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GUI-Based Maintenance Reporting System for Electrical Substations Integrated with PyTesseract OCR

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PyTesseract, Optical Character Recognition, Region of Interest, maintenance report, temperature monitoring, Graphical User Interface.

Abstract

This work focuses on developing a graphical user interface (GUI) system integrated with Optical Character Recognition (OCR) for generating electric substation maintenance reports. The main goal is to automate the process of extracting temperature data from thermal images captured during Condition-Based Monitoring (CBM) tasks using FLUKE equipment. PyTesseract, an OCR engine in Python, reads annotated temperature values such as SP1, SP2, and AVG from the thermal images. The GUI is developed using Tkinter and OpenCV, allowing users to load images, perform OCR on the whole image or by selecting a Region of Interest (ROI), and validate extracted readings. The validated data is then inserted into a structured table and exported into a Microsoft Word report. Evaluation shows that ROI-based OCR significantly improves accuracy compared to whole-image OCR. This system offers a more efficient, user-friendly, and accurate approach for substation data reporting, reducing human error and improving documentation speed for maintenance workflows.

1. Introduction

Condition monitoring is one of the preconditions of condition maintenance. As an important part of secondary equipment condition monitoring, visualization can provide an effective user interface for operating staff to view warnings and a supplementary means to eliminate defects [1]. This project focuses on the development of a GUI-based application that automates the process of temperature data entry from thermal images used in electrical substation maintenance. Substations, including normal, pole-top, compact, and outdoor types, require regular inspection, often involving thermal imaging to detect potential faults. Traditionally, data such as SP1, SP2, and AVG temperature readings are manually extracted from thermal images captured by devices like the FLUKE Ti480 and transferred using Smart View software. However, this manual process is time-consuming and prone to errors. To address this, the project integrates Optical Character Recognition (OCR) using Pytesseract within a custom-developed GUI, allowing for automated detection of temperature values from the entire image or selected regions of interest (ROI). The extracted data is then compiled into a Microsoft Word-based maintenance report, significantly improving reporting speed, accuracy, and efficiency for Condition-Based Monitoring (CBM) under Tenaga Nasional Berhad (TNB) standards.

2. Literature Review

Condition monitoring is important because it provides a clear and continuous process for measuring the health and performance of critical business assets in real time [2]. CBM involves real-time monitoring of equipment condition using diagnostic tools like thermography. Thermal image acquisition devices play a crucial role in ensuring the safety and efficiency of electrical substations. FLIR T1020 [3], Testo 885 [4], Hikmicro M30 [5], FLUKE Ti480 PRO [6] are the equipment that have been used in the thermography testing. Thermographic images detect hotspots and abnormal heating, which signal potential failures in substation components like transformers or cable joints.

2.1 Optical Character Recognition (OCR)

Optical character recognition has become one of the most successful applications of technology in the field of pattern recognition and artificial intelligence [7]. OCR is a technology that converts scanned images of text into machine-readable data. OCR services are widely available to the public. For example, Google Cloud Vision OCR can be used to scan and store documents on a smartphone [8]. PyTesseract is a Python wrapper for Google's Tesseract engine, enabling OCR integration into custom applications. Previous studies show OCR can be effective for temperature reading extraction when combined with preprocessing techniques like thresholding and grayscale conversion.

2.1.1 OCR for Thermal Imaging

Optical Character Recognition (OCR) for thermal imaging combines image processing and text recognition techniques to extract meaningful information from thermal images. These images, often used in industrial and maintenance applications, capture temperature data and annotations critical for diagnostics and reporting. Table 1 shows the comparison of OCR for thermal imaging.

Table 1 Comparison of OCR for thermal imaging

Ref	Year	Methods	Advantages	Disadvantages
[9]	2011	Thermal images are converted to grayscale to isolate text (e.g., temperature scales) from other visual elements.	Eliminates the need for manual input of temperature scale data, saving time and reducing errors.	The temperature value for a specific hotspot is not displayed in the output image.
[10]	2010	Uses OCR scripts to extract temperature scale limits by comparing characters to predefined templates.	Handles images without metadata, avoiding multiple format storage.	OCR may misinterpret characters in low-resolution or poor-quality images.
[11]	2010	Utilizes OCR scripts to process BMP-format thermal images without metadata, isolating temperature scales for analysis.	Easily modifiable to accommodate additional requirements or handle diverse image formats in the future.	The current implementation supports only BMP and requires updates for formats like JPEG or PNG.

2.2 GUI development with Tkinter

wxPython is a cross-platform GUI toolkit for the Python programming language. It allows Python programmers to create programs with a robust, highly functional graphical user interface, simply and easily [12]. Kivy is an open-source Python framework designed for building multitouch applications and supports cross-platform development for mobile and desktop [13]. PyQt is a set of Python bindings for the Qt application framework, a popular choice for creating desktop applications. PyQt is known for its flexibility, extensive features, and robustness. It is suitable for large projects and professional applications [14]. Tkinter is Python's standard GUI toolkit, known for simplicity and efficiency in developing desktop applications [15]. It supports integration with OpenCV for image handling and PyTesseract for OCR, making it a suitable platform for this project. Table 2 shows the comparison of GUI development tools.

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Table 2 Comparison of GUI development tools

Software	Ease of use	Customization	Platform Support	Best use case
PyQt	Moderate	High	Desktop only	Large-scale application
Kivy	Moderate	Moderate	Cross-platform	Mobile apps
wxPython	Moderate	High	Desktop only	Native desktop apps
Tkinter	High	Low	Desktop only	Small, simple project

3. Methodology

The maintenance report generation process is a key part of condition-based monitoring (CBM) in substations and is aimed at automating the extraction of temperature readings from thermal images. A self-developed Graphical User Interface (GUI) was created using Python, which integrates Optical Character Recognition (OCR) through PyTesseract and allows Region of Interest (ROI) selection. The system provides three main approaches: full image OCR, ROI-based OCR, and manual data entry.

Fig. 1 illustrates the complete operational workflow of a self-developed Graphical User Interface (GUI) system for automating the extraction and reporting of thermal temperature data in electrical substations using OCR (Optical Character Recognition). The process begins with launching the GUI, selecting an annotated thermal image, displaying it within the interface, and executing an OCR process on the entire image. If all temperature values—SP1, SP2, and AVG—are detected accurately, the process continues to generate a maintenance report in Microsoft Word format. This includes tabulating the extracted values, saving the data, and completing the report generation. However, if any of the values are missing or incorrectly detected, the user is given the option to use the ROI (Region of Interest) method. Through ROI, the user manually selects specific areas (SP1, SP2, or AVG) on the image to re-perform OCR within that region, helping to reduce noise and improve detection accuracy. If OCR still fails to detect the value, the user may manually input the correct reading. The verified or corrected values are then tabulated. This ROI selection and correction loop continues until all required values are obtained. Alternatively, if the user opts not to use ROI, they may proceed directly to manual data entry. Once all values are collected, either through full-image OCR, ROI-based OCR, or manual entry-the final step involves compiling the results and generating a complete Word report. This flexible and systematic flow ensures a more accurate, efficient, and user-friendly method for generating maintenance reports from thermal images.

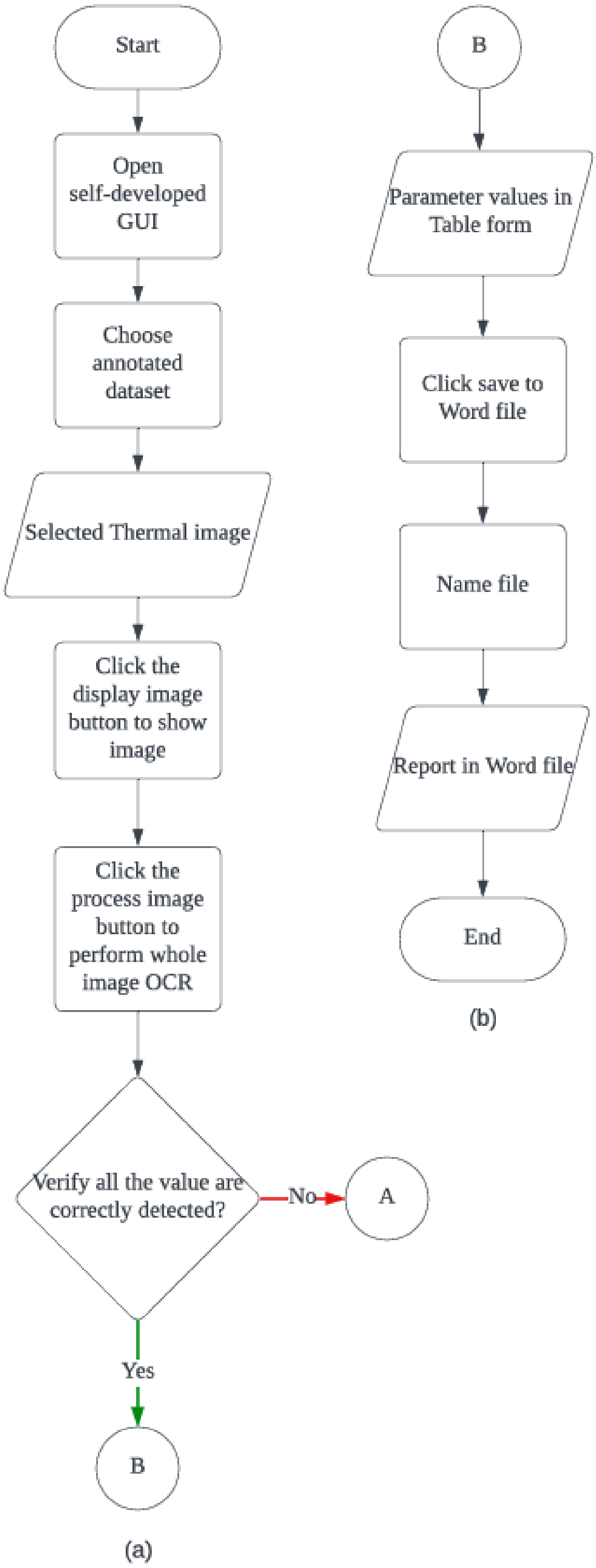


Fig. 1 *Flowchart of the developed system*

(c)

Fig. 1 *Flowchart of the developed system* (*continued*)

4. Results and Discussion

The experimental results and system performance of the developed OCR-based maintenance report system using Tesseract OCR and a custom-built GUI. The analysis covers three main stages: full image text extraction, Region of Interest (ROI)-based verification, and manual correction. The evaluation was conducted using annotated thermal images, focusing on accuracy, speed, and correction capability. The results reveal that the system effectively digitizes maintenance data and performs reliably, especially in handling low-contrast text. However, the findings also highlight areas for improvement in processing complex layouts, reinforcing the system's potential for real-world industrial maintenance documentation.

4.1 Development of an OCR-Based Data Entry GUI for Thermal Images Inside an Electrical Substation

Fig. 2 shows the result of a GUI self-developed interface, which consists of buttons to perform a temperature data extraction with a method of processing the whole image, ROI process, data manual entry, and report generation. Furthermore, the interface also consists of image preview, extracted text, and table preview.

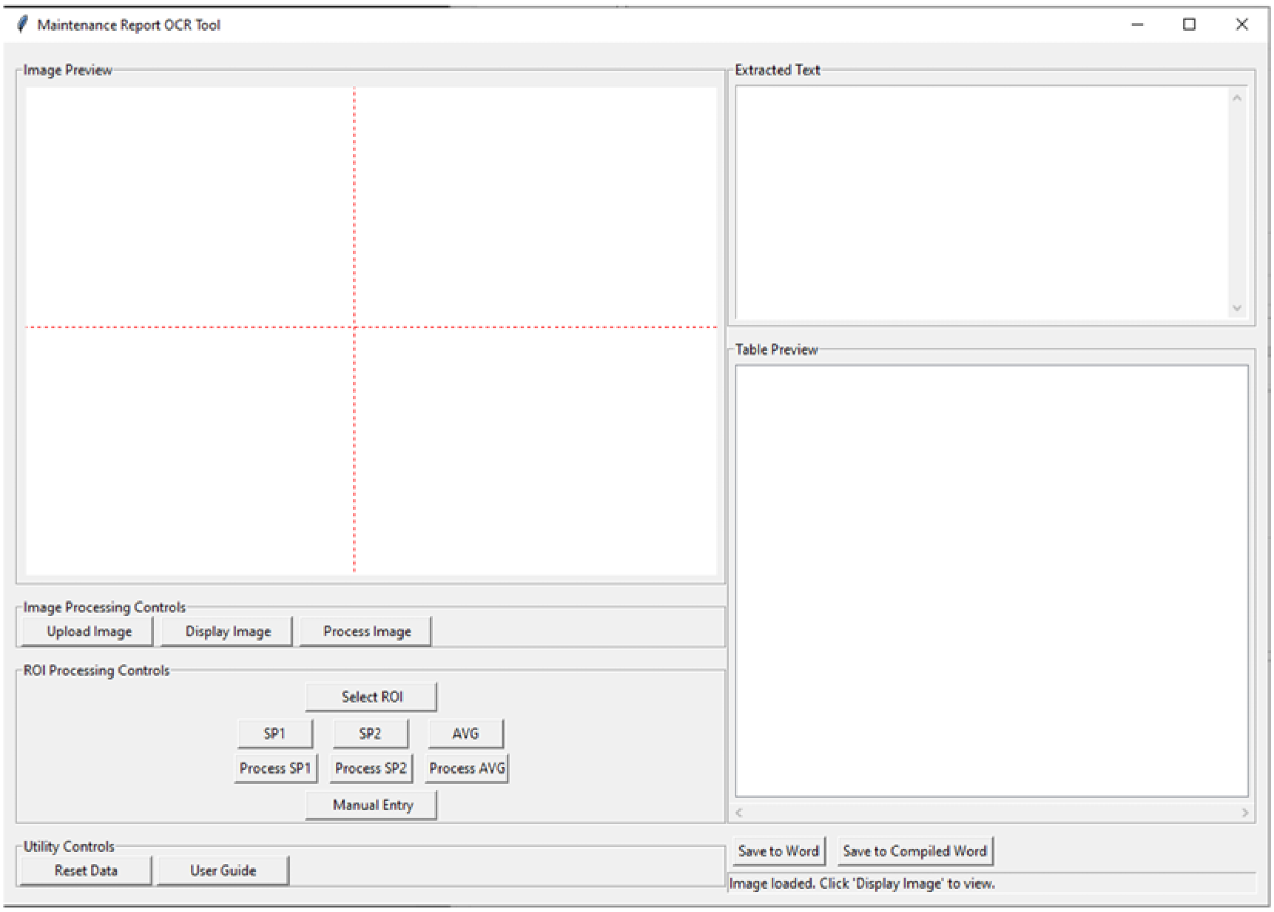
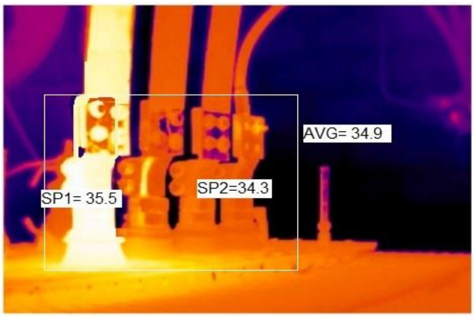
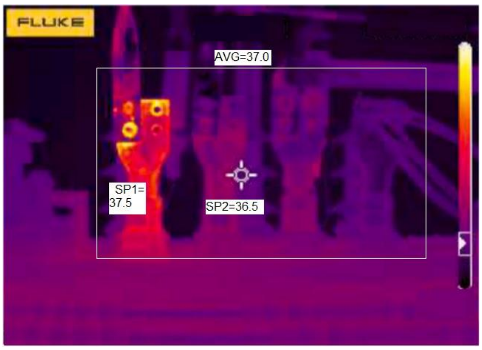
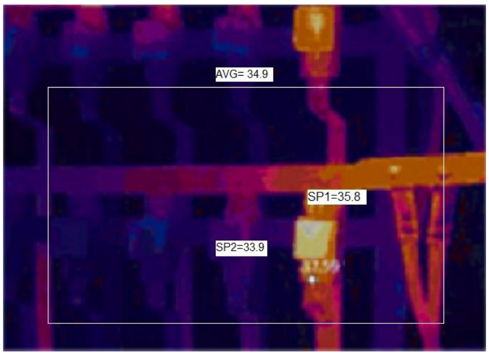
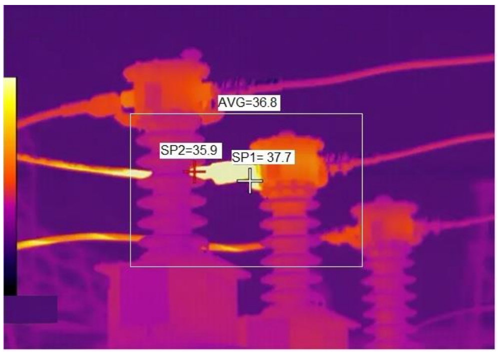


Fig. 2 *Interface of the developed GUI system*

4.2 Application of the PyTesseract OCR Technique for Whole Thermal Image and ROI

Discussing this part, we can provide the result of the usage of the OCR technique on the whole thermal image without any selection of a particular area. The aim is to see how the specific system works at automatically noticing and extracting the temperature readings of SP1, SP2, and AVG in the original image with the help of PyTesseract. A sample thermal image was tested, and the result of the detection is indicated in Table 3, where (✓) indicates the successful detection and (✕) the failure to detect the annotated values. The results show that not all three values could have been successfully extracted in both images, stating some of the limitations of the entire image OCR method. 40 thermal images were tested to examine the detection accuracy.

Table 3 *Example of OCR for whole image analysis*

Thermal Image	SP1 (Detected ✓/ Not detected ✕)	SP2 (Detected ✓/ Not detected ✕)	AVG (Detected ✓/ Not detected ✕)
	✕	✕	✕
	✕	✕	✕
	✕	✕	✕
	✕	✕	✕
Total of detection	9/40	9/40	15/40

This section focuses on evaluating the performance of OCR when applied to specific Regions of Interest (ROI) within thermal images, rather than processing the entire image. By allowing the user to manually select the exact locations of SP1, SP2, and AVG, this method helps minimize background noise and improve text detection accuracy. The table below presents the results of the ROI-based OCR process, where each parameter is assessed for successful detection (✓) or failure (✕). The results show noticeable improvement in accuracy, especially in cases where whole image processing previously failed to detect the values. Table 4 shows an example of OCR for selected ROI analysis.

Table 4 *Example of OCR for selected ROI analysis*

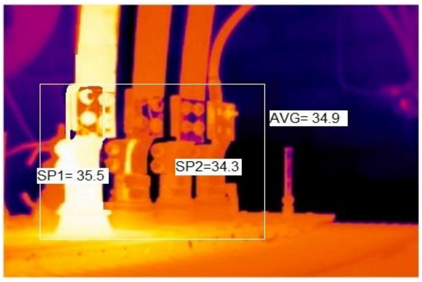
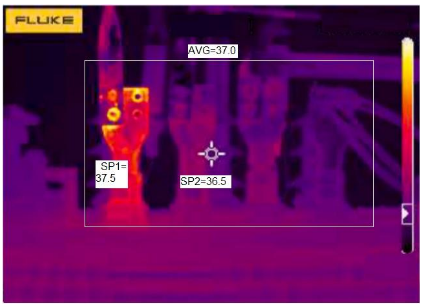
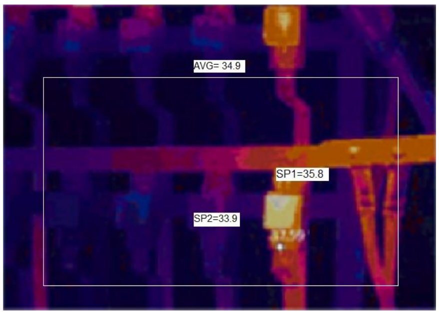
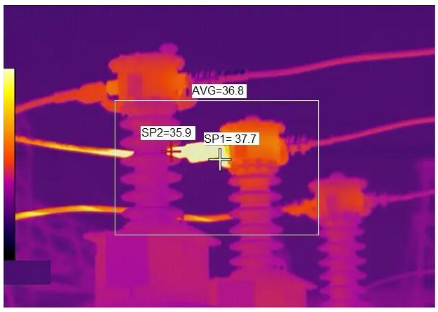
Thermal Image	SP1 (Detected ✓/ Not detected ✕)	SP2 (Detected ✓/ Not detected ✕)	AVG (Detected ✓/ Not detected ✕)
	✕	✓	✕
	✓	✓	✓
	✓	✓	✓
	✓	✓	✓
Total of detection	17/40	17/40	34/40

Table 5 presents a comparative analysis between two OCR processing methods: full-image processing and region of interest (ROI)-based processing. For full-image OCR, the accuracy for SP1 and SP2 was relatively low at 22.5% each, while the AVG detection reached 37.5%. The overall average detection accuracy for this method was calculated at only 27.5%, indicating limitations in handling complex backgrounds, thermal gradients, or text distortion across the entire image.

In contrast, the ROI-based OCR approach demonstrated a substantial improvement in detection accuracy. SP1 and SP2 both recorded 42.5%, while the AVG accuracy reached 85%, resulting in a significantly higher average detection accuracy of 56.67%. This improvement confirms that isolating specific regions helps reduce background noise and enhances the precision of text extraction, making the ROI technique more reliable for thermal image interpretation.

Table 5 *Comparison between the whole image and the selected ROI OCR result performance*

	Accuracy	SP1	SP2	AVG
(*OCR for whole image*)	Individual Accuracy (*OCR for whole image*)	22.5%	22.5%	37.5%
	Average Detected Accuracy [(Accuracy(SP1) + Accuracy(SP2) + Accuracy(AVG)) / 3]		= 27.5%	
(*OCR for selected ROI*)	Individual Accuracy (*OCR for selected ROI*)	42.5%	42.5%	85%
	Average Detected Accuracy[(Accuracy(SP1) + Accuracy(SP2) + Accuracy(AVG)) / 3]		= 56.67%	

4.3 Conversion of the Image and Extracted Data into a Report in Microsoft Word Format

The final phase of the application involves converting both the thermal image and its corresponding extracted temperature data into a comprehensive Microsoft Word (.docx) report. This process is executed automatically through the integrated GUI, which compiles the original thermal image, the OCR-detected values for SP1, SP2, and AVG in a structured table, and the full OCR output text for traceability. By automating this step, the system significantly reduces the need for manual data entry and documentation. It ensures all critical temperature readings are recorded accurately and uniformly, which is essential for condition-based monitoring and future reference. This streamlined reporting method enhances both the efficiency and reliability of substation maintenance documentation. Fig. 3 shows an example of the result of "Save to Compiled Word".

5. Conclusion and Recommendations

In conclusion, this project successfully developed a GUI-based OCR system using Pytesseract to extract temperature data (SP1, SP2, and AVG) from thermal images captured in electrical substations. The system supports full-image OCR, ROI-based extraction, and manual data entry, offering flexibility and efficiency in preparing maintenance reports. The accuracy comparison between methods showed that ROI-based OCR achieved higher detection accuracy (averaging 56.67%) compared to the full-image OCR, which averaged only 27.5%. These results validate the use of targeted ROI selection to enhance detection reliability, especially under complex thermal image conditions. Other than that, users have another alternative option by using the data entry manually entering the parameter. Results showed that ROI-based processing significantly improved detection accuracy compared to full-image OCR. The final output, compiled into a Microsoft Word report, aligns with the standard reporting format. For future improvements, it is recommended that alternative OCR engines like EasyOCR be integrated, preprocessing techniques enhanced, ROI selection automate, database storage is supported, batch processing is enabled, and mobile deployment is considered. These enhancements can further increase the system's reliability, usability, and scalability for real-world maintenance operations.

Maintenance Report Data

Source Image

Measurement Results

Parameter	Value
SP1	35.5
SP2	34.3
AVG	34.9

Source Image

Measurement Results

Parameter	Value
SP1	37.5
SP2	36.5
AVG	37.0

Fig. 3 *Example of the Result of "Save to Compiled Word"*

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Hazli Roslan, Siti Zarina Mohd Muji;* ***data collection:*** *Irfan Hadi Ismail;* ***analysis and interpretation of results:*** *Irfan Hadi Ismail, Suhaila Sari, Nik Shahidah Afifi Md Taujuddin;* ***draft manuscript preparation:*** *Irfan Hadi Ismail, Suhaila Sari. All authors reviewed the results and approved the final version of the manuscript.*

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