Testing ChatGPT with Photovoltaic Electroluminescence Image Analysis

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Abstract: Photovoltaic electroluminescence (EL) testing is one of the most effective methods for assessing the condition of solar panels. The process of analysing a large number of samples requires the application of artificial intelligence (AI). In recent years, many experiments using machine learning have been carried out. ChatGPT is basically a language model developed for conversation and communication. At the same time, it is also suitable for recognizing and studying images. The main goal was to teach the identification of completely inactive photovoltaic cells. The learning methodology was built up from increasingly difficult trials and tests. By the end of the process, the AI demonstrated improvement, as it was able to identify more defective cells.

Keywords: ChatGPT; electroluminescence; photovoltaics

1 Introduction

In recent years, many methods for assessing the condition of photovoltaic (PV) panel systems have been developed. These can be divided into in-situ and ex-situ groups. The advantage of in-situ, i.e., on-site, condition assessments without dismantling or intervention, is that they minimally influence the operation of the system. Thermographic error detection can be considered such a method. During the ex-situ condition assessment, by dismantling the system, the system components can be subjected to further tests, which in laboratory conditions give an accurate and detailed picture of the cause and extent of the failures. Multiple field audits and reliability reports indicate that a large share of PV projects in operation exhibit issues that warrant corrective action, while module-level inspections frequently report double-digit defect rates. For example, a 2025 industry audit found major issues in 85% of projects [1], and a thermographic survey of 3.3 million modules reported 36.6% defective modules [2].

To capture a PV electroluminescence (EL) image, the silicon layer of the PV panel must emit light instead of absorbing it. This is achieved by applying voltage to the module during the test, which causes current to flow, so the module operates as a consumer instead of a generator. Today's increasingly popular LED light sources emit visible light when operated as consumers, but the silicon cells of PV panels emit near-infrared radiation that is invisible to the human eye. Detecting defects in PV cells requires a camera that detects this radiation and makes it visible. Functional (bright) and non-functional (dark) cell regions can be clearly distinguished in such recordings [3-5].

High-resolution cameras are required to detect narrow microcracks. When the resolution is high, a single image may suffice to show the entire module. For lower resolutions, the camera moves across the panel using a scanning mechanism, capturing several images that are later stitched together by software. Alignment errors and other artefacts may occur during this process, degrading image quality. Modern equipment often includes software-based image analysis and defect detection capabilities [6] [7].

Electroluminescence testing provides a detailed and vivid picture of the condition of an entire PV module. However, analysing large EL images can be a time-consuming process for human experts. This raises the question of whether artificial intelligence could assist in this task. ChatGPT, a large language model developed by OpenAI, was selected for the study. The model is based on the Generative Pre-trained Transformer (GPT) architecture, a deep neural network designed for text generation. ChatGPT can engage in real-time communication with humans through natural language processing and text generation. It has been applied across diverse fields, including mechanical, medical, economic, and social research [7] [8].

ChatGPT learns from extensive text databases, recognising patterns and contexts to provide relevant and meaningful responses. It is useful in areas including e-commerce, marketing, education, programming, translation, research, and entertainment. Nevertheless, it is important to note that ChatGPT's responses may be biased, as its training data are created by humans. It may generate inaccurate or misleading content and should not replace human judgment. ChatGPT remains under active development, and its results should be interpreted critically [9] [10].

Although convolutional neural networks (CNNs) are generally the most suitable tools for image analysis tasks such as electroluminescence image evaluation, our research was conducted within a short university project aimed at exploring how the use of ChatGPT might influence academic research and education. Within this framework, the idea emerged to test whether ChatGPT, primarily a language-based model, could interpret visual data when presented with EL images and to evaluate the nature of its responses. This unconventional approach served as both a technical experiment and an educational example of how AI tools can be applied creatively in academic contexts.

2 The First Conversation with ChatGPT

Currently, one of the biggest challenges is that the language used by users is accurately understood by AI algorithms and gives the best answer. One of the terms that users need to understand is prompt engineering. A prompt is the input or instruction that we feed into the language model to get the best answer. The more specific and nuanced our prompt is, the better solution (answer) we will get from the system. The answer can be text, image, sound, video or even a line of code. Prompt engineering is the process of designing how to best instruct the language model, providing appropriate context and guidance. The more detailed and specific the input we provide, the better the answer we get [11] [12].

During the first conversation, we showed an EL image (Figure 1) that we made in a laboratory of the University of Miskolc with a modified Nikon Coolpix B700 digital camera. We then asked ChatGPT what it knew about PV electroluminescence.

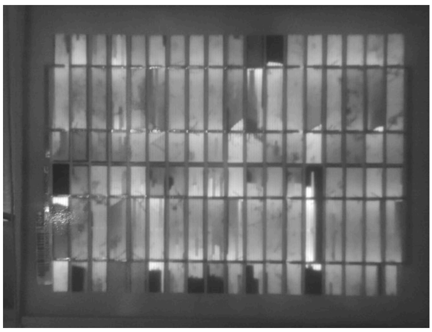


Figure 1

EL image of an average defective PV panel

ChatGPT immediately recognized that the attachment was an EL image of a PV panel. It added a small textual explanation related to the picture, how it should be made, and how it should be interpreted. After that, we asked what else it knew about the EL test. The AI provided a much more detailed answer, in which, among other things, it presented the most common types of PV cell failures.

We continued the conversation with Scholar GPT. Scholar GPT is a specialized version of ChatGPT tailored for academic and research-focused tasks. While basic ChatGPT handles general conversational tasks, Scholar GPT is equipped with advanced tools for scholarly research, data analysis, academic writing, and searching for academic papers.

In several test cases, we instructed ChatGPT to find a limited number of defective cells instead of all of them. This approach was intentional: our aim was not to achieve full defect detection accuracy but to evaluate how ChatGPT's comprehension and precision evolved with increasing task complexity. The focus of the study was therefore on the learning process and communication refinement rather than comprehensive image segmentation.

2.1 ChatGPT's Knowledge in the Field of Photovoltaic Electroluminescence

ChatGPT has broad knowledge in the field of PV electroluminescence. The AI already knew that the brighter areas suggest good material quality and uniformity (Figure 1), which generally indicate a well-functioning cell. However, it is important to perform a detailed analysis to confirm the absence of defects such as cracks, shunts, or other irregularities that could affect the cell's performance. The uniform brightness and the natural appearance of crystal grains without dark spots or irregular patterns are positive signs. In the EL image shown in Figure 1, dark regions typically correspond to areas where the cell is not emitting infrared radiation effectively, which can be due to several reasons:

- Inactive Areas: Portions of the cell might be inactive due to issues like poor material quality, broken connections, or shunting.
- Cracks or Microcracks: These defects can severely impact the performance by interrupting the current flow, leading to localized inactive regions.
- Shunts: These are pathways that allow current to bypass parts of the cell, leading to reduced overall efficiency and dark areas in EL images.
- Degradation: Over time, solar cells can degrade due to environmental factors or material fatigue, leading to reduced performance as seen in darker EL images.

In electroluminescence (EL) imaging of Figure 1, this kind of dark image typically indicates that the cell is not emitting any significant infrared radiation (inactive), which means it is not generating electricity effectively. There are several possible reasons for this:

- Complete Electrical Disconnection: The cell might have lost electrical contact entirely, meaning no current is flowing through it.
- Severe Material Degradation: The cell materials could be so degraded that they no longer support proper electron flow.
- Major Shunting: There could be significant shunts that are causing the current to bypass the cell entirely, resulting in the lack of luminescence.
- Cracking or Fracture: If the cell is physically damaged, such as by cracking, this could disrupt the entire cell's functionality.

2.2. Application of ChatGPT to Analyse Photovoltaic Electroluminescence Images

ChatGPT can provide support in several aspects of solar EL image analysis:

Preprocessing EL Images: This includes noise reduction, contrast enhancement, and image normalization to prepare the images for further analysis.

Defect Detection and Classification: Using image processing techniques or machine learning models to identify and classify defects in solar cells.

Quantitative Analysis: Measuring the size, area, and intensity of defects to quantify their impact on the solar cell's performance.

Visualization: Creating visual representations of the defects and their distribution across the solar cell or module.

Automation: Implementing automated scripts or workflows for processing large sets of EL images.

Subsequently, we attempted to apply the AI for image analysis, but it did not perform successfully. We shared another EL image that contained inactive cells, and we asked in the instructions to mark the inactive cells on a generated image. Figure 2 shows that the AI did not correctly identify the inactive cells when the panel was divided into 10 columns and 6 rows [13-15]. The cell locations were marked by the AI: B2, C1, D3, D4, H5 and H6. However, the true location of inactive cells is A2, B2, C3, D4, I3 and J6. Only B2 and D4 were correct answers. The percentage of correct answers was 33.34%.

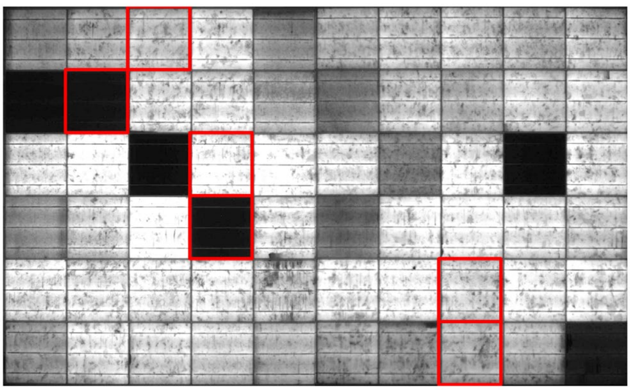


Figure 2
The result of the first image analysis

3 The Training Process for Examining EL Images

For training purposes, Figure 2 was divided into smaller sections to improve the AI's performance. In the first step, we showed standard examples for both fault-free and inactive cells. Then we showed small images consisting of 4 cells. After that, bigger pictures, which consisted of 9 cells. We made sure that the AI received precise instructions. Additionally, it received feedback for both correct and incorrect answers. At the end of the training process, the AI had to analyse an even larger image consisting of 15 cells.

3.1 Trial Testing

In the first step of the teaching process, we showed the AI pictures of three fault-free, functional PV cells (Figure 3). Each image was accompanied by a brief instruction describing that fault-free cells appear bright in EL images. In the images we captured, fault-free cells are characterized by mostly white and grey tones. Crystal grains can be observed on it, the occurrence of which is natural in EL images. Also, the busbars can be observed (three horizontal lines inside the cell in the pictures), which are essential to produce electricity and the progress of the electric current. Scholar GPT analysed the images and interpreted the information attached to the images [16] [17]. It repeated them in text, indicating the successful interpretation and processing of the data.

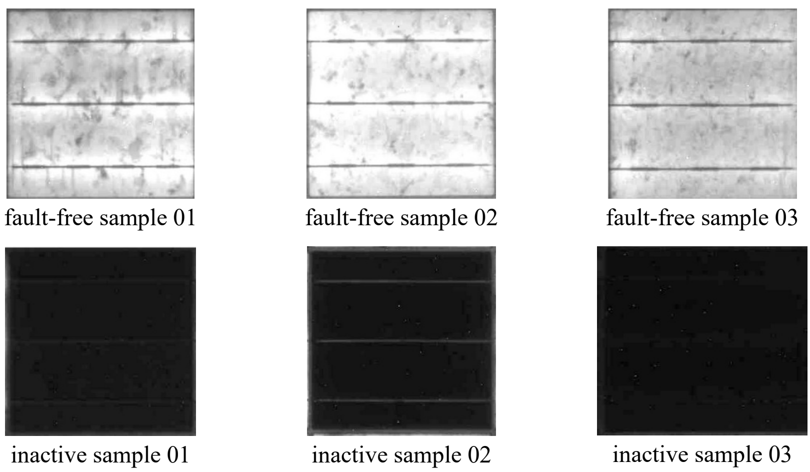
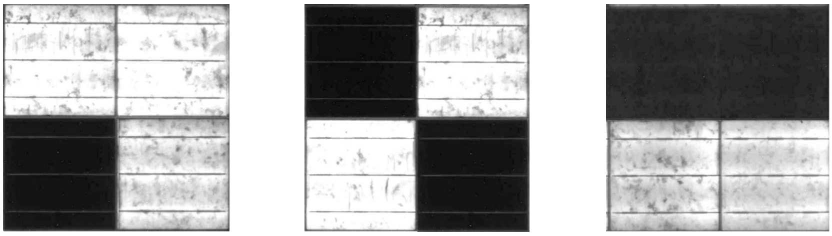


Figure 3
Images of error-free and inactive cell samples for identification

In the next step, we showed the AI a picture of the three completely inactive, non-functioning PV cells (Figure 3). For the images, Scholar GPT has been given a text description such as that non-functioning cells are dark, mostly characterized by black colour. Typically, no other distinguishing features can be observed in the continuous homogeneous black area. There may be cases when the image of the busbars can be discovered. Scholar GPT analysed the images and interpreted the information attached to the images. It repeated them in text, indicating the interpretation and processing of the data.



trial sample 01 trial sample 02 trial sample 03

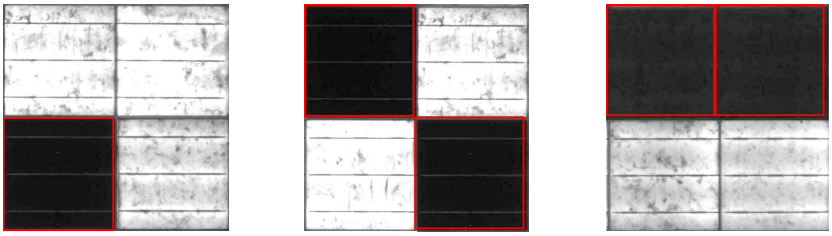
Figure 4
Samples of the trial testing

In the third step, the pilot test could begin. Three EL images were selected for image analysis with ChatGPT. The main aspect of the selection was that the AI could detect the difference between inactive and fault-free cells. Three trial images were analysed (Figure 4). The trial samples are actually image fragments, which are structured in the same way in each case. They consist of four cells in two columns (A and B) and two rows (1 and 2). In all three trial test images, a different pattern can be observed regarding the position of error-free and inactive cells. Since the purpose of the application of AI is to find errors and analyse EL images, the instructions were aimed at identifying inactive cells in all three cases.

In the first trial image, the location of the faulty cell is A2. This sample was easily analysed by Scholar GPT. It should be emphasized that the textual instruction revealed that only one of the four cells is completely inactive. The AI had to look for a completely black cell and found it. The AI generated an image on which the location of the inactive cell was marked with a red square, as well as justified and provided the solution in text.

The second trial test sample already contains two completely inactive cells. In the text instruction, it was only highlighted that in this case the AI must find more faulty cells. We did not mention the exact number of inactive cells. After analysing and processing the image, the AI again gave a textual justification and determined the location of the two faulty cells, which are A1 and B2. The AI generated another image, on which it perfectly marked the location of the inactive cells with red squares.

The third trial test sample, like the second one, contains two completely inactive cells. In the text instruction, it was again emphasized that in this case too, the AI must find several defective cells. We did not mention the exact number of inactive cells. After analysing and processing the image, the AI again gave a textual justification and determined the location of the two faulty cells, which are A1 and B1. The AI generated another image, on which it perfectly marked the location of the inactive cells with red squares in Figure 5. The trial tests were successful overall, in all three cases the AI correctly entered the location of the inactive cell or cells in text form on the first try. In all three cases, Scholar GPT generated an image that accurately marked and determined the position of the inactive cells. At the same time, the AI answers served as positive feedback, according to which all instructions were well explained during the learning process so far.



1st trial test result 2nd trial test result 3rd trial test result

Figure 5
Results of the trial testing

3.2 Analysing More Complex Images

At this point, we thought the AI was ready to be given one level more difficult tasks. The three samples of the first serious analysis were built from 9 and 15 cells (Figure 6 and 7). In the next two samples, the PV cells were arranged in three columns (A to C) and three rows (1 to 3). We continued to strive for the AI to encounter patterns where there is a significant difference between black, defective and light cells. A similarity can be discovered between the sample intended for the first analysis and the second trial test sample.

In this case, two of the nine cells are inactive in the lower part of the image. We did not mention the exact number of inactive cells, but the wording revealed that you should find more than one. The AI identified three inactive cells: A2, B3, and C2. The result can be seen in Figure 6 (a). This was the first incorrect solution of the learning process, and the generated image was not perfectly accurate either.

We corrected Scholar GPT directly, specifying that A2 and B3 were inactive. We have determined that, contrary to its assessment, cell C2 is functional, just as A1, A3, B1, B2, C1 and C3 are also functional. We instructed the AI to incorporate our corrections and regenerate the image. In the corrected answer, it identified only the two truly inactive cells and placed only two red squares on the regenerated image. We tried to draw its attention to the fact that the size and position of the red squares it used as markings were not perfect, but the generated image was still not perfect in Figure 6 (b).

Meanwhile, we came up with the idea that maybe the AI misinterprets the cell boundaries and can be misled by the busbars. However, in another text instruction, we asked for the resizing of the red squares (e.g. 1.2 times larger squares are needed), then the AI marked the inoperable cells with larger squares on the modified image, but the positioning of the red squares was not yet perfect in Figure 6 (c). In the following instruction, we marked the cell boundaries and the location of inactive cells on an edited image. We instructed the AI to divide the image into nine equal parts. Scholar GPT interpreted it as the latter image should be used and corrected this correctly when generating the image in Figure 6 (d).

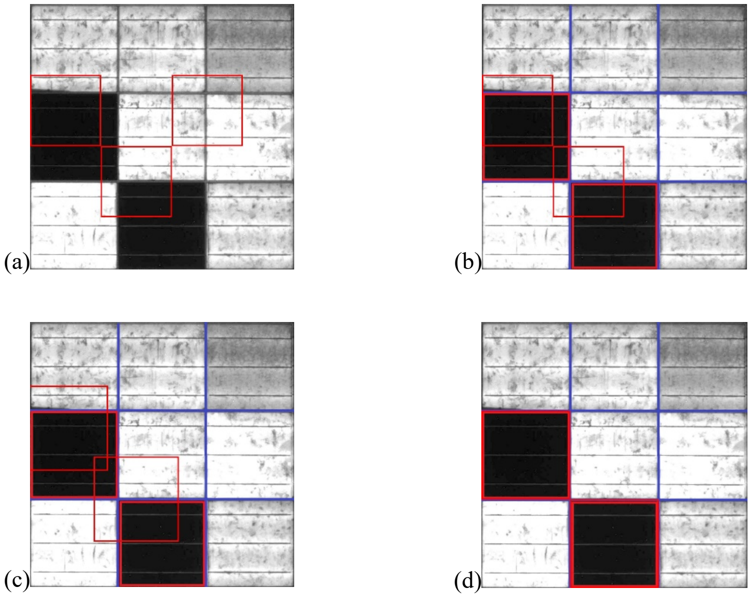


Figure 6
Correction of identification of inactive cells

The sample used for the second analysis also consists of nine cells but already contains three inactive cells. We did not specify the exact number of inactive cells, but the prompt implied that more than one should be found. The AI correctly identified three inactive cells by name: A1, B1 and C2. In this case, the solution to the problem is completely correct, the text answer is correct. On the other hand, the size and placement of the red squares in the generated image were not perfectly accurate this time either in Figure 7 (a).

As a solution, we defined a unit size, among the input instructions we specified how many units wide the entire image is and how many units wide a cell is. Thus, the AI received the information (a ratio) it needed to find its way around the images. After that, the AI placed the squares perfectly in Figure 7 (b).

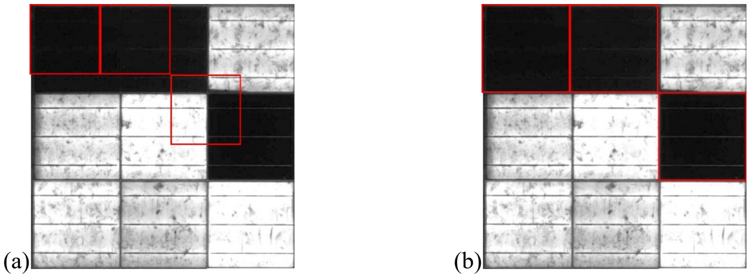


Figure 7
Results of the second sample for test analysis

This was followed by examination of the image of a larger panel consisting of 15 cells. In the panel of Figure 8, the PV cells are arranged in five columns (A to E) and three rows (1 to 3). The panel has four inactive cells, the locations of which are A1, B1, C2 and D3. ScholarGPT's task was once again to find and mark inactive cells. This time, when the image was generated, the placement and size of the red squares matched the dimensions of the cells. The AI correctly identified three of the four inactive cells but marked cell E1 as inactive instead of B1 in Figure 8 (a). Recognizing our previous mistake here, as we only showed the AI very clear error-free cells, we misled it. We created a colour scale showing that there is a wide range of brightness for a defect-free cell in Figure 8 (c). Furthermore, we explained again that we are looking for inactive cells that cannot emit photons and are completely black in colour. Understanding this, the AI generated the correct decipherment, which became accurate in every respect. The four inactive cells were correctly identified, the inactive cells A1, B1, C2 and D3 were marked on the generated image with appropriately sized and well-positioned squares in Figure 8 (b).

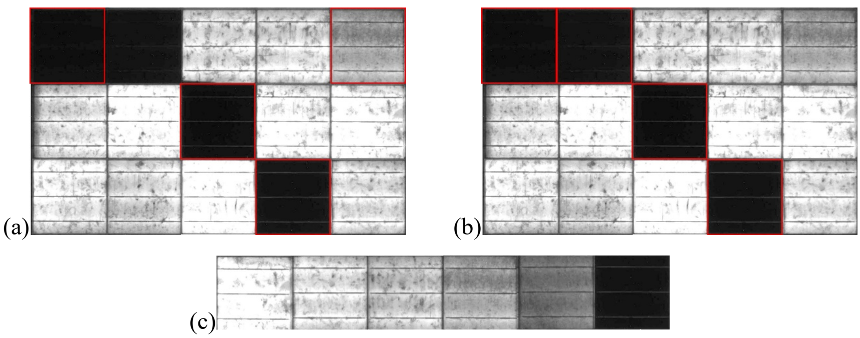


Figure 8
Results of the third sample for test analysis

4 The Last Test

In the final test, we showed Figure 2 to the AI again. The AI needed much more time to perform the analysis than for smaller images. The image of the largest panel consisted of 60 cells. In the panel of Figure 9, the PV cells are arranged in ten columns (A to J) and six rows (1 to 6). The panel has six inactive cells, the locations of which are A2, B2, C3, D4, I3 and J6. The percentage of correct answers was 50% (A2, B2 and J6), which number is higher than in Figure 2.

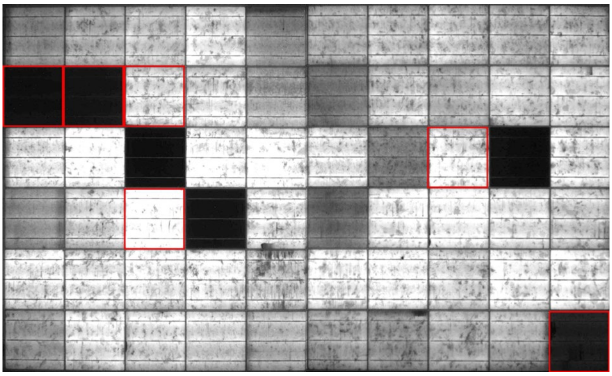


Figure 9
Result of the final test analysis

Finally, the AI received feedback on both correct and incorrect results. It generated a new image, which was still imperfect, although the AI correctly identified cell C3. In this case, the percentage of correct answers was 66.67%. The applicability of ChatGPT, including Scholar GPT, to the analysis of PV electroluminescence images was not continued. It can be said that ChatGPT has improved in EL damage identification.

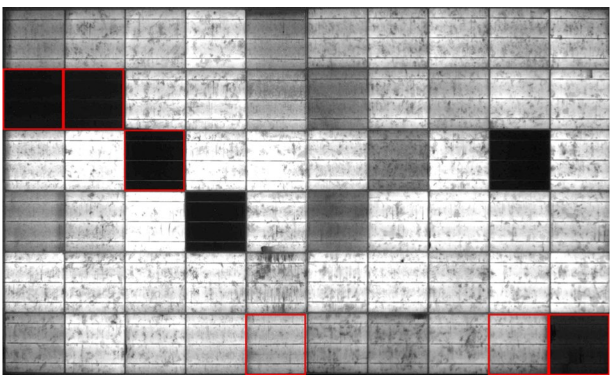


Figure 10
Result of the final test analysis after correction

Conclusions

The research started with the aim of testing whether ChatGPT could replace a human, when analysing PV electroluminescence images. At the beginning of the conversation initiated with AI, we were able to make sure that it has detailed information on the topic. However, ChatGPT was not primarily developed for the feeding of images, but rather, for conversation and communication. During the learning process, we tried to identify inactive cells. In the first image analysis, the AI's accuracy was only 16.7%.

After that, we initiated another conversation and started the teaching process. Initially with simpler tests, then with more complex analyses. The first trial tests went well when we showed the AI an image consisting of a total of 4 cells. When images consisting of larger 9 and 15 cells followed, it happened that the AI incorrectly identified cells, but this could be corrected. There were difficulties during the process, and it turned out to be very instructive for us as well, when we experienced how to communicate with AI. A good example is when it had to learn to interpret the cell boundaries. The experience gained in this field will be very useful if we want to continue this research in the future.

In the final test, when we showed the very first sample again (Figure 9), the Scholar GPT already achieved a better 50% result. After correction, this value increased to 66.7%, which is overall, a significant improvement compared to the first analysis (Figure 2). Future research could extend this work to include the detection of partially inactive cells (such as cracks, fractures, finger interruptions) exhibiting grey-to-black transitions (potential induced degradation), which could be highlighted with yellow markings on the generated images.

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