FRAUD DETECTION OF POWER METER READING USING IMAGE MATCHING WITH INCEPTION V3 CONVOLUTIONAL NEURAL NETWORK

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DEDICATION

This project report is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

I dedicate my dissertation work to my family and many friends. A special feeling of gratitude to my loving parents, who taught me that the best kind of knowledge to have is that which is learned for its own sake. Next, I would also dedicate this work and give special thanks to my girlfriend Vicky Ho, she had accompanied and provide a good mentally support to me throughout the whole education process.

Next, I would like to dedicate my manager which able to provide a strong support for me throughout the Master education process as we know working along with working is not an easy and healthy task. Last but not least, I would also dedicate this dissertation to my many friends and UTM classmate who have supported me throughout the Master process especially member of MSG (Master Support Group) which had provided me a strong mental support when needed. I will always appreciate all they have done.

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I am also indebted to Intel for funding my Master Degree study. Librarians at UTM, Cardiff University of Wales and the National University of Singapore also deserve special thanks for their assistance in supplying the relevant literatures.

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ABSTRACT

Corruption occurs everywhere, and even meter readers can be corrupted. One of the examples is the consumer that is unwilling to pay utility bill will collude with meter reader to manipulate the meter reading for the utilities. For preventing such a thing from happening the utilities company had introduced a method to the meter reader which tells them to attach the meter reading (number) along with the photo of the meter with the reading. The photo will be sent to the company to ensure the meter reading is correct and the number is not created or generated by the meter reader. There is nothing perfect in this world, with this prevention the meter reader is still able to find a loop hole that allows them to manipulate the meter reading. What they do is get the meter reading from another meter and use the number and photo for the other consumer. This causes a lot of issues to the customer. Where the victim will need to pay more than the usual caused by the image of the meter is swapped. In this project, a solution is introduced that is able to reduce fraud from the meter reader by using image matching in fraud detection. This can also reduce the dependency on human checking of the image from the meter reader for the meter reading fraud detection. In this project, image matching algorithm is introduced to match the new meter image with the image from the image database, the image matching algorithm will also inform if any fraud is found from the image through Google Inception V3 as a proposed model with the accuracy of 99.1285%.

ABSTRAK

Rasuah berlaku di mana-mana sahaja, dimana pembaca meter boleh dirasuah. Salah satu contoh ialah pengguna yang tidak mahu membayar juga bil utiliti yang tinggi dan bersekongkol dengan pembaca meter untuk memanipulasi bacaan meter untuk utiliti tersebut. Untuk pencegahan, syarikat utiliti telah memperkenalkan kaedah kepada pembaca meter dengan meminta mereka melampirkan bacaan meter (nombor) bersama-sama dengan foto meter bersama bacaan. Foto akan dihantar ke syarikat untuk memastikan bacaan meter adalah betul dan nombornya bukan dicipta atau dijana oleh pembaca meter. Tiada perkara yang sempurna di dunia, dengan pencegahan ini pembaca meter masih dapat mencari kelemahan sistem dalam memanipulasi bacaan meter. Apa yang mereka lakukan ialah mendapatkan bacaan meter dari meter lain dan menggunakan nombor dan foto untuk pengguna tersebut. Ini menyebabkan banyak isu kepada pelanggan. Di mana mangsa perlu membayar lebih daripada biasa yang disebabkan oleh imej meter ditukar. Dalam projek ini, satu penyelesaian diperkenalkan yang dapat mengurangkan penipuan daripada pembaca meter dengan pemadanan imej dalam pengesanan penipuan. Ini juga dapat mengurangkan pergantungan pada pemeriksaan manusia dari imej dari pembaca meter untuk pengesanan penipuan pembaca meter. Dalam projek ini, algoritma pemadanan imej diperkenalkan untuk memadankan imej meter baru dengan imej dari database, algoritma pemadanan imej juga akan memberitahu jika ada penipuan yang ditemui dari imej. Oleh itu, pembaca meter tidak dapat menukar bacaan meter dengan bacaan meter dari rumah yang berlainan melalui Google Inception V3 sebagai model dengan ketepatan 99.1285 %.

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LIST OF ABBREVIATIONS

BRIEF	-	Binary Robust Independent Elementary Features
CCM	-	Cascading Classification Models
CNN	-	Convolutional Neural Network
CPU	-	Central Processing Unit
GPU	-	Graphics Processing Unit
MEPCO	-	Multan Electric Power Company
ORB	-	Oriented FAST and Rotated BRIEF
PDIS	-	Permanent Disconnected
SIFT	-	Scale Invariant Feature Transform
SURF	-	Speeded Up Robust Features
TNB	-	Tenage Nasional Berhad
TPU	-	Tensor Processing Unit
WAPDA	-	Pakistan Water & Power Development Authority

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CHAPTER 1

INTRODUCTION

1.1 Problem Background

Electricity is the collection of physical phenomena associated with the presence and movement of an electric charge property in a matter of possess(1). In many countries, most electricity is generated by the utility company. Where the generated electricity is then sold to consumer-based on customer usage. Usually, it is in terms of kWh. The price of the energy is based on the number of units that the customer use. Usually, there is a range set by the utility company. The unit range will be split into a few different categories with different prices per kWh. If the electric unit exists a certain category. The total price for the first category will be added to the remaining unit that needs to be paid. And the price for the next category will be more expensive than the previous category.

For example, the first category cap at 500 kWh and cost \$ 0.1001 per kWh, while the remaining unit will be charged for \$0.1500 per kWh. Then **Energy Charge for the first 500 kWh: \$ 0.1001 x 500kWh = \$ 50.05** (1-1) and **Energy Charge for the remaining 1800 kWh: 1800 kWh x \$0.1500 = \$ 270.00** (1-2) below shows the electricity calculation for total electricity usage of 2300kWh. There were two different prices with two different categories (2).

Energy Charge for the first 500 kWh: \$ 0.1001 x 500kWh = \$ 50.05 **(1-1)**

Energy Charge for the remaining 1800 kWh: 1800 kWh x \$0.1500 = \$ 270.00 **(1-2)**

Some of the utility companies might have up to 3 or 4 range categories to segregate the price for the electricity so that customers can pay or less based on the usage. This segregation can give some opportunity to the poor so that they are able to experience the use of electricity as well. This segregation known as tariff rates. Figure 1.1 below shows the example of Tariff Rates done by TNB Malaysia which they split up to 5 categories (3). While Figure 1.2 below shows the tariff rate from MEPCO Pakistan (4). Based on the comparison between the tariff rates below, the tariff rate for Pakistan has a huge jump of range between 1st and 2nd segregation. There is about 238% increment for the 1st step and 126% increment for 2nd step. This is a kind of a square root graph type of increment. While for TNB the increment for the price is quite linear compared to the tariff rate provided by MEPCO Pakistan. There is some good and bad for this kind of situation. Where for MEPCO the customer who uses less electricity can save more. While for whom that overuse the electric range will need to pay much more than other customers.

Tariff Rates

"**Domestic Consumer**" means a consumer occupying a private dwelling, which is not used as a hotel, boarding house or used for the purpose of carrying out any form of business, trade, professional activities or services.

	TARIFF CATEGORY	UNIT	CURRENT RATE (1 JAN 2018)
	Tariff A - Domestic Tariff		
	For the first 200 kWh (1 - 200 kWh) per month	sen/kWh	21.80
	For the next 100 kWh (201 - 300 kWh) per month	sen/kWh	33.40
1.	For the next 300 kWh (301 - 600 kWh) per month	sen/kWh	51.60
	For the next 300 kWh (601 - 900 kWh) per month	sen/kWh	54.60
	For the next kWh (901 kWh onwards) per month	sen/kWh	57.10
	The minimum monthly charge is RM3.00		

Figure 1.1 Tariff rates by TNB Malaysia in the year 2019

SCHEDULE OF ELECTRICITY TARIFFS
FOR MULTAN ELECTRIC POWER COMPANY (MEPCO)

A-1 GENERAL SUPPLY TARIFF - RESIDENTIAL

Sr. No.	TARIFF CATEGORY / PARTICULARS	FIXED CHARGES Rs/kW/M	VARIABLE CHARGES Rs/kWh	GOP Tariff Rationalization Subsidy FIXED CHARGES Rs/kW/M	Subsidy VARIABLE CHARGES Rs./kWh	Surcharge VARIABLE CHARGES Rs./kWh
a)	For Sanctioned load less than 5 kW					
i	Up to 50 Units	-	4.00		2.00	-
	For Consumption exceeding 50 Units		-		-	-
ii	001 - 100 Units	-	9.52		3.73	-
iii	a. 101 - 200 Units	-	12.00		3.89	-
	b. 201 - 300 Units		12.00		1.80	-
iv	301 - 700 Units	-	15.00		-	1.00
v	Above 700 Units	-	16.00		-	2.00
b)	For Sanctioned load 5 kW & above		Peak / Off-Peak		Peak / Off-Peak	Peak / Off-Peak
	Time Of Use	-	16.00 / 10.50		- / -	2.00 / 2.00

As per the Authority's decision residential consumers will be given the benefits of only one previous slab.
Under tariff A-1, there shall be minimum monthly charges at the following rates even if no energy is consumed.

a) Single Phase Connections: Rs. 75/- per consumer per month
b) Three Phase Connections: Rs. 150/- per consumer per month

Figure 1.2 Tariff Rate by MEPCO Pakistan in the year 2019.

Since the step for the tariff rate for MEPCO is huge, the customer will then try to find other methods to allow them to pay the lesser bill. One of the methods is the customer correlate with meter reader by corrupting them to manipulate the meter reading for the customer. This can allow them to pay a lower electricity bill price per month. This issue might not occur in Malaysia since the difference between the price in between categories is not that high as compared to Pakistan.

Few prevention methods could be taken to resolve this issue. One of them is by implementing the smart meter. Smart meter is a type of meter that able to send the meter reading to the utility company automatically without the need of a meter reader to manually read the meter reading (5).Based on study, until the year 2019, there were only 14% of smart meter applications had been implemented in global. The remaining 86% still using a conventional type of meter (6).

For prevention, some utilities company had introduced a method to counter the meter value manipulation fraud, where the prevention method is by requesting the meter reader to attach the image of the meter along with the meter number so that the utilities company can able to make sure the meter value is not manipulated value thus no fraud occur. As shown in Figure 1.3 below are the utilities bill from TNB and in Figure 1.4 below show the utilities bill from MEPCO.

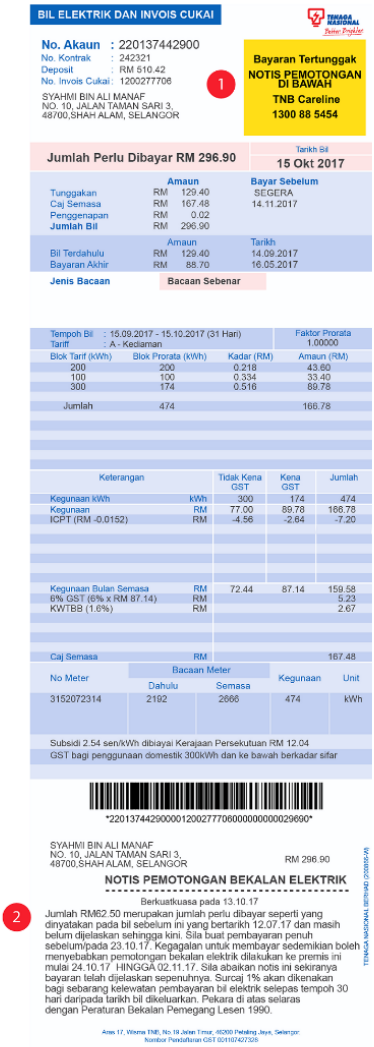


Figure 1.3 Utilities Bill From TNB

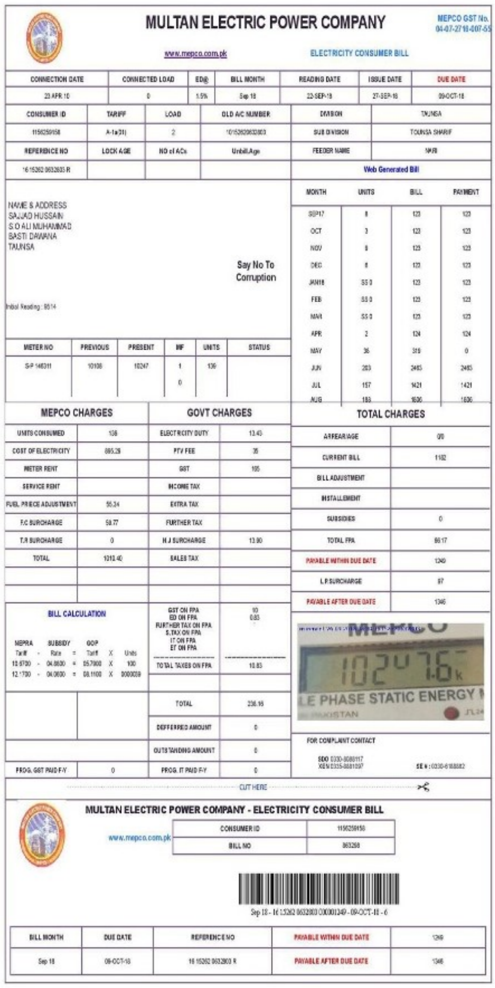
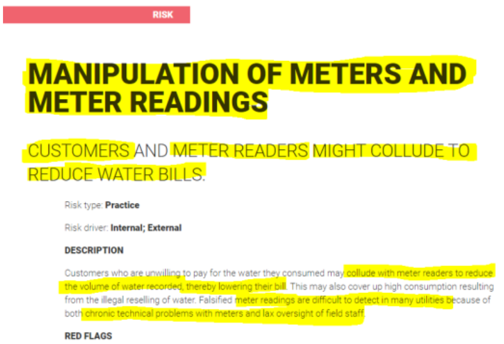


Figure 1.4 Utilities Bill From MEPCO

For example, in Malaysia (TNB) meter reader will go house by house to read the meter reading. Thus, it is all based on the trust between the meter reader and the utilities company. If the meter reader was corrupted, they could reduce the number of meter readings to reduce the price of the customer bill.

Therefore, some companies came out with the idea of attaching the image of the meter as well as the meter reading value inside the utilities bill to prevent the fraud occur. By this action, the meter reader could not able to manipulate the meter reading by just changing the number of meter values. Therefore, fraud able to be reduced. As an example, the utilities bill of MEPCO shown in Figure 1.4 above, the image of the utilities meter needs to attached along with the meter reading inside the utilities bill (7). For utilities bill from TNB no meter image attachment is needed.

Somehow, the meter reader and consumer still able to find a loophole to this prevention method. The loophole is meter reader able to take the meter value from another house. This can allow the meter reader just simply choose a house that has lower meter value and attached the image of the meter (with lower reading) along with the meter reading (with lower reading) inside the utilities bill to the utilities company for representing another house. They can also swap the meter image with another house and cause the owner of the corrupted house to pay less and the owner of a non-corrupted house owner to pay more on the utilities bill. This cause a lot issues for the utilities company, where they need to take care about the losses in term of cost which directly proportional to the loss of the electricity generation, in the meanwhile they lost the trust of the customer as well. In Figure 1.5, Figure 1.6, Figure 1.7, and Figure 1.8 below show the examples of the issues caused by the meter reader.



RISK

MANIPULATION OF METERS AND METER READINGS

CUSTOMERS AND METER READERS MIGHT COLLUDE TO REDUCE WATER BILLS.

Risk type: **Practice**

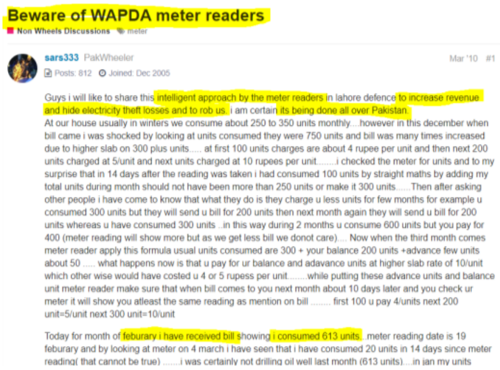
Risk driver: **Internal; External**

DESCRIPTION

Customers who are unwilling to pay for the water they consumed may collude with meter readers to reduce the volume of water recorded, thereby lowering their bill. This may also cover up high consumption resulting from the illegal reselling of water. Falsified meter readings are difficult to detect in many utilities because of both chronic technical problems with meters and lax oversight of field staff.

RED FLAGS

Figure 1.5 Manipulation of Meters and meter reading (8)



Beware of WAPDA meter readers

Non Wheels Discussions meter

sars333 PakWheeler Mar '10 #1

Posts: 812 Joined: Dec 2005

Guys i will like to share this intelligent approach by the meter readers in lahore defence to increase revenue and hide electricity theft losses and to rob us. i am certain its being done all over Pakistan.
At our house usually in winters we consume about 250 to 350 units monthly....however in this december when bill came i was shocked by looking at units consumed they were 750 units and bill was many times increased due to higher slab on 300 plus units..... at first 100 units charges are about 4 rupee per unit and then next 200 units charged at 5/unit and next units charged at 10 rupees per unit........i checked the meter for units and to my surprise that in 14 days after the reading was taken i had consumed 100 units by straight maths by adding my total units during month should not have been more than 250 units or make it 300 units......Then after asking other people i have come to know that what they do is they charge u less units for few months for example u consumed 300 units but they will send u bill for 200 units then next month again they will send u bill for 200 units whereas u have consumed 300 units ..in this way during 2 months u consume 600 units but you pay for 400 (meter reading will show more but as we get less bill we donot care).... Now when the third month comes meter reader apply this formula usual units consumed are 300 + your balance 200 units +advance few units about 50 ..... what happens now is that u pay for ur balance and adavance units at higher slab rate of 10/unit which other wise would have costed u 4 or 5 rupess per unit........while putting these advance units and balance unit meter reader make sure that when bill comes to you next month about 10 days later and you check ur meter it will show you atleast the same reading as mention on bill .... first 100 u pay 4/units next 200 unit=5/unit next 300 unit=10/unit

Today for month of feburary i have received bill showing i consumed 613 units...meter reading date is 19 feburary and by looking at meter on 4 march i have seen that i have consumed 20 units in 14 days since meter reading(that cannot be true) ....i was certainly not drilling oil well last month (613 units)....in jan my units

Figure 1.6 Beware of WAPDA meter readers (9)

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Corruption by the wapda

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I want to draw the attention of the government toward malpractice of the wapda meter readers who are doing corruption. The wapda meters in big and small cities of country have become notorious for cheating and fraud. They enjoy great power and discharge of their duty and they don't visit the premises of a house, factory, hospital or any other places. In this way, they help the people in stealing electricity which is too common in small cities and villages . I request to the concern authorities to stop wapda people doing corruption and punish them as well.

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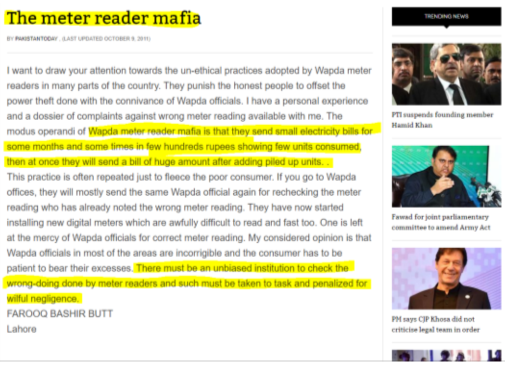
MAHNOOR RAHMDIL,

Makran, July 10.

Figure 1.7 Corruption by the WAPDA (10)



The meter reader mafia

BY PAKISTANTODAY , (LAST UPDATED OCTOBER 9, 2011)

I want to draw your attention towards the un-ethical practices adopted by Wapda meter readers in many parts of the country. They punish the honest people to offset the power theft done with the connivance of Wapda officials. I have a personal experience and a dossier of complaints against wrong meter reading available with me. The modus operandi of Wapda meter reader mafia is that they send small electricity bills for some months and some times in few hundreds rupees showing few units consumed, then at once they will send a bill of huge amount after adding piled up units. .
This practice is often repeated just to fleece the poor consumer. If you go to Wapda offices, they will mostly send the same Wapda official again for rechecking the meter reading who has already noted the wrong meter reading. They have now started installing new digital meters which are awfully difficult to read and fast too. One is left at the mercy of Wapda officials for correct meter reading. My considered opinion is that Wapda officials in most of the areas are incorrigible and the consumer has to be patient to bear their excesses. There must be an unbiased institution to check the wrong-doing done by meter readers and such must be taken to task and penalized for wilful negligence.

FAROOQ BASHIR BUTT

Lahore

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Figure 1.8 The meter reader mafia (11)

To solve the issue that is caused by the meter reader, a solution has been introduced in this project to reduce the fraud. This solution unlocks the potential for image matching regarding fraud detection techniques. In this solution, the image captured by the meter reader previously will be used as a database. A newly taken photo will be inserted into the system and it will be compared with previous database to ensure the image of the meter is matched with the same meter category in the database. Else, if the image does not match, further investigation will be done by the company. By this action, the manipulation of reading by meter reader could be reduced. In the meanwhile, the losses of the cost from power generation for the utilities company can be reduced as well.

1.2 Motivation

To detect the fraud done by the meter reader, human effort is needed. Since there is no such system is able to process all the data inside the database of the company for this type of fraud detection issue. Only by manual comparison between a new image with a previous image inside the database is able to detect the fraud as of now. By using manual fraud detection effort, it is time-consuming to do the image comparison. Lastly, there a thousand of photos that needs to compared day to day since there will be 6 million number of total customers for 13 different districts (12).

1.3 Problem Statement

The following are the problems of this research:

(a) The meter in this industry looks almost similar from one to another. Thus, it is hard to differentiate between meter and meter.

(b) The image is taken with a different angle, rotational, zoom range (scale), crop, lighting, and position. This will cause an issue for image matching.

1.4 Research Objectives

The objectives of this research are:

(a) To propose a method to enhance the fraud detection of meter reading based on meter images.

(b) To design a meter classification system that reduces the complexity of image comparison.

(c) To propose a method on better image detection technique with large data set for consumers.

1.5 Research Scope

Regarding to the scope for this project, the data set of the meter image used in this project is provided by Multan Power Company (MEPCO). From the image provided by Multan Power Company (MEPCO) there are 230,599 images. These 230,599 images represent 39,186 different customers in 13 districts. From these 230,599 images, 4,500 images will be selected for the training in this project and there would be about 48 different categories of data set after the image categorization is done. Next, Transfer learning will be used in this project to reduce the training time as well as increase the accuracy of the model. The training is done offline by using an online tool named "Google Colab". Offline here represent offline model training.

1.6 Proposed Method

As of now, the power utility company (MEPCO) does not have such a system to detect the fraud made by the meter reader, where the power utility company only makes sure that the meter reading from the image is the same as what the meter reader reported. There is no such method to detect if the meter reader changes the meter value by replacing the image of the meter along with the meter value as discussed in Chapter 1.1 above. Thus, in this section, a method is proposed that is able to help the power utility company (MEPCO) to detect the fraud made by the meter reader.

The picture captured by the meter reader will be fed into the algorithm. The system would have the ability to differentiate between different categories of meter types. If the correct picture falls into the same correct category for that customer, then the fraud would be low. Figure 1.9 below shows a simple example of the algorithm that is able to ease the explanation. In Figure 1.9 below, show some of different meter category that able to be differentiated easily. Where the left side of the image is the image that is being fed into the algorithm and right side is the image that has been allocated in the data based. Some comparison is done for the algorithm to select the correct category of meter. With the meter fall into the same category, then the fraud would be low.

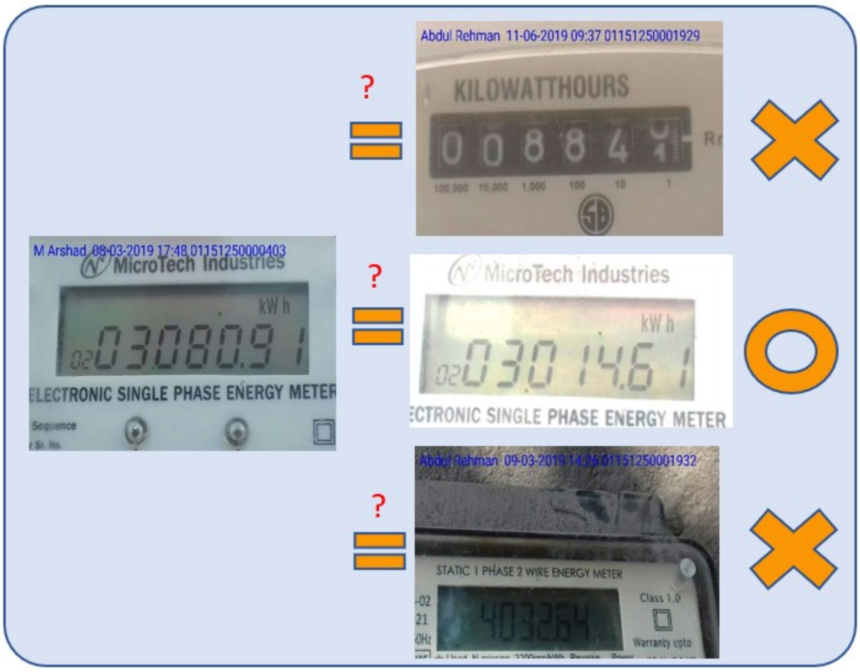

Figure 1.9 Simple example of fraud detection

Figure 1.10 shows the real case example of the fraud that could be done by the meter reader. Based on the diagram shown in Figure 1.10 the top part of the diagram shows the normal condition without fraud occur and the bottom part shows the example of fraud condition. based on the image from left to right is the picture taken by the meter reader from Feb to June. The image inside the red box represents the picture that is newly captured by the meter reader in July as an example. Where in the Normal Condition the expected meter reading would be 937.1 units. If the meter reader had been corrupted, they could replace the images of the meter with lower meter reading from other houses as shown in the red box of fraud condition with the meter reading value of 786.0 units. With the change of meter reading value able to help the customer to save about 187.1 units of electricity. Thus, the customer only needs to pay the utilities bill at a lesser price. Since the image looks alike, thus it is hard for a human to detect the fraud. Figure 1.11 below shows the larger view of the images from the red box in Figure 1.10. In Figure 1.11, there was some annotation to show the differences between the images. If there is no annotation shown, then the difficulty of differentiation the meter would be hard with using human eye. Imagine if there were millions of images to compare then will be a troublesome task.

Figure 1.10 Actual Condition of fraud detection

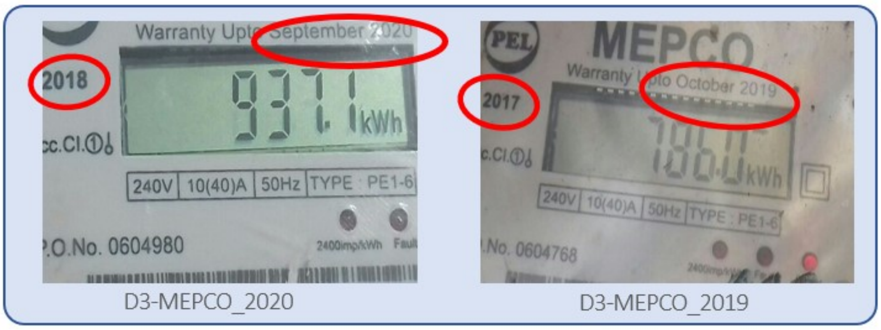

Figure 1.11 The differences between the image from the red box in Figure 1.10

With this proposed method the fraud able to be reduced but not eliminated. This proposed method is not perfect, but this method could able to detect the overall fraud caused by the meter reader. This proposed method is useful because MEPCO will have about 13 districts and approximately 34 million image comparisons that needs to be done by MEPCO's worker manually every month to detect the fraud. As information, until now Malaysia has only 32 million of population (13). Assume, if there is 22 days per month excluding Saturdays and Sundays there would be averagely 1.5 million of images that needs to be compared by the MEPCO's worker per-day to detect fraud for 34 million images.

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