Urban Shield: An IoT-Based Intelligent Manhole Detection and Monitoring System

NAGASHREE K S[1], NIDHI[2], NISHITHA P P[3], Dr. THRISHA V S[4]

[123] UG Student, Department of Computer Science and Engineering, Sir M Visvesvaraya Institute of Technology, Bengaluru, Karnataka, India

[4] Assistant Professor, Department of Computer Science and Engineering, Sir M Visvesvaraya Institute of Technology, Bengaluru, Karnataka, India

---***---

Abstract-*Manhole covers are essential components of urban infrastructure, and their absence, displacement, or damage can create serious safety risks for pedestrians, vehicles, and sanitation workers. Conventional inspection methods rely mainly on periodic manual checks, making continuous monitoring difficult across large urban areas. Existing IoT-based approaches improve monitoring by collecting parameters such as cover status, water level, flooding, gas concentration, and movement through sensors. However, most of these systems primarily depend on sensor measurements and threshold-based alerts, with limited integration of real-time visual analysis and predictive capabilities. This paper presents Urban Shield, an IoT-based intelligent manhole detection and monitoring system that combines IoT sensing, real-time image acquisition, computer vision, artificial intelligence, and a web-based monitoring platform. The system uses IoT devices to collect field information, Python for AI and computer-vision processing, and a trained YOLO model to detect and analyze manhole conditions from captured images. The processed information is integrated with backend and database services and presented through a MERN-based real-time dashboard. The proposed framework also incorporates AI-based analysis for supporting prediction or risk assessment using collected sensor information and detected visual characteristics. By combining physical sensing with visual intelligence, Urban Shield aims to reduce dependence on manual inspection and provide a more integrated approach to real-time urban infrastructure monitoring. Experimental performance measures are to be obtained through model and system evaluation and are not reported without supporting experimental evidence.*

Key Words: IoT, Manhole Detection, Computer Vision, YOLO, Deep Learning, Smart City, Real-Time Monitoring, Predictive Analysis, Urban Infrastructure, Intelligent Monitoring.

1. INTRODUCTION

Manholes are important components of urban infrastructure because they provide access to underground drainage, sewage, communication, electrical, and other utility networks. Despite their limited physical size, manholes can have a significant impact on public safety and urban infrastructure operations. Missing, displaced, damaged, or improperly positioned manhole covers can expose openings on roads and pedestrian areas, creating risks for vehicles and pedestrians. Problems within underground drainage systems can also create unsafe conditions for sanitation workers due to flooding, water accumulation, and exposure to harmful gases. Existing research has identified these issues as important challenges in the management and maintenance of urban manhole infrastructure.

Conventional assessment largely relies on scheduled physical inspections and reports from individuals, making continuous observation difficult across widely distributed manholes. This approach becomes difficult when a city contains a large number of manholes distributed across different locations. Such an approach requires substantial human effort and cannot provide uninterrupted observation of every monitored location. Earlier research has therefore focused on developing automated monitoring systems that can detect abnormal conditions and provide timely information to responsible authorities.

IoT has increasingly been investigated as a means of automating monitoring activities within urban infrastructure. These systems employ sensors to observe parameters including cover movement, inclination, flooding, water level, gas concentration, and open or missing covers. The collected information can be transmitted through communication technologies such as Wi-Fi, GSM, LoRa, and LoRaWAN to monitoring platforms or management authorities. For example, one of the reviewed systems uses acceleration, flooding, and positioning information and transfers the collected status through LoRa to an IoT cloud platform, where abnormal conditions can be monitored and reported.

Although sensor-based monitoring provides useful information about the physical condition of a manhole, sensor readings alone may not describe the complete visual situation at the monitored location. Camera-based image acquisition can provide additional information about the surrounding environment and the visible condition of a manhole. The reviewed literature also includes computer-vision and deep-learning approaches for automated manhole identification, showing the potential of visual intelligence for infrastructure monitoring.

Another area that requires attention is intelligent prediction. Existing monitoring systems can identify abnormal conditions and generate alerts, while some research has discussed using historical data, data mining, and prediction to improve future manhole safety management. However, such predictive functionality is described as a possible future development rather than as an implemented predictive model in the reported smart-light-pole system.

To address these limitations, this paper presents Urban Shield, an IoT-based intelligent manhole detection and monitoring system that combines real-time sensor information, camera-based image acquisition, computer vision, and artificial intelligence. The system uses Python for AI and computer-vision processing and a trained YOLO model for visual manhole detection. The processed information is connected with backend and database services and presented through a MERN-based real-time dashboard. The proposed framework is intended to extend conventional monitoring by combining current condition detection with AI-supported analysis and prediction or risk assessment. In this way, Urban Shield provides an integrated approach to monitoring urban manhole safety while reducing dependence on periodic manual inspection.

2. LITERATURE REVIEW

Manhole monitoring has received increasing attention in smart-city infrastructure because damaged, displaced, missing, or open covers can create hazards for pedestrians, vehicles, and sanitation personnel. Conventional assessment generally depends on scheduled physical inspections, which makes continuous observation difficult when large numbers of manholes are distributed across different locations. Consequently, previous studies have explored IoT technologies, sensor networks, wireless communication, cloud platforms, and automated alert mechanisms for improving urban manhole monitoring.

Singh et al. [1] presented an IoT-based manhole monitoring approach that uses multiple sensing units to observe safety-related conditions. The system considers parameters such as cover status, temperature, toxic-gas concentration, and water-related conditions. When monitored values exceed predefined limits, alerts are communicated to authorized personnel. The study demonstrates how sensor-based monitoring can support remote observation and early warning for hazards associated with drainage infrastructure. The same study highlights the need for intelligent monitoring characteristics such as self-perception, active real-time alerts, reduced management expenses, and shorter repair times. Its literature review also discusses earlier IoT and wireless-sensor approaches for drainage leakage, overflow, environmental monitoring, manhole localization, and sewage blockage detection. These systems demonstrate that sensors can continuously collect physical and environmental parameters and transmit them to monitoring authorities.

Bokshi et al. [2] developed an IoT-based system focused on identifying open or missing manhole covers. NodeMCU and sensing components are used to determine cover status, with the collected information transferred to a central server through Wi-Fi. A web interface provides access to manhole location and status information, while an Android application uses GPS-based location information to warn users approaching an open manhole. The system demonstrates how field-level sensing can be connected with web-based management and public safety notifications.

The open-manhole management system also includes an alert mechanism in which information from multiple NodeMCU devices is received through an API and forwarded to authorities through email, SMS, or phone calls. Its web application allows users and administrators to view manhole positions and open or closed status on a map, while administrators can manage manhole information through the dashboard. This demonstrates the value of connecting field-level sensing with centralized web-based visualization. Mo et al. [3] proposed a manhole safety-monitoring architecture integrated with smart light poles. An STM32F103C8T6 microcontroller processes information associated with cover movement, loss, inclination, flooding, and position. The sensing unit communicates with a nearby gateway through LoRa. Abnormal conditions can be displayed locally and communicated to users through the associated IoT cloud platform. Thus, the proposed architecture combines sensing, wireless communication, local warning, cloud connectivity, and remote management within one monitoring framework.

The smart-light-pole system extends monitoring beyond simple data collection by providing local and remote warning mechanisms. When abnormal information is received, the gateway can display the condition on a screen and activate a voice-broadcast mechanism to warn nearby pedestrians and vehicles. The information is also uploaded to the KitLink IoT cloud platform, where management users can access the status and receive abnormal-condition information. The system therefore combines sensing, wireless communication, local warning, cloud monitoring, and remote management.

The field evaluation reported in this study indicates that the system achieved average recognition delays of 0.33, 0.36, and 0.37 seconds in the three tested areas, with reported recognition accuracy values of 99.23%, 99.01%, and 98.96%, respectively. These results indicate that sensor-based monitoring can provide rapid responses under the tested conditions. However, these values belong to the reported system and should not be directly compared with the performance of a different AI-based system without equivalent experimental conditions.

Wireless communication is another important consideration in distributed manhole monitoring. The smart-light-pole research discusses different communication approaches, including ZigBee, NB-IoT, and LoRa. ZigBee can have limitations in transmission distance, while NB-IoT can require network coverage and associated infrastructure. LoRa is considered useful for long-distance, low-power communication and is therefore suitable for systems in which relatively small amounts of monitoring information must be transmitted from distributed locations.

Tiwari et al. [4] investigated LoRaWAN as a low-power communication approach for distributed manhole-cover monitoring. Their system employs sensing nodes equipped with accelerometers to detect changes such as displacement or damage. Information from the sensing nodes is forwarded through a LoRa gateway to The Things Network (TTN), where the data can be stored and used to generate notifications for maintenance personnel. The study demonstrates the suitability of LoRaWAN for long-range communication in manhole-monitoring applications.

The LoRaWAN system also demonstrates how cloud connectivity can support distributed monitoring. TTN provides a platform through which sensor nodes can be registered, monitored, and accessed in real time. The implemented system integrates the cloud application with email and SMS services so that maintenance personnel can be notified when a manhole cover becomes abnormal. The authors conclude that LoRaWAN can provide low-power and long-distance communication for manhole-cover monitoring and can support rapid notification following damage, displacement, or theft.

Previous research has also investigated visual approaches for identifying manholes from image or spatial data. Such techniques provide information that cannot be obtained solely from physical sensor measurements. Computer-vision methods have been explored for automatically identifying manholes from visual or spatial information. The literature cited in the smart-light-pole study includes work using mobile LiDAR for manhole-cover detection and identification, as well as methods based on image comparison and other recognition techniques. These approaches indicate that visual information can provide an additional source of information beyond physical sensor measurements.

Camera-based monitoring can complement sensor observations by capturing the visible surroundings of a manhole rather than relying only on individual sensor readings. Deep-learning-based object detection can further automate the interpretation of captured images. The reviewed material contains references to computer-vision and recognition approaches, including multi-view manhole detection and recognition, LiDAR-based detection, and image-based rupture detection. However, the uploaded papers do not provide evidence of a complete system in which a trained YOLO model is integrated with real-time IoT sensing and a web dashboard for the specific Urban Shield application.

Beyond detecting existing faults, intelligent monitoring can also be extended toward estimating potential future risks. The systems reviewed in this study primarily respond when an abnormal measurement is detected or when a predefined threshold is crossed. For instance, gas- and water-level monitoring approaches generate alerts after monitored values exceed specified limits, whereas accelerometer-based systems respond to detected cover movement or displacement.

The smart-light-pole study also discusses the use of historical data, data modelling, and data mining for future prediction in manhole safety management [3]. However, this predictive capability is presented as a possible extension rather than as a fully implemented prediction model within the reported system. The study further identifies edge computing as a potential approach for reducing data transmission requirements and improving processing time. The smart-light-pole research discusses the possibility of using historical data, data modelling, and data mining to make regular predictions related to manhole safety management. However, this predictive capability is presented as a direction for further development rather than as a fully implemented predictive model in the reported system. The study also suggests edge computing as a way to reduce data transmission, lower delay, and improve real-time processing.

Overall, previous studies have established several approaches for automated manhole monitoring, including sensor-based condition detection, wireless communication, cloud connectivity, location tracking, and automated warning mechanisms. The reviewed literature also indicates that computer vision and LiDAR can provide additional information for identifying manholes and assessing their visible condition. However, the existing studies do not demonstrate an end-to-end system that combines real-time IoT sensing, camera-based image acquisition, trained YOLO-based detection, AI-supported prediction or risk assessment, backend data management, and an integrated real-time web dashboard. This gap motivates the development of Urban Shield, which brings these capabilities together within a unified intelligent monitoring framework.

3. COMPARATIVE ANALYSIS OF EXISTING SYSTEMS

The reviewed studies demonstrate different approaches to automated manhole monitoring based on their sensing mechanisms, communication technologies, detection techniques, and monitoring platforms. Most existing systems concentrate on detecting a specific physical or environmental condition and generating an alert when an abnormal state is identified. The comparison below highlights the major characteristics of these approaches and identifies the areas addressed by the proposed Urban Shield framework.

Table - 1: Comparative Analysis of Existing Manhole Monitoring Systems

Study	Core Technology	Detection / AI	Main Limitation
Smart Manhole Monitoring	IoT, sensors, GSM/Blynk	Sensor and threshold based	Depends on sensor readings
Open Manhole Management	NodeMCU, Wi-Fi, Web/Android	Sensor-based open/closed detection	Limited visual analysis
Smart Light Pole System	STM32, LoRa, IoT Cloud	Sensor-based movement, tilt, flooding	Prediction proposed as future work
LoRaWAN Monitoring	LoRaWAN, accelerometer, cloud	Sensor-based movement detection	Focused mainly on cover movement
Urban Shield	IoT, Python, YOLO, MERN	YOLO + AI-based analysis	Requires experimental validation

5. PROPOSED SYSTEM

The proposed Urban Shield system is designed as an intelligent IoT-based framework for monitoring and detecting unsafe manhole conditions. Unlike conventional approaches that mainly depend on individual sensor readings and threshold-based alerts, the proposed system combines IoT sensing with real-time image acquisition and artificial intelligence. The collected information is processed to identify manhole-related conditions and is presented through a centralized web-based monitoring interface.

The system consists of several interconnected components, including IoT sensors, a camera-based image acquisition unit, a Python-based AI processing module, a trained YOLO detection model, backend and database services, and a MERN-based real-time dashboard. IoT sensors provide information about the physical or environmental condition of the monitored location, while the camera captures visual information that can be analysed using computer-vision techniques.

Captured frames are passed to the Python processing module, which applies the trained YOLO model for object detection. The detection output is combined with the available sensor information to support condition analysis. Based on the collected observations, the system can provide AI-assisted prediction or risk assessment in addition to conventional condition detection.

Consequently, the framework provides more context than a system that reports sensor abnormalities alone, since visual information can also be considered.

The processed information is then communicated to the backend and stored in the database for further access and analysis. The MERN-based dashboard presents the current status and relevant information to authorized users through a real-time monitoring interface. This architecture enables information collected from the field to be converted into visual and analytical information that can assist monitoring and maintenance activities.

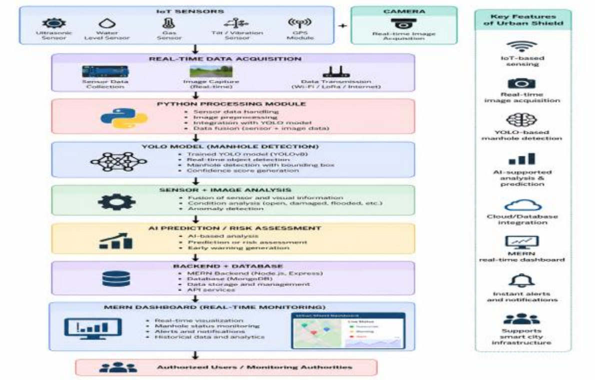

Fig. 1. Overall architecture of the proposed Urban Shield system.

6. SYSTEM METHODOLOGY

The Urban Shield framework processes information through successive stages that include data acquisition, image processing, object detection, condition analysis, data storage, and real-time visualization. The methodology integrates IoT-based sensing and camera-based image acquisition with Python and deep-learning techniques to support intelligent manhole monitoring. The processed information is subsequently made available through a MERN-based dashboard for real-time observation and analysis.

A. Data Acquisition

At the data acquisition stage, IoT devices and a camera collect information from the monitored manhole environment. Sensor measurements provide information about relevant physical or environmental conditions, while the camera captures visual information from the monitored location. The collected data is transmitted to the processing layer for further analysis.

B. Image Processing and YOLO Detection

The captured images are processed using the Python-based computer-vision module. A trained YOLO model is used to identify manhole-related objects in the captured images. The model produces detection information such as the identified object, bounding-box coordinates, and confidence score. This information is used as an input for subsequent condition analysis.

C. Sensor and Visual Data Analysis

The proposed framework combines sensor observations with information obtained from visual detection. This combination provides a broader representation of the monitored condition than relying on an individual sensor reading. The collected information can be analysed to identify potentially abnormal or unsafe manhole conditions.

D. AI-Based Prediction and Risk Assessment

The AI analysis layer is intended to extend conventional threshold-based monitoring by using the collected observations for prediction or risk assessment. The analysis can consider sensor information together with detected visual characteristics to support early identification of conditions that may require attention. The performance of this component will be evaluated using experimental data obtained during system testing.

E. Backend and Database

The processed information is transferred to the backend and stored in the database. The backend manages communication between the Python processing module, database, and monitoring interface. Historical records can also be maintained for subsequent analysis and evaluation of changes in monitored conditions.

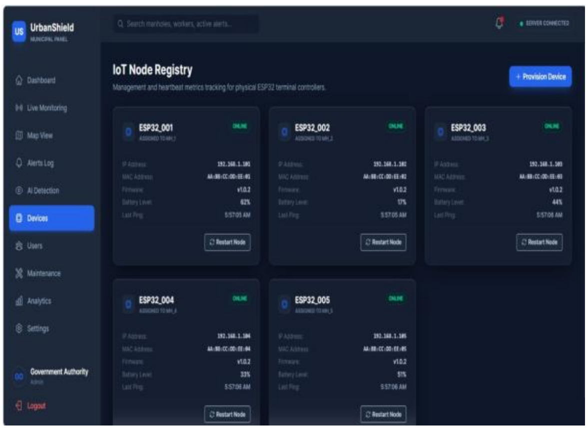

Fig. 2. IoT node registry showing device connectivity, firmware, battery status, and heartbeat information.

F. Real-Time MERN Dashboard

The final processed information is presented through the MERN-based dashboard. The dashboard provides a centralized view of monitored conditions, detected information, alerts, and relevant analysis. This real-time interface allows monitoring personnel to observe system status and respond to potentially unsafe conditions without depending entirely on periodic physical inspection.

Fig.3. Representative manhole conditions considered for monitoring.

7. YOLO MODEL DEVELOPMENT AND TRAINING

The computer-vision component of Urban Shield uses a YOLO-based object-detection model to identify manhole-related conditions from captured images. The YOLO development workflow includes dataset preparation, image annotation, model training, real-time inference, and subsequent performance evaluation. The trained model is integrated with the Python processing module to analyse images received from the camera.

A. Dataset Preparation

The dataset consists of images representing manhole conditions relevant to the proposed monitoring system. The collected images are organized and labelled to identify the target objects required during model training. The prepared dataset is divided into training and validation data to support model development and evaluation.

B. Model Training

The annotated dataset is used to train the YOLO-based object-detection model. During training, the model learns the visual characteristics of the target manhole objects and their corresponding locations within input images. The trained model is subsequently integrated with the Python processing module for inference on newly captured images.

C. Real-Time Detection

During operation, frames captured by the camera are supplied to the trained YOLO model for analysis. The model analyses each input image and generates detection results containing the detected region, bounding-box coordinates, class information, and confidence score. These outputs are forwarded to the subsequent analysis layer for condition assessment.

D. Model Evaluation

The performance of the trained detection model is evaluated using standard object-detection metrics such as precision, recall, mean Average Precision (mAP), and F1-score. These metrics indicate how effectively the model identifies the target classes while limiting incorrect detections.

8. REAL-TIME MONITORING DASHBOARD

The MERN-based dashboard provides a unified interface for visualizing real-time manhole status, sensor observations, detection results, and alerts. The processed information received from the backend is presented in a structured manner to support continuous monitoring.

A. Dashboard Overview

The MERN-based dashboard provides a unified interface for visualizing real-time manhole status, sensor observations, detection results, and alerts. The processed information received from the backend is presented in a structured manner to support continuous monitoring.

B. Real-Time Visualization

The dashboard displays the current condition of monitored manholes together with relevant sensor and detection information. The interface allows authorized users to observe system status through a centralized monitoring platform and reduces the need for repeated manual inspection.

C. Alerts and Monitoring

When abnormal conditions are identified from sensor observations or visual analysis, the corresponding information can be presented through the monitoring interface. This enables monitoring personnel to identify potentially unsafe conditions and take appropriate action based on the available information.

9. RESULTS AND DISCUSSION

The proposed Urban Shield framework integrates IoT-based sensing, camera-based image acquisition, YOLO-based computer vision, AI-assisted analysis, backend services, and a MERN-based monitoring dashboard. The integration of these components provides a unified approach for monitoring manhole conditions and presenting the collected information through a centralized interface.

The system is designed to combine sensor observations with visual information obtained from camera images. While sensor-based monitoring can provide measurements related to physical or environmental conditions, visual analysis provides additional information about the observable condition of the manhole. The combined information can therefore support a broader assessment of the monitored location.

The YOLO-based detection component is intended to identify manhole-related objects from captured images and provide detection information such as bounding-box coordinates and confidence scores. The resulting information can be combined with sensor observations for further condition analysis and AI-assisted risk assessment.

The MERN-based dashboard provides a centralized interface for viewing the processed information. It is designed to present monitoring status, detected conditions, sensor observations, alerts, and historical information. This reduces dependence on periodic manual inspection and provides a more accessible method for monitoring urban manhole infrastructure.

Quantitative evaluation of the trained YOLO model and AI-based prediction component will be carried out using experimental data collected during system testing. Metrics such as precision, recall, mAP, F1-score, detection response time, and system reliability can be used for detailed performance evaluation.

10. CONCLUSION AND FUTURE WORK

The proposed Urban Shield framework presents an integrated approach for intelligent manhole detection and monitoring by combining IoT-based sensing, real-time image acquisition, computer vision, YOLO-based object detection, AI-assisted analysis, backend services, and a MERN-based monitoring dashboard. Rather than relying only on individual sensor readings or scheduled manual inspections, the proposed framework combines physical observations with visual information to provide a broader view of manhole conditions.

The system is designed to collect information from the monitored environment, process camera images using a trained YOLO model, analyse sensor and visual observations, and present the processed information through a centralized real-time dashboard. This integration provides a foundation for identifying potentially abnormal conditions and supporting timely monitoring and maintenance activities.

The proposed framework therefore demonstrates the potential of combining IoT and artificial intelligence for urban infrastructure monitoring. Quantitative performance evaluation of the trained model and prediction component will be carried out using experimental data obtained during system testing.

FUTURE WORK

Future development will focus on improving the detection model using a larger and more diverse dataset containing different manhole conditions, environmental conditions, lighting variations, and camera viewpoints. Further work can also investigate improved AI-based prediction and risk-assessment techniques using historical monitoring data.

The system can additionally be extended with more advanced alert mechanisms, location-based visualization, automated maintenance notifications, and edge-based processing to reduce communication delays. Extensive field testing across multiple locations can be performed to evaluate the reliability, scalability, and practical deployment of the Urban Shield framework.

11. REFERENCES

[1] A. Singh, K. Mishra, S. Kumar, and C. Shankar, “A Smart Manhole Monitoring and Detection System,” International Journal for Research in Applied Science & Engineering Technology (IJRASET), vol. 11, no. V, May 2023, doi: 10.22214/ijraset.2023.53012.

[2] M. A. H. R. Bokshi, A. M. Siam, J. Ferdouse, M. S. Islam, and M. S. Reza, “IoT-based Manhole Management System for Open Manhole Covers,” International Journal of Information Technology and Computer Engineering, vol. 3, no. 6, Oct.–Nov. 2023, doi: 10.55529/ijitc.36.1.7.

[3] F. Mo, L. Yu, Z. Zhang, and Y. Zhao, “Design and Implementation of Manhole Cover Safety Monitoring System based on Smart Light Pole,” Mathematical Problems in Engineering, vol. 2022, Article ID 3081649, 2022, doi: 10.1155/2022/3081649.

[4] A. K. Tiwari, P. Chaudhari, S. Pattewar, and R. Deshmukh, “LoRaWAN Based Manhole Cover Monitoring System,” in Smart Intelligent Computing and Communication Technology, IOS Press, 2021, pp. 429–432, doi: 10.3233/APC210078.

[5] Z. Wei, M. Yang, L. Wang, H. Ma, X. Chen, and R. Zhong, “Customized Mobile LiDAR System for Manhole Cover Detection and Identification,” Sensors, vol. 19, no. 10, p. 2422, 2019.