RiverEye: An Intelligent CCTV-Based Anomaly Detection System for Flood Prevention Caused by Waste in Urban River Streams

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***Abstract*— Flooding is the most frequent natural disaster in Indonesia, with BNPB data showing a sharp increase since 2016, reaching 1,794 incidents in 2021. In 2024, 1,420 flood cases were reported, the majority of which were caused by waste accumulation in river channels. One example is the flood in Gadingrejo Village, Central Java, which submerged 100 houses due to waste obstructing the river flow. This issue motivated the development of RiverEye, an intelligent system based on CCTV and anomaly detection to prevent floods caused by waste in urban river channels. The system is designed using Raspberry Pi cameras, a buzzer as an early warning alarm, and a mini-computer running Artificial Intelligence (AI) models. The research methodology integrates YOLOv8 for object detection of waste and humans, MediaPipe Pose for detecting littering gestures, and face recognition to identify the perpetrators. The system includes a Flask-based monitoring dashboard that displays real-time detection results and a WhatsApp bot for automatic reporting. Testing was conducted on five main functions, achieving an average success rate of 89%, including pose detection 93%, object detection 90%, face recognition 83%, alarm 80%, and WhatsApp bot integration 100%. The findings demonstrate that RiverEye can detect littering behavior quickly and accurately, providing early warnings of potential river obstructions. The system has the potential to be applied as an effective, efficient, and environmentally friendly AI-based disaster mitigation tool. Further research is recommended to expand the testing area, increase the river visual dataset, and develop flood prediction features based on historical data for sustainable implementation.**

***Keywords*—CCTV; waste detection; artificial intelligence; YOLOv8; MediaPipe; face recognition; anomaly detection.**

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I. INTRODUCTION

Historical data from the National Disaster Management Agency (BNPB) shows that national flooding has increased sharply since 2016, with a significant increase occurring in 2020 and peaking at 1,794 incidents in 2021. Although the number decreased in 2022 and 2023, it rose again in 2024 to 1,420 [1]. One of the causes of flooding is the human habit of throwing rubbish carelessly into rivers, which blocks the flow of water and damages river basins, thereby increasing the risk of flooding [2]. Bencana banjir parah yang terjadi di Desa Gadingrejo, Jawa Tengah pada Februari 2025 merupakan bukti nyata bahwa penumpukan sampah di sungai dapat menyebabkan bencana. The severe flooding that occurred in Gadingrejo Village, Central Java, in February 2025 is clear evidence that the accumulation of waste in rivers can cause disasters. Heavy rains caused the Simo and Sinomam Rivers to overflow due to the blockage of waste, inundating approximately 100 homes with water levels reaching 30–50 cm [3]. Even though the government has provided waste management facilities and issued warnings about the negative impact of waste on river flows, many people ignore these warnings [4]. Even though the government has provided waste management facilities and issued warnings about the negative impact of waste on river flows, many people ignore these warnings [5]. The current system for monitoring river waste disposal is still manual. Monitoring is carried out through patrols or public reports, which requires significant time, effort, and operational costs. Furthermore, limited monitoring coverage means that many illegal waste dumps go undetected. This is a major cause of the increasing river pollution, as there is no effective, real-time early detection system [6]. Various types of surveillance cameras (CCTV) can be installed at strategic locations, including streetlight poles, building corners, and riverbanks. The use of CCTV in these locations has become a popular surveillance method for communities to monitor outdoor activities. However, these systems generally only record footage without the ability to automatically detect waste disposal, identify perpetrators, or provide early warnings, thus their effectiveness in preventing river pollution remains limited. [7]. Based on these problems, it is necessary to develop an Artificial Intelligence (AI)-based surveillance camera system that is capable of detecting anomalous activities of indiscriminate waste disposal in urban rivers automatically and in real time.

II. MATERIAL AND METHOD

A. Research Focus and Objective

This research will focus on the development of a system This research focuses on the development of an intelligent system based on CCTV and anomaly detection designed to prevent flooding in urban areas due to the accumulation of waste in river flows. The implementation builds an Artificial Intelligence (AI) based system that combines object detection, motion analysis, and facial recognition in real-time through a Raspberry Pi device connected to a monitoring dashboard and early warning system. The results of this research are expected to facilitate river environmental monitoring, increase the efficiency of detecting waste disposal activities, and support flood disaster mitigation efforts through automatic monitoring and digital reporting [8].

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All analysis results are sent to the Raspberry Pi module, which serves as a control center and system integrator [11]. This module channels detection results to a monitoring dashboard for monitoring officers to view and sends automated reports to the public via a WhatsApp bot as an early warning. Furthermore, the system activates an alarm directly at the scene to provide a rapid response to waste disposal activity.

This system uses three main components in the analysis process: YOLOv8, MediaPipe Pose, and Face Recognition, which work sequentially to detect, recognize, and classify activities in river areas. The YOLOv8 model was trained using a dataset containing 629 garbage images, collected from various lighting conditions and viewpoints in urban river areas. Of these, 300 images were used for model training, 165 images for validation, and 164 for testing. This division was carried out so that the model could identify objects with high accuracy and remain stable when applied to varying field conditions [12]. The steps in the research work process can be explained as follows:

1) Develop an AI-based waste disposal activity detection system by integrating YOLOv8, MediaPipe Pose, and Face Recognition to produce an automatic monitoring system that provides early warning of potential river blockages.

2) Evaluate the performance of the detection system using precision, recall, accuracy, and mean average precision (mAP) indicators as a basis for comparative analysis in determining the optimal performance of the model in real field conditions.

B. Research Materials and Methodology

The material and methodology for the trash detection system focus on the application of Artificial Intelligence (AI) technology based on object detection, facial recognition, and pose estimation. The proposed architecture combines a Raspberry Pi camera as an image acquisition device with a visual analysis system based on the You Only Look Once (YOLOv8) model [13]. Figure 2 shows the RiverEye system process flow which consists of the stages of image capture, video frame extraction, object detection, facial recognition, alarm activation, and sending notifications via WhatsApp bot.

The process begins with collecting a dataset of waste images collected from the river and its surrounding areas. The dataset consists of 629 images of waste objects obtained from images taken under various lighting conditions and angles to increase data diversity. This data is used as the basis for training the YOLOv8 model, which is capable of recognizing various shapes and positions of waste objects in the river area. [14].

The next step is data preprocessing, which aims to prepare the dataset for model training. This stage includes cleaning the data of blurry or duplicate images, adjusting the image size and resolution, and object annotation to mark the location of debris in each image [15]. After the pre-processing process was completed, the dataset was divided into three parts: 300 images for model training, 165 images for validation, and 164 images for testing. This division was intended to ensure the model could be evaluated objectively and had good generalization capabilities to new data [16].

The trained YOLOv8 model is then integrated with MediaPipe Pose to detect human activity that could potentially lead to littering, and with Face Recognition to identify the perpetrator. This process is executed in real time via a Raspberry Pi module that controls the entire system and channels the detection results to a monitoring dashboard [17].

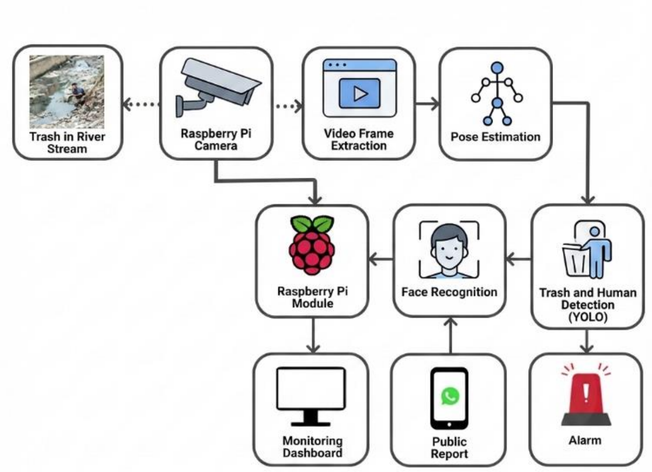

Fig. 1 Proposed Architecture of an Intelligent CCTV-Based System for Anomaly Detection in River Waste Disposal Activities

1) Dataset Collection

The initial block of Figure 2 shows the collection flow for the trash image dataset used in this study. Data was captured using a Raspberry Pi camera that directly recorded river conditions. From these images, 629 trash images were obtained, representing various environmental conditions such as differences in lighting, camera direction, and variations in trash size and type. The dataset was then manually annotated to label the object's position in each image. This annotation process aims to enable the YOLOv8 model to learn to precisely detect trash objects based on their shape and actual position [18].

Once the dataset was prepared, it was divided into three main subsets: 300 images for model training, 165 images for validation, and 164 images for final performance testing. This division allowed the model to be tested on previously unstudied data, resulting in objective and consistent performance measurements [19].

2) Pra-pemrosesan Data

Data preprocessing steps include cleaning blurry or irrelevant images, converting image formats to YOLOv8 compatibility, and normalizing image sizes to maintain consistent input dimensions. The annotation process is performed using a labeling tool to generate bounding box files that serve as training references [20].

The preprocessed data was then used to train the YOLOv8 model with adjusted parameters to achieve a balance between accuracy and detection time. Validation was performed periodically to monitor model performance and prevent overfitting. The final training results were then tested using a test dataset to measure precision, recall, accuracy, and mean average precision (mAP) values as an indicator of system performance [21].

Figure 3 illustrates the data preprocessing process flow in this study. The diagram shows the stages starting from collecting raw images from the Raspberry Pi camera, image selection and cleaning, image format conversion, object annotation using a labeling tool, and dividing the dataset into training, validation, and testing data. This process aims to produce a clean, representative dataset that is ready for use in YOLOv8 model training [22].

Proper data preprocessing directly impacts overall system performance. Clean, structured, and diverse data improves the model's ability to recognize objects in various environmental conditions. Therefore, this stage is a key foundation for the successful development of the RiverEye system as a reliable and efficient automated waste detection solution.

- Feature Blur Detection

The images used in the RiverEye detection system must have sufficient edge sharpness and contrast for accurate object recognition. Therefore, the blur detection stage is implemented using the Laplacian Variance method, which is an approach based on the variance of image gradients to measure the sharpness level. Images with variance values below a certain threshold (e.g., <100) are categorized as blurry and removed from the dataset. This removal of blurry images is important to ensure that the YOLOv8 model only learns from data with clear object edges and contours, thus improving detection accuracy [23].

- Feature Brightness

Uneven brightness levels can cause the model to have difficulty recognizing objects in extreme conditions, such as too dark or too bright. To address this, the average pixel intensity value in each image is evaluated. Images with an average intensity value that is too low (<30) or too high (>220) on a scale of 0–255 are considered uninformative and are removed from the dataset. This step ensures that each image has balanced lighting, maintaining the stability of the model's performance across various river conditions, both during the day and at dusk [24].

- Feature Noise Reduction

Field-recorded image data often contains visual noise caused by weather conditions such as rain, fog, or camera vibration. To mitigate these effects, a noise reduction process using a mild Gaussian Blur or Median Filter is applied. This filter can smooth out noisy areas without obscuring important object details. Thus, this step helps maintain the consistency of the texture pattern in the image background and improves the stability of object detection by the YOLOv8 model [25].

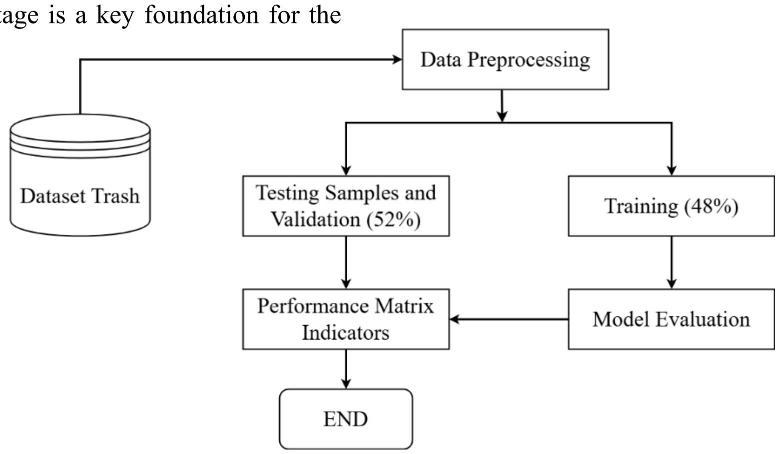

Fig. 2 The workflow of machine learning models

- Feature Resize Normalization

Varying image sizes can lead to inconsistencies in the model training process. Therefore, all images in the dataset were resized to 640×640 pixels. This process also included normalizing pixel values to the 0–1 range to ensure uniform color scales. This normalization is essential for the model to efficiently learn features without being affected by resolution differences between images [26]. Varying image sizes can lead to inconsistencies in the model training process. Therefore, all images in the dataset were resized to 640×640 pixels. This process also included normalizing pixel values to the 0–1 range to ensure uniform color scales. This normalization is essential for the model to efficiently learn features without being affected by resolution differences between images.

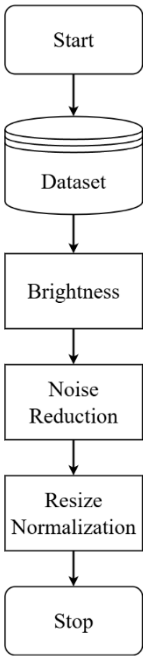

Fig. 3 Workflow of data preprocessing

3) Prediction of Waste Disposal Activities

To this end, this study utilizes three main components: the YOLOv8 model, MediaPipe Pose, and Face Recognition. These three are integrated to perform real-time object detection, motion analysis, and face identification in an urban river environment.

- YOLOv8 (You Only Look Once Version 8)

The YOLOv8 model was used in this study due to its advantages in detection speed and computational simplicity. YOLOv8 operates on the principle of one-stage detection, which simultaneously classifies and positions objects in a single step. This allows the system to recognize objects directly from images without requiring lengthy processing, making it suitable for use in real-time Raspberry Pi-based systems [27].

YOLOv8 serves as the primary model for detecting waste objects on or around river surfaces. Through training on 629 waste images, the model is able to recognize various shapes and positions of waste under different lighting conditions and viewing angles. The resulting confidence score helps the system determine the model's level of confidence in the object's presence, allowing detection results to be visualized as a bounding box within the identified are [28].

Despite its advantages in detection speed and accuracy, YOLOv8 also has limitations. This model is highly dependent on the quality of the dataset used. Blurry, overly dark, or overly bright images can decrease detection accuracy. Furthermore, dynamic river conditions such as water reflections or object movement due to wind can cause detection errors. Therefore, preprocessing steps such as blur detection, brightness adjustment, and noise reduction are essential for the model to function optimally on field data [29].

- MediaPipe Pose

MediaPipe Pose is used to detect and recognize human movements that could potentially involve waste disposal. This system works by identifying 33 key points on the human body (key landmarks) from camera images, such as the position of the hands, shoulders, and head. Through these points, the system can analyze movement patterns such as reaching out, looking down, or throwing something into a river. The main advantage of MediaPipe Pose is its ability to work quickly and efficiently without the need for additional devices such as depth sensors. This model can be run directly in conjunction with YOLOv8 object detection on a Raspberry Pi device. This integration allows the system to not only recognize the presence of waste but also observe the human activities that cause the waste to appear [30].

Namun, akurasi deteksi gerakan dapat dipengaruhi oleh kondisi lingkungan seperti pencahayaan yang kurang, posisi kamera yang terlalu jauh, atau sebagian tubuh yang tidak terlihat (*occlusion*). Agar hasil tetap stabil, kamera diposisikan pada sudut yang sesuai dan citra yang digunakan memiliki tingkat pencahayaan yang cukup agar titik tubuh dapat terdeteksi dengan jelas [31].

- Face Recognition

Facial recognition is used to identify individuals recorded in the system when waste disposal activity is detected. This technology works by comparing recorded facial features with facial data stored in a database. Through facial feature matching, the system can determine whether the detected face matches a previously registered individual [32].

The RiverEye system utilizes facial recognition to support the identification of waste dumpers and provides supporting data for sending notifications via a WhatsApp bot. This system not only detects objects and activities but can also automatically link these activities to the perpetrator's identity. While it boasts a high level of accuracy, facial recognition performance can be affected by lighting, facial angles, or blurry images. Therefore, images are captured with a stable camera position and adequate lighting to ensure clear facial recognition.

4) Performance matrix indicators

To quantitatively assess the performance of the RiverEye trash detection system, several statistical measures were used to evaluate the model's ability to accurately recognize objects, activities, and faces. The evaluation was conducted using four main indicators: precision, recall, accuracy, and mean average precision (mAP). These four metrics provide a comprehensive overview of the system's ability to correctly detect objects, avoid false detections, and maintain consistent results across test data.

Precision indicates the system's accuracy in detecting relevant objects, while recall describes the system's ability to recognize all objects that should have been detected. Accuracy measures the overall proportion of correct predictions relative to the total test data, while mAP serves as a general indicator for assessing the multi-class detection performance of the YOLOv8 model [33].

III. RESULTS AND DISCUSSION

In this study, the RiverEye system was developed using a Raspberry Pi 4 Model B device as the main processing unit (edge computing unit). This device runs the Raspberry Pi OS (Debian 12) operating system with the Linux kernel version 6.1 which has been optimized for real-time visual processing. The RiverEye system utilizes the integration of artificial intelligence to detect, recognize, and classify waste disposal activities in urban river areas. The entire computing process is carried out locally on the Raspberry Pi without relying on a cloud computing system, so it can be operated in the field with high power efficiency.

A 1080p USB camera is used to record activities around the river area and send data to a Raspberry Pi. The system is equipped with a buzzer as an early warning alarm, a UPS (Uninterruptible Power Supply) as a backup power source to maintain operational stability, and a Wi-Fi network to connect the device to a Flask-based monitoring dashboard. The system's software architecture consists of three main artificial intelligence models, namely YOLOv8 as an object detection model, MediaPipe Pose for human body movement estimation, and Face Recognition for perpetrator facial identification. These three models work integratedly in a single pipeline system designed to recognize human presence, detect garbage disposal movements, and perform face matching automatically.

The dataset used in this study consists of 629 river waste images collected from various locations with varying lighting conditions, viewpoints, and waste types. Before being used in model training, the dataset underwent several pre-processing stages to ensure data quality and consistency, including blur detection using the Laplacian Variance method, lighting level adjustment, and the application of a mild Gaussian Blur for noise reduction. All images were normalized to 640×640 pixels to ensure uniform dimensions.

Figure 7 displays the confusion matrix for the classification of waste types detected by the YOLOv8 model. Five main categories were tested: Cans, Plastic Bags, Plastic Bottles, Styrofoam, and Background. The test results show that the model has the highest performance in the Plastic Bottle class with a correct prediction rate of 71 samples, followed by Cans with 42 samples. The Plastic Bag class showed the highest error rate with several samples incorrectly classified as Background or Plastic Bottle. Based on the average calculation, the overall accuracy of the YOLOv8 model for waste type classification reached 84.6%, with an average precision value of 0.86 and recall of 0.82.

The difference in performance between classes is due to the visual similarity between waste types, particularly between plastic bags and plastic bottles, which have similar light reflection characteristics when placed on the water surface. Nevertheless, the models still demonstrated good robustness to varying lighting conditions and camera angles.

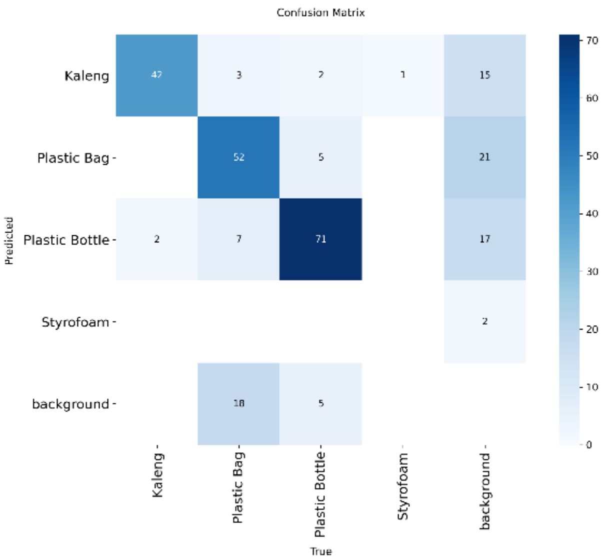

Fig. 4 Correlation of Anomaly Detection features based on training results

TABLE I
PERFORMANCE OF THE MACHINE LEARNING MODELS FOR WASTE AND ANOMALY DETECTION IN URBAN RIVER STREAMS

Model	Function	Dataset Used	Precision	Recall	Accuracy	mAP	Remarks
YOLOv8 (You Only Look Once v8)	Object detection for identifying waste objects such as bottles, cans, and bags in river environments.	629 annotated waste images (5 classes: Kaleng, Plastic Bag, Plastic Bottle, Styrofoam, Background).	0.86	0.82	84.6%	0.86	High accuracy on Plastic Bottle and Kaleng classes; reduced performance on Plastic Bag due to reflection and visual similarity.
MediaPipe Pose	Human pose estimation to detect movements indicating waste disposal activity.	Real-time video frames analyzed through body landmark coordinates.	0.91	0.90	93%	–	Accurate under good lighting; performance decreases under occlusion or poor illumination.

Face Recognition	Facial identification of individuals performing waste disposal actions.	10 registered face images under various lighting and angle conditions.	0.90	0.82	86%	–	Performs well under frontal lighting; accuracy drops with shadow or angled faces.

IV. Conclusion

This research focuses on the development of an intelligent CCTV-based system designed to detect and record illegal waste disposal activities in urban river environments. The system integrates a Raspberry Pi 4 as the main processing unit, employing YOLO (You Only Look Once) for object detection and MediaPipe for human pose estimation. The primary objective is to identify waste-throwing behaviors in real-time through continuous video analysis.

Video data captured by a USB webcam is processed into frames for analysis. The YOLO model is used to detect the presence of humans and waste objects, while MediaPipe estimates body movements to determine dumping actions. When the system detects the concurrent presence of a person, a waste object, and a throwing motion within a single frame, the event is recorded as an instance of waste disposal. The system then performs facial recognition to identify the violator, triggers a buzzer alarm as an early warning, and transmits the event data to a cloud-based monitoring dashboard. In addition, integration with a WhatsApp Bot enables the public to report waste-dumping incidents by sending images, which are automatically analyzed by the AI system and displayed on the monitoring dashboard.

Experimental results demonstrate that the prototype effectively detects illegal waste disposal activities with high accuracy and reliability, even under outdoor environmental conditions. The findings indicate that the combination of YOLO and MediaPipe provides a practical and efficient solution for real-time environmental surveillance using affordable edge-computing devices such as the Raspberry Pi. This system has the potential to support environmental management efforts and enhance community participation in maintaining river cleanliness through intelligent monitoring technology.

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