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Low-Cost Smart Metering Using Deep Learning

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Utility services like electricity, water, and gas are essential for modern living, and their demand has been rising worldwide. However, traditional manual meter reading is a standard procedure for billing purposes. This is not only labor and time-intensive but also prone to mistakes, which results in incorrect billing and revenue losses. In the era of advanced AI, leveraging cutting-edge technology to automate meter readings has become increasingly viable. However, Existing AI-based meter reading systems have limitations in detecting and recognizing meters from a distance. This research addresses these problems by presenting a novel system that utilizes the YOLOv8 model to detect meter screens from a distance. In addition, the system uses a fine-tuned Paddle OCR to recognize meter readings. A Novel dataset curated for the meter screen detection, recognition, and end-to-end OCR tasks related to electricity, gas, and water utility meters has been presented, containing up to 8,044 images. The proposed system was trained and extensively tested on the proposed dataset to gauge its performance. The system achieved an exceptional mean Average Precision (mAP) of 0.995 for both analog and digital meters on the detection task; furthermore, the system achieved an accuracy of 96.92% in the recognition task, which is 70% better than the accuracy of Pre-trained Paddle OCR. Moreover, an all-encompassing evaluation that combines detection and recognition using Paddle OCR and YOLOv8, i.e., the end-to-end OCR task, achieved an accuracy of 97.8%. Lastly, the system achieved an inference speed of up to 6 frames per second, guaranteeing real-time effectiveness.

Keywords: Yolo-v8; Paddle OCR; Meter Detection; Automatic Meter Recognition; Low-cost Smart Metering.

Introduction:

Accurate meter reading is an essential component of the utility industry. However, these utility sectors still rely on traditional manual meter reading, which is time-consuming, labor-intensive, and prone to errors, resulting in huge financial losses. According to the estimation of the World Bank, electricity distribution companies lose 96$ billion in revenue yearly due to billing errors [1]. American electric utility companies experienced an estimated 1–10$ billion USD loss due to billing errors which is 0.5% to 3.5% of its annual GDP [2]. The only energy provider in Peninsular Malaysia, Tenaga Nasional Berhad (TNB) [3], claimed revenue losses of up to 229$ million annually in 2004 due to billing errors. Even though photo billing has become a popular option nowadays, the manual meter reading remains the same. Each month, an employee of the service company goes to each house to take a picture of the meter and manually enter the billing data, which is time-consuming and error-prone [4].

To tackle these issues, Smart meters [5] are introduced for Automatic Meter Reading (AMR); the goal is to automatically record and invoice the reading of gas, water, and electricity. Even though smart meters have been adopted quickly, the standard procedure of manual meter reading in many places, particularly in developing countries, remains the same. Pakistan's energy industry, WAPDA, relies on manual meter readings, which has led to several losses. For utility providers, human errors like misreading or incorrectly recording meter readings can result in improper invoicing and revenue losses. These losses make the power industry less financially viable and may limit its capacity to invest in new and improved infrastructure. Similarly, the utility sectors like Water and Gas have also faced a lot of losses due to manual meter readings. Given the difficulties associated with manual reading processes and the gradual substitution of smart meters for traditional ones [6], [7], there is an increasing demand for image-based methods for text recognition to automate the meter reading process, minimize human errors, and lessen the requirement for substantial human resources [8]. Artificial intelligence (AI) [9], a promising technology, can address the difficulties of manual meter reading in utility industries. The process of reading meters could be revolutionized by implementing AI-based metering technologies. AI technology can deliver precise and timely data, it can automate meter reading which improves billing accuracy and lowers operational costs. AI-based technology, such as object detection [10], can be used to perform meter reading detection using models like Yolo [11], SSD [12], and FAST-RCNN [13]. Additionally, Optical Character Recognition (OCR) technology like Easy OCR [14], Keras OCR [15], and Tesseract OCR [16] can be used for meter reading recognition. Electric, water, and gas utilities stand to gain significantly from using AI and Computer Vision Automatic Meter Reading (AMR) technology in photo billing, making its adoption essential for the utility sector. While AI-based meter reading solutions exist, they have limitations in detecting and recognizing meters from a distance. This study presents a novel approach based on deep learning and advanced computer vision. To address the difficulties associated with detecting and recognizing meters from a distance. The suggested system is thoroughly trained on a variety of meter images taken from a variety of meter models both analog and digital, installed on electricity, gas, and water supplies to improve its detection and recognition performance for long distances. The intended result is a significant improvement in meter reading efficiency, accuracy, and dependability for utility companies across the globe. Specifically designed to operate in real-time from a distance, it utilizes the YOLO-v8 [17] algorithm, which has been trained on a novel custom dataset to provide the best possible detection for analog and digital meters. A novel dataset was also created just for recognition to improve the performance of Paddle OCR [18]. This two-pronged strategy achieves great results.

Literature Review:

The incorporation of AI in automated meter reading (AMR) technology for utility photo billing has recently been possible because of the development of strong AI models. Utility businesses can achieve increased accuracy in meter reading and billing procedures by utilizing AI algorithms, such as deep learning and computer vision techniques, eliminating human errors. However, AMR has several challenges, like image blur, rotated digits, light reflections, and poor image quality. To overcome these drawbacks, Muhammad Waqar et al. [4] proposed an automated method for extracting and identifying numbers from electric meters that uses Faster R-CNN. Using a dataset from Pakistani electrical providers, the model training achieved a promising result, outperforming Single Shot Detector (SSD), Google Vision API, and conventional techniques. Chun-Ming Tsai et al. [6] introduced a digital region detection system for electricity meters, which achieves a higher accuracy of 99% by implementing the SSD deep learning model. Their methodology involves optimizing the SSD model through training on a dataset of 777-meter pictures. Despite this achievement, one of the limitations is that more real-world tests are required for reliable validation. Convolutional neural networks (CNNs) have also shown great potential in solving the difficult automatic meter reading (AMR) task. Chunshan Li et al. [7] proposed a lightweight spliced convolution network for smart water meter reading that substantially reduces computing load and model space while increasing running time. The system's ability to handle data in real time when deployed on a distributed cloud platform validates its accuracy and suitability for industrial use. Rayson Laroca et al. [8] contributed a two-stage method for automatic meter reading (AMR) that uses three CNN-based algorithms (CR-NET, multitask learning, and CRNN) for recognition and Fast-YOLO for detection. With a recognition accuracy of 94.13%, the CR-NET model outperforms both multitask and CRNN models. The study also presents the UFPR-AMR dataset containing 2000 annotated images for meter screen detection. Abdullah Azeem et al. [19] proposed a MaskRCNN (AMR) approach for Detection, Recognition, and Digit Segmentation. The proposed method was assessed on the UFPR-AMR dataset. The suggested method outperforms existing approaches in terms of F-measure and detection accuracy, achieving a prediction rate of 99.82% for counters. An efficient technique for automatic meter reading (AMR) in real-world settings is put forth by Rayson Larcoa et al. [20]. Their method, including corner detection and counter classification, achieved a 34% reduction in reading errors. They also introduced Copel-AMR, a publicly available dataset with 12,500 images of meters; their approach surpassed ten baseline models regarding precision and recognition rate. With 30.64% parameter reduction, Sichao Zhuo [21] presents DAMP-YOLO, a lightweight network for meter reading, by combining DCB, ATA, MDA, and NP with YOLOv8. The model achieves 88.82% mAP50:95, able to recognize objects in real-time on the Jetson TX1. Additionally, Wenwei Lin [22] presents a deep-learning approach for restoring blurry images and recognizing LED digital meters. Polygon-YOLOv5 was used to extract the meter region, and YOLOv5s and CRNN models were employed to recognize the meter readings, achieving 98% accuracy with a 1% missing rate. A sophisticated method for automatic water meter reading was built by Mith Lewis W. Concio et al. [23] using deep learning in a cloud database and mobile app with U-Net binary segmentation for counter detection and Faster RCNN for counter recognition; the pipeline achieves 91.5% accuracy on foreign meters but struggles with 75% accuracy on local meters in the Philippines. Rafaela Carvalho et al. [24] presented a deep-learning model for flow meters and universal controllers as a means of automating manual meter readings. The method consists of screen detection, perspective correction, text detection, template matching, and text recognition. The full pipeline on a taken image takes approximately 1500 milliseconds to complete, whereas screen detection usually takes less than 250 milliseconds. Using YOLO v3 for text extraction and recognition, Muhammad Imran et al. [25] created an automated system for reading electrical energy meters that achieved a 77% precision and 98% recall on a dataset of 10,000-metre images. A lightweight DNN solution for automatic meter reading was introduced by Akshay Kumar Sharma et al. [26], and it outperformed traditional CNN models with 96% accuracy. Although the system contains an Android application for real-time storage and extracts the region of interest, it lacks advanced analysis capabilities and relies on OpenCV for identification. Deyuan Liu [27] combines

YOLOv5s with an enhanced k-means algorithm to detect reflecting places in pointer meters for inspection robots. The solution contains a novel robot pose control mechanism for effectively eliminating reflective surfaces, and it shows applicability in complicated situations with a remarkable accuracy of 80.9%. To automate the collection of water meter data in Morocco Ayman Naim et al. [28] developed an AI system that included a Recognition System built on a Convolutional Neural Network (CNN) model. With 140,000 high-quality digital meter photographs as its training dataset, the CNN model scored an astounding 98.70% accuracy during training.

In this work, we adopt a structured approach to address the problem at hand. Section III outlines our methodology, including details on the employed dataset, the Models used, and our proposed framework. Section IV expounded the experimental setup, covering data pre-processing, network training, and evaluation metrics. Section V delves into the results and discussions regarding the performance of our proposed system. Finally, conclusions are drawn in Section V, encapsulating the findings, contributions, and future directions of this work.

Methodology:

Employed Dataset:

Our process began with the acquisition of a diversified utility meter image dataset to successfully address the detection, recognition, and end-to-end OCR tasks. Therefore, a comprehensive training dataset including 3,905 pictures was produced by incorporating datasets from reliable sources, including the UFPR AMR dataset [8], Water Meters dataset [29], YUVA EB dataset [30], and Gas Meter dataset [31] and around 241 new images were added. The data set's high quality and diversity make it easier to create more sophisticated algorithms and models for detecting and recognizing meter readings. Random samples from the data set are shown in Figure 1 and Figure 2. Furthermore, a separate novel dataset of 3,154 images was gathered and labeled appropriately for optical character recognition by cropping the meter screen regions from the detection dataset. This dataset is unique, as such, a comprehensive dataset is not available elsewhere. Lastly, the end-to-end dataset contained 985 images and was taken as a subset of the detection dataset.

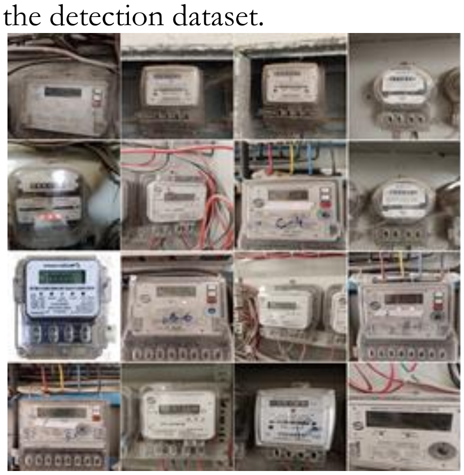

Figure 1: Detection Dataset

Figure 2: Recognition Dataset

YOLO-V8:

The YOLOv8 [17] model is a real-time, one-stage detection system built on Convolutional Neural Networks (CNN), and it is an improvement over the YOLO (You Only Look Once) series. Acknowledged for its effectiveness in fusing features and providing accurate detection outcomes in a lightweight design, YOLOv8 brings new features and enhancements over its predecessors. YOLOv8's anchor-free design, which deviates from conventional anchor-based methods, speeds up non-maximum suppression and improves overall detection efficiency. Designed to meet a variety of research requirements, YOLOv8 offers five different scale models (n, s, m, l, x). Three essential modules make up the network architecture, as shown in Figure 3.

The Head, Neck, and Backbone modules handle prediction output, multi-feature fusion, and feature extraction, respectively. The Backbone module includes the C2F structure and uses the Spatial Pyramid Pooling Fusion (SPPF) to improve gradient flow information while keeping a lightweight profile. To improve model generalization and resilience, the Head module provides a Decoupled Head structure, which extracts target location and category information independently. The Neck module uses a PAN (Path Aggregation Network) and FPN (Feature Pyramid Network) technique for feature fusion. Thus, YoloV8 is the current state-of-the-art in object detection.

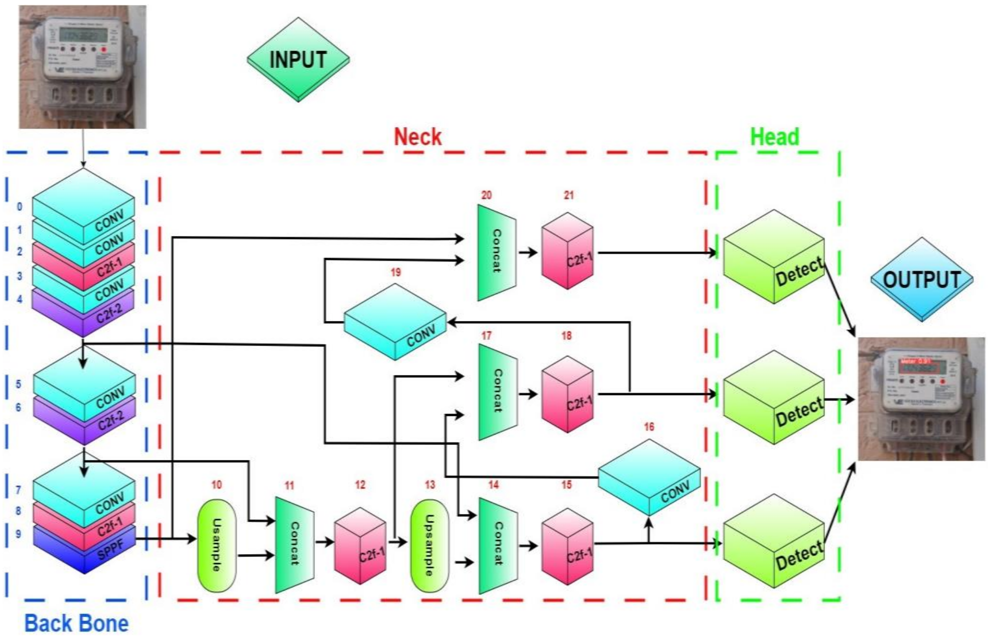

Figure 3: Yolo-v8 Object Detection Architecture

Paddle OCR:

Baidu's Paddle OCR [18] is a powerful OCR model that works with over 25 languages, has pre-trained models, and is very good at recognizing text that is lengthy, vertical, and has digits. It was created by Paddle and uses deep learning to extract text quickly and accurately. PP-OCRv3, the most recent release, offers independent usability for recognition, classification, and detection. In PP-OCRv3, several optimization techniques are added to increase the recognition model's effectiveness and precision. To achieve improved performance, Transformer-based SVTR and CNN-based PP-LCNet are combined in the lightweight text recognition network known as SVTR LCNet, improving prediction speed by 20% without appreciably sacrificing accuracy. The Attention module is used in the GTC method to provide guided CTC training, which enhances accuracy. Text Con Aug is a data augmentation approach used to improve contextual information variety for better model performance. Thus, Paddle OCR is a very diverse model for character recognition.

Proposed Framework:

The detection dataset was used to train various versions of the YOLO models for better bench-marking among which the YOLO V8 model produced the best results for detection. Additionally, Paddle OCR was trained and fine-tuned specifically for Recognition. The validation set was used to thoroughly validate the model's performance. After training, the detection and recognition models are incorporated into a unified workflow. The first step in the method is to take a picture of the meter display or screen, which will used as input into the model. Preprocessing for detection is then carried out. The model evaluates the confidence level after determining the location of the meter screen. The image is sent back to the detection pre-processing stage if the confidence value is less than 0.5. On the other hand, the Detected region is cropped and sent for character recognition preprocessing if the confidence level is higher than 0.5. The intended outcome is attained if the cropped region is Recognized and the model's confidence level is higher than 0.5. If the model's confidence level is less than 0.5, the picture is returned to the detection phase until the model's confidence level rises over 0.5. The Block diagram of the overall working of the system is shown in Figure 4.

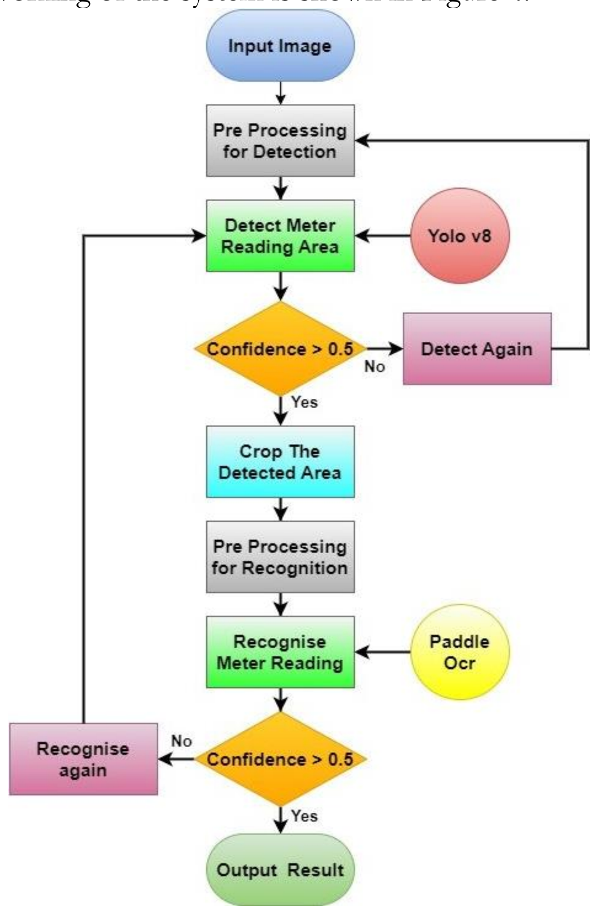

Figure 4: Block diagram of Proposed Framework

Experimental Setup:

Data Pre-Processing:

The Detection dataset was further split into training and validation sets using a split ratio of 70% for training and 30% for validation. Thorough pre-processing procedures, including the elimination of redundant, superfluous, and noisy images, were carried out before the model was trained, and bounding box annotation was used in the training of the detection model on the dataset. To improve the dataset balance and diversity, methods such as image scaling, standardization, and augmentation were also used. The recognition dataset was divided into training and validation sets using 80% and 20% split ratios, respectively. The end-to-end dataset was used to evaluate the overall performance of the proposed system and thus was not split into train and validation ratios. The Bounding box annotation was performed on the detection dataset using the Libeling tool, and the annotation files were saved in Txt format.

Networks Training:

The proposed system in this study was trained and evaluated on a computer running on the Windows 10 OS with Intel Core i7-10700 CPU @ 2.90 GHz, NVIDIA GeForce RTX 3060 12 GB, 16 GB Ram, and the programming language used was Python 3.7 with the PyTorch framework. The training parameters for the detection and recognition are summarized in Table 1.

Table 1: Training Parameters

No.	Detection Parameters	Details	Recognition Parameters	Details
	Parameters for Detection and Recognition Models			
1	Picture size	640 x 640	Picture size	48 x 320
2	Epochs	300	Epochs	500
3	Batch size	16	Batch size	128
4	Optimizer	SGD	Optimizer	Adam
5	Learning rate	0.01	Learning rate	0.001
6	Workers	8	Workers	4
7	Patience	40		

Evaluation Metrics:

To provide a thorough assessment of the proposed system, relevant evaluation metrics were used for each task. F1 score, precision, recall, mAP50, and mAP50-90 were used to measure detection performance; these metrics provide an extensive assessment of the system's efficiency in object detection. For the end-to-end OCR and recognition tasks, metrics like Character Error Rate, Recognition accuracy, and Character Accuracy were used to gauge their performance. CER is more suited for single-word recognition tasks, such as meter readings than Word Error Rate, which is used for sentences. Because the recognition task is unpredictable and the recognized output may contain extra or missing data, we refrained from utilizing precision, recall, or F1 score.

- **F1- Score:**

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{1}$$

- **Precision:**

$$P = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

- **Recall:**

$$R = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3}$$

- **mAP50:**

$$mAP50 = \frac{1}{|X|} \sum_{i=1}^{|X|} AvgP(z_i) \tag{4}$$

Where:
  - $|X|$: Number of queries in the dataset.
  - z_i: i-th query in the dataset.
  - AvgP(z_i): Average precision for the i-th query, using the first 50 items in the ranked list.

- **mAP50-90:**

$$mAP50 - 90 = \frac{1}{|Q|} \sum_{i=1}^{|Q|} AvgP(q_i) \tag{5}$$

Where:
  - $|Q|$: is the total number of queries in the dataset.
  - q_i: represents the i-th query in the dataset.
  - AvgP(q_i): Average precision for the i-th query, using only the top 50 to 90 ranked items.

- **Character Error Rate:**

$$CER = \frac{S + D + I}{C} * 100 \quad (6)$$

Where:
  - S: Substitutions
  - D: Deletions
  - I: Insertions
  - C: Total characters in reference transcription

- **Recognition Accuracy:**

$$A = \frac{N}{T} * 100 \quad (7)$$

Where:
  - N: Correctly recognized meter readings
  - T: Total meter display readings

- **Character Accuracy:**

$$CA = \frac{CC}{TC} * 100 \quad (8)$$

Where:
  - CC: Number of Correct Character
  - TC: Total Characters

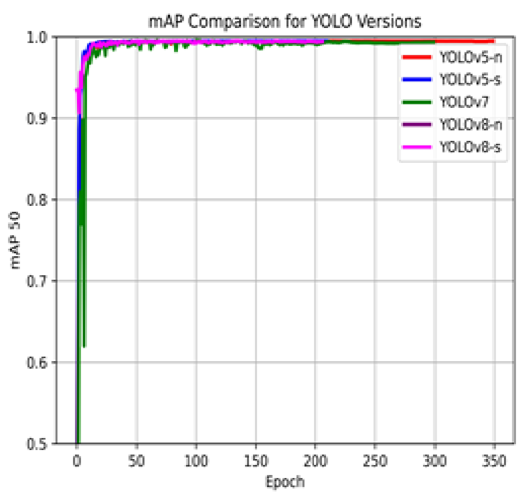

Figure 5: mAP0.5 Training curves

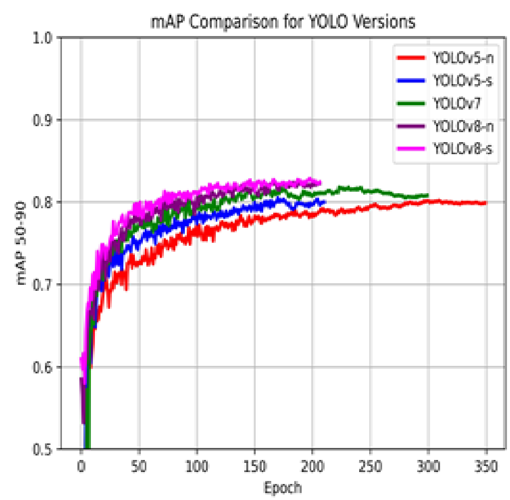

Figure 6: mAP0.5-0.9 Training curves

Results and Discussion:

Using the proposed dataset, the training results of several detection models produced impressive results, as shown in Table 2. Impressively, our system obtained an F1-Score of 99.3%. While every model performed well, YOLOv8 Nano was particularly noteworthy as it produced the greatest results in terms of mAP@50 achieving 0.995, and mAP@50-90 achieving 0.826, mAP50 and mAP50-90 plots of all training models are shown in Figure 5 and Figure 6. At 99.4% and 99.3%, respectively, the meter detection precision and recall hit their peak, and no further optimization was possible. Turning to recognition models, we carefully examined the most famous OCR models like Karas OCR and Paddle OCR. By testing these two OCR models, using a subset of 976 cropped meter screen images from the end-to-end dataset. Paddle OCR was the clear winner, with better performance than its competitor, as shown in Table 3. Therefore, Paddle OCR was fine-tuned on the recognition dataset, and an accuracy of 99.21% was achieved.

When this fine-tuned model was tested using the previous subset dataset, an accuracy of 96.92% with a CER of 0.0054 was achieved.

Table 2: Training results of the Detection Models

Model	Performance Evaluation Metrics for Detection Task				
	F1 Score	Precision	Recall	mAP-50	mAP50-90
YOLOv5-n	99.0%	99.2%	98.9%	**0.995**	0.801
YOLOv5-s	99.2%	99.2%	**99.3%**	**0.995**	0.805
YOLOv7	**99.3%**	99.5%	**99.3%**	0.994	0.817
YOLOv8-n	**99.3%**	99.4%	**99.3%**	**0.995**	**0.826**
YOLOv8-s	**99.3%**	**99.6%**	99.2%	0.994	0.825

Table 3: Bench-marking of Recognition Models

Model	Performance Evaluation Metrics for Recognition Task			
	Accuracy	CA	CER	Training Accuracy
Kera's OCR Pre-trained	1.536%	6.663%	0.8759	Nil
Paddle OCR Pre-trained	19.87%	39.79%	0.5042	Nil
Paddle OCR Fine-tuned	**96.92%**	**99.11%**	**0.0054**	**99.21%**

A. Proposed System Performance:

The fine-tuned YOLOv8 Nano was chosen due to its high inference speed and better results and was combined with Paddle OCR to form the proposed framework which was tested on the end-to-end dataset comprising 987 images, an overall accuracy of 97.8% was achieved encapsulating both detection and recognition performance. The results are visualized in Figure 7. The inference speed of the proposed framework was around 6 frames per second, showcasing real-time performance. This amalgamation of detection and recognition models showcases a promising avenue for bolstering the accuracy and efficiency of meter detection and recognition tasks.

Figure 7: End-to-End OCR Model Results Visualization

Conclusion:

Our primary objective in this research has been to tackle the complex problem of detecting and recognizing both digital and analog meters from a distance. We observed the core limits of current AI systems and presented a groundbreaking solution by utilizing and combining the advanced features of YOLOv8 for meter screen detection and Paddle OCR for digit recognition for an end-to-end OCR system; our study attempted to close this gap and produced an excellent mean Average Precision (mAP) of 0.995 and an F1 score of 99.3%. Furthermore, the recognition performance of the system, powered by 99.21% accuracy Paddle OCR, highlights how effective our suggested method is in addressing the drawbacks of existing systems. We hope to further the progress of meter reading technology by releasing publicly accessible datasets that are expressly intended for detection, recognition, and end-to-end AMR tasks. We aimed to contribute not only to the advancements in meter reading technology but also to provide a benchmark for the research community to evaluate and build upon. Our system's dependability and efficiency are confirmed by the extensive testing on the proposed datasets, which includes a sizable dataset of 8044. There is room for our system to be expanded in the future. Using forecasting models in conjunction with past consumption data is one approach that is worth investigating. This calculated addition might improve meter reading validation, providing a more thorough and precise result.

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