Application of Computer Vision Technologies for Automated Utility Meters Reading

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Keywords: Software Engineering, Computer Vision Techniques, Case Study.

Abstract: This paper presents a study on automated reading of utility meters using two computer vision techniques: an open-source solution Tensorflow Object Detection (Tensorflow) and a commercial solution Anyline. We aimed to identify the limitations and benefits of each solution applied to utility meters reading, especially focusing on aspects such as accuracy and inference time. Our goal was to determine the solution that is the most suitable for this particular application area, where there are several specific challenges.

1 INTRODUCTION

Development and application of smart meters is an active research topic over the last decades, see (Depuru et al., 2011; Benzi et al., 2011; Zheng et al., 2013). The smart devices are elaborated for several types of utilities, e.g., electricity, gas, etc. Their advantage is that the data on energy consumption is recorded and sent automatically to the provider as well as, in some cases, to the corresponding customer. This data can be used for monitoring and billing purposes. This allows more detailed analysis of the consumption patterns as well as the ways to reduce consumption or to schedule the energy-consuming tasks for the time, which is mostly suitable for the energy network (in the terms of payment or the energy load).

The core disadvantage of this solution is that its implementation on a large scale is expensive. In the case customers have to pay for an upgrade to a smart meter, they might prefer to object the upgrade. Some customers perceive that the learning curve for using smart meters is steep, and prefer to avoid using them by this reason. Also, some customers are concerned regarding their privacy while using the smart meters, as the information regarding the usage pattern over the day might be used to identify whether the residents are currently at home, home many of them are at home, etc. Therefore, in some countries the roll out to the smart meter systems is done step-wise, where on the initial stage the roll out is voluntary.

On the other hand, a manual collection of meter readings is not only time consuming, but also sometimes complicated for people with vision impairment. In our earlier work (Spichkova et al., 2019b), we conducted a project in collaboration with Energy Australia, which is an electricity and gas retailing private company that supplies electricity and natural gas to more than 2.6 million residential and business customers throughout Australia. Their solution for non-smart meters was to provide an online portal, where the consumers can update the records on the utility readings. Thus, the consumers had to provide a lot of additional details, and to calculate their utility readings manually. The goal of our previous project was to elaborate an alternative method for the existing system, which would allow for a higher degree of automation to increase the usability of the system. The proposed solution was to use computer vision techniques for capturing readings. We analysed there the following computer-vision technologies: Google Cloud Vision[1] (GCV), Amazon Web Services (AWS) Rekognition[2], Tesseract OCR (Smith, 2007), and Azure's Computer Vision[3]. The study demonstrated that AWS Rekognition provides better results for this application domain. However, it's accuracy was far from ideal: the average accuracy values AWS Rekognition was only 36%.

Contributions: In this paper we present our recent study, where we compared with our previous results two further computer vision technologies, Tensorflow Object Detection (Tensorflow) and Anyline:

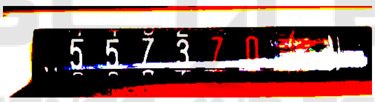
[1] https://cloud.google.com/vision
[2] https://aws.amazon.com/rekognition
[3] https://docs.microsoft.com/en-us/azure/cognitive-services/computer-vision

Spichkova, M. and Van Zyl, J.
Application of Computer Vision Technologies for Automated Utility Meters Reading.
DOI: 10.5220/0009892505210528
In *Proceedings of the 15th International Conference on Software Technologies (ICSOFT 2020)*, pages 521-528
ISBN: 978-989-758-443-5

- Tensorflow is an open-source machine learning system that operates at large scale and offers a multitude of models to be retrained (more than 30), see (Abadi et al., 2016; Abadi et al., 2017). To analyse the Tenserflow results, we applied the corresponding visualisation tool TensorBoard (Wongsuphasawat et al., 2018) that allows to visualise TensorFlow graphs, plot corresponding quantitative metrics, etc.[4]
- Anyline is a commercial solution intended to read utility meters, which also offers a free sample app *Anyline OCR Scanner*[5] that has been used during tests within our project.

The obtained results are significantly better (see Section 4 for details) in the terms of recognition accuracy than the results of our early investigation study within the domain of meter reading recognition (Spichkova et al., 2019b), where we analysed another two computer vision technologies, applied to the same data sets: the results of the current study demonstrate the accuracy up to 92.35%.

(a) Original image with reflections.



(b) Application of the thresholding technique.

(c) Application of the flooding technique.

Figure 1: Reflection issues.

2 BACKGROUND

There are many challenges for application of computer vision technologies for the reading of utility meters, such as:

- *Reflections:* Most meter models encountered has a transparent protective cover, see Figure 1(a), which lead to reflections from it. This becomes problematic for computer vision technologies which includes thresholding/flooding techniques.

[4]https://www.tensorflow.org/guide/summaries_and_tensorboard

[5]https://anyline.com/products/ocr-meter-reading

Thresholding techniques are usually applied to OCR technologies in-order to minimize noise and or to convert to black-and-white images. Figure 1(b) illustrates an application of threshold. The threshold in this case has removed the last digit completely and clipped several other digits. *Flooding* is a technique used to find similar neighbouring pixels. This technique can be used when finding contours of shapes. Figure 1(c) displays flooding made on the last digit. This technique failed to find the contour of the digit and the contour of reflection was found instead.

- *Clipped Digits:* The final digit in analogue meters usually rotate freely. This becomes problematic as the digit becomes clipped and the full digit is not displayed. Figure 2 presents an example of such case: the final digit is both a 2 and a 3 with neither being displayed completely. The computer vision technology would need to be able to read clipped digits.

Figure 2: Clipped Digits.

- *Not all characters and digits, which can be identified on the meter, actually belong to the meter reading:* Utility meters commonly include other text as seen red boxes in Figure 3. The computer vision technology would need to be able to discriminate which digits are part of the meter reading, and which have to be ignored.

Figure 3: Digits on the meter, which do not belong to the meter reading.

- *Blur, noise, warping, etc.:* The grime adds noise to the observed meter. Grime with reflection creates a blur effect around some digits, see Figure 4 (digits 2 and 5). Digits are also observed to be warped along with the shape of the cover, e.g., the digits appear "stretched" or "squashed" depending on observation angle. Furthermore, there can be a significant contrast difference in scenarios where the colour of the digits is mixed. For example, in Figure 4, the final 3 digits (883) have low contrast and are barely observable in comparison to the first 4 digits.

- *Different representation styles (scales, dials and digits) mixed within a meter interface.*
  Utility models observed during the project presented their reading value either through: using rotational dials, using cyclometers, a combination of rotational dials and cyclometers or a singular digital display. The challenge becomes even more complex when the numeric value is displayed on a scale, e.g., as presented in Figure 5:
  - The meter (a) should be read as 5762.615m^3 gas and not 57626,
  - The meter (b) should be read as 14485.68kWh energy and not 14485,
  - The meter (c) should be read as 75691.1kWh energy and not 756911.

  The meters commonly include a decimal point. Most meters include the decimal point as the last digit and can be read and a tenth. Sometimes it is a mixture of a digit and a dial as in Figures 5(b) and (c).

  Some models display three decimal points as seen in Figure 4 (the digits after decimal points are highlighted with red colour), which should read as 2550.883m^3 and not 2550883. Thus, our aim is to identify a computer vision technology that is capable of distinguishing between different numeric scales and be able to detect both digits and rotation of dials.

3 METHODOLOGY

To determine which of these technologies is most suitable for reading utility meters, we elaborated a set of tests that allows us to identify the limitations of each technology by gradually adjusting image blur, noise, gamma or scale.

The following methodology was applied to analyse the techniques:

1. To create a training dataset for the Tensorflow Object Detection framework.
2. To train all the different models using the dataset, which was elaborated at Step 1. This was done through Google ML Engine.
3. To create evaluation datasets for which the technologies can be tested against.
4. To create a test harness for the involved technologies.
5. To run the test harness on the evaluation datasets created from Step 3.

The training dataset is a set of all images found during project duration. The final training dataset consisted of 395 images and 2000 annotations. Unfortunately, this is still considered limited as supplied Tensorflow models were created based upon 2000+ annotations per object.

As the evaluation dataset we used the same images as in our earlier work (Spichkova et al., 2019b), which allowed us to compare the results of application of Tensorflow and Anyline not only with each other, but also with the results of AWS Rekognition (which demonstrated the best but not good enough accuracy in our previous study). Thus, in (Spichkova et al., 2019b), a total of 30 images were selected based on their "uniqueness" – images with unique meters or images with unique lighting. These images were duplicated and modified with various effects in order to test the limitations of the different technologies. These effects are:

- *Scaling:* The dataset was scaled in steps of 0.1 ranging from a scale of 0.1 to 0.9 (10% to 90%) of the original dataset.
- *Blurring:* Blurring was done in steps of 10 from 10 to 90 with an open source blur algorithm that is based on the normalised box filter, see (OpenCV, 2018). The algorithm uses a normalised box filter, the numeral value adjusts the kernel size.
- *Gamma:* The gamma algorithm was used with an open source lookup table algorithm (OpenCV, 2018). The gamma correction to simulate different lightning conditions.
- *Noise:* The noise algorithm is based upon the salt and pepper noise algorithm that adds sharp and sudden disturbances in the image in the form of sparsely occurring white and black pixels, see (Gonzalez and Woods, 2001). This algorithm was included to further test the performance of the various technologies as noise arguably emulates "dirt" on meters.

In contrast to Anyline, Tensorflow's Tensorboard provides more in-depth evaluation of each model and how well each model detects objects for a given dataset, such as:

- single-shot multi-box detector (SSD), see (Liu et al., 2016),
- feature pyramid networks (FPN), see (Lin et al., 2017),
- fast region-based convolutional neural networks (FRCNN), see (Ren et al., 2017).

(a) (b)

Figure 4: Challenging case: (a) Original image; (b) Application of the thresholding technique over the original image.

(a) (b) (c)

Figure 5: Different representation styles (scales, dials and digit) mixed within a meter interface.

Our initial hypotheses in terms of accuracy and detection rates were as follows:

H1: FRCNN model would significantly outperform other models.

H2: SSD model would perform significantly worse than the other models in terms of accuracy.

H3: The lower the image resolution is, the faster inference would occur.

H4: FRCNN would require significantly more time than FPN and SSD models.

As Tensorflow Object Detection only detects objects, the results have to be filtered in order to give a reading. We applied the filtering algorithm presented in Algorithm 1 to

- remove any junk data, i.e., any detected objects for what the identification confidence is $\leq 10\%$,
- remove all duplicates within the geometric region, keeping the results withe the highest identification confidence.

The filtering algorithm can be further improved, if the previous reading of the meter is considered, for which an access to the customer's account is required. We haven't applied this improvement within the comparison study, as the supplied Anyline app cannot include any customer related data.

Results from each dataset and each technology were produced in csv files (a comma-separated values file that allows data to be saved in a tabular format) with the following structure:

```
FileName, InferTime, FilteredReading,
ExpectedReading, IsCorrect
```

where `InferTime` denotes the interference time, which was measured in ms.

Similarly to (Spichkova et al., 2019b), we calculated the accuracy of recognition calculated as the following simple formula (we measure the accuracy in percents, where 100% means a totally accurate recognition):

$$Accuracy = \frac{CorrectResults}{Total} * 100 \qquad (1)$$

where:
$CorrectResults$ is the number of results that match with the original readings completely,
$Total$ presents the total number of images in a dataset. As in our study, we had 30 images in each of the datasets, $Total = 30$.

4 RESULTS AND DISCUSSION

Figures 7-9 present the identified accuracy scores per dataset, where 50% indicates half of the dataset meter images were correctly read.

It is important to mention that both Tensorflow and Anyline were less sensitive to scaling, gamma, and sat and paper issues than to blurring, but, the accuracy of Tensorflow was almost twice higher:

- With low blurring (10BLUR and 20BLUR), Tensorflow performed with 100% accuracy, where the accuracy of Anyline dropped to approx. 63% and 50% respectively.
- For the effect of 50BLUR, the accuracy of Tensorflow FPN and Anyline were approx. 87% and 37% respectively.

Algorithm 1: Filtering of meter readings.

```
j = 1
for all i ← 1,n do
    if confidence(result[i]) > 10%  then
        if result[i] is unique within geometric region then
            list[j] = result[i]
            j = j + 1
        else                                          ▷ where list[k] is the duplicate of result[i]
            if confidence(result[i]) > confidence(list[k]) then
                list[k] = result[i]
            end if
        end if
    end if
end for
Sort list[i] by geometric location from left to right
```

Figure 6: Example of an application of the blurring effect with 90BLUR.

- For the effect of 90BLUR, the accuracy for Tensorflow FRCNN, Tensorflow SSD and Anyline was only 10%, where the accuracy of Tensorflow FPN was approx. 33%. However, the 90BLUR effect means a very blurry image, see Figure 6 for an example.

The overall performance of the Tensorflow models greatly surpass expectations in terms of accuracy, having an average performance of 88.14%, 89.51% and 92.35% for FRCNN, SSD, and FPN, respectively. This is especially remarkable, if we compare it with the average accuracy values from AWS Rekognition was only 36% that demonstrated the best (but not really satisfactory) results within the study presented in (Spichkova et al., 2019b).

TensorBoard confirms the accuracy of the trained models. Scoring a near perfect score of 1.0 is extremely significant is a strong indication that Tensorflow Object Detection is a suitable framework for the automated meter reading.

Anyline performed arguably well having an average performance of 57.16%, and struggled on several utility meter models. The results indicate that Anyline may not have trained or tested their product on a similar utility meters models as used within the Australian

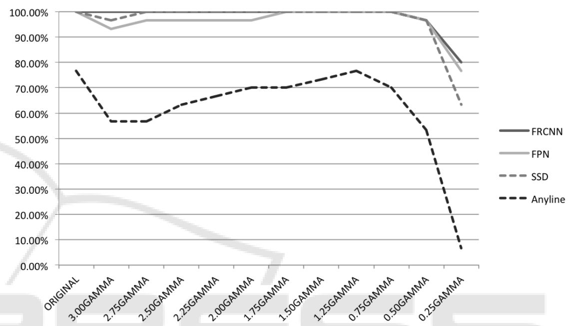


Figure 7: Accuracy scores per dataset: Gamma analysis.

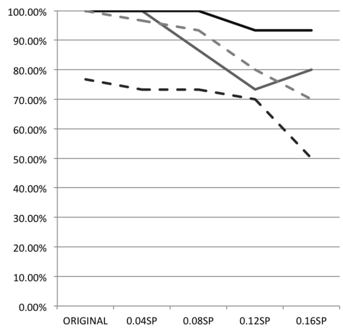
market. The accuracy of Anyline was significantly lower for all data sets: if compared with Tensorflow FPN, the accuracy of Anyline was in average lower approx. 35% lower, where

- the largest differences in the cases of 0.25GAMMA (approx. 70%) and 20BLUR (approx. 57%);
- the largest difference (approx. 23%) was in the cases of 1.25GAMMA, 0.12SP (noise), 90BLUR, and the original data sets.

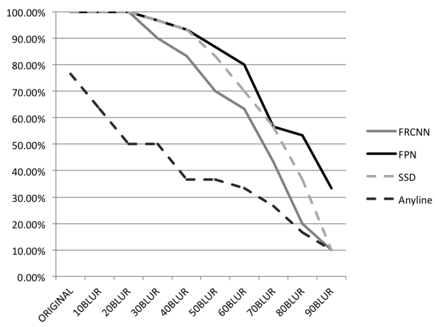
With respect to our hypotheses H1-H4, the results of the conducted study can be summarises as follows:

- H1 and H2 were disproved by the conducted study: In the terms of accuracy, the best performing model was FPN, where FRCNN and SSD were performing slightly worse than the other models.
- H3 was proved as correct.
- H4 was also proved as correct: In average, FRCNN was approx. 2.5 slower than FPM and approx. 3.2 times slower than SSD.

The results for both Tensorflow and Anyline are also significantly better than the results of our



(a)



(b)

Figure 8: Accuracy scores per dataset: (a) Salt and pepper analysis; (b) Blur analysis.

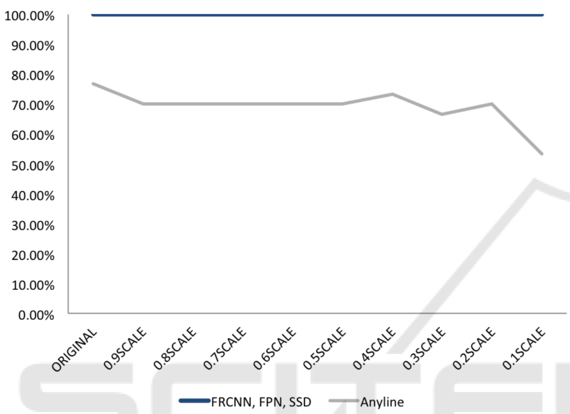


Figure 9: Accuracy scores per dataset: Scale analysis.

early investigation study conducted for the domain of meter reading recognition, where we analysed Google Cloud Vision (GCV) and Amazon Web Services (AWS) Rekognition using the same data sets. The average accuracy values for GCV and AWS Rekognition were just 29% and 36% respectively, see (Spichkova et al., 2019b).

5 RELATED WORK

The research on the smart meter devices and the corresponding analytic was actively conducted over many years, which was reflected not only in research publications but also in patents, see e.g., (Ehrke et al., 2003; Grady et al., 2016; Winter, 2017).

Over the last decade, there were two core research directions in this area: (1) privacy and security aspects of the smart meter application, and (2) smart meters in combination with a smart grid system. In the rest of the section we discuss the most cited (as per Google Scholar) publications, grouped by the research directions.

Privacy and Security Aspects of Smart Meters: This research direction is currently the most active one among the mentioned directions, because the privacy and security concerns provide one of the biggest obstacles for the (potential) users of smart meters. In many cases, data mining and data analytics techniques were applied on the meter reading data, to investigate the above issues questions.

A privacy-preserving smart meter architecture was presented in (Molina-Markham et al., 2010). The authors also conducted a study to demonstrate that the power consumption patterns can help to reveal how many people are in the home, what are their sleeping and eating routines, etc.

A theoretical framework to analyse privacy aspects of smart meters was introduced in (Sankar et al., 2013). A formal framework to quantify the privacy trade off problem in smart meter data was introduced in (Rajagopalan et al., 2011).

An approaches for occupancy detection from electricity consumption data were proposed in (Kleiminger et al., 2013).

The extraction of the households characteristics from the the smart meter data was discussed in (Beckel et al., 2014).

Similarly, the question on what the consumption patterns (created on the basis of the smart meter data) might say about the consumers, was discussed in (Albert and Rajagopal, 2013) and (Beckel et al., 2014).

An approach for non-intrusive occupancy monitoring using smart meters was discussed in (Chen et al., 2013). This work aimed to implement energy-efficiency optimisations based on the information of home's occupancy.

Design of Smart Meters for the Smart Grid: An approach for anonymizing the data sent by a smart meter to achieve security and privacy of the smart grid was proposed in (Efthymiou and Kalogridis, 2010). A smart meter data aggregation approach for smart grids was introduced in (Li et al., 2010). The authors applied homomorphic encryption to solve the privacy issue. An overview of typical smart meter's aspects and functions wrt. smart grid aspects was presented in (Zheng et al., 2013).

6 CONCLUSIONS

We presented the results of a research project, which goal was to provide an alternative method for the current system to update the meter reading data, collected from non-smart utility meters.

Our early investigation study on the recognition accuracy of Google Cloud Vision and AWS Rekognition applied for recognition in utility meter readings, demonstrated very low average accuracy values (29% and 36%, respectively). For this reasons, we conducted a further study to analyse two other computer vision technologies, applied for recognition in utility meter readings:

- an open-source Tensorflow technique (FRCNN, FPN, and SSD models), and
- a commercial solution Anyline.

The study demonstrated that Tensorflow provides significantly better results for our application domain (92.35% for the FPN model), in comparison to Anyline, as well as to Google Cloud Vision and AWS Rekognition.

This research project was conducted under the initiative *Research embedded in teaching*, see (Spichkova, 2019; Simic et al., 2016; Spichkova and Simic, 2017). This initiative was proposed at the RMIT University (Melbourne, Australia) within the Software Engineering projects (SEPs) conducted in collaboration with industrial partners. The aim of this initiative is to encourage students' curiosity for Software Engineering and Computer Science research. To reach this aim we include research components as bonus tasks in the final year projects (on both undergraduate and postgraduate levels), which typically focus on software and system development. Few weeks long research projects have been sponsored by industrial partners, who collaborated with the students and academic advisers through the final year projects. Respectively, the topics of these short research projects focus align the topics final year projects. The successful results of this initiative are presented in (Christianto et al., 2018; Clunne-Kiely et al., 2017; Spichkova, 2018; Spichkova et al., 2018; Spichkova et al., 2019b; Sun et al., 2018; Chugh et al., 2019; Gaikwad et al., 2019; Spichkova et al., 2019a).

ACKNOWLEDGEMENTS

We would like to thank Shine Solutions and Energy Australia for sponsoring this project under the research grant RE-03615.

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