Thailand Water Meter Reading Using Convolutional Neural Networks from Smartphone Imagery

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***Abstract*—Water services are supplied by governmental agencies or private firms in many nations, with water delivered to houses via a network of pipes known as waterworks. The households typically consume water over a period of a month, after which the authority in charge evaluates the total amount of water consumed by each household and provides matching invoices. Thus, every household must install a water meter to ensure precise water consumption measurement. In Thailand, the procedure of collecting and reporting readings from these water meters is currently done manually by staff, which can be time-consuming and error-prone. The research's fundamental purpose is to develop a detection model capable of accurately identifying numbers on water meters within images captured using mobile devices. Convolutional Neural Networks (CNNs) were employed as the primary methodology for constructing the desired predictive models. This research is specifically dedicated to the task of reading values from water meters used in Thailand, encompassing five distinct models of water meters. The accuracy of these models is categorized into two components: one for precisely locating a set of numbers on water meters with a precision rate of 99.7%, and the other for accurately reading these numbers with a precision rate of 96.60%.**

***Index Terms*—Water meter reader, Deep learning, Machine learning, Automated water meter reading**

I. INTRODUCTION

Water is a critical resource essential for various activities of daily life, encompassing drinking, cooking, bathing, and irrigation. Water consumption refers to the quantity of water utilized by individuals, households, businesses, and industries. Nevertheless, fresh, clean water availability is often constrained, underscoring the importance of prudent and efficient water usage to guarantee sufficient supply for all needs. A water meter is a mechanical device designed to gauge the volume of water consumed by a household, business, or other entity. Typically, water utilities install these meters, employing them to determine the precise amount of water used by a specific property. Subsequently, this information forms the basis for water bill calculation for each household.

Previously, the water meter reading process relied on officials physically visiting each household to record meter readings manually, transcribing the observed values onto paper. Subsequently, the recorded values from the current month were subtracted from those of the preceding month for a given household, facilitating the determination of water usage units. This information was essential for calculating water service fees in subsequent steps. Notably, this traditional approach involved human intervention in reading and documenting the meter values, thereby introducing the potential for human errors. Presently, several research initiatives, exemplified by [1] and [2], seek to develop models for automated water meter reading, aiming to replace officials' manual involvement through object detection technology. However, these efforts encounter limitations, particularly in the range of water meter models accommodated within the training datasets. The effectiveness of such models is contingent upon compatibility with water meter models present exclusively in the training dataset, leading to diminished accuracy when applied in Thailand. Additionally, challenges persist in the realm of area detection. As an illustrative example, research proposes a solution involving installing a reading device onto the water meter dial to address these limitations and enhance the reliability of the automated reading process.

The main objective of this study is to develop detection models that are capable of numerically interpreting water meter readings in Thailand. The ultimate objective is to supplant human involvement in reading water meters by employing the developed model, thereby mitigating errors associated with human intervention. This initiative extends to encompass not only the reduction of errors from manual readings but also to facilitate the tracking and monitoring of water usage. Furthermore, the model seeks to contribute to the analysis of data for the effective management and conservation of water resources. The proposed methodology employs object detection technology for area detection and numerical memorization, incorporating the Hough transform technique [3] to optimize the positioning of a set of numbers for enhanced model readability. Additionally, the methodology involves the application of image inversion techniques to improve accuracy, particularly in the context of reading five distinct water meter models utilized in Thailand, each characterized by unique features and colours. Furthermore, the study advocates for the implementation of super-resolution using the LapSRN [4] technique to enhance the resolution of numerical images within the water meter context.

The research work presented in this paper offers a solution to mitigate human error by employing a model for water meter reading, thereby replacing manual readings by humans. This advancement holds the potential for automating service fee billing, as the model's ability to accurately interpret readings allows for real-time calculation of service fees. Moreover, the model demonstrates versatility by supporting the reading of water meters across all five models used in the country.

The subsequent sections of this document are structured as follows: Section II provides a concise overview of related and prior work, Section III outlines the process of numerically interpreting water meters from images, Section IV details the data collection methodology employed in this research, Section V expounds upon the process of Image Preparation, Section V elucidates the Deep Learning Methods applied, Section VII encompasses the experiments and evaluations conducted in the study, and finally, Section VIII presents the Discussion and Conclusion.

II. Previous Work

This section delves into a retrospective analysis of prior research, specifically focusing on the technology of object detection. The field of object detection has witnessed significant progress and evolution, marked by the iterative refinement of methodologies and technologies. In its early phases, object detection heavily leaned on traditional computer vision techniques, including Haar cascades and Histogram of Oriented Gradients (HOG), to discern objects within images. While these methods demonstrated efficacy to a certain degree, they grappled with limitations in handling complex scenarios and diverse object appearances. The advent of deep learning, notably Convolutional Neural Networks (CNNs), heralded a transformative epoch for object detection. The introduction of region-based CNNs (R-CNN) and its variants, such as Fast R-CNN and Faster R-CNN, significantly enhanced accuracy and efficiency. These methodologies introduced the paradigm of region proposals, selecting potential object regions for subsequent processing, thereby substantially expediting detection.

The evolutionary path continued with the introduction of Single Shot Multibox Detector (SSD) and You Only Look Once (YOLO), designed to elevate real-time object detection. Notably, YOLO distinguishes itself by processing images in a single pass, providing concurrent high speed and accuracy. YOLO has undergone iterations, with versions like YOLOv3 and YOLOv4 introducing improvements in accuracy, speed, and adaptability to various object scales and sizes. The transition from region-based CNNs to models like Mask R-CNN has facilitated not just object detection but also instance segmentation, supplying more intricate details about object boundaries. Moreover, the development of EfficientDet and other efficient models has focused on striking a balance between accuracy and computational efficiency, especially pertinent for resource-constrained applications. The ongoing evolution of object detection is characterized by research endeavours exploring innovative architectures, attention mechanisms, and transfer learning approaches. Techniques like self-supervised learning and the integration of object detection with other computer vision tasks continue to shape the landscape, ensuring the continual enhancement and adaptability of object detection systems across diverse domains and applications.

Numerous research initiatives employ object detection for water meter reading, showcasing a keen interest among data science researchers. This interest manifests in the utilization of contemporary technology and image pre-processing methodologies for designing systems that simulate regional water meter readings. In prior studies, methodologies were presented involving the installation of devices onto water meter dials. In the study by [1], an Optical Character Recognition (OCR) technique was employed to decipher numbers in images captured from the device installed on the water meter dial. The reported accuracies were 48%, 75.1%, and 91.64% for three distinct water meter models. Subsequently, [2] introduced a method utilizing deep learning techniques to read numbers from images captured by a device on the water meter dial, demonstrating enhanced accuracy compared to previous research. Further investigations [5] involved a comparative analysis of R-CNN, SSD, and YOLOv3 algorithms, all employing the same deep learning technique. The findings favoured YOLOv3, establishing its superior accuracy over R-CNN and SSD. Additionally, subsequent research [6] innovatively introduced mobile water meter imaging, eliminating the necessity of device installation on the water meter dial. This approach highlighted four crucial points within the water meter reading region. Importantly, the methodology included image rotation to normalize its orientation before utilizing the model for numerical interpretation.

In prior research focused on utilizing Object Detection for water meter reading, limitations were identified. Specifically, constraints were observed in terms of the number of models the detection model could interpret, and the necessity to install a reading device on the water meter dial. This present study introduces methodologies to address both aforementioned challenges. The approach involves developing a model capable of reading water meters across five distinct models prevalent in Thailand. Additionally, image data alignment is applied to facilitate the accurate interpretation of water meter numbers obtained from the installed equipment.

III. Water Meter Reader Framework

The proposed framework with respect to the work presented in this paper is presented in this section. This research work aims to detect the number from the water meter to identify the amount of water usage. Therefore the schematic framework of this research work is presented in Figure 1.

Figure 1 illustrates the water meter reader framework. It can be observed that the framework comprises seven processes: (i) meter area detection, (ii) image alignment, (iii) image transformation, (iv) background detection and conversion, (v) super-resolution, (vi) meter number detection, and (vii) number positioning.

The initial process is meter area detection when the image of the water meter has been obtained using the mobile phone camera. This process aims to identify the area of the number on the meter using the generated meter area detection. The

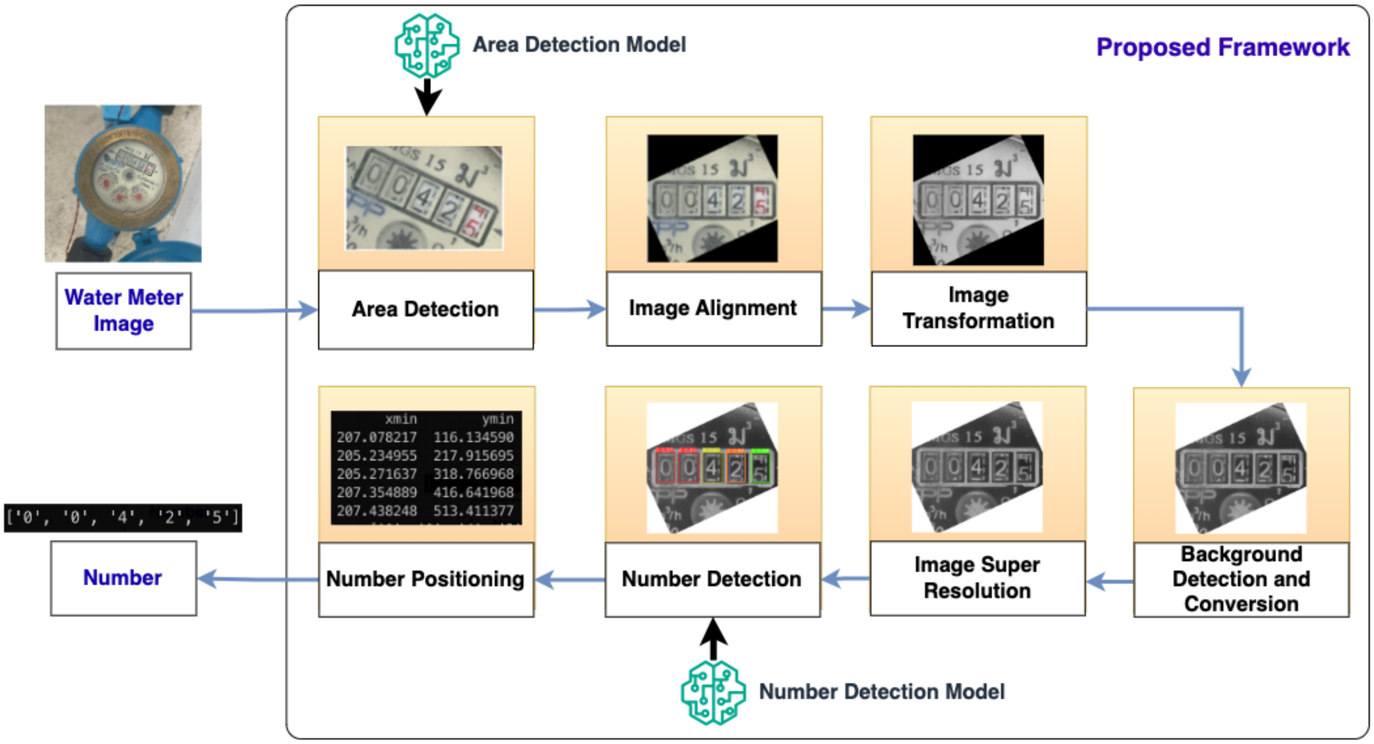


Fig. 1: Water meter reader framework

object detection deep learning method, typically the YOLO algorithm, is used in this research.

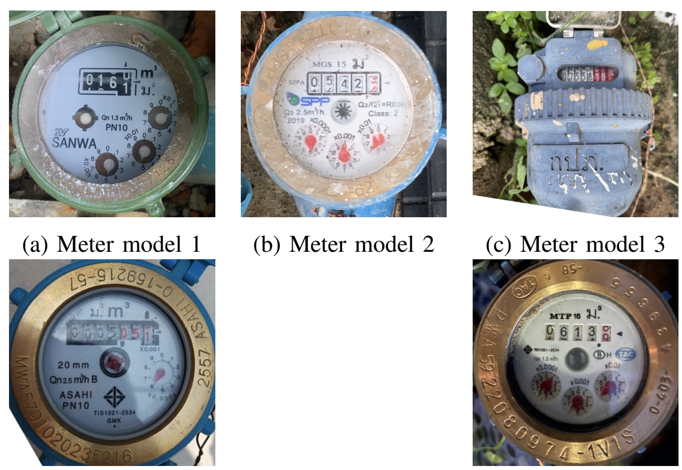
Once the meter area has been detected, due to the image being obtained from an unpredictable environment, the orientation of the image must be rotated to the horizontal direction. Consequently, an alignment process is implemented to rectify the orientation. The Hough transform [3] mechanism is applied to rotate the image in an appropriate direction.

After the image is rotated in the correct direction, to facilitate in number identification process, the image is transformed into appropriate image formats. As mentioned above various models of water meters have been used in this research, thus background detection and conversion are applied. If the white background of the meter area is detected, it will be transformed into a black colour by inverting the image. Then super-resolution technique namely LapSRN is used to refine the image [5].

Then the number in the water meter is detected using the water meter number reader model. Furthermore, the YOLO algorithm is commenced to generate this model. Once the number letters from water are identified, the specified values are arranged using the x and y axes for their position.

IV. Data Collection

A collection of water meter images was captured in the real-world environment at different times using various mobile phones. A collection of obtained images consists of five distinct water meter models as illustrated in Figure 2.



(a) Meter model 1 (b) Meter model 2 (c) Meter model 3

(d) Meter model 4 (e) Meter model 5

Fig. 2: Example images of water meter model

From Figure 2, the characteristics of water meters can be categorized into two categories: (i) light (white) numbers against dark backgrounds (black or red), and (ii) dark numbers against light (white) backgrounds. A total of 1,012 images was obtained, with 678 images assigned to group (i) and 334 images to group (ii). Within each group, the images are further categorized into two subsets: (i) 80% allocated to the training image set, and (ii) the remaining 20% assigned to the validation images. The number of images can be concluded as shown in Table I

TABLE I: The number of images used in this research

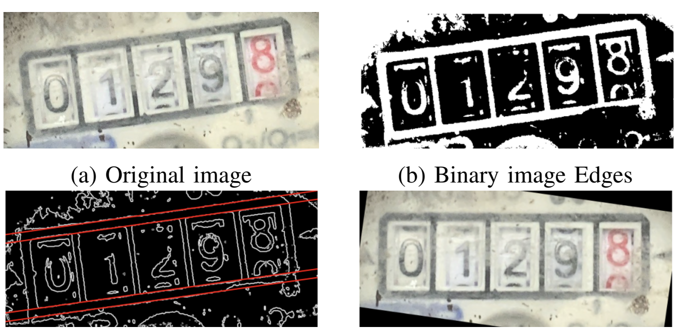
Groups	Train set	Valid set	Total
Light-coloured numbers	542	136	678
Dark numbers	267	67	334
Sum	809	203	1,012

V. Image Preparation

In this research, four image preparation methods have been conducted before the further analysis processes. The image alignment is applied to rotate an image in the correct direction, as detailed in Sub-section V-A. To improve the model performance, image transformations are performed, the detail is given in Sub-section V-B. As mentioned before, there are two main categories of water meter images. Thus background detection and conversion are applied, the detail is explained in Sub-section V-C. Finally, to increase the image resolution, the super-resolution technique is discussed in Sub-section V-D.

A. Image Alignment

Image alignment aims to rotate the water meter area in the correct direction. The orientation of the image is not rotated properly due to the water meter was captured with a mobile device in a real-world environment. The Hough transform technique is employed to deal with this problem. The process of changing image direction is shown in Figure 3. Four steps are performed:(i) import the original water meter image (Figure 3a), (ii) transform and adjust the water meter image into a binary representation (Figure 3b), (iii) fine-tune the water meter image by emphasizing its edges, subsequently determining the tilt angle via the Hough line technique (Figure 3c), and (iv) rotate the image based on the identified angle (Figure 3d).



(a) Original image (b) Binary image Edges

(c) Detected lines (d) Fixed Image

Fig. 3: The example of Hough transform process

B. Image Transformation

The image transformation process aims to transform the image to the most appropriate format for the accurate identification of the numbers. There are various image transformation techniques have been applied. These techniques encompass (i) grayscale [11], (ii) Adaptive Mean Thresholding [12], (iii) TOZERO [13], (iv) binary [14], (v) OTSU [15], (vi) Blur, (vii) HSV [16], (viii) YCbCr [17], (ix) red scale, (x) green scale, and (xi) blue scale.

C. Background Detection and Conversion

As discussed above, water meter images can be categorized into two different groups: (i) white background, and (ii) black background. The aim of the background detection and conversion process is to transform the water meter image to a similar format. In this process, the background colour is identified. If it is a white or light colour, the image conversion is performed. The white or light background is transformed into a black or dark background, and the black or dark numbers are converted into a white or light colour. However, the conversion is not employed if the image has a dark background with light numbers.

D. Super Resolution

Once the area of the water meter has been identified, and the image size is too small, the resolution of the image is not enough for analysis. The objective of this process is to increase the quality of the image. With respect to this research work, the Laplacian Super-Resolution Network or LapSRN is implemented. LapSRN is a type of deep-learning model designed for image resolution enhancement [4]. Thus, LapSRN generates the higher resolution from the lower resolution image.

VI. Object Detection

Object detection is the mechanism to identify and localize objects. It is used to analyze more realistic cases in which multiple objects may exist in an image. The object detection approach, primarily relying on Convolutional Neural Networks (CNN), demonstrates improved precision and reduced testing duration compared to the previous approach. Prior research [6] compared the R-CNN, SSD, and YOLOv3 algorithms to read water metres. YOLOv3 showed the utmost level of accuracy, as indicated by the findings. Therefore, the technique called YOLO has been chosen for this research. You Only Look Once or YOLO is one of the CNN approaches for object detection. YOLO revolutionized real-time object detection by offering a single, unified approach that directly predicts bounding boxes and class probabilities for multiple objects in an image. YOLO has undergone several versions, in the context of this research work, YOLOv5, YOLOv6, YOLOv7, and YOLOv8 are applied.

VII. Experiment and Evaluation

This section describes the experiment and evaluation of the proposed method for reading the number from the water meter. Extensive evaluation was conducted with respect to the proposed approach. This section reports on only the most significant results obtained (space limitations prohibit the inclusion of all findings).

As previously discussed in Section III, there are two different models are used in the research framework: (i) area detection model, and (ii) number detection model. The area detection model is used for identifying the number of areas in the water meter image. Further detail concerning this model generation is provided in the Sub-section VII-A The second model is the number detection model, which is the model used to read the number on a water meter. A set of experiments related to number detection is described in Sub-section VII-B. The performances from the experiments and evaluations were recorded in terms of (i) precision, (ii) recall, (iii) accuracy, and (iv) mean average precision(mAP)

A. Area Detection Model Generation

Area detection model generation is the process of generating the model for identifying an area of a set of numbers on the water meter. To generate the model a set of 1,012 images was used. An image augmentation process was implemented to increase the number of images in this research work. A total of 2,835 images was divided into two different groups: (i) 2,268 as a training set, and (ii) 567 images as a validation set. Before the model generation could be conducted, the image labelling was performed using RoboFlow to identify the interesting areas on the dataset. Once the labelling process was completed, the area detection model generation was then performed. The experiments were executed with 200 epochs and utilized a Tesla T4 GPU. There were four variations of experiment were conducted: (i) YOLOv5, (ii) YOLOv6, (iii) YOLOv7, and (iv) YOLOv8. The obtained results are presented in Table II.

TABLE II: Area detection performance on validation set

Name	Precision	Recall	Accuracy	mAP
YOLOv5	**0.995**	**1.000**	**0.997**	**0.995**
YOLOv6	0.989	0.979	0.984	0.825
YOLOv7	0.994	0.988	0.991	0.858
YOLOv8	**0.995**	**1.000**	**0.997**	0.956

From Table II, it can be concluded that both YOLOv5 and YOLOv8 achieved the highest outcome with an accuracy value of 99.7% on the validation set. However, upon closer examination of the mAP (Mean Average Precision) value, YOLOv5 exhibited more precise area identification with an mAP value of 0.995 or 99.5% on the validation set. Thus, YOLOv5 was chosen for the meter area detection model. The results also highlight that YOLOv5 outperforms versions 6, 7, and 8 in terms of accuracy.

B. Number Detection Model Generation

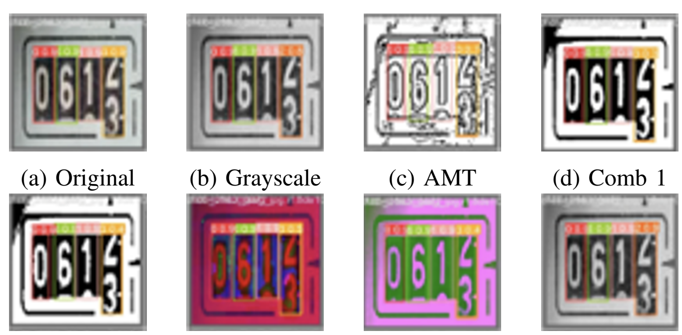
Once the area detection model has been completed the number detection model was then employed. Number detection model generation is a process of constructing a model for number identification or number reading model generation. A set of 1,012 images was used in this study as mentioned in Sub-section IV. Then, the variation of the image preparation processes was performed before the number reading model was generated.

Image alignment employed the Hough transform technique to ensure the set of numbers is horizontal. The detail of image alignment was discussed in Sub-section V-A. This adjustment facilitates the precise specification of each number on the water meter. Furthermore, the image dimensions were evaluated by assessing the width of the image. If the width falls below 500 pixels, the image quality enhancement is then achieved using super-resolution techniques. In the context of this work, LapSRN was then applied as presented in Sub-section V-D.

There are two sets of experiments: (i) to determine the most appropriate image transformation techniques for number detection model generation, and (ii) to identify whether it was better to use the original, grayscale or background conversion.

Subsequently, the image annotation with all classes was referred. The class number 0 to the class number 9 was performed using RoboFlow. When the annotation process was completed, the number detection model generation was then performed. The experiments were executed with 400 epochs and utilized a Tesla T4 GPU. The finding from the prior experiment was that YOLOv5 produced the best results, and then in this set of experiments, YOLOv5 was applied.

a) Number detection models using different image transformation methods: This set of experiments was conducted to determine the most effective image transformation technique for the accurate identification of the number detection model generation. There were 12 image transformation methods: (i) grayscale, (ii) Adaptive Mean Thresholding (AMT), (iii) TOZERO, (iv) binary, (v) OTSU, (vi) Blur, (vii) HSV, (viii) YCbCr, (ix) red scale, (x) green scale, and (xi) blue scale. The examples from image transformation methods are illustrated in Figure 4. Note the 4(d) Comb 1 refers to Blur+BINARY+OTSU and 4(e) Comb 2 refers to BINARY+OTSU. The detection performance obtained is presented in Table III



(a) Original (b) Grayscale (c) AMT (d) Comb 1

(e) Comb 2 (f) HSV (g) YCbCr (h) Red

Fig. 4: Example of image transformation methods

Table III indicated that the Grayscale technique produced the most accurate identification of the numbers on the water meter with an accuracy value of 0.966 or 96.6%.

b) Number detection models using different background conversion methods: The subsequent experiments involved converting the images of the numbers on the water meter to a similar format. Two conditions were considered before utilizing the image background conversion method for number identification. If the image of the numbers on the water meter features a bright background with dark numbers, background conversion is applied. However, the background conversion is

TABLE III: The detection performance on different image transformation

Exp	Colour Space	Precision	Recall	Accuracy	mAP
1	Original	0.952	0.966	0.959	0.937
2	Original on Greyscale	0.945	0.911	0.928	0.887
3	**Grayscale**	**0.970**	**0.956**	**0.963**	**0.955**
4	Mean Thresholding	0.944	0.867	0.906	0.931
5	TOZERO	0.919	0.900	0.910	0.935
6	BINARY+OTSU	0.975	0.920	0.948	0.938
7	Blur+BINARY+OTSU	0.946	0.924	0.935	0.934
8	HSV	0.950	0.944	0.947	0.939
9	YCbCr	0.894	0.928	0.911	0.932
10	Red scale	0.974	0.929	0.952	0.953
11	Green scale	0.926	0.937	0.932	0.941
12	Blue scale	0.944	0.916	0.930	0.939

not employed if the image has a dark background with light numbers.

Hence, three experiments were carried out: (i) Experiment 1, images were employed for training to recognize the original numbers. (ii) Experiment 2, images were also used for training, but the focus was on identifying numbers in grayscale. (iii) Experiment 3 used images for training to recognize the numbers within images that had been subjected to background transformation conditions, the detail of background detection and conversion was described in Sub-section V-C. The detection performance obtained is presented in Table IV.

TABLE IV: The detection performance on different backgrounds

Exp	Colour Space	Precision	Recall	Accuracy	mAP
Exp 1	Original	0.952	0.966	0.959	0.937
Exp 2	Grayscale	0.970	0.956	0.963	0.955
Exp 3	**Conversion**	**0.964**	**0.968**	**0.966**	**0.955**

The outcomes of the background conversion experiment in Table IV demonstrate that the highest performance was obtained from background conversion with an accuracy value of 0.966 or 96.6%. Followed by a grayscale image with an accuracy value of 0.963 or 96.3%. The lowest performance came from an original image with an accuracy value of 0.959 or 95.9%.

Based on the outcomes of the 15 experiments, the procedure for number identification can be outlined as follows. Initially, the image area of images was horizontally aligned using the Hough transform technique. Subsequently, the obtained images underwent quality enhancement using LapSRN and were further converted to grayscale color space and background conversion before being subjected to the model for number identification. This approach yielded an accuracy rate of 96.60%.

VIII. Discussion and Conclusion

Four image preparation methods have been investigated as follows: (i) the image alignment is the process of rotating an area image of a water meter to the horizontal alignment; (ii) the best colour transformation is in the form of a Grayscale image; (iii) background detection and conversion is the process of detecting a white background and converting the image to a black background; (iv) if the width of the detected meter area image is lower than 500 pixels, LapSRN super-resolution was then performed to enhance the image quality. There are two object detection models were generated: (i) the area detection model, YOLOv5 produced the best results with an accuracy value of 99.7%, and (ii) the number detection model, grayscale transformation with background conversion techniques produced the best result with an accuracy value of 96.6%. The next step is to harness this model potential in the development of a system or web application for automated water meter reading, replacing the need for manual value extraction.

References

[1] L. Chaiyarab, G. Dhungyel, and S. Chucherd, “Water Utilization Monitoring System by using Image Processing,” *J. Sci. . . .*, no. January, 2021, [Online]. Available: https://li01.tci-thaijo.org/index.php/scimsujournal/article/view/248723.

[2] A. Naim, A. Aaroud, K. Akodadi, and C. El Hachimi, “A fully AI-based system to automate water meter data collection in Morocco country,” *Array*, vol. 10, no. December 2020, p. 100056, Jul. 2021, doi 10.1016/j.array.2021.100056.

[3] J. Princen, H. K. Yuen, J. Illingworth and J. Kittler, ”A comparison of Hough transform methods,” *Third International Conference on Image Processing and its Applications, 1989.*, Warwick, UK, 1989, pp. 73-77.

[4] Lai, Wei-Sheng, et al. ”Deep laplacian pyramid networks for fast and accurate super-resolution.” *Proceedings of the IEEE conference on computer vision and pattern recognition.* 2017.

[5] Y. Liang, Y. Liao, S. Li, W. Wu, T. Qiu, and W. Zhang, ”Research on water meter reading recognition based on deep learning,” *Sci. Rep.*, vol. 12, no. 1, pp. 1-13, 2022, doi: 10.1038/s41598-022-17255-3.

[6] J. Zhang, W. Liu, S. Xu, and X. Zhang, “Key point localization and recurrent neural network based water meter reading recognition,” *Displays*, vol. 74, no. December 2021, p. 102222, 2022, doi: 10.1016/j.displa.2022.102222.

[7] Passarella, Linsey S., et al. ”Reconstructing high-resolution ESM data through a novel fast super resolution convolutional neural network (FS-RCNN).” *Geophysical Research Letters* 49.4 (2022): e2021GL097571.

[8] Shi, Wenzhe, et al. ”Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network.” *Proceedings of the IEEE conference on computer vision and pattern recognition.* 2016.

[9] Lim, Bee, et al. ”Enhanced deep residual networks for single image super-resolution.” *Proceedings of the IEEE conference on computer vision and pattern recognition workshops.* 2017.

[10] Nagy, A., and Z. Vamossy. ”OpenCV C# wrapper based video enhancement using different optical flow methods in the super-resolution.” *2008 6th International Symposium on Intelligent Systems and Informatics.* IEEE, 2008.

[11] Kanan, Christopher, and Garrison W. Cottrell. ”Color-to-grayscale: does the method matter in image recognition?.” *PloS one* 7.1 (2012): e29740.

[12] Roy, Payel, et al. ”Adaptive thresholding: A comparative study.” *2014 International conference on control, Instrumentation, Communication and Computational Technologies (ICCICCT).* IEEE, 2014.

[13] Anusha, N., K. Bhavana Sai, and K. Srujana. ”Image Segmentation Using ToZero Method and ToZero Inverse Methods.” *ARPN Journal of Engineering and Applied Sciences, ARPN* 13.16 (2018): 4678-4682.

[14] Gong, Yunchao, et al. ”Iterative quantization: A procrustean approach to learning binary codes for large-scale image retrieval.” *IEEE Transactions on pattern analysis and machine intelligence* 35.12 (2012): 2916-2929.

[15] Vijay, Patil Priyanka, and N. C. Patil. ”Grayscale image segmentation using OTSU Thresholding optimal approach.” *Journal for Research* 2.05 (2016).

[16] Junhua, Chen, and Lei Jing. ”Research on color image classification based on HSV color space.” *2012 Second International Conference on Instrumentation, Measurement, Computer, Communication and Control.* IEEE, 2012.

[17] Saleem, Eman, and Nidhal K. El Abbadi. ”Auto colorization of gray-scale image using YCbCr color space.” *Iraqi Journal of Science* (2020): 3379-3386.