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Random Forest Implementation in Prepaid Electric Meter Recognition

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ABSTRACT

Prepaid electricity service provides better flexibility, but it comes with an additional step for the customer. Instead of paying a monthly bill based on electric usage, a prepaid system requires customers to actively predict their electricity usage before they pay for the correct electricity value. This presents a challenge because underestimating electricity usage may lead to a power outage. Therefore, a system that monitors electricity can be developed to address this issue. There are two approaches to developing an electric monitoring system: designing the electric meter equipped with monitoring features and designing an external capturing device to work with the current electric meter. The first approach is costly and requires a meter disassembly. Thus, in this paper, the second approach is used. By utilizing image processing and Random Forest machine learning algorithm, a monitoring device can be developed to read the digital meter's display. Although it may affect performance due to the low-power device, Raspberry Pi 3 and Raspberry Camera are used to provide automation. This method yields an accuracy of 97% using 375 images.

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1. INTRODUCTION

Various research shows that prepaid electricity helps reducing consumer’s electrical usage by providing more control of their electricity management[1]. Prepaid system is also beneficial for electric company since monitoring officers are no longer required. Besides, the digital meter used in prepaid system is a better and more accurate measuring device compared to the electromechanical meter found in a postpaid system [2], which needs manual in-person monitoring [3].

The prepaid electricity service provides additional control, but it also means an added burden for the customer. The customer only needs to pay the monthly bill based on their electricity usage in postpaid service. In a prepaid service, the customer must calculate how much electricity they need and pay for the respective electricity value before use[4]. Miscalculations may result in inadequate electricity, which leads to a power outage. Although the digital meter will alert the customer when the electricity value is low using the built-in alarm, it only provides a localized alert. Besides, the electricity is already low when the alarm is triggered. There is a need to develop a system that monitor customers' electricity status and usage. Therefore, the customers can manage their prepaid electricity system easily.

Monitoring system essentially monitors and captures any data from the object of interest. A simple digital meter has a built-in seven-segment display that shows the remaining electricity balance. Therefore, developing an electricity monitoring system requires a system that can read the seven-segment display. This paper aims to develop a system capable of recognizing a seven-segment display in a digital meter using Computer Vision and Machine Learning.

There are several studies on digital meter seven segment recognition. These papers [5]–[10] work on illuminated or high contrast seven-segment display that helps with contour and edge detection, although one of them [5] focuses on noisy images. Meanwhile, these paper [8], [9], [11]–[15] utilizes deep learning and implemented on high-power devices such as laptops and servers. Only two paper [13],[14] has an automatic or continuous image capturing system.

The proposed method focused on continuous automatic operation and low-power devices. Therefore, microcontrollers and their modules, such as Raspberry Pi 3 and Raspberry Pi Camera are used. This limitation presents a challenge as more processing is required to compensate for the lower image quality compared to a mobile camera-based system. In addition, the development utilizes Itron ACE9000 IBS DS digital meter, which does not have an illumination feature that may affect the low-light reading.

2. METHOD

There are two phases involved in the development as described in Figure 1, namely preprocessing and recognition. Preprocessing prepares the data needed in the recognition phase. It also helps reduce image complexities while preserving data patterns, thus reducing computational costs and improving performance. The result of the preprocessing then feeds into the recognition phase. Random Forest (RF) is used to classify the digit images, converting the image into digital data.

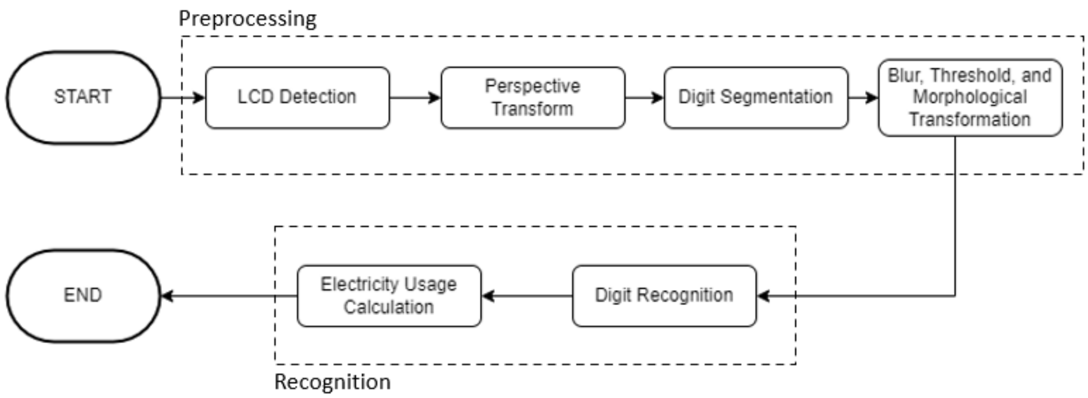


Figure 1. Development phase.

2.1. LCD Detection

LCD detection focuses the computation area on the LCD region and reduces unwanted elements or noises. It starts with finding the contour of every element on the image using contour detection and approximation. Because the screen has a rectangular shape with four corners and takes up a significant portion of the meter, a contour that matches these characteristics is selected. This approach can track the screen position even when the camera position changes, as long as the whole screen is in the frame.

Figure 2. Detected LCD contour.

2.2. Perspective Transform

The camera is not always positioned perfectly in front of the meter, which introduces perspective distortion shown by irregular contour. Perspective Transform fixes the distortion using the four pairs of contour points, resulting in a top-down view of the image shown in Figure 3. This process provides a uniform size for each digit in the LCD.

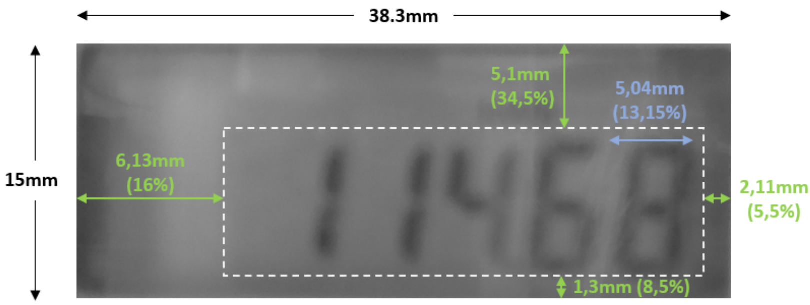
(a)

(b)

Figure 3. Illustration of (a) four points utilized by perspective transform, (b) the gray scaled result.

2.3. Digit Segmentation

Once the top-down view of the screen is acquired, the next step is extracting the seven-segment digits. Because the seven-segment only occupies a portion of the screen, the computation focuses only on the digit segments by removing the display background. This method uses proportional cropping approach that determines the size of the cropping window from the ratio of the element's dimension respective to its total axis length as shown in Figure 4. This method automatically adjusts the size of the cropping window based on the distance of the camera to the display.



(a)

(b)

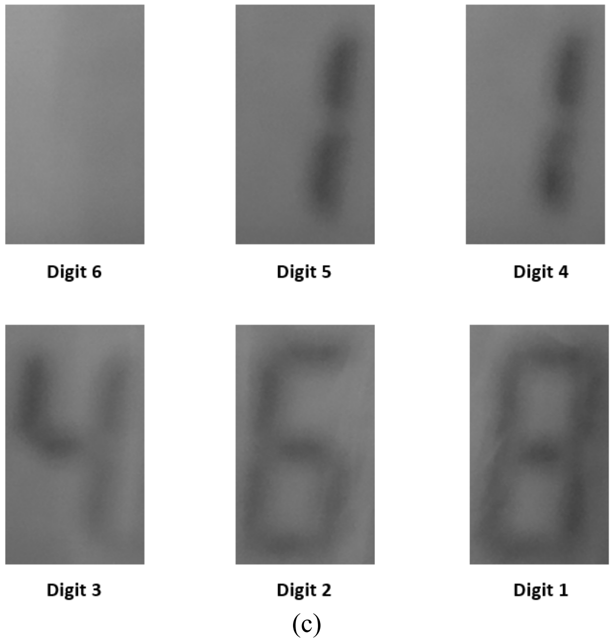


Figure 4. The process of Proportional Cropping. (a) finding the ratio of the padding and seven-segment, (b) removed padding, (c) individual digit segmentation.

2.4. Additional Preprocessing

The individual digit images require further processing before they can be classified. This additional process aims to provide the classifier with a binary image that only contains the information needed by the classifier. The process involves noise removal and contour preservation. First, Gaussian Blur is applied to reduce high-frequency noises. Then, Adaptive Thresholding is performed to create a binary image. To further reduce unwanted noises that persist, Morphological Operation is performed. The results are shown in Figure 5.

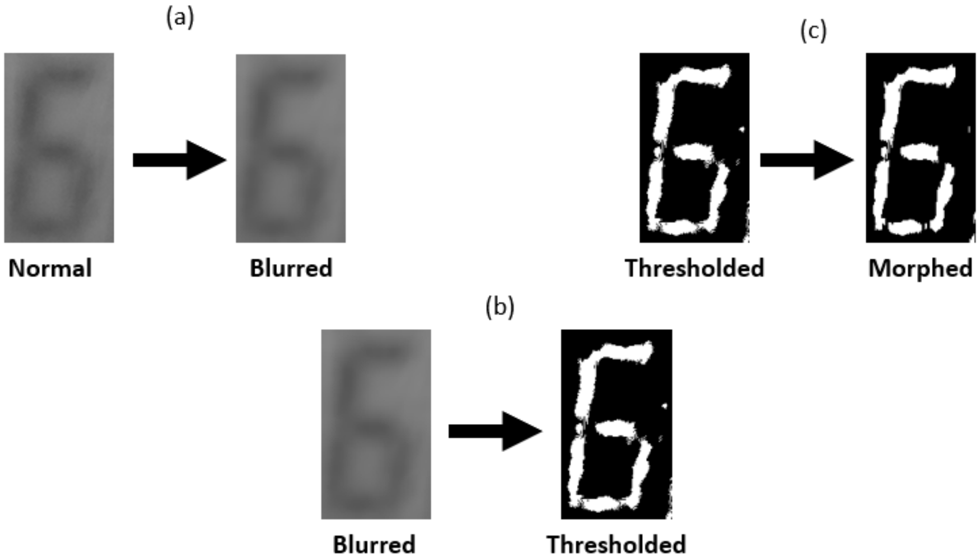


Figure 5. The resulting image from (a) Gaussian blur, (b) Adaptive Thresholding, (c) Morphological Transformation.

2.5. Digit Recognition

The individual digit images from the previous process are then fed into the classifier. In this work, a Random Forest classifier is trained with a collection of binary images representing classes 0 to 9. Each class has the same number of images, except class 0. Since the value of 0 can be represented by two different types of images as shown in Figure 6, this class has double the image compared to the other classes. The system is designed to recognize six digits from the right to the left.

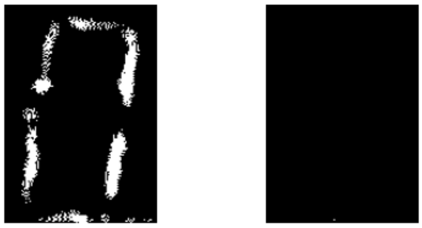


Figure 6. Both images represent the value of 0

3. RESULTS AND DISCUSSION

This section will discuss the methodology of the system testing. In order to assess the overall system performance, a collection of LCD images is captured. The results then analyzed and concluded.

3.1. Classifier Testing

The system is tested using 375 images, representing 0 to 9. The images are distributed evenly for each class, except for class 0 which has double the image. There are two testing parameters namely dataset proportion and hyperparameters. For the first parameter, the dataset will be configured in three different proportions for training and testing as shown in Table 1.

Table 1. Dataset proportion configuration

No.	**Dataset Proportion** Training : Testing
1	220 : 132
2	264 : 88
3	308 : 66

For the second parameter, the hyperparameter will be configured using GridSearchCV which will create classifier models with a combination of defined hyperparameters. Then, it cross-validates all models to select the best-performing model. The hyperparameter configuration is shown in Table 2.

Table 2. Hyperparameter configuration for GridSearchCV

No.	**Hyperparameter**	**Range Value**
1	n_estimator	[50, 100, 150, …, 1500]
2	max_depth	[default, 2, 3, 4, …, 15]
3	min_sample_split	[default, 2, 3, 4, …, 10]

After fitting the classifier with the configured parameter, the resulting model is then validated using validation data with 20 repetitions. The average of the accuracy score will be used as the final score for that particular model. Table 3 shows the results of all models.

Table 3. Classifier testing result

Model Number	Parameter Configuration		Best Parameter	Average Validation Accuracy (%)
	Hyperparameter with GridSearchCV	Dataset Proportion		
1	n_estimators: 50, 100, 150 … 1500	220 : 132	n_estimators: 200	94,924
	max_depth: default		-	
	min_sample_split: default		-	
2	n_estimators: 50, 100, 150, …, 1500		n_estimators: 600	94,886
	max_depth: 2, 3, ..., 15		max_depth: 10	
	min_sample_split: default		-	
3	n_estimators: 50, 100, 150, …, 1500		n_estimators: 600	94,621
	max_depth: 2, 3, ..., 15		max_depth: 10	
	min_sample_split: 2, 3, …, 10		min_sample_split: 2	
4	n_estimators: 50, 100, 150 … 1500	264 : 88	n_estimators: 450	95,966
	max_depth: default		-	
	min_sample_split: default		-	
5	n_estimators: 50, 100, 150, …, 1500		n_estimators: 950	95,511
	max_depth: 2, 3, ..., 15		max_depth: 12	
	min_sample_split: default		-	
6	n_estimators: 50, 100, 150, …, 1500		n_estimators: 950	95,454
	max_depth: 2, 3, ..., 15		max_depth: 12	
	min_sample_split: 2, 3, …, 10		min_sample_split: 2	
7	n_estimators: 50, 100, 150 … 1500	308 : 66	n_estimators: 600	97,879
	max_depth: default		-	
	min_sample_split: default		-	
8	n_estimators: 50, 100, 150, …, 1500		n_estimators: 1100	97,803
	max_depth: 2, 3, ..., 15		max_depth: 11	
	min_sample_split: default		-	
9	n_estimators: 50, 100, 150, …, 1500		n_estimators: 1100	97,652
	max_depth: 2, 3, ..., 15		max_depth: 11	
	min_sample_split: 2, 3, …, 10		min_sample_split: 2	

The testing phase produced 9 models with various parameter configurations and accuracy. The accuracy of all models is greater than 90% with the lowest and highest scores being 94,621% and 97,879% respectively. This 3,258% difference indicates that both parameters have an impact on the model performance.

The dataset proportion has the largest impact on model performance, accounting for a 2,945% difference in accuracy. The lowest and highest accuracy is scored by the 220:132 dataset and 308:66 dataset respectively. This suggests that performance improves as the amount of training dataset increases as shown in Table 4.

Table 4. Accuracy improvement on each dataset configuration

No.	**Dataset Proportion** Training : Test	**Accuracy Improvement** (Compared to the lowest accuracy)
1	220:132	+ 0%
2	264 : 88	+ 1,032%
3	308 : 66	+ 2,945%

In contrast, hyperparameter configuration only accounts for a 0,347% accuracy difference. It also seems that adding more parameters into GridSearchCV will negatively affect performance. In all dataset configurations, there is a slight yet consistent decrease in accuracy whenever a new parameter is introduced as shown in Table 5.

Table 5. Accuracy improvement on each hyperparameter configuration

No.	**GridSearchCV Configuration**	**Average Accuracy Improvement** (compared to the lowest accuracy on the same dataset configuration)
1	n_estimators	+ 0,347%
2	n_estimators + max_depth	+ 0,190%
3	n_estimators + max_depth + min_sample_split	+ 0%

4. CONCLUSION

The test shows that the best model yields a high performance despite only using 20 images for each class (except for class 0 with double the image). Although this method works well with blur images from the Raspberry Pi Camera, this method is still susceptible to display reflection or any external illumination disturbance since the display does not have internal backlighting. To tackle this issue, this method can be supplemented by additional lighting and a shade to provide uniform lighting. In addition, a better camera module may provide a significant boost to the recognition performance.

REFERENCES

[1] A. P. Opoko and A. A. Asinobi, “Users’ perception of the impact of prepaid metering on their energy consumption behaviour: A case study of Victoria Garden City, Lekki, Lagos State,” in *IOP Conference Series: Earth and Environmental Science*, 2021, vol. 665, no. 1. doi: 10.1088/1755-1315/665/1/012052.

[2] D. Gunawan, D. Erwanto, and Y. Shalahuddin, “Studi Komparasi Kwh Meter Pascabayar Dengan Kwh Meter Prabayar Tentang Akurasi Pengukuran Terhadap Tarif Listrik Yang Bervariasi,” *Setrum Sist. Kendali-Tenaga-elektronika-telekomunikasi-komputer*, vol. 7, no. 1, p. 158, 2018, doi: 10.36055/setrum.v7i1.3408.

[3] PT. Perusahaan Listrik Negara, “Keuntungan Listrik Pintar.” https://web.pln.co.id/pelanggan/listrik-pintar/keuntungan-listrik-pintar (accessed Jul. 31, 2022).

[4] K. Karim, M. Jibril Tajibu, F. Retno, I. Reviane Tri Abdi, and S. Undai Nurbayani, “View of Consumer Behavior in Using Prepaid Electricity Systems in the Covid-19 Pandemic Period in

Makassar City, Indonesia," *Int. J. Energy Econ. Policy*, vol. 11, pp. 172–177, 2021, Accessed: Aug. 19, 2022. [Online]. Available: https://www.econjournals.com/index.php/ijeep/article/view/11403/6075

[5] T. Kasar, "Recognition of Seven-Segment Displays from Images of Digital Energy Meters," in *Lecture Notes in Networks and Systems*, 2019, vol. 43, pp. 1–10. doi: 10.1007/978-981-13-2514-4_1.

[6] S. Popayorm, T. Titijaroonroj, T. Phoka, and W. Massagram, "Seven Segment Display Detection and Recognition using Predefined HSV Color Slicing Technique," in *JCSSE 2019 - 16th International Joint Conference on Computer Science and Software Engineering: Knowledge Evolution Towards Singularity of Man-Machine Intelligence*, 2019, pp. 224–229. doi: 10.1109/JCSSE.2019.8864189.

[7] V. Shenoy and O. Aalami, "Utilizing Smartphone-Based Machine Learning in Medical Monitor Data Collection: Seven Segment Digit Recognition," in *AMIA ... Annual Symposium proceedings. AMIA Symposium*, 2018, vol. 2017, pp. 1564–1570.

[8] Z. Zhang, Z. Hua, Y. Tang, Y. Zhang, W. Lu, and C. Dai, "Recognition method of digital meter readings in substation based on connected domain analysis algorithm," *Actuators*, vol. 10, no. 8, pp. 1–14, 2021, doi: 10.3390/act10080170.

[9] U. Suttapakti, T. Titijaroonroj, W. Nunsong, and D. Kakanopas, "Seven Segment Display Detection and Recognition via Deep Learning Technique," pp. 1–4, 2022, doi: 10.1109/ecti-con54298.2022.9795620.

[10] D. Tsiktsiris, K. Kechagias, M. Dasygenis, and P. Angelidis, "Accelerated Seven Segment Optical Character Recognition Algorithm," *5th Panhellenic Conf. Electron. Telecommun. PACET 2019*, pp. 1–5, 2019, doi: 10.1109/PACET48583.2019.8956283.

[11] C. N. Truong, N. Q. H. Ton, H. P. Do, and S. P. Nguyen, "Digit detection from digital devices in multiple environment conditions," *Proc. - 2020 RIVF Int. Conf. Comput. Commun. Technol. RIVF 2020*, pp. 5–7, 2020, doi: 10.1109/RIVF48685.2020.9140775.

[12] H. Shuo, Y. Ximing, L. Donghang, L. Shaoli, and P. Yu, "Digital recognition of electric meter with deep learning," *2019 14th IEEE Int. Conf. Electron. Meas. Instruments, ICEMI 2019*, pp. 600–607, 2019, doi: 10.1109/ICEMI46757.2019.9101443.

[13] A. K. Sharma and K. K. Kim, "Lightweight CNN based Meter Digit Recognition," *J. Sens. Sci. Technol.*, vol. 30, no. 1, pp. 15–19, 2021, doi: 10.46670/jsst.2021.30.1.15.

[14] A. Wannachai, W. Boonyung, and P. Champrasert, "Real-Time Seven Segment Display Detection and Recognition Online System Using CNN," in *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST*, 2020, vol. 329 LNICST, pp. 52–67. doi: 10.1007/978-3-030-57115-3_5.

[15] E. Finnegan, M. Villarroel, C. Velardo, and L. Tarassenko, "Automated method for detecting and reading seven-segment digits from images of blood glucose metres and blood pressure monitors," *J. Med. Eng. Technol.*, vol. 43, no. 6, pp. 341–355, 2019, doi: 10.1080/03091902.2019.1673844.