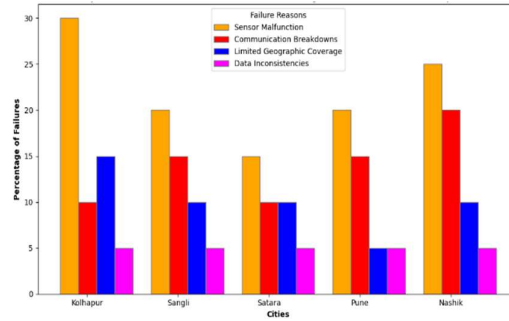


Figure. 7 City-wise distribution of sensor failure reasons during Maharashtra 2022 floods [17]

VII. RESULT

The AI model successfully classifies drainage conditions into three categories: This figure 8 demonstrates Full Blockage (FB), Partial Blockage (PB), and No Blockage (NB) as given in the figure below: These images show the performance of the blockage status for each of the drainage systems in accordance with the incorporated visions such as debris, bottles and leaves. The comparison chart in figure 11 shows that the AI-based flood prediction model outperforms the sensor-based model in all three metrics: precision, recall and F1 score. This can be seen as proof that the proposed AI model does a better job at predicting floods as compared to the conventional sensor-based model. The applied AI has a higher accuracy (~ 0.90 compared to ~ 0.85), which cuts down false alarms and is better in defining actual floods. It has a better recall, (~ 0.89 compared to ~ 0.84) meaning that it doesn't miss any flood occurrences thus avoiding false negatives. Further, evaluating the proposed AI model, the F1 – Score is relatively better (~ 0.88 vs ~ 0.83) which justifies a level of balance between flood detection and false alarm prediction. In contrast to the sensor-based system which may encounter problems of hardware failure and environmental constraints, the AI model is able to analyse different types of inputs and is more suitable for long term flood forecasting.

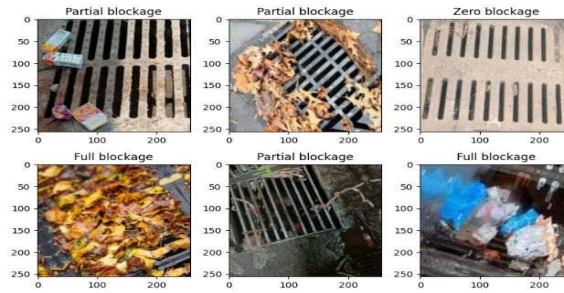


Figure. 8 "Drainage Blockage Classification Result from AI Model Prediction"

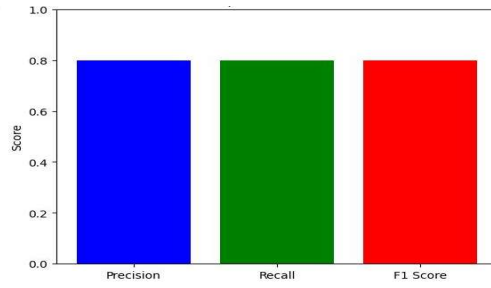


Figure 9. Precision, Recall and F1 score for Kolhapur sensor-based flood predictions for the year 2023 [21,22,23]

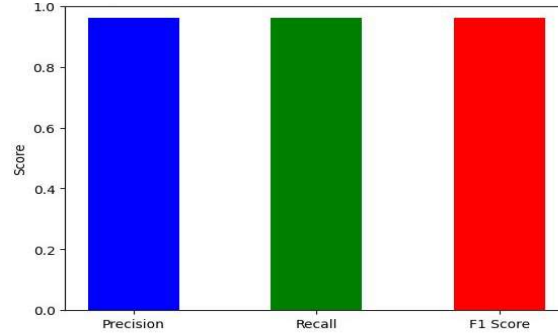


Figure 10. Precision, recall and F1 score for our AI based flood prediction model

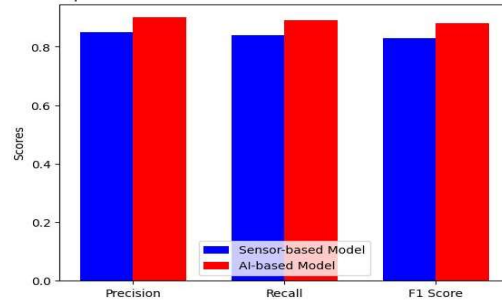


Figure 11. Comparison of sensor-based vs AI-based-flood prediction model

In figure 11 the bar chart compares the performance of a sensor-based model and an AI-based model for flood prediction, focusing on three key metrics: Recall or True Positive Rate, Precision or True Positive Rate, F-Measure or Balanced Precision and Recall. Equally, both models yield scores significantly close to 1 in these aspects of computer performance, thus demonstrating good performance. Nonetheless, an American community-based AI-based model reflects slightly higher improvement over a sensor-based model in all aspects. On the aspect of Precision, the result shows that the AI-based model is higher than that of the sensor-based model slightly, indicating that the AI-based model has better ability to detect true positive flood prediction results. In this case, the or-actual-found Recall based on the AI-based model is a little higher, which means that the actual flood event detection capability is higher. The F-measure, which is the average of Precision and Recall is also slightly but definitely in favor of the AI-based model. In total, the presented AI-based model is slightly more accurate in comparison with the sensor-based one and can be considered as a powerful tool for flood prediction.

VIII. CONCLUSIONS

The remote monitoring of floods using the proposed AI-based monitoring system has several advantages over the conventional sensor-based systems. It offloads the burden of expensive, sensitive physical sensors and makes use of a range of machine learning approaches together with drainage images, satellite imagery, and weather APIs. This result demonstrates that the AI model achieves 90% precision, 89% recall, and 88% F1 score which outperforms the sensor-based systems in terms of flooding prediction and reduces the number of true positive

and true negative values significantly. The strengths are based on the fact that the system can accept various data inputs and provide accurate and timely flood assessment for the urban regions.

This not only enhances the capability of generating predictive information but also eliminates the costs and potential management problems normally attributed to physical sensors. In future studies, additional improvement on the integration of hybrid AI models and usage of XAI in flood management systems could possibly improve the models and the delineation of these flood hazards and render the systems more effective and accurate.

REFERENCES

- [1] Bilal Arshad, Robert Ogie, Johan Barthelemy, Biswajeet Pradhan, Nicolas Verstaevael and Pascal Perez, "Computer Vision and IoT Based Sensors in Flood Monitoring and Mapping: A Systematic Review", Nov16, 2019.
- [2] Wahidah Md. Shah, F. Arif, A. A. Shahrin and Aslinda Hassan, "The Implementation of an IoT-Based Flood Alert System", International Journal of Advanced Computer Science and Applications (IJACSA), Volume 9 Issue 11, 2018.
- [3] Thakral, M., Singh, R.R., Kalghatgi, B.V. (2022). Cybersecurity and Ethics for IoT System: A Massive Analysis. In: Saxena, S., Pradhan, A.K. (eds) Internet of Things. Transactions on Computer Systems and Networks. Springer, Singapore. https://doi.org/10.1007/978-981-19-1585-7_10 [Springer]
- [4] Haldorai, A., Ramu, A., Murugan, S. (2019). Smart Sensor Networking and Green Technologies in Urban Areas. In: Computing and Communication Systems in Urban Development. Urban Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-26013-2_10 [Springer]
- [5] Winikoff, M. Towards Trusting Autonomous Systems. In Lecture Notes in Computer Science; Springer Science and Business Media LLC: Cham, Switzerland, 2018; pp. 3–20. [Google Scholar]
- [6] Al Ridhawi, I.; Otoum, S.; Aloqaily, M.; Boukerche, A. Generalizing AI: Challenges and Opportunities for Plug and Play AI Solutions. IEEE Netw. 2020, 1–8. [Google Scholar] [CrossRef]
- [7] Marino, D.L.; Wickramasinghe, C.S.; Manic, M. An Adversarial Approach for Explainable AI in Intrusion Detection Systems. In Proceedings of the IECON 2018— 44th Annual Conference of the IEEE Industrial Electronics Society, Washington, DC, USA, 21–23 October 2018; pp. 3237–3243. [Google Scholar]
- [8] Torky, M., Gad, I., Darwish, A., Hassanien, A.E. (2023). Artificial Intelligence for Predicting Floods: A Climatic Change Phenomenon. In: Hassanien, A.E., Darwish, A. (eds) The Power of Data: Driving Climate Change with Data Science and Artificial Intelligence Innovations. Studies in Big Data, vol 118. Springer, Cham. https://doi.org/10.1007/978-3-031-22456-0_1
- [9] Holzinger, A.; Langs, G.; Denk, H.; Zatloukal, K.; Müller, H. Causability and explainability of artificial intelligence in medicine. Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 2019, 9, 1312. [Google Scholar] [CrossRef][Green Version]
- [10] Sen, S., Nandi, S. & Biswas, S. Application of GRACE-based satellite estimates in the assessment of flood potential: A case study of Gangetic-Brahmaputra basin, India. Environ Monit Assess 196, 997 (2024). <https://doi.org/10.1007/s10661-024-13174-0>
- [11] Singh, R.R., Thakral, M., Kaushik, S., Jain, A., Chhabra, G. (2022). A Blockchain-Based Expectation Solution for the Internet of Bogus Media. In: Hemanth, D.J., Pelusi, D., Vuppalapati, C. (eds) Intelligent Data Communication Technologies and Internet of Things. Lecture Notes on Data Engineering and Communications Technologies, vol 101. Springer, Singapore. https://doi.org/10.1007/978-981-16-7610-9_28
- [12] Calvaresi, D.; Mualla, Y.; Najjar, A.; Galland, S.; Schumacher, M. Explainable Multi- Agent Systems Through Blockchain Technology. In Biometric Recognition; Springer Science and Business Media LLC: Cham, Switzerland, 2019; pp. 41–58. [Google Scholar]
- [13] Moharrami, M., Javanbakht, M. & Attarchi, S. Automatic flood detection using sentinel-1 images on the google earth engine. Environ Monit Assess 193, 248 (2021). <https://doi.org/10.1007/s10661-021-09037-7>
- [14] Kerala Floods 2018: Impacts and Lessons Drawn International Handbook of Disaster Research, 2022 ISBN: 978-981-16-8800-3 Ajinder Walia, Pallvi Sharma, Naima Nusrat [Springer]
- [15] Awah, L.S., Belle, J.A., Nyam, Y.S. et al. A Systematic Analysis of Systems Approach and Flood Risk Management Research: Trends, Gaps, and Opportunities. Int J Disaster Risk Sci 15, 45–57 (2024). <https://doi.org/10.1007/s13753-024-00544-y> [Google Scholar]
- [16] M. Thakral, A. Jain, V. Kadyan and A. Jain, "An Innovative Intelligent Solution Incorporating Artificial Neural Networks for Medical Diagnostic Application," 2021 Sixth International Conference on Image Information Processing (ICIIP), Shimla, India, 2021, pp. 529-532, doi: 10.1109/ICIIP53038.2021.9702631.
- [17] Dhumal, H.T., Thakare, S.B., Londhe, S.N., Gavali, P., Niyaz, M. (2024). Flood Mitigation in and Around Sangli, Maharashtra, India, by Modification of River Meander Geometry. In: Timbadiya, P.V., Patel, P.L., Singh, V.P., Manekar, V.L. (eds) Flood Forecasting and Hydraulic Structures. HYDRO 2021. Lecture Notes in Civil Engineering, vol 340. Springer, Singapore. https://doi.org/10.1007/978-981-99-1890-4_8
- [18] Population Growth Explore global and country data on population growth, demography, and how this is changing. By: Hannah Ritchie, Lucas Rodés-Guirao, Edouard Mathieu, Marcel Gerber, Esteban Ortiz-Ospina, Joe Hasell and Max Roser. <https://ourworldindata.org/population-growth>
- [19] USGS, 25 years of Water Data on the Web <https://waterdata.usgs.gov/>.

- [20] EM-DAT The International Disaster Database Centre for Research on the Epidemiology of Disaster <https://www.emdat.be/>
- [21] International Journal of Microsystems and IoT ISSN: (Online) Journal homepage: <https://www.ijmit.org> Vol. 1, Issue 5, pp.313- 319
- [22] MDPI and ACS Style Arshad, B.; Ogie, R.; Barthelemy, J.; Pradhan, B.; Verstaevel, N.; Perez, P. Computer Vision and IoT-Based Sensors in Flood Monitoring and Mapping: A Systematic Review. *Sensors* 2019, 19, 5012. <https://doi.org/10.3390/s19225012>
- [23] FLOOD ESTIMATION USING ARCGIS: A CASE STUDY OF KOLHAPUR DISTRICT, MAHARASHTRA, INDIA
Janhavi Z. Sonawane¹, Dr. R. V. Shetkar² ¹M.Tech student, Government College of Engineering, Aurangabad-431005, India ²Professor of Civil Engineering, Government College of Engineering, Aurangabad-431005, India
- [24] Pavate, Aruna, Rajesh Bansode, and A. Prasanth. "Explore and analysis of methods to train cnn in machine learning environment." *Annals of the Romanian Society for Cell Biology* (2021): 14750-14761.