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Water Meter Detection System Using YOLOv11 with Variations in Image Augmentation Techniques and Integrated into Telegram

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Abstract

While accurate water management is crucial for public utilities, manual meter reading remains inefficient due to recording errors and high operational costs. This study proposes an automatic water meter reading detection system based on YOLOv11 with a variety of image augmentation techniques integrated into Telegram. The dataset was obtained through a combination of ESP32-CAM image captures and online sources totaling 1,207 images, followed by labeling on Roboflow and augmentation in the form of flipping, rotation, saturation, and noise. The YOLOv11 model was trained on Google Colab using an A100 GPU with 100 epochs. Performance evaluation was conducted using Precision, Recall, mAP50, and mAP50-95 metrics. The results showed that the application of augmentation significantly improved model performance, with Precision of 95.9%, Recall of 98.2%, and mAP50 of 97.4%. The combination of four augmentation techniques produced the highest mAP50-95 value of 0.575, indicating the model's robustness against variations in field conditions. The system is also capable of automatically sending detection result notifications via Telegram, enabling its implementation for real-time remote monitoring. Compared to previous studies with YOLOv4 and YOLOv5, this approach proved to be superior in terms of accuracy and efficiency. These findings indicate that the integration of YOLOv11 with image augmentation techniques and IoT support has the potential to be an optimal solution in the modernization of digital water meter reading.

Keywords: *Water Meter Detection, YOLOv11, Image Augmentation*

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INTRODUCTION

Access to clean water is a fundamental human right, essential for social well-being, economic prosperity, and the prevention of human suffering (Gleick, 1998). However, rapid urbanization and population growth have placed immense pressure on water resources, with projections suggesting that a significant portion of the global population will face high water scarcity by 2050 (Gupta, Pandey, Feijóo, Yaseen, & Bokde, 2020). In countries like Indonesia, the management of water resources remains a complex challenge, characterized by a paradox of hydrological abundance and persistent inequities in access, often hindered by weak enforcement of regulatory frameworks (Pambudi & Pramujo, 2025). To mitigate these issues, water utilities must prioritize the reduction of Non-Revenue Water (NRW) through efficient network monitoring and accurate billing systems (Elkharbotly, Seddik, & Khalifa, 2022; Ramos et al., 2023).

In the operational cycle of water distribution, the accurate acquisition of consumption data from household meters is critical (Li et al., 2024). While Smart Water Grids and Digital Twins offer real-time monitoring of pressure and flow to enhance system efficiency, their widespread implementation is frequently hampered by high costs and technical hurdles in developing regions (Gupta et al., 2020; Ramos et al., 2023). Consequently, many utilities still rely on manual maeter reading, which is prone to human error, labor-intensive, and lacks the transparency needed for accountable resource management (Hussain et al., 2017; Naim, Aaroud, Akodadi, & El Hachimi, 2021). Although IoT-based smart meters have been introduced to automate this process, they often face significant challenges regarding data security, reliability, and the need for expensive infrastructure overhauls (Gupta et al., 2020; Sidharth et al., 2022).

Computer vision (CV) and deep learning (DL) have emerged as transformative solutions for automating object recognition tasks across various industries, including aset management and smart city surveillance (Javaid, Sattar, & Ilchenko, 2025; Jiang, Messner, & Matts, 2023; Tsirtsakis, Zacharis, Maraslidis, & Fragulis, 2025). Specifically, the "You Only Look Once" (YOLO) framework has set the benchmark for real-time object detection due to its optimal balance between speed and accuracy (Bochkovskiy, Wang, & Liao, 2020; Redmon & Farhadi, 2018). Over the years, the YOLO architecture has undergone significant evolution, with versions such as YOLOv8 and its successors introducing attention mechanisms and dynamic convolution to enhance performance in detecting small objects under challenging conditions (Murat & Kiran, 2025; Varghese & M., 2024). These advancements have allowed for successful industrial applications, ranging from soccer match analysis to

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workpiece stud leakage detection (Cong, Lv, Feng, & Zhou, 2022; Puspita, Naufal, & Zami, 2025).

Despite the proliferation of DL-based object detection, its application in reading mechanical water meters in natural scenes remains problematic (Li et al., 2024). Environmental factors such as varying lighting, physical obstructions, and the weathered condition of the meters often degrade the accuracy of standard models (Li et al., 2024; Puspita et al., 2025). While some efforts have been made to automate meter data collection, these systems often rely on earlier versions of AI architectures that may not fully leverage recent breakthroughs in parameter efficiency and training speed offered by newer families of models like EfficientNetV2 or the latest YOLO iterations (Kang, Hu, Liu, Zhang, & Cao, 2025; Tan & Le, 2021). Furthermore, the effectiveness of detection systems in the field is highly dependent on advanced data augmentation strategies—such as Mosaic, Mixup, and Cutmix—which are essential for addressing class imbalance and improving robustness in unstructured environments (Puspita et al., 2025).

Although previous studies have explored mechanical water meter recognition using convolutional neural networks, there is significant research gap concerning the implementation and optimization of the YOLOv11 architecture specifically for water meter consumption acquisition. Most existing literature focuses on older versions (YOLOv3 to YOLOv8) and fails to provide a systematic evaluation of how specific combinations of advanced augmentation techniques impact the generalization ability of YOLOv11 in the face os complex environmental noise (Kang et al., 2025; Murat & Kiran, 2025). This study addresses these limitations by evaluating the effectiveness of YOLOv11 in detecting water meters under diverse field conditions. By identifying the optimal augmentation configuration, this research aims to produce a robust and accurate detection system that supports sustainable water resource management and provides a cost-effective alternative for utilities in developing countries (Mhlanga, 2025).

RESEARCH METHOD

Experimental Setup and Hardware

The experimental framework was established using an integrated hardware and software configuration to ensure stable data acquisition and efficient computational processing. The hardware setup comprised a mid-range computational node powered by a multi-core processor (up to 4.2 GHz) as the primary processing unit, interfaced with an ESP32-CAM module featuring an OV2640 sensor for real-time image acquisition of mechanical analog water meters. On the software front, the Arduino IDE was utilized for firmware development to configure the sensor as an IP-based local web server, while Roboflow served as the primary platform for dataset annotation and augmentation. High-performance model training was executed within the Google Colaboratory environment, leveraging an NVIDIA A100 GPU to accelerate the YOLOv11 learning process. Finally, Visual Studio Code was employed for developing the inference scripts and managing the deployment phase, which included a real-time notification system integrated with the Telegram Bot API for remote monitoring.

Experimental Framework and Dataset Development

The systematic research workflow for

automatic water meter reading is divided into several interconnected phases, as illustrated in the methodology flowchart (Figure 1). The process begins with dataset acquisition, where 1,207 images were compiled from two primary sources: targeted web scraping via Google Images and direct acquisition using an ESP32-CAM module. This dual-source approach ensures a high level of diversity in digit fonts, backgrounds, and lighting conditions. Following data collection, all images were uploaded to the Roboflow platform for manual annotation, where bounding boxes were meticulously applied to identify ten numeric classes (digits 0–9). These annotations were exported in the YOLO standard format, generating localized metadata in .txt files containing normalized coordinates (x, y, w, h) for each object.

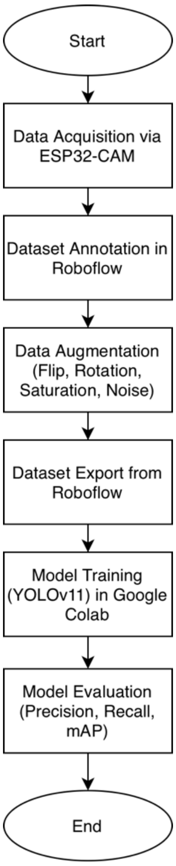

Figure 1. Proposed research workflow for digit recognition

To ensure the robustness and generalizability of the detection model, the annotated dataset was partitioned into three subsets using a 70:20:10 ratio, resulting in 845 images for training, 241 images for validation, and 121 images for testing. The research further evaluates model performance through eight distinct augmentation scenarios to simulate real-world environmental challenges. These scenarios involve geometric transformations, such as horizontal and vertical flips and rotations between −27° and +27°, as well as photometric adjustments including saturation variations (−95% to +95%) and the injection of Gaussian noise up to 10% of total pixels. By comparing the baseline model against these augmented configurations, the study systematically identifies the optimal parameters for the YOLOv11 architecture in recognizing water meter digits under unstructured outdoor conditions.

Model Training and System Implementation

To enhance the accuracy and robustness of the YOLOv11 model, a series of data augmentation techniques were systematically implemented to simulate real-world environmental challenges. These techniques involve geometric transformations, including horizontal and vertical flips to reduce overfitting and rotations between −27° and +27° to handle various installation angles. Additionally, photometric adjustments such as saturation variations (−95% to +95%) and Gaussian noise injection (up to 10% of pixels) were applied to ensure model independence from lighting fluctuations and sensor interference. As synthesized in the experimental design, these methods were tested across eight distinct scenarios to identify the optimal configuration for recognizing digits in unstructured outdoor settings.

The training phase was conducted within the Google Colaboratory environment, leveraging the high-performance computational power of an NVIDIA A100 GPU. The dataset, managed through the Roboflow platform, was integrated using API-based scripts to ensure seamless data flow into the training pipeline. The YOLOv11 model was trained for 100 epochs, a duration sufficient for the neural network to achieve weight convergence by optimizing the loss function. Throughout this process, key performance metrics, including Mean Average Precision (mAP), Precision, and Recall, were recorded to monitor the model's learning progress. The final trained weights were automatically archived to Google Drive, providing a ready-to-deploy model for real-time testing and performance evaluation.

The final implementation involves a synchronized integration between the ESP32-CAM firmware and a Python-based inference script executed in Visual Studio Code. The ESP32-CAM functions as a localized web server, accessible via a local IP address, providing a live stream interface for parameter adjustment and image capture as shown in Figure 2. The inference engine captures these frames every 1–3 seconds, applying the pre-trained YOLOv11 model to detect and localize numeric digits. A post-processing logic is then utilized to sort the detected bounding boxes based on their horizontal coordinates (x), ensuring the correct reconstruction of the water meter reading. Finally, the system utilizes the Telegram Bot API to transmit the detection results and visualized images to a remote device (Figure 3), establishing an automated, real-time monitoring system with integrated error handling for continuous operation.

Figure 2. ESP32-CAM live stream output and parameter control interface.

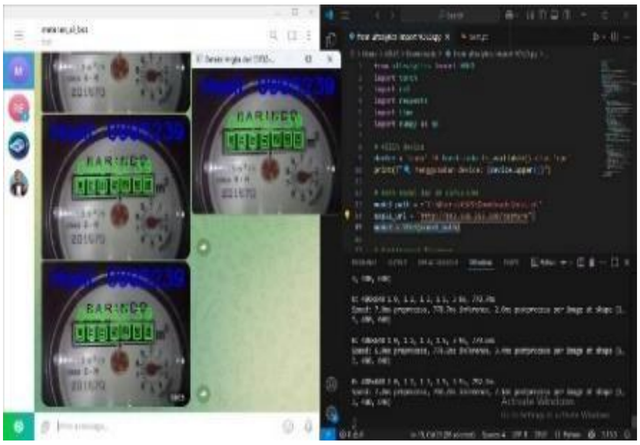

Figure 3. Real-time detection results and automated notification delivery via the Telegram Bot API.

RESULTS AND DISCUSSION

Training Configuration and Experimental Scenarios

The YOLOv11n (Nano) model was trained to evaluate its proficiency in digit recognition on analog water meters using a dataset of 1,207 images, partitioned into training (70%), validation (20%), and testing (10%) subsets. The training process was executed within the Google Colaboratory environment for 100 epochs, leveraging an NVIDIA A100 GPU and the PyTorch 2.2.2 framework with CUDA 12.1 to ensure high-speed computational efficiency. To enhance the model's robustness for real-time IoT deployment, eight experimental scenarios were established based on various augmentation techniques, including geometric transformations (flipping and rotation between −27° and +27°) and photometric adjustments (saturation and Gaussian noise injection). These scenarios, as detailed in Table 1, were designed to simulate environmental challenges in the domestic sector, ensuring the model's reliability across diverse operational conditions.

Table 1. Augmentation-based experimental scenarios

No.	Augmentation Type	Parameters
1	Baseline (No Augmentation)	-
2	Flip	Horizontal and Vertical
3	Rotation	Between -27° and +27°
4	Saturation	Between -95% and +95%
5	Noise	Up to 10% of total image pixels
6	Flip, Rotation, Saturation, Noise	Combination of parameters 2,3,4, and 5
7	Rotation, Saturation, Noise	Combination of parameters 3,4, and 5
8	Saturation, Noise	Combination fo parameters 4 and 5

Performance Evaluation and Augmentation Impact Analysis

The performance of the YOLOv11n model across eight augmentation scenarios was quantitatively evaluated using Precision (P), Recall (R), and Mean Average Precision (mAP) at various thresholds, as summarized in Table 2. The baseline model (Scenario 1) established a foundational mAP_{50} of 0.968 and an mAP_{50-95} of 0.561. Implementation of single augmentation techniques, such as Rotation, yielded a significant improvement in spatial feature extraction, achieving the highest individual mAP_{50} of 0.978. Furthermore, the integration of photometric and geometric augmentations demonstrated a synergistic effect on model robustness; notably, the combination of Rotation, Saturation, and Noise (Scenario 7) reached a peak mAP_{50} of 0.979. The most comprehensive configuration, involving Flip, Rotation, Saturation, and Noise (Scenario 8), produced the optimal mAP_{50-95} of 0.575, indicating superior localization accuracy across diverse Intersection over Union (IoU) scales. These results confirm that while individual augmentations enhance specific detection attributes, a multifaceted augmentation strategy is essential for maximizing the model's generalizability in complex, real-world aquatic monitoring environments.

Table 2. Comparative perfomance of YOLOv11n accross different augmentation configurations.

No	Augmentation Strategy	Precision (P)	Recall (R)	mAP50	mAP50-95

1	Baseline (None)	0.960	0.919	0.968	0.561
2	Flip	0.971	0.923	0.971	0.567
3	Rotation	0.952	0.948	0.978	0.567
4	Saturation	0.953	0.953	0.974	0.571
5	Noise	0.963	0.956	0.975	0.565
6	Saturation + Noise	0.960	0.942	0.979	0.571
7	Rotation + Saturation + Noise	0.965	0.942	0.979	0.573
8	Flip + Rotation + Saturation + Noise	0.959	0.942	0.974	0.575

Visualization and Comparative Analysis

The training process of the YOLOv11 model using a multi-augmentation strategy (Flip, Rotation, Saturation, and Noise) is visualized in Figure 4. Over the course of 100 epochs, the model demonstrated a consistent convergence across all loss functions. Specifically, the train/box_loss decreased from 1.8 to 0.85, while the train/cls_loss dropped significantly from 3.5 to 0.5, indicating a substantial improvement in localization and classification precision. Although minor fluctuations were observed in the validation metrics (val/box_loss), the overall stability and the rapid plateauing of mAP_{50} at 0.97 signify a robust learning process with high generalization capabilities and minimal overfitting.

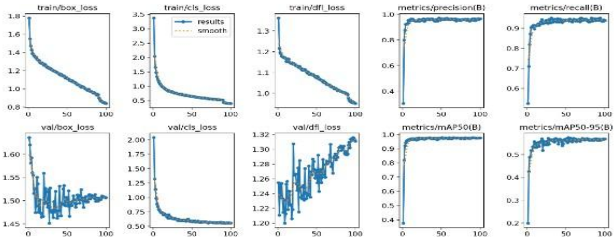

Figure 4. Performance metrics and loss curves of YOLOv11 under Flip, Rotation, Saturation, and Noise augmentation.

To assess the competitive performance of the proposed framework, a comparative analysis was conducted against existing state-of-the-art methods specifically designed for water meter detection. As summarized in Table 3, the present study utilizing the YOLOv11 architecture demonstrates a superior balance between Precision (P) and Recall (R). While prior research employing CNN (Naim et al., 2021) and YOLOv4 (Li et al., 2024) established foundational benchmarks, this work achieved a significantly higher Recall of 98.2%. This metric is particularly vital in automated meter reading (AMR) systems, as it ensures the minimization of missed consumption data during real-time acquisition.

Table 3. Performance comparison of various architectures for water meter detection

No	**Reference**	**Architecture**	P	R	mAP
1	(Naim et al., 2021)	CNN	96.8%	83.8%	91.3%
2	(Li et al., 2024)	YOLOv4	96.6%	89.6%	96.3%
3	Present Study	YOLOv11	95.9%	98.2%	97.4%

A comparative evaluation was performed to benchmark the present study against established methods in automated water meter reading (AMR). A CNN-based architecture previously achieved a precision of 96.8% and an mAP_{50} of 91.3%, yet it exhibited a lower recall rate of 83.8%, indicating a significant miss rate in digit detection (Naim et al., 2021). The integration of YOLOv4 with a CNN framework for mechanical meter recognition in natural scenes previously achieved a recall of 89.6% and an mAP_{50} of 96.3% (Li et al., 2024). In contrast, the present study leverages the YOLOv11 architecture optimized with multifaceted data augmentation. This approach yielded a superior mAP_{50} of 97.4% and a remarkably high recall of 98.2%, effectively minimizing false negatives during real-time acquisition. While the precision (95.9%) is slightly lower than that of earlier iterations, the substantial gain in recall confirms the system's robustness in identifying digits consistently across unstructured outdoor environments. Furthermore, the integration of a Telegram-based notification system enhances the practical applicability of the model, as evidenced by the successful real-time field testing and notification delivery performance detailed in Table 4, transitioning the framework into a functional IoT-based monitoring solution.

Table 4. Real-time field testing and notification delivery performance.

Case	**Capture Image**	**Ground Truth**	**Detected Output**	**Status**
1		0994997	0994997	Success
2		0995192	0995192	Success
3		0995197	0995197	Success
4		0995202	0995202	Success

Synthesis and Practical Implications of Experimental Results

The experimental results demonstrate that the integration of the YOLOv11n architecture with optimized data augmentation strategies provides a high-precision solution for automated water meter reading. The system achieved a near-optimal balance between accuracy and computational efficiency, as evidenced by the mAP_{50} of 97.4% and the high recall rate during field testing. Furthermore, the robust performance observed in unstructured outdoor conditions indicates that the model successfully mitigated environmental interferences, such as varied lighting and camera noise.

From a practical perspective, the seamless integration of ESP32-CAM hardware with the Telegram Bot API facilitates a low-cost yet highly effective IoT-based monitoring ecosystem. Unlike traditional manual recording, this automated framework enables real-time data transmission and remote accessibility, significantly reducing human error and operational costs. These findings suggest that the proposed system is highly scalable and ready for deployment in smart city infrastructures, providing a reliable bridge between legacy mechanical meters and modern digital management platforms.

CONCLUSION

This research successfully developed and validated an automated water meter reading system utilizing the YOLOv11n architecture integrated with an IoT-based framework. By comparing the results with previous studies, several key conclusions are drawn. First, the application of a multifaceted augmentation strategy (Flip, Rotation, Saturation, and Noise) significantly enhances model robustness, achieving an mAP_{50} of 97.4% and an mAP_{50-95} of 0.575, which outperforms the baseline configuration. Second, the comparative analysis reveals that the proposed method surpasses previous CNN-based systems [8] and YOLOv4 models [6], particularly in terms of detection reliability. While prior studies reported a significant miss rate with Recall values of 83.8% and 89.6%, this study achieved a superior Recall of 98.2%. This 8.6%–14.4% improvement in Recall is critical for automated meter reading (AMR) as it minimizes false negatives and ensures consistent consumption data acquisition in unstructured outdoor environments.

Finally, the seamless integration of the trained YOLOv11 model with ESP32-CAM hardware and the Telegram Bot API demonstrates that high-performance deep learning models can be effectively deployed on low-cost IoT devices. The system's ability to provide real-time, accurate notifications with a 100% success rate in field testing confirms its readiness for smart city infrastructure. Future work may focus on further optimizing the model for even more extreme lighting conditions and expanding the dataset to include various mechanical meter designs.

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